The Role of Caseworkers in the Labor Market Integration of Young Unemployed: Evidence from France*

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Abstract

In France, specific agencies called "missions locales" are dedicated to help young people who experience difficult school-to-work transitions. We propose to use the quasi-random assignment of caseworkers in selected agencies to evaluate how they can affect youths' professional trajectories. In terms of employment, we show that being assigned to a caseworker whose value added is one standard deviation above the average caseworker increases the number of days of employment by 14% within two years after the first meeting. In terms of training, the mean effect is 28%. In the end, we find that caseworkers are either specialized in employment or training but the more able ones direct their youths to specific vacancies and they keep contacts via emails, sms or phone calls.

Keywords: Youth unemployment, Caseworker assistance, Labor market policy
JEL codes: C39, J08, J68

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1 Introduction

The difficult school-to-work transition of young people is largely the result of problems between the demand for employment by firms - some of which are structurally constraints with major recruitment difficulties - and the supply of labor by young people who lack the necessary references to find jobs that suit them. Indeed, the lack of knowledge about companies and career prospects for young people with few qualifications, most often accentuated by a lack of a private network, is a major obstacle to access to employment (Kramarz and Skans, 2014).

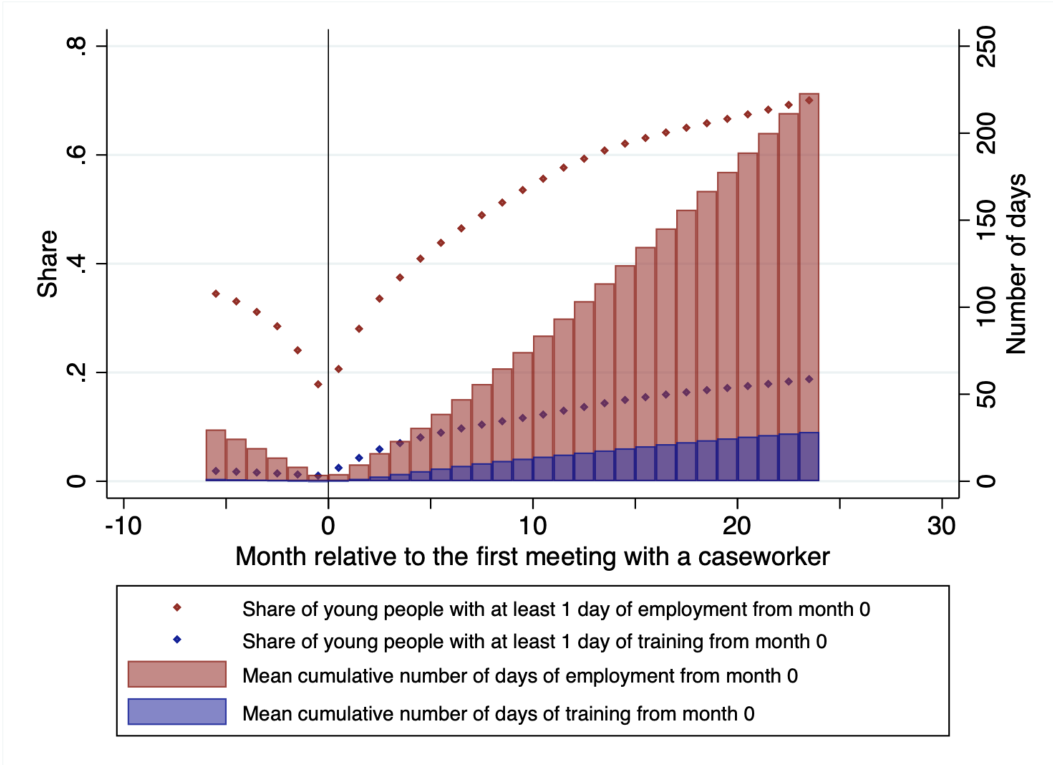
To help this population overcoming those difficulties that have been aggravated after the 2008 financial crisis, European countries adopted the Youth Guarantee (YG) scheme in 2013. Under this scheme, countries have to propose an adequate solution to each young individual who is not in employment, education or training (NEET) within the first four months after leaving school (Escudero and Mourelo, 2017). As a consequence, the supply of active labor market policies is key in the attempts to reduce the matching frictions between youths and firms. More financial and personnel means have been devoted to public agencies that serve as intermediaries between the two parties in the labor market.

Therefore, many young people can turn to public agencies that supply job search assistance to enter the labor market. In France, the majority of young NEETs turn to such agencies (Borel, 2022; Arnoult and Ghrairie, 2022). The main operator dedicated to youths is called "mission locale". There are about 439 main centers and 7,000 related agencies for a total of 10,000 workers spread across France. These centers target young people aged between 16- and 25-year-old who are out-of-school. Their main purpose is to provide labor market related assistance through meetings with caseworkers and group activities. They also provide assistance related to broader social issues like health, administrative, housing, and even penitential issues. About 1.1 million of young people are in contact with an agency every year and about 400,000 young people newly enroll every year.

Data indicate that young people go to these agencies when their labor market prospect is decreasing or very low as shown in Figure 1. After registering to an agency though, their labor market situation seems to improve as the cumulative number of days of employment or training is increasing, so as the share of young people. Because labor market related assistance is mainly provided by caseworkers at the individual level with one-to-one meetings, this paper asks to what extent do caseworkers matter for young people labor market integration?

Surprisingly, the academic literature investigating the role and the effectiveness of the assistance provided by these agencies is scarce. A randomized experiment led from 2011 to 2013 by Aeberhardt et al. (2014) has shown that a 2-year formalized job search assistance program increased the attendance of young people to individual meetings with their caseworkers. However, the employment rate of the treated group was the same than of the one of the control group (those without the contract) one- and two-years after they started assistance. Another

Figure 1: Labor market situation of young people registered in a youth agency



Note: Month 0 is the month of the first meeting with a caseworker that occurred between July 2017 and December 2018 in any "mission locale" agency in France.
Source: IMILO-FORCE (2021), N=622,057, authors' calculations.

recent study analyzed the progressive introduction of a job search assistance program across territories and months between 2014 and 2016 and suggests positive results about youths' employment outcomes. Young people enrolled in this program are expected to participate to more individual meetings and collective workshops during the first two months and are required to have employment situations (such as immersion, internship or temporary work) afterwards (Gaini et al., 2018; Filipucci, 2022). Considering the central role of caseworkers among the human resources providing public services, it is a crucial matter to analyze their influence in the labor market integration of young unemployed.

This is what we propose to do in this paper. We rely on the national information system of the French "missions locales" and administrative data on employment and training to analyze the effect of assistance by caseworkers on the labor market integration of youths. In particular, we take advantage of the data on Paris where the assignment of caseworkers to youths is quasi-random. Regular caseworkers rotate among themselves according to a schedule planed several weeks or months in advance to welcome youths coming at the agency for the first time. For agencies in Paris, the caseworker that youths meet during the first meeting becomes by default the caseworker that conducts and supervises the whole job search process.

We will refer to such caseworkers as *referee caseworkers*. We extend our sample to agencies within centers that are part in the top 50 regarding the number of first meetings to check the consistency of our results and still satisfying the econometric requirements to properly identify the effects of caseworkers.

Both quantitative and qualitative evidence indeed suggest an as-if random assignment between caseworkers and young people in Paris agencies. We find no particular pattern in the timing at which caseworkers do first meetings within an agency during a particular month or year. We then show that the characteristics of caseworkers are not correlated with the characteristics of young people, especially when we take into account the agency and the month of the first meeting. The same conclusion holds when considering our extended sample with agencies among the top 50. We have further information for Paris agencies which come from discussions with the board of directors of those agencies and a qualitative work. Informal discussions highlighted the process of first meeting allocations among caseworkers. They bargain among each other on the day they will do first meetings based on their agenda, the activity they have already planed, and the total number of young people they already assist. Even though some caseworkers may choose some particular days because they expect some particular youths, it is highly unlikely that they non-randomly sort with all the youths who come to an agency for the first time during they service. Descriptive statistics also show some differences across caseworkers' activity, especially on the number of digital contacts or on the employment and training situations of the newcomers that constitute their portfolio. All the evidence suggest that caseworkers do differ in the way they assist young people and that the quasi-random assignment allows us to highlight causal effects.

We measure the ability of caseworkers to put young people into jobs or training via their value added in terms of the total number of days of employment or the total number of days of training during a two-year period after registration and the first meeting. Conditional to the agency and month of the first meeting, we compute for each caseworker the average of the difference between the observed number of days of employment and the predicted number of days for all the young people in their respective portfolio. If all the caseworkers were of the same ability, we should find no difference in the averages of the difference between the observed and predicted situations of young people. Yet, we find that caseworkers have different value added and use this measure to identify the causal impact of caseworkers on youths' labor market outcomes.

As placebo tests, we first look at the effect of caseworkers before their assignment to young people and reassuringly find no significant impact on the number of days of employment or training of young people. After young people registered to an agency and assignment to a caseworker is settled, we find that being assigned to a caseworker whose value added is one standard deviation (sd) above the mean increases the total number of days of employment by 0.12 sd on average within the next two years. Depending on the specification, this effect represents an absolute increase of 28 days or a relative increase of 14%. In terms of training, we find that being assigned to a caseworker who is one sd above the mean (in the training value-added distribution) increases the total number of days of employment by 0.1 sd, which corresponds to an absolute increase of 9 days or a relative effect of 28%. Looking at the timing of the effect, more able caseworkers in terms of employment mostly help young people during the second year of assistance, while those who more able in terms of training mostly help youths during the first year. Additionally, these positive effects remain when looking at other employment and training outcomes such as the probability to be in employment at least one day per month, or the total number of hours of training in long-duration training. Results are similar when checking their robustness with our extended sample including agencies in the top 50 regarding the number of first meetings.

We also look at the potentially heterogeneous effects of caseworkers insofar they can vary according to the type of youth they receive. While we do find higher effects for females on training placement and for youths with Sub-Saharan African origin on employment situations, we have no explanation for these results yet. The effect of high training value-added caseworkers also seems mostly decreasing when the education level of youths is increasing, while caseworkers with higher employment value-added mostly help youths who already have a vocational degree. Turning to the underlying mechanisms, we find that caseworkers who are better at employment placement are not better at training placement, and vice-versa. More specifically, caseworkers who do better in employment do more employment propositions by directing youths to specific vacancies, while those who do better in training direct youths to specific training slots. These results are in line with the results of Glover (2021) who shows that caseworkers in French job centers are more effective when they direct job seekers to specific vacancies. We finally find that more able caseworkers, whether in terms of employment or training, have more numerous contacts with their youths via emails, sms or phone calls. These digital contacts seem crucial in explaining why caseworkers have different impact on youth professional trajectories. We explain this fact by the specific population they assist insofar young people who are NEET have severe lack of confidence and present behavioral biases that impend their labor market integration (Jellab, 1998; Babcock et al., 2012).

These results thus contribute to the literature on caseworkers(-like) effects. Although this methodology is primarily used in the economics of education to measure the impact of teachers on students outcomes (Rivkin et al., 2005; Chetty et al., 2014b; Gilraine and Pope, 2021) and in the economics of law to look at the effect of specific judges on sentences for individuals or on wage penalties for firms (Dobbie et al., 2018; Cahuc et al., 2020), it is recently used to evaluate the impact of caseworkers from job centers on the unemployment duration of job seekers. Schiprowski (2020) find that job seekers who have unexpectedly lost one meeting with caseworkers – who are in the upper-half value-added distribution – stayed unemployed by 12 additional days in Switzerland. The effect is then an increase in the unemployment spell by

≈5%. Buskjær Rasmussen (2021) finds that job seekers who are assigned to caseworkers who are one standard deviation above the mean have a shorter unemployment duration by around 1 week in Denmark, that corresponds to a treatment effect of ≈5%. Cederlöf et al. (2020) find a one standard deviation increase in the value-added of caseworkers increases the job finding rate of job seekers by ≈5-8% in Sweden. Very recently in France, Dromundo and Haramboure (2021) find that having caseworkers from job centers ("Pôle emploi") in Paris who are one standard deviation above the mean increases the probability of finding a job by ≈8.5%. In this paper, we find that caseworkers devoted to a population that face the most difficulty to enter in the labor market (young NEETs) help youths to enter either in employment (≈ +14%) or in training (≈ +28%). We also find that more able caseworkers direct their youths to specific vacancies related to where they are the more able, i.e. employment or training. Yet, whatever their specialization, more able caseworkers have significantly more contacts with their youths outside the walls of the agencies. In addition to direction to specific vacancies, it seems crucial for the caseworkers to keep in touch with this vulnerable population in order to a certain level of motivation and search effort.

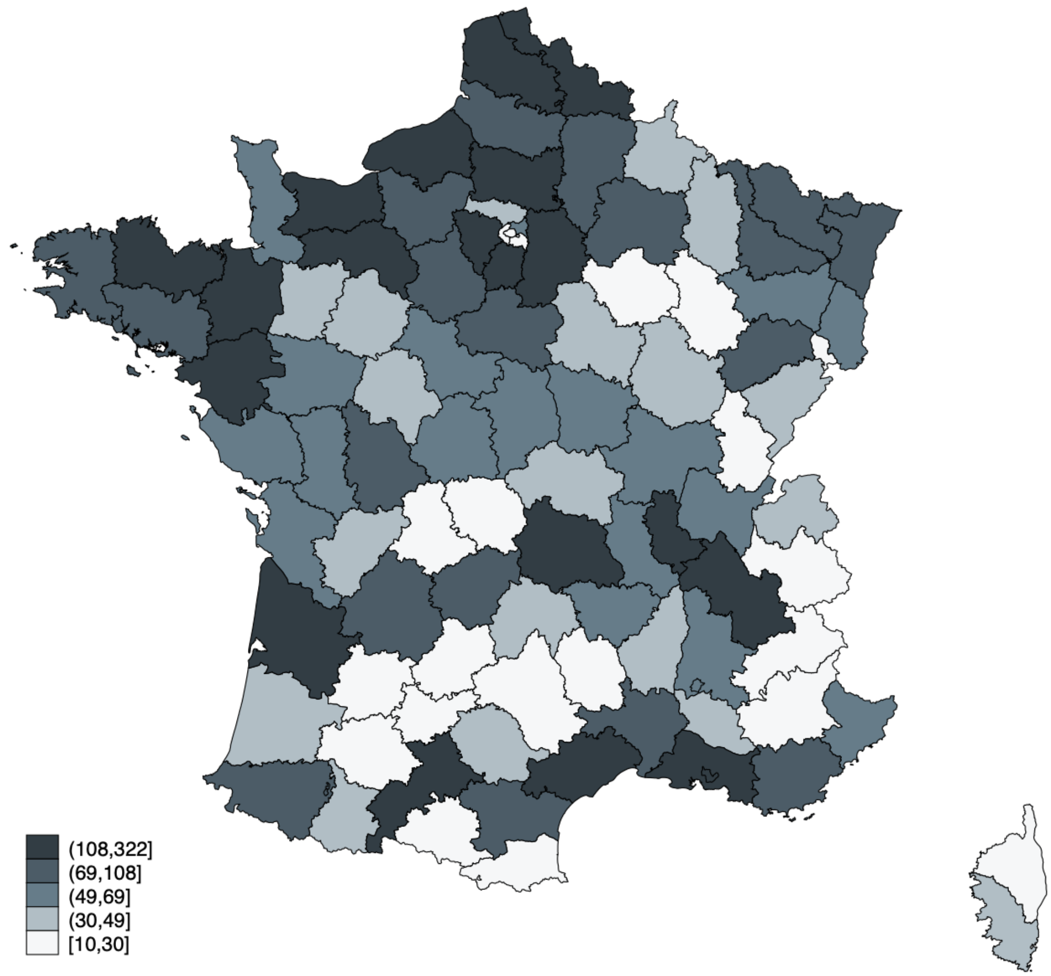
We also contribute to the literature on school-to-work transitions and active labor market policies by looking at the efficiency of job search assistance directly at the caseworker level. Although we have little information on how young people experience school-to-work transitions (Ryan, 2001; Bertschy et al., 2009; Kramarz and Skans, 2014; Doruk and Pastore, 2020; Comi et al., 2022) and quantitative policy evaluations indicate a low effectiveness of job search assistance programs for young people out of school (Caliendo and Schmidl, 2016; Kluve et al., 2019), we show that young people who face the most difficulties to enter in the labor market after school (with or without having graduated) can be assisted effectively by some caseworkers when they turn themselves to public agencies.

The rest of the paper is organized as follows. Section 2 presents the institutional background related to the "mission locale" agencies. Section 3 describes our data sources and the activity of young people and caseworkers in these agencies. Section 4 explains the methodology to construct unbiased caseworkers value added estimators. Section 5 shows the impact of caseworkers assistance on youth employment and training situations, and its heterogeneity. Section 6 breaks the underlying mechanisms down and describes what differentiates more able to less able caseworkers. Section 7 concludes.

2 Institutional background

The "*missions locales pour l'insertion professionnelle et sociale des jeunes*" are public centers created in 1982 to assist young people who seek for labor market related assistance. They have been part of the French public employment service since 2004. Young people can also go to these centers to find broader social assistance in terms of health, administration, housing,

Figure 2: Repartition of "*Missions Locales*" centers and agencies in Metropolitan France



Note: There are at least ten agencies that youths can join to enroll within each French *departement*.
Source: IMILO (extraction date: October 2021), authors' calculations.

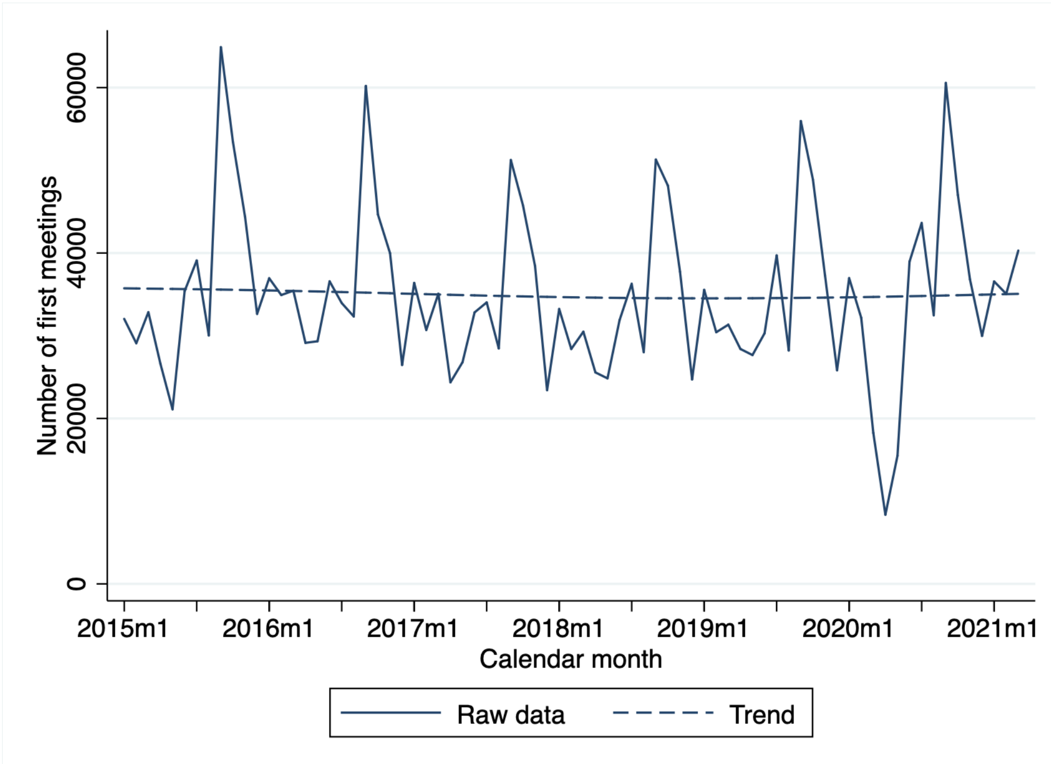
etc. The only conditions are that they must be between 16 and 25 years old and out of school.

France counts a total of 440 centers and 7,000 related agencies. The distribution of agencies is rather heterogeneous across the territory but there are at least ten agencies per department that youths can join to enroll as shown in Figure 2. In accordance, young people can reach an agency within a reasonable amount of time, especially if they are located in a city.

Several partnerships are made with other public institutions to inform and direct young people to these agencies. At the national level, the union of the "missions locales" network (UNML) has an agreement with the Ministry of the Army to detect young people who are out of school and direct them to the nearest agency. There have also agreements with the Ministry of Education so they send a list of school dropouts to a dedicated platform called PAIO.[1] In

[1] "*Permanences d'accueil, d'information et d'orientation.*"

Figure 3: Evolution of the number of monthly first meetings from 2015 to 2021



Note: Number of monthly first meetings in "*Missions locales*" agencies.
Source: IMILO (extraction date: October 2021), authors' calculations.

addition, agencies have an agreement with the Ministry of Labor such that young people who registered to job centers (*Pôle emploi*) are directed to the "missions locales" agencies if they have problems or constraints that go beyond the scope of finding a job (e.g. financing a driving license, finding an apartment, etc.). Otherwise, there is no homogeneous information campaign to attract young people. Indeed, the agencies act like a decentralized network and establish collaborations with other partners at the local level.

Figure 3 actually shows the number of young people who experienced their first meeting over time. Although raw data clearly indicate seasonality in the timing of the first meetings, with high peaks in September, the trend indicates a rather stable number of newcomers from January 2015 to January 2021. Every year, around 400,000 young people do their first meeting in an agency and more than 1,000,000 young people are in touch with a caseworker at least once.

The first meeting is rather important in the dynamic of youth activities within agencies because it allows the caseworker to gather information on youths' socio-demographic situations and on their requests regarding employment or social issues. Given the situation, caseworkers mostly help young people by assisting and guiding them towards employment and/or training opportunities. They meet young people via individual meetings and keep contacts via emails, sms, or phone calls. They can also animate collective workshops for specific programs, run information sessions on specific topics, and do administrative tasks like filling forms for financial assistance, reporting activity, etc[2].

In 2014, these agencies put in place a new paradigm with the introduction of a national program called "*Garantie jeunes*". Caseworkers were told to put emphasis on labor market integration. The main objective of the caseworkers was to put young people into employment as often as possible so they can experience different jobs and discover their interests in a more practical way. But it may be difficult for caseworkers to put youths with low qualification in employment, so they can also choose to direct them to training. Therefore, we aim at analyzing the effect of caseworkers on the labor market integration of young people in employment and training.

3 Data

We first present the data sources upon which we rely for the analysis. We then describe the sample restrictions we applied to construct our final sample. We finish by showing some descriptive evidence on youth and caseworker activities in agencies.

3.1 Data Sources

We rely on new and exhaustive administrative databases at the caseworker-youth level to carry the statistical and econometric analyses.

Our primary source of data corresponds to the centralized information system of the agencies (IMILO). It gives access to very detailed information about both youths and caseworkers. For youths, we have socio-demographic data including names, education attainment, address, or housing condition. This information system serves a management log for caseworkers. They are able to see the paths of the youths and direct them to whatever is proposed within the agency. Since caseworkers are required to fill information for agencies to receive public funding, we can construct a detailed record of their follow-up at the agency from the first meeting with a caseworker to their last contact. It includes various kind of interactions they had with caseworkers (meetings, participation to workshops, digital contacts...) as well as participation to specific programs offered at the agency. Concerning caseworkers, we have limited information on the socio-demographic characteristics including the gender, the date of birth, and the names. Nonetheless, we are able to build their entire activity in the agency.

[2] A minimum of two years of higher education is required to become a caseworker and they start with a gross wage around €2,000. They are expected to display good social skills related to availability, understanding, patience, dynamism, well-organization, showing initiative, etc.

Our second main source of data is an administrative database which gather information on the (un-)employment spells and entries in vocational training (FORCE). It allows us to complement the information we have on the youths with their previous and subsequent labor market outcomes relative to their enrollment at a public agency. This database covers the period from the first quarter of 2017 to the third quarter of 2020. We were able to merge this database with IMILO on the personal records of young people. Additional to the activity of young people in youth agencies, we have all the labor contracts they have signed in that period, including the dates, type and occupation, and the period of training including the dates, type and qualification level.[3]

We finally rely on the NAMSOR API[4] which allows to classify personal names by country of origin or ethnicity. Thus, we have been able to categorize all youths and caseworkers by country of origin. We then constructed a dummy variable indicating whether the individual belongs to the Northern-African or Sub-Saharan African region and are thus defined as member of the *ethnic minority* group. This information lets us dive into potential sorting between youths and caseworkers but also into heterogeneous effects since this population suffers significant discrimination in France (Duguet et al., 2010).

3.2 Final sample

We are able to follow the activity of young people both in public agencies and in the labor market by merging the administrative data together.[5] Nevertheless, we had to apply some restrictions on the youth labor market situation before and after the entry in agencies and on regular caseworkers who assist youths to employment.

First, we consider the Paris center and its agencies insofar the assignment mechanism between youths and caseworkers is *as-if* random. We develop this point in the following Section 4 and consider an extended sample to check the robustness of our results. Figure A.1 in Appendix A shows the ranking of centers according to the number of first meetings done between January 2017 and December 2018. We keep centers in mainland France that have done more than 3,000 first meetings over this period.

Second, we keep observations without missing values in socio-demographic and labor market characteristics. We also get rid of young people who did not a regular one-to-one first meeting with a caseworker when entering into an agency for the first time. The latter condition is to ensure the quasi-randomness of assignment of caseworkers to youths.[6]

[3] Note that this database only include professional experiences in the private sector, leaving out public sector and self-employment experiences. While the former should represent a very low share of youths, the latter could be more detrimental since the development of digital-related activities (ILO, 2020).

[4] https://namsor.app.

[5] The Ministry of Labor (DARES) created a list of merged id from both IMILO and FORCE based on civil state information including the name, gender, date of birth, and place of birth.

[6] 92% of young people registered in an agency for the first time via an individual meeting, 7% do it via a

Third, we apply additional restrictions to ensure econometric feasibility. Among the set of restrictions, we restrict the sample of young people who registered in a "mission locale" agency between January 2017 and December 2018.[7] We drop agency $\times$ month cells with less than four youths, two caseworkers, and two youths per caseworkers so each cell has a minimum of four observations (2 youths $\times$ 2 caseworkers). Finally, we consider caseworkers who did first meetings for at least one month per quarter over the two years period. This latter condition ensures that caseworkers are present during the entire period that is used to compute our value added estimators.

Table B.1 in Appendix B list all the restrictions we applied and the related number of observations. We end up with 6,906 youths and 36 caseworkers in our main sample for Paris, and more than 43,000 youths and 302 caseworkers in our extended sample.

3.3 Descriptive evidence

We now describe our population of youths and caseworkers with respect to the entire population in those selected agencies and in all the agencies in France.

3.3.1 Youths' characteristics and activity

Table B.2 in Appendix B summarizes youth characteristics both in the full samples and in our analysis samples. Globally, there are almost no difference in youths characteristics between the analysis samples and their respective complete samples, both for Paris and the extended one. We clearly see that youths in our extended samples have socio-demographic characteristics that are closer to those in the full sample including all the 808,222 youths registered between 2017 and 2018 than youths in Paris. In our main sample, including only agencies located in Paris, we have more males, more school dropouts, less youths with a driving license, more youths who have a foreign nationality or an African ethnicity, and finally less youths who rent their own shelter most likely explained by the higher price of renting in Paris.

In terms of labor market situations, young people have a limited experience before they register to an agency and did a first meeting with a caseworker. Table 1 shows that youths have worked between 15 and 25 days on average during the 6-month period preceding registration. This decreases to 1 day only regarding training situation. Yet, those figures have increased during the 24-month period succeeding registration. While the time span after registration is longer than before, the number of days of employment increases steadily so it was about 50

specific collective information session, and 1% via a collective workshop.

[7] For the econometric analysis, we consider only youths who registered between July 2017 and December 2018 so we can follow young people in the labor market six months before and twenty-four months after the first meeting with a caseworker. We extend the analysis sample to January 2017 only to compute our caseworker fixed effects with higher precision.

Table 1: Summary statistics on youth activity and labor market situation

	All sample	Paris sample		Extended sample	
		Full	Analysis	Full	Analysis
	(1)	(2)	(3)	(4)	(5)
Before joining agency (6-month period)					
Number of days of employment	26.96	24.16	14.08	25.13	16.70
	(53.36)	(52.32)	(36.93)	(51.65)	(39.11)
Number of days of training	1.13	1.24	0.71	1.25	0.84
	(11.13)	(12.21)	(8.74)	(11.78)	(9.34)
Number of days of open unemployment	30.12	17.71	19.17	30.23	28.36
	(54.93)	(44.27)	(45.65)	(54.95)	(53.62)
After joining agency (24-month period)					
Number of days of employment	217.96	210.50	202.08	212.10	210.60
	(239.67)	(243.43)	(226.12)	(237.62)	(225.21)
Number of days of training	26.93	28.00	32.07	28.24	30.59
	(76.65)	(81.33)	(85.82)	(77.81)	(80.77)
Number of days of open unemployment	210.31	117.97	126.71	209.41	200.81
	(236.08)	(189.16)	(190.64)	(235.19)	(226.49)
Number of individual meetings	7.96	4.70	4.91	7.77	7.68
	(9.03)	(4.76)	(4.86)	(8.89)	(9.02)
Number of collective workshops	3.91	2.57	2.90	3.64	3.45
	(9.79)	(6.52)	(6.97)	(9.52)	(9.06)
Number of information sessions	0.47	0.21	0.24	0.44	0.37
	(1.69)	(0.64)	(0.67)	(1.54)	(1.77)
Number of contacts with the caseworker	15.64	14.01	14.97	16.21	14.13
	(23.32)	(19.81)	(20.19)	(22.63)	(19.81)
Enrolled in a national program	0.71	0.56	0.58	0.71	0.74
	(0.45)	(0.50)	(0.49)	(0.45)	(0.44)
Enrolled in a specific program	0.81	0.69	0.71	0.80	0.82
	(0.40)	(0.46)	(0.45)	(0.40)	(0.39)
N	808,222	17,832	6,906	242,236	43,166

Note: Paris and extended samples are described in Section 3.2.
Source: IMILO (extraction date: October 2021) and FORCE, authors' calculations.

days on average 6-month after registration, to climb up to around 210 days on average after 24-month.

During this 2-year period, youths who remain in the agencies did on average 5 to 7 individual meetings with a caseworker,[8] participate to 3 collective workshops, less than 1 information sessions, and have 15 digital contacts with their caseworker. Figure A.2 in Appendix A on the share of youth with at least one event complements the picture. The share of youths who had at least one individual meeting during a month decreases rapidly to 20% two months after the first meeting and this share stabilizes at 10% after six months. Since their is no requirement in terms of meetings with a caseworker, especially for youths who are not registered in a specific

[8]Figure A.4 in Appendix A shows that when young people have between 5 and 7 meetings with a caseworker, more than 60% of them were with the referee caseworker, i.e. the one who did the first meeting.

program,[9] agencies consider youths who have at least one digital contact with their referee caseworker during the last six months as "active".

Using this indicator to analyze the survival of youths in agencies, Figure A.3 in Appendix A shows that 75% of the youths are still active in their agency one year after they did their first meeting, and this share decreases to 25% after two years. Complementary statistics show that youth who are still active after two years have accumulated less experience in the labor market that those who exited previously.

Finally, Figure A.5 in Appendix A shows the number and type of requests made by youths according to the number of months relative to the first meeting. Young people request mostly about employment-related situation such that they want information on specific jobs or training contents. In accordance, caseworkers make a similar number of employment-related propositions, around 1.5 during the first two months, and less than one afterward.

3.3.2 Caseworkers' characteristics and activity

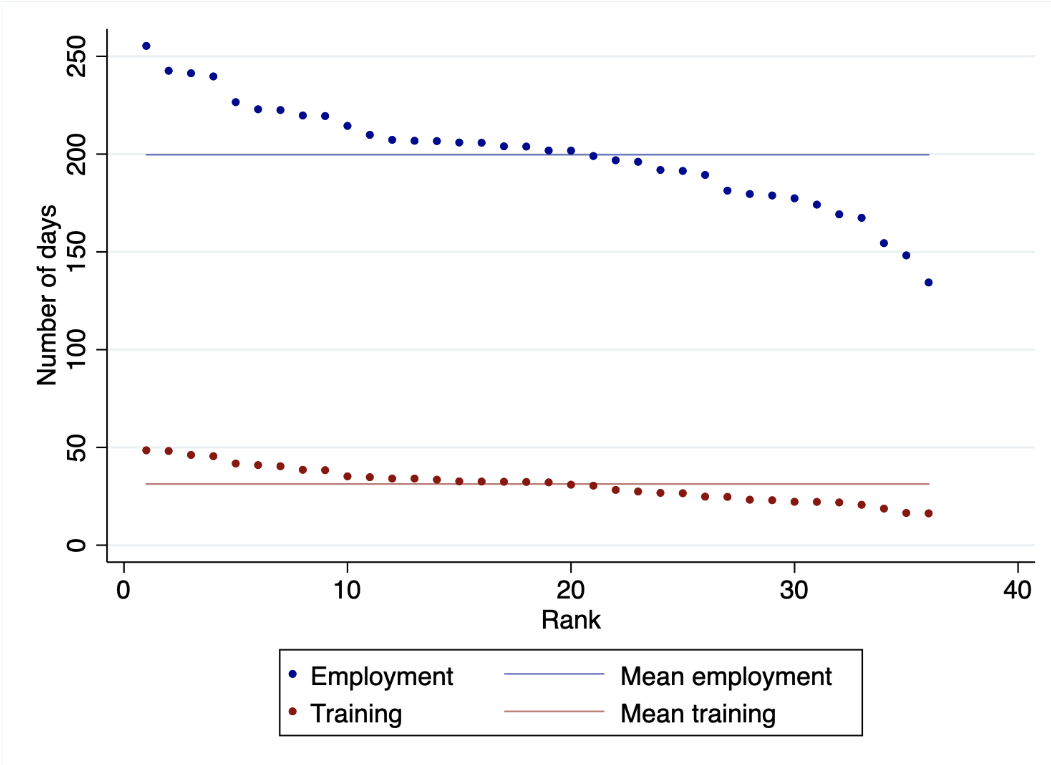
Turning to caseworkers now, we find less differences in the few socio-demographic characteristics we have between our samples as shown by Table B.3 in Appendix B. Between 70% and 80% of caseworkers are female and they are aged around 45-year old on average when they first met youths. The only difference we see is that caseworkers have more often an African origin in Paris agencies, around 20%, in comparison with caseworkers in the rest of France, around 10%.

In terms of activity, caseworkers in our analysis samples have around 150 youths in their portfolio, which is 50% higher than the caseload of caseworkers when looking at the full samples. We explain this difference by the restrictions we apply to construct our analysis samples. Indeed, we keep only caseworkers who are present at least a month during each quarter between January 2017 and December 2018. This condition ensures that we analyze the effect of caseworkers that assist young people to enter in the labor market. As caseworkers in those public agencies can also help youths according to other social-related issues, the latter do not supervise the entire paths of youths within the agencies but help them on specific matters instead. Focusing on labor market related caseworkers, Figure A.7 in Appendix A shows how the caseload per caseworker, split in tercile, is evolving during the period. Although there few variations over time, the main difference lies in the size of the caseload across caseworkers. Those in the first tercile have an average of 100 youths while those in the third tercile have an average of 200 youths.

Figure A.8 in Appendix A on the number of meetings per caseworker and Figure A.9 in Appendix A on the number of contacts per caseworker add elements to the story. The activity of caseworkers in terms of individual meetings shows that caseworkers in the third tercile do

[9] Figure A.6 in Appendix A shows that up to 1/3 of the young people do not register to any specific program during the two-year period.

Figure 4: Ranking of caseworkers (Paris sample)



Note: Caseworkers are ranked according to the average employment (in blue) and training (in red) situation of the youths who constitute their caseload 24 months after the first meeting.

twice as much as the caseworkers in the first tercile, for an average of 80 meetings per month versus 40. The discrepancy is even larger regarding digital contacts between caseworkers and youths. Caseworkers in the first tercile have between 100 and 200 digital contacts (emails, sms or phone calls) per month with their youths during a year, while those in the first and second tercile have less than 10 and 25 contacts per month respectively.

Actually, Adjeoda (2021) finds that caseworkers in Paris agencies differ according to their own style but not according to the youths they receive. She assisted to 45 first meetings led by 12 caseworkers from October 2020 to February 2021 that she classified via a PCA-like analysis. She finds that some caseworkers adopt a didactic approach and try to put the youth into action (write a proper resume, look for job vacancies...), while on the opposite others focus much on the administrative tasks that must be filled and do not ask youths to prepare something for the second meeting.

Those differences across caseworkers may have an impact on the labor market integration of young people. Figure 4 shows the ranking of caseworkers given the employment or training situations of young people 24-month after they did their first meeting between 2017 and 2018. In terms of employment, we see that the caseworker who is ranked first has youths who have worked around 250 days on average while the caseworker who is ranked last has youths who have worked less than 150 days on average. The difference is lower in terms of training but goes from 50 days to 25 days on average. We show in the next section that these differences are mostly attributable to caseworkers rather than youth characteristics since caseworkers are assigned to youths on an as-if random process.

4 Empirical strategy

We first provide evidence supporting our identifying assumption that there is no systematic sorting between youths and caseworkers within agencies and time period (e.g. month). We then present our methodology to estimate caseworkers value added.

4.1 Exogeneity of caseworkers assignment

For the main agencies in France, we had direct background information indicating that there is no specific rule that would make certain caseworkers more likely to be assigned to certain youths based on their respective characteristics. Young people seeking help from these agencies must come in person at one of the agencies. On the day the youths come, they meet with one of the caseworker who has been assigned to that day to welcome new youths. Indeed, caseworkers are assigned to calendar days rather than to youth directly, on a rotation basis planned several weeks in advance. The timing of caseworker assignments is primarily based on the caseworker's workload at the time they decide. It is important to note that the caseworker automatically becomes the youth's primary supervisor and contact for the remainder of the youth's follow-up.

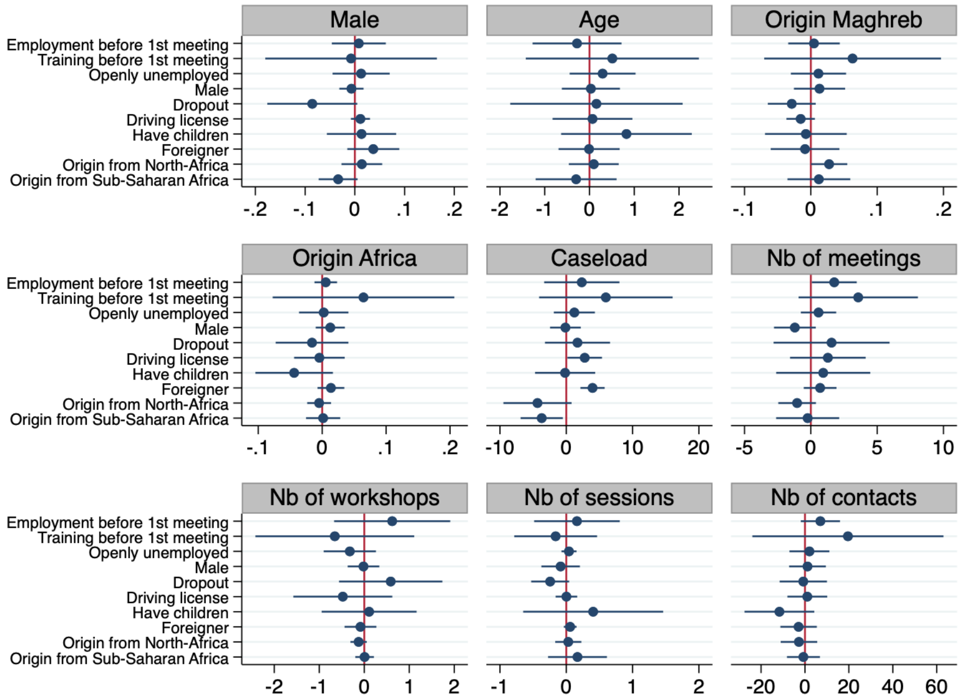
In Paris, between 2 and 4 different caseworkers are present each day to do the first meetings from Monday morning to Friday afternoon, excluding Thursday morning because of team meetings.[10] Table B.5 and Table B.6 in Appendix B shows the correlations between day of the week and youth and caseworker characteristics respectively. We see first very few sorting between the day of the week and some youth characteristics. For instance, young people who have more previous employment experience come more often on Thursdays and less often on Fridays than youths who have less employment experience. Turning to caseworkers, we see for instance that male caseworkers do more first meetings on Fridays and less first meetings on Wednesdays and Thursdays than female caseworkers.[11]

However, caseworkers assignment is expected to be exogenous from youths characteristics within a given agency and time cell. Within agencies, on the one hand, because caseworkers

[10] Figure A.10 in Appendix A indeed shows that there are less first meeting performed during Thursdays in Paris agencies.

[11] Table C.1 and Table C.2 in Appendix C shows also some sorting between youth' and caseworker' characteristics and the day of the first meeting for the extended sample.

Figure 5: Correlation between youths' and caseworkers' characteristics (Paris sample)



Note: Each square shows the estimates from an OLS regression of a specific caseworker characteristics on all its youths' characteristics.

are typically assigned to only one agency over the period (at least in terms of first meetings) and because youth characteristics are not distributed evenly across agencies. Within time cells, on the other hand, because caseworkers differ in their distribution of assignments over time, so does the distribution of youth characteristics.

Based on these elements, our identifying assumption is that caseworkers assignment is quasi-random conditional on agency and time period. To check the credibility of this claim, we first propose to examine the correlation between the characteristics of youths and the characteristics of their assigned caseworker for the agencies of Paris. In each panel, Figure 5 presents the estimated coefficients from OLS regression of a given caseworker characteristic on youths' characteristics. Youth characteristics include socio-demographics listed in Table B.2 in Appendix B and pre-determined labor market characteristics. For caseworkers characteristics, we have gender, age and ethnic background suggested by personal names as well as variables related to their activity and experience at the agency. Overall, the evidence for Paris displays a large proportion of very small and insignificant coefficients, suggesting that there is no systematic sorting between caseworkers and youths.

The same conclusions holds when considering the extended sample as shown by Figure

C.2 in Appendix C. Although we do not have direct information on the assignment rules in these other agencies, we take this as suggestive evidence that our working hypothesis of quasi random assignment of caseworkers within agencies and time cells is credible not only for the Paris agencies but also for the others.

As a second check for our identifying assumption we propose a placebo test of the relation between caseworkers value added and pre-determined (i.e. before the first meeting with the assigned caseworker) labor market outcomes. If our caseworkers value added are somehow capturing unobserved heterogeneity in youths' potential outcomes - instead of the causal impact of caseworkers only-, then caseworkers value added should be also correlated with pre-determined labor market outcomes of youths. On the contrary, if caseworkers value added do not correlate with pre-determined labor market outcomes of youths, it will be consistent with the hypothesis that they are exogenous from youth's potential outcomes. As shown in section 5 below, placebo tests do not detect any significant relationship between pre-determined labor market outcomes and our caseworker value added.

4.2 Caseworkers value added

Relying on the quasi-random allocation of caseworkers to youths conditional on agency and month, we construct caseworkers *valued added* measures to identify the causal impact of individual caseworkers on youths' labor market outcomes.

Let's first consider a reduced form model of the outcome Y_i of youth i at the time $t+s$ after the first meeting in month t:

$$Y_{i,t+s} = \beta X_i + \gamma_{a\times t} + \epsilon_{i,t+s} \tag{1}$$

X_i is a vector of pre-determined youth characteristics, $\gamma_{a\times t}$ denotes fully interacted agency and month fixed effects and $\epsilon_{i,t+s}$ is the residual representing unobservable factors.

We can decompose the residual as follows:

$$\epsilon_{i,t+s} = \mu_{j,t} + \nu_{i,t+s} \tag{2}$$

where $\mu_{j,t}$ is the caseworker j assigned to the youth i component and $\nu_{i,t+s}$ is an idiosyncratic youth-level variation.

One may further decompose the caseworker component $\mu_{j,t}$ as:

$$\mu_{j,t} = \mu_j + \phi_{j,t} \tag{3}$$

where μ_j is the constant caseworker effect and $\phi_{j,t}$ captures random fluctuations in caseworker effectiveness. The caseworker effect μ_j may be interpreted as the quality or value-added of the caseworker, since it captures the caseworker's individual impact on the labor market outcome of the youth Y_i.

The identifying assumption is that youths assigned to caseworkers, conditional on $\gamma_{a\times t}$, have similar potential labor market outcomes. We thus use 2 broad labor market outcomes to measure caseworkers' value-added: i) The cumulative number of days of employment during a 24-month period, and ii) the cumulative number of training of employment during a 24-month period. Given the assumption and the outcomes, we can estimates μ_j from OLS regressions such that:

$$\hat{Y}_i = Y_i - \hat{\beta}X_i - \hat{\gamma}_{a\times t} \tag{4}$$

and we then define caseworkers fixed effects as

$$\bar{\mu_j} = \frac{1}{n_j}\sum_{i\in I_j}\hat{Y}_i \tag{5}$$

However, even unbiased, $\bar{\mu_j}$ estimates will contain considerable noise as they are based on a finite - potentially low in our case - number of observations. It means that the variance of $\bar{\mu_j}$ estimates will be an upward biased measure of the true variance of caseworkers effects. To address this issue, we follow the literature on teacher value added (Jackson, 2018; Kraft, 2019), as well as the papers on caseworker fixed effects (Mulhern, 2020; Buskjær Rasmussen, 2021). We adopt a model based approach to directly estimate the variance of counselor effectiveness. Then, we use these variance estimates to construct empirical Bayes estimates which shrink the estimates towards the mean (of zero since we standardized everything) based on their reliability.

We consider a mixed effects model where where caseworkers effects are considered as random, which allows us to directly estimate their variance. To distinguish between the time-consistent dimension of caseworkers effects, μ_j, and their fluctuations over time, we also include $\phi_{j,t}$ – nested within caseworkers – to capture monthly random shocks in caseworker effect such as unplanned absence for instance.

$$Y_i = \beta X_i + \mu_j + \phi_{jt} + \gamma_{a\times t} + \epsilon_i \tag{6}$$

This model is estimated by restricted maximum likelihood. Under the assumption of joint normality, it gives consistent estimates for the variance of caseworkers effects $\hat{\sigma}_\mu$, $\hat{\sigma}_\phi$ and youth level disturbance $\hat{\sigma}_\epsilon$. We can then define our empirical Bayes estimates as:

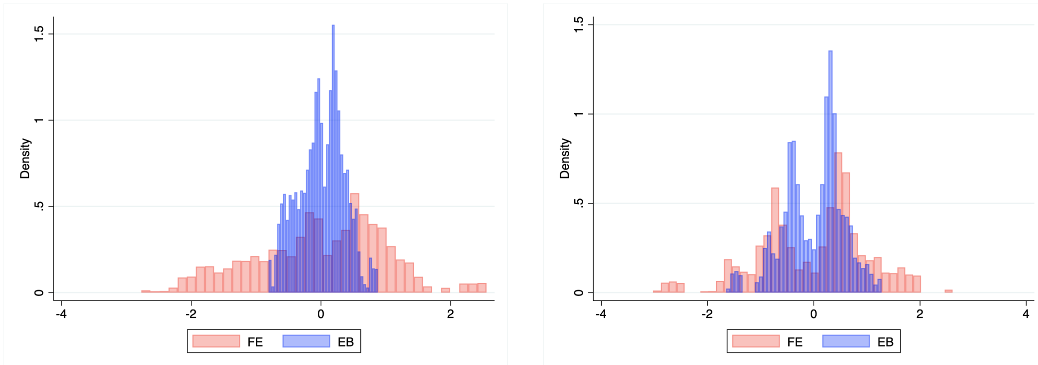
$$\hat{\mu_j}^{EB} = \bar{\mu_j} \times \frac{\hat{\sigma}^2_\mu}{\hat{\sigma}^2_\mu + (\sum_t 1/(\hat{\sigma}^2_\phi + \frac{\hat{\sigma}^2_\epsilon}{n_{jt}}))^{-1}} \tag{7}$$

where $\bar{\mu_j}$ corresponds to the caseworker j mean of youths outcome residuals as defined in equation (5).

Figure 6: Distribution of Empirical Bayes vs. Fixed Effects estimates (Paris sample)

(a) Employment

(b) Training



Note: Note: The EB estimates are obtained with equation (X) and FE estimates are also obtained with this equation but without the shrinkage factor λ_j defined in equation (Y).

Finally, to obtain our caseworkers valued added measures we compute leave-out empirical Bayes estimates by replacing $\bar{\mu}_j$ in equation (7) by $\bar{\mu}_{j,-t}$. Indeed, to avoid mechanical endogeneity, the estimate of caseworker value added should not be based on the youth whose outcome we are trying to predict. Our estimate of caseworkers value added are thus defined as:

$$\tilde{\mu}^{EB}_{j,-t} = \bar{\mu}_{j,-t}.\lambda_j \tag{8}$$

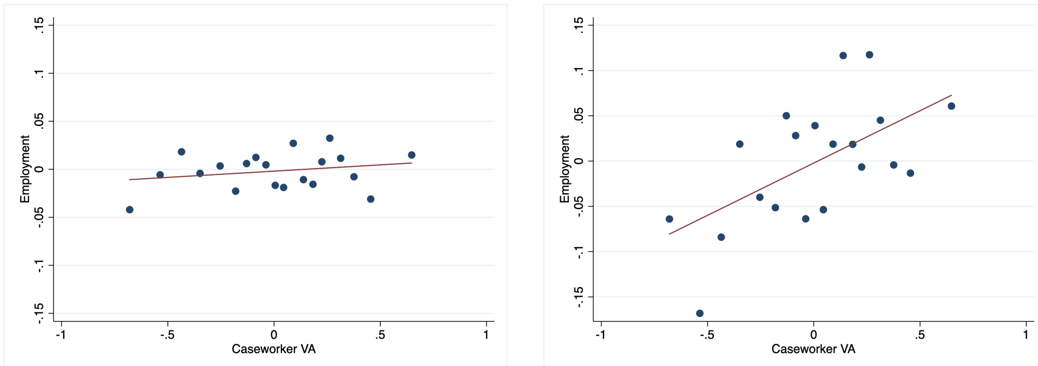
where λ_j is the shrinkage factor defined in equation (7).

Compared to fixed effects estimates, empirical Bayes estimates are shrank toward 0 as much as (i) the number of observations for caseworker j is small, (ii) the month-to-month fluctuations in caseworker effect are high, or (iii) the youth-level error is high. Figure 6 shows the respective distributions of fixed effects vs. empirical Bayes caseworkers estimates. As expected, the distribution of fixed effects estimates is much wider than the one of empirical Bayes estimates, which suggests that there is considerable noise in fixed effects estimates of caseworkers effect.

As a last check for our value-added (VA) estimators, we look at the correlation between those and youth fixed characteristics. While those characteristics should be related to the outcome, they should not be correlated with our VA estimators insofar i) they are used in the regression determining the caseworker fixed effects, and ii) caseworkers value-added should be independent of youth characteristics given the quasi-random assignment process. This is what we actually find as shown in Table B.7 and B.8 in Appendix B for both outcomes.

Figure 7: Effects of caseworker VA on predicted and observed employment (Paris sample)

(a) Predicted outcome (b) Observed outcome



Note: The figures show binscatters of caseworker value-added and youth predicted and actual outcomes. The figure on the left shows youths' predicted outcomes based on the cumulative number of days of employment 6 months before the first meeting. The figure on the right shows youth observed outcomes (cumulative number of days of employment within the 24 months after the first meeting).

5 Caseworkers effects

In this section, we first present our results regarding the causal effect of caseworkers on youths subsequent labor market outcomes: to what extent do caseworkers matter for the labor market integration of young unemployed? Then, we analyze the heterogeneity of these effects: do caseworkers assistance is more beneficial for some youths than others?[12]

5.1 On employment

We begin with the main tests described in Chetty et al. (2014a) for examining forecast bias and predictive validity of our caseworker VA estimators. For the forecast bias, we use the cumulative number of days of employment during the six-month period prior to agency registration as a proxy to predict the main outcome (the cumulative number of days of employment during the 2-year period after registration). Then we regress this predicted outcome on caseworker value-added. This forecast bias test provides an estimate of the proportion of variation in value-added that comes from sorting on unobserved characteristics. Figure 7a shows that caseworker value-added is not significantly related to the prediction of the main outcome, indicating that selection bias within agencies is not a significant issue. As pointed out by Mulhern (2020), "*this is also consistent with the large literature on teachers suggesting*

[12] All the results are replicated for the extended sample and shown in Appendix C. They are qualitatively similar to those obtained for Paris agencies but with smaller magnitude and moire noise, mostly because the sample should include some agencies for which the assignment between caseworkers and youths is not random. For precaution, we thus let these results in appendix but use them as robustness checks for our main results.

Table 2: Caseworkers impact on youth employment (Paris sample)

Employment (std)	Before 1st meeting		After 1st meeting			
	(1)	(2)	(3)	(4)	(5)	(6)
Caseworker VA (std)	0.0496	0.0210	0.1050**	0.1300**	0.0938**	0.1253**
	(0.0363)	(0.0355)	(0.0409)	(0.0519)	(0.0397)	(0.0514)
Employment before 1st meeting (std)					0.2267***	0.2235***
					(0.0162)	(0.0164)
Outcome mean	14.1	14.1	202.1	202.1	202.1	202.1
Outcome standard deviation	36.9	36.9	226.1	226.1	226.1	226.1
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Agency x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
95% Winsorization of VA	No	Yes	No	Yes	No	Yes
R-squared	0.0862	0.0879	0.0648	0.0681	0.1121	0.1142
Observations	5,358	5,106	5,358	5,106	5,358	5,106

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the caseworker level. Caseworker VA is computed on the number of days of employment 24 months after the first meeting according to equation (8). Individual characteristics include all the characteristics listed in Table B.2 in Appendix B.

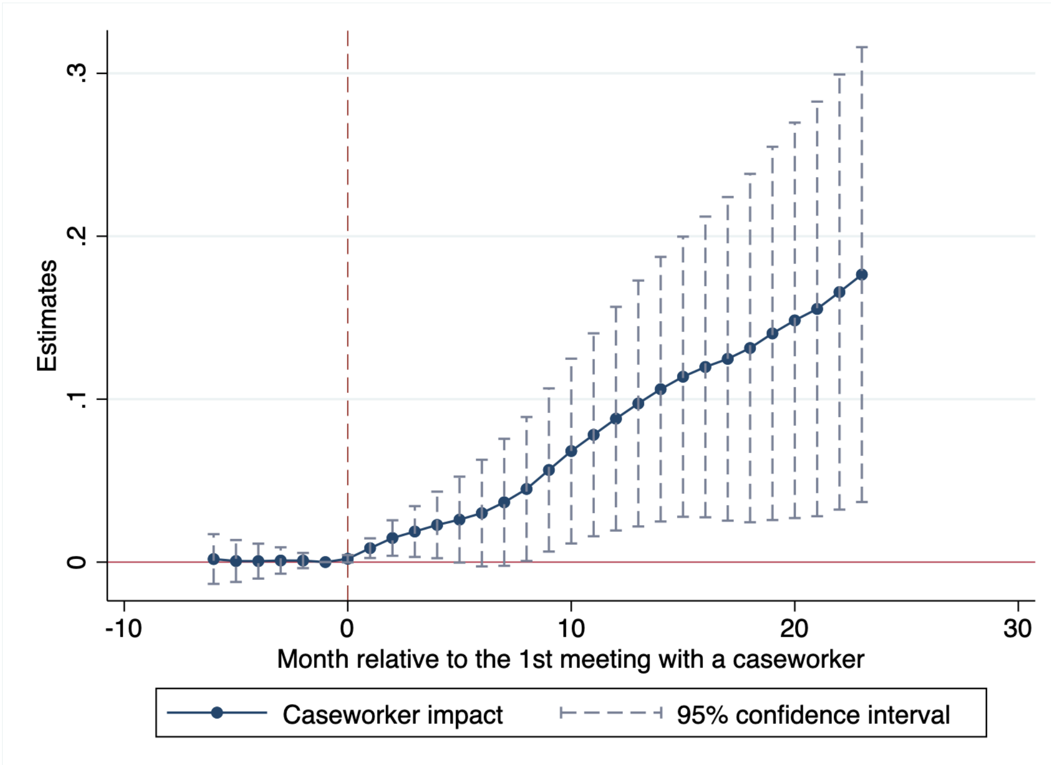
that the selection on observables assumption is sufficient for computing unbiased estimates of teacher value-added".

On the contrary, Figure 7b shows a clear and positive correlation between caseworker value-added and the observed employment after registration. To quantify the effect of caseworkers, we regress the employment outcome of youths on caseworker value added and agency × month fixed effects. To ease interpretation, caseworker valued added are standardized such that we are capturing the causal effect of a caseworker that is predicted to be one standard deviation above average. Table 2 presents our results regarding the cumulative number of days of employment which is our main outcome for employment.

Similar to the forecast bias, we directly perform placebo tests by considering the number of days worked before the first meeting with the assigned caseworker. Indeed, ex-ante labor market outcomes should not be related to caseworkers VA if our identifying assumption is valid. We find that caseworker VA estimates are both small in magnitude and statistically insignificant. After the first meeting, we find that being assigned to a caseworker whose valued added is one standard deviation above average leads to a sizable increase in the total number of days of employment within the two-year period. The magnitude of the effect is between .10 and .13 standard deviation (sd). In line with the placebo tests, introducing the ex-ante employment outcome has only a moderate effect on caseworkers' VA estimates, although it is highly correlated with ex-post outcome as we could expect. The results are robust to a 95% winsorization of the sample based on caseworkers VA. Taking the estimate of column (6) from Table 2, which is our preferred specification, and given the mean and standard deviation of the outcome, this corresponds to an average treatment effect on the treated (ATT) of approximately 14%.

To study the timing of this effect, we show how the effect of being assigned to a caseworker who is one standard deviation above average evolves over time in Figure 8 for Paris agencies. We first see that caseworkers have again no impact in the period before the first meeting,

Figure 8: Effect on the cumulative number of days of employment over time



Note: Month 0 corresponds to the month of the first meeting.

which is reassuring since they have supposedly not met, nor been sorted, with the youths. After registration and assignment though, we see that caseworker, who are one standard deviation above average, have a moderate impact during the first year of assistance, which is barely significant at the 95% confidence level. This effect steadily increases up to the end of the second year of assistance and reaches 0.18 sd, which corresponds to an ATT of 20%.

We now consider alternative outcomes to evaluate the effect of caseworker value added on the employment situations of youths. More specifically during the 24-month period after registration, we look at the impact of caseworkers on the probability to be in employment at least one day, the probability to be in employment at least one day per month, the number of days of employment per month, the cumulative number of days of employment in stable jobs (including permanent contract and temporary contract lasting more than six months), and the cumulative number of days of employment in permanent jobs only. Table 3 indicates the results from regressions similar to column (6) of Table 2. Results are summarized in Table 3. We find that the effect of caseworkers who are one standard deviation above the average caseworker is rather stable across the outcomes, ranging from +10% on the probability to be in employment at least one day to +17% on the total number of days worked under permanent contracts.

Table 3: Caseworkers impact on other youth employment outcomes

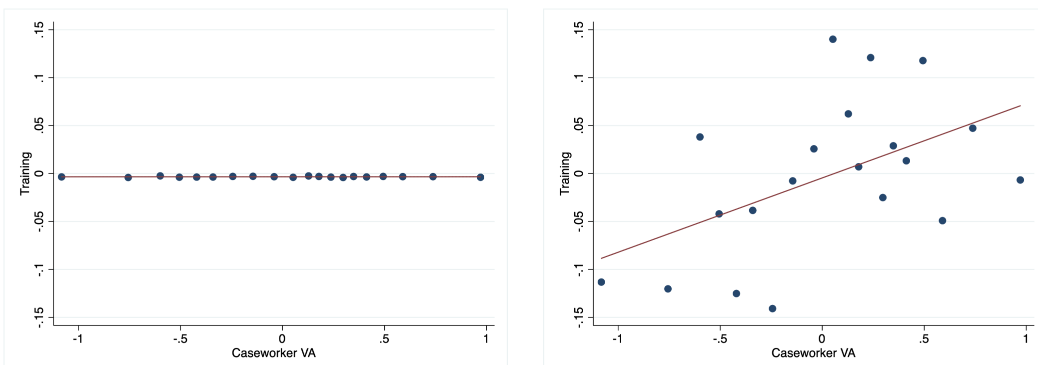
Outcome	Mean	Sd	Caseworker VA	ATT	Significance
	(1)	(2)	(3)	(4)	(5)
Working at least 1 day	.6646	.4721	.1429	+10.2%	***
Working at least 1 day per month	.2825	.4502	.0916	+14.6%	**
Number of days of employment per month	7.33	12.61	.0902	+15.5%	**
Cumulative number of days of employment	202.08	226.11	.1253	+14.0%	***
Cumulative number of days of employment in stable job	151.35	213.29	.1002	+14.1%	**
Cumulative number of days of employment in permanent job	93.98	179.23	.0892	+17.0%	**

Note: Estimates are obtained with OLS regressions including individual characteristics, agency × month fixed effects, employment situation before the first meeting, and caseworkers winsorized at the 95% level. Standard errors are below coefficients in parentheses and clustered at the caseworker level. Permanent job include *CDI* contract. Stable job include *CDI* contract and *CDD* that lasts more than six months.

Figure 9: Effects of caseworker VA on predicted and observed training (Paris sample)

(a) Predicted outcome

(b) Observed outcome



Note: The figures show binscatters of caseworker value-added and youth predicted and actual outcomes. The figure on the left shows youths' predicted outcomes based on the cumulative number of hours of training 6 months before the first meeting. The figure on the right shows youth observed outcomes (cumulative number of hours of training within the 24 months after the first meeting).

5.2 On training

We do an analogous analysis on training outcomes as we did for employment in the above Section 5.1. We begin with the forecast bias test. Here, we use the cumulative number of days of training during the six-month period prior to agency registration as a proxy to predict the main outcome (the cumulative number of days of training during the 2-year period after registration). Then we regress this predicted outcome on caseworker value-added. Figure 9a shows that caseworker value-added is not significantly related to the prediction of the main outcome, indicating that selection bias within agencies is still not a significant issue.

Reassuringly, Figure 9b shows a clear and positive correlation between caseworker value-added and the observed training situation after registration. To quantify the effect of caseworkers, we again regress the training outcome of youths on caseworker value added and agency × month fixed effects. Table 4 presents our results regarding the cumulative number of days of training during the 2-year period that follows registration.

Table 4: Caseworkers impact on youth training

Training (std)	Before 1st meeting		After 1st meeting			
	(1)	(2)	(3)	(4)	(5)	(6)
Caseworker VA (std)	-0.0026	-0.0073	0.0911***	0.1064***	0.0911***	0.1065***
	(0.0182)	(0.0251)	(0.0229)	(0.0345)	(0.0229)	(0.0346)
Training before 1st meeting (std)					0.0177	0.0193
					(0.0137)	(0.0144)
Outcome mean	0.7	0.7	32.1	32.1	32.1	32.1
Outcome standard deviation	8.7	8.7	85.8	85.8	85.8	85.8
Individual characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Agency x Month FE	Yes	Yes	Yes	Yes	Yes	Yes
95% Winsorization of VA	No	Yes	No	Yes	No	Yes
R-squared	0.0382	0.0432	0.0607	0.0631	0.0610	0.0634
Observations	5,358	5,118	5,358	5,118	5,358	5,118

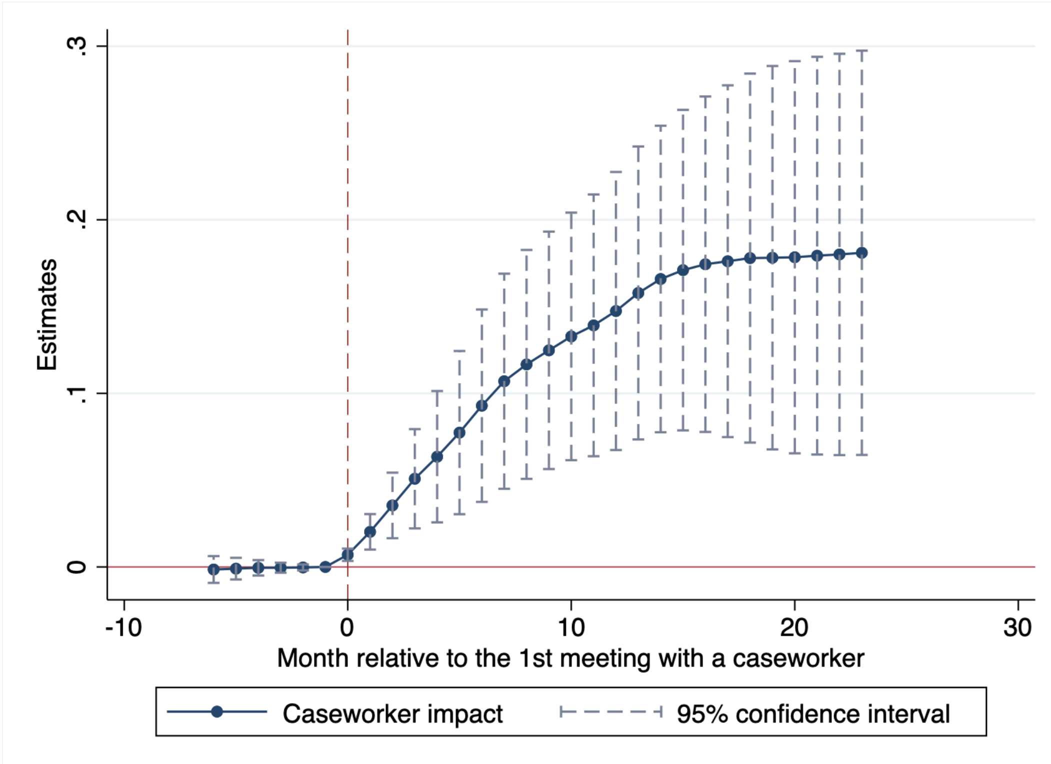
Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the caseworker level. Caseworker VA is computed on the number of hours of training 12 months after the first meeting according to equation 8. Individual characteristics include all the characteristics listed in Table B.2 in Appendix B.

Then, we perform placebo test by considering the number of days of training before the first meeting with the assigned caseworker. We find that caseworker VA estimates are nearly zero and statistically insignificant. After the first meeting though, we find that being assigned to a caseworker whose valued added is one standard deviation above average leads to a sizable increase in the total number of days of training within the two-year period. The magnitude of the effect is quite robust and is approximately .1 standard deviation (sd). In line with the placebo tests, introducing the ex-ante training outcome has no effect on caseworkers' VA estimates and it is also not correlated with ex-post outcome. This absence of correlation is not surprising either since a very low share of youths (less than 0.5%) have experienced training situations before they register to an agency. The results are also robust to a 95% winsorization of the sample based on caseworkers VA. Taking the estimate of column (6) from Table 4, which is still our preferred specification, and given the mean and standard deviation of the outcome, this corresponds to an average treatment effect on the treated (ATT) of approximately 28%.

We also study the timing of this effect and show that the effect of being assigned to a caseworker who is one standard deviation above average evolves significantly over time in Figure 10. We see that contrary to employment, caseworkers have a large impact that increases during the first of assistance to reach .18 sd, but then this effect is stabilizing during the second year. We interpret this finding as the necessity for caseworkers to train youths in the first place because of a lack of skills that impend them to find a suitable job on the labor market.

As for employment, we now consider alternative outcomes to the training situations of youths. More specifically during the 24-month period after registration, we look at the impact of caseworkers on the probability to be in training at least one day, the probability to be in training at least one day per month, the number of days of training per month, the cumulative number of days of training in long-duration training (i.e. more than six months), and the

Figure 10: Effect on the cumulative number of days of training over time



Note: Month 0 corresponds to the month of the first meeting.

cumulative number of hours of training both in all and long-duration training. Table 5 indicates the results from regressions similar to column (6) of Table 4. Results are summarized in Table 5. We find that the effect of caseworkers who are one standard deviation above the average caseworker is still twice as large as the effect on employment also quite stable across the outcomes, ranging from +30% on the probability to be in employment at least one day per month to +31% on the total number of days trained under long-duration training. We also notice that the effects remain strong and significant when looking at the number of hours done in training.

5.3 Heterogeneity

We now investigate if the influence of caseworkers is more pronounced for some youths than others. In particular, we consider four subgroups of young people according to their gender, age, educational level, and ethnic origin. Figure 11 shows the estimates of caseworker value-added on both the employment and training outcomes from OLS regressions similar to columns (6) in Table 2 and Table 4.

Figure 11a indicates the effect for males and females on both employment and training,

Table 5: Caseworkers impact on other youth training outcomes

Outcome	Mean	Sd	Caseworker VA	ATT	Significance
	(1)	(2)	(3)	(4)	(5)
Training at least 1 day	.1814	.3854	.0906	+19.3%	***
Training at least 1 day per month	.0414	.1992	.0639	+30.7%	***
Number of days of training per month	1.07	5.48	.0633	+32.4%	***
Cumulative number of days of training	31.76	85.04	.0951	+25.5%	***
Cumulative number of days of training in long-duration training	17.41	69.29	.0786	+31.3%	**
Cumulative number of hours of training	13.57	45.90	.0788	+26.7%	**
Cumulative number of hours of training in long-duration training	8.54	41.24	.0563	+27.2%	*

Note: Estimates are obtained with OLS regressions including individual characteristics, agency × month fixed effects, training situation before the first meeting, and caseworkers winsorized at the 95% level. Standard errors are below coefficients in parentheses and clustered at the caseworker level. Long-duration training are training that lasts more than six months.

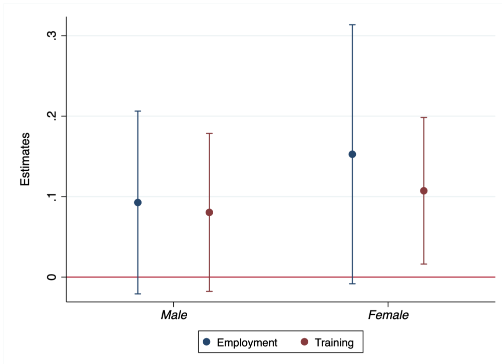
Figure 11b for different age groups, Figure 11c for different education levels, and finally Figure 11d for youths with African-related ethnicity. Overall, we find that females benefit the most from having high value added caseworkers in terms of training to enter into training and that youths with sub-Saharan African origin benefit the most from having high value added caseworkers in terms of employment to enter into employment. We have no particular explanations for these effects to arise significantly yet.

Regarding age, the influence of caseworkers - as measured by our value added - seems to be decreasing as the age goes up whereas we could think of the opposite. Indeed, we clearly see in the data that older youths have more labor market experience than younger youths, therefore more able caseworkers could benefit from this previous experience to easily help them. Yet, older youths may have particular constraints that make caseworkers assistance less effective. On the contrary, when young people arrive in the agency before 21 years old, it seems that they can mostly benefit from more able caseworkers although the effect is not statistically different from zero for minors. We think that very young adults have a profile such that more able caseworkers can help them effectively depending on their specialization in employment or training.

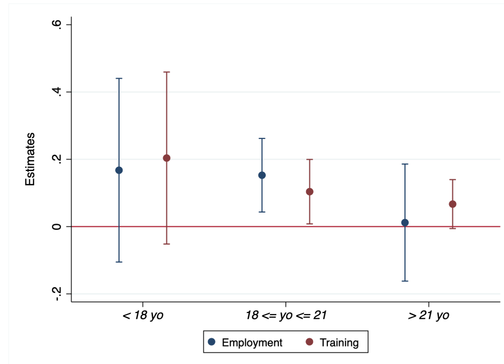
Lastly, we see a clear decreasing effect of caseworkers in terms of training as the educational level of youths gets higher. As these young people have in principle sufficient skills to enter in the labor market, caseworkers who are better at placing youths into training may think that it is not necessary to upgrade their skills or it may be due to the lack of vocational training vacancies at higher levels. In terms of employment, we see a positive effect of more able caseworkers only for young people with a two-year vocational degree. These young people indeed learned skills that were devoted to specific occupations. So being assigned to a caseworker that performs better in terms of employment access most likely help these youths whereas school dropouts must first acquire some skills via training.

Figure 11: Heterogeneous effects of caseworker on employment and training (Paris sample)

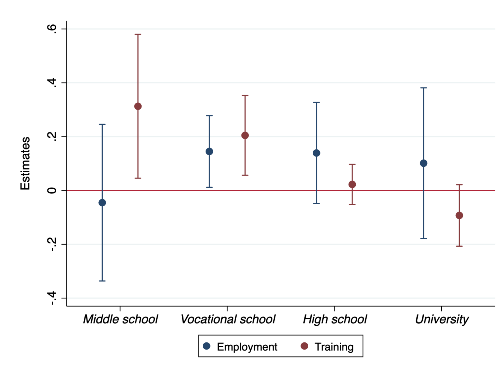
(a) Gender



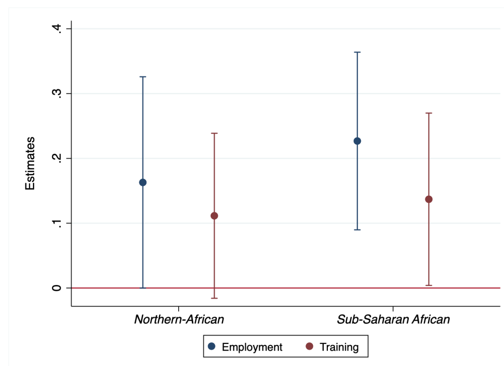
(b) Age



(c) Education



(d) Ethnicity



Note: The estimates are obtained from regressions equivalent to Column (6) in Table 2.

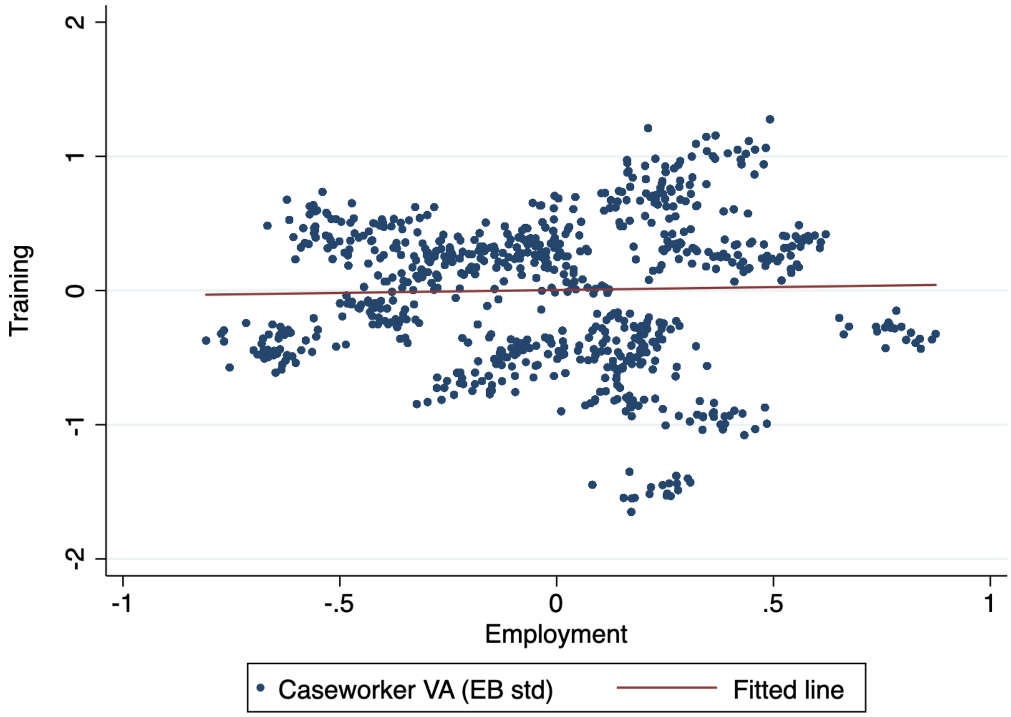
6 Mechanisms

Similar young people who are assigned to different caseworkers when they come to a public assistance agency will end up with different labor market trajectories. Is it because of the personality of the caseworkers? Or is it because of their practices?

Figure 12 shows in the first place that caseworkers who perform better at placing youths into employment are not the same that those who do better at placing youths into training. Indeed, there is no correlation between our two value-added estimators, suggesting that caseworkers are specializing in one of the two dimension.

Unfortunately, we do not have sufficient data on the socio-demographic characteristics of caseworkers that will allow us to investigate whether more able caseworkers have different personality traits than others. Other studies thus might be helpful in this matter. In particular, Cederlöf et al. (2021) find that cognitive ability and personal experience of unemployment are not related to caseworker performance when assisting adult job seekers. They solely find that

Figure 12: Correlation between VA measures on employment and training (Paris sample)



Note: Value added is measured on the number of days of employment 24 months after the first meeting in the y-axis, and on the number of hours of training 11 months after the meeting in the x-axis.

caseworkers who have more than two years of experience perform better than those with less. As we lack of data, we leave this question open in our article especially as those personality traits may be correlated to the practices of caseworkers, which are found to be correlated with performance.

Table 6 shows some correlations between our value-added estimators, whether in terms of employment in columns (1) and (2) or of training in columns (3) and (4), and some caseworkers' practices. There are differences and similarities between caseworkers who perform better in the two dimensions. First, we see that the number of individual meetings is not related to caseworkers performance. This finding is not line with the main result of Schiprowski (2020) where she finds that one meeting lost because of unplanned absence increases the unemployment duration of job-seekers by 5%. One possible explanation in our case is that it is not the quantity of meetings that is important, but the quality of those especially with young people that cannot be captured in our data. Another explanation may be due to the portfolio composition of caseworkers as the variance of youth situations is large. Maybe few meetings are necessary for young people who are more able to start a job or a training, while for other youths, caseworkers may need more meetings to find a proper situation canceling the effect.

Table 6: Correlation of caseworkers VA with practices (Paris sample)

Caseworker VA (std)	Employment		Training	
	(1)	(2)	(3)	(4)
Nb of individual meetings	0.0012	0.0006	-0.0057	-0.0051
	(0.0027)	(0.0031)	(0.0048)	(0.0043)
Nb of collective workshops	-0.0219**	-0.0201**	0.0014	0.0143
	(0.0099)	(0.0084)	(0.0119)	(0.0093)
Nb of information sessions	0.0332	0.0316	-0.1672**	-0.1827***
	(0.0336)	(0.0260)	(0.0829)	(0.0597)
Nb of administrative tasks	-0.0008	0.0012	-0.0011	0.0018
	(0.0068)	(0.0068)	(0.0108)	(0.0096)
Nb of digital contacts	0.0216***	0.0183***	0.0148***	0.0069***
	(0.0019)	(0.0018)	(0.0027)	(0.0019)
Nb of job propositions	0.0015***	0.0017***	0.0011	0.0007
	(0.0005)	(0.0004)	(0.0007)	(0.0007)
Nb of training propositions	-0.0157***	-0.0161***	0.0124***	0.0135***
	(0.0027)	(0.0028)	(0.0036)	(0.0036)
Nb of project propositions	-0.0041	-0.0060**	-0.0084*	-0.0071
	(0.0025)	(0.0028)	(0.0049)	(0.0046)
Nb of other propositions	-0.0057**	-0.0057**	-0.0099***	-0.0088***
	(0.0022)	(0.0022)	(0.0029)	(0.0028)
Observations	6,906	6,566	6,906	6,571
R-squared	0.1320	0.1504	0.0983	0.1281
Individual characteristics	Yes	Yes	Yes	Yes
Agency x Month FE	Yes	Yes	Yes	Yes
95% Winsorization of VA	No	Yes	No	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. Caseworker VA is computed on the number of days of employment 24 months after the first meeting according to equation (X).

Subsequently, caseworkers who do better in employment animate less collective workshops, while those who do better in training animate less information sessions. In those workshops, caseworkers train mostly young people to find a job by themselves, while in the information sessions, caseworkers share information on specific topics mostly related on social issues such as shelter, health, etc. Caseworkers who spend more time in those activities may have less time devoted to direct assistance and help in the matching process. This may be more detrimental as we see that caseworkers who do better in employment are those who make more job propositions and similarly for training. On average, caseworkers do 6.5 job propositions during the 2-year period of assistance. Therefore, results indicate that 1 additional job propositions would only increase the employment value-added of caseworkers by .0015 sd, leaving the caseworkers in the same 49th percentile of the employment VA distribution. Regarding training propositions for which the average is 1.7 propositions, 2 additional propositions would correspond to a shift from the 44th to the 46th percentile in the training VA distribution, which is again very low.

In addition to job and training propositions, caseworkers who maintain contacts digitally via sms, emails or phone calls with their youths are those who have higher value-added,

Table 7: Correlation of caseworkers VA with placement into programs (Paris sample)

Caseworker VA (std)	Employment		Training	
	(1)	(2)	(3)	(4)
Program: Diagnostic	-0.0217	-0.0236	0.0699**	0.0603**
	(0.0168)	(0.0169)	(0.0289)	(0.0294)
Program: PACEA	0.1138	0.0967	0.0772	-0.0801
	(0.0700)	(0.0653)	(0.0961)	(0.0743)
Program: CEP	-0.0416	-0.0375	-0.1552	0.0186
	(0.0706)	(0.0626)	(0.0962)	(0.0770)
Program: PPAE	-0.0080	-0.0032	0.0414**	0.0294*
	(0.0119)	(0.0113)	(0.0175)	(0.0174)
Program: GJ	-0.0337**	-0.0363***	0.0063	0.0158
	(0.0144)	(0.0137)	(0.0248)	(0.0215)
Program: AIJ	0.0104	-0.0098	0.0441	-0.0092
	(0.0273)	(0.0187)	(0.0358)	(0.0285)
Program: other	-0.0412***	-0.0421***	0.0294	0.0181
	(0.0141)	(0.0138)	(0.0177)	(0.0145)
Observations	6,906	6,566	6,906	6,571
R-squared	0.0673	0.0863	0.0863	0.1206
Individual characteristics	Yes	Yes	Yes	Yes
Agency x Month FE	Yes	Yes	Yes	Yes
95% Winsorization of VA	No	Yes	No	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. Caseworker VA is computed on the number of days of employment 24 months after the first meeting according to equation (X).

whether in terms of employment or training. The magnitude is even higher than making 1 additional job or training proposition since having 1 additional digital contact with a youth increases the value-added of caseworkers between 0.015 and 0.2 sd. Since it is less costly in time to write a message or a small email to keep in touch with youths than finding a suitable propositions, there is room for improvement to help effectively young people. Having 24 more digital contacts over the 2-year period, which corresponds to 1 additional contact per month (the mean is 15 over the 2-year period), would increase the place of caseworkers from the 49th to the 86th percentile in the employment VA distribution, and from 44th to the 75th percentile in the training VA distribution. The data we have do not store the content of the messages, nor the phone calls. We are not able to know if these contacts are made i) to motivate the youths in their job effort, ii) to maintain the matching effective, or iii) to inform the youths that the caseworker is watching them.[13]

Finally, we see few correlations between our VA estimators and placement into job search programs. On the one hand, we see that caseworkers who put their youths in the "Garantie jeunes" (GJ) program or in other local programs have lower value-added than caseworkers who

[13]We plan to look at the timing of these digital contacts given the timing at which young people find a job or a training after the first meeting. This might help us to better understand how these contacts are used by caseworkers even though the content of the messages is key.

do not. One possible explanation is that these caseworkers prefer to outsource the assistance in the matching process to other workers animating these programs with the hope youths will find a suitable solution because of the program. Especially as the GJ program is a national-wide workfare programs for youths with very low prospects of employment. Concerning the local programs, the wide variety over the 2-year period do not allow us to draw any clear conclusion.

On the other hand, we see that caseworkers who establish a formal diagnosis or co-animate a PPAE program[14] have higher training value-added. "Diagnostic" program is not a program per se. It is a framework introduced in January 2017 to help caseworkers formalizing the assistance they will provide to young people. This framework was not compulsory until January 2019, but caseworkers that were eager to use it could during the first month after the first meeting, establish a clear path of assistance in accordance with the needs of the youths. It seems that caseworkers who used the most this tool were also the ones who put greater interest in finding a proper solution to young people, suitable training in this case. It is not surprising then to see that caseworkers who do better in training are also the ones who put their youths into the PPAE program which is co-animation of assistance within vocational training in partnership with job centers. In France, most of the training, and especially the training followed by youths, are training that are financed by these job centers, making it necessary for the "mission locale" caseworkers to cooperate with in order to place youths in training.

7 Conclusion

Our results suggest that caseworkers can significantly affect the employment prospects of young people. Young unemployed assigned to a caseworker whose value added is one standard deviation above the average, in the respective distribution, are working 28 days, or 14%, more than other youths over a period of 2 years after the first meeting. In terms of training, youths experience an additional 9 days which corresponds to relative effect of 28%. These magnitudes are higher than the ones found in other recent studies looking at the effect of caseworkers (Mulhern, 2020; Buskjær Rasmussen, 2021; Dromundo and Haramboure, 2021), but in line with those measured for teachers according to the performance of students on maths and reading in the US (Hanushek and Rivkin, 2010). More specifically, caseworkers who do better in employment or training are those who direct their youths with specific propositions and mostly those who have several contacts via emails, sms or phone calls. The latter aspect seems crucial in the assistance of young people to ameliorate the matching process as most of the young people who came to these agencies suffer from motivation and self confidence issues.

[14] "Projet personnalisé d'accès à l'emploi", or *personalized project to employment access.*

References

Adjeoda, Schanice, "Mieux comprendre les modalités d'entretien de premier accueil à la MLP: Esquisse d'une typologie," Technical Report, École des Hautes Études en Santé Publique 2021.

Aeberhardt, Romain, Vera Chiodi, Bruno Crépon, Mathilde Gaini, and Augustin Vicard, "Revenu contractualisé d'autonomie," Technical Report, CREST/EEP CREDOC October 2014.

Arnoult, Emilie and Jihène Ghrairie, "Vers quel intermédiaire de placement se tournent les jeunes qui recherchent leur premier emploi ?," *Dares Analyses*, 2022, *1.*

Babcock, Linda, William J. Congdon, Lawrence F. Katz, and Sendhil Mullainathan, "Notes on behavioral economics and labor market policy," *IZA Journal of Labor Policy*, 2012, *1* (2).

Bertschy, Kathrin, Alejandra Cattaneo, and Stefan Wolter, "PISA and the Transition into the Labour Market," *LABOUR*, 2009, *23*, 111–137.

Borel, Marie, "Quelle proximité entre le Service public de l'emploi et les jeunes en dispositifs d'insertion professionnelle ?," *Dares Analyses*, 2022, *15.*

Cahuc, Pierre, Stéphane Carcillo, Bérengère Patault, and Flavien Moreau, "Judge Bias in Labor Courts and Firm Performance," *CSPP Working Paper*, 2020, *2020-10.*

Caliendo, Marco and Ricarda Schmidl, "Youth unemployment and active labor market policies in Europe," *IZA Journal of Labor Policy*, 2016, *5* (1).

Cederlöf, Jonas, Martin Söderström, and Johan Vikström, "What makes a good caseworker?," 2020.

_ , _ , and _ , "What makes a good caseworker?," Technical Report, Working Paper 2021.

Chetty, Raj, John N. Friedman, and Rockoff Jonah E., "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review*, 2014, *104* (9), 2593–2632.

_ , _ , and _ , "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood," *American Economic Review*, 2014, *104* (9), 2633–2679.

Comi, Simona Lorena, Mara Grasseni, and Federica Origo, "Sometimes It Works! The Effect of a Reform of the Short Vocational Track on School-to-Work Transition," *IZA Discussion Paper Series*, 2022.

Dobbie, Will, Jacob Goldin, and Crystal S. Yang, "The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges," *American Economic Review*, 2018, *108* (2), 201–240.

Dromundo, Sofia and Antton Haramboure, "Do Job Counselor Matter? Measuring Counselors value-added in Job Search," *Three essays on labor market policies: job search assistance and digital tools*, 2021, *Manuscript Université Paris 1 Panthéon-Sorbonne.*

Duguet, Emmanuel, Noam Leandri, Yannick L'Horty, and Pascale Petit, "Are Young French Jobseekers of Ethnic Immigrant Origin Discriminated against? A Controlled Experiment in the Paris Area," *Annals of Economics and Statistics*, 2010, *99/100*, 187–215.

Escudero, Veronica and Eva Lopez Mourelo, "The European Youth Guarantee: A systematic review of its implementation across countries," *ILO Working Paper*, 2017, *21.*

Filipucci, Francesco, "What Do NEETs Need? The Joint Effect of Active and Passive Labor Market Policies," *Job market paper*, 2022.

Gaini, Mathilde, Marine Guillerm, Solène Hilary, Emmanual Valat, and Philippe Zamora, "Résultats de l'évaluation quantitative de la Garantie jeunes: quels publics, quels accompagnements et quelles trajectoires des bénéficaires ?," *Travail et Emploi*, 2018, *N°153.*

Gilraine, Michael and Nolan G. Pope, "Making Teaching Last: Long-Run Value-Added," *NBER Working Paper Series*, 2021, *29555.*

Glover, Dylan, "Job Search and Intermediation under Discrimination: Evidence from Terrorist Attacks in France," *Job market paper*, 2021.

Hanushek, Eric A. and Steven G. Rivkin, "Generalizations about Using Value-Added Measures of Teacher Quality," *American Economic Review: Papers & Proceedings*, 2010, *100* (2), 267–271.

ILO, "Global Employment Trends for Youth 2020: Technology and the future of jobs," Technical Report, International Labour Organization 2020.

Jackson, C Kirabo, "What do test scores miss? The importance of teacher effects on non–test score outcomes," *Journal of Political Economy*, 2018, *126* (5), 2072–2107.

Jellab, Aziz, "De l'insertion à la socialisation. Mission locale, jeunes 16-25 ans et problématique de l'exclusion," *Formation Emploi*, 1998, *62*, 33–47.

Kluve, Kluve, Susana Puerto, David Robalino, Jose Romero, Friederike Rother, Jonathan Stöterau, Felix Weidenkaff, and Marc Witte, "Do youth employment programs improve labor market outcomes? A quantitative review," *World Development*, 2019, *114*, 237–253.

Kraft, Matthew A, "Teacher effects on complex cognitive skills and social-emotional competencies," *Journal of Human Resources*, 2019, *54* (1), 1–36.

Kramarz, Francis and Oskar Skans, "When Strong Ties are Strong: Networks and Youth Labour Market Entry," *Review of Economic Studies*, 2014, *81*, 1164–1200.

Mulhern, Christine, "Beyond teachers: Estimating individual guidance counselors' effects on educational attainment," *Unpublished manuscript, RAND Corporation*, 2020.

Rasmussen, Mette Buskjær, "Empirical essays on the effectiveness of active labor market policies: Caseworkers, vocational training & statistical profiling," Technical Report, University of Copenhagen, Department of Economics 2021.

Rivkin, Stevenn G., Eric A. Hanushek, and John F. Kain, "Teachers, Schools, and Academic Achievement," *Econometrica*, 2005, *73* (2), 417–458.

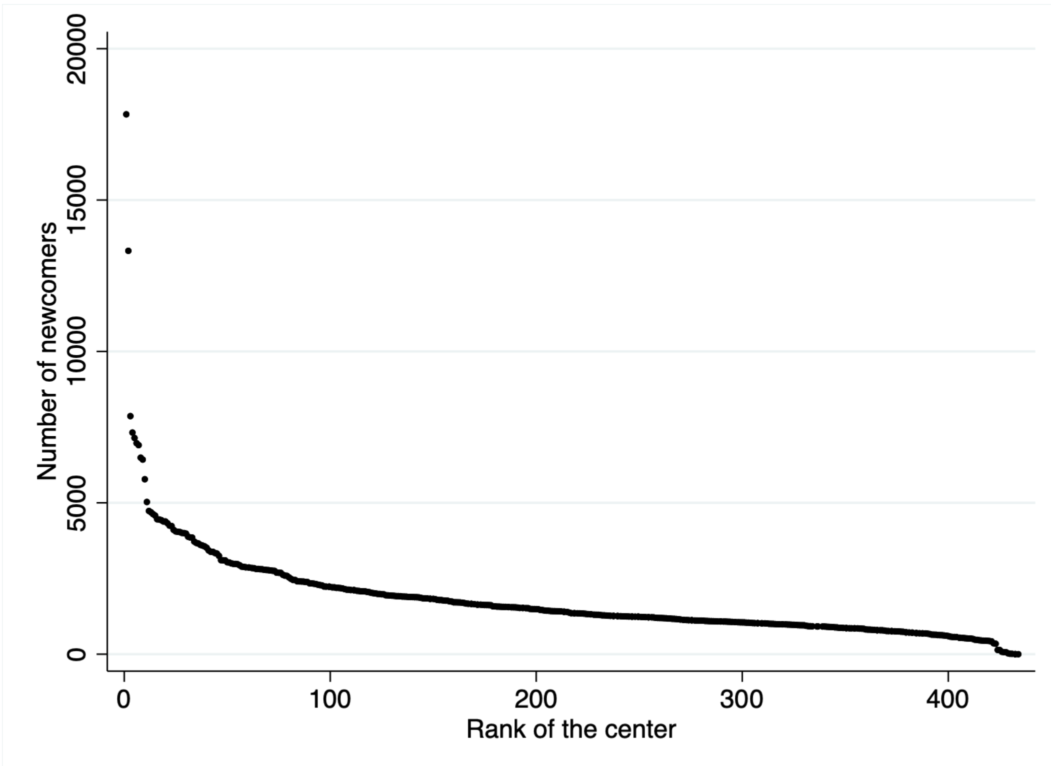
Ryan, Paul, "The School-to-Work Transition: A Cross-National Perspective," *Journal of Economic Literature*, 2001, *39*, 34–92.

Schiprowski, Amelie, "The role of caseworkers in unemployment insurance: Evidence from unplanned absences," *Journal of Labor Economics*, 2020, *38* (4), 1189–1225.

Ömer Doruk and Francesco Pastore, "School to Work Transition and Macroeconomic Conditions in the Turkish Economy," *IZA Discussion Paper Series*, 2020.

A Supplementary Figures

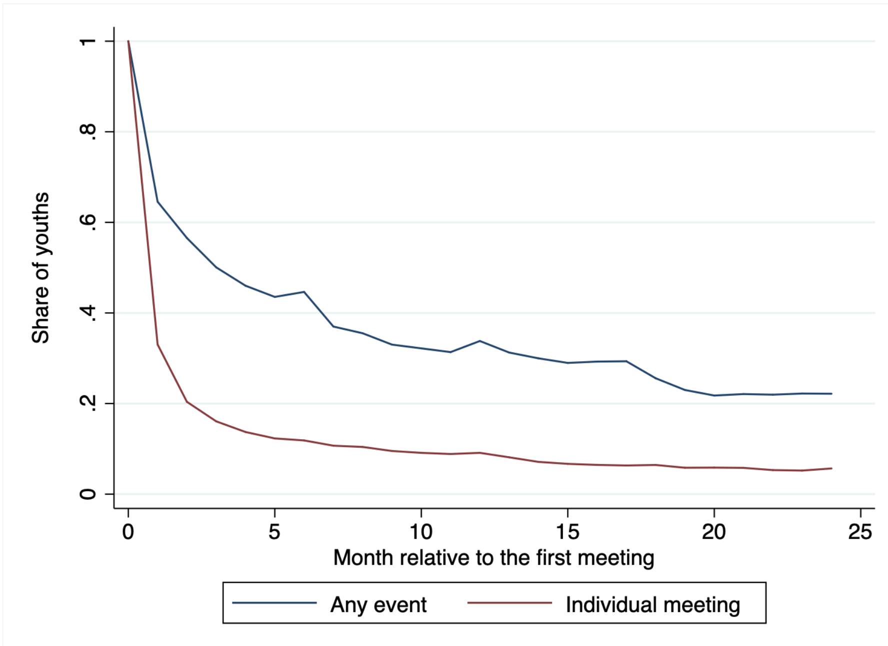
Figure A.1: Ranking of “missions locales” centers according to the number of first meetings between January 2017 and December 2018



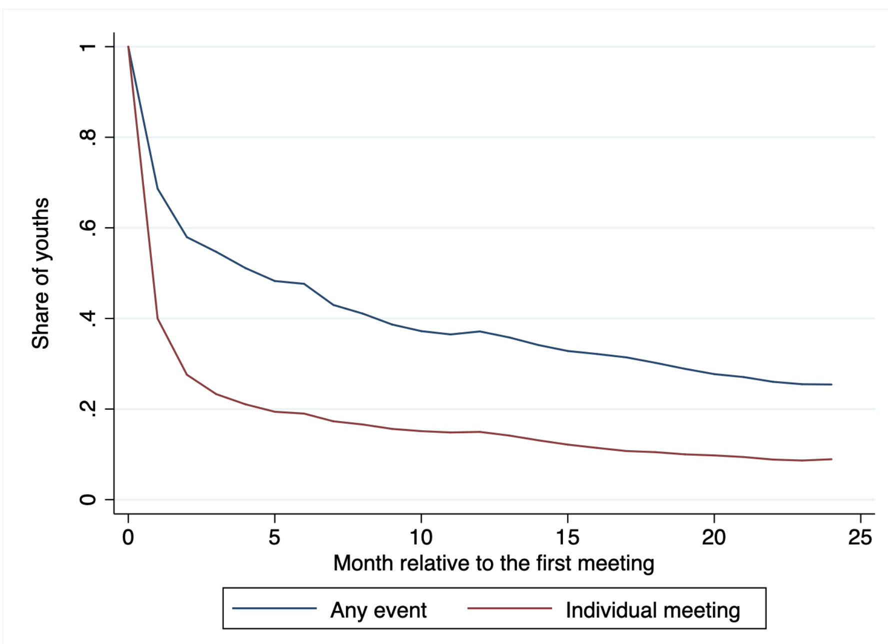
Note: Each dot corresponds to a “mission locale” center. Paris is ranked first, Marseille second...
Source: IMILO (extraction date: October 2021), authors’ calculations.

Figure A.2: Share of youths with at least one event per month

(a) Paris sample



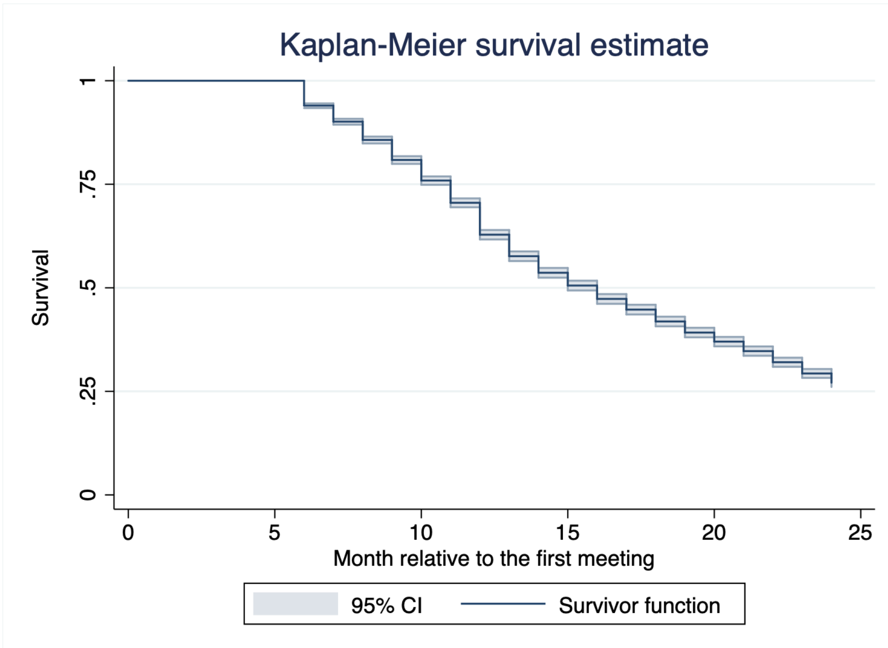
(b) Extended sample



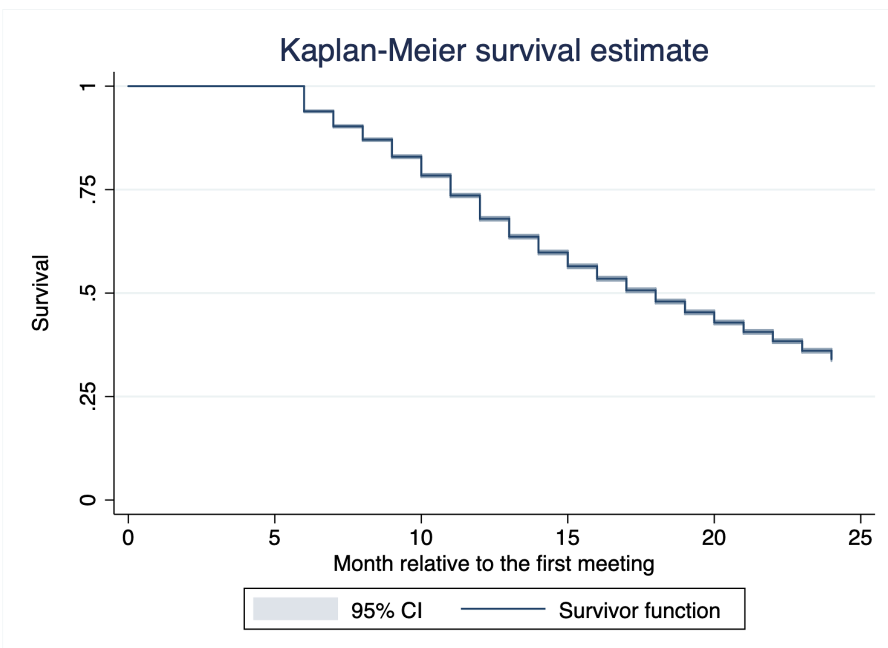
Note: Month 0 is the month of the first meeting with a caseworker that occurred between January 2017 and December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.3: Survival of youths within an agency

(a) Paris sample



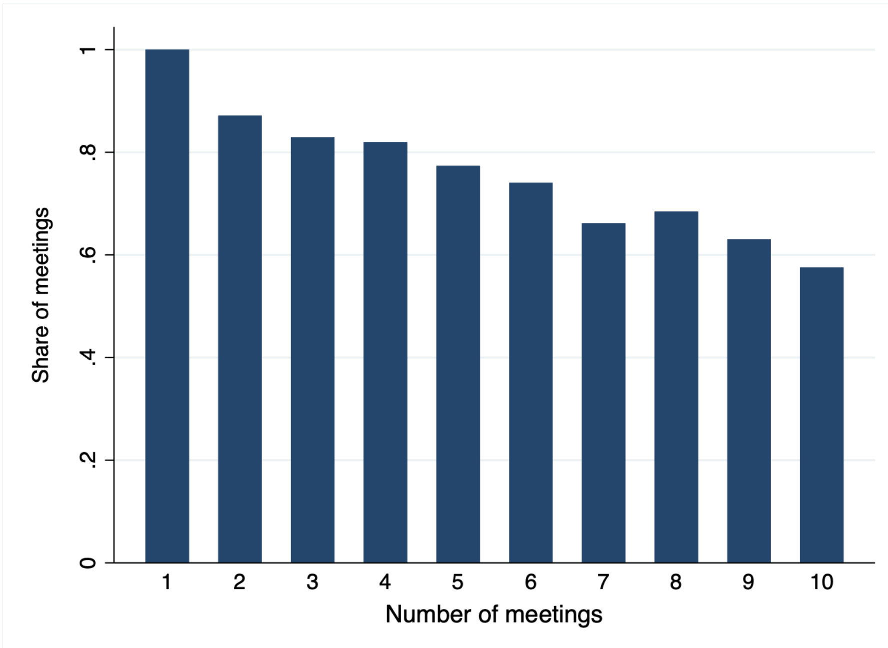
(b) Extended sample



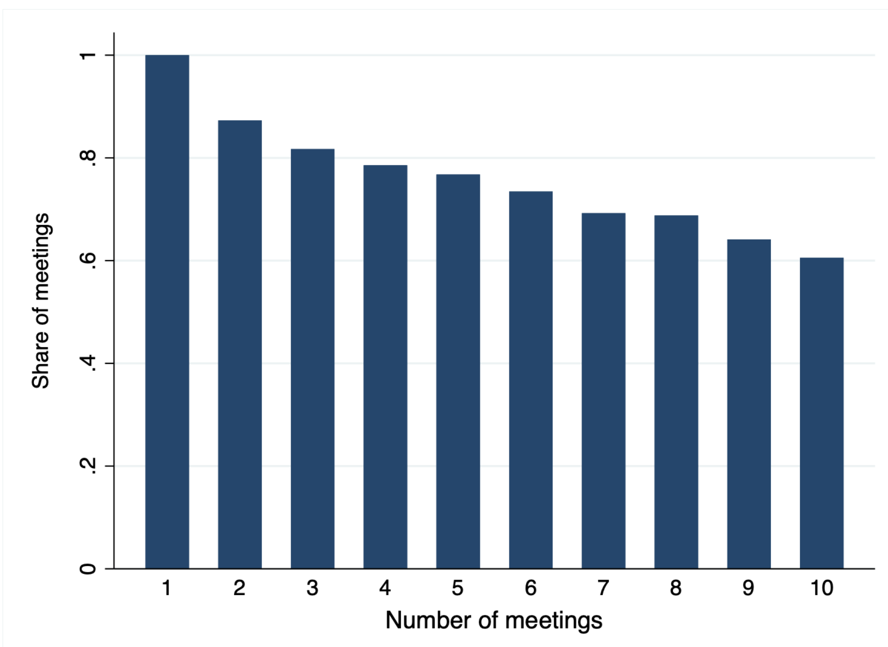
Note: Month 0 is the month of the first meeting with a caseworker that occurred between January 2017 and December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.4: Share of meetings with the referee caseworker

(a) Paris sample



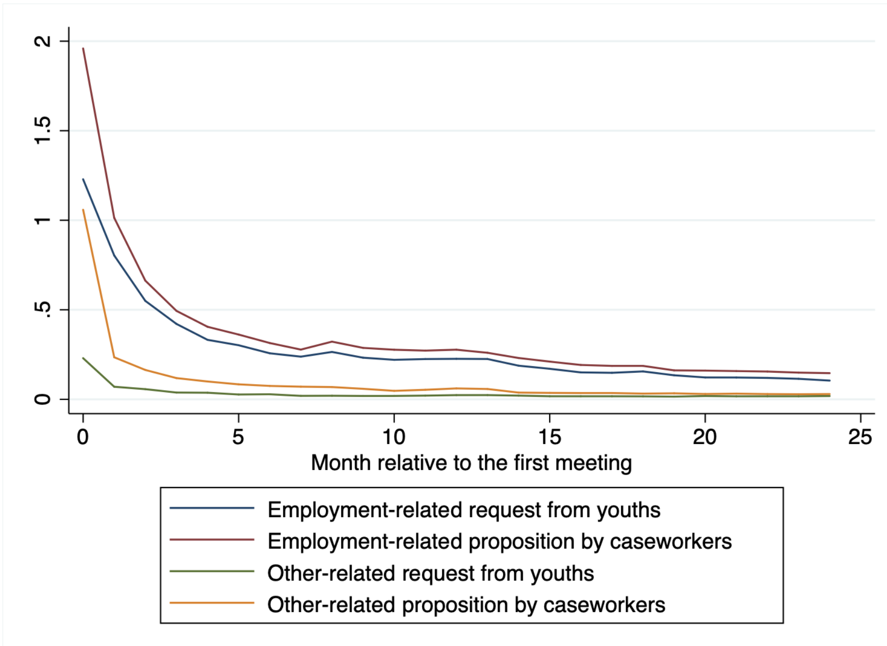
(b) Extended sample



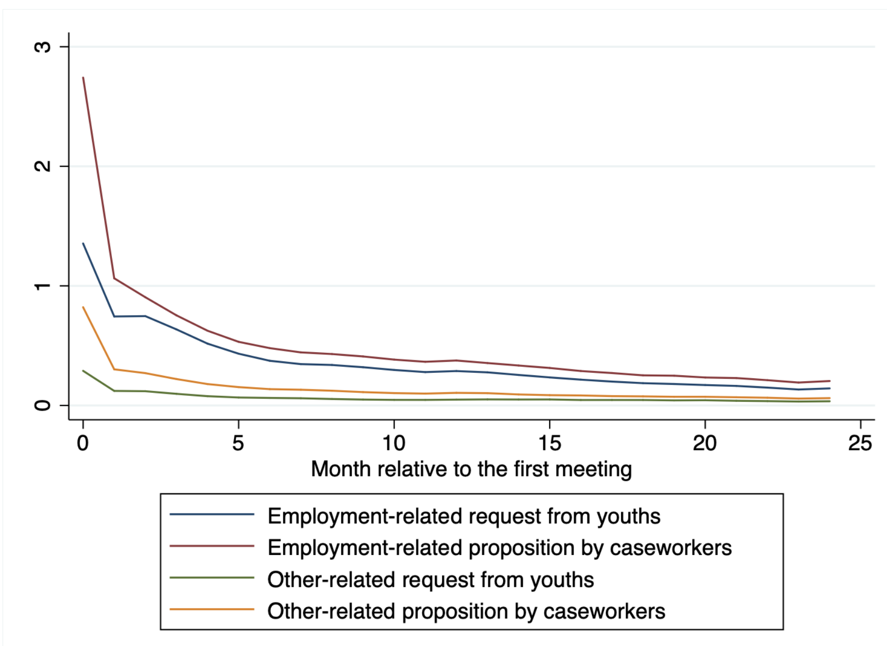
Note: The referee caseworker is the caseworker who did the first individual meeting with a youth for registration.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.5: Requests made by youths and propositions received from caseworkers

(a) Paris sample



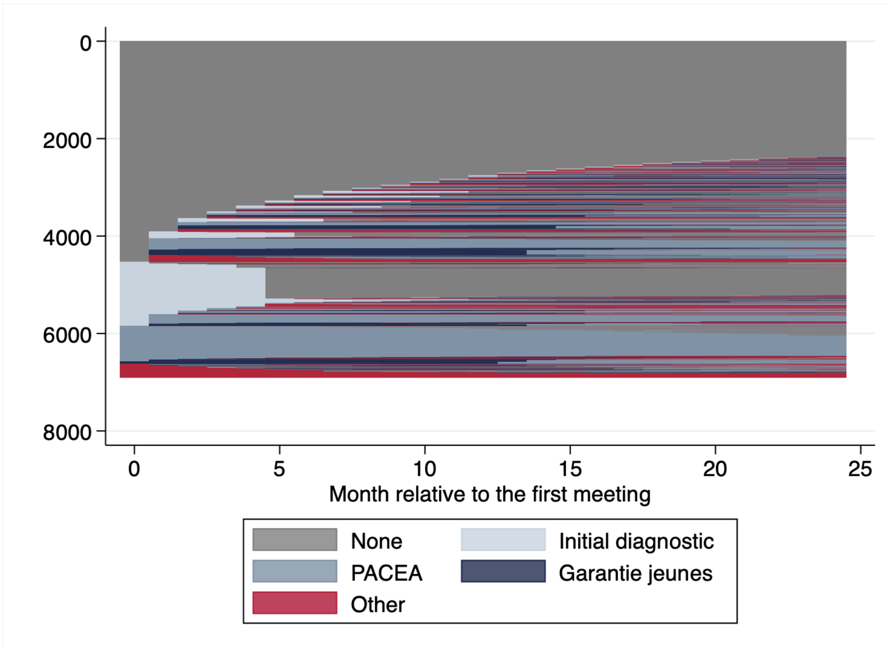
(b) Extended sample



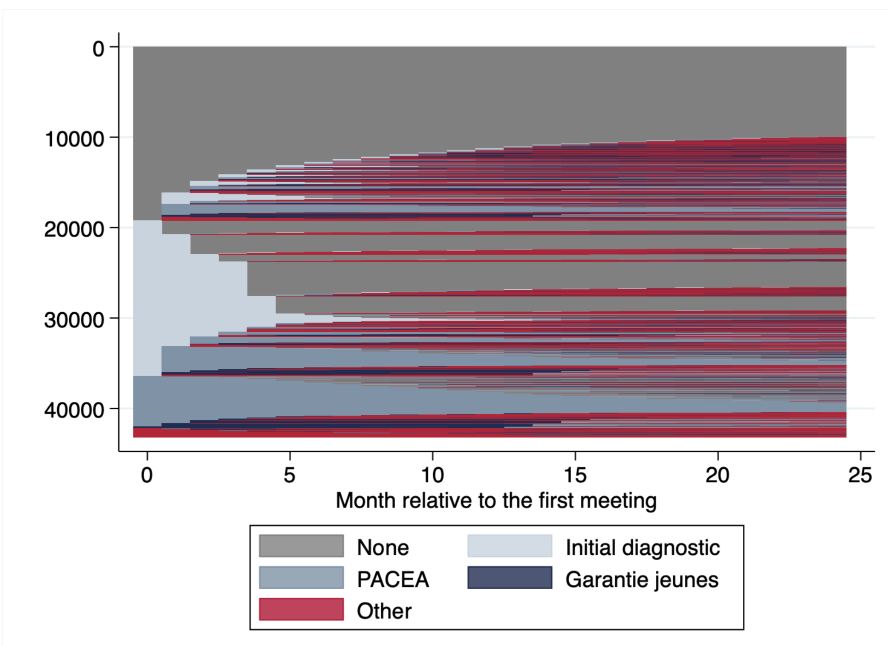
Note: Month 0 is the month of the first meeting with a caseworker that occurred between January 2017 and December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.6: Sequence index plot of youths within programs

(a) Paris sample



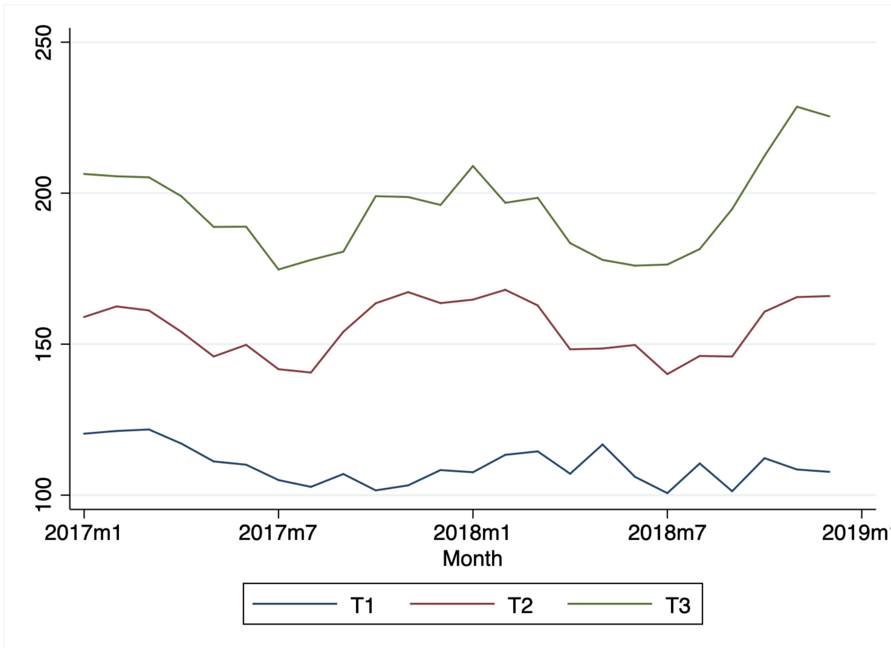
(b) Extended sample



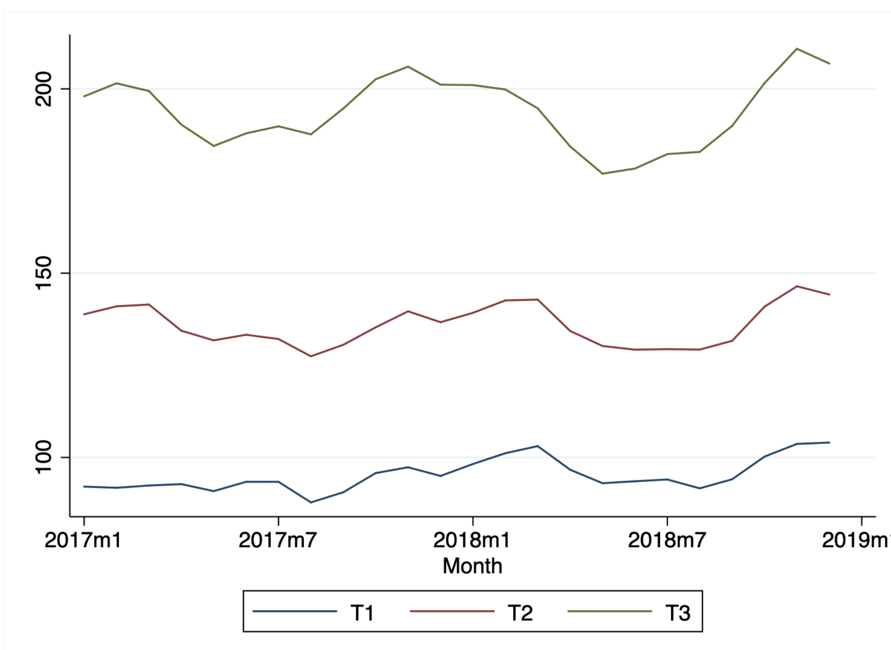
Note: Month 0 is the month of the first meeting with a caseworker that occurred between January 2017 and December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.7: Evolution of the caseload per caseworker

(a) Paris sample



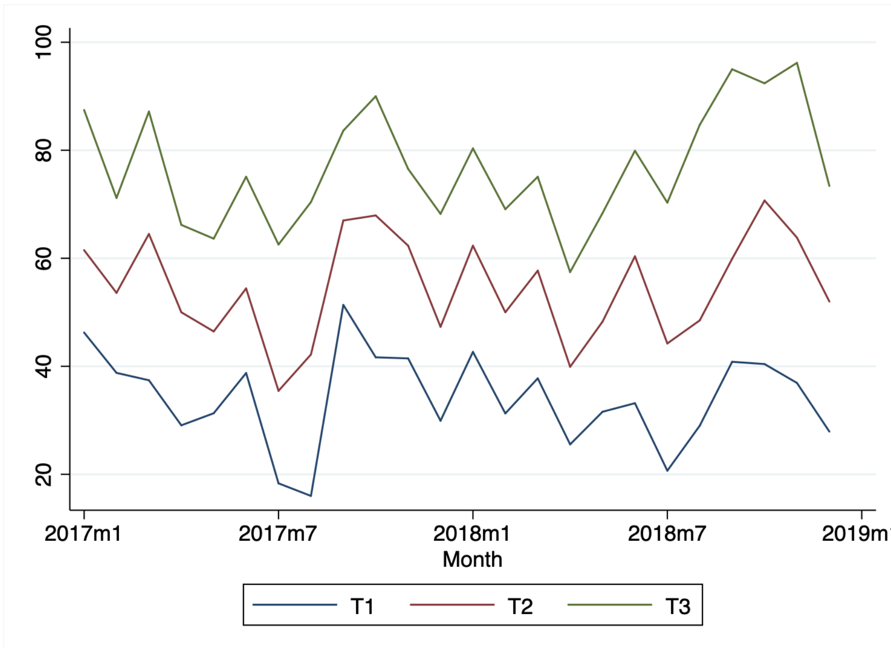
(b) Extended sample



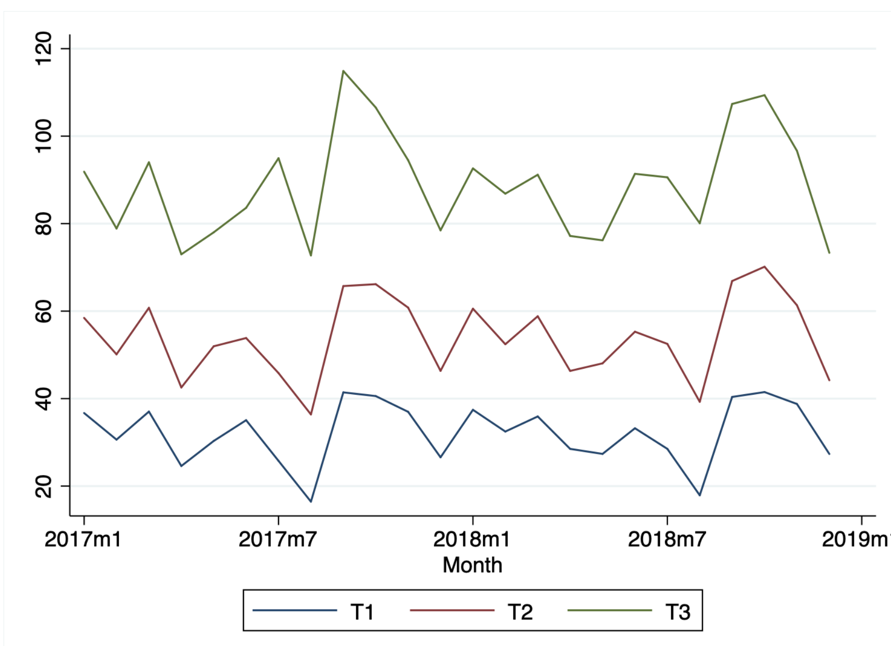
Note: Caseworkers are classified in terciles according to their monthly caseload from January 2017 to December 2018. The caseload of a caseworker is constituted by any youth they had met, at least once during a month for a period of a six months.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.8: Evolution of the number of individual meetings per caseworker

(a) Paris sample



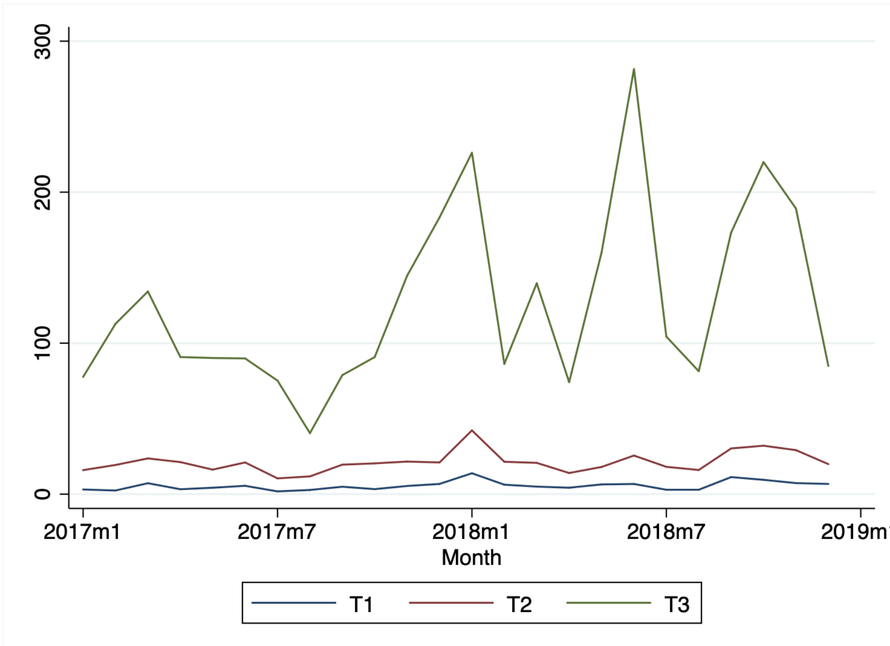
(b) Extended sample



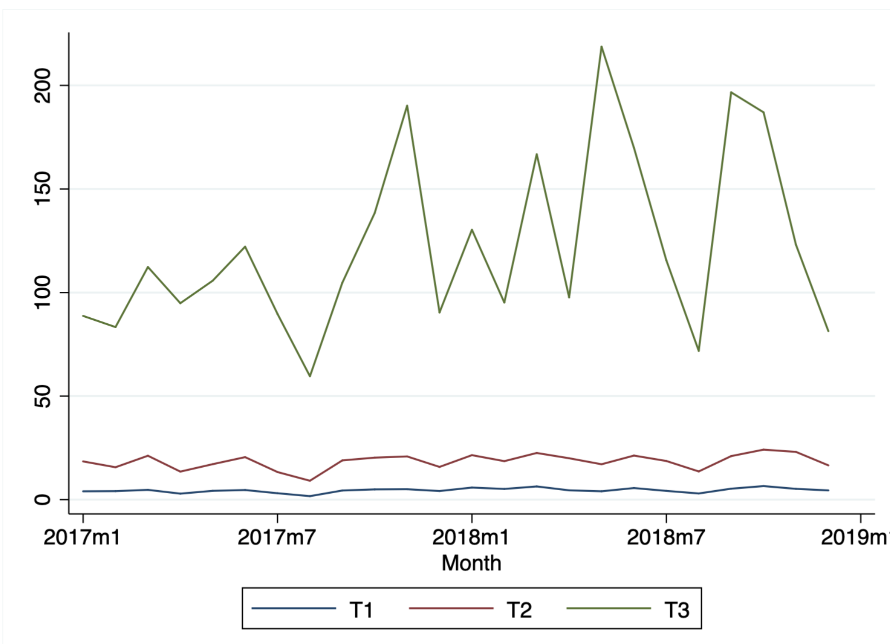
Note: Caseworkers are classified in terciles according to the number of individual meetings they performed each month from January 2017 to December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.9: Evolution of the number of digital contacts per caseworker

(a) Paris sample



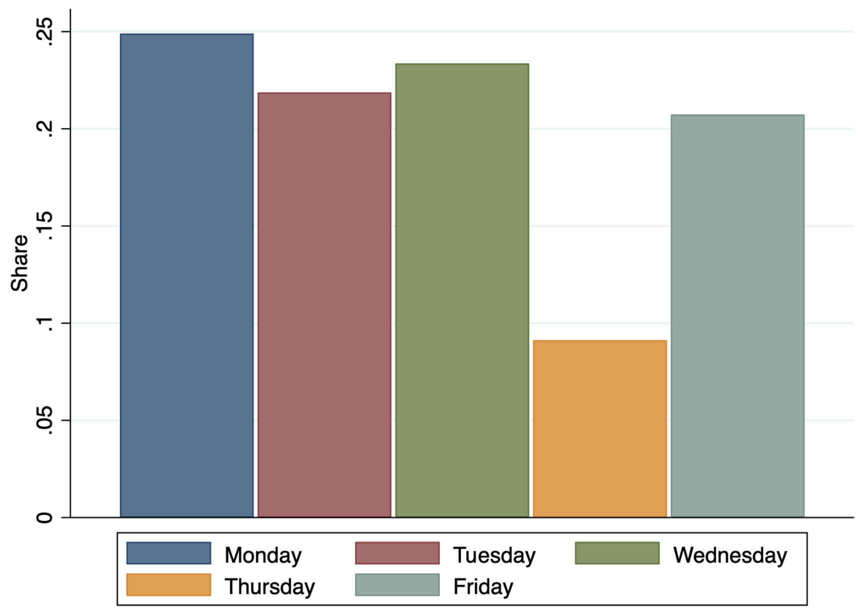
(b) Extended sample



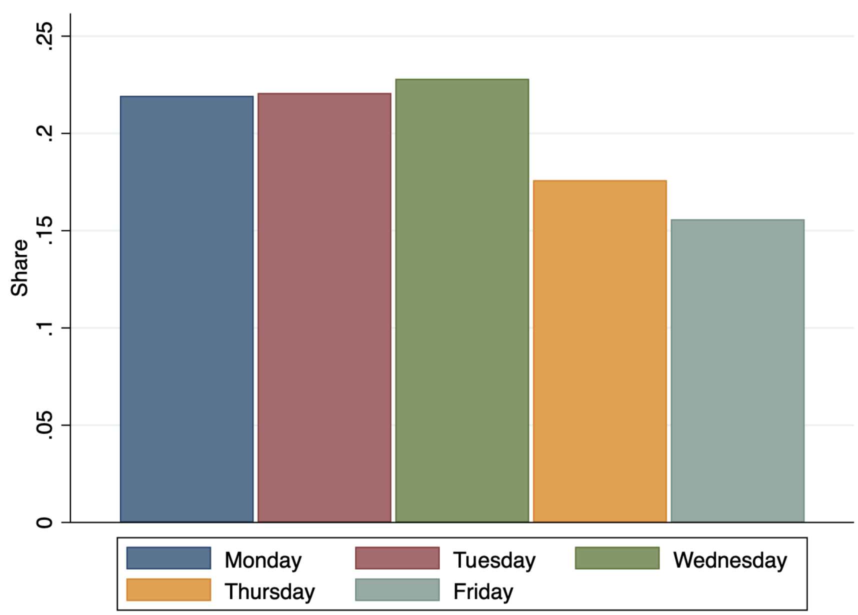
Note: Caseworkers are classified in terciles according to the number of contacts they had each month from January 2017 to December 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

Figure A.10: Histogram of the days of first meetings

(a) Paris sample



(b) Extended sample



Note: Days of the first meeting include days between January 1st, 2017 and December 31, 2018.
Source: IMILO (extraction date: October 2021), authors' calculations.

B Supplementary Tables

Table B.1: Construction of the samples and related number of observations

Filters	Paris	Extended
	(1)	(2)
0. Initial number of observations	17,832	242,236
1. No missing values in characteristics	17,826	221,302
2. Only regular first meetings	12,225	134,679
3. Econometric feasibility	6,906	43,166
Min date of the first meeting = 01/01/2017		
Max date of the first meeting = 12/31/2018		
Min number of youths by cell = 4		
Min number of caseworkers by cell = 2		
Min number of youth per caseworker by cell = 2		
Min number of years by caseworker = 2		
Min number of quarters by caseworker = 8		
Min number of months by caseworker = 8		
Min number of months per year by caseworker = 4		
Min number of caseworkers by agency overall = 3		
Over 01/2017-12/2018		
Number of centers	1	30
Number of agencies	6	62
Number of caseworkers	36	302
Min number of years per caseworker	2	2
Min number of quarters per caseworker	8	8
Min number of months per caseworker	15	14
Min number of months per year per caseworker	7	5
Min number of 1st meetings per caseworker	64	43
Min size of caseload per caseworker	65	52
Min number of caseworkers per agency	4	3
Per cell (Agency x Month)		
Min number of caseworkers per cell (Agency × Month)	5	2
Min number of youths per caseworker per cell (Agency × Month)	2	2

Note: This table reports the number of observations in our samples after each step of the construction for the econometric analysis and some statistics to check the consistency with the filters. The extended sample includes Paris center. Characteristics include all the characteristics listed in Table B.2 in Appendix B and in Table 1 in Section 3.3. Regular first meetings are individual meetings with caseworkers that do job search assistance.

Table B.2: Summary statistics on youth characteristics

	All sample	Paris sample		Extended sample	
		Full	Analysis	Full	Analysis
	(1)	(2)	(3)	(4)	(5)
Male	0.52	0.56	0.58	0.52	0.54
	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
Age	19.69	20.54	20.00	19.89	19.58
	(4.64)	(2.41)	(2.15)	(5.00)	(2.18)
Dropout	0.08	0.14	0.14	0.09	0.10
	(0.27)	(0.34)	(0.35)	(0.29)	(0.31)
Driving license	0.39	0.20	0.17	0.35	0.28
	(0.49)	(0.40)	(0.37)	(0.48)	(0.45)
Children	0.07	0.05	0.04	0.07	0.05
	(0.26)	(0.21)	(0.20)	(0.26)	(0.23)
Foreign nationality	0.12	0.30	0.28	0.16	0.19
	(0.33)	(0.46)	(0.45)	(0.36)	(0.40)
Northern African origin	0.13	0.18	0.18	0.16	0.20
	(0.33)	(0.39)	(0.38)	(0.37)	(0.40)
Sub-Saharan African origin	0.14	0.35	0.37	0.16	0.20
	(0.34)	(0.48)	(0.48)	(0.37)	(0.40)
Rent shelter	0.21	0.13	0.10	0.23	0.22
	(0.41)	(0.33)	(0.29)	(0.42)	(0.41)
Came on relatives advice	0.55	0.54	0.56	0.54	0.58
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)
N	808,222	17,832	6,906	242,236	43,166

Note: Paris and extended samples are described in Section 3.2.
Source: IMILO (extraction date: October 2021), authors' calculations.

Table B.3: Summary statistics on caseworker characteristics

	All sample	Paris sample		Extended sample	
		Full	Analysis	Full	Analysis
	(1)	(2)	(3)	(4)	(5)
Gender (male)	0.20	0.23	0.31	0.21	0.24
	(0.40)	(0.42)	(0.47)	(0.41)	(0.43)
Age at the first meeting	41.96	43.94	45.95	41.79	45.07
	(11.49)	(17.85)	(8.89)	(11.74)	(8.86)
Northern African origin	0.10	0.20	0.22	0.12	0.15
	(0.30)	(0.40)	(0.42)	(0.33)	(0.36)
Sub-Saharan African origin	0.07	0.15	0.11	0.07	0.06
	(0.25)	(0.36)	(0.32)	(0.25)	(0.24)
Caseload at the first meeting	92.86	102.99	154.78	95.95	143.82
	(66.87)	(69.44)	(43.06)	(70.83)	(50.42)
N	10,321	142	36	2,921	302

Note: Paris and extended samples are described in Section 3.2.
Source: IMILO (extraction date: October 2021), authors' calculations.

Table B.4: Summary statistics on labor market characteristics

	All sample	Paris sample		Extended sample	
		Full	Analysis	Full	Analysis
	(1)	(2)	(3)	(4)	(5)
Unemployment rate	8.85	7.15	8.10	9.32	9.54
	(2.11)	(1.34)	(.)	(2.11)	(2.04)
Labor market tightness	2.44	3.36	4.60	2.91	3.05
	(1.06)	(1.75)	(.)	(1.02)	(0.93)
Share of permanent job vacancies	0.57	0.72	0.67	0.62	0.59
	(0.08)	(0.06)	(.)	(0.12)	(0.05)
Share of part-time job vacancies	0.14	0.11	0.11	0.14	0.14
	(0.02)	(0.00)	(.)	(0.02)	(0.01)
Share of difficult hiring projects	0.49	0.48	0.46	0.47	0.47
	(0.07)	(0.03)	(.)	(0.07)	(0.07)
Share of seasonal hiring projects	0.23	0.12	0.12	0.20	0.19
	(0.09)	(0.00)	(.)	(0.07)	(0.06)
N	287	2	1	66	28

Note: Paris and extended samples are described in Section 3.2. Summary statistics on labor market characteristics are at the commuting zone level.
Source: IMILO (extraction date: October 2021), authors' calculations.

Table B.5: Correlations between the day of the first meeting and youths' characteristics (Paris sample)

	Monday	Tuesday	Wednesday	Thursday	Friday
	(1)	(2)	(3)	(4)	(5)
Employment before 1st meeting	-0.0085	-0.0073	0.0161	0.0220**	-0.0223**
	(0.0098)	(0.0069)	(0.0146)	(0.0065)	(0.0077)
Training before 1st meeting	0.0038	0.0440	-0.0386	-0.0201	0.0109
	(0.0442)	(0.0532)	(0.0408)	(0.0450)	(0.0461)
Openly unemployed	-0.0054	0.0024	-0.0034	0.0039	0.0026
	(0.0135)	(0.0169)	(0.0208)	(0.0081)	(0.0186)
Male	0.0052	0.0019	0.0097	-0.0013	-0.0154
	(0.0113)	(0.0131)	(0.0092)	(0.0082)	(0.0077)
Age	0.0101	-0.0282	-0.0060	-0.0006	0.0247
	(0.0159)	(0.0192)	(0.0156)	(0.0130)	(0.0135)
Dropout	0.0421	-0.0246	0.0113	-0.0096	-0.0192
	(0.0221)	(0.0144)	(0.0269)	(0.0108)	(0.0179)
Driving license	-0.0192*	0.0288	-0.0104	0.0184	-0.0176
	(0.0076)	(0.0166)	(0.0125)	(0.0119)	(0.0161)
Children	0.0093	0.0156	0.0003	-0.0184	-0.0067
	(0.0261)	(0.0227)	(0.0505)	(0.0170)	(0.0451)
Foreign nationality	0.0086	-0.0118	0.0062	-0.0012	-0.0019
	(0.0136)	(0.0106)	(0.0133)	(0.0044)	(0.0130)
Northern-African origin	-0.0122	0.0234	0.0213	-0.0209**	-0.0117
	(0.0206)	(0.0221)	(0.0121)	(0.0063)	(0.0173)
Sub-Saharan African origin	0.0096	0.0052	0.0017	-0.0071	-0.0094
	(0.0217)	(0.0193)	(0.0133)	(0.0080)	(0.0119)
Rent shelter	-0.0015	-0.0141	-0.0072	-0.0124	0.0352
	(0.0243)	(0.0143)	(0.0165)	(0.0107)	(0.0211)
Came on relatives advice	0.0208	-0.0010	-0.0000	-0.0142	-0.0057
	(0.0165)	(0.0100)	(0.0159)	(0.0079)	(0.0127)
Observations	5,355	5,355	5,355	5,355	5,355
R-squared	0.0810	0.0596	0.0412	0.0631	0.1014
Agency x Month FE	Yes	Yes	Yes	Yes	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. 3.2.

Table B.6: Correlations between the day of the first meeting and caseworkers' characteristics (Paris sample)

	Monday	Tuesday	Wednesday	Thursday	Friday
	(1)	(2)	(3)	(4)	(5)
Male	0.0467	-0.0221	-0.0357*	-0.0474*	0.0585***
	(0.0287)	(0.0218)	(0.0147)	(0.0204)	(0.0106)
Age	-0.0011	-0.0067***	0.0043	0.0007	0.0028
	(0.0014)	(0.0015)	(0.0022)	(0.0013)	(0.0017)
Northern-African origin	0.0134	-0.0309	0.0144	-0.0092	0.0122
	(0.0235)	(0.0383)	(0.0308)	(0.0290)	(0.0169)
Sub-Saharan African origin	-0.0195	-0.1116**	0.0488	0.0004	0.0819
	(0.0266)	(0.0415)	(0.0425)	(0.0193)	(0.0550)
Caseload	-0.0003	0.0003	0.0001	0.0001	-0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
Nb of appointments	0.0008*	-0.0007	0.0006	-0.0001	-0.0006
	(0.0003)	(0.0006)	(0.0006)	(0.0005)	(0.0006)
Nb of first meetings	0.0014	0.0011	0.0022	-0.0013	-0.0034
	(0.0022)	(0.0010)	(0.0016)	(0.0010)	(0.0025)
Nb of individual meetings	-0.0000	-0.0004	-0.0013	-0.0004	0.0020**
	(0.0007)	(0.0007)	(0.0010)	(0.0006)	(0.0008)
Nb of collective workshops	-0.0002	-0.0004	0.0004	-0.0001	0.0004
	(0.0008)	(0.0012)	(0.0005)	(0.0003)	(0.0013)
Nb of information sessions	0.0013	0.0002	-0.0020	0.0018**	-0.0013
	(0.0018)	(0.0011)	(0.0013)	(0.0006)	(0.0012)
Nb of administrative tasks	0.0006	0.0007	-0.0002	-0.0010**	-0.0001
	(0.0008)	(0.0004)	(0.0006)	(0.0003)	(0.0005)
Nb of digital contacts	-0.0002**	-0.0000	0.0002**	0.0001	-0.0001**
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
Observations	5,358	5,358	5,358	5,358	5,358
R-squared	0.0819	0.0729	0.0504	0.0672	0.1118
Agency x Month FE	Yes	Yes	Yes	Yes	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. 3.2.

Table B.7: Exogeneity of caseworkers VA (Employment – Paris sample)

	Employment	Caseworker EB		
	(1)	(2)	(3)	(4)
Male	-0.1206***	-0.0151	-0.0140	-0.0121
	(0.0290)	(0.0100)	(0.0119)	(0.0077)
Age	0.3720***	0.0342	0.0349	0.0233
	(0.0387)	(0.0220)	(0.0231)	(0.0215)
Dropout	-0.1992***	0.0218	0.0253	0.0176
	(0.0393)	(0.0294)	(0.0284)	(0.0315)
Driving license	0.2606***	0.0190	0.0179	0.0123
	(0.0349)	(0.0115)	(0.0119)	(0.0106)
Children	-0.3036***	-0.0134	-0.0156	-0.0315
	(0.0471)	(0.0134)	(0.0109)	(0.0261)
Foreign nationality	0.0335	0.0002	-0.0004	0.0041
	(0.0275)	(0.0181)	(0.0189)	(0.0192)
Northern-African origin	-0.1052**	0.0036	-0.0002	-0.0075
	(0.0311)	(0.0160)	(0.0165)	(0.0120)
Sub-Saharan African origin	0.0378	-0.0003	-0.0011	0.0013
	(0.0350)	(0.0123)	(0.0125)	(0.0090)
Rent shelter	0.0626*	0.0108	0.0104	0.0120
	(0.0257)	(0.0148)	(0.0145)	(0.0162)
Came on relatives advice	0.0110	0.0242	0.0247	0.0297*
	(0.0263)	(0.0155)	(0.0149)	(0.0139)
Observations	6,906	6,906	6,906	6,566
R-squared	0.0691	0.0640	0.0790	0.0973
Agency x Month FE	Yes	Yes	Yes	Yes
Date First Meeting FE	Yes	No	Yes	Yes
95% Winsorization of VA	No	No	No	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. FE and EB estimates are computed on the number of days of employment 24 months after the first meeting, according to equation (X) and (X) respectively.

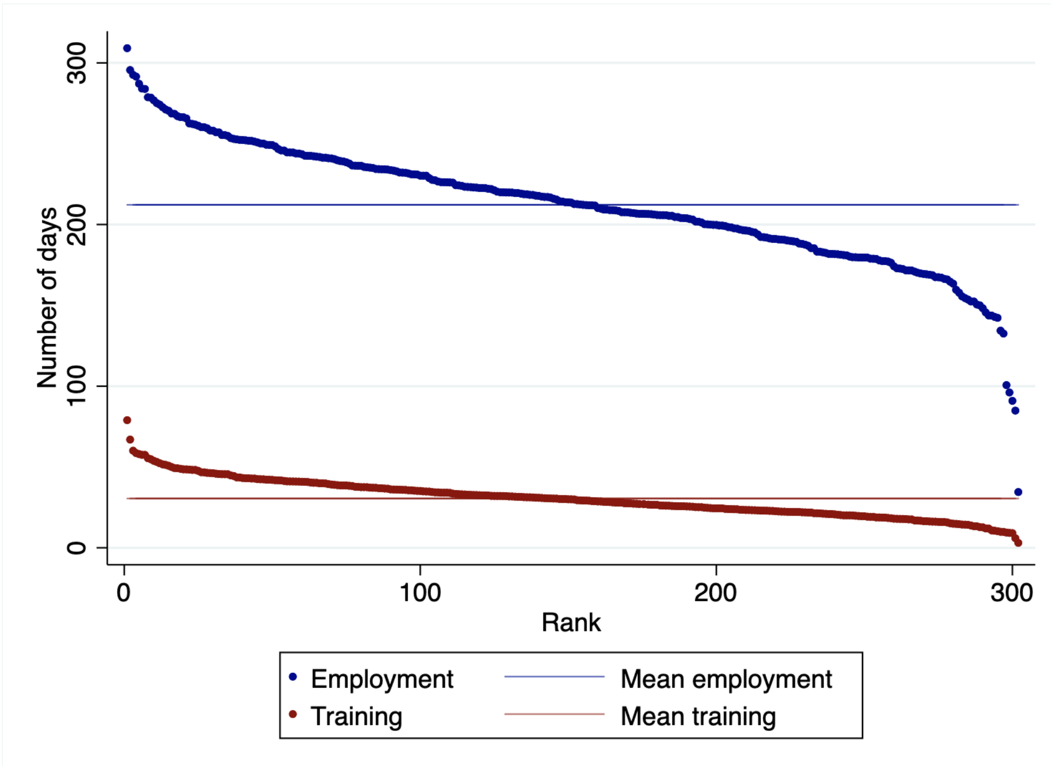
Table B.8: Exogeneity of caseworkers VA (Training – Paris sample)

	Training	Caseworker EB		
	(1)	(2)	(3)	(4)
Male	0.0435	-0.0040	-0.0033	-0.0169
	(0.0382)	(0.0205)	(0.0194)	(0.0135)
Age	-0.0571	-0.0162	-0.0188	0.0141
	(0.0479)	(0.0407)	(0.0407)	(0.0252)
Dropout	0.3643***	-0.0803	-0.0793	0.0206
	(0.0567)	(0.0999)	(0.1009)	(0.0479)
Driving license	-0.0648*	0.0005	-0.0028	-0.0095
	(0.0272)	(0.0141)	(0.0145)	(0.0127)
Children	0.1367	0.0117	0.0153	0.0155
	(0.0955)	(0.0348)	(0.0342)	(0.0407)
Foreign nationality	0.0143	0.0249	0.0251	-0.0113
	(0.0523)	(0.0358)	(0.0348)	(0.0190)
Northern-African origin	0.0075	-0.0301*	-0.0303*	-0.0229*
	(0.0299)	(0.0139)	(0.0143)	(0.0103)
Sub-Saharan African origin	0.1460***	-0.0147	-0.0152	-0.0118*
	(0.0213)	(0.0074)	(0.0079)	(0.0054)
Rent shelter	-0.0126	0.0046	0.0051	0.0023
	(0.0505)	(0.0347)	(0.0341)	(0.0265)
Came on relatives advice	0.0326	-0.0326	-0.0314	-0.0272
	(0.0319)	(0.0436)	(0.0424)	(0.0434)
Observations	6,906	6,906	6,906	6,571
R-squared	0.0566	0.0864	0.1000	0.1408
Agency x Month FE	Yes	Yes	Yes	Yes
Date First Meeting FE	Yes	No	Yes	Yes
95% Winsorization of VA	No	No	No	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. FE and EB estimates are computed on the number of days of employment 24 months after the first meeting, according to equation (X) and (X) respectively.

C Exogeneity for Extended sample

Figure C.1: Ranking of caseworkers(Extended sample)



Note: Caseworkers are ranked according to the average employment (in blue) and training (in red) situation of the youths who constitute their caseload 24 months after the first meeting.

Table C.1: Correlations between the day of the first meeting and youths' characteristics (Extended sample)

	Monday	Tuesday	Wednesday	Thursday	Friday
	(1)	(2)	(3)	(4)	(5)
Employment before 1st meeting	-0.0003	-0.0023	-0.0056	0.0104*	-0.0021
	(0.0051)	(0.0057)	(0.0051)	(0.0054)	(0.0044)
Training before 1st meeting	0.0278	0.0107	0.0037	-0.0279*	-0.0143
	(0.0178)	(0.0198)	(0.0210)	(0.0142)	(0.0135)
Openly unemployed	0.0040	-0.0012	0.0035	-0.0080	0.0018
	(0.0102)	(0.0066)	(0.0068)	(0.0061)	(0.0047)
Male	0.0026	-0.0095*	-0.0004	0.0074*	-0.0001
	(0.0047)	(0.0054)	(0.0049)	(0.0040)	(0.0039)
Age	0.0051	-0.0080	0.0073	-0.0094	0.0050
	(0.0070)	(0.0078)	(0.0062)	(0.0069)	(0.0047)
Dropout	0.0103	-0.0097	-0.0025	0.0070	-0.0051
	(0.0094)	(0.0099)	(0.0103)	(0.0080)	(0.0078)
Driving license	0.0037	-0.0005	-0.0002	0.0040	-0.0070
	(0.0060)	(0.0057)	(0.0053)	(0.0058)	(0.0050)
Children	-0.0026	-0.0065	-0.0032	0.0212**	-0.0090
	(0.0094)	(0.0094)	(0.0111)	(0.0106)	(0.0081)
Foreign nationality	-0.0034	-0.0056	0.0093	-0.0063	0.0059
	(0.0062)	(0.0053)	(0.0063)	(0.0059)	(0.0048)
Nothern-African origin	0.0022	0.0129**	-0.0023	-0.0069	-0.0058
	(0.0081)	(0.0057)	(0.0069)	(0.0053)	(0.0051)
Sub-Saharan African origin	0.0072	0.0041	-0.0000	-0.0063	-0.0049
	(0.0079)	(0.0075)	(0.0051)	(0.0055)	(0.0047)
Rent shelter	0.0053	0.0068	-0.0147**	0.0006	0.0020
	(0.0065)	(0.0054)	(0.0060)	(0.0067)	(0.0047)
Cam on relatives advice	-0.0274	0.0162*	0.0125**	-0.0092	0.0078
	(0.0173)	(0.0083)	(0.0056)	(0.0125)	(0.0071)
Observations	33,940	33,940	33,940	33,940	33,940
R-squared	0.1147	0.0905	0.0724	0.0988	0.1398
Agency x Month FE	Yes	Yes	Yes	Yes	Yes

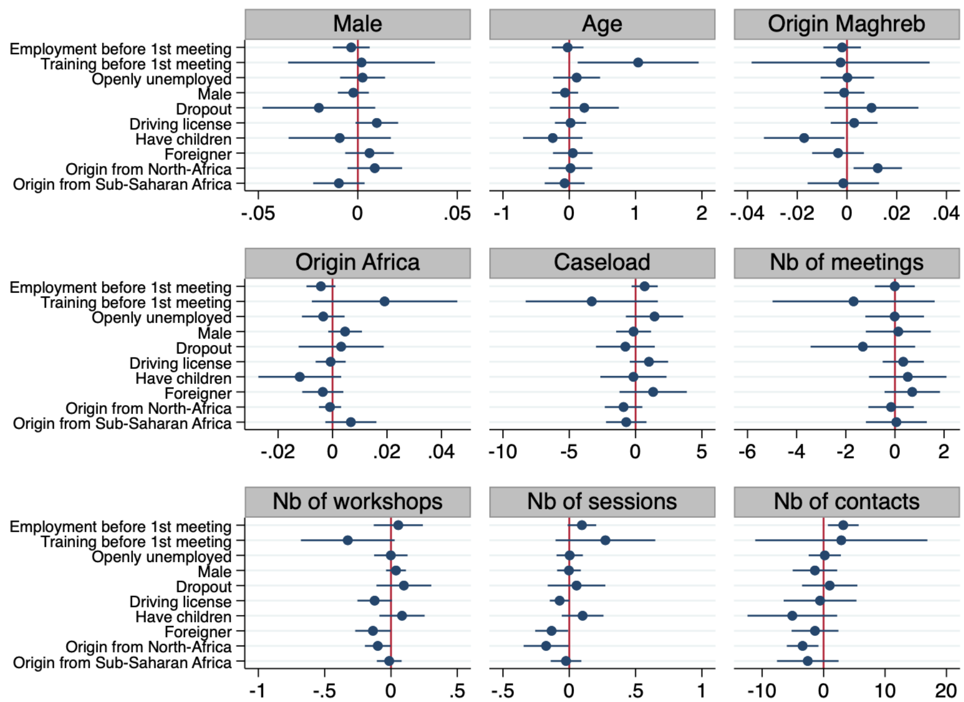
Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. 3.2.

Table C.2: Correlations between the day of the first meeting and caseworkers' characteristics (Extended sample)

	Monday	Tuesday	Wednesday	Thursday	Friday
	(1)	(2)	(3)	(4)	(5)
Male	-0.0074	0.0024	0.0240	-0.0302*	0.0113
	(0.0282)	(0.0182)	(0.0279)	(0.0154)	(0.0140)
Age	0.0003	-0.0016	-0.0014	0.0025***	0.0002
	(0.0012)	(0.0012)	(0.0016)	(0.0009)	(0.0011)
Northern-African origin	0.0104	-0.0253	0.0243	-0.0046	-0.0048
	(0.0215)	(0.0339)	(0.0443)	(0.0219)	(0.0200)
Sub-Saharan African origin	0.0219	-0.0590**	0.1126***	-0.0352	-0.0404
	(0.0333)	(0.0236)	(0.0394)	(0.0216)	(0.0277)
Caseload	-0.0003	0.0000	0.0005***	-0.0003	0.0000
	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Nb of appointments	0.0001	0.0003	0.0000	-0.0000	-0.0004
	(0.0005)	(0.0006)	(0.0005)	(0.0005)	(0.0004)
Nb of first meetings	0.0016	-0.0009	-0.0011	0.0004	0.0000
	(0.0021)	(0.0011)	(0.0009)	(0.0009)	(0.0008)
Nb of individual meetings	-0.0001	0.0000	-0.0001	0.0002*	0.0000
	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Nb of collective workshops	0.0004	0.0000	0.0014	-0.0012	-0.0005
	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0008)
Nb of information sessions	0.0022***	-0.0008	-0.0010	-0.0005	0.0001
	(0.0008)	(0.0006)	(0.0007)	(0.0011)	(0.0007)
Nb of administative tasks	0.0002	-0.0001	-0.0002	-0.0000	0.0001
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Nb of digital contacts	0.0000	-0.0000	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	33,971	33,971	33,971	33,971	33,971
R-squared	0.1159	0.0923	0.0794	0.1032	0.1408
Agency x Month FE	Yes	Yes	Yes	Yes	Yes

Note: Estimates are obtained with OLS regressions. Standard errors are below coefficients in parentheses and clustered at the agency × month level. 3.2.

Figure C.2: Correlation between youths' and caseworkers' characteristics (Extended sample)



Note: Each square shows the estimates from an OLS regression of a specific caseworker characteristics on all its youths' characteristics.