Types in Job Search Effort

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Public employment services are increasingly using online job platforms to help unemployed job seekers find jobs. This paper shows that these policies implicitly target those who benefit the most from them. The reason is that search intensity on online job platforms is characterized by "types": more-educated job seekers with better language and digital skills use the online job platform more intensively throughout their unemployment spell. Moreover, these high-types in online search effort are also more likely to take-up in-person job search assistance and, if they do, are more responsive to it. Using data from a public employment service, the paper provides causal evidence for the existence of types and presents a job search model to rationalize its findings.

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1. Introduction

Public Employment Services (PES) are increasingly using information and communication technologies to help unemployed individuals find jobs. In a survey of 25 PES, the European Commission (2019) found that in 2019, 18% of PES were actively experimenting with online recommender and profiling tools, and a further 35% were planning to start experimenting with them in the future. Also, 76% of PES were exploring AI-based matching technologies, while slightly more than 50% planned to use AI for forecasting a job seeker's unemployment duration.

These technologies are fundamentally changing the way job seekers search for jobs and how PES can support them in this process. Previous studies have shown how digital technologies can lower search frictions and increase job finding.[1] However, this paper argues that using digital tools to support job seekers can also come with important challenges. Specifically, it shows that the use of online job platforms also results in "types" of unemployed job seekers who differ in their job search intensity on online job platforms. Moreover, these types also differ in their take-up of in-person job search assistance and, if they do, their responsiveness to it. Consequently, types differ in their job finding rates because of an unintended targeting of job search assistance.

To explain the existence of types in online job search effort, the paper first presents a model in which job seekers differ in their costs of search effort. This model builds on the job search model presented in Le Barbanchon, Schmieder, and Weber (2024). It focuses on the search behavior of unemployed individuals who choose their job search effort and their reservation wage in each period, allowing for heterogeneity among individuals in their costs of job search effort. The model predicts persistent heterogeneity or "types in job search effort": individuals with lower costs of effort search more intensively for new jobs throughout their unemployment spells. Moreover, simulating the impact of in-person job search assistance as a temporary reduction in the costs of search effort shows that types with lower search costs are more responsive to it. Consequently, types with lower costs of search effort have shorter unemployment spells because online job platforms and in-person assistance implicitly target those who benefit most from them.

The paper then provides empirical evidence using data from a job search assistance program for the unemployed in Flanders, the Dutch speaking part of Belgium, called the Service Line. The Service Line provides an online job platform on which unemployed

[1] See Le Barbanchon, Schmieder, and Weber (2024) for an overview.

individuals can independently search for work, along with in-person assistance from PES caseworkers. The variation in search effort on the online job platform is largely explained by individual fixed effects, highlighting the importance of time-persistent heterogeneity or "types in online job search effort". Proving that types with high online search intensity are also more likely to take-up in-person assistance from a PES caseworker *and* are more responsive to it is complicated by the self-selection of types into in-person assistance.[2] To overcome this challenge, this paper draws from recent advances in Difference-in-Differences (DiD) designs with staggered treatment timing, allowing for the self-selection of types into the timing of in-person assistance when estimating its causal impact.[3]

The paper also shows that types can be predicted based on observed personal characteristics. Types with high online search effort (i.e., those who persistently use the online job platform more intensively) are primarily women with a bachelor degree and good knowledge of Dutch, without previous unemployment spells, who have logged into the online job platform at least once early in their unemployment spell. Additionally, the paper shows that most of these individual characteristics are also strong predictors of job finding. Finally, the paper demonstrates that there is negative duration dependence in online search effort for all types, suggesting that the impact of job search assistance through online job platforms quickly diminishes over the unemployment spell.

Our paper contributes to several existing studies. Some studies have analyzed job search behavior, with the majority focusing on moral hazard in unemployment insurance (UI).[4] Using data on unemployed job seekers in Germany, DellaVigna et al. (2022) provides experimental evidence that UI decreases the job-finding rate in the beginning of an unemployment spell and then exhibits a spike at the point of benefit exhaustion. Also using German data, Lichter and Schiprowski (2021) exploits a reform of UI policies to show that unemployment benefits reduce the number of job applications. Marinescu and Skandalis (2021) uses data on unemployed job seekers in France to find that UI depresses job search efforts early in unemployment spells. However, effort increases

[2]Bias from selection into assistance programs is a well known problem. See Ashenfelter (1978); LaLonde (1986); Angrist and Imbens (1991); Heckman, Ichimura, and Todd (1997). A more recent example is Mogstad, Santos, and Torgovitsky (2018).

[3]See Baker, Larcker, and Wang (2022); Callaway and Sant'Anna (2021); Sun and Abraham (2021).

[4]One notable exception is the analysis of job application behavior in Denmark by Fluchtmann et al. (2024). The focus of their work is to examine variation in the types of jobs applied for, both over the unemployment duration and between job seekers. This paper similarly examines sources of overall variation in job search behavior but crucially evaluates how such heterogeneity interacts with active labor market policies.

and remains high when unemployment benefits expire. Although these papers focus on job search behavior, as this paper does, they evaluate the impact of unemployment benefits. In contrast, this paper examines how the design of active labor market policies affects job search effort and job finding.

Closer to this paper is Schiprowski et al. (2024) which merges the data on search effort used in DellaVigna et al. (2022) with data on interactions with PES caseworkers and vacancy referrals.[5] Exploiting quasi-random variation in the timing of these interactions and referrals, the paper leverages a simple event-study specification to examine the dynamics of job search effort around these events. It finds that job search effort is higher on the day of the event. However, the authors are cautious in interpreting this as a causal effect because the spike in job search effort could (mechanically) capture the time spent in the meeting with the PES caseworker or in reading the referred vacancies. As will become clear below, this paper finds similar effects from a meeting with a PES caseworker. However, the meeting with the PES caseworker is excluded from the measure of job search effort. Moreover, the point of the empirical analysis in this paper is not to test whether a single interaction with a PES caseworker has a sizable impact on overall job search effort and job finding. Instead, the point of the empirical analysis below is to test whether types in job search effort and job finding exist.

Our paper also contributes to a growing body of work examining online job platforms and recommender systems. Belot, Kircher, and Muller (2019) shows that automating advice to job seekers using an online job platform reduces search costs and increases job finding. Algorithms that recommend occupations (Belot, Kircher, and Muller 2025; Altmann et al. 2023) or redirect job seekers towards less congested vacancies (Behaghel et al. 2024; Bied et al. 2023; Le Barbanchon, Hensvik, and Rathelot 2023) have also been shown to reduce search frictions and increase job finding rates.[6] Our contribution to this literature is twofold. First, we focus on heterogeneity in the use of an online job platform, as will become clear below. Second, we not only measure job finding but also directly observe job search effort on the platform.

Finally, our results are informative about the optimal design of job search assistance. Even if all unemployed job seekers have access to the same assistance in theory, in

[5]There is a small literature studying the impact of caseworker meetings with job seekers. However, these rarely observe search effort as an outcome and, instead, estimate impacts on job finding. See, for example, Schiprowski (2020).

[6]For a more comprehensive review of the literature, see Kircher (2022) and Le Barbanchon, Schmieder, and Weber (2024).

practice, we find that assistance targets those who benefit from it the most. This is in line with other studies showing that programs can effectively screen out those who need the program the most. Examples include self-selection into the Supplemental Nutrition Assistance Program (SNAP) (Finkelstein and Notowidigdo 2019; Giannella et al. 2024), mental health insurance (Shepard and Wagner 2025), disability programs (Deshpande and Li 2019), clean water subsidies (Dupas et al. 2016), electricity pricing plans (Ito, Ida, and Tanaka 2023), and pension schemes (Arulsamy and Delaney 2022).[7]

The remainder of the paper is structured as follows. Section 2 discusses how job search assistance for the unemployed is organized in Flanders, Belgium. Section 3 presents a job search model with heterogeneity in the costs of search effort, predicting that types with lower costs search more intensively throughout their unemployment spells and are more responsive to policies that temporarily reduce these costs. Section 4 explains our data, and Section 5 outlines our DiD research design to causally estimate a job seeker's response in terms of online search effort to a one-time interaction with a PES caseworker while allowing for the self-selection of types in the timing of this interaction. Section 6 presents our estimates. Section 7 shows that types in job search effort and job finding can be predicted using observed individual characteristics. Finally, Section 8 shows that there is negative duration dependence in job search effort for all types, making types less predictive of job search effort in prolonged unemployment spells. Section 9 concludes.

2. Job search assistance for the unemployed

In this section, we discuss job search assistance for the unemployed in Flanders, the Dutch speaking part of Belgium. The Flemish Public Employment Service (PES) is responsible for assisting unemployed individuals in their search for new jobs.

2.1. The Service Line

When registering as unemployed, individuals start a new trajectory on the Service Line which is outlined in Figure 1. On the first or second day of unemployment, the Service Line sends an e-mail to each newly registered unemployed worker asking them to complete five assignments on the PES' Online Job Platform (OJP) within 28 days.

[7]Some studies, however, find that self-selection into policies results in higher social welfare compared to automatic enrollment. See, for example, Rafkin, Solomon, and Soltas (2023).

These five assignments require the unemployed worker to log in to the OJP and do the following: 1) read her rights and obligations; 2) write and upload a CV; 3) complete a search profile; 4) save relevant vacancies in a personal folder; and 5) indicate which selection of new relevant vacancies can be sent to her email address. On day 22 of unemployment, the Service Line sends the unemployed worker a reminder to complete these tasks if she has not done so already.

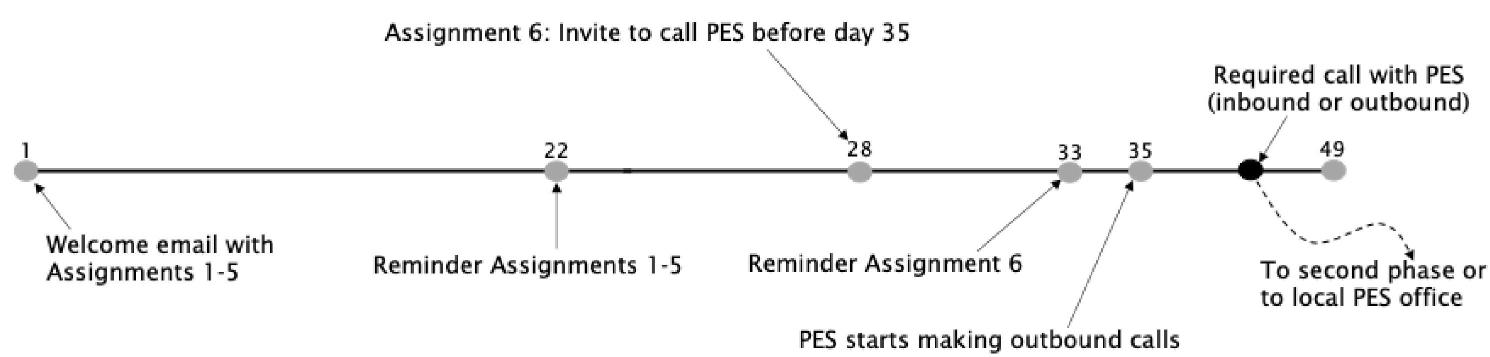
On day 28 of unemployment, the Service Line sends the sixth assignment to each unemployed job seeker by e-mail. The sixth assignment is a request to call the PES within a week, before the 35th day of unemployment. On the 33rd day, each individual receives a reminder to make the call if it has not already been made. On the 35th day, the PES lists all job seekers who did not make an inbound call. In the following two weeks, between days 35 and 49, the PES uses this list to make outbound calls. The list is updated continuously by removing job seekers who responded to the PES' outbound call or who made an inbound call after day 35. Job seekers can make an inbound call after day 35 if they responded late to the request by the PES to contact them before that day or if they responded to a missed outbound call made by the PES. The main goal of the call is an assessment by the PES of a job seeker's self-reliance.[8] If the PES caseworker finds that a job seeker is sufficiently self-reliant, the first phase of job search assistance ends, and the second phase starts.

If referred to the second phase, job seekers are expected to search for a job independently for 77 days.[9] On the 77th day of the second phase, job seekers are again contacted by the PES with a request to call the PES by phone within a week. Similar to the first phase, the PES makes outbound calls to job seekers who did not respond in the previous week. Again, the main goal of this call is for the PES caseworker to assess job seekers' self-reliance. If found sufficiently self-reliant, a job seeker's second phase ends, and a similar but final third stage begins. If the caseworker does not find a job seeker sufficiently self-reliant in the first, second, or third phase, the job seeker's case on the Service Line is closed, and the job seeker is referred to her local PES office for in-person assistance. The same is true for job seekers who are still unemployed at the end of the third phase.

[8] A limited number of assessments by caseworkers occur in calls before day 28 or after day 49. However, the content of assessment calls that happen outside the context of the sixth assignment is different and is not the focus of our analysis, as will become clear below.

[9] See Appendix A.1 for details.

FIGURE 1. **The Service Line, first phase**



Source: Flemish PES.

2.2. The assessment call in the first phase of the Service Line

The inbound or outbound assessment call, as part of the sixth assignment in the first phase of the Service Line, lasts about 20 minutes. During this call, the PES caseworker follows a detailed script that consists of three parts[10]: a) an introduction to check how the job seeker is doing, completion of personal details if still missing, and whether the job seeker is actively searching for a job; b) a middle part motivating the job seeker to use the OJP to search for, save, and apply to vacancies, as well as an assessment by the PES caseworker regarding whether the job seeker can search independently and start the second phase of the Service Line, or whether she cannot search independently and needs personal assistance from her local PES office; and c) a final part that summarizes the call and outlines the next steps.

2.3. The Online Job Platform (OJP)

Not long after its launch in 1999, the OJP became the most important channel for unemployed workers to search for jobs and for employers to post vacancies.[11] In 2001, the PES further improved its online services by sending job seekers or employers a text or email message when a relevant vacancy or job seeker was added to the OJP. In 2004, the PES also expanded its call center by introducing a free telephone number that anyone could call at any time during business hours. In 2018, the PES redesigned its support for unemployed job seekers by integrating its OJP and call center services, resulting in the Service Line. In 2021, the year we use in our analyses below, all individuals registered as newly unemployed started a new trajectory on the Service Line.

After logging into the OJP, a job seeker can upload their CV. The OJP also creates an individual-specific search profile using an individual's past work experience, as well as a list of occupations in which they are interested. The OJP then shows the individual a curated list of vacancies that aligns with her search profile. In addition, a job seeker can save vacancies to a personal folder on the OJP, request that the OJP send relevant vacancies by email, and apply to vacancies on the OJP.[12] The PES collects and stores

[10] See Appendix A.2 for more information about the script used by caseworkers.

[11] After several years of experimenting with a vacancy database stored in offline terminals, the Flemish PES was the first European PES to make its vacancy database available online in 1995. In 1997, it added a database with information on unemployed job seekers that employers could consult online. Two years later, the PES integrated both databases into an Online Job Platform (OJP).

[12] The latter is used less frequently since companies tend to provide their own hyperlink in the vacancy text through which candidates can apply.

data about each unemployed job seeker's search effort on the OJP. Together with other personal data, the PES also uses a job seeker's search effort in a machine learning model to predict each individual's probability of finding a job within six months. This prediction is made on a daily basis, and its aim is to inform PES caseworkers when deciding whether to refer individuals to the next phase of the Service Line or to a local PES office at the end of an assessment call.

2.4. Importance of the OJP

We sent an online survey to each individual in our sample, further explained below, approximately 6 weeks into their unemployment spell. Of those who received the survey, 13% completed the questionnaire. Respondents are somewhat older and more likely to be women. In terms of education and migration background, however, they are similar. In this online survey, we ask respondents about their search behavior across seven channels, including the OJP, other job platforms, social media, and temporary help agencies. For each of the seven channels, we ask whether they use them and, if so, for how many hours per week. We also asked respondents to rank the channels by order of importance. Finally, for those job seekers who found work by the time the survey took place, we also asked through which channel they found their jobs.

The OJP is reported to be the most important channel for job search, both in terms of time spent on it and its ranking.[13] While job seekers clearly divide their time across multiple channels, 70% mentioned that they at least used the OJP once in the past week, which far exceeds the use of any other channel. The OJP also has the highest average ranking of 2 out of 7 channels. When looking at the small and selected sample of job seekers who found work by the time of the survey, 17% report having found work through the OJP, which is only exceeded by the 24% who found work through a temporary help agency.

3. A model of job search effort with types

This section builds on the workhorse job search model presented in Le Barbanchon, Schmieder, and Weber (2024). The model focuses on the job search decisions of an unemployed worker who chooses both job search effort and whether to accept a job

[13] See Appendix A.3 for details.

offer that pays a certain wage. As in (one version of) their model, we assume that job seekers are heterogeneous in their costs of job search effort. However, we also extend their model in two important ways that are relevant to our setting. First, we model and simulate the impact of the assessment call in the first phase of the Service line as a temporary reduction in the costs of job search effort, such that types with lower costs of job search effort respond more strongly to it.[14] Second, we assume that the expected wage decreases over time to generate negative duration dependence in job search effort, as we observe in our data.

3.1. Environment

Each unemployed job seeker optimally chooses their search effort, $e_d > 0$, and reservation wage, ϕ_d, in each period d of their unemployment spell. Search effort determines the probability of receiving a job offer, $s_d = f(e_d)$, with $f(.)$ being a continuous function that is strictly increasing in e_d. If a job offer is received, it is assumed that the job contains a wage drawn from a known wage offer distribution $F_d(w)$. The costs of search effort are given by a continuous function $c(e_d)$ which is assumed to be strictly convex.

Job seekers discount future flow utility at a rate of δ. Per-period flow utility is given by the constants $u(b)$ when unemployed and by $v(w)$ when employed.[15] Once a job is accepted, the job seeker keeps it indefinitely. This leads to the following equation for the value of employment:

$$V^E_{d+1} = v(w)/(1-\delta) \tag{1}$$

The value function for unemployment is captured by the following Bellman equation:

$$V^U_d = \max_{e_d} \left\{ u(b) - c(e_d) + \delta \left(f(e_d) \int \max\left(V^E_{d+1}, V^U_{d+1}\right) dF_d(w) + (1 - f(e_d))V^U_{d+1} \right) \right\} \tag{2}$$

Using that $s_d = f(e_d)$, this can be rewritten as:

$$V^U_d = \max_{s_d} \left\{ u(b) - \tilde{c}(s_d) + \delta \left(s_d \int \max\left(V^E_{d+1}, V^U_{d+1}\right) dF_d(w) + (1 - s_d)V^U_{d+1} \right) \right\} \tag{3}$$

[14] In contrast, Le Barbanchon, Schmieder, and Weber (2024) simulates how different types of job seekers respond differently to the expiration of unemployment benefits after 12 months.

[15] The assumption that unemployment benefits are constant over time is consistent with actual benefits for unemployed job seekers in our sample.

where $\tilde{c}(s_d)$ is defined as $\tilde{c}(s_d) \equiv c(f^{-1}(s_d))$.

Given that the reservation wage, ϕ_{d+1}, is the minimum wage for which a job seeker is willing to start a job in the next period, this equation can be rewritten as:

$$V_d^U = \max_{s_d} \left\{ u(b) - \tilde{c}(s_d) + \delta \left(s_d \int_{\phi_{d+1}}^{\infty} \left(V_{t+d}^E - V_{d+1}^U \right) dF_d(w) + V_{d+1}^U \right) \right\} \tag{4}$$

Using the definition of the reservation wage further allows us to rewrite equation (1) as:

$$V_{d+1}^U = v(\phi_{d+1})/(1-\delta) \tag{5}$$

3.2. First-order conditions

The first order condition determining optimal search effort is where its marginal cost equals its marginal benefit:

$$\tilde{c}'(s_d^*) = \delta \int_{\phi_{d+1}^*}^{\infty} \left(V_{d+1}^E - V_{d+1}^U \right) dF_d(w) \tag{6}$$

with $\tilde{c}'(.)$ the first-order derivative of $\tilde{c}(.)$. Using that $v(w) = (1-\delta)V_{d+1}^E$ and $v(\phi_{d+1}) = (1-\delta)V_{d+1}^U$, we can rewrite this as:

$$s_d^* = \tilde{c}'^{-1} \left(\frac{\delta}{1-\delta} \int_{\phi_{d+1}^*}^{\infty} \left(v(w) - v(\phi_{d+1}^*) \right) dF_d(w) \right) \tag{7}$$

Moreover, combining equations (1), (4) and (5) determines the optimal reservation wage:

$$v(\phi_d^*) = (1-\delta)(u(b) - \tilde{c}(s_d^*)) + \delta v(\phi_{d+1}^*) + \delta s_d^* \int_{\phi_{d+1}^*}^{\infty} \left(v(w) - v(\phi_{d+1}^*) \right) dF_d(w) \tag{8}$$

3.3. Steady state

Further, assume that the wage offer distribution is stationary in all periods $d \geqslant S$ and is given by $F_S(w)$. This implies constant optimal values s_S^* and ϕ_S^* for all $d \geqslant S$. Equation (7) then becomes:

$$s_S^* = \tilde{c}'^{-1} \left(\frac{\delta}{1-\delta} \int_{\phi_S^*}^{\infty} \left(v(w) - v(\phi_S^*) \right) dF_S(w) \right) \tag{9}$$

and equation (8) becomes:

$$v(\phi_S^*) = u(b) - \tilde{c}(s_S^*) + \frac{\delta}{1-\delta} s_S^* \int_{\phi_S^*}^{\infty} \left(v(w) - v(\phi_S^*)\right) dF_S(w) \tag{10}$$

Equations (9) and (10) constitute a system of two equations in two unknowns, s_S^* and ϕ_S^*. Once these equations are solved for the steady-state values of optimal search effort and the reservation wage, all other values of s_t^* and ϕ_t^* can be obtained through backward induction using equations (7) and (8).

3.4. Multiple types in the cost of job search effort

Assume that there are two types of unemployed job seekers who differ in their costs of search effort. In particular, assume that the cost of search effort is given by:

$$\tilde{c}(s_d) = k_j \frac{s_d^{(1+\gamma)}}{(1+\gamma)} \tag{11}$$

with $j = 1, 2$ and such that $0 < k_1 < k_2$, and with $\gamma > 0$. That is, unemployed job seekers with k_1 have lower search costs than those with k_2.

When unemployed job seekers differ in their costs of search effort, aggregate outcomes at time d are weighted averages of job seekers who are still unemployed at time d. These aggregation weights are time-varying because heterogeneity in job search effort results in different job finding rates. Consequently, the composition of types in the pool of unemployed job seekers will endogenously change over time. We denote the share of unemployed job seekers with k_1 at time d as $q_{1,d}$.

3.5. Modeling negative duration dependence in job search effort

To model duration dependence in job search effort, we assume that $u(b) = \ln(b)$ and that the probability density function of the wage offer distribution is lognormal:

$$\ln_d(w) \sim N(\mu + \pi \, max\{S - d, 0\}, \sigma^2) \tag{12}$$

Note that the mean of this probability density function is decreasing in d before reaching a constant steady state of μ in period S. This assumption implies that there will be negative duration dependence in job search effort (and hence in job finding rates), which we observe in our data below.

The assumed negative duration dependence in the average wage can be interpreted in several ways. One interpretation is that prolonged unemployment spells lower labor productivity, resulting in lower wages. Another interpretation is that prolonged unemployment discourages job seekers from looking for work, resulting in a decline in the quality of job search and, therefore, in the returns to job search effort.

3.6. Simulating the impact of the assessment call

The main goal of the inbound or outbound call, as part of the sixth assignment in the first phase of the Service Line, is an assessment by the PES of a job seeker's self-reliance. During this call, however, the PES caseworker also checks and motivates the job seeker to search for jobs using the OJP. We model this intervention as a temporary reduction in the cost of job search effort. Specifically, we simulate a one-period 35% reduction in the search costs for each type by multiplying each k_j by a factor of 0.65 in $d = 5$.

To simulate the model, we take parameter values from Le Barbanchon, Schmieder, and Weber (2024) for δ, k_1, k_2, γ, μ, and σ. Because their simulated model with multiple types does not allow for a time-varying wage offer distribution, thereby implicitly setting $\pi = 0$, we instead assume that $\pi = 0.5$. Finally, we assume that the initial share of k_1 types is $q_{1,0} = 0.5$ and that $S = 25$.[16]

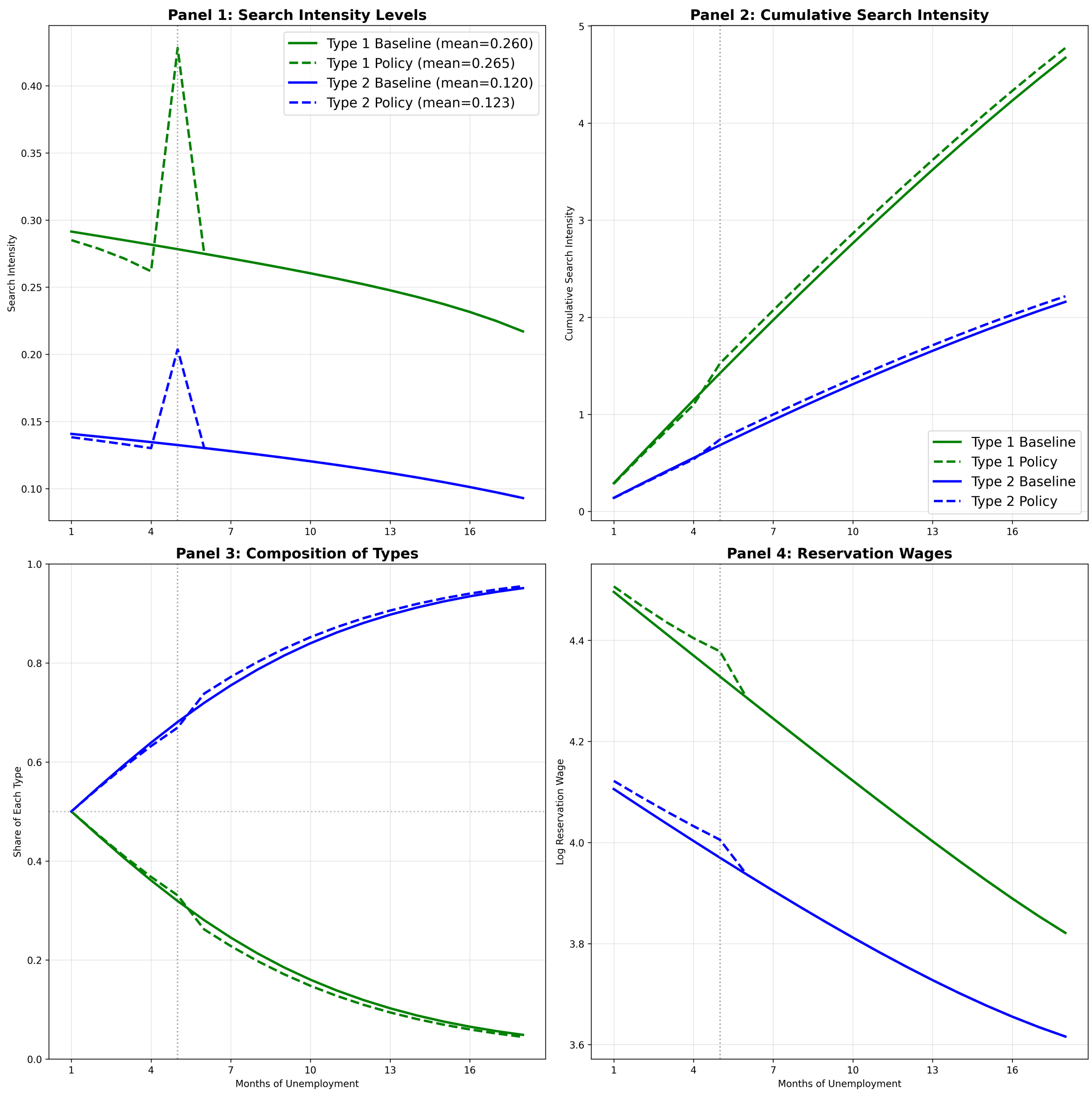
The solid lines in Figure 2 show the baseline behavior of job seekers with low costs of job search effort, k_1 (green line), and high costs of job search effort, k_2 (blue line). Panel 1 plots job search effort, which is consistently higher for job seekers with low costs of job search effort. The panel also shows that job search effort declines over time for both types, indicating negative duration dependence in job search effort. Panel 2 shows job search effort, as in Panel 1, but now cumulative over the unemployment spell.

Panel 3 of Figure 2 shows the share of k_1 and k_2 types, captured by the green and blue lines respectively, assuming that both groups are equally large at the start. Not surprisingly, the share of k_1 types is decreasing over time because job seekers with k_1 search more intensively and, therefore, find jobs faster. Finally, panel 4 plots the optimal paths for reservation wages. Because job seekers with k_1 consistently generate more job offers, they have higher reservation wages throughout their unemployment spells. However, reservation wages for both types decrease over time.[17]

The dashed lines in Figure 2 simulate the impact of the assessment call. Panel 1

[16] See Appendix B.1 for details.
[17] Appendix B.2 further shows simulations for exit hazard and survival rates.

FIGURE 2. **Simulation of job search effort with and without the assessment call**



Notes: Panel A plots the level of job search effort. Panel B shows cumulative job search effort. Panel C plots the composition of types by unemployment duration. Panel D displays reservation wages. Time periods are months of unemployment. Blue lines represent job seekers with low costs of job search effort, k_1. Green lines represent job seekers with high costs of job search effort, k_2. Solid lines simulate the baseline model, and dashed lines augment the baseline model with the assessment call.

shows that both types of job seekers increase their search effort when the assessment call takes place. Importantly, the figure also shows that job seekers with k_1 are more responsive to the assessment call than job seekers with k_2. Although the assessment call treats all unemployed job seekers equally, those with lower costs of job search effort respond more strongly to it. Consequently, the assessment call increases the difference between both types in cumulative search effort (panel 2). The assessment call also results in a faster shift over time in the pool of unemployed workers away from job seekers with low costs of job search effort (panel 3), despite a stronger increase in their reservation wage (panel 4).[18]

The simulations in Figure 2 assume that unemployed job seekers differ in their costs of job search effort, and that the assessment call temporarily lowers these costs. While intuitive, unemployed job seekers can also differ in ways other than the costs of their job search efforts. For example, different wage offer distributions could also result in heterogeneous search effort over the unemployment spell. To understand whether types in wage offer distributions could also generate the patterns in Figure 2, we estimated an alternative version of the model where $k_1 = k_2$ but $\mu_1 > \mu_2$, while maintaining the assumption that the assessment call reduces the costs of job search effort. This version of the model generates qualitatively identical patterns to those in Figure 2.[19] Most importantly, we still find that the assessment call increases job search effort more for unemployed job seekers with higher mean wage offers.

4. Data

Our main data consist of the total inflow of individuals entitled to unemployment benefits between March 1 and September 9, 2021, in Flanders. To qualify as newly unemployed, a previous unemployment spell must have ended at least 6 months ago. Due to the generous unemployment benefit system in Belgium, no previous employment is mandatory to receive unemployment benefits. Hence, our data also include individuals who are looking for work after graduating. In total, we observe 36,343 unemployed individuals. For each of these individuals, we combine various data.

[18] Also, note that job seekers search somewhat less intensively and have somewhat higher reservation wages in anticipation of the assessment call, but this anticipation effect is relatively small. In our setting, unemployed job seekers are not informed about the assessment call before day 28 of their unemployment spell, making anticipation unlikely.

[19] See Appendix B.3 for details.

4.1. Personal characteristics

From the administrative registry of the PES we observe several personal characteristics at the start of the unemployment spell, such as age, gender, education, whether individuals have recently graduated without work experience, whether they have a labor disability, a migration background, self-reported knowledge of Dutch, their municipality of residence, and the channel through which they registered as unemployed.

Column (1) of Table 1 summarizes some characteristics of the total inflow of newly unemployed individuals between March 1 and September 9, 2021, in Flanders. Half have post-secondary education (48%), with a third being recent graduates. The total sample is balanced in terms of gender, almost all possess at least a good knowledge of Dutch (90%), most were born in Belgium (78%), over half (56%) are younger than 30, and most live in (sub)urban areas (92%).

4.2. Job search effort

We observe individuals' interactions with the Service Line on a daily basis. Most importantly, we observe the day on which the assessment call is made, whether it was an inbound or outbound call, and whether the job seeker was characterized as self-reliant or referred to a local PES office for personal assistance. We also observe the day on which they complete their assignments 1 to 5.

We measure individuals' job search behavior on the OJP daily. Namely, the number of times someone logged into the OJP, the number of saved vacancies on the OJP, and the number of vacancies emailed by the OJP to a job seeker. Receiving vacancies by email from the OJP also requires logging in, setting up a specific search query, and requesting that new vacancies within that query be sent via email. Therefore, we use the number of logins per day or per week as our main measure of job search effort. In additional analyses, we also use a dummy variable to indicate whether someone saved vacancies on the OJP, as well as the number of vacancies received by mail.

4.3. Job finding

We observe when individuals leave unemployment on a monthly basis. Namely, the PES provides an indicator at the end of each month of whether a job seeker has found work. This indicator is based on the combined information from two administrative sources: the registration of employment contracts and those of the self-employed. For each

TABLE 1. **Sample Characteristics**

	column %		
	total (1)	selected (2)	dropped (3)
Education			
Primary	5.62	4.18	6.21
Some secondary	13.47	11.55	14.26
Secondary	19.22	18.44	19.54
Higher professional	26.42	24.29	27.30
Bachelor	22.03	24.19	21.15
Master	13.18	17.35	11.47
missing	0.05	0.00	0.07
Recently graduated			
Yes	30.59	25.06	32.87
No	69.41	74.94	67.13
Gender			
Male	48.40	44.51	50.00
Female	51.60	55.49	50.00
Knowledge of Dutch			
None	2.77	2.37	2.94
Limited	6.72	6.57	6.78
Good	14.45	14.04	14.61
Very Good	75.66	77.02	75.10
missing	0.40	0.00	0.56
Region of birth			
Belgium	77.98	78.61	77.72
Europe	5.69	6.07	5.53
Non-Europe	16.33	15.32	16.75
Age (at inflow)			
<24y	34.63	27.02	37.75
25-29y	21.96	20.12	22.71
30-34y	12.68	14.51	11.93
35-44y	18.40	22.20	16.84
45-59y	12.34	16.15	10.77
Urbanisation of residence			
Urban	23.36	25.73	22.39
Sub-urban	68.74	66.95	69.47
Rural	7.90	7.32	8.14
Referred to local PES office based on assessment call			
Yes	22.85	33.07	18.65
No	30.44	66.93	15.46
No assessment call	46.71	0.00	65.88
Number of unique individuals	36,343	10,579	25,764

Notes: Column (1): Total inflow sample of newly registered unemployed between 1 March 2021 and 9 September 2021 in Flanders. Column (2): Observations in our main estimating sample. Column (3): Observations not in our main estimating sample. Urbanization of residence is based on the municipality of residence, merged with the labeling by Eurostat of degree of urbanization. Knowledge of Dutch is self-reported. Disability refers to any officially recognized disability, mental or physical.

unemployed job seeker, we know whether they found a job before 1 October 2022. That is, unemployment spells are censored at 18 months for those who became unemployed on 1 March 2021 and at approximately 12 months for those who became unemployed on 9 September 2021.

Our data also contain personalized job finding predictions made by a Machine Learning algorithm developed by the PES.[20] An ML score represents the predicted probability that someone will find work within the next six months.[21] Importantly, the algorithm also uses previous unemployment spells as one of its predictors, which we do not observe directly. Predictions are made daily for each individual, and the model is re-estimated every month. For our analyses below, we use the first score given to a job seeker on day 7 of their unemployment spell and their ML score on day 28.

4.4. Sample restrictions

(i) Of the 36,343 newly registered unemployed, we only keep individuals for whom we observe an assessment call with the PES. The main reason for not observing an assessment call is that individuals leave unemployment during the first two months. After this first selection, we are left with 17,614 unique individuals.

(ii) Our empirical design below requires that we observe individuals at least 5 days after their assessment call to estimate dynamic treatment effects. Therefore, we drop 193 job seekers who find work within 5 days after the assessment call, leaving us with a sample of 17,421 individuals.

(iii) Almost everyone logs into the OJP on the first day of unemployment to access their proof of registration as unemployed, which is needed to claim unemployment benefits. Afterwards, 2,572 individuals never log into the OJP again. Dropping these individuals further restricts the sample to 14,849 job seekers. Consequently, the comparison in the causal parameters estimated below exclude those who never log into the OJP after the first day of unemployment.

(iv) We focus on assessment calls that took place between days 28 and 49 of unemployment because we know the script that structured the calls that took place in the context of the sixth assignment. Importantly, these calls must contain an explicit

[20] See Appendix C for details.

[21] Ernst, Mueller, and Spinnewijn (2024) examines the predictive power of this score compared to a caseworker's assessment of a job seeker's self-reliance during the assessment call. They find that a caseworker's assessment adds value to a ML score, suggesting that caseworkers have relevant private information when making their assessment.

encouragement by the PES caseworker to make use of the OJP. A limited number of assessment calls happen before day 28 if, for example, an unemployed individual calls the Service Line and that call evolves into an assessment decision by the PES caseworker. However, these early calls do not follow the same script such that their content could be very different. There are 1,875 individuals with an assessment before day 28, and they are dropped from our estimating sample.

(v) A limited number of assessment calls took place after day 49, and it is very likely that also these calls deviated from the script for calls used between days 28 and 49. For example, they may have a more threatening content that job seekers need to comply with the requests made by the PES. The 1,693 individuals with assessment calls after day 49 are kept for a robustness check, but excluded from our main analyses. This results in a main estimating sample of 10,579 unique individuals.

Column (2) of Table 1 shows summary statistics for our main estimating sub-sample, and column (3) shows the characteristics of individuals who have been dropped due to the restrictions discussed above. Column (2) shows that our main estimating sub-sample is somewhat more highly educated, less likely to be a recent graduate, more likely to be female, and somewhat older. The bottom panel in Table 1 shows that in our main estimating sample, a third of individuals are referred to their local PES office for personal assistance, and two thirds are referred to the second phase of the Service Line after their assessment call.

5. Event-study Difference-in-Differences design

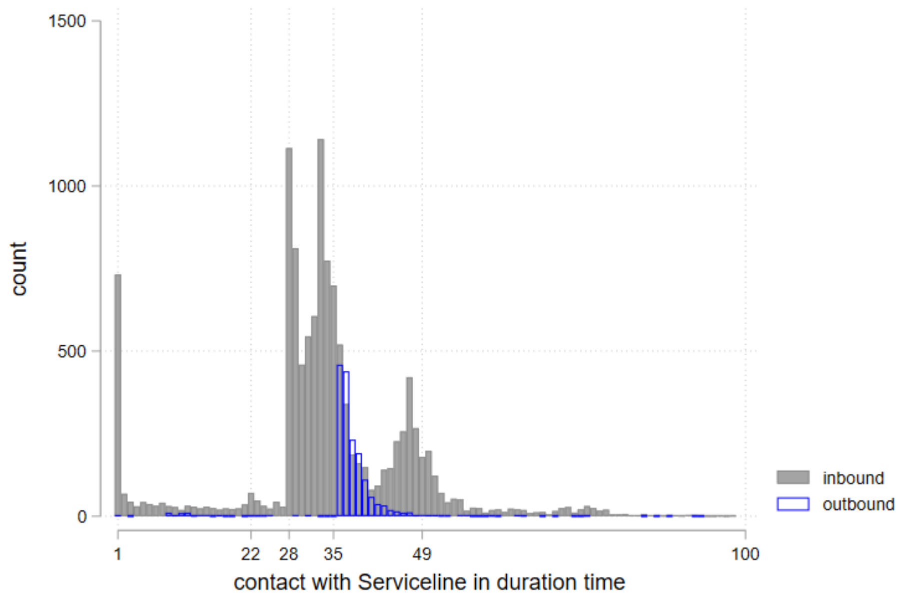
5.1. Inbound and outbound assessment calls

Figure 3 shows the number of assessment calls by day of contact in terms of duration time.[22] For some job seekers, this assessment call takes place upon being registered as unemployed. These are job seekers who cannot independently search for work and whose cases are therefore immediately transferred to their local PES offices. For the remainder of job seekers, there are relatively few assessments up to day 28 of unemployment, the day when they receive the sixth assignment, which is a request to call the PES.

Between days 28 and 35, assessments based on inbound calls increase, with spikes

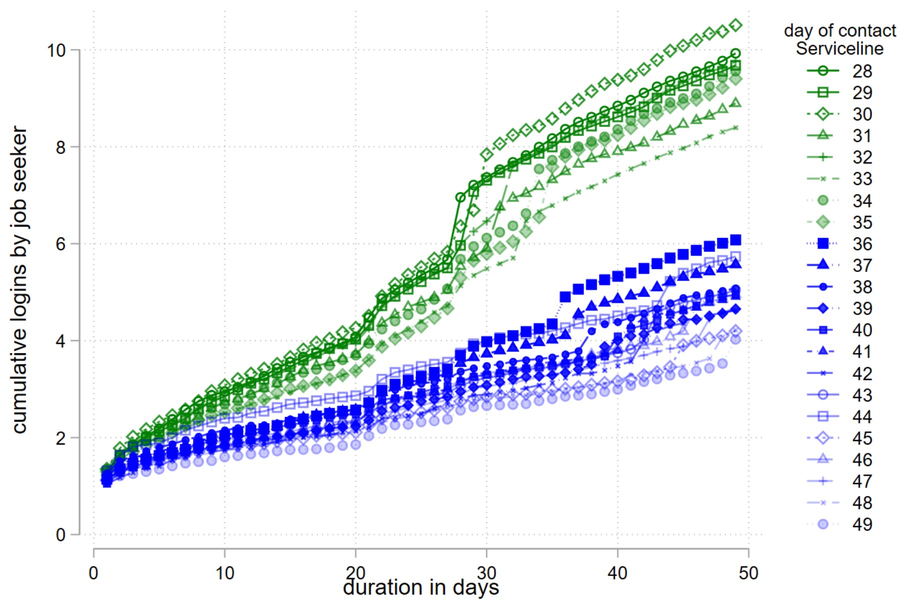
[22] Data for Figure 3 are based on restricting the sample by steps (i)-(iii) but not (iv)-(v) discussed above.

FIGURE 3. **Inbound and outbound calls by day of contact**



Notes: This figures shows the density of job seekers by day at which they have their assessment call with the PES. We split calls by whether they were initiated by the job seeker (inbound) or the PES (outbound). The x-axis is cut at 100 days. This leaves out 581 job seekers of the total 14,849 selected for this figure.

FIGURE 4. **Cumulative logins by day of assessment call**



Notes: This is a binscatter of the mean cumulative logins of job seekers across duration time. Job seekers are split by the day at which they have an assessment call. Green lines presents all days of contact before the PES starts making outbound calls. Blue lines present all days of contact afterwards.

on days 28 (when they receive the assignment) and 33 (when they receive a reminder). From day 36 onward, the PES starts making outbound calls based on a continuously updated list of job seekers who have not yet made an inbound call. When the PES cannot reach a job seeker, it leaves a message asking them to return the call. The rise in the number of inbound calls in the run-up to day 49 is explained by job seekers who return missed outbound calls from the PES. In summary, the timing of telephone calls observed in our data corresponds closely to the timing of events in Figure 1.

5.2. Cumulative logins by day of assessment call

Figure 4 plots the average *cumulative* logins over duration time per group of job seekers whose call with a PES caseworker took place on any given day between days 28 and 49. The green lines represent groups of job seekers who make inbound calls between days 28 and 35. The blue lines represent groups that had their calls (either inbound or outbound) with the PES caseworker on some day between 36 and 49.[23]

Figure 4 visualizes several insights. First, job seekers who call the PES before day 36 are more likely to log in throughout their unemployment spells. This corresponds to the solid lines in Panel B of Figure 2, in which job seekers with low search effort costs self-select to make an inbound call before day 35. Second, the figure suggests an overall positive impact of the assessment call on logins to the OJP; when a cohort is treated, the average cumulative logins increase. Moreover, this increase in average cumulative logins seems larger for cohorts treated before day 36. This is consistent with the dashed lines in panel B (and panel A) of Figure 2, in which job seekers with low search effort costs are more responsive to the assessment call. Third, and also in line with our simulations above, the impact of the assessment call on OJP logins is short-lived. That is, the OJP does not seem able to capture a job seeker's attention for long after the assessment call.

To examine the impact of the assessment call on job search effort more causally, we use an event-study Difference-in-Differences (DiD) design, utilizing the timing of the assessment call for identification. Denote a job seeker by i, duration time by d, and the day of the assessment call by g with $28 \leq g \leq 49$. If job seeker i actually logs into the OJP on day d, we have that $Y_{i,d} = 1$ (and $Y_{i,d} = 0$ otherwise). Define g_i as the day in duration time when a job seeker i has her assessment call, and define the cohort of all

[23]Data for Figure 4 are based on all data restrictions (i)-(v) discussed above.

job seekers who have their calls on the same day as g. Job seeker i's potential use of the OJP is written as $Y_{i,d}(g')$, capturing whether or not she would have used the OJP on day d if she had had her call on any given day g'. Finally, event-time is defined as $e \equiv d - g$ and chosen to be between $-20 \leq e \leq 5$.

5.3. Parameters of interest

Parameters of interest are the dynamic treatment effects of the encouragement to use the OJP during the assessment call on day g, compared to having the assessment call later, on the number of logins to the OJP:

$$ATT(e) \equiv \sum_{g} \omega_{g,e} ATT(g, e) \tag{13}$$

with $\omega_{g,e}$ aggregation weights and $ATT(g, e)$ cohort-specific treatment effects given by:

$$ATT(g, e) \equiv \mathbb{E}\left[Y_{i,g+e}(g) - Y_{i,g+e}(g')|g_i = g\right] \tag{14}$$

for any g' such that $g + e < g' \leq 49$.

Under the three identifying assumptions listed below, each parameter in equation (14) is identified by a DiD estimand:

$$\begin{aligned} ATT(g, e) = \; & \mathbb{E}[Y_{i,g+e}|g_i = g] - \mathbb{E}[Y_{i,g-2}|g_i = g] \\ & - \left[\mathbb{E}[Y_{i,g+e}|g_i = g'] - \mathbb{E}[Y_{i,g-2}|g_i = g']\right] \end{aligned} \tag{15}$$

for all g' satisfying $g+e < g' \leq 49$. The expression on the right-hand side can be estimated using data and one of several DiD estimators.

5.4. Identifying assumptions

a. The *Stable Unit Treatment Value Assumption (SUTVA)* requires that:

$$\mathbb{E}[Y_{i,g+e}|g_i = g] = \mathbb{E}[Y_{i,g+e}(g)|g_i = g] \tag{16}$$

which states that i's actual outcomes depend only on her own treatment assignment. This assumption seems reasonable given that the use of the OJP is non-rivalrous.

b. *No-anticipation* rules out that treated cohorts anticipate their treatment:

$$\mathbb{E}[Y_{i,g+e}(g)|g_i = g] = \mathbb{E}[Y_{i,g+e}(g')|g_i = g] \text{ for all } -20 \leq e \leq -1 \tag{17}$$

for any g' such that $g + e < g' \leq 49$. This assumption is likely to hold because individuals are asked on day 28 to make a call in the following week and because they do not know that they will be encouraged to use the OJP during the call.

c. *Parallel trends* require that average outcomes for the treated change in the same way as for the controls in the absence of treatment. Choosing $e = -2$ as the reference day, the parallel trends assumption is given by:

$$\mathbb{E}[Y_{i,g+e}(g')|g_i = g] - \mathbb{E}[Y_{i,g-2}(g')|g_i = g] = \mathbb{E}[Y_{i,g+e}(g')|g_i = g'] - \mathbb{E}[Y_{i,g-2}(g')|g_i = g'] \tag{18}$$

for all g' satisfying $g + e < g' \leq 49$. Strictly speaking, the parallel trends assumption only needs to hold for $0 \leq e \leq 5$. However, assuming it also holds in pre-treatment periods allows us to test whether $ATT(g, e) = 0$ for $-20 \leq e \leq -1$. If this is not the case, the parallel trends assumption is unlikely to hold post-treatment as well.

5.5. Self-selection into day of contact

Our DiD design allows for selection in the timing of the assessment call based on an individual's type in the costs of job search effort. To see this, note that equation (18) holds if the change in OJP logins over time, in the absence of an assessment call, is independent of the actual day of contact g_i:

$$Y_{i,g+e}(g') - Y_{i,g-2}(g') \perp g_i \tag{19}$$

This does not exclude that g_i is correlated with a time-invariant component in $Y_{i,g+e}(g')$ and $Y_{i,g-2}(g')$, such as an individual's time-persistent type in the costs of job search effort. Our DiD design still identifies the causal impact of the assessment call on job search effort, even if types of costs in job search effort self-select into different days of contact, as is clearly the case in Figure 4.

6. The impact of the assessment call on job search effort

6.1. Average treatment effects

To estimate $ATT(e)$ when the day of contact is not randomly assigned across treatment cohorts, we first use a stacked DiD estimator.[24] This requires two steps: manipulating the data and running a Two-Way Fixed-Effects (TWFE) regression.

First, for each of the 19 treatment cohorts $28 \leq g \leq 46$, create a group-specific data set $i \in \mathcal{I}(g)$ with treatment units $g_i = g$ and control units $g_i = g'$ with $g + 5 < g' \leq 49$.[25] In each group-specific data set, write duration time d as event time $e = g - d$. Then stack all group-specific data sets into a single stacked data set.

Second, run the following TWFE regression with individual and duration fixed effects using the stacked dataset:

$$Y_{i\in \mathcal{I}(g),d\in \mathcal{D}(g)} = \alpha_{i\in \mathcal{I}(g)} + \alpha_{d\in \mathcal{D}(g)} + \sum_{e=-20,e\neq -2}^{-1} \gamma_e^{PRE} D_e \times D_i + \sum_{e=0}^{5} \gamma_e^{POST} D_e \times D_i + \varepsilon_{i\in \mathcal{I}(g),d\in \mathcal{D}(g)} \tag{20}$$

with $\alpha_{i\in \mathcal{I}(g)}$ cohort by individual fixed effects, $\alpha_{d\in \mathcal{D}(g)}$ cohort by duration fixed effects, $D_e = \mathbb{1}\{e = d - g\}$, $D_i = \mathbb{1}\{G_i = g\}$, and $\varepsilon_{i\in \mathcal{I}(g),d\in \mathcal{D}(g)}$ an error term.[26] OLS estimates of γ_e^{POST} are estimates of $ATT(e)$ as a variance-weighted average of $ATT(g, e)$.[27] We choose $e = -2$ as the reference day. Standard errors are clustered at the treatment level, i.e. all job seekers who have contact on the same day constitute one cluster.

Panel A of Figure 5 shows the point estimates for γ_e^{PRE} and γ_e^{POST}. The mean number of logins during the observation window is 0.075 logins per day, or 1 login every 15 days. This is also the mean number of logins at the reference point for the stacked sample. On the day of the assessment call, the effect size is 0.6 logins per day, or 1.2 logins per 2 days, which is large relative to the average of 1 login per 15 days.

[24] Assuming that treatment timing is random is stronger than the parallel trends assumption. If treatment timing were truly random, Roth and Sant'Anna (2023) proposes an estimator that is more efficient.

[25] This excludes the "forbidden comparisons" discussed in Goodman-Bacon (2021).

[26] Including individual fixed effects (instead of treatment-group fixed effects) weakens the parallel trends assumption because all moments in equation (18) are now conditional on unobserved individual time-invariant characteristics.

[27] OLS implicitly chooses $\omega_{g,e}$ in equation (13) by giving more weight to larger $\mathcal{I}(g)$ and to $\mathcal{I}(g)$ in which the fraction of treated individuals is closer to 0.5.

As was already suggested by Figure 4, Panel A of Figure 5 also shows that the impact of the assessment call is short-lived: individuals only log into the OJP on the day of the assessment call. Several different specifications (e.g., using a daily login dummy or saved vacancies instead of a login count, including individuals with assessment calls after day 49 as controls, adding calendar-year fixed-effects, and using alternative measures of job search effort) yield identical results.[28]

6.2. Treatment effect heterogeneity by type of costs in job search effort

Figure 4 suggested that types with low costs of job search effort not only self-select into making inbound calls before day 36, but they also respond more strongly to the encouragement during the assessment call to log into the OJP. One way to more formally test for treatment effect heterogeneity is to estimate equation (20) separately for individuals who have their assessment calls before and after day 36. Panel B of Figure 5 shows that the instantaneous treatment effect for cohorts making a call before day 36 is almost twice as large, in line with the predictions in panel A of Figure 2.

Moreover, we estimate $ATT(g, e)$ for each g and e using Callaway and Sant'Anna (2021) (CS).[29] For a panel of job seekers who remain unemployed for at least 49 days, the CS estimator imputes each of the DiD estimands in equation (15). First, using a logit to estimate a propensity score, it constructs an Inverse Probability Weight (IPW) that gives more weight to control-group individuals (those with g' such that $g+e < g' \leq 49$) who have similar time-invariant characteristics to those in the treatment cohort. Second, using a regression model, it includes a Regression-Adjustment (RA) correction of the predicted changes in outcomes for control-group individuals with characteristics similar to those in the treatment cohort.

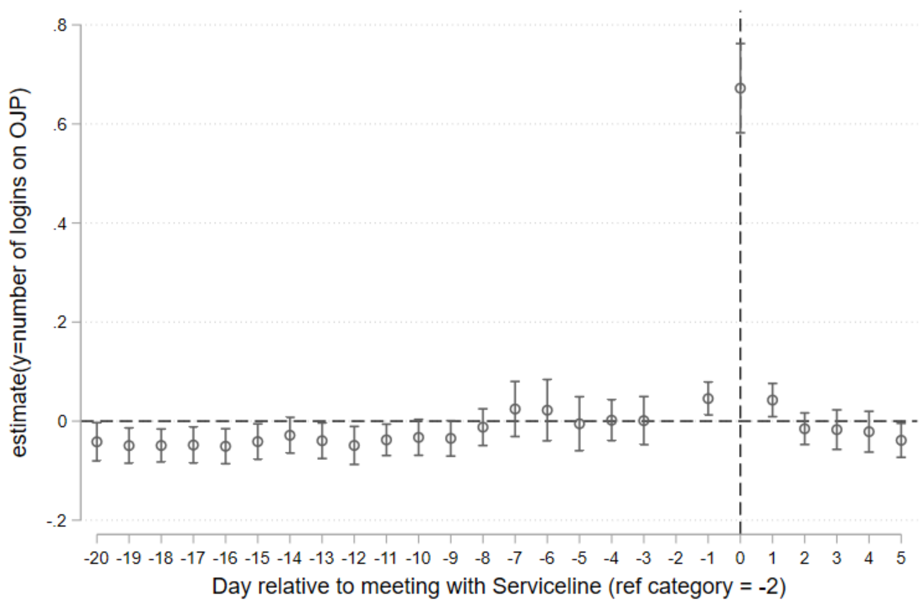
CS shows that as long as either IPW or RA is correctly specified, the CS estimator is the best estimator that does not rely on additional functional form restrictions. Moreover, because the predicted propensity scores and regression corrections are conditional on time-invariant characteristics, all moments in equation (18) need to hold conditional on those time-invariant characteristics, which weakens the parallel trends assumption. The CS estimator, however, also imposes an additional identifying assumption that at

[28] See Appendix D.1 for details. Using vacancy applications as an outcome renders positive average treatment effects, although smaller and noisier due to the limited and selective usage of vacancy applications through the OJP. Vacancy applications that go directly through the recruiting employer are not visible to us.

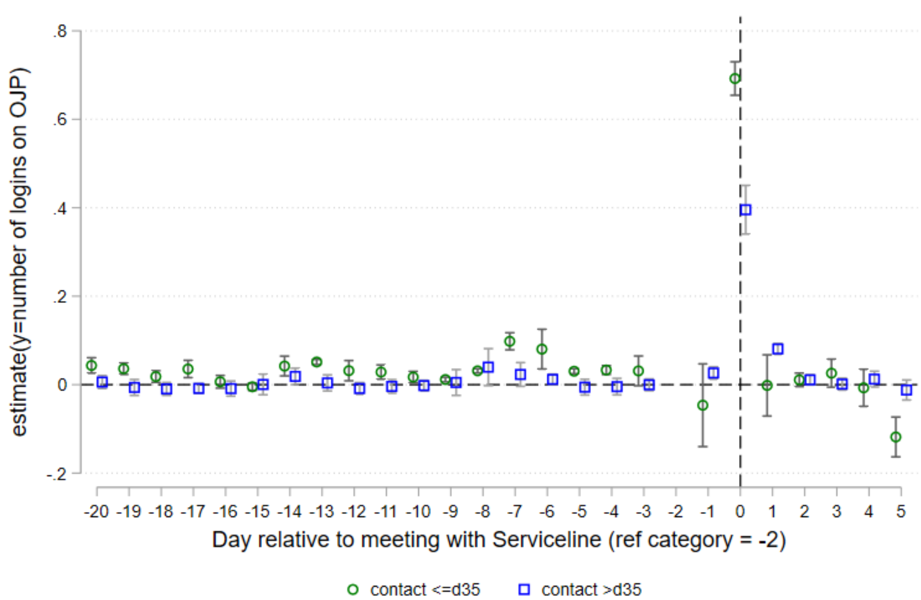
[29] see Appendix D.2 for details.

FIGURE 5. **OJP logins after the assessment call**

A. **Average treatment effects**

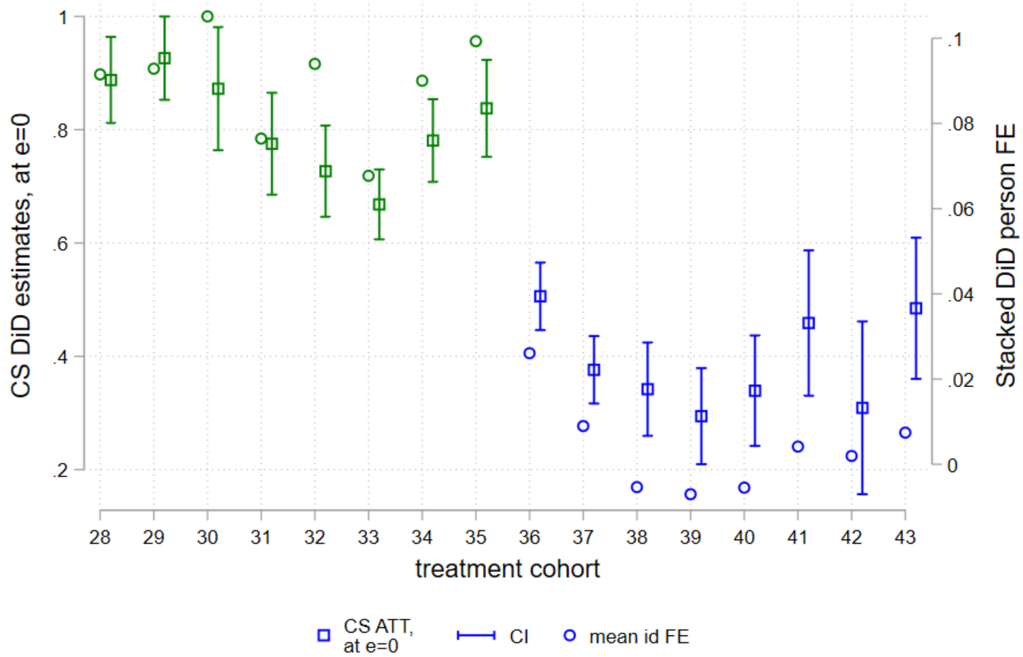


B. **Heterogeneity by day of contact** ≤ 35



Notes: These are the coefficiënts from the stacked DiD design, equation 20. Panel A uses 19 cohorts that have an assessment call between days 28 and 46 as treatment groups. Panel B runs equation 20 separately for cohorts of job seekers with assessment calls before and after day 35 as treatment groups.

FIGURE 6. **Treatment effects by cohort and selection into treatment**



Notes: Squares represent the estimated ATT_g0 by treatment cohort g. Circles represent person fixed effects extracted from the estimation represented in Figure 5, Panel A, the coefficiënts from the stacked DiD design, equation 20. Each circle represents the average of person fixed effects of treated individuals, by treatment cohort.

least some individuals in the control-group have the same time-invariant characteristics as those in each treatment cohort. Finally, confidence intervals can be computed using CS's multiplier bootstrap procedure with standard errors clustered at the cohort level.

The squared point estimates in Figure 6 show the CS estimates of $ATT(g, 0)$ on the left y-axis for each g on the x-axis. In line with Panel B of Figure 5, the treatment effects are estimated to be approximately twice as large for cohorts making inbound calls before day 36. The circles on the right y-axis of Figure 6 provide an estimate of person fixed effects from equation (20) averaged across individuals for each cohort, showing that $ATT(g, 0)$ and $\mathbb{E}[\alpha_{i\in \mathcal{J}(g)}|D_i = 1]$ are highly correlated. This shows that types with low costs of job search effort, who self-select to make inbound calls, are also more responsive to PES treatment. Finally, aggregating the CS estimates of $ATT(g, e)$ across g to obtain CS estimates for $ATT(e)$ gives qualitatively identical results compared to those in panel A of Figure 5.[30]

[30]CS and stacked DiD do not estimate the same $ATT(e)$ for three reasons: 1) the aggregation weights $\omega_{g,e}$ are different; 2) the control groups are defined as $g' > g + e$ for CS and $g' > g + 5$ for stacked DiD ; 3) CS requires that individuals remain unemployed for at least 49 days, whereas stacked DiD requires that

7. Types in job search effort

7.1. Predicting job search effort

The previous section argued that types with low costs in job search effort self-select into job search assistance and are also more responsive to it. This subsection shows that these types can be predicted based on observed time-invariant individual characteristics.

Assume that the number of logins to the OJP by individual i on day d of unemployment is given by:

$$Y_{i,d} = Y_d(X_i^d) + \eta_{i,d} \tag{21}$$

with X_i^d a vector of time-invariant individual characteristics. Although the functional form $Y_d(\cdot)$ is generally allowed to change with d, we choose $d = 28$ such that we focus on $Y_{28}(\cdot)$ in this subsection.[31] We define $Y_{i,d}$ as the average number of weekly logins across weeks for as long as the job seeker remains unemployed after day 28. Finally, we assume that the term $\eta_{i,d}$ is white-noise with a mean of zero.

Regressing equation (21) gives Table 2. Column (1) includes observed time-invariant personal characteristics, showing that women with a bachelor degree and good knowledge of Dutch use the OJP more intensively. Column (2) adds a prediction by the PES of an individual's job finding probability within the next 6 months using the Machine Learning algorithm discussed above. Importantly, the algorithm also uses previous unemployment spells as one of its features, which we do not observe directly. Therefore, we add an individual's first Machine Learning (ML) score, which is computed at the beginning of her unemployment spell. The estimated coefficient is positive and significant, suggesting that job seekers with a 10 percentage point higher ML score have higher weekly logins after day 28 by an average of 0.028.

Columns (3) and (4) add two measures of search effort before day 28. These measures are the number of completed assignments 1 to 5 and the average daily logins to the OJP, respectively. The coefficient for average daily logins before day 28 is positive and significant, suggesting that login behavior in the first month is predictive of logins for the remainder of unemployment duration. Finally, column (5) shows that our point estimates do not change if we further add several controls. These additional controls are

individuals in $\mathcal{I}(g)$ remain unemployed for at least $g + 5$ days.

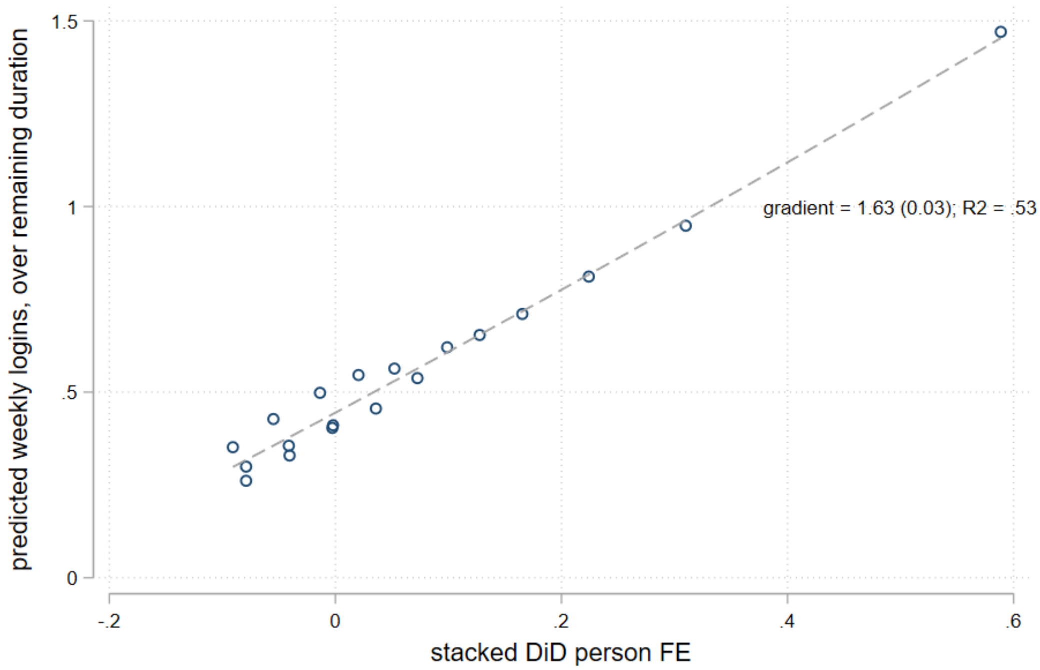
[31] We return to the importance of functional form changes in $Y_d(\cdot)$ in the next subsection.

TABLE 2. **Average weekly OJP logins over remaining unemployment duration, at day 28 of the unemployment spell**

	average weekly logins				
	(1)	(2)	(3)	(4)	(5)
Education (ref.: Primary)					
Some secondary	0.027	0.040	0.039	0.045	0.026
	(0.041)	(0.041)	(0.040)	(0.036)	(0.036)
Secondary	0.069*	0.067*	0.055	0.053	0.045
	(0.039)	(0.039)	(0.038)	(0.035)	(0.034)
(Higher) professional	0.070*	0.065*	0.053	0.046	0.032
	(0.039)	(0.039)	(0.038)	(0.034)	(0.034)
Bachelor	0.170***	0.135***	0.104***	0.083**	0.079**
	(0.039)	(0.039)	(0.039)	(0.035)	(0.035)
Master	0.116***	0.081**	0.033	0.043	0.030
	(0.040)	(0.040)	(0.039)	(0.036)	(0.036)
Recent graduate (Yes=1)	0.080***	0.057**	0.036	0.011	0.050**
	(0.026)	(0.026)	(0.026)	(0.023)	(0.024)
Gender (Male=1)	-0.076***	-0.074***	-0.063***	-0.041***	-0.039***
	(0.014)	(0.014)	(0.014)	(0.013)	(0.013)
Knowledge of Dutch (ref.: None)					
Limited	0.101*	0.101*	0.102**	0.101**	0.080*
	(0.053)	(0.053)	(0.052)	(0.047)	(0.047)
Good	0.240***	0.216***	0.215***	0.217***	0.204***
	(0.049)	(0.049)	(0.048)	(0.044)	(0.044)
Very good	0.250***	0.209***	0.185***	0.175***	0.168***
	(0.048)	(0.048)	(0.047)	(0.043)	(0.044)
Migrant (Yes=1)	-0.015	0.003	0.015	0.012	0.009
	(0.020)	(0.020)	(0.020)	(0.018)	(0.019)
First ML job finding score		0.424***	0.324***	0.223***	0.282***
		(0.059)	(0.059)	(0.053)	(0.054)
Job search effort on OJP before day 28					
No. of completed assign. 1-5			0.062***	0.001	0.003
			(0.003)	(0.003)	(0.003)
Average daily OJP logins				2.040***	2.008***
				(0.041)	(0.042)
Constant	0.202	0.007	0.050	-0.132	0.104
	(0.138)	(0.140)	(0.138)	(0.124)	(0.139)
R-squared	0.020	0.025	0.060	0.236	0.282
Additional controls	NO	NO	NO	NO	YES

Notes: For each regression, the dependent variable is average weekly OJP logins across weeks for as long as the job seeker remains unemployed after day 28. The mean of the dependent variable is 0.53. For each regression, the number of observations is 10,579. All regressions include a constant and controls for age and its square. The last column adds the calendar month of registration as newly unemployed, the channel of registration, and municipality of an individual's residence as additional controls. The dummy Migrant is 1 for individuals who are not born in Belgium.

FIGURE 7. **Predicted weekly OJP logins after day 28 and DiD individual fixed-effects**



Notes: Binscatter of predicted weekly OJP logins averaged across weeks for as long as the job seeker remains unemployed after day 28 and estimated individual fixed-effects in daily OJP logins before day 49 from equation (20).

the calendar month of registration as newly unemployed, the channel of registration, and the municipality of an individual's residence.

If observed time-invariant personal characteristics are predictive of types in job search effort, predictions from column (5) in Table 2 should be positively correlated with the estimated individual fixed effects from equation (20). To show that this is the case, Figure 7 presents a binned scatterplot of both estimates. Predictions from column (5) of Table 2 predict weekly OJP logins averaged across weeks for as long as the job seeker remains unemployed after day 28, whereas the estimated individual fixed-effects from equation (20) capture individual-specific daily OJP logins before day 49. The binscatter shows that both estimates are strongly positively correlated. This suggests that primarily women with a bachelor degree and good knowledge of Dutch, without previous unemployment spells, and who have logged into the OJP before day 28 are "high-types" in job search effort.

7.2. Persistence in job search effort

The previous subsection showed that time-invariant individual characteristics predict weekly OJP logins averaged across weeks for as long as the job seeker remains unemployed after day 28, because there exist types in job search effort. A stronger test of this hypothesis would be to see if these time-invariant characteristics can also predict time-persistent heterogeneity in job search effort. Therefore, rewrite the variance in job search effort among individuals unemployed on day d as follows:

$$
\begin{aligned}
var(Y_{i,d}) &= cov(Y_{i,d}, Y_{i,d}) \\
var(Y_{i,d}) &= cov(Y_{i,d}, Y_{i,d} + Y_{i,d'} - Y_{i,d'}) \\
var(Y_{i,d}) &= cov(Y_{i,d}, Y_{i,d'}) + cov(Y_{i,d}, Y_{i,d} - Y_{i,d'})
\end{aligned}
\tag{22}
$$

where $Y_{i,d'}$ are OJP logins in period d' for the group of job seekers who are unemployed on day d. The first term in equation (22) captures time-persistent heterogeneity in job search effort, and the second term captures transitory heterogeneity.

Focusing only on time-persistent heterogeneity and using equation (21), we can write:

$$
\begin{aligned}
cov(Y_{i,d}, Y_{i,d'}) &= cov(Y_d(X_i^d) + \eta_{i,d}, Y_{d'}(X_i^d) + \eta_{i,d'}) \\
cov(Y_{i,d}, Y_{i,d'}) &= cov(Y_d(X_i^d), Y_{d'}(X_i^d))
\end{aligned}
\tag{23}
$$

where $Y_{d'}(X_i^d)$ are the predicted outcomes in period d' for the group of unemployed job seekers observed in period d, allowing the functional form of $Y(.)$ to be d' specific. If types in job search effort truly exist, we would expect this covariance to be significant. Intuitively, among individuals who remain unemployed for at least d periods, those with higher predicted job search effort after d periods should also have higher predicted job search effort after d' periods into their unemployment spell.

To see that this is the case, the columns in Table 3 present regression estimates of equation (21) using different groups of individuals at various months into their unemployment spells. Column (1) is the last column in Table 2, using individuals who are unemployed on day 28. Column (2) runs the same regression using individuals who remain unemployed for at least two months, column (3) uses the sample of individuals who remain unemployed for at least three months, and so on up to the group of individuals who are unemployed for six months or longer.

TABLE 3. **Predicting OJP logins over remaining unemployment duration, at different months into the unemployment spell**

	(1)	(2)	(3)	(4)	(5)	(6)
	normalized weekly logins					
VARIABLES	remaining duration, after					
	month 1	month 2	month 3	month 4	month 5	month 6
Education (ref.: Primary)						
Some secondary	0.026	0.004	0.025	0.020	0.009	0.015
	(0.036)	(0.028)	(0.027)	(0.024)	(0.022)	(0.019)
Secondary	0.045	0.011	0.028	0.020	0.004	-0.006
	(0.034)	(0.027)	(0.026)	(0.023)	(0.021)	(0.018)
(Higher) professional	0.032	0.023	0.035	0.042*	0.005	0.012
	(0.034)	(0.027)	(0.025)	(0.022)	(0.021)	(0.018)
Bachelor	0.079**	0.041	0.053**	0.036	0.011	0.018
	(0.035)	(0.027)	(0.026)	(0.023)	(0.022)	(0.019)
Master	0.030	0.016	0.050*	0.028	0.011	0.009
	(0.036)	(0.028)	(0.027)	(0.024)	(0.023)	(0.020)
Recent graduate (Yes=1)	0.050**	-0.022	0.015	0.024	0.028	-0.002
	(0.024)	(0.019)	(0.020)	(0.019)	(0.018)	(0.017)
Gender (Male=1)	-0.039***	-0.018*	-0.004	-0.009	-0.017*	-0.005
	(0.013)	(0.010)	(0.010)	(0.009)	(0.009)	(0.008)
Knowledge of Dutch (ref.: None)						
Limited	0.080*	0.058	0.042	0.053*	0.036	0.032
	(0.047)	(0.036)	(0.033)	(0.029)	(0.026)	(0.023)
Good	0.204***	0.130***	0.089***	0.076***	0.054**	0.035
	(0.044)	(0.034)	(0.031)	(0.028)	(0.025)	(0.022)
Very good	0.168***	0.121***	0.107***	0.085***	0.065***	0.042*
	(0.044)	(0.034)	(0.031)	(0.027)	(0.025)	(0.022)
Migrant (Yes=1)	0.009	0.009	0.006	0.003	0.011	0.005
	(0.019)	(0.015)	(0.014)	(0.013)	(0.012)	(0.011)
First ML job finding score	0.282***	-0.012	-0.004	0.055	0.066*	0.078**
	(0.054)	(0.043)	(0.042)	(0.038)	(0.037)	(0.033)
Job search effort on OJP before day 28						
No. of completed assign. 1-5	0.003	0.003	0.004	0.004	0.005**	0.003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Average daily OJP logins	2.008***	1.047***	0.808***	0.516***	0.420***	0.299***
	(0.042)	(0.034)	(0.035)	(0.032)	(0.033)	(0.030)
Constant	0.104	0.232**	0.051	-0.045	0.000	-0.059
	(0.139)	(0.109)	(0.108)	(0.098)	(0.094)	(0.083)
Observations	10,579	9,336	6,872	5,545	4,751	4,116
R-squared	0.282	0.195	0.199	0.177	0.156	0.109
Additional controls	YES	YES	YES	YES	YES	YES
Mean	.53	.27	.23	.19	.15	.12

Notes: Column (1) is the last column in Table 2, using individuals who are unemployed on day 28. Column (2) runs the same regression using individuals who remain unemployed for at least 2 months, column (3) uses the sample of individuals who remain unemployed for at least 3 months, and so on up to the group of individuals who are unemployed 6 months or longer.

TABLE 4. **Rank correlations of predicted logins at different months into the spell**

	Spearman rank correlation pairwise for months:					
	1	2	3	4	5	6
1	1.00					
2	0.83	1.00				
3	0.77	0.89	1.00			
4	0.68	0.77	0.88	1.00		
5	0.62	0.66	0.75	0.85	1.00	
6	0.52	0.46	0.51	0.58	0.72	1.00

Notes: These are the predictions from the models represented in the columns of Table 3.

For the group of individuals who remain unemployed for at least 6 months, indicate their characteristics by X_i^6. Then, predict $\hat{Y}_6(X_i^6)$ using the coefficients in column (6). For the same group of individuals, also predict $\hat{Y}_5(X_i^6)$ using the coefficients from column (5). We can then estimate the pairwise rank correlation between both sets of predictions, which is 0.72 as shown in the sixth row and fifth column of Table 4. We repeat this exercise for each row and column, showing that there exists significant time-persistent heterogeneity in job search effort. This is evidence that types in job search effort exist and that these types can be predicted based on observed individual characteristics.

7.3. Types in job finding

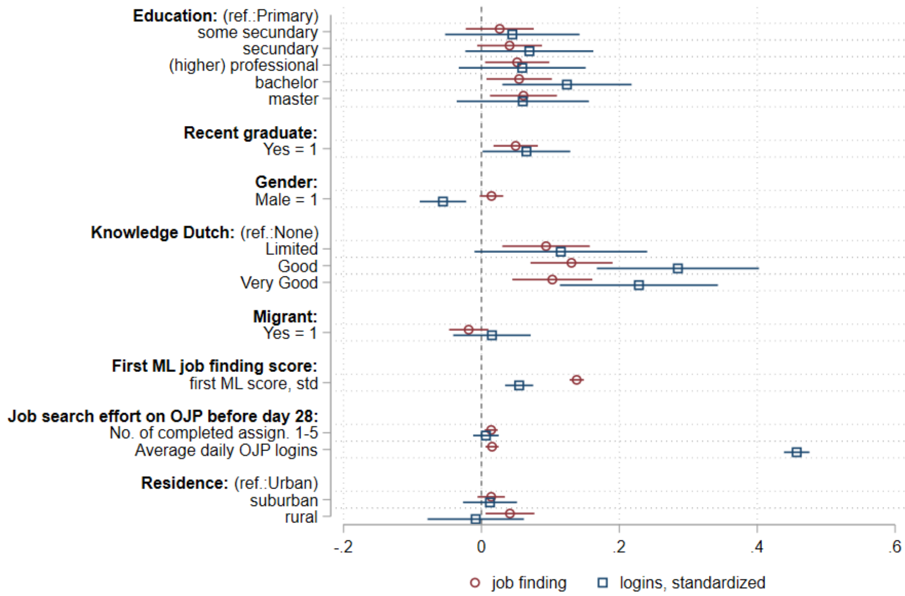
Our model in section 3 assumed that job finding is a strictly increasing function of job search effort. If so, types with lower costs in job search effort should also be types with higher job finding rates. To see whether this is the case, define an indicator variable $F_{i,d}$ that equals 1 if individual i finds a job in the six months following period d. Further assume that:

$$F_{i,d} = F_d(X_i^d) + \nu_{i,d} \tag{24}$$

with X_i^d the same vector of time-invariant characteristics of individuals observed at time d as in equation (21). Just as with job search effort, the functional form $F_d(\cdot)$ is allowed to vary with d for some specifications, and $\nu_{i,d}$ is a white noise error term.

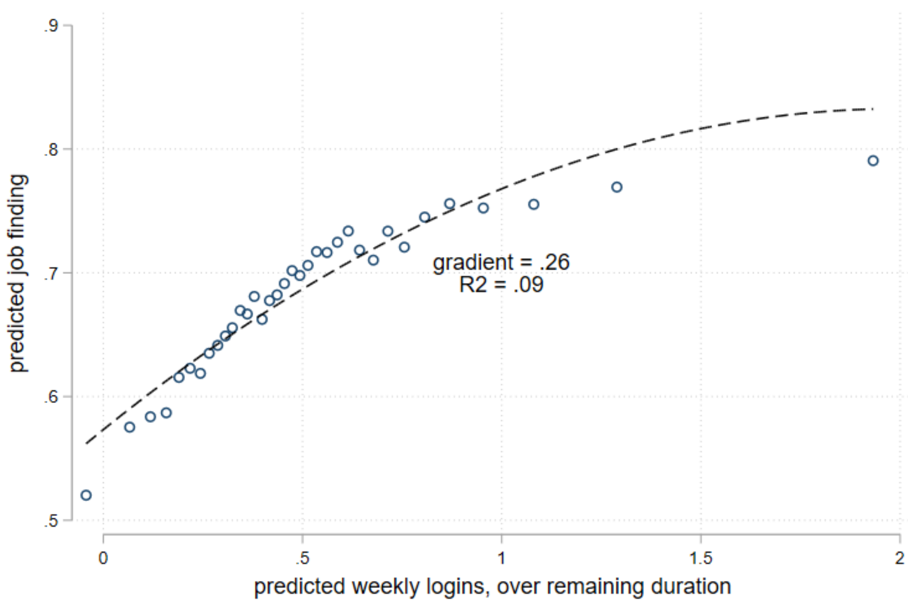
We estimate equation (24) using a linear probability model. Figure 8 shows the estimated coefficients using the specification in column (5) of Table 2 to predict an

FIGURE 8. **Estimated coefficients for job finding and OJP logins**



Notes: Estimated coefficients using the specification in column (5) of Table 2. To ease the comparison of point estimates, all continuous regressors have been normalized to have a mean of zero and a standard deviation of one.

FIGURE 9. **Predicted job finding rates and OJP logins**



Notes: Predicted values are computed using the coefficients in Figure 8.

individual's probability of finding a job within six months on day 28. The figure also plots regression coefficients from the same specification using job search effort as the dependent variable (as was already reported in column (5) of Table 2). To ease the comparison of point estimates, we have normalized each continuous regressor to have a mean of zero and a standard deviation of one.

What Figure 8 shows is that the time-invariant individual characteristics that are strong predictors of job search effort are also strong predictors of job finding: having higher levels of education, a good knowledge of Dutch, a higher first ML job finding score, and a more intensive use of the OJP during the first month of unemployment. Figure 9 further illustrates this by displaying a binscatter of predicted job finding rates and average weekly OJP logins.[32]

8. Duration dependence in job search effort

Our model in section 3 assumed that there is negative duration dependence in job search effort. To see whether this is true in our data, start by defining the density of predicted job search effort at time d as $g(Y_d(X_i^d))$. Panel A of Figure 10 plots these densities for each month $d = 1, 2, \ldots, 6$ of unemployment duration. It is clear from the figure that both the average and the variation in job search effort decrease with unemployment duration. However, this does not necessarily mean that there is strong negative duration dependence in job search effort for all types, because the changes in the densities plotted in panel A of Figure 10 could be due to dynamic selection.

Therefore, we construct counterfactual densities of predicted job search effort using the estimated coefficients reported in each column of Table 3. Define $g(Y_{d'}(X_i^d))$ as the counterfactual density for individuals who have been unemployed for at least d months, while using the estimated coefficients for month d'. We can then decompose the difference in actual densities between months d and d' as:

$$g(Y_d(X_i^d)) - g(Y_{d'}(X_i^{d'})) = \left\{ g(Y_d(X_i^d)) - g(Y_{d'}(X_i^d)) \right\} - \left\{ g(Y_{d'}(X_i^{d'})) - g(Y_{d'}(X_i^d)) \right\} \quad (25)$$

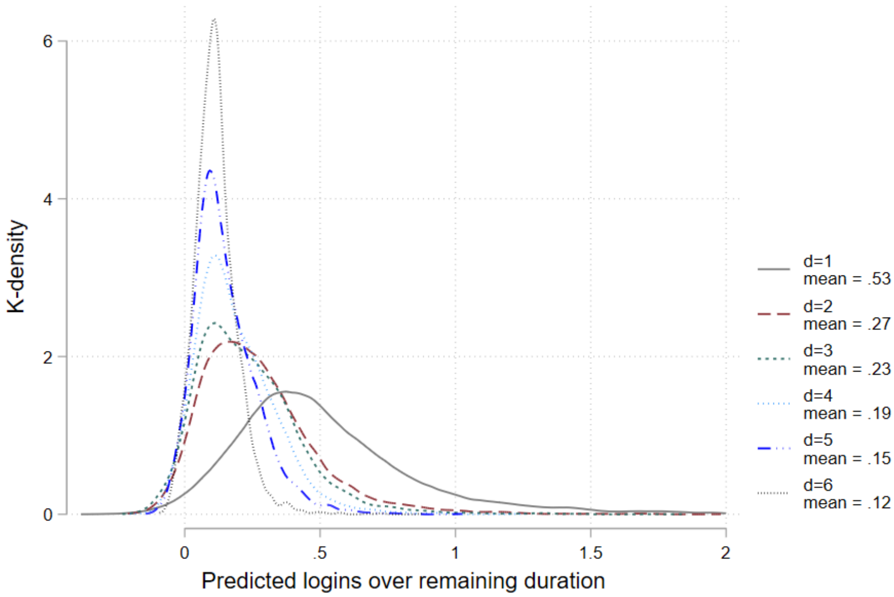
where the first term in curly brackets captures duration dependence in job search effort, and the second term in curly brackets captures dynamic selection.

Panel B of Figure 10 plots the actual densities (the solid kernels) for the first month,

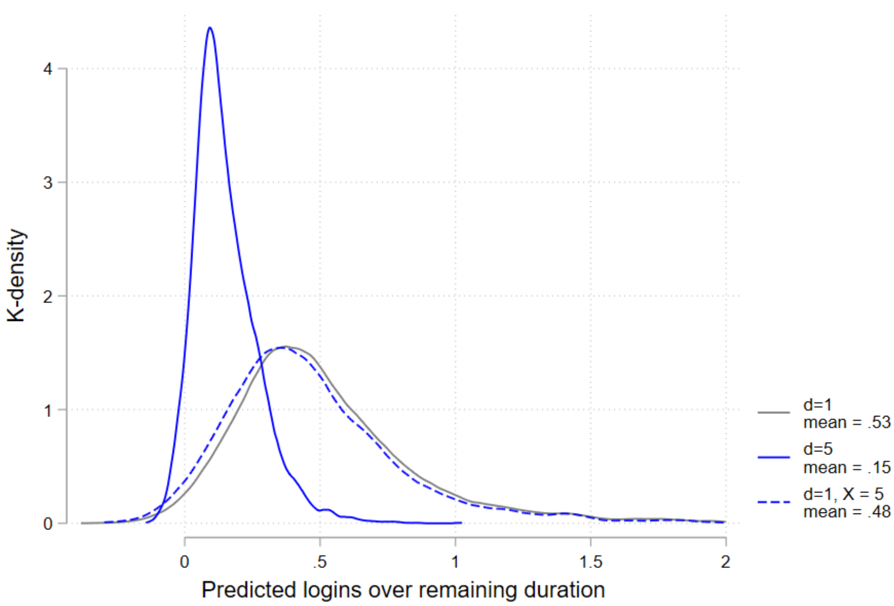
[32] See Appendix E for additional analyses.

FIGURE 10. **Actual and counterfactual densities in predicted job search effort**

A. **Heterogeneity in predicted OJP logins, at different months into the unemployment spell**



B. **Actual and counterfactual predicted OJP logins, at months 1 and 5 into the unemployment spell**



Notes: Panel A: Kernel densities of predicted logins over remaining duration by months based on the predictions from the models represented in the columns of Table 3. Panel B: The solid kernels are densities of predicted OJP logins over remaining duration after the first and fifth month of unemployment. Predictions are based on columns (1) and (5) in Table 3. The dashed kernel is the counterfactual density of predicted OJP logins for individuals who are unemployed for at least five months but using the coefficients estimated in column (1) of Table 3.

$g(Y_1(X_i^1))$, and for the fifth month, $g(Y_5(X_i^5))$, in unemployment. The figure also plots the counterfactual density, the dashed kernel of $g(Y_1(X_i^5))$, which represents the density of predicted job search effort for job seekers who remain unemployed for at least five months, assuming that their time-invariant characteristics maintain their predictive power from the first month of unemployment.

The first term in curly brackets in equation (25), which captures duration dependence, is given by the difference between $g(Y_5(X_i^5))$ and $g(Y_1(X_i^5))$. The second term in curly brackets, which captures dynamic selection, is given by the difference between $g(Y_1(X_i^1))$ and $g(Y_1(X_i^5))$. Because the difference between $g(Y_5(X_i^5))$ and $g(Y_1(X_i^5))$ is large, and between $g(Y_1(X_i^1))$ and $g(Y_1(X_i^5))$ is small, negative duration dependence in job search effort is much more important than dynamic selection.[33]

9. Conclusion

Public Employment Services (PES) are increasingly using information and communication technologies to help unemployed individuals find jobs. New technologies, such as online job platforms with AI-based matching technologies, are fundamentally changing the way job seekers search for jobs and how PES can support them in this process. Previous studies have shown how digital technologies can lower search frictions and increase job finding by widening the scope of job search and redirecting job seekers to better job opportunities.

However, this paper demonstrates that designing such active labor market policies poses several challenges. One challenge is that there are "types in search effort" because some job seekers are more likely to take up assistance and, if they do, are more responsive to it. So, even if policies cannot discriminate between unemployed job seekers in theory, in practice, they are likely to target those who benefit from them the most. Another challenge is that there is negative duration dependence in search effort on online job platforms, independent of type. This suggests that the impact of job search assistance in using online job platforms quickly diminishes over the course of the unemployment spell.

A better design of online job platforms could tackle these challenges. Examples

[33] Note that we could also add and subtract $g(Y_5(X_i^1))$ instead of $g(Y_5(X_i^1))$ in equation (25). Doing this gives similar results. Our result is consistent with some studies (e.g. Zuchuat et al. (2023)), but not with others (e.g. Mueller and Spinnewijn (2023)).

include facial recognition for logging in instead of having to enter a username and password, an interactive chatbot, or instantaneous translation into a foreign language. Additionally, online job platforms could learn from the psychology of social media algorithms. Social media platforms have transformed not only how we connect but also how we think, feel, and behave. In a similar fashion, job search algorithms can be personalized to retain attention, reshape perception, and even redefine identity in order to optimize job search effort and job finding in a world increasingly guided by data-driven engagement.

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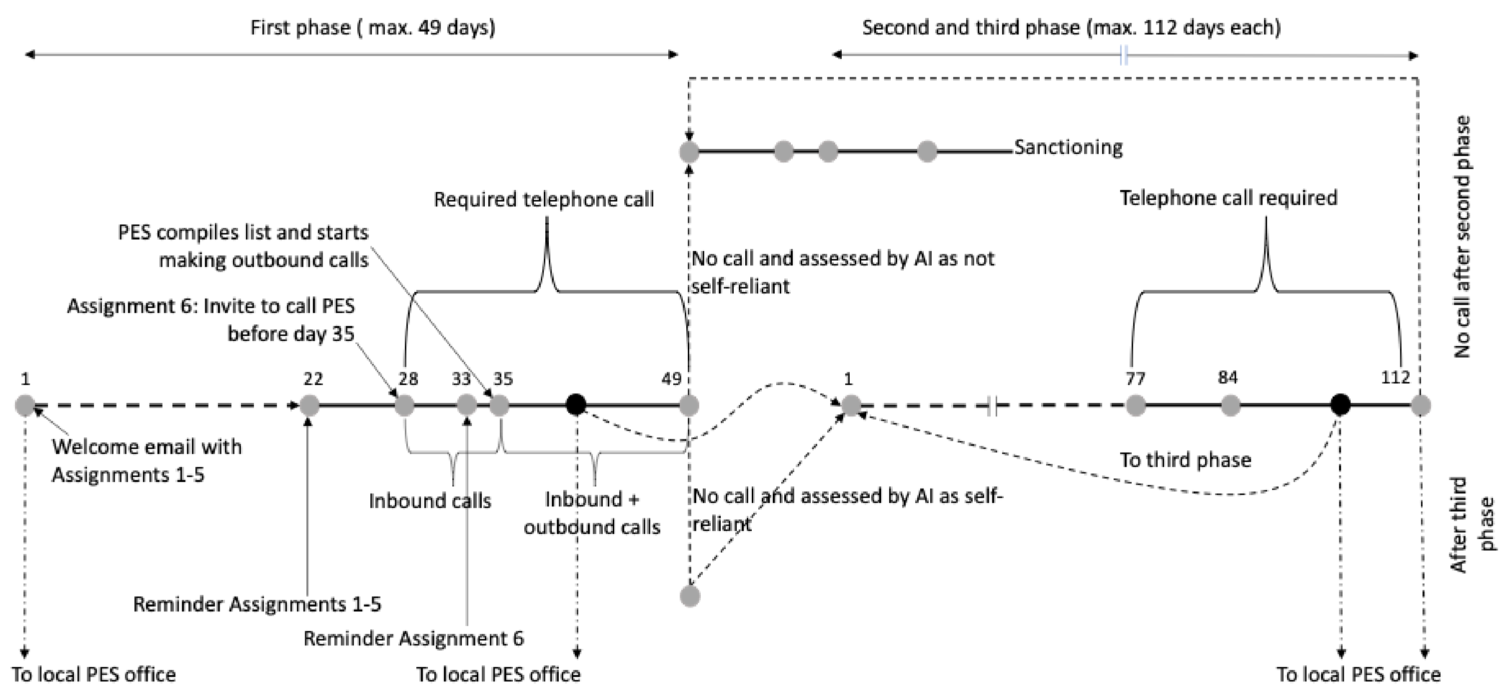
Appendix A. Job search assistance for the unemployed

A.1. The Service Line

FIGURE A1. **The Service Line, all phases**



Source: Flemish PES.

A.2. The assessment call

What follows is a stylized version of the template used by caseworkers to conduct the assessment call. A full version cannot be shared due to the intellectual property rights of the VDAB.

A.2.1. Introduction Phase

- Introduction and verification of contact details
- Explanation of call purpose and estimated duration
- Review of file completeness and contact information
- Assessment of digital literacy level
- Discussion of mutual expectations between agency and job seeker
- Overview of rights and obligations
    - Right to support and guidance
    - Right to benefits (where applicable)
    - Obligation to follow up on assigned tasks
    - Obligation to respond to invitations and job offers
    - Obligation to actively search for employment
- Review of profile visibility and vacancy matching

A.2.2. Motivation and Assessment Phase

- Discussion of previously assigned tasks
    - Evaluation of task completion
    - Review of job search activities
- Analysis of job search progress: steps to work
    - Number of vacancies identified
    - Number of applications submitted
    - Explain and motivate use of various tools on Online Job Platform
    - Documentation of application activities
- Identification of potential barriers
    - Nature of barriers (digital, motivational, practical)
    - Possible solutions or support needed
- Assessment of self-reliance level
    - Digital competence evaluation

  - Need for additional support determination
- Assignment of new tasks based on assessment

A.2.3. Conclusion Phase

- Summary of discussion points
- Confirmation of agreed actions
- Overview of new assignments
- Scheduling of follow-up contact
- Provision of contact information for questions
- Confirmation that appointment details will be sent

  If referral to regional office is required:
- Confirmation of scheduled appointment (date, time, location)
- Explanation of tasks to be completed before appointment
- Provision of regional contact information

A.2.4. Afterwork

- Complete conversation report
- Record of assessment and rationale for classification
- Documentation of application activities discussed
- Record of assigned tasks
- Recommendations for follow-up support (if applicable)

A.3. The importance of OJP

The questionnaire was sent out by PES as part of the research project during approximately the fifth week of unemployment. The questionnaire was sent out via e-mail to everyone who was newly registered as unemployed during our period of analysis. 13% responded and was merged using confidential identifiers by employees of the PES.

TABLE A1. **Importance of OJP for job search by the unemployed**

	last week			
	hours search mean	used at all %	ranking	found work col %
vdab MLB	1.70	70.95	2.4	17.50
social media	1.26	48.69	3.8	11.81
temp agencies	0.86	36.85	4.0	24.86
commercial jobsite	0.89	41.54	4.3	3.24
company website	0.76	33.49	4.3	11.42
own network	0.70	34.50	4.4	14.78
vdab local branch	0.11	6.73	5.8	11.87
open application	0.40	23.42		4.51
printed media	0.12	10.11	7.0	0.00
Observations	1420			200

Notes: These are summarized survey responses that have been reweighted by characteristics: age, employment duration, region of birth, education and sex. The ranking question was formulated as follows: how would you rank the following channels as being best to search *for you*.

Appendix B. A model of job search effort with types

B.1. Simulation of the impact of the assessment call

During the assessment call, the PES caseworker checks and motivates the job seeker to search for jobs using the OJP. We model this intervention as a temporary reduction in the cost of job search effort. Specifically, we simulate a one-period 35% reduction in the search costs for each type by multiplying each k_j by a factor of 0.65 in $d = 5$.

To simulate the model, we take parameter values from Le Barbanchon, Schmieder, and Weber (2024) for δ, k_1, k_2, γ, μ, and σ. Because their simulated model with multiple types does not allow for a time-varying wage offer distribution, thereby implicitly setting $\pi = 0$, we instead assume that $\pi = 0.5$. Finally, we assume that the share of k_1 types in $d = 0$ is $q_{1,0} = 0.5$. The following table summarizes the parameter values used in Le Barbanchon, Schmieder, and Weber (2024) in column (1) as well as those used in our simulation in column (2).

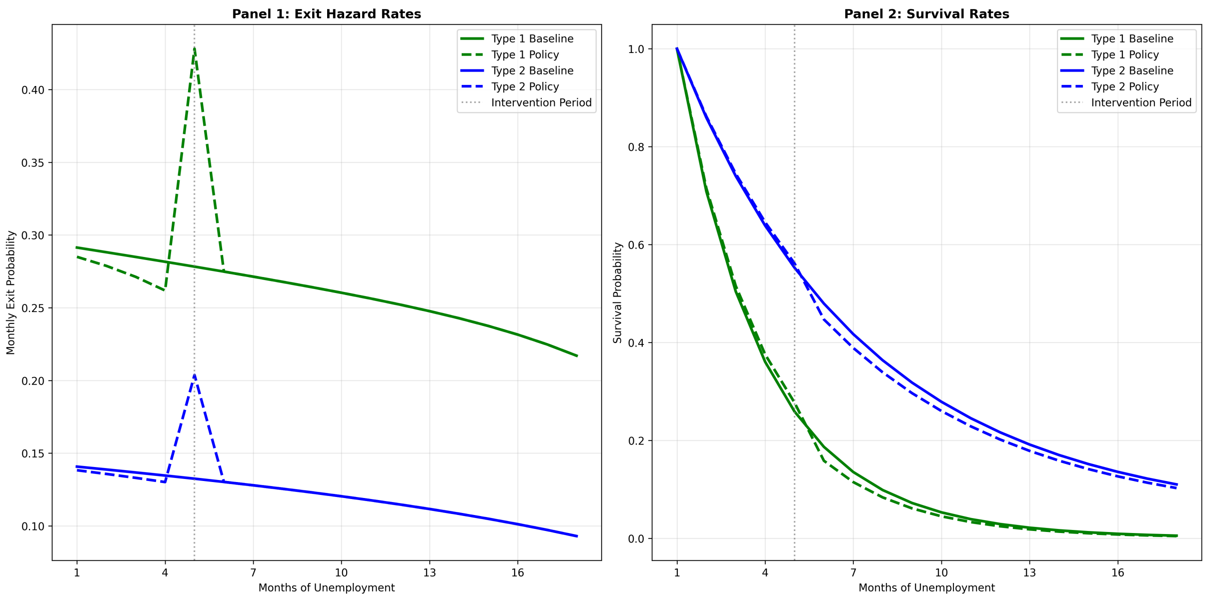
TABLE B1. **Model parameters**

	Le Barbanchon et al. (1)	this paper (2)
δ	0.95	0.95
k_1	47	47
k_2	148	148
k_3	6.90	0.00
k_4	0.23	0.00
γ	1.00	1.00
μ_1	4.04	4.04
μ_2	3.62	4.04
μ_3	4.24	0.00
μ_4	3.45	0.00
σ	0.01	0.01
π	0.00	0.05
$q_{1,0}$	0.33	0.50
$q_{2,0}$	0.33	0.50
$q_{3,0}$	0.24	0.00
$q_{4,0}$	0.01	0.00

Notes: Column (1) estimates are taken from `https://github.com/johannes-schmieder/Job-Search-Model-HoLE-Chapter/tree/main/search_model_4Type`. Column (2) represent estimates as implemented in this paper.

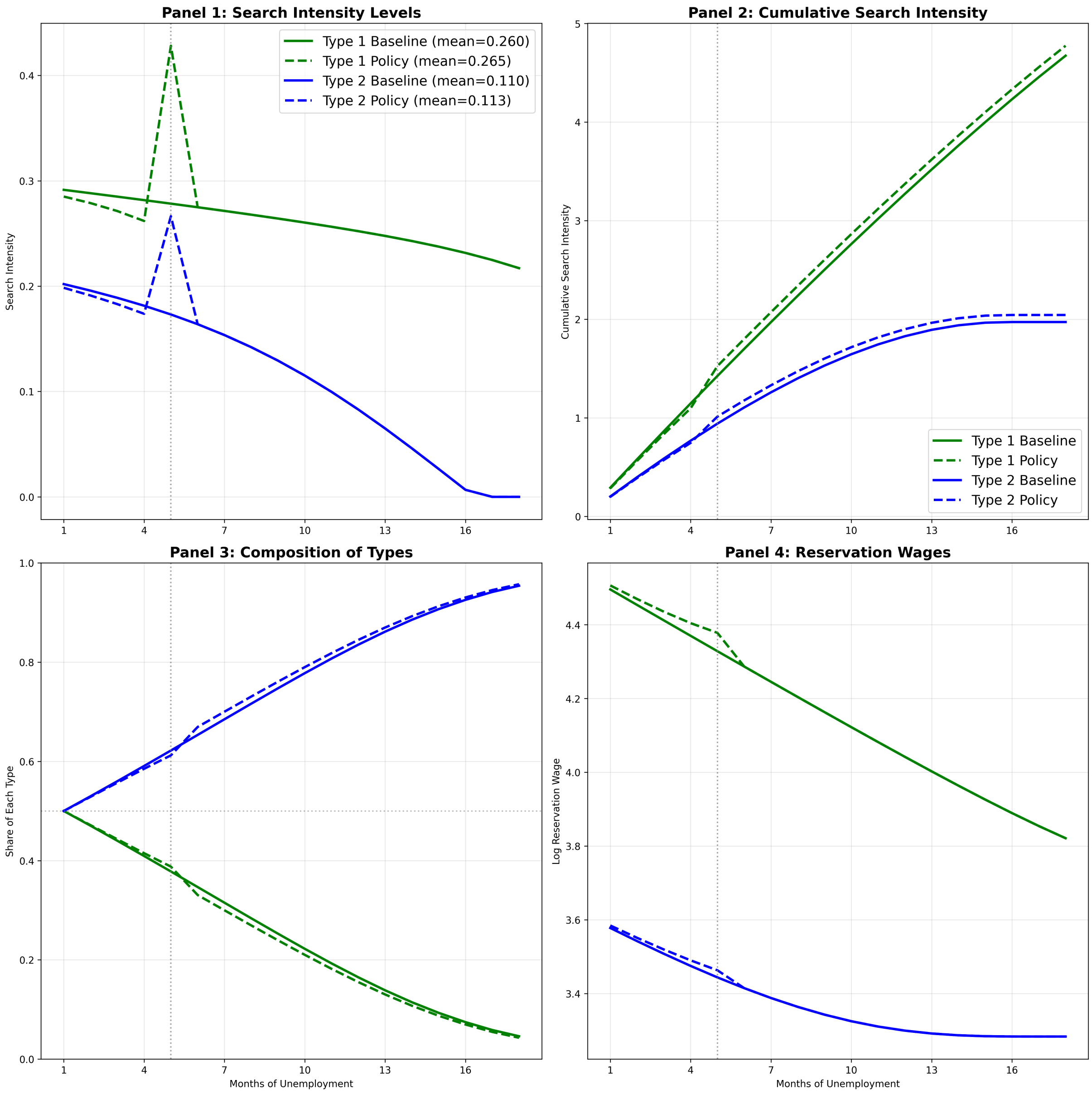
B.2. Simulations for hazard and survival rates

FIGURE B1. **Simulation of job search model with 2 types, with and without job search assistance policy**



B.3. Assuming types with different wage offer distributions

FIGURE B2. **Simulation of job search model with 2 types in μ, with and without job search assistance policy**



Appendix C. ML scores

C.1. ML algorithm

’Chance of Work’ is the first internal AI application developed as part of the ’Next Best Steps’ (NBS) project. The aim of this project is to develop AI applications that support the mediator in assessing and mediating a job seeker in a data-driven way. The first model of the NBS project is the estimation of the chance of employment. This estimate is an objective measurement of the distance to the labor market.

C.1.1. Functional model

The model (a random forest model) predicts the chance that a job seeker without work will work for at least 28 days within 6 months. Work is broadly defined here as the ’outflow to work’, including interim work and part-time work. However, job seekers who are not employable, unavailable, or who have an exemption do not receive a prediction based on the reasoning that this group does not actively look for work. In addition, customers with an incomplete profile on the OJP do not receive a prediction.

The information used to make the prediction (the ’features’) includes the current and previous periods of unemployment, file data from the OJP (desired professions and regions, language skills, studies, etc.), age, work experience, and online activity on the OJP (updating CVs, managing competencies, logging in, etc.).

C.1.2. Output

This model has been making predictions on a daily basis since it was put into production on 14/10/2018. The percentages are then converted to a color, currently as follows:

- -1 = black => deliberately blocked files (see earlier)
- <35% ⇒ Red
- 35-49.99% ⇒ Orange
- 50-64.99% ⇒ Yellow
- >= 65% ⇒ Green

These colors are used to prioritize the call lists that are part of the assessment call, with the difference that currently yellow and orange are counted together as 1 group. First the black ones are called, then the reds, then the orange ones and finally, if there is capacity left, the greens.

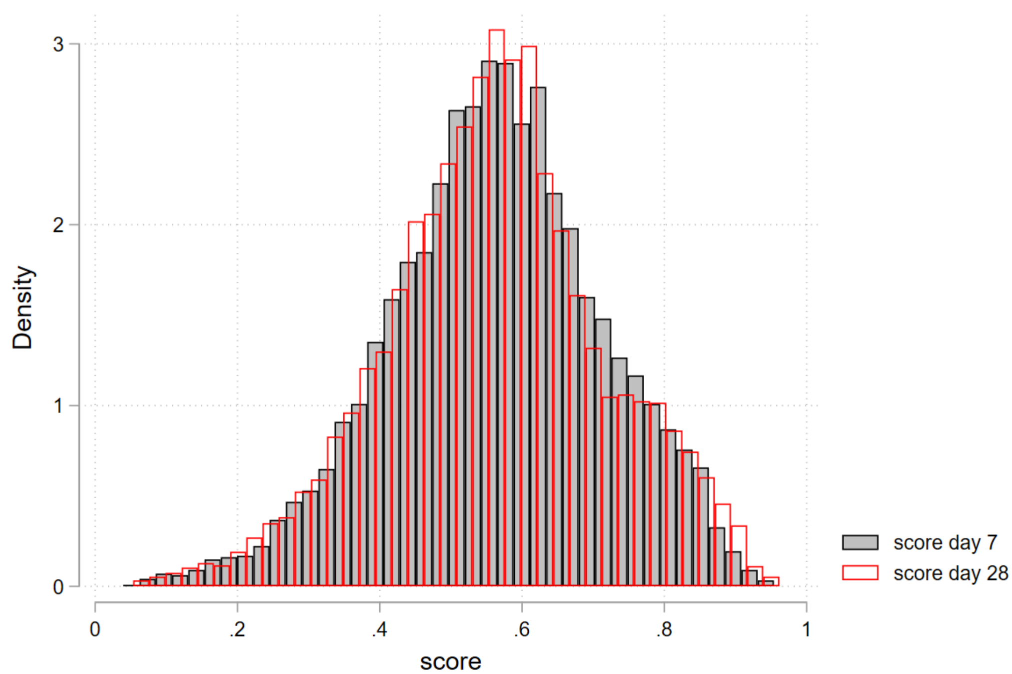
C.2. ML scores

TABLE C1. **Day in unemployment spell when first score is observed**

Day	%	N
1	88.02	9,312
2	10.35	1,095
3	1.06	112
4	0.44	47
5	0.08	8
6	0.03	3
7	0.02	2
Total	100.00	10,579

Notes: These are the observations for whom we observe a first non-missing score during the first 7 days: 26.389 - 16 (nothing observed) - 272 (only -1 throughout) - 691 (first score>-1 after day 7).

FIGURE C1. **Heterogeneity in ML scores**



Notes: These are the ML scores of our sample on day 7 and day 28.

TABLE C2. **Summary characteristics of the score over the first 28 duration days**

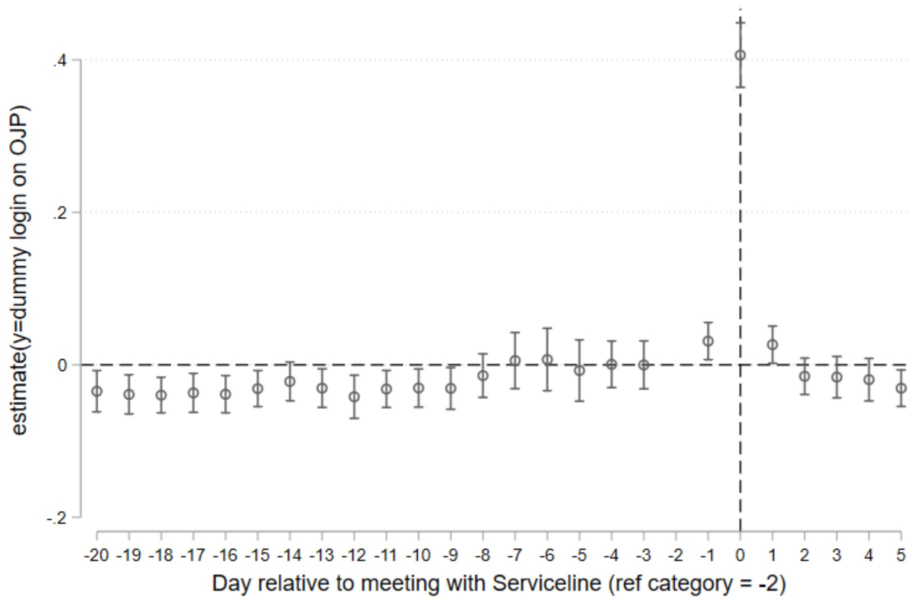
day of duration	N score	Mean score	Sd score
1	9,312	0.56	0.14
2	10,407	0.56	0.14
3	10,519	0.56	0.14
4	10,566	0.56	0.15
5	10,573	0.56	0.15
6	10,575	0.56	0.15
7	10,577	0.56	0.15
8	10,578	0.56	0.15
9	10,578	0.56	0.15
10	10,578	0.56	0.15
11	10,578	0.56	0.15
12	10,579	0.56	0.15
13	10,579	0.56	0.15
14	10,579	0.56	0.15
15	10,579	0.56	0.15
16	10,579	0.56	0.15
17	10,579	0.56	0.15
18	10,579	0.56	0.15
19	10,579	0.56	0.15
20	10,579	0.56	0.15
21	10,579	0.56	0.15
22	10,579	0.56	0.15
23	10,579	0.56	0.15
24	10,579	0.56	0.15
25	10,579	0.56	0.15
26	10,579	0.56	0.15
27	10,579	0.56	0.15
28	10,578	0.56	0.15
Total	294,683	0.56	0.15

Notes: These are the mean, standard deviation and number of observations for the ML score of our sample over the first 28 days of duration.

Appendix D. The impact of the assessment call on job search effort

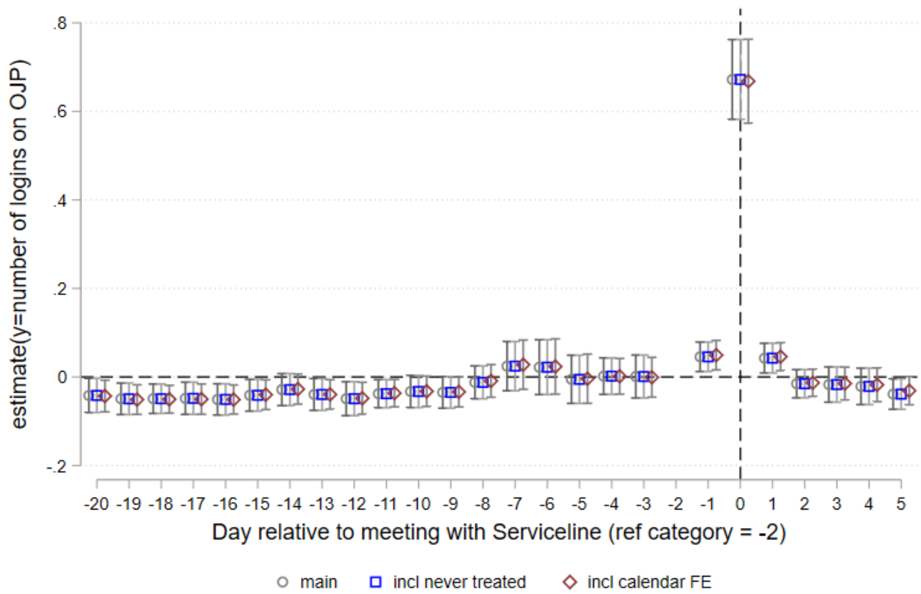
D.1. Average treatment effects

FIGURE D1. **Stacked DiD with login dummy as outcome**



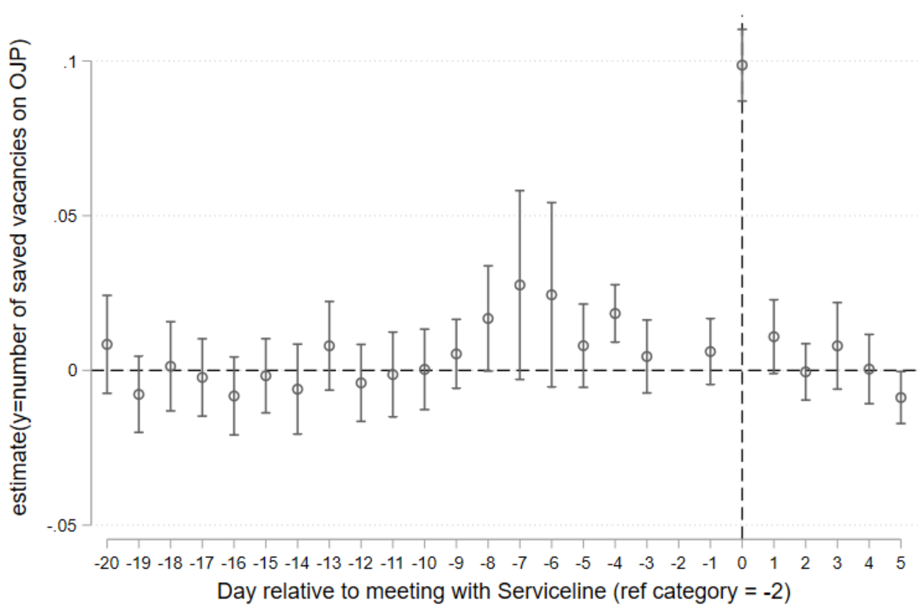
Notes: These are the coefficiënts from the stacked DiD design, equation (20). Two-way fixed effects are individual-by-cohort fixed effects and duration time fixed effects. In addition, we control for the timing at which job seekers hand in assignments during the first 28 days. Different from the average treatment effect in the main text, the outcome variable is a zero-one dummy for whether a job seeker logged in.

FIGURE D2. **Stacked DiD with never-treated controls and calendar-year fixed effects**



Notes: These are the coefficiënts from the stacked DiD design, equation (20). Two-way fixed effects are individual-by-cohort fixed effects and duration time fixed effects. In addition, we control for the timing at which job seekers hand in assignments during the first 28 days. Next to repeating the coefficiënts from the main specification as shown in Figure 5, we add in two other specifications. First, we allow those with assessment calls after day 49 to act as controls. Second, we add calendar-year fixed effects.

FIGURE D3. **Saved vacancies around assessment call, average treatment effects**



Notes: These coefficiënts are estimates of γ_e in equation (20) with number of saved vacancies as outcome. Mean number of vacancies saved on -2 reference point is 0.027 per day.

D.2. Heterogeneity in treatment effects across cohorts

For a balanced panel of job seekers who remain unemployed for at least 49 days, the estimator for any given g and e is given by:[34]

$$ATT(g,e) = \mathbb{E}\left[\left(\frac{D_i}{\mathbb{E}[D_i]} - \frac{\frac{p(X_i)(1-D_i)}{1-p(X_i)}}{\mathbb{E}\left[\frac{p(X_i)(1-D_i)}{1-p(X_i)}\right]}\right)\left(Y_{i,g+e} - Y_{i,g-2} - \Delta Y_i(X_i, G_i = g')\right)\right] \tag{A1}$$

with g' such that $g + e < g' \leq 49$. The term $p(X_i) \equiv P(D_i = 1|X)$ is the propensity score of $D_i = 1$ conditional on X_i using the sample of job seekers with $G_i = g$ or g'.[35] The Inverse Probability Weight (IPW) $p(X_i)/(1 - p(X_i))$ gives more weight to control-group observations with higher $p(X_i)$.[36] The term $\Delta Y_i(X_i, G_i = g')$ is a Regression-Adjustment (RA) term defined as the expected change in Y_i among control-group observations with characteristics X_i. That is, $\Delta Y_i(X_i, G_i = g') \equiv \mathbb{E}[Y_{i,g+e} - Y_{i,g-2}|X_i, G_i = g']$. For job seekers with $D_i = 1$ and characteristics X_i, the term $\Delta Y_i(X_i, G_i = g')$ is the counterfactual change in outcome between $g + e$ and $g - 2$ if they would have received treatment on day g' instead of g.

For each g and e, the CS estimator first estimates $p(X_i)$ using job seekers in treated as well as control groups using a logit as a working model for the propensity score. It also estimates coefficients in $\Delta Y_i(X, G_i = g')$ only using the sample of control units and a linear regression model. The CS estimator then plugs in estimated fitted values for each individual in treated as well as control groups together with sample analogues of other expectations in equation (A1). Callaway and Sant'Anna (2021) show that, as long as the working model for either IPW or RA estimators is correctly specified, the CS estimator is the most precise estimator (with minimum asymptotical variance) among all (regular) estimators that does not rely on additional functional form restrictions, i.e the CS estimator is doubly robust. Finally, (simultaneous) confidence intervals can be computed using Callaway and Sant'Anna (2021)'s multiplier bootstrap procedure with standard errors clustered at the treatment-cohort level.

[34] All moments in equations (16), (17), and (18) are now conditional on X_i.

[35] Note that we must have that $p(X_i) < 1$. This imposes the additional identifying assumption that every individual has a strictly positive probability of being in the untreated group conditional on X_i. This identifying assumption is known as the overlap assumption.

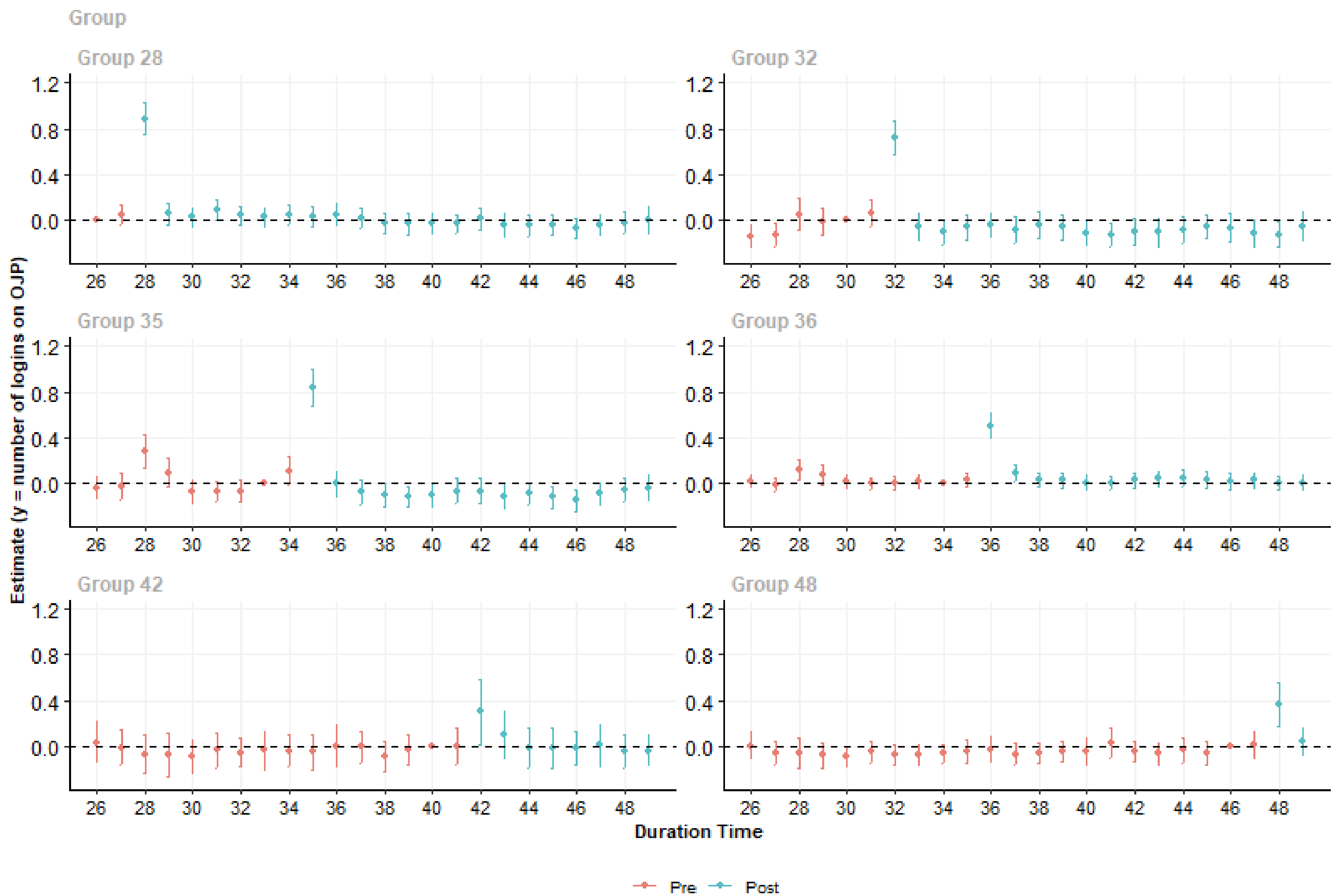
[36] The expectation in the denominator normalizes these weights to sum to unity. This normalization also minimizes the instability of the estimator due to very high weights when $p(X_i)$ is close to 1.

TABLE D1. **Group-specific ATT estimates**

cohort	event time										
	-5	-4	-3	-2	-1	0	1	2	3	4	5
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
28	0.00	0.00	0.01	.	0.05	0.89	0.06	0.03	0.09	0.04	0.03
	(0.02)	(0.02)	(0.02)		(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
29	0.01	0.04	0.02	.	0.09	0.93	0.1	0.08	0.05	0.05	0.02
	(0.03)	(0.02)	(0.02)		(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.02)
30	-0.12	-0.12	-0.15	.	-0.02	0.87	-0.04	-0.1	-0.22	-0.29	-0.25
	(0.04)	(0.04)	(0.04)		(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
31	-0.03	0.04	0.14	.	0.08	0.78	0.1	0.00	0.03	0.02	0.04
	(0.03)	(0.03)	(0.04)		(0.03)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
32	-0.13	0.06	-0.01	.	0.06	0.73	-0.05	-0.1	-0.06	-0.04	-0.08
	(0.03)	(0.04)	(0.03)		(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
33	0.08	0.02	0.02	.	0.01	0.67	0.08	0.02	0.03	0.01	-0.01
	(0.03)	(0.02)	(0.02)		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
34	0.03	0.03	-0.01	.	0.11	0.78	0.05	0.00	-0.01	-0.03	-0.05
	(0.03)	(0.02)	(0.02)		(0.03)	(0.04)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
35	-0.07	-0.07	-0.07	.	0.11	0.84	0.00	-0.07	-0.1	-0.11	-0.1
	(0.03)	(0.03)	(0.02)		(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
36	0.00	0.00	0.01	.	0.04	0.51	0.09	0.04	0.03	0.01	0.00
	(0.01)	(0.02)	(0.02)		(0.01)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
37	0.00	0.01	0.00	.	0.03	0.38	0.1	0.03	0.02	0.01	-0.01
	(0.01)	(0.02)	(0.02)		(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
38	-0.03	-0.03	-0.02	.	0.00	0.34	0.09	-0.02	0.00	0.01	0.02
	(0.02)	(0.02)	(0.02)		(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
39	-0.05	-0.04	-0.01	.	0.04	0.29	0.05	0.02	-0.03	0.04	0.01
	(0.02)	(0.02)	(0.02)		(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
40	-0.03	-0.01	-0.02	.	0.01	0.34	0.1	-0.01	0.01	0.06	0.04
	(0.02)	(0.02)	(0.02)		(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
41	-0.01	0.03	0.03	.	0.05	0.46	0.08	0.04	0.00	0.02	0.00
	(0.02)	(0.03)	(0.04)		(0.04)	(0.07)	(0.04)	(0.04)	(0.02)	(0.04)	(0.03)
42	0.00	-0.09	-0.02	.	0.00	0.31	0.11	-0.01	-0.02	-0.02	0.01
	(0.04)	(0.04)	(0.03)		(0.04)	(0.08)	(0.06)	(0.04)	(0.04)	(0.04)	(0.05)
43	0.00	0.00	-0.03	.	0.13	0.48	0.04	0.02	-0.01	0.01	-0.02
	(0.03)	(0.04)	(0.03)		(0.06)	(0.06)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
44	0.00	0.04	0.03	.	0.07	0.45	0.15	0.07	0.12	0.03	0.03
	(0.02)	(0.03)	(0.03)		(0.03)	(0.07)	(0.05)	(0.03)	(0.05)	(0.02)	(0.03)
45	-0.02	-0.01	0.04	.	0.06	0.41	0.02	0.01	0.02	0.03	
	(0.02)	(0.02)	(0.03)		(0.03)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	
46	-0.06	-0.07	-0.02	.	0.02	0.4	0.04	-0.02	0.00		
	(0.04)	(0.03)	(0.04)		(0.03)	(0.05)	(0.04)	(0.03)	(0.04)		
47	0.01	0.02	0.01	.	0.05	0.44	0.1	0.03			
	(0.02)	(0.02)	(0.02)		(0.02)	(0.04)	(0.03)	(0.02)			
48	-0.06	-0.03	-0.05	.	0.01	0.37	0.04				
	(0.03)	(0.03)	(0.02)		(0.03)	(0.05)	(0.03)				
49	-0.01	-0.02	-0.01	.	0.05	0.4					
	(0.04)	(0.03)	(0.03)		(0.03)	(0.06)					

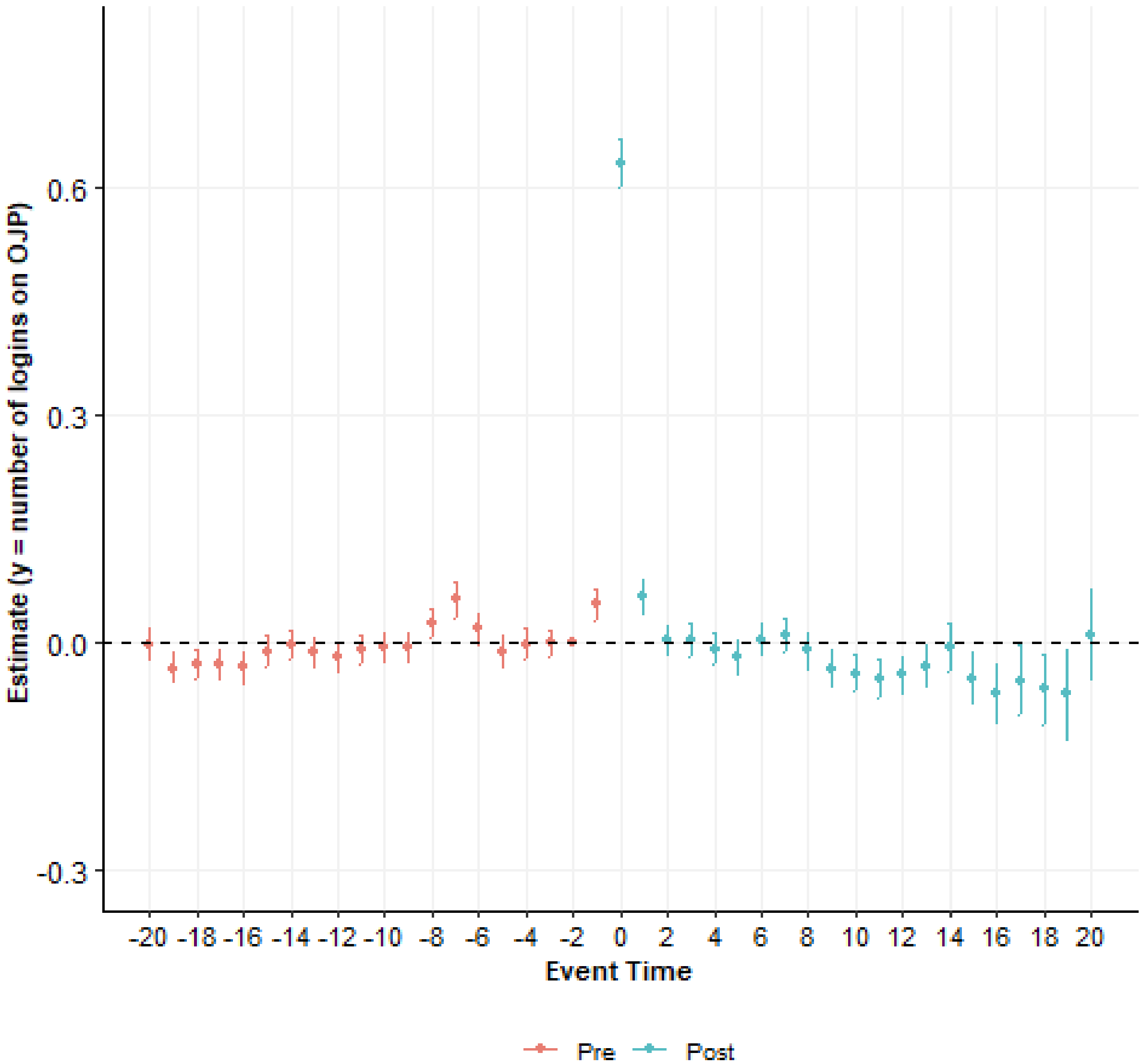
Notes: These estimates are the result of estimating equation A1 using the Callaway and Sant'Anna (2021) estimator. Variables included in the propensity score $p(X_i)$ are: ag, sex, region of birth, knowledge of Dutch, educational attainment, the degree of urbanization of their municipality, the number of automatic assignments 1 to 5 that they sent before day 28. We only present event time -5 to 5. The total panel sample consisted of duration time 16 to 49.

FIGURE D4. **Logins around assessment call, by day of contact**



Notes: These are the coefficiënts from estimating equation A1, methodology by Callaway and Sant'Anna (2021). Variables included in the propensity score $p(X_i)$ are: ag, sex, region of birth, knowledge of Dutch, educational attainment, the degree of urbanisation of their municipality, the number of automatic assignments 1 to 5 that they sent before day 28. The estimation window consisted of duration time 16 to 49. Please see Appendix Table D1 for the full set of group-specific ATT estimates.

FIGURE D5. **Logins around assessment call, aggregated to event time**



Notes: These are the coefficiënts from estimating equation A1, methodology by Callaway and Sant'Anna (2021). They are aggregated according to a single event-time. X-axis is trimmed to values - 20 and 20. Variables included in the propensity score $p(X_i)$ are: ag, sex, region of birth, knowledge of Dutch, educational attainment, the degree of urbanisation of their municipality, the number of automatic assignments 1 to 5 that they sent before day 28. The estimation window consisted of duration time 16 to 49. See Appendix Table D1 for the full set of group-specific ATT estimates.

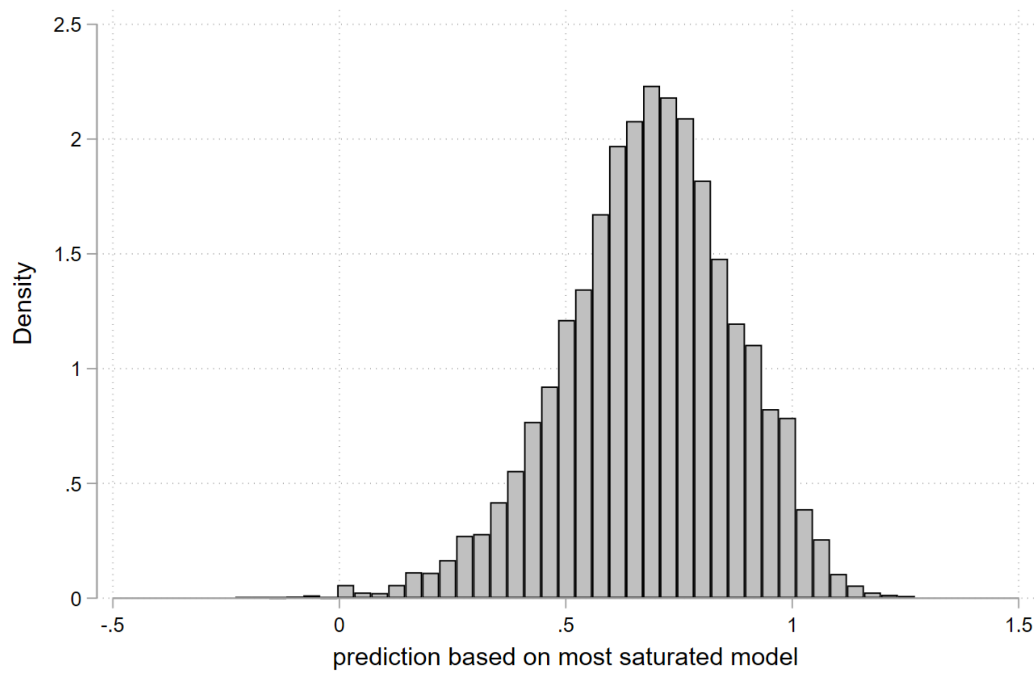
Appendix E. Types in job finding

TABLE E1. **Predicting job finding on day 28**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	job finding ≤ 6 months					
# of assignments handed in <d28	0.0175***	0.0177***	0.0107***	0.00992***	0.00904***	0.00585***
	(0.00221)	(0.00221)	(0.00220)	(0.00222)	(0.00224)	(0.00218)
mean daily logins <d28	0.111***	0.113***	0.0926***	0.115***	0.108***	0.0807***
	(0.0302)	(0.0301)	(0.0296)	(0.0304)	(0.0305)	(0.0296)
tightness		0.0434***	0.0267***	0.0267***	0.0278***	0.0200**
		(0.00850)	(0.00839)	(0.00854)	(0.00858)	(0.00833)
first ML score						0.969***
						(0.0385)
age			-0.00314	-0.000204	0.000896	5.24e-05
			(0.00438)	(0.00444)	(0.00452)	(0.00438)
age2			3.67e-05	-4.25e-06	-1.78e-05	2.48e-05
			(5.79e-05)	(5.87e-05)	(5.97e-05)	(5.79e-05)
isced = 2, some secundary			0.0116	0.00688	-0.00870	0.0172
			(0.0257)	(0.0260)	(0.0274)	(0.0266)
isced = 3, secundary			0.0526**	0.0545**	0.0410	0.0383
			(0.0245)	(0.0248)	(0.0261)	(0.0253)
isced = 4, (higher) professional			0.0773***	0.0677***	0.0549**	0.0428*
			(0.0243)	(0.0245)	(0.0259)	(0.0251)
isced = 6, bachelor			0.139***	0.131***	0.118***	0.0464*
			(0.0244)	(0.0248)	(0.0263)	(0.0256)
isced = 7, master			0.137***	0.135***	0.121***	0.0497*
			(0.0250)	(0.0255)	(0.0271)	(0.0264)
recent graduate			0.115***	0.0922***	0.0907***	0.0517***
			(0.0166)	(0.0171)	(0.0173)	(0.0168)
knowledge of Dutch = 2, Limited			0.108***	0.101***	0.0800**	0.0733**
			(0.0334)	(0.0337)	(0.0360)	(0.0350)
knowledge of Dutch = 3, Good			0.224***	0.193***	0.177***	0.120***
			(0.0310)	(0.0318)	(0.0353)	(0.0343)
knowledge of Dutch = 4, Very Good			0.249***	0.220***	0.186***	0.0950***
			(0.0293)	(0.0304)	(0.0354)	(0.0345)
labour disability			-0.0463*	-0.0649**	-0.0652**	-0.00897
			(0.0257)	(0.0261)	(0.0262)	(0.0255)
Constant	0.627***	0.620***	0.356***	0.344***	0.540***	0.138
	(0.00682)	(0.00695)	(0.0866)	(0.0979)	(0.142)	(0.139)
Observations	10,579	10,579	10,579	10,579	10,579	10,579
R-squared	0.012	0.014	0.059	0.093	0.118	0.170
Mean jobfinding	.682	.682	.682	.682	.682	.682
Inflow month FE	NO	NO	NO	YES	YES	YES
Registration channel	NO	NO	NO	YES	YES	YES
Municipality FE	NO	NO	NO	YES	YES	YES
Migration FE	NO	NO	NO	NO	YES	YES

Notes: This regression predicts finding a job from day 28. "Number of assignments handed in before day 28" measures the number of assignments that were handed in by the job seeker before day 28. There are 5 assignments sent out at the start of the spell to everyone. Therefore, this variable ranges from 0 to 5. Registration channel contains a categorical variable for the mode of registration, in-person, online or automatically through administrative status. Migration FE contains a combination of FE for nationality and country of birth. “recent graduate” refers to job seekers that receive unemployment benefits while searching for work after graduation. “Labour disability” is a dummy for having a registered physical or mental disability to work.

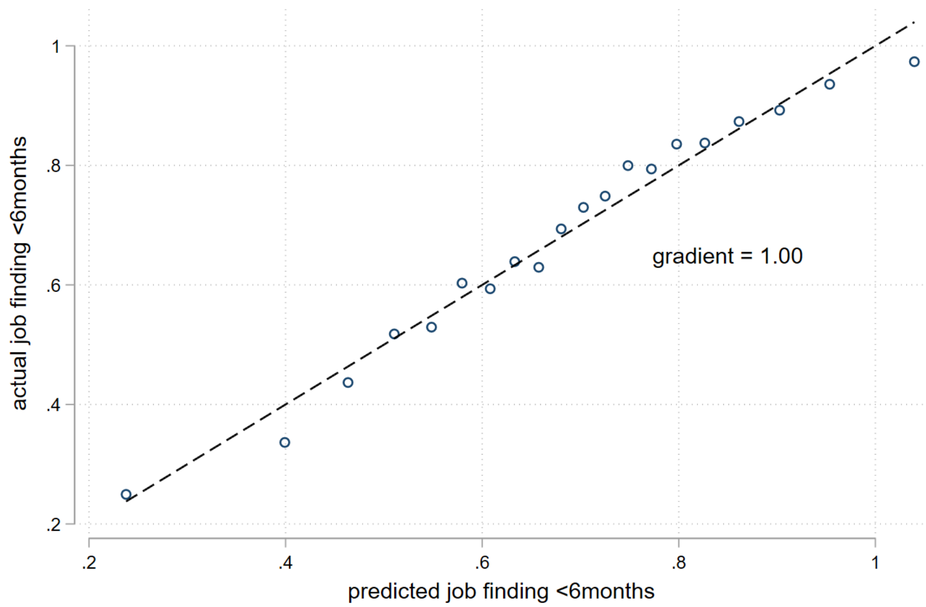
FIGURE E1. **Heterogeneity in predicted job finding rates**



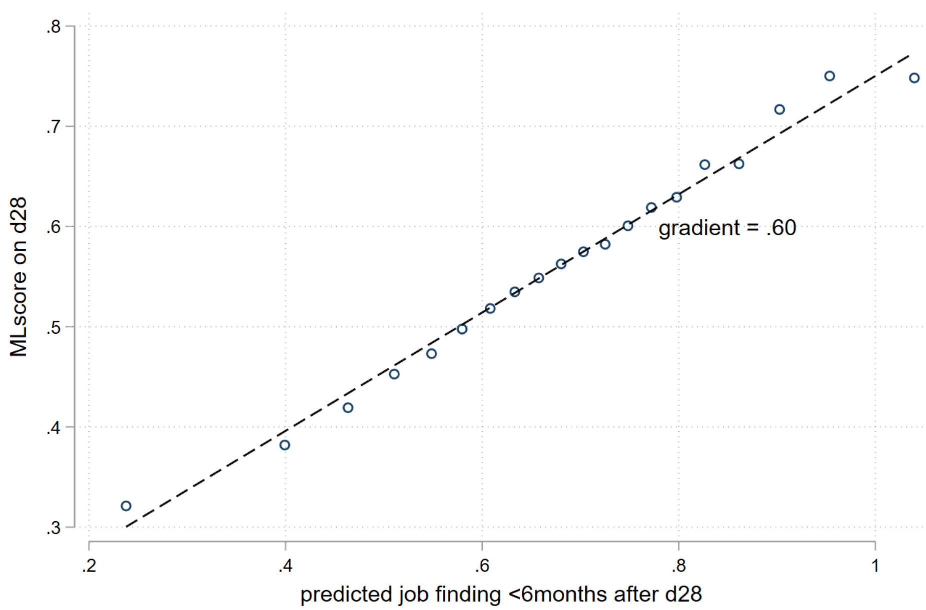
Notes: Based on final column of Table E1.

FIGURE E2. **Predicted versus actual job finding rates and ML scores**

A. **Predicted versus actual job finding rates**



B. **Predicted job finding rates versus ML scores**



Source: VDAB **Notes:** Panel A: Binscatter comparing actual and predicted probabilities of the regression in final column of Table E1. Panel B: Binscatter comparing predicted probabilities of the regression in final column of Table E1 with the ML score on day 28.

TABLE E2. **Predicting job finding at month d into the spell**

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	job finding ≤ 6 months, after					
	month 1	month 2	month 3	month 4	month 5	month 6
# of assignments handed in before d28	0.00585***	0.00530**	0.00454	0.00337	0.00331	0.00849**
	(0.00218)	(0.00234)	(0.00300)	(0.00350)	(0.00390)	(0.00422)
mean daily logins <d28	0.0807***	0.0637**	0.0980**	0.110**	0.0672	0.0169
	(0.0296)	(0.0323)	(0.0417)	(0.0481)	(0.0572)	(0.0614)
tightness	0.0200**	0.0169*	0.0183	0.0134	0.0209	0.00668
	(0.00833)	(0.00950)	(0.0113)	(0.0155)	(0.0189)	(0.0223)
first ML score	0.969***	0.941***	0.873***	0.829***	0.694***	0.545***
	(0.0385)	(0.0410)	(0.0509)	(0.0580)	(0.0637)	(0.0682)
age	5.24e-05	0.00419	0.0104*	0.0120*	0.0146**	0.0183**
	(0.00438)	(0.00468)	(0.00586)	(0.00675)	(0.00742)	(0.00792)
age2	2.48e-05	-2.93e-05	-0.000126	-0.000145	-0.000190*	-0.000248**
	(5.79e-05)	(6.18e-05)	(7.72e-05)	(8.86e-05)	(9.76e-05)	(0.000104)
isced = 2, some secundary	0.0172	0.0120	0.00128	0.0217	0.0253	-0.00136
	(0.0266)	(0.0279)	(0.0333)	(0.0369)	(0.0395)	(0.0417)
isced = 3, secundary	0.0383	0.0355	0.0251	0.0146	0.0246	-0.00139
	(0.0253)	(0.0266)	(0.0318)	(0.0354)	(0.0379)	(0.0399)
isced = 4, (higher) professional	0.0428*	0.0499*	0.0353	0.0459	0.0502	0.0380
	(0.0251)	(0.0264)	(0.0316)	(0.0352)	(0.0378)	(0.0396)
isced = 6, bachelor	0.0464*	0.0563**	0.0616*	0.0574	0.0598	0.0488
	(0.0256)	(0.0270)	(0.0325)	(0.0363)	(0.0391)	(0.0412)
isced = 7, master	0.0497*	0.0632**	0.0739**	0.0858**	0.0667	0.0770*
	(0.0264)	(0.0278)	(0.0335)	(0.0377)	(0.0410)	(0.0433)
recent graduate	0.0517***	0.0564***	0.0849***	0.0520*	0.0305	0.0287
	(0.0168)	(0.0181)	(0.0237)	(0.0284)	(0.0319)	(0.0346)
knowledge of Dutch = 2, Limited	0.0733**	0.0809**	0.0645	0.0388	0.0494	0.0949*
	(0.0350)	(0.0362)	(0.0414)	(0.0452)	(0.0484)	(0.0512)
knowledge of Dutch = 3, Good	0.120***	0.107***	0.0860**	0.0534	0.0475	0.0903*
	(0.0343)	(0.0357)	(0.0410)	(0.0449)	(0.0483)	(0.0515)
knowledge of Dutch = 4, Very Good	0.0950***	0.0900**	0.0838**	0.0608	0.0496	0.0934*
	(0.0345)	(0.0358)	(0.0411)	(0.0451)	(0.0485)	(0.0516)
labour disability	-0.00897	-0.0185	-0.0555	-0.0549	-0.0377	-0.0299
	(0.0255)	(0.0274)	(0.0339)	(0.0376)	(0.0398)	(0.0410)
Constant	0.138	0.0260	-0.0880	-0.0392	-0.0968	-0.185
	(0.139)	(0.152)	(0.189)	(0.205)	(0.236)	(0.263)
Observations	10,579	9,504	6,944	5,593	4,786	4,199
R-squared	0.170	0.169	0.160	0.146	0.139	0.144
Mean job finding	.682	.676	.587	.519	.472	.435
Inflow month FE	YES	YES	YES	YES	YES	YES
Registration channel FE	YES	YES	YES	YES	YES	YES
Migration FE	YES	YES	YES	YES	YES	YES
Municipality FE	YES	YES	YES	YES	YES	YES

Notes: The first column is therefore identical to the final column of Table E1. Registration channel contains a categorical variable for the mode of registration, in-person, online or automatically through administrative status. Migration FE contains a combination of FE for nationality and country of birth. "recent graduate" refers to job seekers that receive unemployment benefits while searching for work after graduation. "Labour disability" is a dummy for having a registered physical or mental disability to work.

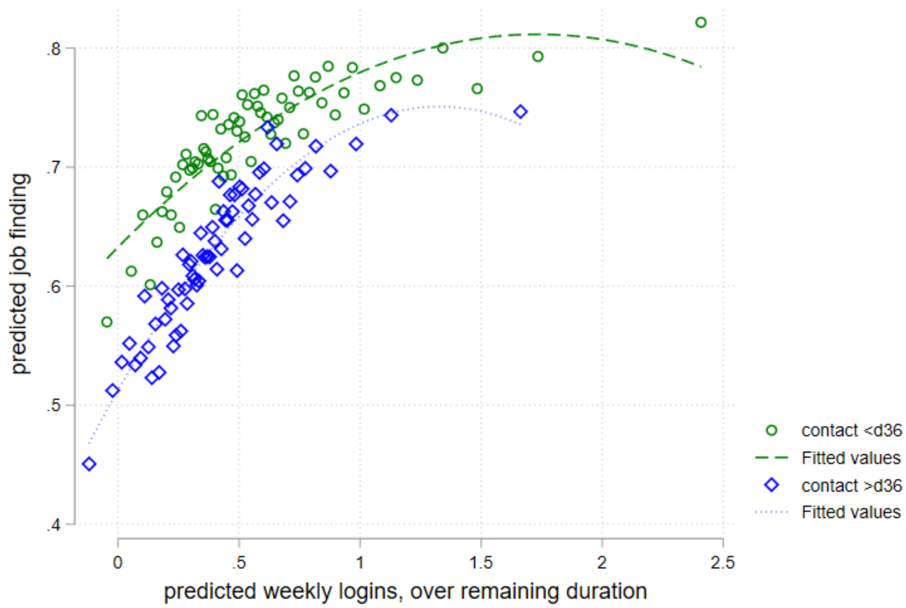
TABLE E3. **Rank correlations of predicted job finding at month d into the spell**

	Spearman rank correlation, pairwise for months:					
	1	2	3	4	5	6
1	1.00					
2	0.97	1.00				
3	0.89	0.93	1.00			
4	0.77	0.83	0.92	1.00		
5	0.67	0.73	0.82	0.91	1.00	
6	0.57	0.64	0.72	0.82	0.88	1.00

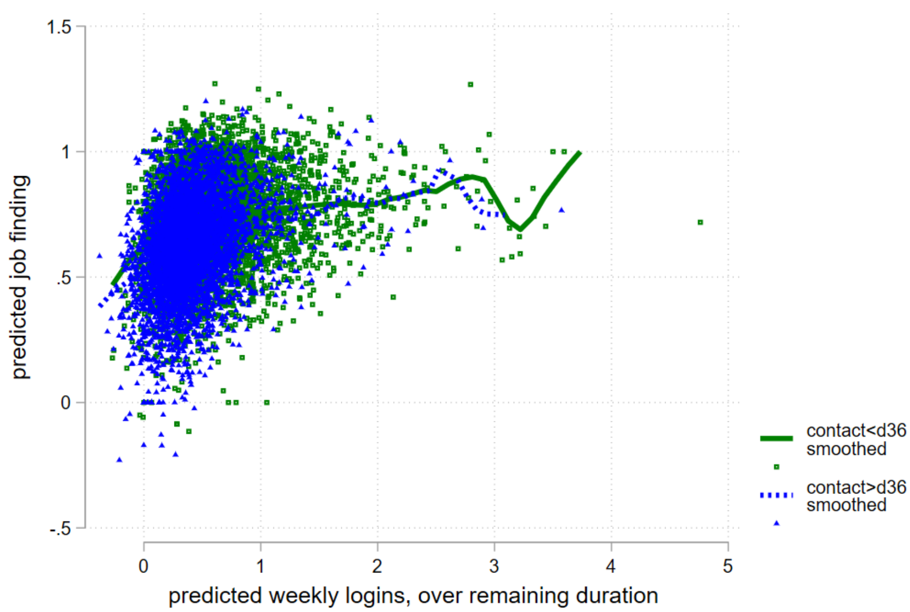
Notes: These are the predictions from the models represented in the columns of Table E2.

FIGURE E3. **Predicted logins and job finding by contact before and after day 36**

A. **Binscatter**



B. **Individual predictions and smooth local polynomial**



Notes: Panel A plots individual predictions and smooth local polynomials from final columns of Tables 2 and E1, but split over whether or not a job seeker had contact before day 36. Panel B shows similar predictions by whether or not a job seeker had an ML score > 0.66 on day 28.