Why Finding a Job Gets Harder: Applications vs Interviews

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Abstract

Job finding chances deteriorate as job search spells lengthen, and how much job search compared to firms callback contribute to negative duration dependence is an important question. We quantify the relative contribution of applications to jobs and callbacks to the overall decrease in the number of job interviews and job offer rate in a novel database that contains applications, callbacks, and job offers for several thousand job seekers in Switzerland. We address dynamic selection in job applications leveraging the panel structure of the data, and argue that dynamic selection can be characterized by characteristics firms observe on a CV. Our results show that both job-seekers' effort and firm's response to applications decrease steadily over time, also when controlling for individuals' heterogeneity. The combination of those negative trends leads to a large decrease in the number of job interviews and job offer rate over time. Approximately half of the empirical decrease in the job offer rate is attributable to diminishing search effort, while the remaining half is due to changes in recruiters' behavior. In a world without duration dependence, the job offer rate faced by the unemployed individuals would be flat.

JEL Classification: J24, J64

Keywords : job search, duration dependence, search effort, application success, ap- plication channels

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1. Introduction

The negative impact of unemployment duration on employment perspectives has been documented for long: job seekers' chances of leaving unemployment are getting slimmer as their spell lengthens (Van den Berg and Van Ours (1996), Machin and Manning (1998)), a phenomenon which is commonly referred to as negative duration dependence. The literature has come up with various explanation for this negative duration dependence in the job finding rate. On the labor demand side, job seekers could be discriminated against by potential employers who may consider the length of their current unemployment spell as signals of their low level of productivity or evidence of their human capital decay (Vishwanath (1989), Ljungqvist and Sargent (1998)). If firms actually use the (elapsed) unemployment duration as a screening device, job applicants will irremediably face a decrease in the callbacks from employers they apply to (Oberholzer-Gee, 2008a; Kroft et al., 2013; Eriksson and Rooth, 2014)). On the supply side, unemployed individuals might also play a direct role in the observed decrease in the job finding rate, notably through the way they apply. Typically, if job seekers tend to send less applications as they move forward in their spells (Faberman and Kudlyak, 2019), their chances of being hired will also decrease gradually. The same reasoning applies to the quality of job search. Even tough the negative duration dependence relationships in supply and demand factors have both already been studied from a quantitative perspective using empirical or experimental techniques, the question of their role in the observed decrease in the success of job search remains unanswered.

Our paper addresses the question of the duration dependence in the callback rate and in individuals' search effort in a joint framework, and aim to quantify the respective contributions of both sides of the labor market in the observed decrease in unemployeds' job finding rate. To this effect, we use a novel administrative source of data for Switzerland which provides us with information on the quantitative search effort provided by job seekers (*i.e.* the number of job applications sent per month), as well as information on the reply by firms (*i.e.* whether a specific application receives a callback for an interview and, eventually, whether it is followed by a job offer). Based on this data source, we construct a monthly panel database at the unemployment spell level and define various search indices of interest, whose goals are to quantify the job search process on the two sides of the labor market. On the labor supply side, we define the absolute monthly number of job applications sent as a proxy for the search effort provided by the job seekers; on the labor demand side, we measure firms' response through the individual-level callback and the job offer conversion rates (*i.e.* the conversion rate of job interviews into job offers). Using appropriate identification strategies to purge our estimates of dynamic selection, we exploit those detailed indices to shed light on the structural duration dependence affecting labor supply and demand. Eventually, the relative contributions of those two factors in the observed decrease in the chances of obtaining a job offer are quantified, as part of a job offer rate decomposition exercise.

The contribution of our study is threefold. First, we quantitatively assess the role of labor supply and labor demand in the observed decrease in the chances of finding a new job in a unite framework. Previous literature on the topic has suggested duration dependence in the labor supply (*i.e.* search effort) and demand (*i.e.* firms' reply) as the main explanations for the observed negative relationship between elapsed unemployment duration and the job finding rate. Those studies have mainly focused on each side of the market in isolation: the literature initiated by Kroft et al. (2013) studies the labor demand in an experimental context, through the use of audit studies, while the recent strand of literature led by Faberman and Kudlyak (2019) focuses on changes in the search effort provided by job seekers with respect to the length of their job search spells. If both strands of the literature find strong evidence of negative duration dependence in the specific aspect of job search they are interested in, none has yet been able to directly quantify the role played by labor demand or labor supply in the empirical negative duration dependence in the chances of finding a new job.
Second, we generalize previous results of the literature by analysing representative samples of the unemployed population in Switzerland. Most studies analysing the duration dependence in the callback rate is based on audit studies conducted on very specific samples, mostly made of white collar workers, while the literature on job search effort initially focused on online job search platforms. Our unique dataset allows us to study the duration profile in both job search effort and callbacks from a broader perspective, by looking not only at specific sub-groups of the job seeker population, but at a representative sample of Swiss unemployed.
Third, we are among the first to report direct empirical evidence on the job offer rate. This measure is commonly formalized in theoretical models of job search (*i.e.* arrival rate of job offer), but has yet not been directly studied from an empirical perspective, most of the related work having focused on the job finding rate. Our study shows that both measures are effectively closely related and that they exhibit very similar duration profiles.

Our paper is part of a large and flourishing literature on job search dynamics. Since the pioneer theoretical work of McCall (1970), Pissarides (1985) or Mortensen and Pissarides (1994), which model frictions in the labor market in a stationary framework, non-stationarity has been introduced in search models in order to allow for a greater flexibility in outcomes' dynamics (Van den Berg, 1990). One typical prediction of those augmented models is what is referred to as *negative duration dependence in employment prospects*, due for example to stigma effects (Vishwanath, 1989) or skills depreciation (Ljungqvist and Sargent, 1998). From an empirical perspective, this negative relationship between unemployment duration and the chances of finding a new occupation has been widely documented, such as in Van den Berg and Van Ours (1996) or Machin and Manning

(1998). Those empirical papers have yet rapidly encountered a key issue in the evaluation of the true duration dependence affecting job seekers' chances of re-employment: dynamic selection due to individual heterogeneity. In other words, when relying on cross-sectional unemployment spell datasets, researchers may miss some important (un)observed factors correlated with the overall duration of unemployment and with the job-finding probability. Historically, and for data-availability reasons, complex and somewhat restrictive distributional assumptions have been made to be able to identify the true duration dependence relationship in the job finding rate. On top of their reliance on a restrictive econometric framework, the empirical literature has for long studied the duration dependence in the job finding rate only from a matching perspective, without looking at the underlying mechanisms at play. More recently, exploiting experimental methods and longitudinal data, the literature has directed its attention to the study of labor supply and demand dynamics.

On the labor demand side, the experimental literature led by Kroft et al. (2013) has tried to evaluate the relationship between elapsed unemployment duration and the callback rate by firms, using audits studies in the context of randomized control trials. The reasons why the focus has been put on the callback rate are twofold. First, the audit studies framework does not allow researchers to keep on studying applications' outcome at later stage than the first-interview stage. Second, the evaluation of ulterior outcomes such as hiring can be tedious, since it might depend on factors that remain unobserved by the researchers. The key result of this literature is that elapsed unemployment duration effectively affects the chances of being called back. Kroft et al. (2013) find that the decrease in the callback rate mainly occurs during the first months of unemployment (before the 6-8 month of unemployment) and that this effect depends on socio-demographic characteristics and labor market tightness. In their field experiment, Eriksson and Rooth (2014) find that unemployment history (past unemployment spells) have a limited impact on the callback rate due to offsetting effects of subsequent employment spells, whereas current unemployment spells's duration seems to negatively affect the chances of being called back. The authors argue that their results provide evidence that unemployment duration conveys a negative signal on the productivity of unemployed individuals. Finally, Farber et al. (2016) find no evidence of a negative duration dependence in the callback rate, but their sample only consists of a specific subset of the working population (administrative support jobs targeted by female workers with four years of college), which rises concerns about the external validity of their findings. In their discussion, Farber et al. (2016) also argue that the decrease in the (absolute) number of callbacks, the leading index for job finding at the application stage, depends on three different factors: (i) negative dynamic selection, (ii) changes in search behavior and (iii) structural duration dependence[1].

[1] *i.e.* the negative relationship between callbacks and unemployment duration that is neither due to negative selection, nor changes in search behavior, and that is typically caused by changes in labor demand factors.

The dynamics of labor supply has also attracted the attention of researchers in the recent years. Job search at the unemployed level has recently been studied under the scope of beliefs. Spinnewijn (2015) develops a theoretical model to study the impact of (biased) job seekers' beliefs on the optimal design of unemployment schemes. Among others, his model predicts that biased unemployed individuals overestimate their chances of exiting unemployment and, consequently, put too little effort in their job search. Those results are confirmed by **?**, who report empirical evidence that job seekers are indeed subject to an optimistic bias in the US, and that this bias is not adjusted downwards when job seekers remain unemployed. If those studies recognize that labor supply is potentially subject to duration dependence, they do not directly quantify those dynamic aspects, perhaps due to the lack of relevant data. Only recently has a first paper addressed the question of duration dependence in job search from the perspective of the job seeker. In their study, Faberman and Kudlyak (2019) use longitudinal data at the individual level from an online job platform to track the dynamics of search effort (measured as the weekly number of job applications), along search spells. Thanks to this novel data source, the authors are able to control for individual heterogeneity, which plays a crucial role in the dynamic selection process. Among others, their results show that the longer the duration of (elpased) unemployment, the lower the level of search effort, which contradicts the predictions of standard job search models involving a modelization of job search effort (Pissarides (2000), Chapter 5). This study hence emphasizes the potential role played by labor supply factors in the negative duration dependence observed in employment prospects.
However, Faberman and Kudlyak (2019) only observe a narrow subset of job applications, since they exclusively focus on job applications posted on a specific online platform. Moreover, by focusing solely on job search intensity from a quantitative perspective, their work neglects an important aspect of job search: its qualitity. It is obvious that most qualitative aspects of job applications cannot be changed by job seekers (*e.g.* previous work experience, education, etc.). Nevertheless, some aspects of the applications can still be adapted in order to increase the chances of an individual application to be retained by a potential employer. One typical and crucial qualitative aspect of job applications emphasized by the literature is the channel used for the applications, and more precisely, the importance of social contacts when applying. Their role as a screening device in the context of hiring was first formalized by Montgomery (1991) and has been confirmed empirically at multiple occasions since then. For instance, Hensvik and Skans (2016) find that firms recruit first from the social network of their employees, while Burks et al. (2015)'s findings suggest that workers who are referred by one of their contacts are more likely to be hired and that the resulting worker-firm matches tend to last substantially longer. Consequently, when analyzing duration dependence in search behavior, it is crucial to consider both the quantiative and qualitative aspects of job search.

The rest of the paper is organized as follows. Section 2 presents the innovative dataset we use and describes conceptually how observable pieces of information can be used to measure duration dependence in labor supply and demand. Section 3 presents some descriptive patterns related to duration dependence in job search. Section 4 presents our identification strategies to measure structural duration dependence on the two sides of the labor market. Section 5 presents a decomposition exercise to measure the contribution of labor supply and demand factors to the overall decrease in the job offer rate. Section 6 concludes and discusses some policy implications.

2. Data and conceptual framework

This section presents the data we use to quantify the job search process and its duration dependence in the context of Swiss labor markets. The data are directly related to a conceptual framework describing how agents interact in the labor market, and how their actions can be measured through observable indices.

2.1 Data

Our analysis of job search dynamics is based on administrative data on the job search process of Swiss unemployed. Our primary data source consists of official job search diaries collected by Swiss Public Employment Services (PES), through the form *Nachweis der persnlichen Arbeitsbemhungen* (PAB, *Proof of personal search efforts*).[2] Those data were collected in the period ranging from April 2012 to March 2013, in five different cantons: Bern (BE), St. Gallen (SG), Vaud (VD), Zug (ZG) and Zrich (ZH). The search diaries are filled on a monthly basis by unemployed workers and are part of their obligations towards the unemployment insurance: they "*must be able to demonstrate [their] efforts [in order to find a job]*".[3] Due to the legal aspect of those documents, the reported information can be considered as highly reliable. Despite being self-reported, the information are checked on a regular basis by the caseworkers in charge of the job seekers, typically in the context of fortnightly personal meetings at the PES. The genuineness and validity of each application, as well as the additionally reported application-level outcomes, are notably assessed in a careful manner.

The diaries contain detailed information on search activities conducted by individuals within a given month of unemployment. Beside recording precise information on the applications sent by job-seekers, *i.e.* the date, the channel used (in person, written or by phone) and whether the application is referred by the caseworker, the forms also contain detailed application-level information on the (intermediary) outcomes of each application. More precisely, we observe for each application whether it leads to a job interview, and ultimately to a job offer. These additional application-level data represent one of the main innovation of our study, as they enable us to precisely and rigorously track job search activity and success in an real-life environment. Unfortunately, the data do not report any information on the application-level targeted position. Put differently, no information is recorded, at the application level, on the (potential) employer side.

We complement this primary data source with additional administrative data on job seek-

[2] A copy of the standardized PAB form can be found in the Appendix, in Figure A13.

[3] *Loi fédérale du 25 juin 1982 sur l'assurance-chômage obligatoire et l'indemnité en cas d'insolvabilité (LACI)*; RO 1982 2184. Retrieved 19$^{\text{th}}$ February 2020 from https://www.admin.ch/opc/fr/classified-compilation/19820159/index.html.

ers' characteristics, employment status and labor market history. Part of these data originate directly from the PES and contain information on socio-demographic and unemployment related characteristics. This second source of data notably provides us with information on the age of the job seekers, their residential status, level of education, biological sex, the occupational sector they target, the public employment centre to which they are affiliated and the caseworkers that are in charge of supervising them. We also retrieve additional information on job seekers' earnings using social security data. This dataset enables use to construct a monthly panel database that tracks the labor income flows of all observed individuals in the first two databases, and helps us to define the unemployment spells covered by the fixed observation window of April 2012 to March 2013, during which we collect the search diaries.

At this point, it is worth emphasizing that our study focuses on unemployment spells rather than on non-employment spells. This methodological choice is related to the reliability of the information contained in the search diaries during unemployment months: job seekers have to fill in the PAB form diligently, as long as they are perceiving unemployment benefits. Limiting our analysis to the months during which individuals are actually unemployed hence increases the reliability of our data and of our measures of job search. Also, the observation windows for all datasets are not the same. The PAB dataset, which is limited to the period April 2012 to March 2013, restricts the range of observable months of unemployment. Unemployment spells are well defined, thanks to the information contained in the social security data. All in all, the stock sampling procedure on which the PAB sample is based implies that some of the spells that we observe are left, right or left-right censored.

Our data contain information on 602'190 job applications sent by 14'829 unemployed individuals, for a total of 58'936 monthly-individual observations. The detailed structure of our database of analysis is reported in Table A7 in the appendix, while Table A5 and Table A6 report descriptive statistics on the unemployed individuals in our sample. Those are 40.6 years old on average, and a slight majority of them are male. Most of them have achieved an apprenticeship (48%) or reached the primary level of education (27%), and more than half of them own the Swiss nationality. In terms of job search, the sampled individuals send 10.55 applications and are invited to 0.4 job interview per month on average. This corresponds to an average application-level callback rate of 3.8%. The average monthly number of job offers amounts to 0.075. Also, most of the applications are done in written form (61%), while the phone and personal application channels account each for approximately 15% of all the applications. The remaining applications involve more than one channel. The exact construction and interpretation of the above mentioned job search indices is further discussed in the next sub-section, which relates the observable data to our conceptual framework of analysis.

2.2 Job search measures

Job search is a dynamic matching process between job seekers and firms. The process of finding a job can decomposed in two stages. First, job seekers actively search for opened vacancies and apply to them. Having received the applications, contacted firms decide whether to callback the applicants and to invite them for a job interview. In case this first screening-stage is successful, firms proceed to a second screening, in the form of a job interview. Based on all the information they have collected, firms eventually decide whether to make a job offer to the selected applicants. This job offer, is eventually accepted or not by the job seeker, and the new working relationship can start. This two-stage process is depicted schematically in Figure A14, in the appendix. If this detailed job search procedure has been formalized extensively from a theoretical perspective, it has so far received limited attention from the empirical literature, presumably for data availability reasons. Our study proposes to have a new look at this process, by leveraging on the detailed PAB data, which can directly be linked to the conceptual framework described above.

Our novel dataset enables us to quantify the search process on the two sides of the market in a highly detailed manner. Regarding job seekers, we measure the number of job applications each job seeker sends within a month, as e.g. Faberman and Kudlyak (2019), Arni and Schiprowski (2019) and Marinescu and Skandalis (2021). Due to the monthly calendar timing of the recording of the PAB forms, we naturally consider the number of job applications sent by individual i in unemployment month t as our quantitative measure of the search effort she provides, a measure which we denote A_{it}.

On top of information on search effort, the PAB forms record additional detailed information on firms' response to each single application a. Regarding the first stage of the recruiting process, we know whether each application ends up in an interview. We denote this specific binary application-level piece of information on callbacks C_{ait}. Taken individually, this binary variable is only informative on the outcome of each individual application. Aggregated across all applications sent by an individual within a given month of unemployment, it provides us with a valuable probabilistic measure on firms' response, for each applicant i in month t. In line with the literature (Kroft et al. (2013), Eriksson and Rooth (2014)), we refer to this probabilistic measure as the (individual-level and time-varying) callback rate.

We apply a similar coding procedure for the second step of the hiring process, *i.e.* the conversion of a job interviews into job offers. However, according to our conceptual framework, any job offer necessarily requires a preceding job interview. In our data, some interviews are hence imputed when a job offer is recorded without any preceding interview. This imputation process has a limited impact on the distribution of job interviews: only 2'629 interviews are imputed, to be compared to the 19'824 interviews recorded before imputation (imputation only concerns 11.7% of the interviews we eventually study).

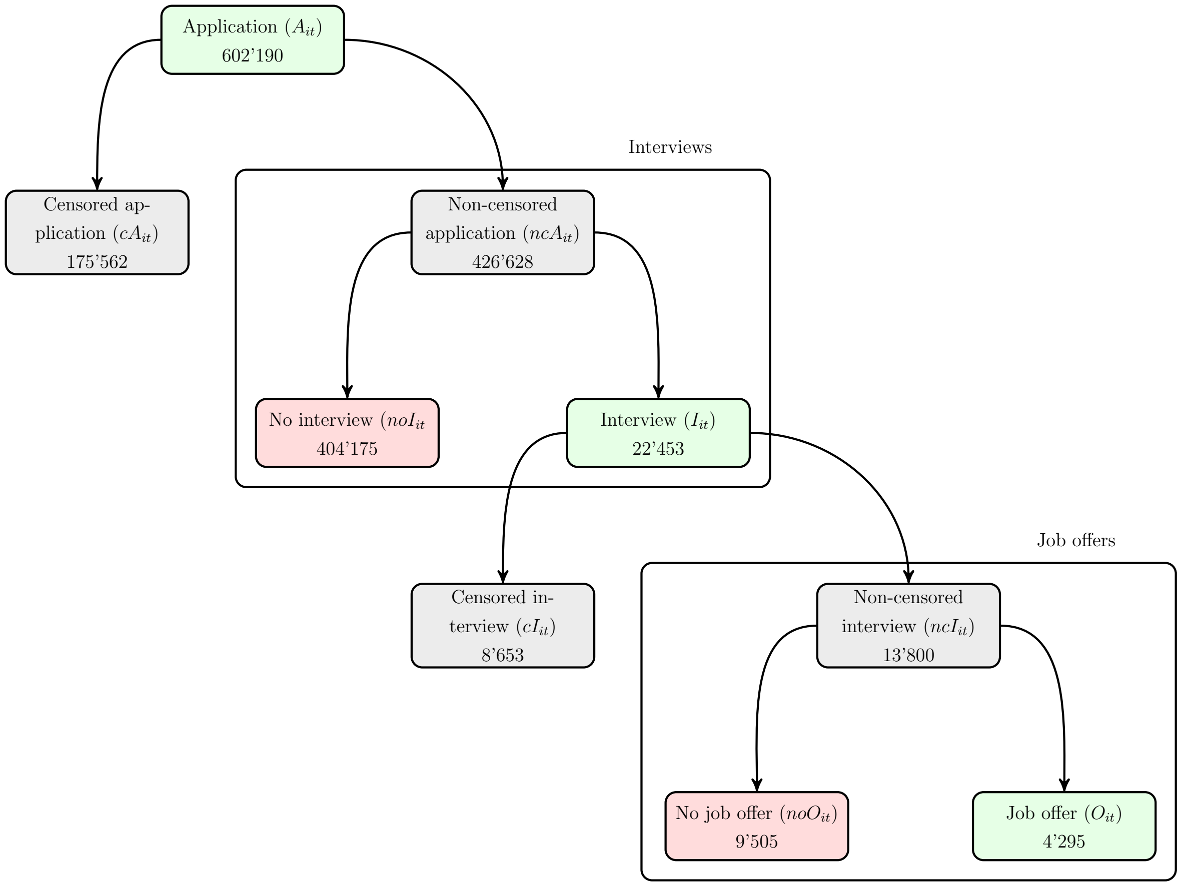
Following the same coding procedure as in the first-stage, we define the binary indicator O_{ait}, which takes the value one when a job offer is recorded. Again, this variable enables us to define the aggregate job offer conversion rate, defined as the ratio between job offers and job interviews, and which measures firms' response in the second stage of the recruiting process. Note that the computation of job offer conversion rate is based exclusively on applications which were successful in the interview stage.
So far, we have distinguished job seekers' behavior (search effort A_{it}) from firms' responses (callbacks C_{ait} and job offers O_{ait}). The data also naturally provide us with information on the matching between the two types of agents, at the two stages of the hiring process. More precisely, we know how many interviews are obtained by each individual in a given month (I_{it}), and ultimately, the number of job offers that are made to each of them (J_{it}). This last variable is used in the definition of the so-called job offer rate: $JR_{it} = \mathbb{P}(J_{it} > 0)$. This binary indicator, which reports whether at least one job offer was obtained by individual i in unemployment month t, represents a relevant proxy for the job finding rate, as it will be discussed later on. The definitions of all the series of interest are summarized in Table A10.

At this point, it is worth discussing the central question of censoring in the PAB data. Due to the monthly timing of the recording of the information, some application-level pieces of information might remain missing at the end of the month of recording, when the forms are checked by the caseworkers. These pieces of information are supposed to be filled in ulterior meetings, but in some cases they are never updated. As display in Figure 2.1 and in line with our conceptual framework, two types of censoring can occur in the PAB form. First, some applications can be censored, if they are coded as "Still open", without any additional outcome. This is the case of approximately 29% of the observed applications. Second, some applications which have reached the interview stage, may still be processed by the time the forms are collected. Those censored interviews, for which we do not know whether a job offer was made, represent 1.5% of all applications, and less than 40% of the recorded job interviews. Since our goal is to study the duration dependence in job search, this data censoring limitation might be problematic if the censoring pattern was systemically correlated with duration. However, the censoring pattern in our data seems to be relatively constant with respect to elapsed unemployment duration, as it can be observed in Figure A15 in the appendix. Consequently, the censoring issue should remain a minor concern for our analysis of duration dependence in job search. Nevertheless, as a matter of completeness, we analyze both types of series, censored and non-censored, along the analytical part of this paper.

2.3 Conceptual Framework

Job search and firms' callback and hiring decisions have been extensively modeled. Here, we outline conceptually how to think of them.

Figure 2.1: Conceptual framework and Information censoring



Job applications are one element of job search effort. High and low application intensity, decline over time (Faberman and Kudlyak). Costs and benefits. Stock of job offers... Targeting of job search.

Firms' decisions: Jarosch and Pilossoph organize finding that callback declines... Firms have a threshold in unemployment duration (learn about quality), and hire those who meet expectations. Interview chance declines, but chance to be hired not necessarily.

Both sides are potetially connected (in an optimizing frameork): job seekers should apply more likely to those applications with high interview/callback chances. e.g. Matching models do this... but little heterogeneity, statistical learning, etc.

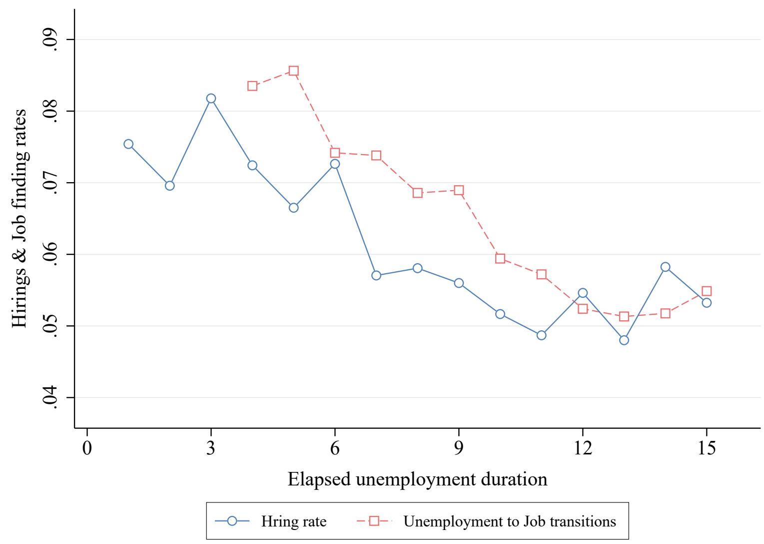
Applications and call back combine to provide job offers...

3.1 Job offer rate

Figure 3.2 reports the empirical unemployment-to-employment transition rate faced by individuals in our sample, in red. The transition rate to jobs starts at approximately 8.5 percents in month 3, it decreases gradually before reaching a stable 5 percents-level after 12 months of unemployment. In the same figure, we report one of our alternative measures of job search success, which we observe through the PAB data: the job offer rate, *i.e.* the share of individuals who receive at least one job offer in the corresponding month of unemployment, $JR_{it} = \mathbb{P}(J_{it} > 0)$. The job offer rate also exhibits a strong negative duration dependence profile: it decreases from approximately 8 percent in month 2 to 5 percent in month 10. Despite sharing very similar duration profiles, the job offer rate declines earlier than the transition rate to jobs, because job offers precede employment. Job offers are informative on the transitions from unemployment-to-employment.

As an additional check of the validity of the information encoded in the job offer indicator, we conduct a graphical event study of income trajectories, based on "events" reported in the PAB forms. We consider two groups of individuals : (a) those who have reported at least one job offer during the observation period covered by the PAB dataset and (b) those who have not recorded such piece of information during the same period. For the former group, we define the date of the (individual-level) event $t = 0$ as the month in which the

Figure 3.2: Unemployment-to-employment transition rate & Job offer rate



Note: this graph reports the empirical monthly (non-censored) job offer rate (in blue) and transition rate from unemployment to employment (in red).

last job offer is recorded; for the later group, the individual-level date of the event $t = 0$ corresponds to the month when the last PAB form is filled in. We then study how income sources vary around these critical dates, using the information on income contained in the social security data, which covers a wider observation period than the PAB data.

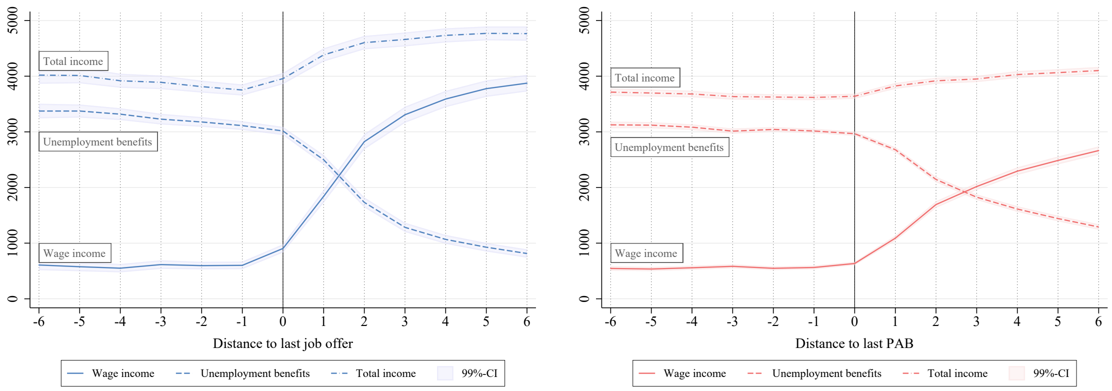
The results of this graphical analysis are depicted in Figure 3.3, where we report the average income paths (labor income vs. unemployment benefits) for the two groups around $t = 0$. In both cases, the months $t > 0$ are associated with an increase in the level of labor income. However, the increase in this income source is much steeper for those who have reported at least one job offer: on average, those individuals see a sharp increase in their labor income in the months right after the recording of their last job offer, from CHF 700.- in ($t = -1$) to CHF 3300.- after three months ($t = +3$). Those who have not reported any job offer face a more modest increase in their labor income, from CHF 700.- in ($t = -1$) to CHF 2000.- in ($t = +3$), after they filled their last form. While this increasing pattern in the labor income is expected for group (a), it might look puzzling, at first sight, that people in group (b) also see an increase in their labor income in $t > 0$. This pattern is however rationalizable given that the information contained in the PAB forms is right-censored with respect to unemployment spells, due to the fixed observation window for this specific data source, while information on income is not. Put differently, some unemployment-to-employment exits in panel (b) might occur after the end of the PAB observation period, and corresponding job offers might simply not appear in the PAB forms. Consequently, the most important aspects of this figure are not the two income paths *per se*, but the difference between those. In that respect, the information contained in the last job offer indicator turns out to be a good predictor of re-employment, given the large gap between the two income curves in panel (a) and (b).

3.2 Empirical duration dependence in job seekers and firms' behaviors

The job offer rate, as observed in our data, mimics well the duration dependence in the job finding rate. We now provide evidence on its two key determinants, job applications in a month (A_{it}) and interview callback per application (C_{ait}). Job applications and interview callback produce the number of interviews per month (I_{it}), which is a key determinant of the job offer rate (O_{ait}). First, the average monthly number of job applications is at most slightly decreasing with respect to unemployment duration: in panel (A) of Figure 3.4, the empirical average number of job applications decreases from 10.9 in month $t = 1$ to 10.0 in month $t = 15$. A similar, but even less pronounced pattern, can be observed for the average number of non-censored job applications. The average callback rate appears to decrease rapidly and importantly with respect to unemployment duration, and this whether it is measured on all applications or non-censored applications. In panel (B) of Figure 3.4, the (non-censored) callback rate decreases from almost 0.075 in month $t = 1$ to less than 0.04 in month $t = 15$. A proportional decrease is observed for the overall

Figure 3.3: Event study - Income paths before after last event
Last application vs. Last job offer

(a) Event : last job offer (b) Event : last application

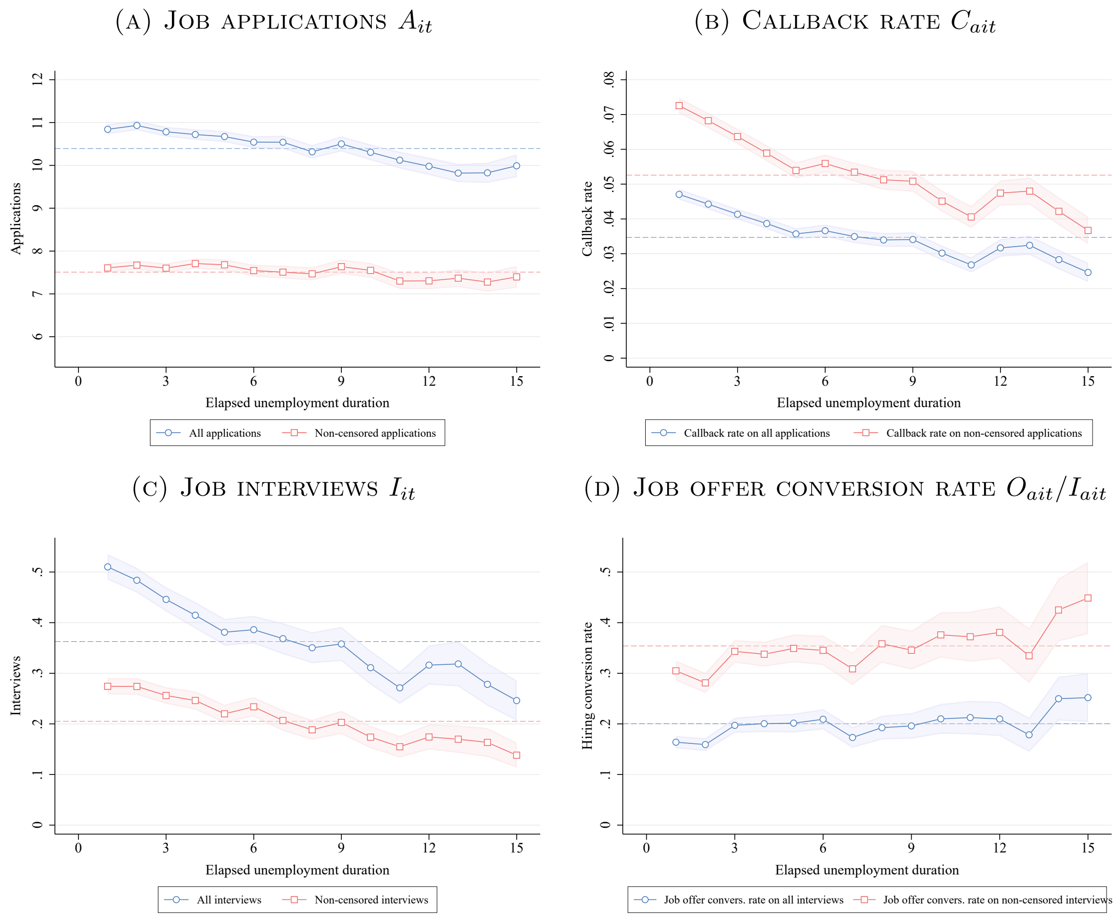


Note: this graph reports the average income paths (wage income, unemployment benefits and total income) before/after the last event in the recorded PAB forms. This last event can either be (a) the last job offer (for those who have reported at least one job offer, in blue) or (b) the last application (for those who have not reported any job offer, in red). 99% confidence intervals for the averages are also reported.

callback rate, measured on all applications. Those simultaneous decreases in job search effort and in firms' callback rate translate into an important reduction in the monthly number of job interviews. In panel (C) of Figure 3.4, the average value of this matching indicator decreases from 0.50 in month $t = 1$ to approximately 0.25 in $t = 15$, in the case where all job interviews are considered. A proportional decrease can be observed for non-censored interviews over the same time-span (from 0.30 to 0.15). Finally, regarding the job offer conversion rate, it seems that the share of interviews which are eventually converted into job offers is relatively constant over time: in panel (D) of Figure 3.4 a slight, yet almost insignificant increase, in the job offer conversion rate can be observed, whether it is computed on censored or non-censored interviews.

Overall, from a purely descriptive point of view, the job search process in Switzerland exhibits marked duration dependence in several dimensions: job search effort tends to decrease slightly over time, while firms' response seems to be time dependent mostly in the first stage of the recruiting process, *i.e.* at the interview stage. Obviously, those descriptive patterns do not account for the mechanical dynamic selection process that affects our sample: the pool of individuals who are observed in the early months of unemployment are not directly comparable to those who are observed in the latter stages of it. Consequently, the previously emphasized duration profiles might not only be due to changes in job seekers' behavior (*e.g.* motivation, decreasing job opportunities) and firms' response (*e.g.* discrimination against long-term unemployed, skills decay), but also to mechanical

Figure 3.4: Empirical duration dependence in job search



Note: this graph reports the empirical duration dependence in (a) job search effort (App_{it}), (b) the callback rate (CR_{it}), (c) the number of job interviews (Int_{it}) and (d) the job offer conversion rate ($jOffCRit$). 95%-confidence intervals are reported.

dynamic selection. The ultimate goal of this paper, and of the next sections, is hence to properly identify the net (of dynamic selection) duration dependence in jobs search, in order to quantify how job search effort, firms' responses, job interviews and job offers would evolve, if the composition of the studied sample were maintained constant.

4. Measuring Duration Dependence Net of Dynamic Selection

In this section, we present our empirical approach to uncover the net duration dependence in job search effort and in firms' responses, *i.e.* the callback rate and the job offer rate. Our goal is to quantify the amount of duration dependence in job seeker and firm behavior net of dynamic selection. That is, we define net duration dependence in job search effort as the change in the average number of job applications as a function of elapsed unemployment duration, keeping constant heterogeneity in job seeker characteristics and local labor market conditions. Similarly, we define net duration dependence in the callback rate and the job offer rate as the change with elapsed unemployment duration, keeping constant job seeker and application characteristics as well as local labor market conditions. Later in this section, we report results on the estimated net duration dependence profiles, which will serve as building blocks for the job offer decomposition exercise in section 5.

4.1 Empirical Approach

Regarding search effort, a major challenge lies in capturing the individual heterogeneity of job seekers. Specifically, we want to take into account the possibility that job seekers with characteristics associated with longer potential unemployment durations search systematically less or more than job seekers with shorter potential unemployment durations. In order to deal with this potential dynamic selection, we follow the approach proposed by Faberman and Kudlyak (2019) and Fluchtmann and Maibom (2019) and control for time-constant individual fixed effects as well as time-varying individual characteristics and local labor market conditions. More precisely, we estimate the following model:

$$A_{it} = \alpha_i^A + f^A(t;\phi^A) + X_{it}\beta^A + \delta_{mk}^A + \varepsilon_{it}^A \tag{4.1}$$

where A_{it} corresponds to the number of job applications sent by individual i in her t^{th} month of unemployment, α_i^A an individual-specific fixed effect, X_{it} a row vector containing time-varying individual characteristics, δ_{mk}^A a fixed effect capturing changing local labor market conditions in market m and calendar quarter k,[4] and ε_{it}^A is an idiosyncratic shock. The parametric function $f^A(t;\phi^A)$ measures the duration dependence in job search effort, net of dynamic selection based on observed and unobserved heterogeneity.

In order to recover the net duration dependence in firms' responses to job applications we proceed as follows. In our context, the response of the firm takes place in two steps. First, it chooses whether or not to call the applicant back to invite him or her to a job interview. Then, conditional on the interview having taken place, the firm decides whether to make

[4] In our baseline estimates, local labor markets are defined based on the occupational sector targeted by the job seeker, following the Swiss Standard Classification of Occupations (SSCO 2000).

a job offer to the applicant. Hence, we aim to quantify how the probability to be invited to a job interview and the probability to receive a job offer change as a function of elapsed unemployment duration, while keeping constant job seeker and application characteristics as well as local labor market conditions. As for search effort, the empirical patterns of duration dependence observed in firms reactions may partially reflect dynamic selection, a mechanical process that we would like to purge our estimates of in order to retrieve the net duration dependence in firms responses.

Since we observe a single unemployment spell for every individual only and the incidence of job interviews and job offers does not vary sufficiently within individuals over time we cannot simply condition on individual-level fixed effects as we do in the context of search effort in Equation (4.1). Moreover, as job interviews and job offers are closely related to exit from unemployment, they are necessarily positively correlated with unemployment duration at the individual level. Put differently, job interviews and job offers tend to be concentrated at the end of an unemployment spell, while they are more likely to be zero in the preceding months. In such a context, using an approach based on individual-level fixed effects gives rise to a mechanical correlation between the elapsed unemployment duration and the idiosyncratic error term of a given individual, as it can be inferred from Figure C21. The resulting within-estimates of net duration dependence end up being upward biased, since positive values of the dependent variables are more likely to be observed during the late stages of unemployment, as shown in Zuchuat (2022).

Therefore, at this stage, we exploit our detailed application-level data to condition on exactly the same set of information a firm has on a job-seeker when it receives the application and decides to call the applicant back. We use our rich data to construct an index capturing the propensity that an application sent out early during the unemployment spell receives a positive response from the firm. We include this index in the specification of the interview probability and the job offer rate to control for dynamic selection. Specifically, to construct the index, we include all those variables that capture the information that is typically contained in the job seekers CV and in the application itself.[5] As CV characteristics, we consider age, education, residential status, sex, and targeted occupational sector of the applicant, all provided through the unemployment office data, as well as additional information on the labor market history, obtained from the social security data. Further, we consider information on the caseworker or public employment service to which the job seeker is affiliated. As application characteristics, we consider the application channel (*i.e.* in person, by phone, in written form), an indicator for whether the application is in response to a referral by the caseworker and a measure of search intensity corresponding to the estimated individual job search fixed effect $\hat{\alpha}_i^A$.

For each individual, we use the first month in which the job search behavior is documented

[5]See also Table C13 in the Appendix for an overview of the information used.

in the data. We denote this month as τ_i. We then estimate a binary outcome model for the probability to be invited to a job interview at the application level in month $\tau_i = \tau_i^A$, *i.e.* the first month when applications are recorded for individual i, using the above mentioned variables as controls. We proceed analogously for the job offer rate, except that we use for each individual the first month when an application with the outcome invitation for interview is sent out, since job offers are conditional on obtaining a job interview (we denote this month as $\tau_i = \tau_i^I$). Formally, for an application sent out in month τ_i, we define an indicator for receiving an invitation to an interview as $C_{ai\tau_i} = \mathbb{1}[\tilde{C}_{ai\tau_i} > 0]$, and an indicator for receiving a job offer as $O_{ai\tau_i} = \mathbb{1}[\tilde{O}_{ai\tau_i} > 0]$, where $\tilde{C}_{ai\tau_i}$ and $\tilde{O}_{ai\tau_i}$ denote the latent propensity to receive an invitation to an interview and to receive a job offer. We model the latent propensities in month τ_i as:

$$\tilde{C}_{ai\tau_i} = \vartheta_0 + X^1_{i\tau_i}\vartheta_1 + X^2_{ai\tau_i}\vartheta_2 + \delta^I_{mk} - \nu_{ai\tau_i} \tag{4.2a}$$

$$\tilde{O}_{ai\tau_i} = \varphi_0 + X^1_{i\tau_i}\varphi_1 + X^2_{ai\tau_i}\varphi_2 + \delta^O_{mk} - \eta_{ai\tau_i} \tag{4.2b}$$

where $\tau_i = \tau_i^A$ in Equation (4.2a) and $\tau_i = \tau_i^I$ in Equation (4.2b). The row vector $X^1_{i\tau_i}$ contains the individual-level characteristics, the row vector X^2_{ait} the application level-characteristics, δ^I_{mk} and δ^O_{mk} are fixed effects capturing the conditions in local labor market m in calendar quarter k, $\nu_{ai\tau_i}$ and $\eta_{ai\tau_i}$ are idiosyncratic error terms. Hence, the conditional probability to be invited to a job interview and the probability to receive a job offer in response to an application sent out in month τ_i are given by:

$$\gamma^C(X_{ai\tau_i}) = \mathbb{P}(C_{ai\tau_i} = 1|X_{ai\tau_i}) = \mathbb{P}(\vartheta_0 + X^1_{i\tau_i}\vartheta_1 + X^2_{ai\tau_i}\vartheta_2 + \delta^I_{mk} > \nu_{ai\tau_i}) \tag{4.3a}$$

$$\gamma^O(X_{ai\tau_i}) = \mathbb{P}(O_{ai\tau_i} = 1|X_{ai\tau_i}) = \mathbb{P}(\varphi_0 + X^1_{i\tau_i}\varphi_1 + X^2_{ai\tau_i}\varphi_2 + \delta^O_{mk} > \eta_{ai\tau_i}) \tag{4.3b}$$

where $X_{ai\tau_i} = (X^1_{i\tau_i}, X^2_{ai\tau_i}, m, k)$, $\tau_i = \tau_i^A$ in the first equation, and $\tau_i = \tau_i^I$ in the second.

We then fit logit models to obtain the parameter estimates $\hat{\vartheta}' = (\hat{\vartheta}_0, \hat{\vartheta}_1, \hat{\vartheta}_2)$ and $\hat{\varphi}' = (\hat{\varphi}_0, \hat{\varphi}_1, \hat{\varphi}_2)$ and to predict the corresponding conditional *ex-ante* probabilities for all months $t \geq \tau_i$. The resulting predicted probabilities, $\hat{\gamma}^C_{ait} = \hat{\gamma}^C(X_{ait})$ and $\hat{\gamma}^O_{ait} = \hat{\gamma}^O(X_{ait})$, hence capture the propensity with which an application sent out in month t receives a positive response from the firm, if the firms behavior was kept as it was early in the unemployment spell, in month τ_i. We then use the log of these *ex-ante* probabilities to control for dynamic sorting based on observables when we estimate the net duration dependence in the firms responses. Specifically, we estimate the following two models using all months $t \geq \tau_i$:

$$\mathbb{P}(C_{ait} = 1|X_{ait}) = \mathbb{P}(C^*_{ait} > 0|X_{ait}) = \mathbb{P}\big(\alpha^C + f^C(t; \phi^C) + \beta^C \ln(\hat{\gamma}^C_{ait}) + \delta^C_{mk} > \varepsilon^C_{ait}\big) \tag{4.4a}$$

$$\mathbb{P}(O_{ait} = 1|X_{ait}) = \mathbb{P}(O^*_{ait} > 0|X_{ait}) = \mathbb{P}\big(\alpha^O + f^O(t; \phi^O) + \beta^O \ln(\hat{\gamma}^O_{ait}) + \delta^O_{mk} > \varepsilon^O_{ait}\big) \tag{4.4b}$$

where $\beta^C \ln(\hat{\gamma}^C_{ait})$ and $\beta^O \ln(\hat{\gamma}^O_{ait})$ control for dynamic selection, while $f^C(t;\phi^C)$ and $f^O(t;\phi^O)$ measure the net duration dependence in the interview probability and the job offer rate.[6]

4.2 Results

We now report the results of the estimation of net duration dependence in job search effort, the interview probability/callback rate and job offer rate. Those results are presented under the form of the estimated parametric functions $f^A(t;\hat{\phi}^A)$, $f^C(t;\hat{\phi}^C)$ and $f^O(t;\hat{\phi}^O)$. For each variable, we report the estimation results for all applications or all interviews, as well as the results based exclusively on non-censored applications or interviews.

Job Seeker Behavior

We first report the estimation results for the search effort A_{it}. Table 4.1 reports the incremental estimation process of Equation (4.1), where the parametric net duration dependence function $f^A(t;\phi^A)$ is specified linearly, *i.e.* $f^A(t;\phi^A) = \phi^A t$. Panel A reports the estimation results for all applications, while panel B reports similar results for the subset of monthly observation with at least one non-censored application. In column (1), it can be observed that, in a bivariate regression, elapsed unemployment duration and search effort are negatively and significantly correlated, as suggested by the descriptive results. Once individual, policy and LLMC controls are added, respectively in columns (2), (3) and (4), this negative and significant pattern remains observed, despite being slightly attenuated. When fixed effects are uniquely included in the regression, as in column (5), the estimated negative linear duration dependence parameter increases by a very large amount (in absolute terms). This change in the estimated $\hat{\phi}^A$ coefficient is revealing of the degree of unobserved heterogeneity that characterizes the job-seekers in our sample: unobserved heterogeneity in search effort is highly and positively correlated with the (potential) completed unemployment duration. Put differently, individuals who remain unemployed longer *ex-post* tend to apply more on average, and this at any point in time of their unemployment spell. This results, which was key in Faberman and Kudlyak (2019), is effectively observed in our data: in Figure C22 in the appendix, the estimated $\hat{\alpha}^A_i$ from Equation (4.1) appear to be strongly positively correlated with (censored) completed unemployment duration.[7] Finally, in the full model reported in column (6), the estimated linear duration dependence turns out to be strongly negative and highly significant: each month of elapsed unemployment duration leads to an average marginal decrease of -0.22 in the overall number of applications sent, and a corresponding -0.16 decrease in the average number of non-censored applications.

[6] Note that we additionally control for whether the application is part of the reference sample τ_i, so as to control for potential over-fitting issues.

[7] This graphical analysis is limited to the sample of individuals whose unemployment spells are not right-censored.

Table 4.1: Job search effort A_{it} - Linear duration dependence

	(1)	(2)	(3)	(4)	(5)	(6)
A. All applications						
Elapsed u. duration	-0.0772***	-0.0513***	-0.0344***	-0.0393***	-0.1890***	-0.2163***
	(0.0078)	(0.0078)	(0.0071)	(0.0070)	(0.0117)	(0.0245)
	[-0.0076]***	[-0.0050]***	[-0.0034]***	[-0.0038]***	[-0.0185]***	[-0.0212]***
Individual controls	No	Yes	Yes	Yes	No	Yes
Policy controls	No	No	Yes	Yes	No	Yes
LLMC	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
adj.-R^2	0.0051	0.0348	0.1776	0.1909	0.4939	0.5005
Observations	58936	58936	58936	58936	58936	58936
F-linearity	1.1291	1.0099	1.0726	1.0952	1.1924	1.3902
p-value linearity	0.3254	0.4395	0.3771	0.3559	0.2730	0.1482
B. Non-censored applications						
Elapsed u. duration	-0.0245***	-0.0141*	-0.0229***	-0.0264***	-0.1458***	-0.1594***
	(0.0073)	(0.0074)	(0.0065)	(0.0064)	(0.0110)	(0.0237)
	[-0.0034]***	[-0.0020]*	[-0.0032]***	[-0.0037]***	[-0.0201]***	[-0.0220]***
Individual controls	No	Yes	Yes	Yes	No	Yes
Policy controls	No	No	Yes	Yes	No	Yes
LLMC	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
adj.-R^2	0.0006	0.0190	0.1769	0.1867	0.5032	0.5088
Observations	55145	55145	55145	55145	55145	55145
F-linearity	1.0752	0.9970	1.2011	1.2677	1.7556	1.9379
p-value linearity	0.3746	0.4529	0.2663	0.2187	0.0391	0.0186

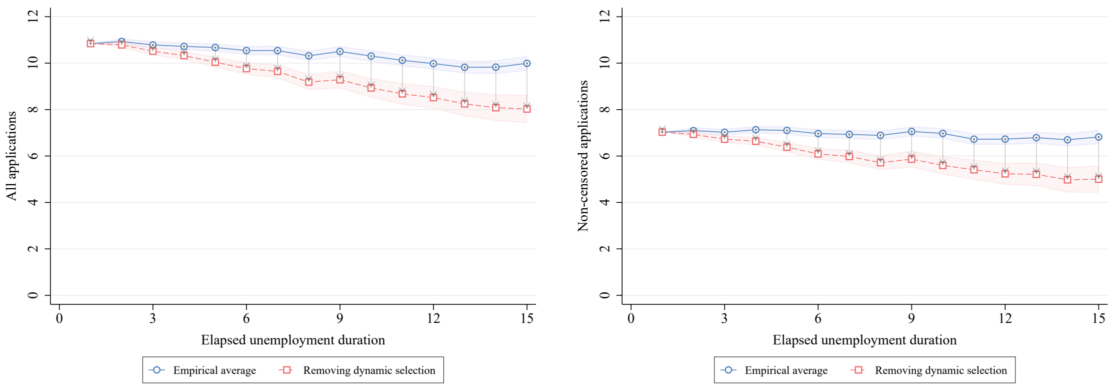
Note: this table reports the estimation results of Equation (4.1), where $f^A(t;\phi^A)$ is specified as a linear function of elapsed unemployment duration. Relative coefficients, with respect to the average number of job applications sent in month $t = 1$ are reported in brackets. Errors are clustered at the individual level. Stars indicate the following significance levels: 0.1 *, 0.05 **, 0.01 ***.

At this point, it might be argued that the choice of a linear functional form for $f^A(t;\phi^A)$ is to some extent simplistic. We assess the linearity assumption in the job search effort duration dependence by specifying a fully saturated version of the $f^A(t;\phi^A)$ function. The graphical results of this model are reported in Figure 4.5 and tend to confirm the *a priori* simplistic assumption made on the shape of $f^A(t;\phi^A)$: from a graphical perspective, the structural duration dependence in the job search effort appears to be essentially linear. This results is also confirmed by the linearity test reported in Table 4.1, at least for the results on all applications (panel A), and by the estimation results of quadratic linear duration dependence in job search reported in Table C16 in the appendix. Note that in the rest of the paper, we will make use of the conservative saturated duration dependence estimates.

Another aspect of our analysis that might be subject to concerns is whether the number of job applications sent by an individual within a month really correspond to a measure of the search effort provided by job seekers. More precisely, it might be argued that some of the applications only aim to fulfill the search requirements set by the unemployment

Figure 4.5: Job search effort A_{it} - Saturated duration dependence

(a) All applications (b) Non-censored applications



Note: these graphs report the duration dependence in the number of job applications sent per month of elapsed unemployment. The blue curve reports the empirical duration dependence, while the red curve reports the structural duration depndence, corresponding to equation Equation (4.1), where $f(t;\phi^A)$ is specified as a saturated function of all months of elapsed unemployment. Panel (a) reports the results for all applications, while panel (b) reports the results for non-censored applications. 95%-confidence intervals based clustered standard errors are reported.

benefit regime. In the Swiss context, those search requirements usually amount to 8 to 10 applications to be sent per month, an institutional obligation which can clearly be observed through the modes of the empirical distribution of the number of applications sent per month, in Figure B20. As an additional robustness check we consider an alternative measure of search effort, which we refer to as excess job search. This measure is based on our baseline index of search effort A_{it}, from which we subtract the generic search requirement $\underline{A} = 8, 10$. Also, this newly defined variables are restricted to be non-negative, so as to truly capture job search in excess to the baseline requirements. Our alternative measures of search effort are thus defined as $A_{it}^{\underline{A}} = \max\{A_{it} - \underline{A}, 0\}$, where $\underline{A} = 8, 10$. Based on these new variables, we estimate a model akin to the one described by Equation (4.1), including an individual fixed effect. However, due to the count nature and the high skewness of the $A_{it}^{\underline{A}}$ variable, we rather resort to the fixed effect Poisson model in this case, following a pseudo-maximum likelihood procedure (Wooldridge, 1999). The corresponding results are reported in Table C12 and tend to corroborate our baseline estimates: the level of effort provided by job seekers is affected by significant negative duration dependence, whatever the measure of excess search effort we consider.

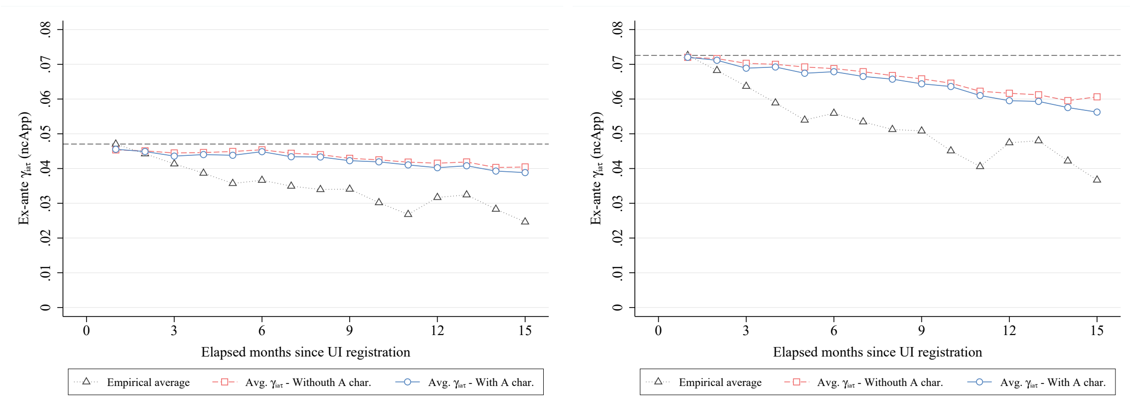
Firm Behavior

We now move on to the analysis of the duration dependence in firms' response. We first evaluate the validity of our identification strategy for the first-stage of the recruiting process, *i.e.* the callback rate stage. In a first step, we assess whether the conditioning variables in $X^1_{i\tau_i}$ and $X^2_{ai\tau_i}$ are predictive for the obtention of a job interview in the reference months τ_i. The estimation results of equation Equation (4.2a) are reported in Table C14. Perhaps not surprisingly, most conditioning variables turn out to be highly predictive for a positive application-level callback, whether we consider callbacks on all applications or non-censored applications. Those results suggest that a significant part of the first-stage screening process made by the firms is based on the conditioning variables $X^1_{i\tau_i}$ and $X^2_{ai\tau_i}$, which constitute presumably most of the information set of the firm at this stage of the recruitment. Next, holding firms' responses constant at their initial level, we asses whether the change in the composition of the sample with respect to duration is able to explain part of the overall decrease in the empirical callback rate. In that respect, we predict the *ex-ante* probabilities $\hat{\gamma}^C_{ait}$ based on equation Equation (4.3a), compute their average and plot the corresponding series together with the empirical average of the callback rate. The results of this procedure are depicted in Figure 4.6, for both callbacks on all and non-censored applications, and support the idea that a non-negligible part of the empirical decrease in the callback rate is due to dynamic selection: the average value of the *ex-ante* probability based on observables in X^1_{it} and X^2_{ait} is decreasing over time, suggesting that dynamic selection is partially based on those variables.

Based on the computed *ex-ante* probabilities, we then estimate equation Equation (4.4a). The corresponding results for the case where the duration function $f^C(t; \phi^C)$ is specified linearly are reported in Table 4.2, for both the callback rate on all applications and non-censored applications. Columns (1a) and (2a) show the estimated linear average marginal effect of duration on the probability of a positive callback (in percentage points) when we do not control for dynamic selection, while columns (1b) and (2b) report similar results when the dynamic selection process is accounted for through $\ln(\hat{\gamma}^C_{ait})$. Note that in those

FIGURE 4.6: CALLBACK RATE - AVERAGE *ex-ante* PROBABILITY $\hat{\gamma}_{ai\tau}$

(A) ALL APPLICATIONS (B) NON-CENSORED APPLICATIONS



Note:

Table 4.2: Callback rate C_{ait} - Linear duration dependence

	All applications		Non-censored applications	
	(1a)	(1b)	(2a)	(2b)
Dependent variable: Calllback rate [in pp]				
Elpased unemployment duration	-0.1483***	-0.1144***	-0.2418***	-0.1519***
	(0.0141)	(0.0133)	(0.0219)	(0.0203)
Ex-ante probability $\hat{\gamma}_{ai\tau}$		3.2586***		5.2074***
		(0.0770)		(0.1229)
Observations	602190	602190	426628	426628
Pseudo-R^2	0.0031	0.0760	0.0041	0.0988

Note: ...

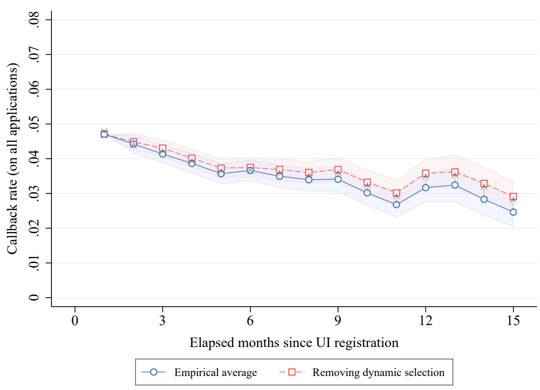
specifications, we additionally control for the reference months τ_i during which the computation of the *ex-ante* probabilities is based, to avoid over-fitting. Consistently with our previous results, the figures reported in Table 4.2 indicate that part of the decrease in the empirical callback rate is due to dynamic selection based on X^1_{it} and X^2_{ait}: the estimated average marginal effects of duration decrease by respectively one third and one half when accounting for $\ln(\hat{\gamma}^C_{ait})$, whether we consider the callback rate on all or non-censored applications.

This can also be observed through the high significance of the parameters associated to $\ln(\hat{\gamma}^C_{ait})$, which suggests that this proxy summarizes reasonably well the baseline chances of the individuals to be invited to a job interview.

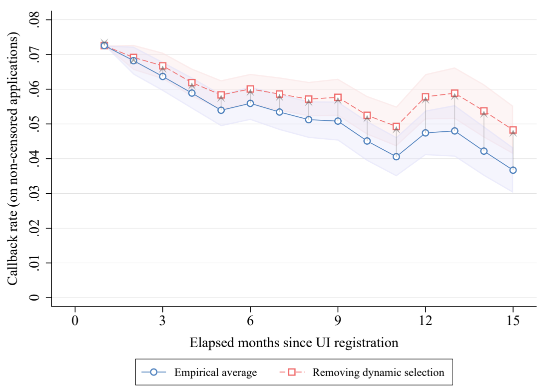
As for job seekers' behavior, we extend the analysis by relaxing the functional form of $f^C(t;\phi^C)$. Figure 4.7 report the results of Equation (4.4a) when $f^C(t;\phi^C)$ is specified as

Figure 4.7: Callback rate C_{ait} - Saturated duration dependence

(a) On all applications



(b) On non-censored applications



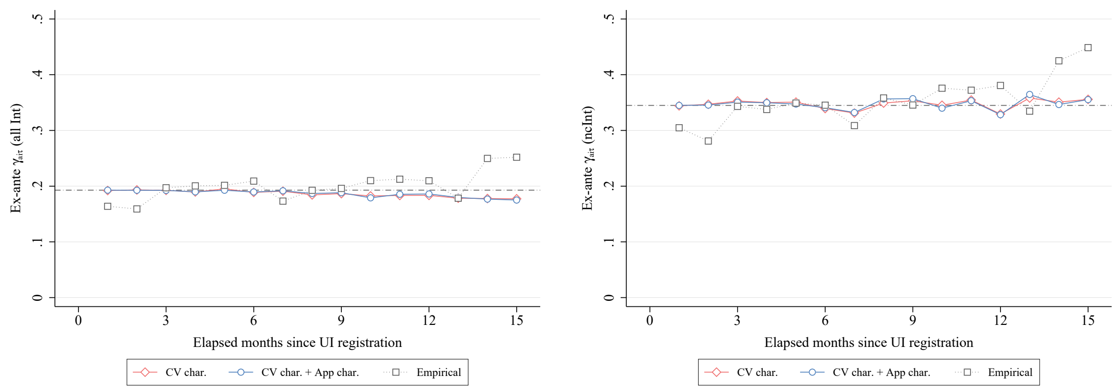
Note: ...

a saturated function of elapsed unemployment duration t. These results are consistent with those for the linear specification: once we account for dynamic selection, part of the overall decrease in the empirical callback rate disappears. In terms of quantification, net duration dependence, as measured by $f^C(t;\phi^C)$, explains approximately 1 percentage point of the overall decrease in the empirical callback rate on all applications after 15 months of unemployment, and almost 2 percentage points for the callback rate computed only on non-censored applications. Overall, our results are in line with previous related findings (Kroft et al. (2013), Eriksson and Rooth (2014)): they suggest that net duration dependence still plays an important role in the overall decrease in the chances of obtaining a job interview, and this even after controlling for job seekers' heterogeneity.

After studying duration dependence in the callback rate, we now focus on the second part of the recruiting process: the job offer conversion stage, which is conditional on obtaining a job interview in the first place. We follow the same procedure as for the job interview stage, except that we estimate Equation (4.2b) and Equation (4.4b). Results for the relevance of $X^1_{i\tau_i}$ and $X^2_{ai\tau_i}$ as predictors of a successful conversion of job interviews into job offers are reported in Table C15. Again, it seems that some of the conditioning variables are predictive in term of the obtention of a job offer. However, as depicted in Figure 4.8, the average *ex-ante* probability of obtaining a job offer conditional on a job interview is essentially flat with respect to elapsed unemployment duration. This result indicates that the variables in X^1_{it} and X^2_{ait} do not explain much of the empirical duration dependence in the job offer conversion stage. Such pattern eventually translates into an estimated net duration profile in the job offer conversion rate which is very close to its empirically observed equivalent, as displayed in Figure 4.9. Put together, those results suggest that only few dynamic selection based on the X_{it} variables occurs at the moment

FIGURE 4.8: JOB OFFER CONVERSION RATE - AVERAGE *ex-ante* PROBABILITY $\hat{\gamma}_{ai\tau}$

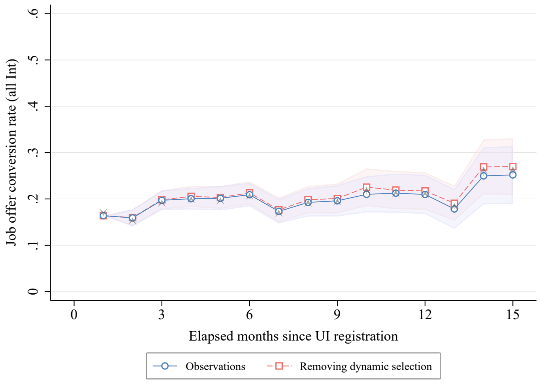
(A) ALL JOB INTERVIEWS (B) NON-CENSORED JOB INTERVIEWS



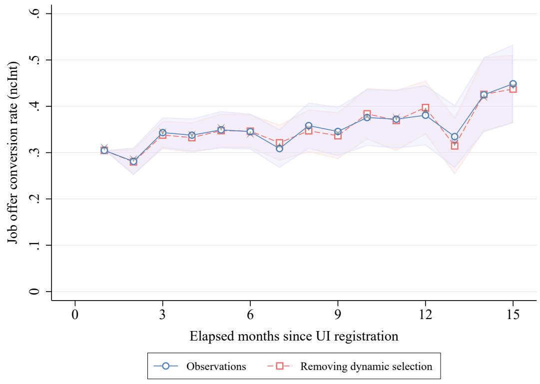
Note:

Figure 4.9: Job offer conversion rate - Estimated duration dependence

(a) All job interviews



(b) Non-censored job interviews



Note:

of the decision of the firms whether to make the applicants a job offer. Put differently, it seems that most of the screening process by the firms occurs in the first stage of the recruiting process. In that sense, and given the information set we observe, the second stage of the hiring process can be viewed as an idiosyncratic outcome, which depends mostly on the specific match between each firm and applicant, as in standard stochastic search and matching models (Mortensen and Pissarides, 1994).[8]

Overall, results on the duration dependence in firms' response indicate that most of the dynamic selection takes place in the first stage of the recruiting process, at the moment of calling back applicants for a job interview. Not controlling for this dynamic selection process in the callback rate leads to a over-estimation of the duration dependence due to firm's callback behaviour. Our results also show that the decision whether to make the applicants a job offer, conditional on a job interview, is marginally affected by dynamic selection.

[8] We cannot rule out that there is still some form of dynamic selection based on unobserved characteristics that are typically revealed at the moment of the interview. However, those information remain unobservable to us and cannot be controlled for in our conditioning approach.

5. Decomposition of Duration Dependence in Job Offers

The results we presented in the previous section highlight that both job seeker behavior and firm behavior exhibit negative duration dependence. These two sets of results are important *per se*, in the sense they corroborate previous findings by the literature in a much broader context than those studied so far. However, our data enable us to go a step further, as they allow us to quantify the relative contributions of job seeker and firm behavior to the overall decrease in the job offer rate, a direct proxy for job finding. In this section, we proceed to a decomposition exercise to quantify the contributions of net duration dependence in job search effort and job interviews to the overall duration dependence in the job offer rate. The idea behind this analysis is to assess how the job offer rate would evolve, were the different channels of net duration dependence to be shut down. We start by a formal description of the decomposition exercise, before turning to the results.

5.1 Decomposition Procedure

We conduct the job offer decomposition exercise at the person-month level, using the empirical estimates of net duration dependence in search effort and callback rate, based on Equation (4.1) and Equation (4.4a). For each individual and month, we estimate the expected number of job applications and the probability to be invited to an interview, with and without net duration dependence. In addition, we estimate the expected number of job applications and the probability to be called back with and without duration dependence, for each month of unemployment, keeping the sample composition as in the first month of unemployment. In this way, we can assess to what extent compositional changes affect our decomposition results. Combining the different series with and without duration dependence, we can evaluate the individual contribution of duration dependence in job seeker and firm behavior to the decrease in the number of job interviews and the probability of receiving a job offer, both based on the observed sample composition and on the sample composition as of month one.

First, we estimate the expected number of applications under duration dependence for every individual i still unemployed in month t of elapsed unemployment by

$$\hat{A}_{it}^{DD} \equiv \hat{A}_{it} = \hat{\alpha}_i^A + f^A(t;\hat{\phi}^A) + x_{it}\hat{\beta} + \hat{\delta}_{mk}^A \quad \text{for } i \in \mathcal{S}_t \text{ and } t \geq 1\,,$$

that is, the fit from Equation (4.1), and where $\mathcal{S}_t$ denotes the set of individuals still observed in unemployment month t. Similarly, we estimate the expected number of applications of individual i in month t of elapsed unemployment absent of duration dependence by

$$\hat{A}_{it}^{NDD} \equiv \hat{A}_{it} - f^A(t;\hat{\phi}^A) \quad \text{for } i \in \mathcal{S}_t \text{ and } t \geq 1\,.$$

Further, we estimate the expected number of applications with and without duration dependence in unemployment month t for every individual i regardless of whether they are still observed in t, *i.e.* for all $i \in \mathcal{S}_1$. Keeping the sample composition fixed as of $t = 1$, the expected number of applications under duration dependence is given as

$$\hat{A}_{it}^{DD,\bar{S}} \equiv \hat{A}_{i1} + f^A(t; \hat{\phi}^A) - f^A(1; \hat{\phi}^A) \quad \text{for } i \in \mathcal{S}_1 \text{ and } t \geq 1$$

and the expected number of applications absent of duration dependence as

$$\hat{A}_{it}^{NDD,\bar{S}} \equiv \hat{A}_{i1} \quad \text{for } i \in \mathcal{S}_1 \text{ and } t \geq 1\,,$$

where the latter is constant over time. The variables $\hat{A}_{it}^{DD,\bar{S}}$ and $\hat{A}_{it}^{NDD,\bar{S}}$ are used to estimate the expected application series absent of dynamic selection.

Next, we proceed in an analogous way to estimate the interview probabilities with and without duration dependence. For every application a of job seeker i still unemployed in unemployment month t, we obtain an estimate of the expected probability to be invited to an interview under duration dependence as

$$\hat{C}_{ait}^{DD} \equiv \hat{C}_{ait} = F(\hat{C}_{ait}^{*}) \quad \text{for } i \in \mathcal{S}_t \text{ and } t \geq 1\,,$$

where $\hat{C}_{ait}^{*}$ is the estimated latent propensity to be called back according to Equation (4.4a) and F the logistic cdf, and under no duration dependence as

$$\hat{C}_{ait}^{NDD} \equiv F\big(\hat{C}_{ait}^{*} - f^C(t; \hat{\phi}^C)\big) \quad \text{for } i \in \mathcal{S}_t \text{ and } t \geq 1\,.$$

Keeping the composition of the sample as of month one of unemployment, we estimate the expected probability to be invited to an interview under duration dependence as

$$\hat{C}_{ait}^{DD,\bar{S}} \equiv F\big(\hat{C}_{ai1}^{*} + f^C(t; \hat{\phi}^C) - f^C(1; \hat{\phi}^C)\big) \quad \text{for } i \in \mathcal{S}_1 \text{ and } t \geq 1$$

and under no duration dependence as

$$\hat{C}_{ait}^{NDD,\bar{S}} \equiv F(\hat{C}_{ai1}^{*}) \quad \text{for } i \in \mathcal{S}_1 \text{ and } t \geq 1\,.$$

The application-level callback rate series are then aggregated to the personal-monthly level by computing their average across job applications sent by individual i in month t, *i.e.* $A_{it}^{-1} \sum_{a=1}^{A_{it}} \hat{C}_{ait}^{k}$, with $k \in \{DD; NDD; DD, \bar{S}; NDD, \bar{S}\}$.[9]

The monthly series on job applications and callback rates are then cross-combined in order to obtain additional series for the number of job interviews at the person-month level. Precisely, the individual-monthly series for the callback rate are multiplied by the

[9]Note that we cannot directly sum application-level callback probabilities across the baseline and counterfactual application series, $\hat{A}_{it}^{DD}$ and $\hat{A}_{it}^{NDD}$, since those are typically non-integer values, in contrast to the observed series A_{it}.

expected number of applications, with and without duration dependence, so as to obtain baseline and counterfactual series for the expected number of job interviews obtained by job seeker i in month t. Those series are exclusively obtained through our empirical models' predictions, and are formally defined as

$$\begin{aligned}
\hat{I}_{it}^{DD} &= \hat{A}_{it}^{DD} \cdot A_{it}^{-1} \sum_{a=1}^{A_{it}} \hat{C}_{ait}^{DD} \\
\hat{I}_{it}^{NDD\text{-}A} &= \hat{A}_{it}^{NDD} \cdot A_{it}^{-1} \sum_{a=1}^{A_{it}} \hat{C}_{ait}^{DD} \\
\hat{I}_{it}^{NDD\text{-}C} &= \hat{A}_{it}^{DD} \cdot A_{it}^{-1} \sum_{a=1}^{A_{it}} \hat{C}_{ait}^{NDD} \\
\hat{I}_{it}^{NDD} &= \hat{A}_{it}^{NDD} \cdot A_{it}^{-1} \sum_{a=1}^{A_{it}} \hat{C}_{ait}^{NDD}
\end{aligned}$$

which can be summarized as $\hat{I}_{it}^{k}$, where $k \in (DD, NDD\text{-}A, NDD\text{-}C, NDD)$ stands respectively for *"duration dependence", "no duration dependence in A_{it}", "no duration dependence in C_{ait}"* and *"no duration dependence (at all)"*. Similar series are also built for the case where the sample composition is held constant, *i.e.* sample $\bar{S}$ series.

The final step of the decomposition exercise requires to formally link job interviews to job offers. So far, we have considered a framework in which job offers are conditional on obtaining job interviews. This sequential procedure, which has enabled us to split the analysis of the duration dependence in firms' behavior in two stages, *i.e.* the callback and job offer conversion stages, turns out to be inapplicable in the context of our decomposition exercise. As a matter of fact, the baseline and counterfactual series $\hat{I}_{it}^{k}$ are probabilistic: they correspond to the expected number of job interviews obtained by each individual i in month t under the different scenarios. Consequently, conditioning the second-stage analysis on the positive realization of the first step of the recruiting process, *i.e.* the invitation to a job interview, is not possible here.
To circumvent this issue, we directly link the number of job interviews obtained in response to all applications sent by individual i in month t to the probability of obtaining at least one job offer in response to these same applications. We thus conceive a job offer production function, whose specification is based on our previous empirical results on the application-level job offer conversion rate. Those have shown that only few dynamic selection based on the information set X_{it} we observe remains at the second stage of the hiring process: the successful conversion of a job interview into a job offer is essentially an idiosyncratic outcome, resulting from the specific match between the firm and the applicant. This idiosyncratic match might yet still be affected by net duration dependence. Consequently, we model the job offer production function, which we estimate on all person-

month observations, as

$$JR_{it} = \mathbb{I}\Big(J_{it} > 1\Big) = \mathbb{I}\Big(\sum_a O_{ait} > 1\Big) = \theta_{0t} + \theta_{1t} \cdot I_{it} + \varepsilon^J_{it}$$

where JR_{it} is a binary variable taking the value 1 if at least one job offer is obtained by individual i in month t, and corresponds to the job offer rate at the person-month level. According to this specification, net duration dependence in the job offer rate might occur through two different channels: θ_{0t} and θ_{1t}. The set of parameters θ_{1t} is of interest to us at this point, as it captures the duration dependence in firms' responses to job interviews, *i.e.* the duration dependence in the conversion of job interviews into job offers. The parameters θ_{0t}, for their part, capture changes in the job offer rate that are not directly attributable to the conversion of job interviews into job offers. They typically encompass changes in the pool of observed individuals, who are heterogeneous in their *ex-ante* probability of obtaining a job interview in the first stage of the recruiting process.
The results of the estimation of the job offer production function are reported in Figure D23. Perhaps not surprisingly, the estimated $\widehat{\theta}_{1t}$ parameters turn out to be pretty stable over time. These results mimic the relatively stable, possibly slightly increasing, job offer conversion rate at the application level that we documented in the previous section. Regarding the estimates of the $\widehat{\theta}_{0t}$ parameters, they exhibit a clear decreasing pattern. Again, this result is expected given that those parameters capture the negative dynamic of the first stage of the hiring process.

Back to the decomposition exercise, we use the set of estimated coefficients $\{\widehat{\theta}_{0t}, \widehat{\theta}_{1t}\}$ together with the probabilistic interview series $\hat{I}^k_{it}$ in order to build series for the monthly job offer rate $\widehat{JR}^k_{it}$, with and without net duration dependence in the job offer conversion rate. In the counterfactual case, with no duration dependence, we assume that $\theta_{1t} = \bar{\theta}_1 \; \forall \, t$, *i.e.* it is constant with respect to elapsed unemployment duration. This assumption is based on the observation that the application-level job offer rate is almost flat with respect to t. Also, following our previous line of argument, we allow θ_{0t} to be time-varying, since this specific parameter does not capture the duration dependence in the job offer rate caused by firms' behavior at the job offer conversion stage.[10] The series we construct are defined as follows:

$$\begin{aligned}
\widehat{JR}^{DD}_{it} &= \widehat{\theta}_{0t} + \widehat{\theta}_{1t} \cdot \hat{I}^{DD}_{it} \\
\widehat{JR}^{NDD\text{-}A}_{it} &= \widehat{\theta}_{0t} + \widehat{\theta}_{1t} \cdot \hat{I}^{NDD\text{-}A}_{it} \\
\widehat{JR}^{NDD\text{-}CO}_{it} &= \widehat{\theta}_{0t} + \widehat{\bar{\theta}}_{1} \cdot \hat{I}^{NDD\text{-}C}_{it} \\
\widehat{JR}^{NDD}_{it} &= \widehat{\theta}_{0t} + \widehat{\bar{\theta}}_{1} \cdot \hat{I}^{NDD}_{it}
\end{aligned}$$

The details on the construction of all the series of interest are reported in Table 5.3.

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[10] Alternative results where θ_{0t} is not time-varying are also reported as a matter of comparison.

Table 5.3: Decomposition Exercise : Details

	Net duration dependence in: Applications	Calllback rate	Job offer rate
Number of applications			
$\hat{A}_{it}^{DD}$	Yes	$\emptyset$	$\emptyset$
$\hat{A}_{it}^{NDD}$	No	$\emptyset$	$\emptyset$
Callback rate			
$\hat{C}_{ait}^{DD}$	$\emptyset$	Yes	$\emptyset$
$\hat{C}_{ait}^{NDD}$	$\emptyset$	No	$\emptyset$
Number of interviews			
$\hat{I}_{it}^{DD}$	Yes	Yes	$\emptyset$
$\hat{I}_{it}^{NDD\text{-}A}$	No	Yes	$\emptyset$
$\hat{I}_{it}^{NDD\text{-}C}$	Yes	No	$\emptyset$
$\hat{I}_{it}^{NDD}$	No	No	$\emptyset$
Job offer rate			
$\hat{J}R_{it}^{DD}$	Yes	Yes	Yes
$\hat{J}R_{it}^{NDD\text{-}A}$	No	Yes	Yes
$\hat{J}R_{it}^{NDD\text{-}CO}$	Yes	No	No
$\hat{J}R_{it}^{NDD}$	No	No	No

Note : this table describes in details how the various series (in the rows) in the decomposition exercise are built. A "Yes" indicates that net duration dependence in the specific channel (in the column) is maintained, while a "No" indicates that the duration mechanism is shut down. $\emptyset$ symbols indicate that the channel in the corresponding column is not yet at play for the series in question.

5.2 Decomposition Results

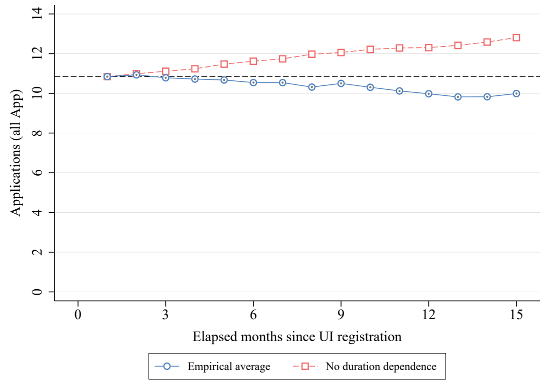
We now present the results of our decomposition exercise. We report graphical evidence on the role of net duration dependence in the empirical decrease in the search effort (number of applications), the (application-level) callback rate, the number of interviews, and the job offer rate. For each set of results, we report the counterfactual series in red, *i.e.* the *NDD* series where at least one duration dependence channel is shut down, together with the baseline estimated series without duration dependence in blue, *i.e.* the *DD* series. Note that both series still exhibit some form of duration dependence, due to dynamic selection. The empirical average duration profile of each series is also reported on the graphs as dotted gray dots, so as to assess the quality of the baseline fit. Finally, as a matter of comparison, we report for each set of results, the decomposition exercise based either on all applications or on non-censored applications.

We first report the decomposition results for the job search effort and the callback rate

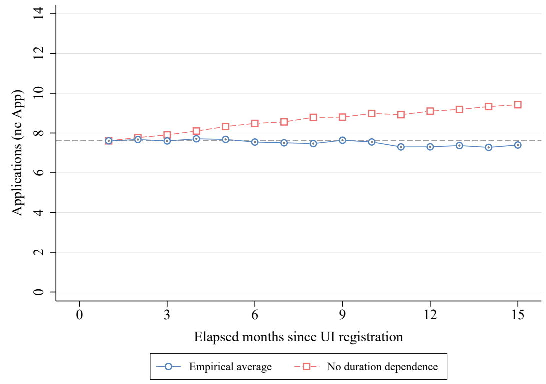
Figure 5.10: Counterfactual search effort and Callback rate

(a) Search effort

All applications

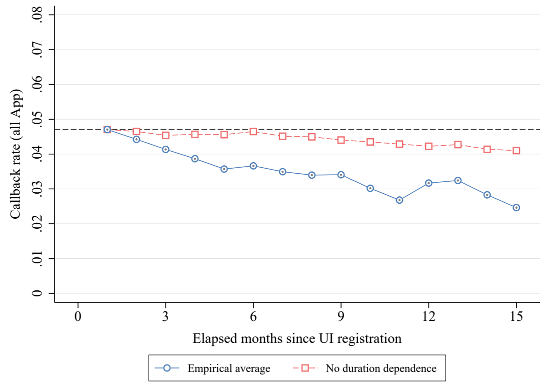


Non-censored applications

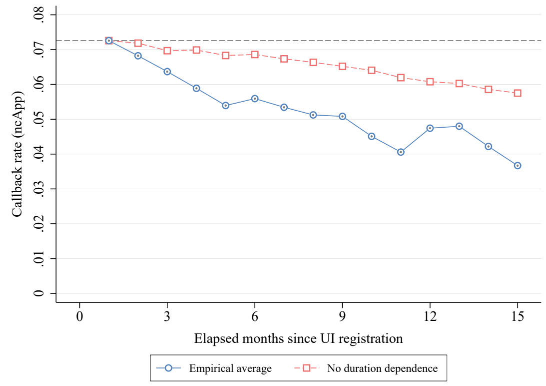


(b) Callback rate

On all applications



On non-censored applications



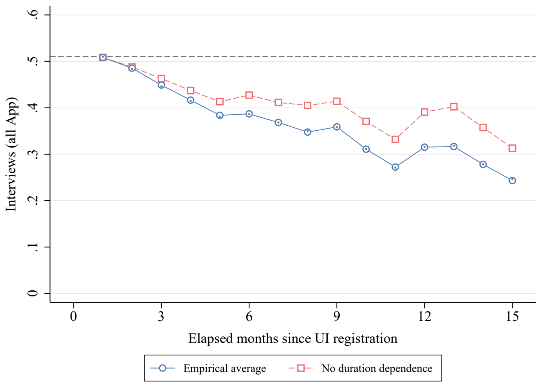
in Figure 5.10. Both counterfactual series tend to corroborate the previously emphasized dynamic selection processes. In Panel (A), it can clearly be observed that, were net duration dependence in search effort to disappear, the search effort provided by job seekers in our observed sample would tend to increase with respect to elapsed unemployment duration. Such pattern is due to the fact that job seekers who have longer completed unemployment duration and who appear later in our sample tend to apply more on average, and this at any point of their unemployment spells. Also, the removal of net duration dependence in the callback rate would lead the duration profile of the callback rate in our sample to be flatter,as shown in Panel (B). Nonetheless, part of the decrease in the empirical callback rate would still subsist, due to negative dynamic selection.

Removing negative net duration dependence in the search effort and callback rate translates into similar counterfactual paths for the monthly number of job interviews. Panels (A), (B) and (C) from Figure 5.11 present respectively the average of the counterfactual

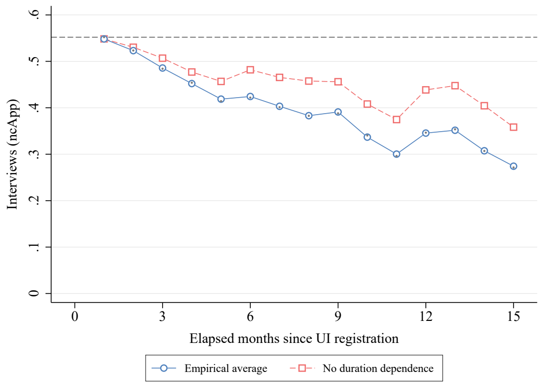
Figure 5.11: Counterfactual job interviews

(a) No duration dependence in search effort

On all applications

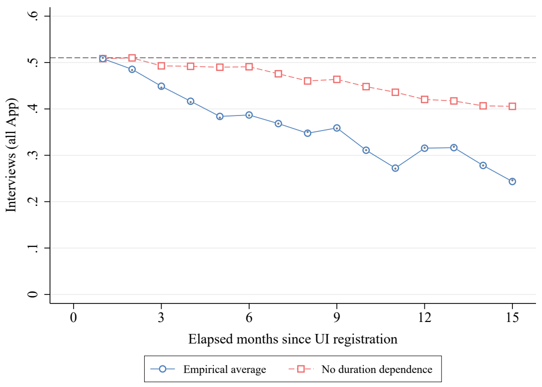


On non-censored applications

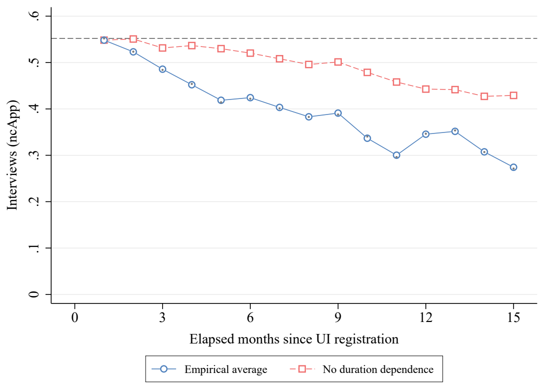


(b) No duration dependence in callback rate

On all applications

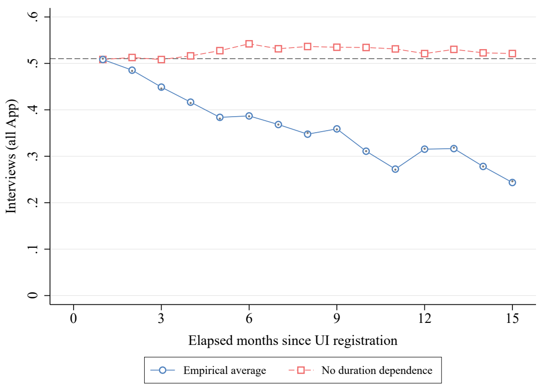


On non-censored applications

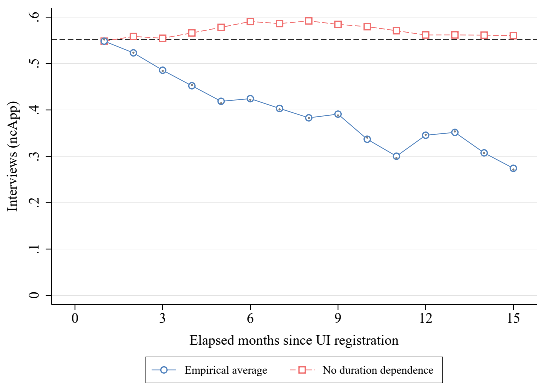


(c) No duration dependence in search effort, nor callback rate

On all applications



On non-censored applications

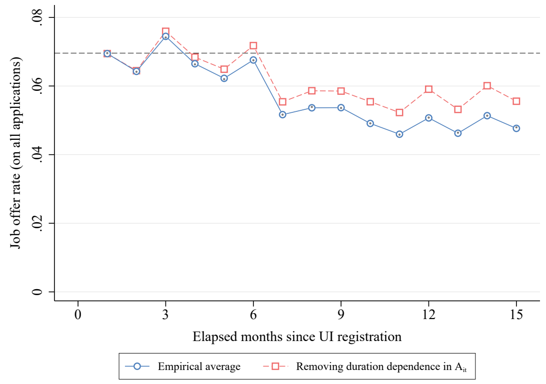


Note:

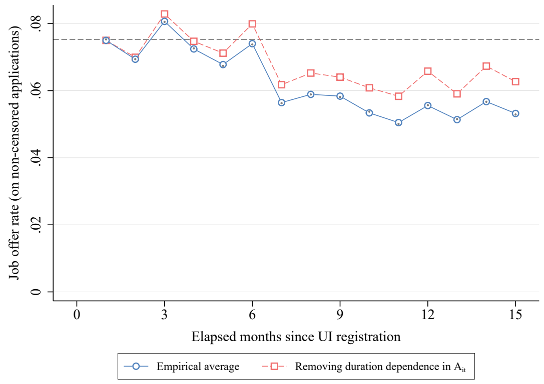
Figure 5.12: Counterfactual job offer rate

(a) No duration dependence in search effort

All applications

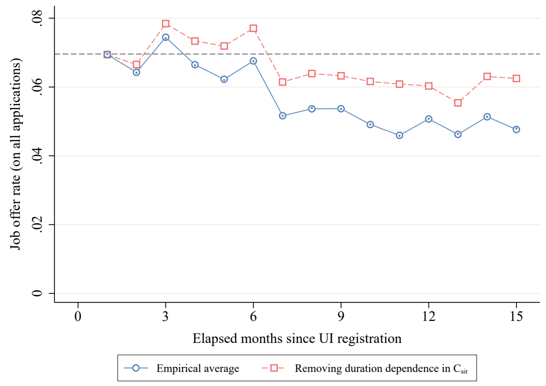


Non-censored applications

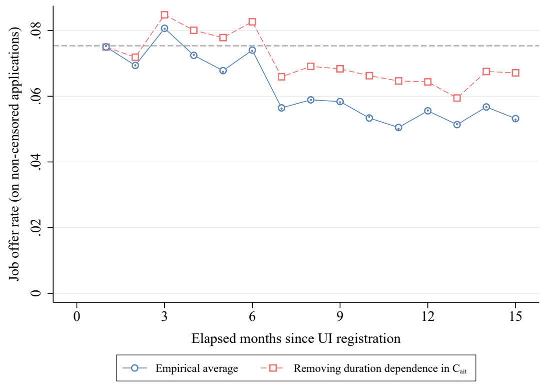


(b) No duration dependence in callback rate

All applications

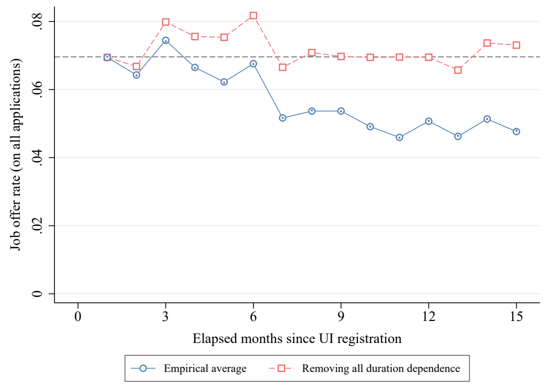


Non-censored applications

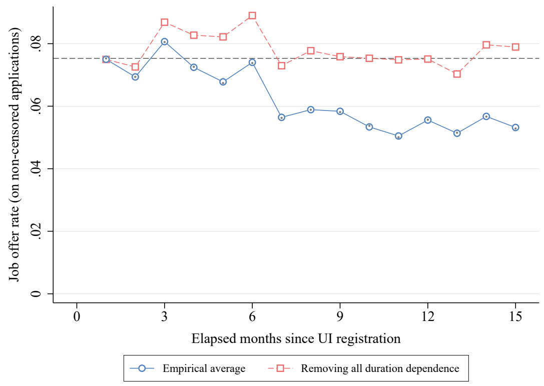


(c) No duration dependence in search effort, nor callback rate

All applications



Non-censored applications



Note:

series $\hat{I}_{it}^{NDD\text{-}A}$, $\hat{I}_{it}^{NDD\text{-}C}$ and $\hat{I}_{it}^{NDD}$, together with the baseline series $\hat{I}_{it}^{DD}$. The first point to be noted is that the baseline estimated average series does pretty well at replicating the observed empirical averages in the monthly number of job interviews, the blue line being typically aligned on the gray dots. More interestingly, both players in the labor market seem to contribute to the empirical decrease in the number of job interviews in a similar manner. Were job search to be maintained at its initial level, the decrease in the absolute number of job interview after 15 months of unemployment would amount only to -0.19 compared to the empirically observed decrease of -0.27, and this whether we consider the decomposition based on all or non-censored applications. If, on the contrary, the callback rate were not to be affected by net duration dependence, the decrease in the number of job interviews after 15 months would amount only to -0.13 instead of -0.27, depending on the set of results we refer to. Finally, were both duration dependence channels to be shut down, the empirically observed decrease in the monthly number of job interviews with respect to unemployment duration would be close to zero. This result suggests that, in a world where job seekers' and firms' behaviors would not be duration dependent, the average duration profile of job interviews observed empirically would essentially be flat, and this in spite of dynamic selection still being at play. The intuition behind this result is pretty straightforward: in a counterfactual context where there is no duration dependence in search effort nor in the callback rate, although job seekers face negative selection from the recruiting firms, they can countervail this disadvantaging mechanism by providing a higher level of search effort, so as to maintain an almost constant number of invitations to job interviews over the course of their unemployment spell.

The same patterns mechanically translate into the job offer rate. In Figure 5.12, we report the average job offer rate in our sample when (A) there is no duration dependence in job search effort, (B) there is no duration dependence in firms' responses (both at the application-level callback and job offer conversion rates) and (C) when all duration dependence channels are set to zero.[11] Similarly to the interview results, it can be observed that when duration dependence in the job search effort and in the callback rate is removed one after another, the job offer rate tends to flatten, to approximately the same extent. Also, were both channels to be shut down at the same time, the empirically observed job offer rate in our sample would become almost flat. Again, those results suggest that, in the absence of negative structural duration dependence on the job seekers' and firms' sides, unemployed individuals are able to maintain an almost constant job offer rate by

[11] Note that, in line with the decomposition formal description, we shut down duration dependence at the job offer conversion stage by estimating a constant θ_1 parameter for all month of unemployment in the job offer production function, but still allow θ_{0t} to vary with duration t, as this parameter does not capture the duration dependence in the second stage of the recruiting process. Alternative results, where the duration dependence in the job offer rate is shut down in another manner, are presented in the appendix, in Figure D24 and Figure D25.

compensating lower callback rate through higher search effort, the net duration dependence in the job offer conversion stage playing only a marginal role.

Table 5.4: Contribution of duration dependence in job seeker and firm behavior to the decrease in $\hat{I}_{it}$ and $\widehat{JR}_{it}$

Interviews	$\widehat{I}_{it}^{DD}$		$\widehat{I}_{it}^{NDD\text{-}A}$		$\widehat{I}_{it}^{NDD\text{-}C}$		$\widehat{I}_{it}^{NDD}$	
Month 1	0.5084	(100.00)	0.5084	(100.00)	0.5084	(100.00)	0.5084	(100.00)
Month 3	0.4489	(88.30)	0.4630	(91.06)	0.4929	(96.94)	0.5083	(99.97)
Month 5	0.3838	(75.50)	0.4133	(81.28)	0.4899	(96.36)	0.5275	(103.74)
Month 7	0.3684	(72.45)	0.4116	(80.95)	0.4758	(93.58)	0.5315	(104.54)
Month 9	0.3590	(70.61)	0.4140	(81.43)	0.4637	(91.21)	0.5348	(105.19)
Month 11	0.2724	(53.57)	0.3320	(65.29)	0.4359	(85.73)	0.5312	(104.48)
Month 13	0.3166	(62.26)	0.4024	(79.14)	0.4172	(82.06)	0.5302	(104.28)
Month 15	0.2435	(47.89)	0.3130	(61.57)	0.4055	(79.76)	0.5213	(102.52)
Job offer rate	$\widehat{JR}_{it}^{DD}$		$\widehat{JR}_{it}^{NDD\text{-}A}$		$\widehat{JR}_{it}^{NDD\text{-}CO}$		$\widehat{JR}_{it}^{NDD}$	
Month 1	0.0694	(100.00)	0.0694	(100.00)	0.0694	(100.00)	0.0694	(100.00)
Month 3	0.0745	(107.23)	0.0759	(109.36)	0.0784	(112.97)	0.0798	(115.00)
Month 5	0.0622	(89.63)	0.0649	(93.45)	0.0719	(103.59)	0.0753	(108.53)
Month 7	0.0517	(74.39)	0.0554	(79.77)	0.0615	(88.52)	0.0665	(95.84)
Month 9	0.0537	(77.32)	0.0585	(84.27)	0.0633	(91.11)	0.0697	(100.44)
Month 11	0.0460	(66.17)	0.0523	(75.28)	0.0609	(87.64)	0.0695	(100.16)
Month 13	0.0462	(66.58)	0.0532	(76.60)	0.0554	(79.80)	0.0657	(94.64)
Month 15	0.0477	(68.62)	0.0556	(80.01)	0.0625	(90.01)	0.0730	(105.21)

Finally, we report detailed results on the contribution of each net duration dependence channel to the empirical decrease in the number of interviews and job offer rate, in Table 5.4. Regarding the first stage of the hiring process, the empirically observed duration dependence in the number of job interviews amounts to approximately 52% over 15 months. Were net dependence in job search to disappear, the decrease in the number of job interviews would only amount to 38% over 15 months, while it would be limited to 25% in case the callback rate by firms would not be affected by duration dependence. If both channels of duration dependence were to be shut down at the same time, the decrease in the number of job interviews in our sample would be very limited, to 4% over 15 months. A similar reduction in the duration profile of the job offer rate is observed: in the absence of structural duration dependence, the job offer rate would be almost flat, compared to the 31% we empirically observe in our sample. These results once again corroborate the fact that both sides of the market play a role in the observed decrease in the number of job interview and job offer rate with respect to elapsed unemployment duration. From a quantitative perspective, its seems that the relative contributions of job seekers and firms to this empirical decrease in job search outcomes are relatively similar, but a slightly hire share of it can be attributed to the labor demand side. All in all, removing net duration dependence in job seekers' and/or firms' behavior would lead to a substantial flattening of the duration profile in the job search outcomes.

6. Conclusion

This paper aims to measure the extent to which elapsed unemployment duration affects job search dynamics. Using search diaries filled by Swiss unemployed, we construct a monthly panel database at the spell level and study how job search effort and callback rate to job applications evolve over time. Based on these novel data, we isolate the net-of-dynamic-selection component of duration dependence. In the case of job applications, we follow a fixed effect approach in order to control for both observed and unobserved heterogeneity at the individual level. Such strategy turns out to be invalid when estimating the duration profile in the callback rate; the nature of the variable is such that the within-error component and the within-unemployment duration are positively correlated, hence leading to an upward bias in the duration profile estimated by means of the fixed effect approach. We develop an alternative identification strategy, exploiting the observable characteristics to the recruiters at the moment of the screening procedure, to measure net duration dependence in the callback and job offer conversion rates. Those estimates are then used to quantify the contributions of changes in job seekers' and firms' behaviors to the overall empirical decrease in the number of job interviews and job offer rate.

The findings of our study are multifold. First, within their unemployment spells, job seekers send gradually fewer applications per month. This result is robust to and even accentuated when (un-) observed heterogeneity is controlled for. Those results are consistent with previous research on the topic, whose findings suggest that individuals whose completed unemployment spells are longer tend to apply more, and this at any point of their unemployment spells. Second, we find that the above noted decrease in search intensity is accompanied by a similar reduction in the probability of being interviews by firms: the longer the elapsed duration of unemployment, the lower the probability of being invited to a job interview. This result is again in line with previous experimental studies on the topic, and turn out to be verified on a more general scale. Third, we show that the conjunction of these two negative trends in the job search process translates into a large reduction in the monthly number of job interviews and in the resulting job offer rate: 50% of the overall decrease in the job offer rate can be attributed to changes in job seeker's behavior, while the remaining 50% are due to the recruiters' behavior. Overall, if both net duration channels were to be shut down, the empirical job offer rate faced by the individuals in our sample would essentially be flat: unemployed whose completed unemployment duration is longer would compensate lower callback rates through higher search intensity.

So far, most of the empirical literature on duration dependence in job search has emphasized the necessity to disentangle the role of dynamic selection and structural duration dependence in the decrease of the job finding rate. The relative contributions of labor demand and labor supply factors to the overall decrease in the structural and economically meaningful negative trend in the job finding rate has yet remained unexplored. Our study suggests that the duration profile in this last component is actually due to changes in both job seekers' and recruiting firms' behavior. Taking this last point into account is crucial when designing policies which seek to reintegrate unemployed into the labor market more rapidly. Future research on the topic should thus not only focus on the impact of government policies on labor demands responses (*i.e.* job interview, hiring), but also explore how those policies affect the behavorial components of job search on the job seeker side.

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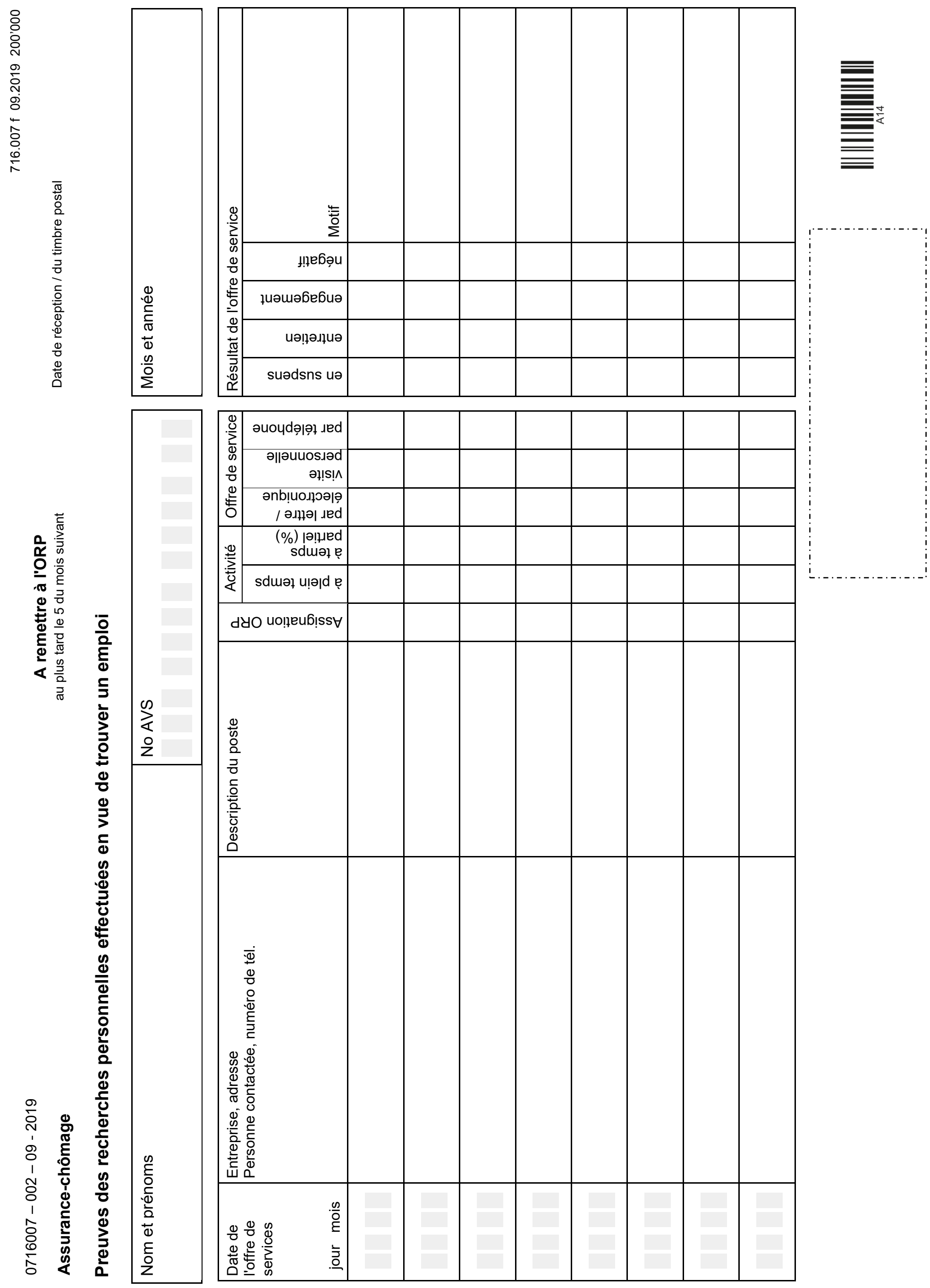
A. Data and conceptual framework

Figure A13: PAB form



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au plus tard le 5 du mois suivant

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Date de réception / du timbre postal

Nom et prénoms	No AVS	Mois et année

Date de l'offre de services (jour mois)	Entreprise, adresse Personne contactée, numéro de tél.	Description du poste	Assignation ORP	Activité: à plein temps	Activité: à temps partiel (%)	Offre de service: par lettre / électronique	Offre de service: visite personnelle	Offre de service: par téléphone	Résultat de l'offre de service: en suspens	Résultat de l'offre de service: entretien	Résultat de l'offre de service: engagement	Résultat de l'offre de service: négatif	Résultat de l'offre de service: Motif

A14

Figure A14: Job search conceptual framework

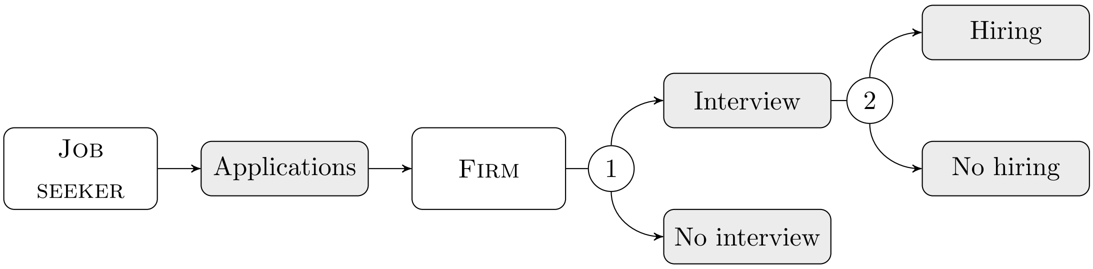
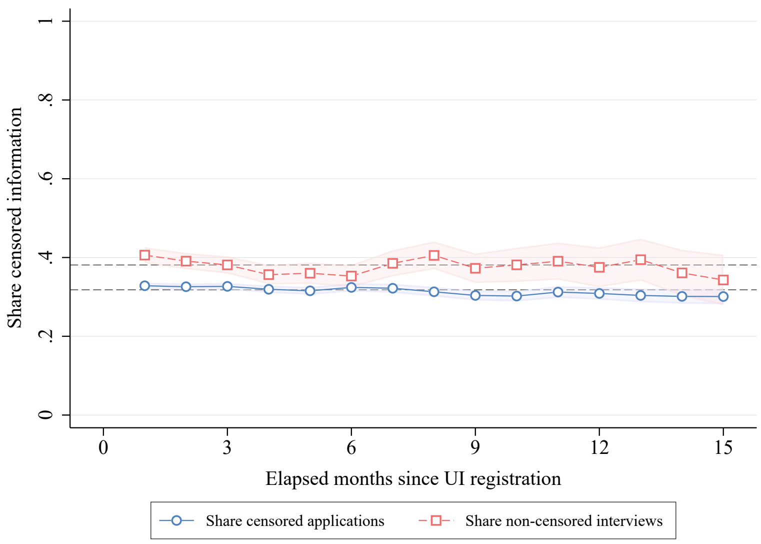


Figure A15: Share of censored applications and interviews with respect to elapsed unemployment duration

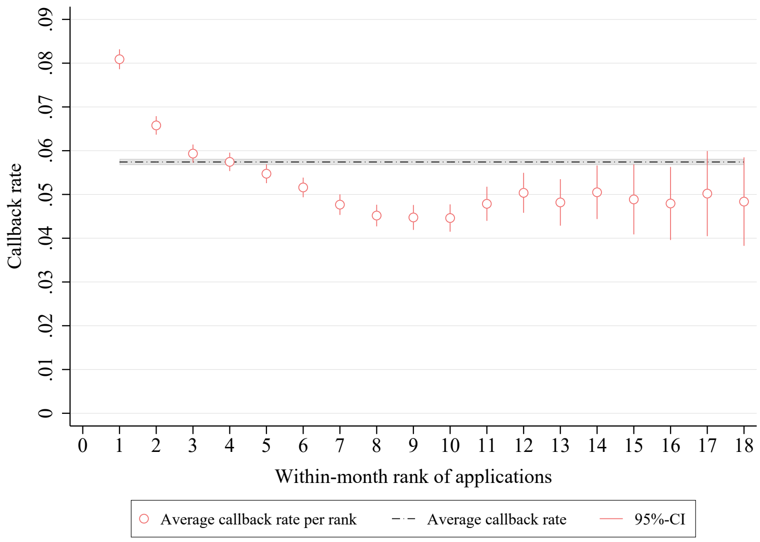


Note: this figure reports the average share of censored applications and job interviews, with respect to elapsed unemployment duration. 95% confidence intervals for the mean are also reported.

Table A5: Sample description - Numerical job search and socio-demographic characteristics

	Mean	SD	Min	Median	Max	Obs.
A. Job search - Monthly level						
Applications	10.554	4.697	1	10	30	58936
Non-censored applications	6.938	4.645	0	7	30	58936
Interviews	0.398	0.961	0	0	9	58936
Non-censored interviews	0.225	0.640	0	0	9	58936
Job offers	0.075	0.334	0	0	9	58936
Job offer rate = $\mathbb{1}$(Job offers > 0)	0.061	0.239	0	0	1	58936
B. Job search - Application level						
Callback rate (on all A)	0.038	0.191	0	0	1	602190
Callback rate (on ncA)	0.057	0.233	0	0	1	426628
Job offer conversion rate (on all I)	0.188	0.391	0	0	1	22453
Job offer conversion rate (on ncI)	0.333	0.471	0	0	1	13800

Figure A16: Within-month rank of applications and callback rate



Note:...

Table A6: Sample description - Categorical socio-demographic characteristics

	Absolute frequency	Relative frequency	Cum. rel. frequency
Education			
Primary	3994	26.94	26.94
Apprenticeship	7126	48.06	74.99
High school	602	4.06	79.05
Prof. diploma	996	6.72	85.77
UAS	675	4.55	90.32
University	1435	9.68	100.00
Residential permit			
CH-nationality	8087	54.54	54.54
C-permit	3733	25.18	79.71
B-permit	2703	18.23	97.94
Other permit	305	2.06	100.00
Canton			
BE	3523	23.76	23.76
SG	2008	13.54	37.30
VD	3278	22.10	59.41
ZG	322	2.17	61.58
ZH	5697	38.42	100.00

Note: this table reports (weighted) descriptive statistics on numerical variables observed in our sample of analysis.

Table A7: Database structure

# individuals	# applications	# monthly-individual obs.	Monthly observations per individual: Minimum	Average	Max
14829	602190	58936	1	4	12

Note: this table reports (weighted) descriptive statistics on categorical variables observed in our sample of analysis.

Table A8: PAB forms - Distribution of application types

	Absolute frequency	Relative frequency
Non-censored applications	426628	70.85
Censored applications	175562	29.15
Applications	602190	100.00
Non-censord interviews	13800	61.46
Censored interviews	8653	38.54
Interviews	22453	100.00
Job offer	4295	31.12
No job offer	9505	68.88

Table A9: PAB forms : definition of the indices

			Interview	Still open	Job offer	No job off.	Absolute freq.	Relative freq.
ncA	ncI	O	☑	☑	☑	☑	93	0.02
			☑	☑	☑	☐	558	0.09
			☑	☐	☑	☑	55	0.01
			☑	☐	☑	☐	960	0.16
			☐	☑	☑	☑	78	0.01
			☐	☐	☑	☑	543	0.09
			☐	☑	☑	☐	501	0.08
			☐	☐	☑	☐	1507	0.25
		noO	☑	☑	☐	☑	3775	0.63
			☑	☐	☐	☑	5730	0.95
	cI		☑	☑	☐	☐	4676	0.78
			☑	☐	☐	☐	3977	0.66
			☐	☑	☐	☑	125597	20.86
			☐	☐	☐	☑	278578	46.26
cA			☐	☑	☐	☐	141516	23.50
			☐	☐	☐	☐	34046	5.65
Total							602190	100.00

Table A10: Job search series

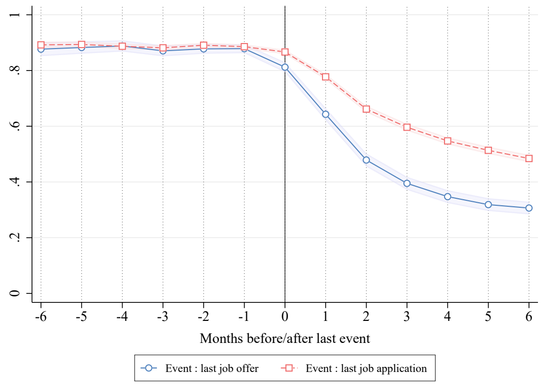
Series	Description
Job seeker	
A_{it}	# of job applications sent by individual i in unemp. month t
ncA_{it}	# of non-censored job applications sent by individual i in unemp. month t
Firm's response	
C_{ait}	interview obtained by individual i in month t following application a based on all applications
ncC_{ait}	interview obtained by individual i in month t following non-censored application a based on non-censored applications
O_{ait}	job offer obtained by individual i in month t following application a based on all interviews
ncO_{ait}	job offer obtained by individual i in month t following application a based on non-censored interviews
Matching	
I_{it}	# of interviews obtained by individual i in unemp. month t
ncI_{it}	# of non-censored interviews obtained by individual i in unemp. month t
J_{it}	# of job offers obtained by individual i in unemp. month t

Note: this table reports all job search indices of interest and their descriptions.

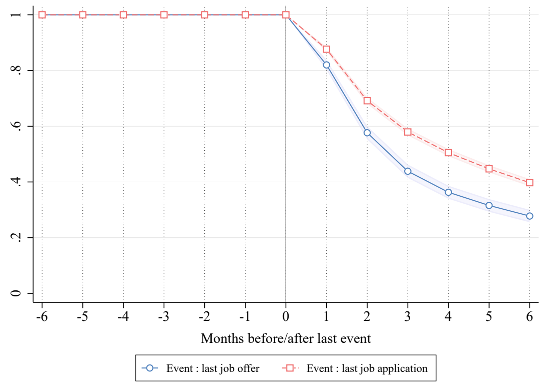
B. Descriptive patterns

Figure B17: Event study - Labor status before after last event
Last application vs. Last job offer

(a) Non-employment



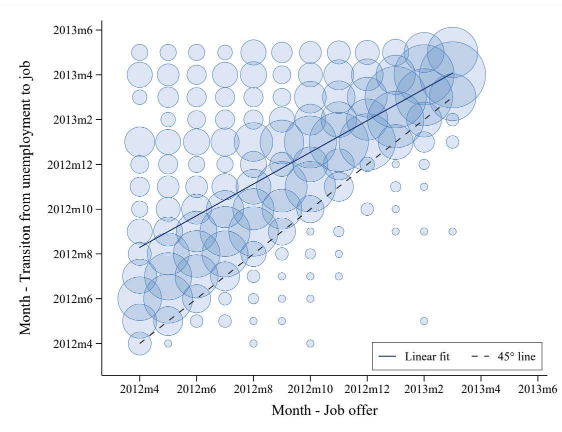
(b) Unemployment



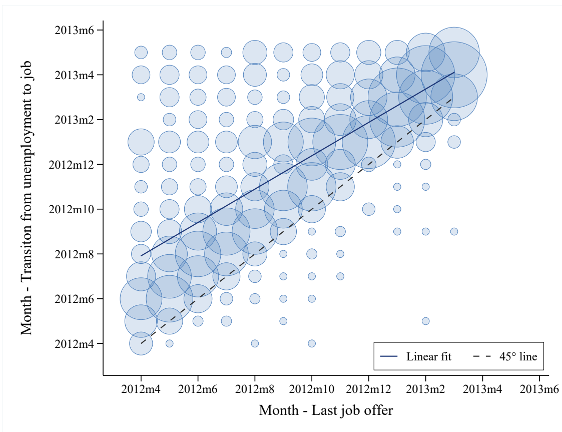
Note: this graph reports the average share of individuals who are (a) non-employed and (b) unemployed, before/after the last event in the recorded PAB forms. This last event can either be (1) the last job offer (for those who have reported at least one job offer, in blue) or (2) the last application (for those who have not reported any job offer, in red). 99% confidence intervals for the average shares are also reported.

Figure B18: Timing of job offers and transitions from unemployment to job

(a) All job offers



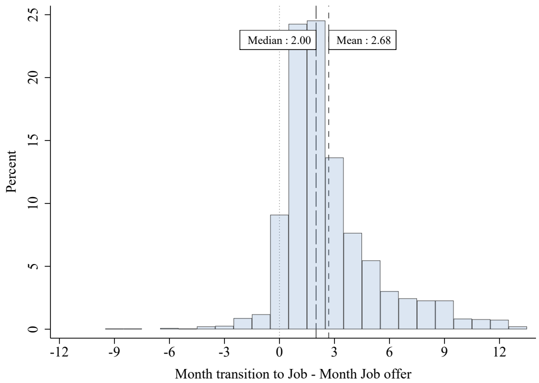
(b) Only last job offer



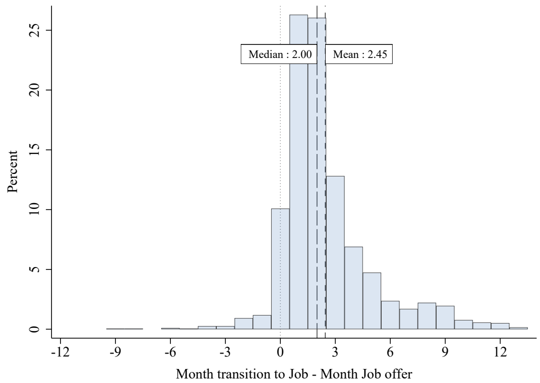
Note: this graph reports the relationship between (1) the month of the job offer(s) and (2) the month of the transition from non-employment to employment. Each dot is weighted according to the number of observations for each duplet of months. The month of the job offer(s) either relates to all the job offers recorded by the individuals (panel a) or to the last job offer recorded recorded by them (panel b). The 45 line and the linear fit between the two dates is also reported.

Figure B19: Timing of job offers and transitions from unemployment to job
Differences between the two dates

(a) All job offers



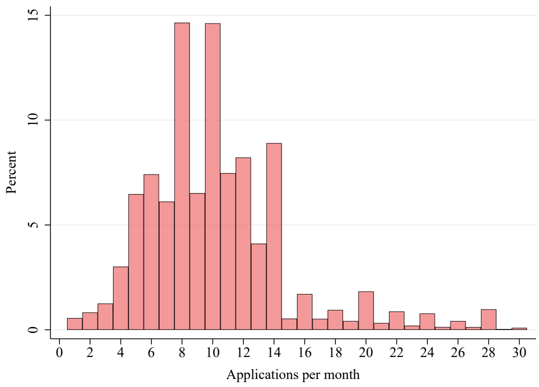
(b) Only last job offer



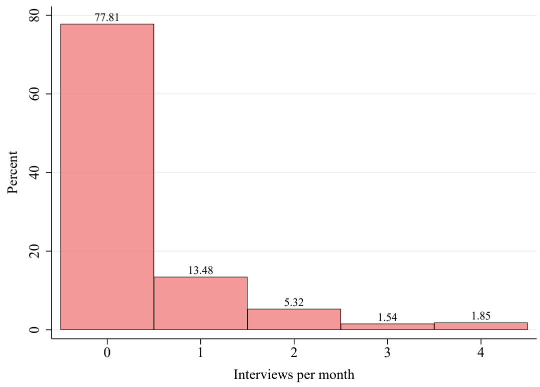
Note: this graph reports the empirical distribution of the difference between (1) the month of the job offer(s) and (2) the month of the transition from non-employment to employment. The month of the job offer(s) either relates to all the job offers recorded by the individuals (panel a) or to the last job offer recorded recorded by them (panel b).

Figure B20: Empirical distribution of search effort A_{it} and interviews I_{it}

(a) Applications A_{it}



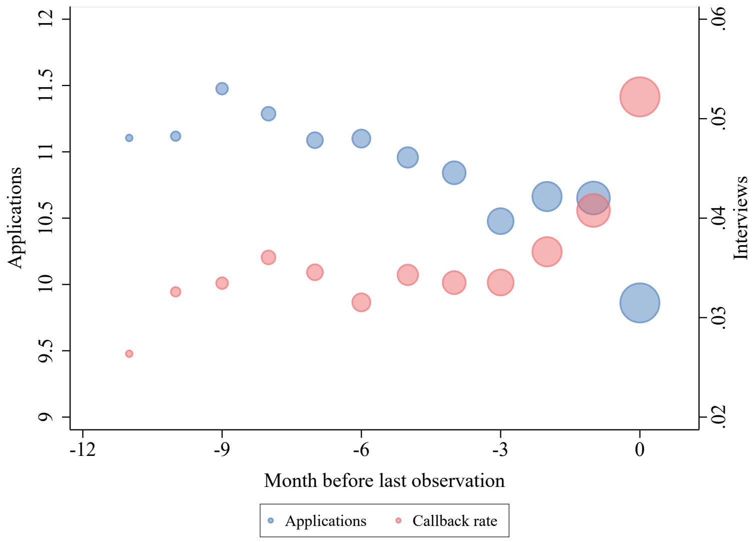
(b) Interviews I_{it}



Note: ...

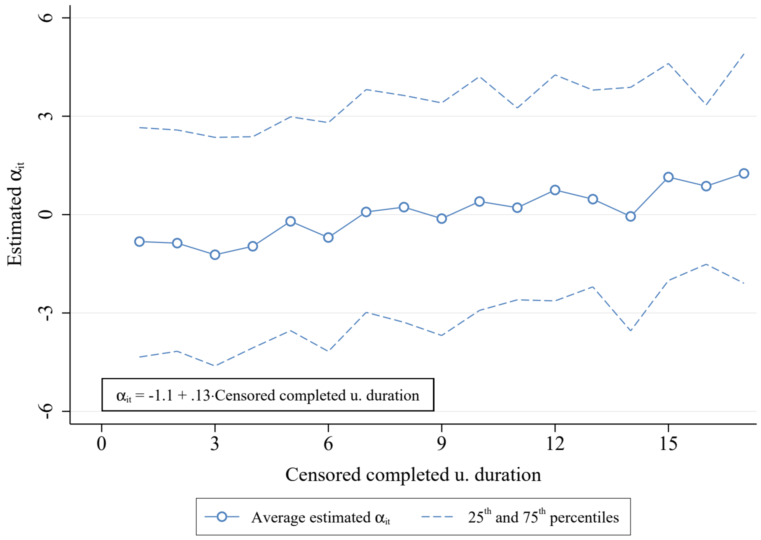
C. Duration dependence

Figure C21: Callback rate and Applications per Month before last observation



Note:

Figure C22: Estimated $\hat{\alpha}_i^{App}$ and (censored) completed unemployment duration



Note: this figure report the average estimated $\hat{\alpha}^A ppi$ parameters from equation **??**, for each month of censored completed unemployment duration, where the censored completed unemployment duration corresponds to the maximum unemployment duration observed for each individual in the sample.

Table C11: Individual fixed effects $\widehat{\alpha}_i$ and individual characteristics

	Parameters $\widehat{\beta}$	St. Errors $\widehat{\sigma}_\beta$
Dependant variable : $\widehat{\alpha}_i$		
Age category: (ref. $18-24$)		
$25-30$	0.0428	(0.1215)
$30-35$	-0.1313	(0.1237)
$35-40$	-0.1967	(0.1293)
$40-45$	-0.2632*	(0.1311)
$45-50$	-0.2522	(0.1328)
$50-55$	-0.3402*	(0.1378)
$55-60$	-0.6602***	(0.1500)
> 60	-2.5619***	(0.1695)
Level education: (ref. Primary School)		
Apprentice.	0.0856	(0.0756)
High school	0.3419*	(0.1687)
Professional mat.	-0.1043	(0.1419)
UAS	-0.1988	(0.1902)
University	-0.5451***	(0.1356)
Residence permit: (ref. Swiss)		
C-permit	0.3404***	(0.0754)
B-permit	0.5429***	(0.0913)
Other permit	0.2776	(0.1905)
Civil status: (ref. Single)		
Married/Separated	0.0042	(0.0729)
Widow(er)	0.4042	(0.3430)
Divorced	0.0795	(0.1063)
Occupation: (ref. Agriculture)		
Industry & Craft	0.4931*	(0.2421)
IT	0.4297	(0.2648)
Construction	0.2249	(0.2528)
Commercial	0.7562**	(0.2423)
Hotelling	1.0573***	(0.2423)
Administrative	1.1721***	(0.2491)
Health & Educ.	-0.0369	(0.2517)
Other	0.9122***	(0.2528)
Canton: (ref. Bern)		
SG	-2.5396***	(0.0851)
VD	2.3706***	(0.1233)
ZG	1.2515***	(0.1270)
ZH	0.5611***	(0.0866)
Continuous characteristics		
ln(previous wage)	0.3703***	(0.0573)
Unemployment history	-0.5639*	(0.2210)
Female	-0.0153	(0.0678)
Constant	7.2855***	(0.5099)
adj.-R^2	0.1985	
Observations	14829	

Note: ...

Table C12: Excess job search effort : linear duration dependence

	$\underline{A} = 8$		$\underline{A} = 10$	
Dep. variable : Excess Search Effort				
Elapsed unemployment duration	-0.0616***	-0.0605***	-0.0892***	-0.0843***
	(0.0026)	(0.0055)	(0.0040)	(0.0082)
	[-0.1940]	[-0.1905]	[-0.1778]	[-0.1679]
Individual controls	No	Yes	No	Yes
LLMC	No	Yes	No	Yes
Fixed effects	Yes	Yes	Yes	Yes
Observations	45355	45355	37279	37279
Log-likelihood	-80876	-80446	-65579	-65180

Note: ...

Table C13: Firms' response : List of controls in X^1_{ait} and X^2_{it}

List of variables	Visibility to the recruiter	Information level
$\underline{X^2_{it}}$		
Age	Age_i	Observable
Education	$Education_i$	Observable
Sex	Sex_i	Observable
Civil status	$CivilStatus_i$	Observable
Residence permit	$ResidencePermit_i$	Observable
Unemployment history (month unemployed)	$MonthsUnemployed_i$	Inferrable
Employment history (previous wage)	$PreviousWage_i$	Inferrable
$\underline{X^1_{ait}}$		
Application channel	$ApplicationChannel_{ai}$	Observable
Caseworker	Cw_i	Observable
Referral by the caseworker	$CwReferral_{ai}$	Observable
Search effort proxy	$AverageApplications$ (or α_i^{App})	Inferrable

Table C14: *Ex-ante* probability of a job interview
Estimation in the reference months

	All applications		Non-censored applications	
	Marginal effects	SE	Marginal effects	SE
Dependent variable: Callback rate [in pp]				
Age category				
$25-30$	-0.0910	(0.3983)	-0.0383	(0.5983)
$30-35$	-0.5574	(0.3812)	-0.5397	(0.5696)
$35-40$	-0.1996	(0.4046)	-0.5538	(0.5972)
$40-45$	-0.7427*	(0.3932)	-1.1288*	(0.5856)
$45-50$	-0.8635**	(0.3847)	-1.3916**	(0.5710)
$50-55$	-1.1153***	(0.4069)	-1.6762***	(0.6084)
$55-60$	-2.1035***	(0.4081)	-3.1507***	(0.6029)
> 60	-2.9613***	(0.4380)	-4.7572***	(0.6419)
Residential status				
C-permit	-0.8029***	(0.2436)	-1.1682***	(0.3614)
B-permit	-0.9274***	(0.2545)	-1.0323**	(0.4033)
Other permit	-1.5456***	(0.5966)	-1.4995	(0.9268)
Education status				
Apprentice.	2.0781***	(0.2160)	3.1280***	(0.3243)
High school	1.2510***	(0.4279)	2.3051***	(0.7130)
Professional mat.	3.2328***	(0.4303)	4.9116***	(0.6350)
UAS	3.1583***	(0.5045)	5.0192***	(0.7552)
University	2.6197***	(0.3902)	4.5276***	(0.6150)
Female	0.2529	(0.1978)	0.2018	(0.2960)
Labor market history				
ln(previous wage)	1.0983***	(0.1791)	1.4561***	(0.2608)
Unemployment history	-3.2544***	(0.7503)	-4.3603***	(1.1204)
Applications				
Phone	-0.4267**	(0.1918)	-2.3187***	(0.2500)
Personal	4.2048***	(0.3809)	3.3749***	(0.4875)
Other	7.3780***	(0.3626)	10.4913***	(0.5254)
CW referral	3.0428***	(0.3439)	4.5772***	(0.5198)
Search effort proxy	-0.0927***	(0.0263)	-0.1548***	(0.0381)
Policy controls	CW		CW	
LLMC	Yes		Yes	
Observations	153225		111353	
Pseudo-R^2	0.0995		0.1191	

Note: ...

Table C15: *Ex-ante* probability of a job offer, conditional on a job interview
Estimation in the reference months

	All interviews		Non-censored interviews	
	Marginal effects	SE	Marginal effects	SE
Dependent variable: Job offer conversion rate [in pp]				
Age category				
$25-30$	2.6388	(2.0708)	2.6081	(2.8315)
$30-35$	1.3871	(2.0203)	1.3875	(2.8278)
$35-40$	-1.2602	(2.0682)	1.1307	(2.9621)
$40-45$	-1.5298	(2.0799)	0.6032	(2.9419)
$45-50$	-0.1673	(2.0102)	0.4299	(2.8224)
$50-55$	-1.3209	(2.1355)	-0.9600	(2.9908)
$55-60$	3.8210	(2.6558)	3.3478	(3.3728)
> 60	2.4409	(3.3529)	6.3833	(5.2064)
Residential status				
C-permit	-2.5893**	(1.2593)	-0.7012	(1.9228)
B-permit	2.4962	(1.6049)	4.2423*	(2.2743)
Other permit	-0.2224	(3.8596)	7.0302	(4.8881)
Education status				
Apprentice.	-3.2703**	(1.5891)	-5.8803***	(2.2804)
High school	-5.7758**	(2.7528)	-10.5432***	(3.8561)
Professional mat.	-4.3454*	(2.3669)	-10.4465***	(3.1038)
UAS	0.0101	(2.7983)	-5.4637	(3.4214)
University	-8.3210***	(2.1194)	-13.0511***	(3.1344)
Female	-0.3985	(1.1450)	-2.3733	(1.6041)
Labor market history				
ln(previous wage)	-2.8332***	(0.9425)	-5.5486***	(1.3590)
Unemployment history	6.0952	(3.8597)	2.6655	(5.6600)
Applications				
Phone	12.1926***	(1.9008)	15.6533***	(2.5566)
Personal	5.1888***	(1.4441)	9.6165***	(2.2069)
Other	4.6514***	(1.1045)	7.4278***	(1.5260)
CW referral	1.1186	(1.9959)	6.3298*	(3.3301)
Search effort proxy	-0.1529	(0.1497)	-0.3178	(0.2195)
Policy controls	ORP		ORP	
LLMC	Yes		Yes	
Observations	12086		8208	
Pseudo-R^2	0.0612		0.0962	

Note: ...

Table C16: Applications : quadratic duration dependence

	(1)	(2)	(3)	(4)	(5)	(6)
A. All applications						
Elapsed u. duration	-0.0607***	-0.0366	-0.0107	-0.0235	-0.1721***	-0.2265***
	(0.0232)	(0.0228)	(0.0213)	(0.0211)	(0.0270)	(0.0343)
Elapsed u. duration^2	-0.0011	-0.0009	-0.0015	-0.0010	-0.0011	0.0007
	(0.0014)	(0.0014)	(0.0013)	(0.0013)	(0.0016)	(0.0016)
Individual controls	No	Yes	Yes	Yes	No	Yes
Policy controls	No	No	Yes	Yes	No	Yes
LLMC	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
adj.-R^2	0.0051	0.0351	0.1788	0.1920	0.4942	0.5012
Observations	59236	59236	59236	59236	59236	59236
B. Non-censored applications						
Elapsed u. duration	-0.0418*	-0.0213	-0.0594***	-0.0604***	-0.1694***	-0.1946***
	(0.0236)	(0.0234)	(0.0212)	(0.0212)	(0.0244)	(0.0317)
Elapsed u. duration^2	0.0004	-0.0001	0.0017	0.0016	0.0016	0.0024
	(0.0015)	(0.0014)	(0.0013)	(0.0013)	(0.0015)	(0.0015)
Individual controls	No	Yes	Yes	Yes	No	Yes
Policy controls	No	No	Yes	Yes	No	Yes
LLMC	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
adj.-R^2	0.0012	0.0191	0.1808	0.1912	0.5008	0.5068
Observations	52044	52044	52044	52044	52044	52044

Note: this table reports the estimation results of **??**, where $f(t;\beta)$ is specified as a quadratic function of elapsed unemployment duration. Errors are clustered at the individual level. Stars indicate the following significance levels: 0.1 *, 0.05 **, 0.01 ***.

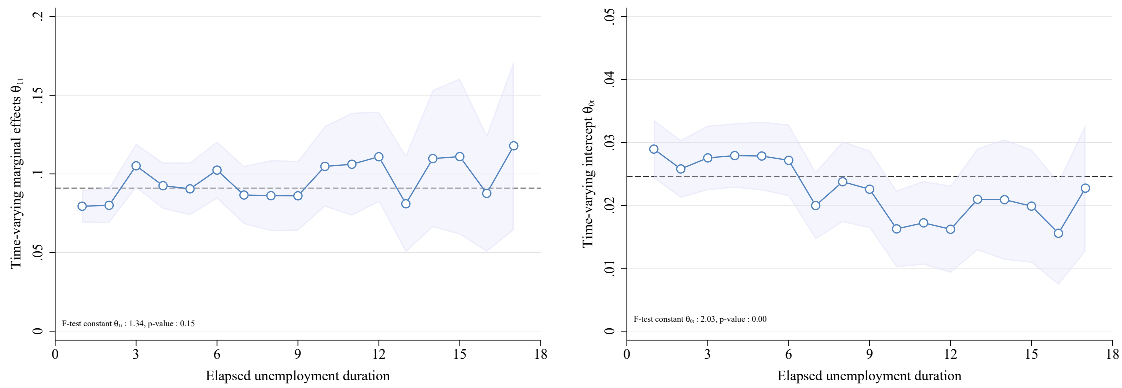
Table C17: Interviews and job offers - Estimation in the reference months ▯

	Job interviews		Job offers	
	(1)	(2)	(3)	(4)
Elapsed unemployment duration	-0.0016***	-0.0009***	0.0035***	0.0045***
	(0.0002)	(0.0001)	(0.0010)	(0.0009)
Proxy $\ln(\rho)$		0.0323***		0.8334***
		(0.0009)		(0.0361)
Observations	595350	595350	22327	22327
Pseudo R^2	0.0032	0.0794	0.0011	0.0465

D. Decomposition exercise

Figure D23: Time-varying θ_0 and θ_1

(a) θ_1 (b) θ_0

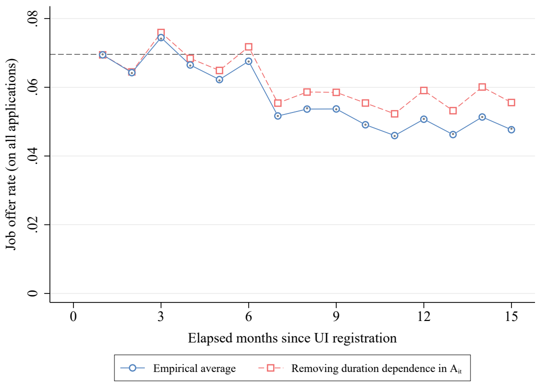


Note: this figure report the estimated θ_{1t} and θ_{0t} parameters from equation **??**,, based on the entire sample observed. 95% confidence intervals based on clustered standard errors are reported. The dashed line corresponds to the estimated marginal effect in the constrained model where $\theta_{1t} = \theta_1$ or $\theta_{0t} = \theta_0$ is constant for all months of unemployment duration.

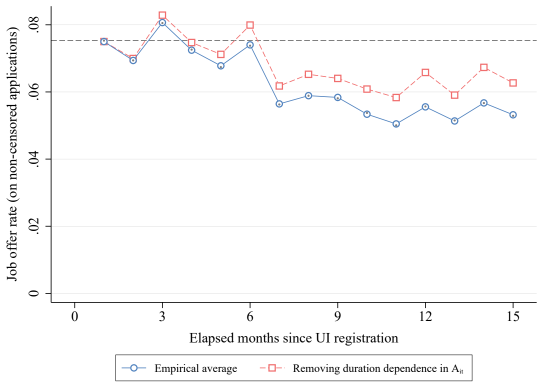
Figure D24: Counterfactual job offer rate $J_{it} = \mathbb{P}(I_{it} > 0)$
Constant $\bar{\theta}_1$ and $\bar{\theta}_0$ over the course of unemployment

(a) No duration dependence in A_{it}

All applications

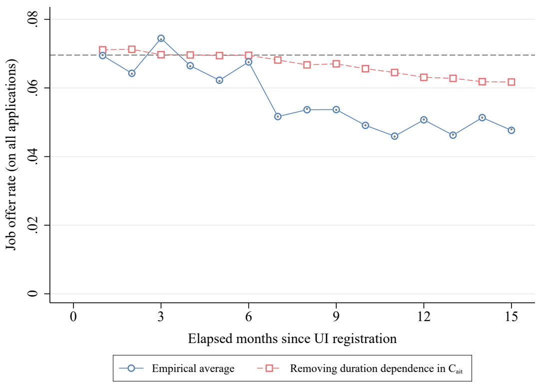


Non-censored applications

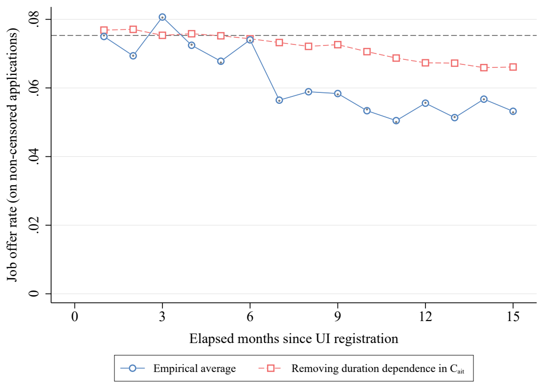


(b) No duration dependence in C_{ait}

All applications

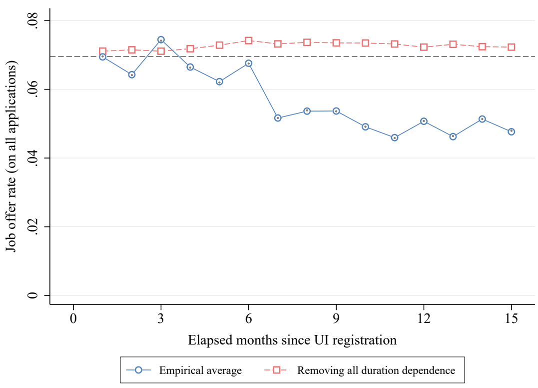


Non-censored applications

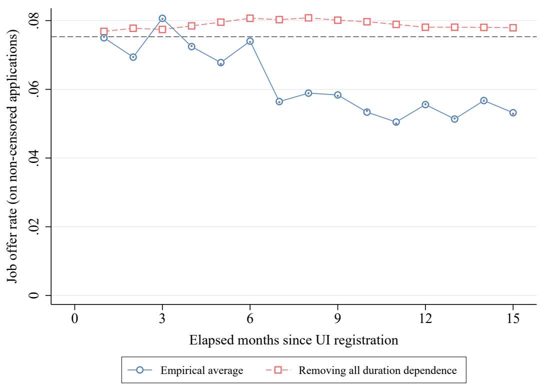


(c) No duration dependence in A_{it}, nor in C_{ait}

All applications



Non-censored applications

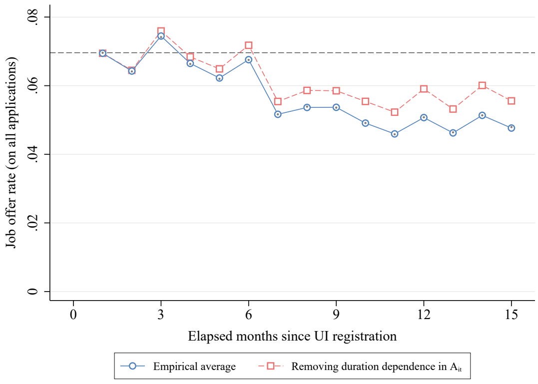


Note:

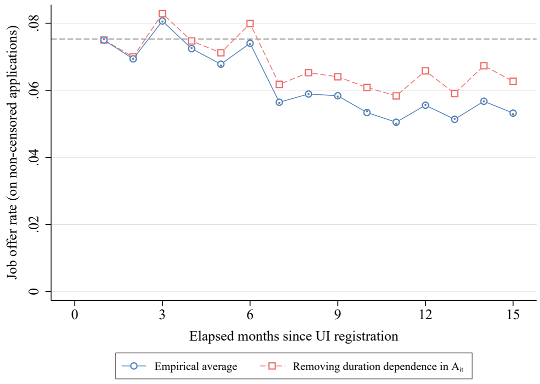
Figure D25: Counterfactual job offer rate $J_{it} = \mathbb{P}(I_{it} > 0)$
θ_{1t} and θ_{0t} maintained at their initial values

(a) No duration dependence in A_{it}

All applications

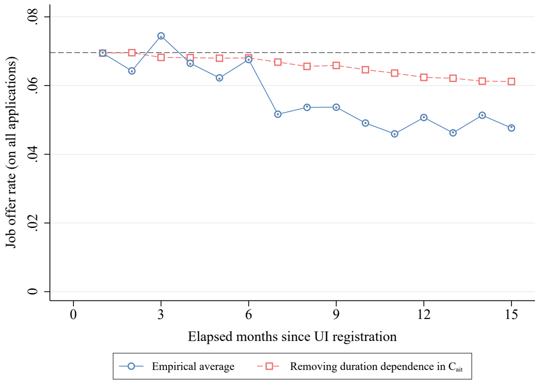


Non-censored applications

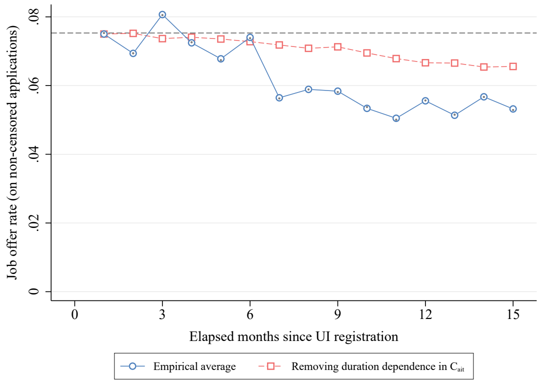


(b) No duration dependence in C_{ait}

All applications

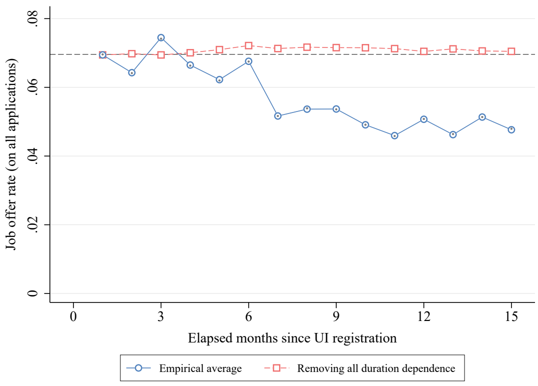


Non-censored applications

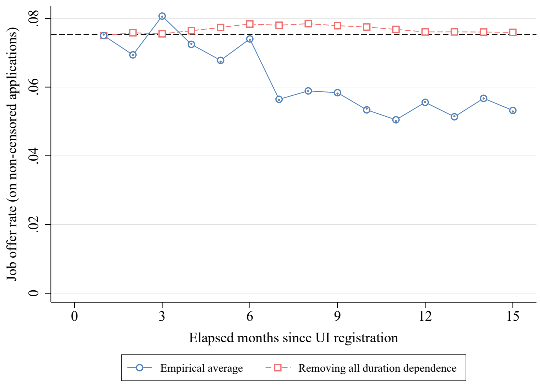


(c) No duration dependence in A_{it}, nor in C_{ait}

All applications



Non-censored applications



Note: