Duration Dependence in Finding a Job: Applications, Job Interviews, and Job Offers

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Abstract

The job finding rate declines with the duration of unemployment. While this is an old and well established fact, it is still not well understood. Our paper makes two contributions. The first is empirical. We use "monthly search diaries", a novel data source collected by Swiss public employment offices. A monthly search diary records all applications sent by a job seekers; and it indicates – for each single application – whether the employer followed up with a job interview and/or a job offer. Based on more than 600,000 applications sent by 15,000 job seekers, we find negative duration dependence in applications; negative duration dependence in job interviews; but positive duration dependence in job offers (conditional on a job interview).

Our second contribution is theoretical. We rationalize our empirical findings in a model of statistical discrimination, incorporating not only workers' search decisions but also employers' interview- and job-offer decisions. Our model captures the empirical duration patterns surprisingly well. We also provide a comprehensive discussion of our evidence in light of other theories explaining duration dependence in unemployment such as: taste discrimination against the long-term unemployed, stock-flow matching, depletion of a job seeker's personal network, and changes in application targeting/quality over time.

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1. Introduction

The labor market is characterized by a high degree of informational frictions. In this search and matching context, job seekers and firms do not match directly, but rather encounter each other through a complex job search process, during which information is revealed on both sides of the market. Labor matching has for long been documented as exhibiting negative duration dependence: the longer a job seeker remains unemployed, the lower the probability that she transits from unemployment to employment. Conceptually, part of the decline in job finding chances is due to the direct effect elapsed unemployment duration has on agents' behaviors, both on the supply and demand sides of the labor market. Alternatively, this pattern can be partially explained by workers' heterogeneity and dynamic selection, as unemployed faced with systematically lower employment prospects tend to be over-represented at later stages of unemployment.

Studies that have sought to disentangle the sources of duration dependence in job search have typically focused on the ultimate job finding outcome. However, job finding is far from being a simple one-step process: it involves several distinct stages from the sending of applications by the job seeker, to the decision by the firm whether to make a job offer to the applicant, through the intermediary screening stages. Given the current state of the literature, we lack empirical evidence and theoretical understanding about the effect duration has on these sequential decisions, the role of heterogeneity in their dynamics and how they eventually contribute to the decline in job finding chances.

In this paper, we use granular administrative data on 600,000 job applications made by Swiss unemployed to study the different stages of the job search process. For each of these stages, we document how job seekers or firms' behaviors evolve with respect to elapsed unemployment duration. We also assess the contribution of workers' heterogeneity to the observed duration patterns, and measure the net effect of duration on each of these sequential decisions.

On the firm's side, we find evidence of a large and marked decline in the chances that an application results in a job interview, a "callback", for applications sent out later in the spell, compared to those sent earlier on. To address the compositional change in the pool of job seekers sending applications in late and early duration periods, we control for applications' baseline chances of leading to a job interview, by conditioning on the likely information set that is available to firms when making callbacks decisions. Once controlling for these *ex-ante* chances of leading to an interview, applications sent to firms still face lower callback chances as unemployment duration elapses, but this decline is only about half as strong compared to the observed callback probability. The observed callback probability declines more strongly than the controlled one due to negative dynamic selection, *i.e.* the pool of applications observed at late duration periods have substantially lower *ex-ante* callback chances. We further show that this change in composition arises because job seekers with the highest callback chances tend to exit the observed sample.

We apply the same methodology to the choice of the firm whether to convert a job interview into a job offer, focusing on those applications that first lead to a job interview. In contrast to the callback decision, we find that the job offer conversion decision is positively correlated with duration in the raw data: the probability with which job interviews are converted into job offers is slightly increasing over time. This pattern is rationalizable in a context with dynamic selection : as time passes by, the pool of workers who remain unemployed and who get interviewed becomes more homogeneous, hence leading to a higher probability of securing a job offer conditional on an interview. In line with this argument, we find that observed workers' heterogeneity plays a limited role at this stage of the recruitment process, as controlling for observed unemployed characteristics does not significantly affect the estimated duration profile of the job offer conversion probability.

On the job seeker's side, we find that search effort, as measured by the number of applications sent out per month, decreases slightly and steadily over the course of unemployment. Just like for firms' decisions, this descriptive pattern encompasses both the net effect of duration and the effect of dynamic selection due to workers' heterogeneity. As application effort is observed repeatedly for each job seeker in our data, we can use fixed effects models to control for observed and unobserved individual characteristics. Once heterogeneity is accounted for, we find a much stronger net effect of duration on application effort. Heterogeneity hence entails positive dynamic selection at the application phase: high-application-effort job seekers tend to remain unemployed longer, hence contributing to flattening the duration profile of application effort in the raw data.

Taken altogether, our empirical findings are consistent with a statistical learning view of the labor market, with imperfect information on workers' productivity. We extend Jarosch and Pilossoph (2019) framework, who develop this view for firms, by adding statistical learning on the labor supply side. In this framework, firms use elapsed unemployment duration in addition to observed heterogeneity to infer the productivity of applicants, when deciding whether to call them back for a job interview. Unemployment duration however does not contain additional information and does not reduce applicants' chances at the job offer conversion stage, as their productivity level is revealed during the interview. In turn, the overall decline in firms' responses entails a decrease in application effort by job seekers, who anticipate firms' discriminating behavior towards long unemployment duration in a forward-looking manner. In this framework, net duration patterns on both sides of the market are rooted in statistical discrimination from firms towards longer-term unemployed.

Some of the patterns we document are also coherent with competing theories of job search, such as application targeting, stock-flow matching or social capital exhaustion. However, we find little supportive evidence for these alternative mechanisms. Not only do we observe few changes in application targeting over time, whether in terms of occupational targeting or skills requirements, but we also find little evidence of adjustments in applications quality, notably in terms of the channels used when contacting firms. In particular, applications in person, which are shown to be significantly more successful, represent a relatively stable share of all applications at each unemployment duration.

Our paper addresses various strands of the vast literature on job search and labor markets dynamics. We first contribute to the literature on the role of workers' heterogeneity in explaining duration dependence in job finding. Since the seminal study of Van den Berg (1990), which generalized non-stationarity in job search models, a long standing debate has emerged on whether the decline in job finding chances is due to dynamic selection and workers' heterogeneity, or to genuine duration dependence in agents' behaviors. Focusing on the exit rate out of unemployment, Van den Berg and Van Ours (1996) find that heterogeneity explains most of the decline in job finding, for most socio-demographic groups in the US. Alvarez et al. (2016) find similar results based on a dynamic model of transitions in and out of employment, with arbitrary heterogeneity across workers. The authors estimate their model using social security data for Austrian workers who experience two or more unemployment spells, and find that dynamic selection is a critical source of duration dependence. The same type of approach is taken by Ahn and Hamilton (2020), who find similar results for the US. More recently, Mueller et al. (2021) exploits job seekers' elicited beliefs about job finding to shed light on the sources of negative duration dependence in the job finding rate. They find evidence of substantial heterogeneity across job seekers, resulting into substantial dynamic selection that explains most of the observed decline in job finding chances. Consistent results are found by Mueller and Spinnewijn (2023), who exploit rich administrative data from Sweden to study the predictability and determinants of long-term unemployment. The authors find large amount of heterogeneity in job seekers' employability, and argue that at least half of the decline in job finding over the unemployment spell is driven by dynamic selection.

Our study further contributes to two additional strands of the job search literature, which examine changes in agents' behavior as potential drivers of job finding dynamics. Firstly, we address the literature on firms' decisions during the recruitment process, and how those evolve with respect to elapsed unemployment duration. In their seminal study, Kroft et al. (2013) study duration dependence in the probability that a job application ends up into a callback for a job interview. Based on an experimental audit setup, the authors find that the chances of getting a callback from firms decrease sharply in the early months of unemployment, this decline varying according to local labor market conditions. Their results are consistent with screening models in which employers use unemployment duration as a signal of workers' unobserved productivity (Vishwanath, 1989; Lockwood, 1991). A similar experimental approach has been followed by Oberholzer-Gee (2008), Eriksson and Rooth (2014) and Nüß (2018) for Switzerland, Sweden and Germany respectively. All studies come up with consistent results: the duration of the contemporaneous unemployment spell reduces the probability of being called back by firms. Again, the authors interpret these results as elapsed unemployment duration conveying a stigmatic signal about job seekers' productivity. In contrast, Farber et al. (2016) find no negative effect of unemployment duration on the callback probability for the sub-market of experienced college-educated females applying for administrative support jobs. The authors argue that these results might be due to the specific group of workers they analyse. More recently, Jarosch and Pilossoph (2019) have taken a more structural view at the negative duration dependence in the callback probability. Using a frictional job search model where employers endogenously discriminate against longer-term unemployed, the authors are able to replicate the decline in job interviews over the course of unemployment. Their structural approach allows to further assess the consequences of firms' callback behavior for job finding. They find that the decline in callbacks has a limited impact for unemployment exit, as job interviews lost in the first place would have had little chance to be converted into job offers, and eventually hirings. The authors hence interpret negative duration dependence in the callback probability as being largely driven by dynamic selection and statistical discrimination.

Secondly, we add up to the increasing literature on the dynamics of job search effort provision by job seekers. Recent papers have shown that the decline in search effort might be a major driver of decreasing job finding chances. Exploiting online job application data, Faberman and Kudlyak (2019) study the dynamics of search effort along job search spells in the US. Using the weekly number of applications sent out per month as proxy, they show that search effort is decreasing with the duration of the job search spell. Their main result is robust and even accentuated when controlling for individual heterogeneity through individual fixed effects. Fluchtmann et al. (2021) find consistent results for the universe of Danish job seekers. The authors use information from an online job search monitoring platform, which is legally constraining for unemployed. Their evidence show that the monthly average number of applications recorded on the platform is relatively constant over the duration of unemployment, in the raw data. However, once job seekers' heterogeneity is accounted for through individual fixed effects, application effort is found to decline markedly within unemployment spells. Using similar administrative data, Marinescu and Skandalis (2021) analyse the dynamics of application effort in France, with a specific focus on unemployment benefits exhaustion. Their descriptive analysis shows a net empirical decline in the number of applications sent out per month, both for job seekers that are eligible and non-eligible to unemployment benefits. However, after accounting for compositional changes through spells fixed effects, the authors find limited evidence of decreasing search effort for non-eligible unemployed, whereas application effort is found to be increasing for eligible unemployed until the end of the eligibility period. These mixed results using applications as job search effort proxy echoe those relying on survey data: Krueger et al. (2011) report evidence that the time devoted to job search decreases sharply over the course of unemployment, while DellaVigna et al. (2022) show that search effort is flat in early months of unemployment, increasing before and decreasing after benefit exhaustion.

The contributions of our paper to the existing job search literature are manifold. First of all, we document new duration dependence patterns for the entire sequence of decisions of the job search process, from applications to job offers, through callbacks, all in a unified empirical framework. Especially, we provide unseen empirical evidence on firms' behavior beyond callback decisions, *i.e.* what are the chances of job seekers to obtain a job offer after having been interviewed.

Since our empirical analysis is based on real-world data, we are also able to discuss how heterogeneity and dynamic selection on the one side, and net duration dependence on the other side, contribute to the observed duration patterns. Our results corroborate the previous finding that individual heterogeneity is a major driver of duration dependence in job search. They further highlight the mulit-dimensional role of heterogeneity, which affects differently the sequentaial phases of job search, as well as their dynamics. Specifically, dynamic selection is found to be positive for application effort, leading to an attenuation of its negative duration profile in the raw data. In contrast, dynamic selection turns out to be negative for callback decisions, while it does not play much role at the time when interviews are converted into job offers. In addition, when accounting for heterogenity, we find evidence of a net effect of duration at each phase of the job search process, whether negative for job seekers' application and firms' callback decisions, or positive for job offer conversion.

Our comprehensive empirical evidence allow to better identify which type of model is susceptible to generate the observed duration dependence relationships. The picture that emerges from our empirical exercise is surprisingly consistent with a statistical learning view of the labor market. Our augmented version of Jarosch and Pilossoph (2019), with an additional job application phase, is able to explain most of the patterns we observe empirically. According to this framework, unemployment duration is used by firms at the callback stage to infer applicants' quality, but plays no negative role when firms decide whether to convert interviews into job offers. Faced with declining callback and job offer chances, job seekers endogenously reduce their job application effort, which further dampens job finding chances.

Our findings have important implications for our understanding of labor markets functioning. They suggest that the dynamics in job finding chances can be attributed both to workers' heterogeneity and to the net effect of duration. In particular, the latter is found to be negative for firms' callback decisions and for job seekers' application effort. According to our structural model, these net duration effects are generated endogenously and result from statistical discrimination by firms. In a context with informational frictions with respect to job seekers' productivity, elapsed unemployment duration might have detrimental effects on the two sides of the labor market, if the signal conveyed by duration is an important input of firms' recruitment decisions. From a policy perspective, our study emphasizes the importance of providing better information on job seekers skills and experience already in the early phases of the job search process, so as to reduce the detrimental effects of longer unemployment duration on job seekers' and firms' behaviors, and to improve labor matching efficiency.

The rest of this paper is organized as follows. Section 2 describes the institutional context of our study. In section 3, we present the data we use in our empirical exercise and show how those can be exploited to measure job search outcomes. We also provide descriptive evidence on job offers as proxy for job finding, and discuss how those can be decomposed using the granular information contained in our data. Sections 4 and 5 represent the core of our empirical analysis. In section 4, we study the dynamics of application effort, as measured by the number of applications sent out per month. After presenting descriptive evidence on its decline, we study its dynamics net of compositional effects. We proceed the same way in section 5 for firms' responses, *i.e.* callback and job offer conversion decisions. In section 6, we present a job search model with statistical discrimination that rationalizes the patterns we find empirically. We also discuss alternative mechanisms that might explain our findings. Section 7 concludes.

2. Institutional context

Swiss workers are entitled to unemployment benefits if they contribute at least twelve months within two years prior to the beginning of their unemployment spells.[1] The typical potential benefit duration amounts to 12 or 18 months and is a function of the contribution period, age and family situation of unemployed. The replacement rate ranges from 70% to 80%, depending on the level of the insured salary and the presence of children in the household. Job seekers who intend to claim unemployment benefits have to register at a regional Public Employment Service (PES) office. Offices are organized at the cantonal level and exert some discretion over the implementation of unemployment policies. Once registered at a regional PES center, unemployed are assigned to a caseworker, either based on caseworkers' caseload, their occupation or at random (Behncke et al., 2010).

One of the main tasks conducted by caseworkers consists in monitoring the unemployed's job search activity. According to the legal framework, unemployment benefit recipients "*must be able to demonstrate [their] effort [to find a job]*".[2] To make this assessment by caseworkers possible, the unemployed have to document their search activity in job search diaries using pre-defined forms.[3] These forms contain detailed information on all applications made by job seekers, in each month of their unemployment spells. They include information on applications dates, application channels (written, personal or by phone), the work-time percentage of targeted positions (full-time or part-time), whether applications result from caseworker referrals, as well as short job vacancy descriptions. Most importantly, these documents report information on applications' outcomes (callback, job offer, negative or still open), which can be used to quantify applications' success.

[1]This section overlaps considerably with a similar section in Zuchuat (2023b).

[2]*Loi fédérale du 25 juin 1982 sur l'assurance-chômage obligatoire et l'indemnité en cas d'insolvabilité (LACI)*; RO 1982 2184. Retrieved 19$^{\text{th}}$ October 2022 from https://www.admin.ch/opc/fr/classified-compilation/19820159/index.html.

[3]A copy of the standardized form in French can be found in the Appendix, in Figure A1.

Job search diaries are filled in and submitted to PES offices on a monthly basis, together with copies of job applications. These documents serve as a basis for monitoring by caseworkers, who make sure that minimum search requirements are met. Those are defined both in quantitative terms, *i.e.* a minimum number of job applications to be made per month, and in qualitative terms, as caseworkers review copies of job applications to assess their truthfulness (Arni and Schiprowski, 2019). In case of non-compliance with those requirements, job seekers are notified and potentially sanctioned by a benefit cut.[4] Caseworkers and job seekers update information on the success of job applications for up to two months after the job application has been sent out. This provides detailed and accurate information on success of job applications, *i.e.* whether they lead to a callback for a job interview, or a job offer.

3. Data sources

3.1 Data and empirical measurements

Our empirical investigation of job search dynamics relies on various Swiss administrative data sources. Our main source of information stems from search diaries filled in by unemployed at PES. For the purpose of this study, paper-format documents were transcripted into numeric format a two different occasions, based on a stock-flow sampling design.[5] The main large-scale data collection took place between April 2012 and March 2013, in five different Swiss cantons (Zürich, Bern, Vaud, Zug and St-Gallen), and provides us with our *Main sample* of analysis. This sample covers several hundred thousand job applications and contains most information reported in the job search diaries, with the exception of the information on the posted occupation or on the firm. We supplement this *Main sample* with an *Auxiliary sample*, which originates from a smaller-scale data collection. This one took place from July 2007 to March 2008 in the canton of Zurich only. This additional sample contains all information recorded in the job search diaries, including the occupation targeted by each application and the posting firm. Due to its limited size, the *Auxiliary sample* is principally used in the context of analyses requiring information on occupations. Taken together, these two data sources provide information on job applications and their success at a highly granular level.

We complement search diaries data with information on job seekers' characteristics, which we retrieve from PES registers. Those contain demographic (*e.g.* age, education level, residence status, etc.), job-search related (*e.g.* desired occupation), as well as unemployment institutions-related (*e.g.* caseworker and PES identifiers) information. In addition, we collect information on job seekers employment status and labor market history from social

[4]The average size of a sanction amounts to 5.5 days of unemployment benefits, around CHF 900.- on average (Arni and Schiprowski, 2019).

[5]This means that we observe all job seekers that were unemployed at the start of the study, and also all those job seekers who entered unemployment during the observation period.

security registers, for the *Main sample* exclusively. This enables us to track job seekers' labor income and unemployment benefits flows before, during and after their unemployment spells. All complementary information are available on an individual-monthly basis and are merged with job search diaries data using individual social security identifiers and calendar months.

We restrict our analysis samples to job applications during months with benefits receipt. This choice is motivated by data reliability: only unemployment benefits beneficiaries have the legal obligation to fill in search diaries, and for those the truthfulness of recorded information is diligently checked by caseworkers. Additionally, we focus on individuals for whom socio-demographic and employment history information are non-missing, these pieces of information playing an important role in our identification strategy. In the end, our *Main sample* of analysis contains 600'323 applications sent by 14'798 individuals, while the *Auxiliary sample* is made of 24'770 applications sent by 655 unemployed.[6]

3.2 Job search outcomes

Job search diaries provide a unique, granular and comprehensive source of information to study the sequential phases of the job search process.[7]

We observe the universe of applications a_{ijt} sent out by job seeker i to job vacancy j in month t of her unemployment spell, where $a_{ijt} = 1$ if the job seeker sends the application, while $a_{ijt} = 0$ if she does not apply to the vacancy. The total number of applications made by job seeker i in unemployment month t is then $A_{it} = \sum_{j=1} a_{ijt}$. This provides us with a direct quantitative measure of search or application effort, recently used in the empirical job search literature (Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021; Fluchtmann et al., 2021). Furthermore, we know firms' responses to each application a_{ijt}, by means of two binary and sequential success indicators. First, we observe whether a job application is followed by a callback for job interview c_{ijt}, a common measure of applications success in audit studies (Oberholzer-Gee, 2008; Kroft et al., 2013; Eriksson and Rooth, 2014; Farber et al., 2016; Nüß, 2018), where $c_{ijt} = 1$ if the job seeker receives a callback and $c_{ijt} = 0$ otherwise. Second, we have access to a never-seen piece of information that goes beyond callbacks: we know whether an application that first led to a job interview eventually ends up in a job offer o_{ijt}, with $o_{ijt} = 1$ if the job seeker receives a job offer for vacancy j.[8] As for applications, we can construct the numbers of callbacks, $C_{it} = \sum_{j=1} a_{ijt} \cdot c_{ijt}$, and the number of job offers $O_{it} = \sum_{j=1} a_{ijt} \cdot c_{ijt} \cdot o_{ijt}$, obtained by

[6] Socio-demographic and labor market history-related information on job seekers belonging to each of the two samples are reported in Table A1.

[7] The initial idea of using this type of information to analyse labor market outcomes originate from **?**.

[8] In our conceptual framework, the two success indicators are sequential, *i.e.* a job offer can only occur conditional on a callback. This sequence is sometimes not verified empirically, *i.e.* a job offer is recorded without a preceding callback. This might for instance be the case if the interview and job offer took place within the same month of unemployment (inbetween two meetings at the PES office), and the caseworker only requires the job seeker to fill in the job offer tickbox. In those cases, we impute a job interview.

individual i in unemployment month t. These monthly aggregates of search activity and firms' responses measure how applications translate into interviews and job offers, and serve as labor matching proxies.

We report descriptive statistics on our empirical job search measures for the *Main sample* in Table 3.1.[9] Panel A reports statistics for application-level outcomes, while panel B focuses on outcomes measured at the individual-monthly level.

As shown in Panel A, the average probability of getting a callback after sending out an application amounts to 4%. This number is slightly lower compared to evidence from audit studies, possibly because of different callback definitions.[10] The probability of obtaining a job offer out of an application amounts to 0.9%. This corresponds to an average job offer conversion probability, *i.e.* the probability of obtaining a job offer conditional on a callback, of 22.5%. Panel B shows that the average monthly number of job applications sent out by unemployed equals 10.55, while the monthly average numbers of callbacks and job offers obtained per month amount to 0.399 and 0.075 respectively. Translated in terms of extensive margins, the probabilities of obtaining at least one job offer or at least one job interview in a given month of unemployment are equal to 22.6% and 6.1%.[11]

Table 3.1: Descriptive statistics, *Main sample*

	Mean	SDV	Min	Median	Max	N
A. By application						
$\mathbb{P}(c_{ijt} = 1)$, callback prob. [in %]	4.013	19.626	0.000	0.000	100.000	600323
$\mathbb{P}(o_{ijt} = 1)$, job offer prob. [in %]	0.905	9.468	0.000	0.000	100.000	600323
$\mathbb{P}(o_{ijt} = 1 \mid c_{ijt} = 1)$, job offer conversion prob. [in %]	22.515	41.769	0.000	0.000	100.000	22422
B. By monthly-individual						
A_{it}, nbr. applications	10.553	4.698	1.000	10.000	30.000	58755
C_{it}, nbr. callbacks	0.399	0.961	0.000	0.000	9.000	58755
O_{it}, nbr. job offers	0.075	0.334	0.000	0.000	9.000	58755
$\mathbb{P}(C_{it} > 0)$, prob. a.l. one interview [in %]	22.551	41.792	0.000	0.000	100.000	58755
$\mathbb{P}(O_{it} > 0)$, prob. a.l. one job offer [in %]	6.108	23.947	0.000	0.000	100.000	58755
C. Sample structure						
Time-period				04.2012 - 03.2013		
Region				BE, SG, VD, ZG, ZH		
Nbr. applications				600323		
Nbr. monthly-individual				58755		
Nbr. individuals				14798		

Note: This table reports descriptive statistics about our *Main sample* of study. Panels A and B report descriptives on application-level and individual-monthly-level job search outcomes respectively. Panel C provides information about the sample structure.

[9] Corresponding figures for the *Auxiliary sample* can be found in the appendix, in Table A2.

[10] In audit studies, callbacks are sometimes refer to as any reply from firms, from "asking for additional information" to "inviting for a job interview". In our case, a callback is registered only when firms invite the applicants for a job interview.

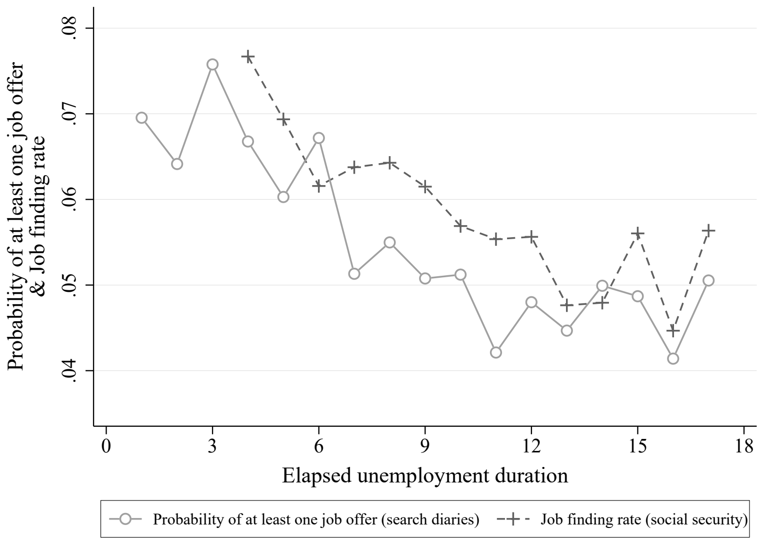
[11] Summary statistics obtained on the *Auxiliary sample* are qualitatively similar, even though the callback and job offer probabilities (and consequently the numbers of callbacks and job offers) are relatively higher. These discrepancies might be due to differences in data recording across institutions, local labor market conditions or macroeconomic conditions at the time of data collection.

3.3 Decomposing job offers using job search diaries information

Job search diaries are designed to provide a reliable and in-depth description of the job search process leading to job offers. Based on search diaries, we identify all individuals who receive at least one job offer out of the applications they send in month t, or $\mathbb{1}(O_{it} > 0)$. We define the (empirical or theoretical) expectation of this outcome for individuals who are still applying for jobs in month t of unemployment as $\mathbb{E}_t\big[\mathbb{1}(O_{it} > 0)\big] = \mathbb{P}_t(O_{it} > 0)$. This expression defines the probability that an individual still unemployed in unemployment month t receives at least one job offer in that same month.

Existing empirical analyses focus on duration dependence in the job finding rate (or unemployment-to-employment transition rate). Conceptually, this one is closely related to the probability of obtaining at least one job offer, computable from job search diaries data. This can be seen in Figure 3.1, where the probability $\mathbb{E}_t\big[\mathbb{1}(O_{it} > 0)\big]$ is plotted together with the average monthly job finding rate.[12] The job finding rate exhibits a typical negative duration dependence behavior: in early months of unemployment, the instantaneous chances of transiting from unemployment to employment are relatively high (around 8%), before decreasing to levels close to 4-5% after 12 months. The probability of getting at least one job offer follows a similar dynamics. However, the two curves do not overlap

Figure 3.1: Monthly probability of at least one job offer and job finding rate



Note: This figure depicts the empirical duration dependence in the monthly probability of obtaining at least one job offer (computed on search diaries data) and the monthly job finding rate (computed on social security data).

[12]The job finding rate is computed using social security data, that are only available for the *Main sample*. Conceptually, the job finding rate is defined using a binary indicator which takes the value 1 if job seeker i leaves unemployment for a job after t months of unemployment, and zero otherwise. In our context, a job seeker is considered as having found a job if her monthly labor earnings exceed 2,000 CHF. This is equivalent to 50% of the unofficial minimum wage in Switzerland (4,000 CHF monthly). In most cases, the job finding rate and the probability of getting at least one job offer coincide, with a certain time-lag.

perfectly, the job finding rate typically corresponding to a right-shift of the job offer curve. This pattern is due to the timing of data recording: job search diaries report applications dates and not dates at which job offers are made. Given that recruiting processes can expand over a certain period and that job starting dates might be delayed, such shift between the two curves is expected. As an additional check, we proceed to an event-study that tracks the evolution of monthly labor income flows after the recording of a job offer. Corresponding results are reported in Figure A2 in the Appendix and show that job offers are strongly predictive of increases in labor income.[13]

We show above that job search diaries provide reliable information on job offers, which are predictive of job finding. The innovative aspect of our data is that they do not restrict us to the sole analysis of the final outcome of job search. Their granularity allows to analyze duration dependence at various stages of this process, and facilitates the assessment of the contribution of heterogeneity to this phenomenon.

At a basic level, the probability of obtaining at least one job offer (and the job finding rate eventually) are driven by the number of job offers obtained per month, O_{it}.[14] The latter depends on the number of job applications sent in a month multiplied by the average success probability of job applications sent in that month. In our context, a job application is successful if it first leads to a job interview, and then to a job offer. Using our notation above, the expected number of job offers for individuals sending applications in month t is[15]

$$\mathbb{E}_t\left[O_{it}\right] = \mathbb{E}_t\left[A_{it} \cdot \mathbb{P}(o_{ijt} = 1)\right] = \mathbb{E}_t\left[A_{it} \cdot \mathbb{P}(c_{ijt} = 1) \cdot \mathbb{P}(o_{ijt} = 1 | c_{ijt} = 1)\right]. \tag{3.1}$$

This simple conceptual framework highlights three stages of the process which leads to a job offer: job seekers' application effort (measured by the total number of applications sent to firms in a month, A_{it}), the probability that an application ends up in an interview (or callback probability, $\mathbb{P}(c_{ijt} = 1)$), and the chances of having a job offer if interviewed (or job offer conversion probability, $\mathbb{P}(o_{ijt} = 1 | c_{ijt} = 1)$). All three steps of this process are observed empirically thanks to the job search diaries data, as described schematically in Figure A4, in the Appendix.

We further decompose the empirical decline in job offers between month t and the initial

[13] Figure A2 shows that labor income increases after the recording of the last job search diary, even in the absence of a job offer. This pattern is expected, given that we observe social security data up to 2015, while job search diaries were only collected until March 2013. Put differently, the graph also shows the evolution of labor income flows for individuals who have been unemployed after March 2013, a period during which we did not collect any diary, and who eventually found a job.

[14] Figure A3 in the Appendix shows that the empirical average number of job offers per month $\mathbb{E}_t\left[O_{it}\right]$ is closely related to the empirical monthly probability of obtaining at least on job offer $\mathbb{E}_t\left[\mathbb{1}(O_{it} > 0)\right]$, which in turn directly affects the job finding rate.

[15] The sequential aspect of the process implies that $\mathbb{P}(o_{ijt} = 1 | c_{ijt} = 0) = 0$.

month 0 as follows

$$\mathbb{E}_t[O_{it}] - \mathbb{E}_0[O_{i0}] = \underbrace{\mathbb{E}_t[O_{it} - O_{i0}]}_{\text{Net duration effect}} + \underbrace{\mathbb{E}_t\big[O_{i0}\big] - \mathbb{E}_0\big[O_{i0}\big]}_{\text{Compositional change}}. \tag{3.2}$$

This standard equation states that the observed decrease in job offers is made of two components. First, the decline in job offers for the set of job seekers who are unemployed in month t, $\mathbb{E}_t\big[O_{it} - O_{i0}\big]$, which we refer to as the net duration dependence. Second, the change in the composition of the pool of individuals looking for a job between t and 0, $\mathbb{E}_t\big[O_{i0}\big] - \mathbb{E}_0\big[O_{i0}\big]$. This compositional change creates the challenge for empirical identification of net duration dependence.

Information on job offers O_{it} alone is not sufficient to fully understand how duration dependence and compositional changes participate to the reduction in job finding chances. Although, search diaries data allow dissecting the reasons for reduced labor market matching success in a uniquely powerful manner. To see why, let us rewrite equation (3.2) as

$$\begin{aligned}
\mathbb{E}_t\big[O_{it}\big] - \mathbb{E}_0\big[O_{i0}\big] = \; & \mathbb{E}_t\big[(A_{it} - A_{i0}) \cdot \mathbb{P}(o_{ijt} = 1)\big] \\
+ \; & \mathbb{E}_t\big[A_{i0} \cdot \big(\mathbb{P}(o_{ijt} = 1) - \mathbb{P}(o_{ij0} = 1)\big)\big] \\
+ \; & \mathbb{E}_t\big[A_{i0} \cdot \mathbb{P}(o_{ij0} = 1)\big] - \mathbb{E}_0\big[A_{i0} \cdot \mathbb{P}(o_{ij0} = 1)\big],
\end{aligned} \tag{3.3}$$

where $\mathbb{P}(o_{ijt} = 1) = \mathbb{P}(c_{ijt} = 1) \cdot \mathbb{P}(o_{ijt} = 1|c_{ijt} = 1)$. The decline in job offers is now expressed as a sum of products between applications sent by job seekers, A_{it}, and the probability that applications result in a job offer, $\mathbb{P}(o_{ijt} = 1)$. This latter component can again be decomposed into the product of two probabilities characterizing firms' sequential decisions, *i.e.* callback and job offer conversion decisions. Learning about duration dependence hence requires understanding how job seekers' application effort and firms' responses to applications evolve along unemployment.

Going forward, in Section 4, we will discuss an empirical approach to model job seekers' decision, who control the number of job applications they send out per month. Specifically, we study the dynamics of application effort, A_{it}, with respect to elapsed unemployment duration. Since we observe applications for each job seeker repeatedly, we address individual (un-)observed heterogeneity with fixed effects models. Thanks to this powerful approach, we are able to uncover the genuine decline in applications for a fixed set of individuals, *i.e.* those still sending applications in month t, *i.e.* $\mathbb{E}_t\big[A_{it} - A_{i0}\big]$. We can also readily discuss compositional changes between the pool of job seekers looking for a job in month t compared to the initial period, *i.e.* $\mathbb{E}_t\big[A_{i0}\big] - \mathbb{E}_0\big[A_{i0}\big]$. This first analysis provides us with a unique opportunity to discuss the role of unobserved individual heterogeneity in shaping the first stage of the job offer arrival process.

In Section 5, we take firms' perspective and study their responses to applications. Addressing heterogeneity and duration dependence in the context of firms' decisions is more challenging. Positive values of c_{jit} and o_{jit} are not repeatedly observed along unemployment spells, but are rather concentrated at their end. This data specificity prevents us from adopting the same fixed effects approach as for applications.

To study how the probability of calling back an applicant, $\mathbb{P}(c_{jit} = 1)$, changes with elapsed unemployment duration, we rely on the nature of this first decision by the firm. This one is arguably based on job seeker's observed characteristics, but the recruiter may use elapsed unemployment duration to infer the likely unobserved characteristics of the applicant, as models of statistical discrimination would imply (Jarosch and Pilossoph, 2019). To deal with individual heterogeneity, we condition our estimates on the *ex-ante* probability of each application to end up in a positive callback. This application-specific *ex-ante* chance is computed using the information set observed by firms when making callback decisions in the very early stage of the unemployment spell and aims to control for endogeneity of sample selection, in the spirit of a control function approach (Matzkin, 2003). As an alternative approach, we also directly condition on a large set of characteristics that are observed both to firms and us. We then examine the net duration dependence in the callback probability by contrasting the chances of callbacks for applications sent in month t compared to the chances these same applications would have had, when sent in month 0, *i.e.* $\mathbb{E}_t\big[\mathbb{P}(c_{jit} = 1) - \mathbb{P}(c_{ji0} = 1)\big]$. Conversely, we study how the composition of job applications changes by contrasting the *ex-ante* chances of a callback between applications sent in month t and month 0, *i.e.* $\mathbb{E}_t\big[\mathbb{P}(c_{ji0} = 1)\big] - \mathbb{E}_0\big[\mathbb{P}(c_{ji0} = 1)\big]$.

Finally, we analyze the dynamics of the job offer conversion probability, $\mathbb{P}(o_{ait} = 1 | c_{ait} = 1)$. We address heterogeneity through the same control function approach as in the callback phase. Importantly, the decision whether to make a job offer to the interviewee differs conceptually from the callback decision, as the interview provides new information on the suitability of the applicant for the position. Any information already known at the callback stage is therefore likely to play a less important role at the job offer conversion stage.[16]

4. Job seekers: job applications

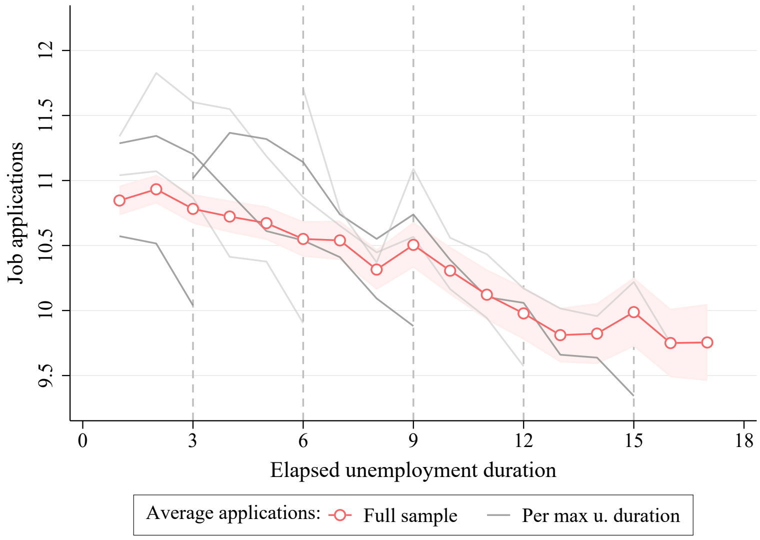
We first study how application effort changes over the course of unemployment. After providing descriptive evidence on job applications dynamics, we present our identification strategy to measure net duration dependence in the number of applications, accounting for individual heterogeneity, before discussing our main results.

4.1 Descriptive analysis

Figure 4.1 describes the change in the average monthly number of job applications A_{it} with respect to elapsed unemployment duration, in red. On average, job seekers send around 11 applications in their first month of unemployment, a number that decreases

[16]Ideally, we would also condition on information obtained during the job interviews, but those remain unobserved to us.

Figure 4.1: Empirical duration dependence in application effort



Note: This figure describes the empirical duration dependence in application effort, measured by the monthly number of job applications A_{it}. 95%-confidence intervals are reported. The graph also depicts the average duration profiles in A_{it} for spells subsamples, defined based on the maximal unemployment duration observed for each spell (1-3, 4-6, 7-9, 10-12, 12-15, $>$ 15 months).

down to 9.75 after fifteen months spent unemployed. These *prima facie* evidence suggest that the number of applications sent by job seekers is slightly decreasing with respect to elapsed unemployment duration. However, since applications are observed on a rapidly changing pool of job seekers, this pattern encompasses both dynamic selection and the net effect of duration. To visualize the role played by individual heterogeneity in the raw-data pattern, we plot the same relationship for different subsamples, defined according to the (individual) maximal unemployment duration observed in the sample.[17] Corresponding duration profiles are also reported in Figure 4.1, as gray lines.

Two key facts emerge from this graphical subsample analysis, in line with previous findings in the literature (Faberman and Kudlyak, 2019; Fluchtmann et al., 2021). First, there seems to exist differences in levels between individuals who remain unemployed for a short and long period of time: job seekers who are observed at later stages of unemployment tend to write more applications, at any duration. Second, when accounting for differences in levels, the net duration profiles computed on the various subsamples appear to be steeper than their counterpart based on the full sample, and essentially parallel.[18] Taken altogether, these descriptive patterns suggest that the monthly number of applications sent out by unemployed declines more strongly within individuals than across unemployed, indicating that the net effect of duration on application effort is potentially stronger that what raw data suggest.

[17] The subsamples are defined according to the following within-spells maximal unemployment duration intervals: 1-3, 4-6, 7-9, 10-12, 12-15 and $>$ 15.

[18] Faberman and Kudlyak (2019) find a similar pattern for applications in the context of an online job search platform.

4.2 Empirical approach

We develop an empirical strategy to identify the net effect of duration on application effort and to assess how individual heterogeneity contributes to its empirical decline. Exploiting the longitudinal aspect of our data, we follow a within-estimation approach with fixed effects at the individual level. Our baseline specification writes as

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

where i stands for individuals and t for elapsed unemployment duration. The function $f^A(t;\phi^A)$ corresponds to the parametric estimate of the net effect of duration on the monthly number of applications. This effect is estimated net of individual observed characteristics X_{it} and local labor market conditions (in occupational sector m and calendar quarter k).[19] Moreover, it is obtained conditional on individual fixed effects α_i. ε_{it} represents an idiosyncratic error term.

The main strength of our specification lies in the within-individual identification of the net duration effect. The set of individual fixed effects α_i controls for any form of (time-constant) observed and unobserved individual heterogeneity. This rules out spurious duration dependence generated by dynamic selection based on hard-to-quantify individual characteristics, such as job seekers productivity, labor market history, professional network and intrinsic motivation. This approach has already been applied for application effort by recent studies (Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021; Fluchtmann et al., 2021) and delivers reliable estimates of net duration dependence when the dependent variable is not directly related to exits from the observed sample (Zuchuat, 2023a).

Our approach for applications also resembles Mueller and Spinnewijn (2023), who discuss the role of heterogeneity in shaping long-term unemployment on the basis of observed pre-unemployment characteristics of individuals. We can go, however, beyond their setting by focusing on applications, which are repeated within individuals. This provides us with a means to discuss the role of observed and unobserved heterogeneity at the application phase, while they assume unobserved heterogeneity to be orthogonal to observed heterogeneity.

4.3 Results

4.3.1 Main results

We report step-by-step estimates of equation (4.1) using OLS in Table 4.1, where the net effect of duration is specified linearly, *i.e.* $f^A(t;\phi^A) = \phi^A t$. Standard errors are clustered at the individual level and reported in parentheses. Coefficients in relative terms are reported in squared brackets. Column (1) reports estimates from a bivariate model, where

[19] As a matter of simplification, indices m and k are omitted for other elements than δ_{mk} in the regression equation.

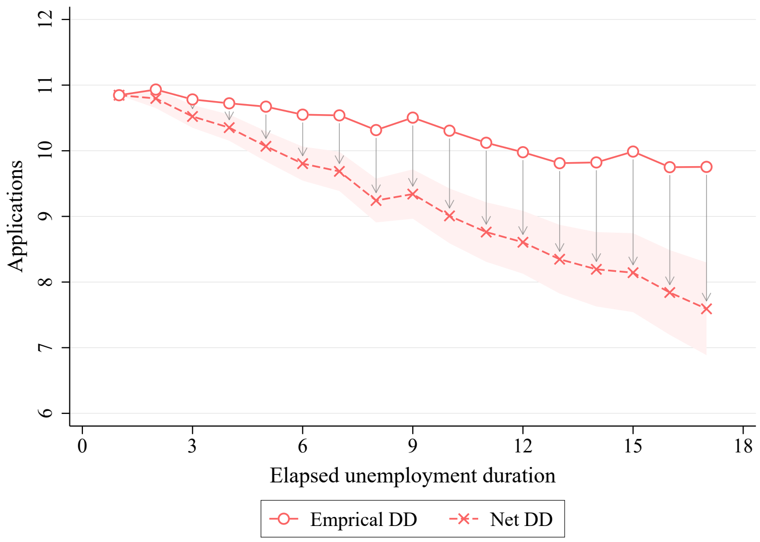
Table 4.1: Duration dependence in application effort, linear specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable : application effort A_{it}						
Elapsed unemployment duration	-0.078***	-0.053***	-0.035***	-0.040***	-0.214***	-0.217***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.010)	(0.021)
	[-0.718%]	[-0.487%]	[-0.326%]	[-0.367%]	[-1.976%]	[-2.003%]
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
Mean outcome 1^{st} month	10.846	10.846	10.846	10.846	10.846	10.846
adj.-R^2	0.005	0.038	0.179	0.192	0.486	0.498
N. observations	58755	58755	58755	58755	58755	58755

Note: This table reports empirical estimates of equation (4.1) using OLS, where the parametric duration function $f^A(t; \phi^A)$ is specified linearly. Each column sequentially adds a set of controls or FE. Errors are clustered at the individual level and reported in parentheses. Coefficients in relative terms (standardized with respect to the average in the first month of unemployment) are indicated in squared brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

application effort is regressed on elapsed unemployment duration only. The estimated duration coefficient is negative and strongly significant, just like descriptive evidence suggest. Adding sequentially individual, policy and local labor market conditions controls in columns (2) to (4) tends to attenuate the duration parameter value, which remains negative and strongly significant though. In column (5), we regress the monthly number of applications on elapsed unemployment duration, including individual fixed effects only. In contrast to controlling for observed characteristics, this leads to a dramatic increase in the estimated duration parameter, in absolute terms. Further adding individual controls in column (6) virtually does not affect the estimated value of the interest coefficient: accord-

Figure 4.2: Duration dependence in application effort, saturated specification



Note: This figure reports empirical estimates of equation (4.1), where the parametric duration function $f^A(t; \phi^A)$ is specified in a saturated manner. Estimated are obtained based on the full specification, including controls and individual fixed effects. 95%-confidence intervals based on standard errors clustered at the individual level are reported. The average empirical duration dependence pattern in A_{it} is also reported, as a solid line.

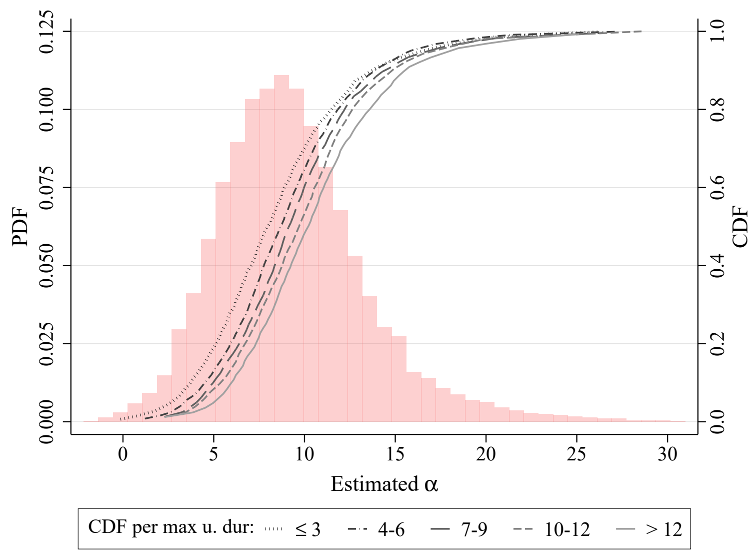
ing to our full specification, one additional month of unemployment leads to a decrease of -0.22 applications per month on average, or about one application less after 5 months.

We assess non-linearity in the net duration dependence in application effort by estimating our model with a saturated specification of $f^A(t;\phi^A)$, *i.e.* one dummy per month of elapsed unemployment. Corresponding results are reported graphically in Figure 4.2. They show that the decrease in the number of application due to elapsed unemployment duration is essentially linear.

The above results emphasize the crucial role played by individual unobserved heterogeneity and dynamic selection in the decline of application effort with respect to elapsed unemployment. At the application phase, dynamic selection is positive: job seekers who remain unemployed for a longer period of time send systematically more applications, at any duration. Heterogeneity hence tends to attenuate the net effect of duration on application effort in the raw data; once it is accounted for, applications' duration profile becomes much steeper. To further explore this point, we plot the distribution of estimated $\hat{\alpha}_i$ in Figure 4.3. This graph shows that the distribution of $\hat{\alpha}_i$ shifts rightwards as we consider individuals who leave unemployment after 12 months or longer, compared to the fixed effect of individuals who leave in the first three months, hence confirming positive dynamic selection with respect to application effort.[20]

To better understand who hide behind those longer-term high-application-effort individuals, we regress estimated $\hat{\alpha}_i$ on observed individual characteristics. Partial correlation

Figure 4.3: Unobserved heterogeneity in application effort, empirical distribution



Note: This figure plots the distribution of the estimated α_i in equation (4.1). The global empirical density is represented by the histogram in red. The cumulative distributions for different subsamples, defined based on the maximal unemployment duration observed per spell, are reported as gray lines.

[20] Positive dynamic selection at the application phase can also be seen in Figure B1, which plots the average estimated $\hat{\alpha}_i$ in Figure 4.3 for all individuals observed at duration t.

coefficients are reported in Table B1 in the Appendix. They reveal that job seekers who provide more application effort are more likely to be women, younger, not to be native and not to hold a tertiary education degree. They also tend to have higher past labor earnings and are less likely to have experienced unemployment previously. The table also reveals the existence of substantial variation in job application effort according to occupational sectors and local labor market institutions (canton, PES or caseworkers, depending on the specification).

4.3.2 Robustness

We proceed to several robustness checks, to assess the validity of our baseline findings of a negative net effect of elapsed unemployment duration on application effort.

First, we consider an alternative model specification. Given the count data nature of the dependent variable, we estimate a Poisson-pseudo maximum likelihood model with fixed effects. Corresponding results are reported in Table B2 in the Appendix, and are very close to our baseline OLS estimates, both qualitatively and quantitatively. Specifically, accounting for unobserved heterogeneity through fixed effects consistently leads to a marked steepening in the estimated effect of duration (from a semi-elasticity of -0.9% to -2.1%).

Second, we consider alternative measures of application effort. In Switzerland, job search effort is monitored by caseworkers based on job search diaries and search requirements. The latter are defined in terms of minimal number of job applications to be sent per month. As a result, it is common to observe some bunching around the standard minimal search requirements values, $\underline{A} = 8, 10$.[21] Also, some applications might not directly result from job seekers' private search activity, but rather from intervention by caseworkers. For instance, caseworkers may refer job seekers to apply to jobs (Zuchuat, 2023b). For that reasons, it might be argued that the total number of applications sent per month, A_{it}, does not validly measure application effort. As a robustness check, we re-estimate our model using alternative search effort measures as dependent variables: excess application effort $\bar{A}_{it} = \max(0, A_{it} - \underline{A})$, above the search requirements thresholds $\underline{A} = 8, 10$, and the monthly number of applications which do not result from caseworker referrals. Corresponding estimates are reported in Table B3 and are very much in line with our baseline findings.

Third, we discuss the existence of a potential within-estimation duration bias in our baseline estimates. As shown in Zuchuat (2023a), using fixed effects models to estimate duration dependence relationships with data subject to attrition might entail a strong bias in the estimated duration parameters. This is notably the case if the dependent variable is closely related to the attrition mechanism, as this generates a mechanical and undesirable correlation between the within-time regressor and the within-error term. Such situation shall not occur in our context, given that applications are observed repeatedly within unemploy-

[21] This point can be observed in Figure B3, where we plot the empirical distribution of application effort. Modes are typically observed at $A_{it} = 8$ and 10.

ment spells, and do not directly translate into exits from the observation sample. As an additional check, we re-estimate our baseline specification on a subsample that does not include the last observation of each non-right-censored spell, *i.e.* on individual-monthly observations that are not contemporaneous to an unemployment exit. Corresponding estimation results are reported in Table B4 and turn out to be highly similar to our baseline estimates.

All in all, this first empirical section emphasizes the existence of a sizeable net effect of duration on job application effort. Such pattern might arise from various reasons, from stock-flow job postings (Salop, 1973), to discouragement (**?**), through changes in application strategy (Galenianos and Kircher (2009); Wright et al. (2021); Lehmann (2023)). Our reduced-from analysis does not enable us to determine directly which exact mechanism is at play in our context. Nevertheless, studying how firms react to applications over time might help us to pine down which explanation is susceptible to explain the observed dynamics in job application effort.

5. Firms' responses: callbacks and job offers

We now study how firms' responses to job applications change over the course of unemployment, exploiting our data at the application level. We first present descriptive evidence about the dynamics of the callback and job offer conversion probabilities, before turning to our empirical approach to disentangle the net effect of duration from dynamic selection.

5.1 Descriptive analysis

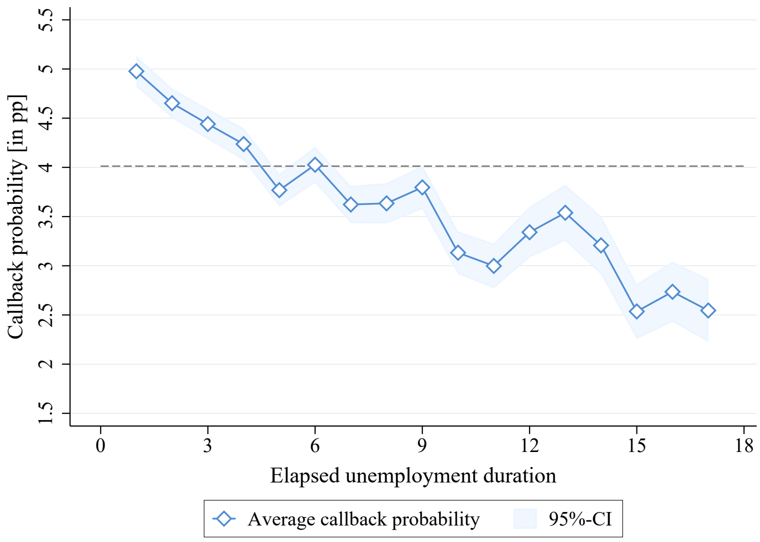
Our conceptual framework formalizes firm's recruitment process as two sequential decisions. First, the firm chooses whether to call back an applicant for a job interview; second, conditional on a callback, it decides whether to make a job offer to the interviewee. The empirical relationships between those two decisions and elapsed unemployment duration are depicted in Figure 5.1.

Panel A represents the average (application-level) callback probability for each month of elapsed unemployment, computed on all applications observed in the sample. The graph emphasizes a substantial decrease in the chances of getting a positive reply from firms at the first stage of the recruitment process, from 5% in the first month to 2.5% after fifteen months. This pattern echoes results from audit studies, which finds evidence of negative duration dependence in the callback probability (Oberholzer-Gee, 2008; Kroft et al., 2013; Eriksson and Rooth, 2014; Nüß, 2018). Unlike experimental audit studies, we observe this pattern in an empirical setup; just like for application effort, it might capture some form of dynamic selection. This empirical aspect of our data represents a valuable addition to audit studies, as it enables us to examine the role played by individual heterogeneity in the decreasing chances of going through the first stage of firms' recruitment process.

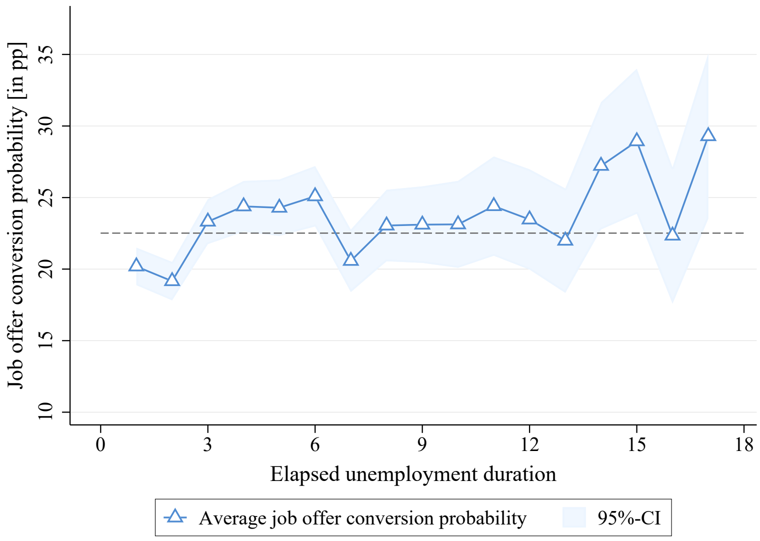
In panel B, we report descriptive evidence of duration dependence in the next step of the

Figure 5.1: Empirical duration dependence in firms' responses

(A) Callback probability



(B) Job offer conversion probability



Note: These graphs depict the empirical duration patterns in the callback probability (panel A) and in the job offer conversion probability (panel B). Panel A is based on all applications, while panel B is based exclusively on applications that previously led to a job interview. Application-level observations are weighted according to the inverse of the number of applications sent by individual i in month t, so as to put equal weight on all individual-monthly units.

hiring process. The graph plots the average monthly (application-level) probability with which callbacks are converted into job offers, for applications that previously led to job interviews. In contrast to callback decision's dynamics, the empirical duration profile of the job offer conversion probability is non-negative, and even slightly increasing. In early months of unemployment, 20% of callbacks are converted into job offers. From month three onwards, the job offer conversion probability stabilizes around 25%, before reaching 30% after fifteen months. In spite of this slight positive duration dependence in the job offer conversion probability, we still observe a strong negative relationship between the application-level probability of getting a job offer (out of sending an application) and elapsed unemployment duration, as shown in Figure C1 in the Appendix.

Taken altogether, these *prima facie* evidence suggest that elapsed unemployment duration enters firms' decision process negatively mostly at the callback stage of the screening process. In contrast, duration does not seem to reduce unemployed chances of obtaining a job offer, once interviews have taken place. These evidence are in line with previous findings from experimental studies, but are novel in important dimensions. Given that our data are not limited to the firm's first response by design, we are able to discuss the dynamics of firms' behavior beyond the mere job interviews. Moreover, contrary to audit studies, which are based on standardized fake applications, our results are obtained in a real-life setup. Consequently, they encompass both the net effect of duration and dynamic selection, which we seek to disentangle in the following.

5.2 Empirical approach

Distinguishing the role played by individual heterogeneity and dynamic selection from the net effect of duration for firms' responses requires an alternative identification strategy. Applying the same fixed effects approach as for application effort would indeed be misleading. Since the dependent variables, either callbacks or job interviews, represent direct proxies for unemployment exits and sample attrition, the fixed effects estimator of duration parameters is subject to a within-estimation duration bias (Zuchuat, 2023a). Intuitively, as positive values of c_{ijt} and o_{ijt} tend to be concentrated at the end of the spells (see Figure C2 in the Appendix), positive realizations of the within-error term are more likely to occur for positive values of the within-time regressor. Consequently, using the fixed effects approach for this type of outcomes entails a sizeable positive mechanical correlation between the error term and time regressor, which translates into a large bias in the estimated net duration parameters.

Our alternative identification strategy to measure the net duration profiles of firm's decisions is based on characteristics of individuals and job applications which are known by the firm prior to its callback decision. Inspired by Mueller and Spinnewijn (2023), we exploit our detailed application-level data to condition on the same set of information a firm has on an applicant, when it receives her application and decides whether to call her back for an interview. Specifically, we use our rich data to construct an index capturing the *ex-ante* 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 callback and job offer conversion probabilities to control for dynamic selection when measuring net duration dependence in firms' responses, in the spirit of a control function approach (Matzkin, 2003).

Our index is based on all those variables that capture the information that are typically contained in the job seeker's CV and in the application itself. 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 labor market history, retrieved from the social security registers. Further, we consider information on the caseworker or PES office to which the job seeker is affiliated. As application characteristics, we consider the application channel (*i.e.* in person, by phone, written), an indicator for whether the application results from a caseworker referral, the within-month rank of the application and a measure of search intensity (the estimated individual application fixed effect $\hat{\alpha}_i$).

To construct the application-specific *ex-ante* propensity of success, we start by using the first month in which individual i's job search behavior is documented in the data. We denote this month τ_i. For the callback stage, this individual-specific reference month corresponds to the first month when individual i starts recording applications, *i.e.* $\tau_i = \tau_i^A$. For the job offer conversion stage, it is equal to the first month when job seeker i records an interview, as job offers are conditional on having been called back, *i.e.* $\tau_i = \tau_i^C$. For each of the two stages, we estimate a binary outcome model for the application-level probability of obtaining a callback or a job offer (conditional on a callback) in the corresponding reference month. We model the latent propensities $\tilde{c}_{ij\tau_i}$ and $\tilde{o}_{ij\tau_i}$ in month τ_i as

$$\tilde{c}_{ij\tau_i} = \vartheta_0 + X^1_{i\tau_i}\vartheta_1 + X^2_{ij\tau_i}\vartheta_2 + \delta^c_{mk} - \nu_{ij\tau_i} \tag{5.1a}$$

$$\tilde{o}_{ij\tau_i} = \varphi_0 + X^1_{i\tau_i}\varphi_1 + X^2_{ij\tau_i}\varphi_2 + \delta^o_{mk} - \eta_{ij\tau_i} \tag{5.1b}$$

where $\tau_i = \tau_i^A$ in equation (5.1a) and $\tau_i = \tau_i^C$ in equation (5.1b). The row vector $X^1_{i\tau_i}$ contains the individual-level characteristics, the row vector $X^2_{ij\tau_i}$ the application-level characteristics, δ^c_{mk} and δ^o_{mk} are fixed effects capturing the conditions in local labor market m in calendar quarter k, $\nu_{ij\tau_i}$ and $\eta_{ij\tau_i}$ are idiosyncratic error terms. The conditional *ex-ante* probabilities of obtaining a callback and a job offer (conditional on a callback) in month τ_i are given by

$$\gamma^c(X_{ji\tau_i}) = \mathbb{P}(c_{ij\tau_i} = 1|X_{ij\tau_i}, a_{ij\tau_i} = 1) = \mathbb{P}(\vartheta_0 + X^1_{i\tau_i}\vartheta_1 + X^2_{ij\tau_i}\vartheta_2 + \delta^c_{mk} > \nu_{ij\tau_i}) \tag{5.2a}$$

$$\gamma^o(X_{ij\tau_i}) = \mathbb{P}(o_{ij\tau_i} = 1|X_{ij\tau_i}, c_{ij\tau_i} = 1) = \mathbb{P}(\varphi_0 + X^1_{i\tau_i}\varphi_1 + X^2_{ij\tau_i}\varphi_2 + \delta^o_{mk} > \eta_{ij\tau_i}) \tag{5.2b}$$

where $X_{ij\tau_i} = (X^1_{i\tau_i}, X^2_{ij\tau_i}, \delta^y_{mk})$, with $y = c, o$. Again, $\tau_i = \tau_i^A$ in the first equation and $\tau_i = \tau_i^C$ in the second.

We estimate equations (5.2a) and (5.2b) using logit models, respectively on applications in the reference month $t = \tau_i^A$, and on callbacks in the reference month $t = \tau_i^C$. We retrieve parameters estimates $\hat{\vartheta}' = (\widehat{\vartheta}_0\ \widehat{\vartheta}_1\ \widehat{\vartheta}_2)$ and $\widehat{\varphi}' = (\widehat{\varphi}_0\ \widehat{\varphi}_1\ \widehat{\varphi}_2)$ and predict the conditional *ex-ante* probabilities for all subsequent months $t \geq \tau_i$, that is to say the probability of a callback for all applications in $t \geq \tau_i^A$, and the probability of a job offer conversion for all callbacks in $t \geq \tau_i^C$. The resulting predicted probabilities, $\widehat{\gamma}^c_{ijt} = \widehat{\gamma}^c(X_{ijt})$ and $\widehat{\gamma}^o_{ijt} = \widehat{\gamma}^o(X_{ijt})$, capture the propensity with which an application sent out in month t

receives a positive response from the firm, if the firm's behavior was kept as it was early in the unemployment spell, in month τ_i.

Finally, we estimate the net duration dependence in firms' responses using the logarithm of the *ex-ante* probabilities to control for dynamic sorting based on observables. Specifically, we estimate the following two binary outcome models using respectively all applications in months $t \geq \tau_i^A$ and all callbacks in months $t \geq \tau_i^C$:

$$\mathbb{P}(c_{ijt} = 1 | \, \widehat{\gamma}^c_{ijt}, a_{ij\tau_i} = 1) = \mathbb{P}\Big(\alpha^c + f^c(t; \phi^c) + \beta^c \ln(\widehat{\gamma}^c_{ijt}) > \varepsilon^c_{ijt}\Big) \tag{5.3a}$$

$$\mathbb{P}(o_{ijt} = 1 | \, \widehat{\gamma}^o_{ijt}, c_{ij\tau_i} = 1) = \mathbb{P}\Big(\alpha^o + f^o(t; \phi^o) + \beta^o \ln(\widehat{\gamma}^o_{ijt}) > \varepsilon^o_{ijt}\Big) \tag{5.3b}$$

where $\beta^c \ln(\widehat{\gamma}^c_{ijt})$ and $\beta^o \ln(\widehat{\gamma}^o_{ijt})$ control for dynamic selection, whereas $f^c(t; \phi^c)$ and $f^o(t; \phi^o)$ measure the net duration dependence in the callback and job offer conversion probabilities.[22]

5.3 Results

5.3.1 Main results

We report logit estimates for the *ex-ante* callback and job offer conversion probabilities defined in equations (5.2a) and (5.2b) in Table C1, in the Appendix. Observed characteristics are found to predict the *ex-ante* callback probability significantly, with older job seekers and those writing many applications receiving lower callbacks, while those with high education, and a high wage receiving callbacks with higher probability. Applications in person, and those referred by caseworkers tend to receive more callbacks. Job offers (conditional on callbacks) are not significantly predicted by age or residence permit, but job seekers with higher education and high previous wage are found to stand a lower chance of receiving a job offer. Overall *ex-ante* callbacks are predicted with a higher pseudo-R^2 (of around 11 percent) than *ex-ante* job offer conversions (pseudo-R^2 is 6 percent).

We now present evidence on the relationships between the *ex-ante* chances of positive responses by firms and elapsed unemployment duration in Figure 5.2. This provides insight on the role of heterogeneity and how the pool of applications evolves dynamically.

Figure 5.2A shows evidence for callbacks. The left graph depicts the empirical average callback probabilities and average *ex-ante* callback probabilities for all applications, in months $t \geq \tau_i^A$. As previously emphasized, the observed chances of being interviewed decrease strongly over the course unemployment, from around 5 percent to 2.5 percent (solid line). The *ex-ante* prediction of a positive callback (dashed line) also exhibits a substantial decline with respect to elapsed unemployment duration, from around 5 percent to less than 4 percent. This suggests that a sizeable part of the reduction in the callback chances is related to the quality of job applications. However, duration itself still seems to

[22] Alternatively, we directly control for observables X_{ijt} in equations (5.3a) and (5.3b) instead of controlling for the logarithms of the *ex-ante* chances $\widehat{\gamma}^c_{ijt}$ and $\widehat{\gamma}^o_{ijt}$. These alternative results are reported along our *ex-ante* chances specification in the next subsection.

directly affect firms' callback decisions, as suggested by the steeper profile in the empirical callback probability compared to its *ex-ante* counterpart.

The right graph of Figure 5.2A further characterizes the dynamic selection process in the callback phase. It provides additional information on the distribution of the *ex-ante* chances of a callback for the pool of job applications sent out at each duration of the unemployment spell. The quality of the pool of job applications deteriorates substantially, with the best applications (95$^{\text{th}}$ percentile) having an almost 15 percent callback chance in the first month, and around 10.5 percent after fifteen months, whereas the lowest quality applications have very low callback chances throughout the spell (approximately 1 percent). This suggests that high-quality applications tend to disappear from the applications pool, as job seekers who write those get invited to job interviews, receive job offers and exit unemployment. Controlling for heterogeneity in the quality of applications hence seems to be crucial, if we seek to have a precise idea on whether there truly exists net duration dependence in callback decisions.

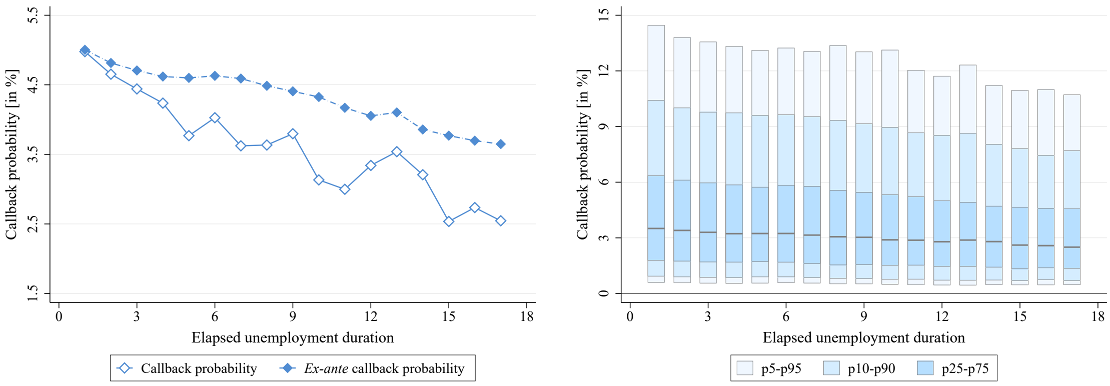
Figure 5.2B depicts a completely different picture for the job offer conversion stage. As previously emphasized, the observed duration profile in the job offer conversion probability is slightly increasing over the whole duration of the unemployment spell. It also appears to be essentially flat for intermediary durations: from month three to thirteen, the average probability that an interview converts into a job offer amounts to approximately 24 percent, regardless of when the application that led to the interview takes place. This is also the case for the *ex-ante* chances of the interview to be transformed into a job offer, which are globally constant over time. Importantly, the *ex-ante* probability of a job interview to convert into a job offer is statistically related to job seekers' and applications' characteristics. However, the distinguishing difference between callbacks and job offer conversions is that firms do not reduce the chances of offering a job to an interviewee whose application arrives late in the spell. If anything, the probability of obtaining a job offer after being interviewed is somewhat higher for the long-term unemployed than for the short-term unemployed.

The limited role of observable characteristics at this stage of the recruitment process is also visible on the right graph of Figure 5.2B, which presents additional evidence on the distribution of the *ex-ante* job offer conversion chances, for each month of unemployment. The graph shows that the *ex-ante* quality of interviewees, as predicted from their observed characteristics, remains constant over the spell of unemployment. The median chances of securing the job conditional on an interview are around 21 percent, with both substantially higher and lower chances of getting a job offer. Unlike callbacks, the *ex-ante* quality of interviewees measured by observable characteristics remains constant, regardless of the time when the interview occurs. This second decision by the firm is thus likely to be based on information that are unobserved to us, or that are idiosyncratic to each worker-firm match. In the end, firms seem to make limited use of elapsed unemployment duration to infer applicant's quality when deciding whether to make her a job offer.

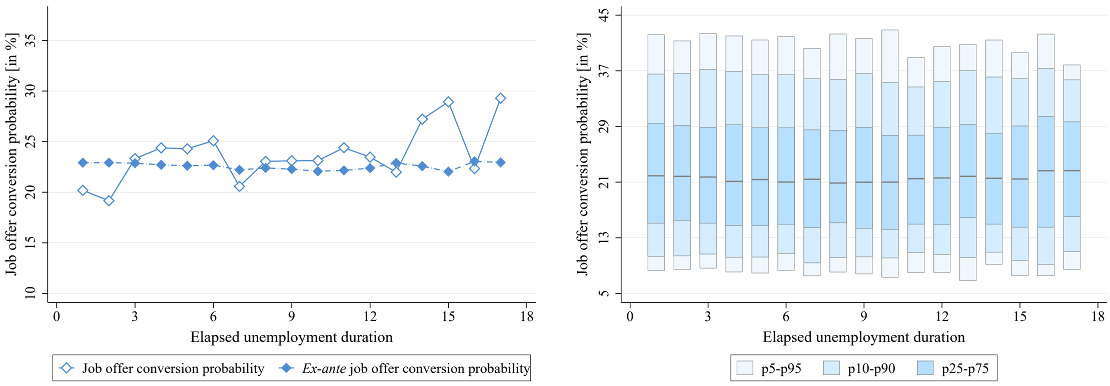
We next provide estimates of the net effects of duration on the probability of a callback

Figure 5.2: Job seekers' *ex-ante* chances and elapsed unemployment duration

(A) Callback probability



(B) Job offer conversion probability



Note: This figure reports evidence on the relationships between *ex-ante* applications success chances $\widehat{\gamma}^{c}_{ait}$, $\widehat{\gamma}^{o}_{ait}$ and elapsed unemployment duration. Panel A depicts descriptive evidence for the callback probability, while panel B focuses on the job offer conversion probability. For each panel, the left graph represents the average empirical duration profiles of the probability of a positive response by firms (solid line) and of its *ex-ante* counterpart (dashed line). The right graph depicts summary statistics on the distribution of the *ex-ante* chances of a callback and job offer conversion, for each month of elapsed unemployment.

or a job offer conversion, formalized in equations (5.3a) and (5.3b). Table 5.1 presents estimates for a linear specification of the duration effects. Columns (1)-(3) report results for callbacks, while columns (4)-(6) focus on job offer conversions.

Column (1) shows that the probability of a callback decreases by approximately 0.15 percentage points per additional month spent unemployed, in the raw data. Directly, controlling for individual and applications characteristics, policy controls and local labor market conditions dampens the decline in the callback probability to less than 0.1 percentage points per additional month in unemployment, as shown in column (2). Alternatively, controlling for the logarithm of the *ex-ante* callback chances of job applications in column (3) delivers a similar role for prolonged unemployment duration, a reduction of 0.1 percentage point for each additional month spent unemployed.

As the callback probability declines in a somewhat non-linear fashion with elapsed unemployment duration, we probe results from a model that leaves duration dependence of the

Table 5.1: Duration dependence in firms' responses, linear specification

	Callback probability			Job offer conversion probability		
	(1)	(2)	(3)	(4)	(5)	(6)
Elapsed unemp. dur.	-0.155***	-0.097***	-0.096***	0.350***	0.429***	0.380***
	(0.015)	(0.015)	(0.015)	(0.099)	(0.097)	(0.094)
	[-3.117%]	[-1.945%]	[-1.921%]	[1.736%]	[2.123%]	[1.883%]
ln(Ex-ante chance)			3.364***			18.805***
			(0.094)			(0.863)
Individual controls	No	Yes	No	No	Yes	No
Policy controls	No	Yes	No	No	Yes	No
LLMC	No	Yes	No	No	Yes	No
Control for ex-ante pr.	No	No	Yes	No	No	Yes
Pseudo R^2	0.003	0.094	0.075	0.001	0.050	0.044
N. observations	600323	600323	600323	22422	22422	22422

Note: This table reports estimates of net duration dependence in the callback and job offer conversion probabilities. Columns (1)-(3) report estimates for callbacks and correspond to equation (5.3a). Columns (4)-(6) focus on job offer conversions and correspond to equation (5.3b). Application-level observations are weighted by the inverse of the monthly number of applications sent out by individual i in month t, so as to put equal weight on all monthly-individual observations. Coefficients correspond to average marginal effects and are reported in percentage points. Errors are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

callback probability fully unrestricted, in Figure 5.3A. Recall that the observed callback probability decreases from 5 percent to 2.5 percent. The callback probability adjusted for dynamic selection, which we obtain from a model like column (3) of Table 5.1, but where the $f^c(t; \phi^c)$ function is specified in a saturated manner, is substantially higher: it decreases from 5 percent in the first month to 3.5 percent after fifteen months.

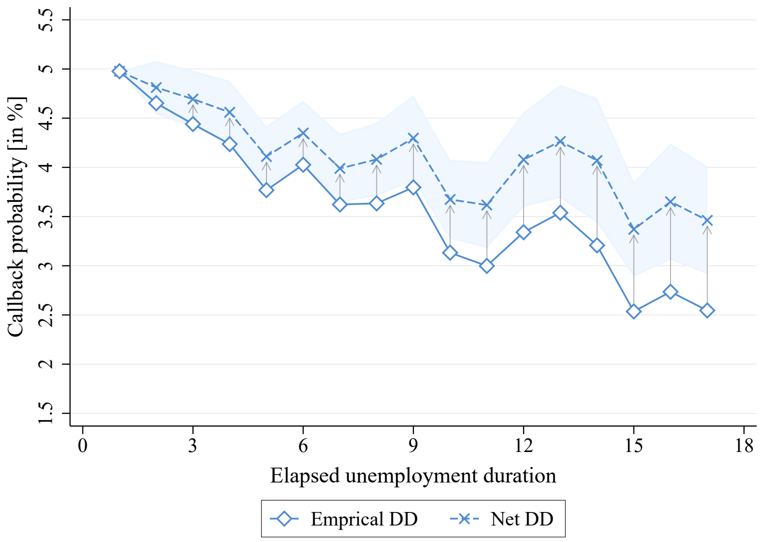
After accounting for individual heterogeneity, the decline in callback chances for long-term unemployed appears real, and might be responsible for part of the decrease in job finding chances over time. Quantitatively, the net decline in the callback probability amounts to about two thirds of the observed decline. Our estimates are surprisingly similar to Kroft et al. (2013), who find a 3.7 percentage points decline for 36 months of unemployment, equivalent to a monthly decrease of 0.1 percentage points in callback chances.

Turning to the results for the conversion of interviews into job offers, we find significantly positive duration dependence in the raw data, consistently with our descriptive evidence. Column (4) of Table 5.1 shows that the job offer conversion probability increases by 0.35 percentage points for each additional month spent unemployed. Directly controlling for observed heterogeneity slightly increases the duration dependence parameter in column (5), whereas controlling for *ex-ante* job offer conversion chances does not affect it in column (6). Again, we probe for non-linear duration dependence patterns in a version of the model used in column (6) of Table 5.1, where duration dependence is left unrestricted. Results in Figure 5.3B show graphically that observed characteristics do not affect estimates of the job offer conversion duration profile at all, which remains positive and aligned on the pattern obtained on the raw data.

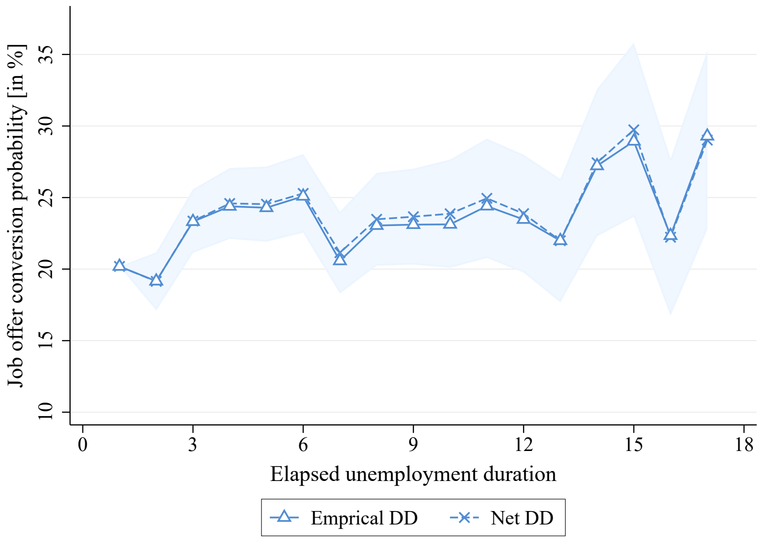
Our empirical analyses suggest that the net effect of duration on job offer conversion is positive, meaning that this second decision by the firm does not exacerbate the decline in job finding chances. Intuitively, positive duration dependence at the job offer conversion

Figure 5.3: Net duration dependence in firms' responses, saturated specification

(A) Callback probability



(B) Job offer conversion probability



Note: This figure depicts estimates of equations (5.3a) and (5.3b), where the duration functions $f^c(t; \phi^c)$ and $f^o(t; \phi^o)$ are fully saturated. Panel A relates to the callback probability, while panel B focuses on the job offer conversion probability. The solid lines depict empirical average duration profiles computed on the raw data, while the dashed lines represent the corrected average duration profiles that control for the *ex-ante* chances of job seekers to obtain a callback or a job offer conversion. 90% confidence intervals for the corrected duration profiles based on clustered standard errors at the individual level are reported.

stage might arise from the reduction in applicants' heterogeneity in the callback phase: as interviewees tend to become more homogeneous over time, their chance of obtaining a job offer after being interviewed might be increasing with elapsed unemployment duration. Alternatively, this positive duration profile might be due to learning on the job seeker's or employer's side. For instance, job seekers' learning may occur because they participate in several interviews, and learn about the recruiting process from previous failed interviews. However, Figure C3 in the Appendix tends to invalidate this mechanism. The duration profile of job offer conversion for job seekers who attempt their first interview does not differ much from its counterpart for follow-up interviews, with different employers on different jobs. In both cases, the conversion probabilities are higher for interviews undertaken at a later stage of the unemployment spell.

When contrasting results for the callback and job offer conversion stages, it appears that the two differ tremendously. At the callback stage, firms pick job applications from the available pool of applicants, and this pool depletes leaving those applicants that are less likely and able to receive callbacks. This process hence affects the composition of the pool of job seekers strongly. The situation differs for job offer conversion: firms make offers to interviewees, but the chances of a job offer, which are still related to individual characteristics, do not decline with elapsed duration of unemployment, but rather increase. These results highlight two interesting insights: the duration of unemployment negatively affects the callback stage, as emphasized by audit studies (Oberholzer-Gee, 2008; Kroft et al., 2013; Eriksson and Rooth, 2014; Nüß, 2018), but does not reduce job seekers' chances in the job offer conversion phase (Jarosch and Pilossoph, 2019). Job seekers lose out on some interviews through duration dependence in callbacks, but long-term unemployed do not seem to be further discriminated when firms make their job offer decisions. All told, our results are coherent with a statistical learning view of the labor market, a view we explore and outline more fully in the next section of the paper.

5.3.2 Robustness

Our identification of the net effect of duration on firms' responses is based on a conditional independence assumption: we suppose we observe all relevant information to the recruiting firm, at the moment when it evaluates applications sent by job seekers. This assumption is reasonably met for callbacks, as we observe most information that is relevant for this decision in our data. Our approach is thus similar in essence to Mueller and Spinnewijn (2023), both being based on rich administrative data sources to proxy job seekers' chances of obtaining positive responses from firms.

In the previous section, we consistently show that our set of conditioning variables mostly play a role in the first phase of firms' screening process, which is typically based on CV information. To further assess the relevance and predictability of our conditioning variables, we re-estimate equations (5.3a) and (5.3b) using additional controls from our administrative data, which are supposedly unobserved by firms when they first screen applications. Those additional variables consist in information collected by the caseworker at the occasion of her first meeting with the job seeker at the PES office (job seeker's employability, job seeker's degree of mobility) and additional information that is not disclosed to the firm by the job seeker when applying (experience of sick days during the unemployment spell). Given that these variables are not directly observed by firms when they screen applications, we expect their role to be minor when measuring net duration dependence in the callback phase. In contrast, their role is possibly greater when estimating the net duration profile in the job offer conversion probability, as more information on the job seeker is revealed to the firm through the interview.

Duration dependence estimates for this extended model together with our baseline results are reported in Table 5.2. As expected, adding these controls leads to a more marked change in the pseudo-R^2 for the job offer conversion stage (+20%) compared to the callback stage (+5%). This can also be seen through the parameter associated with the *ex-ante* application success probability, which increases more markedly for job offer conversion compared to callbacks (in columns 3 and 4). Consequently, the change in the estimated net duration effect is virtually zero for callbacks, while it is slightly larger for job offer conversion (in relative terms). These results support the idea that our baseline set of conditioning variables capture most individual heterogeneity that is relevant at the callback stage, and that we truly capture the net duration profile of callback chances. They also point towards the fact that additional information is revealed during the job interview, and that those might affect firm's decisions whether to make a job offer to the interviewee. Even though such information remains unobserved in our context, it should have a limited impact on the net duration profile of job offer conversion we estimate.

Table 5.2: Duration dependence in firms' responses, control for non-CV information

	(1)	(2)	(3)	(4)
A. Callback probability				
Elapsed unemp. duration	-0.097***	-0.094***	-0.096***	-0.092***
	(0.015)	(0.015)	(0.015)	(0.014)
ln(Ex-ante chance)			3.365***	3.372***
			(0.094)	(0.092)
Individual controls	Yes	Yes	No	No
Policy controls	Yes	Yes	No	No
LLMC	Yes	Yes	No	No
Control for ex-ante pr.	No	No	Yes	Yes
Info not on CV	No	Yes	No	Yes
Pseudo R^2	0.094	0.099	0.075	0.079
N. observations	600323	600323	600323	600323
B. Job offer conversion probability				
Elapsed unemp. duration	0.430***	0.407***	0.381***	0.362***
	(0.097)	(0.097)	(0.094)	(0.094)
ln(Ex-ante chance)			18.829***	19.637***
			(0.868)	(0.810)
Individual controls	Yes	Yes	No	No
Policy controls	Yes	Yes	No	No
LLMC	Yes	Yes	No	No
Control for ex-ante pr.	No	No	Yes	Yes
Info not on CV	No	Yes	No	Yes
Pseudo R^2	0.050	0.060	0.044	0.054
N. observations	22422	22422	22422	22422

Note: This table reports estimates of net duration dependence in the callback and job offer conversion probabilities, for our baseline set of conditioning variables (columns 1-3) and the extended set of conditioning variable, including non-CV characteristics (columns 2-4). Panel A reports estimates for callbacks, whereas panel B reports estimates for job offer conversion. Application-level observations are weighted by the inverse of the monthly number of applications sent out by individual i in month t, so as to put equal weight on all monthly-individual observations. Coefficients correspond to average marginal effects and are reported in percentage points. Errors are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

6. Rationalizing the evidence

6.1 What do we know?

So far, we have examined the dynamics of the different phases of the job search process. From a purely descriptive view, we find evidence of a slight decline in the monthly number of applications sent out by job seekers with respect to elapsed unemployment duration. The decrease in application effort is concurrent to a large reduction in the probability of each application to lead to a callback for a job interview. In contrast, the probability with which interviews are converted into job offers is slightly increasing over time.

The contribution of individual heterogeneity to these empirical patterns is contrasted. On the job seeker's side, we find evidence of positive dynamic selection with respect to application effort. As longer-term unemployed apply more at any duration, heterogeneity tends to attenuate the net effect of duration in the raw data. The opposite is true for callback decisions by firms: individuals who remain unemployed longer tend to face lower chances of being called back, at any duration. Consequently, dynamic selection is negative at this stage, and tends to exacerbate the duration profile of the callback probability in the raw data.[23] Finally, workers' characteristics play a minor role in the last phase of the job search process, when interviews are converted into job offers: controlling for observed heterogeneity virtually does not affect the duration profile of the job offer conversion probability, which is still estimated to be positive.

All things considered, our results corroborate the findings that individual heterogeneity is an important driver of duration dependence in job finding. However, our analysis suggests that the role of heterogeneity is not uni-dimensional, as it affects the duration profiles of job seekers and firms' behaviors differently. Moreover, even after accounting for heterogeneity, we find that duration itself still affects directly and negatively application effort provision by job seekers, and firms' callback decisions. In contrast, duration is found to have a limited positive effect on the final decision of the job search process, *i.e.* firms' choice of converting job interviews into job offers. In the next section, we present a job search model with statistical discrimination, that rationalizes the evidence we have emphasized so far.

6.2 Duration based discrimination in job search

6.2.1 The model

We develop a job search model with statistical discrimination to rationalize our empirical findings in an equilibrium framework. The model builds on Jarosch and Pilossoph (2019), which constructs a frictional labor market characterized by two-sided heterogeneity, pos-

[23] Consequent to dynamic selection being positive with respect to job application effort, and negative with respect to the callback probability, we find that high application-effort individuals face lower callback chances. This can be seen in Figure C4A, where we plot the relationship between the α_i estimated from section 4 and the individual-specific average of the empirical (or *ex-ante*) callback probability, from section 5. The same relationship is plotted for the job offer conversion probability, in Figure C4B.

itive assortative matching, and a multi-stage hiring process (callback and interview/job offer conversion stage). This setting lends itself naturally to generating negative duration dependence at the callback stage as an endogenous response to negative dynamic selection of lower-ability workers at longer unemployment duration. Intuitively, unemployment duration conveys a signal to firms about the average ability of the applicant: the longer the unemployment spell, the higher the likelihood that the applicant is of low ability and, therefore, the smaller the pool of firms that is willing to interview her.

To study duration dependence in workers' and firms' decisions jointly, we augment Jarosch and Pilossoph (2019) framework with endogenous search effort by workers.[24] In practice, we add a preliminary stage at the beginning of the hiring process in which workers decide how many job applications to send out, i.e., how much application intensity to exert. Crucially, optimal application intensity is increasing in the job offer probability (per unit of application intensity). As long as the latter declines with unemployment duration, *e.g.* because of firms discriminating against longer unemployment duration, job seekers find it optimal to reduce their application intensity over the unemployment spell. This allows us to rationalize net duration dependence both on the worker and firm side as an equilibrium response to negative dynamic selection of workers' ability at longer unemployment duration. In what follows, we lay down the main elements of the model and then highlight their role to rationalize our empirical findings.

Environment

We consider a discrete-time economy populated by a unit mass of workers, who differ by their permanent ability $x \sim \mathcal{L}(x)$, $x \in \mathcal{X} = (\underline{x}, \overline{x})$, and a continuum of firms with an outstanding mass V of job vacancies differing by their productivity $y \sim F(y)$, $y \in \mathcal{Y} = \big(\underline{y}, \overline{y}\big)$. As in Falk et al. (2006), workers differ in their search efficiency $\epsilon(x)$, which catches cross-sectional differences in application channels or search technology. Workers with higher ability on the job are also more efficient in search, that is, $d\epsilon(x)/dx > 0$[25]. Both workers and firms are risk-neutral and discount the future at common rate $\beta \in (0, 1)$. Workers and firms interact in a frictional labor market under a random search protocol. Search-and-matching frictions are represented by an exogenous separation probability δ_H and the endogenously determined job finding probability $O(x, \tau)$, where $\tau \in \mathbb{N}$ stands for elapsed unemployment duration.[26] The exogenous separation probability δ_H comprises both quits to unemployment with probability δ_L and job-to-job transitions with com-

[24] The possibility of augmenting the model with endogenous search effort is already hinted at in footnote 47 of Jarosch and Pilossoph (2019). However, the authors did not pursue such research address since it would allegedly have led to mitigating the impact of firms' discrimination on the job finding rate, the authors' goal being to quantify an upper bound to such an impact.

[25] Positive correlation between ability on the job and search efficiency is motivated by the empirical evidence that the callback probability is lower for workers sending out more applications reported in Figure C4A.

[26] The job finding probability in our structural model is the theoretical counterpart of the expected (number of) job offers in the empirical part of the paper, for reasons that will become clear later on.

plementary probability $\delta_H - \delta_L$. Following Blanchard and Diamond (1994) and Shimer (2005b), we allow for coordination frictions in the form of multiple applications per vacancy.

Job seekers can actively influence their job finding probability by exerting search effort. Search effort s is made up by the product between search efficiency $\epsilon(x)$ and application intensity a (which, with some abuse of notation, can be thought of as the number of applications):

$$s(x, \tau) = \epsilon(x)a(x, \tau) \tag{6.1}$$

Intuitively, a job seeker's job finding probability is higher either if she sends out more application (higher a) or if she sends out applications of higher quality (higher ϵ).

Job finding comes as the result of a three-step hiring process. First, workers decide how much application intensity a to exert, subject to an increasing and convex search cost function $\sigma\left(s(a)\right),\ \sigma'(s) > 0,\ \sigma''(s) > 0$ (Pissarides, 2000)[27]. Second, workers' job applications come together with firms' vacancies with exogenous probability $\lambda\epsilon(x)$, where λ catches market-wide meeting frictions. Upon meeting, the only relevant information released to firms from workers' applications is the length of their unemployment spell. Based on this piece of information only, firms decide whether to call the applicant back for a job interview at cost κ. Finally, conditional on interviewing the applicant, the firm gets to know her true ability type x and decides whether to offer her a job.

Match output is governed by a production technology $p(x, y)$ characterized by positive assortative matching, *i.e.* the most productive firms are the most selective in terms of workers' ability[28]:

$$p(x, y) = \begin{cases} x + y & \text{if } x \geq y \\ 0 & \text{else} \end{cases} \tag{6.2}$$

A worker is hence qualified for a job if her ability x exceeds firms' productivity y.[29] For any (x, y) pair, define a qualification index $\mathcal{Q}$ such that:

$$\mathcal{Q}(x, y) = \mathbb{1}\{x \geq y\} \tag{6.3}$$

Workers enjoy a flow value of leisure b while unemployed. Following Hall (2005), wages are rigid and fixed at $\omega \in \left(b, p(\underline{x}, \underline{y})\right)$ for the entire duration of the match. Unlike in Jarosch and Pilossoph (2019), employed workers are therefore strictly better-off than unemployed,

[27]Notice that the cost depends on the total amount of search effort exerted – not only on application intensity.

[28]We adopt the modified Albrecht and Vroman (2002)'s production function proposed by Jarosch and Pilossoph (2019) as it grants an intuitive notion of worker's qualification for a job.

[29]Throughout we assume that any qualified worker is profitable for the firm.

thus providing a motive for exerting search effort.

Workers

Workers are either matched to a firm or unemployed. Unemployed workers choose how much application intensity a to exert at each unemployment duration τ, so as to maximize the value of unemployment. The values of unemployment and employment can be expressed recursively as

$$U(x,\tau) = \max_{\hat{a}\geq 0}\ b - \sigma\left(s(\hat{a})\right) + \beta\Big[U(x,\tau+1) + \hat{a}\cdot o(x,\tau)\ \big(W(x) - U(x,\tau+1)\big)\Big] \quad (6.4)$$

$$W(x) = \omega + \beta\Big[W(x) + \delta_L\big(U(x,0) - W(x)\big)\Big] \quad (6.5)$$

where $o(x,\tau)$ denotes the job offer probability per unit of application intensity, which encompasses worker's search efficiency $\epsilon(x)$, as well.
In words, the value of unemployment at duration τ is made up by the flow value of leisure net of search effort costs and a continuation value, which equals the discounted value of unemployment at duration $\tau+1$ plus the expected capital gain upon finding a job. The latter is composed of the job finding probability $O(x,\tau) \equiv a\cdot o(x,\tau)$ times the expected capital gain upon finding a job. The value of employment equals the flow value of the wage rate and a continuation value, which accounts for stochastic separations into the zero-duration unemployment state. Since wages are rigid, productivity heterogeneity across firms does not translate into wage dispersion, so the standard option value embedded in the unemployment state disappears. Consequently, workers' reservation wage boils down to b and every job offer is accepted in equilibrium.[30]
Optimal application intensity balances the marginal cost of exerting higher application intensity to the expected marginal benefit of meeting a vacancy. The latter is made up by the marginal increase in job finding probability from higher application intensity multiplied by the discounted capital gain upon employment:

$$a(x,\tau) : \underbrace{\sigma'\left(s(a)\right)\epsilon(x)}_{\text{marginal cost}} = \underbrace{\beta\ o(x,\tau)\ \Big[W(x) - U(x,\tau+1)\Big]}_{\text{marginal benefit}} \quad (6.6)$$

Optimal application intensity at unemployment duration τ depends on the value of unemployment at duration $\tau+1$, thus making the application decision non-stationary. Specifically, the model generates negative duration dependence in search effort if and only if the marginal benefit of application intensity decreases with elapsed unemployment duration τ[31]. Since the job offer probability is linear in search efficiency and the search effort cost

[30]As job offers and hirings coincide in the model, $O(x,\tau)$ characterizes both the job finding probability and the probability that a worker obtains a job offer out of one unit of application intensity.

[31]The necessary and sufficient condition for negative duration dependence in application intensity to arise at duration τ is that the reduction in job offer probability, *i.e.* $\frac{\partial o(x,\tau)}{\partial \tau} < 0$, dominates the increase in the

function is convex, higher-ability workers have both higher marginal benefit due to higher job offer probability per unit of search effort (because they are qualified for more jobs) and higher marginal cost of exerting application intensity (because each unit of application intensity is more costly). As a result, whether higher-ability workers exert more or less application intensity is qualitatively ambiguous as it depends on which of the two opposing forces dominates[32]. If the marginal cost force dominates in the cross section, workers with low ability exert higher application intensity than high-ability ones, thus generating positive dynamic selection of workers with higher application intensity over the unemployment spell, as detected in the data.

Firms

Firms can either be matched with one worker or not. In the latter case, the value of the firm, J_v, is assumed to be zero. As a result, the value of a filled job, $J(x, y)$, is simply given by the present discounted value of flow profits.

$$J_v = 0 \tag{6.7}$$

$$J(x, y) = \frac{p(x, y) - \omega}{1 - \beta(1 - \delta_H)} \tag{6.8}$$

Upon receiving a worker's application, the firm decides whether to call her back for a job interview, based on her elapsed unemployment duration τ only, at cost κ. After the interview takes place, the firm discovers the worker's true ability x and decides whether to offer her a job.

In the first phase of the recruitment process, for any (y, τ) pair, define a callback index $\mathcal{C}$ such that:

$$\mathcal{C}(y, \tau) = \mathbb{1}\left\{\int \max\left\{J(x, y), 0\right\} \mu(x|\tau)\ dx \geq \kappa\right\} \tag{6.9}$$

where $\mu(x|\tau)$ is the conditional density of workers' ability at unemployment duration τ – the key equilibrium object driving statistical discrimination. In words, a firm calls back an unemployed worker with elapsed unemployment duration τ if the expected value of matching to this worker exceeds the interview cost κ. Since higher-ability workers exits unemployment more quickly, the worker ability distribution $\mu(x|\tau)$ displays negative dynamic selection. Therefore, the callback indicator is weakly decreasing in unemployment duration and, faced with multiple job applications, firms find it optimal to rank applicants

capital gain upon employment due to the depletion of the value of unemployment as the unemployment spell lengthens, *i.e.* $U(x, \tau + 1) < U(x, \tau)$.

[32]The same result obtains if workers are risk-averse through a wealth effect in application intensity. Faberman and Kudlyak (2019) alludes in footnote 27 to a dominant wealth effect in search effort as a possible explanation for the evidence that workers with lower job prospects or located in less tight labor markets search more intensely. However, neither our data nor theirs allow testing for such potential wealth effect empirically.

according to their unemployment duration starting with the shortest. Upon calling back the lowest-duration applicant (as long as it is profitable according to 6.9), the firm calls back the next applicant, as well[33], if:

$$\int \max\left\{J(x,y) - J(\hat{x},y), 0\right\} \mu(x|\tau)\ dx \geq \kappa \tag{6.10}$$

where $\hat{x}$ represents the ability of the previous applicant, which is revealed at the interview stage. Denoting as $z^c(x,y,\tau)$ the measure of search effort crowding out a job seeker with ability x and unemployment duration τ in contact with a job of productivity y at the callback stage (derived in Appendix D), the callback probability writes:

$$c(x,\tau) = \lambda\epsilon(x) \int \mathcal{C}(y,\tau) \exp\left\{-\frac{z^c(x,y,\tau)}{V}\right\}\ dF(y) \tag{6.11}$$

In the second phase of the recruitment process, *i.e.* conditional on calling back the applicant, the firm gets to know worker's true ability during the interview. As a result, the firm is willing to make a job offer to any worker who is qualified for its production technology, according to equation (6.2), regardless of unemployment duration. Since any job offer is accepted by the worker, define a job offer indicator $\mathcal{O}$ such that:

$$\mathcal{O}(x,y,\tau) = \mathcal{Q}(x,y)\mathcal{C}(y,\tau) \tag{6.12}$$

Denoting as $z(x,y,\tau)$ the measure of search effort crowding out a job seeker with ability x and unemployment duration τ in contact with a job of productivity y in hiring (derived in Appendix D), the job offer conversion probability writes:

$$o(x,\tau)|c(x,\tau) = \frac{\int \mathcal{O}(x,y,\tau) \exp\left\{-\frac{z(x,y,\tau)}{V}\right\}\ dF(y)}{\int \mathcal{C}(y,\tau) \exp\left\{-\frac{z^c(x,y,\tau)}{V}\right\}\ dF(y)} \tag{6.13}$$

In words, a firm makes a job offer to the highest-ability worker that grants it positive flow profits, after discovering her type during the interview. Finally, the job offer probability (per unit of application intensity) is defined as:

$$o(x,\tau) \equiv c(x,\tau) \cdot o(x,\tau)|c(x,\tau) = \lambda\epsilon(x) \int \mathcal{O}(x,y,\tau) \exp\left\{-\frac{z(x,y,\tau)}{V}\right\}\ dF(y) \tag{6.14}$$

Absent statistical discrimination, *i.e.* if $\kappa = 0$, such job offer probability would read:

$$o^{ND}(x) = \lambda\epsilon(x) \int \mathcal{Q}(x,y) \exp\left\{-\frac{z^{ND}(x)}{V}\right\}\ dF(y) \tag{6.15}$$

[33]Following Jarosch and Pilossoph (2019), we assume that by interviewing another candidate the firm does not lose the option of hiring any of the previously interviewed applicants.

where $z^{ND}(x)$ is the measure of search effort crowding out a job seeker with ability x absent discrimination (derived in Appendix D).

Contrasting equations (6.14) and (6.15), we notice that statistical discrimination by firm y affects a worker's job offer probability if and only if $\mathcal{Q}(x, y) = 1$, that is, if the worker is denied an interview for a job she would have been qualified for.

Stationary equilibrium

Closing the model requires to specify the equilibrium conditions for the measure of unemployed, as well as the unemployment composition across ability types and unemployment duration. To do so, we solve the model in stationary equilibrium.

Type-specific unemployment rate equals the sum of the measure of unemployed across all durations

$$u(x) = \sum_{\tau=0}^{\infty} u(x, \tau) \tag{6.16}$$

$$\text{where } u(x,\tau) = \begin{cases} \delta_L\big(1 - \sum_{t=0}^{\infty} u(x,t)\big) & \text{if } \tau = 0 \\ u(x,\tau-1) \cdot \big[1 - a(x,\tau-1)\ o(x,\tau-1)\big] & \text{if } \tau > 0 \end{cases}$$

The key equilibrium object of the model is the conditional density of worker types x at duration τ, which is defined as

$$\mu(x|\tau) = \frac{s(x,\tau)\ u(x,\tau)\ \ell(x)}{\int s(\tilde{x},\tau)\ u(\tilde{x},\tau)\ d\mathcal{L}(\tilde{x})} \tag{6.17}$$

where $\ell(x) = \mathcal{L}'(x)$ is the probability density function of x.

Definition 1. *A stationary equilibrium of this economy is a triple* $\{a(x,\tau), o(x,\tau), u(x,\tau)\}$*, where application intensity satisfies equation (6.6), the job offer probability satisfies equation (6.14), and the unemployment rate satisfies equation (6.16).*

Equilibrium characterization

We are now in the position to discuss the mechanism behind the duration dependence patterns observed in the data through the lens of our structural model. Upon meeting a worker with unemployment duration τ, firms form an expectation about her ability based on $\mu(x|\tau)$. Since workers with high ability x match more easily according to the production technology (6.2), the density $\mu(x|\tau)$ is featured by negative dynamic selection, with low-ability workers being over-represented at longer unemployment duration with respect to the unconditional density. Such negative dynamic selection entails a net negative duration dependence in the callback probability according to equation (6.11), as firms use elapsed unemployment duration as a screening device when choosing whether to call back an applicant for an interview. Proposition (1) provides a sufficient condition for the callback probability to exhibit net negative duration dependence.

Proposition 1. *If* $\int \max\{J(x,y),0\}\, d\mathcal{L}(x) > \kappa\ \forall y$ *and* $F(y \in \mathcal{Y} : J(\underline{x}, y) < \kappa) > 0$*, then the callback probability exhibits negative net duration dependence.*

Proof. See Jarosch and Pilossoph (2019). □

Negative dynamic selection in worker ability further entails that the pool of job applicants becomes increasingly more homogeneous as unemployment duration lengthens, with low-ability workers accounting for a progressively larger share of job seekers. As a result, the signal embedded in unemployment duration becomes increasingly more informative about worker's ability, thus making firms callbacks more targeted. If such improvement in callback targeting is strong enough, the job offer conversion probability exhibits positive net duration dependence. Intuitively, if the set of firms that discriminate against unemployment duration is mostly composed by firms the worker is not qualified for, the denominator of equation (6.13) will decrease with τ much quicker than the numerator, thus raising the job offer conversion rate over an unemployment spell. Lemma 1 spells out a sufficient condition for the job offer conversion probability to exhibit positive net duration dependence.

Lemma 1. *Let* $\alpha(x, \tau+1)$ *be the share of firms such that* $\mathcal{C}(y,\tau) > \mathcal{C}(y, \tau+1)$ *which a worker of ability* x *is qualified for, i.e.* $\alpha(x,\tau+1) \equiv \frac{\int \Delta\mathcal{C}(y,\tau+1)\mathcal{Q}(x,y)dF(y)}{\int \Delta\mathcal{C}(y,\tau+1)dF(y)}$*. The job offer conversion probability of a worker* x *exhibits positive duration dependence if* $\alpha(x,\tau+1) < o(x,\tau)|c(x,\tau)\ \forall\tau$*.*

Proof. See Appendix D. □

Overall, however, negative net duration dependence in the callback probability generates negative duration dependence in the job offer probability equation (6.14). This is the case since search-and-matching frictions imply that a positive measure of workers of any ability type will be present at any unemployment duration. As a result, the job offer probability of workers who are qualified for firms that are not willing to call them back because unemployed for too long is bound for decreasing with duration. In equilibrium, workers optimally respond to negative duration dependence in the job offer probability by scaling down their application intensity over the unemployment spell according to equation (6.6), which therefore exhibits net negative duration dependence as well – at least once the reduction in job offer probability materializes[34].

6.2.2 What drives duration dependence?

We can draw a clear parallel between our structural model and equation (3.2), describing the empirical decomposition of duration dependence in job offers. Noting that the job

[34]Since wages are rigid in duration, if negative duration dependence in the job offer conversion probability does not kick in since the first month of unemployment, job seekers may find it optimal to first *increase* their application intensity in anticipation of the job offer probability decline, and then reduce it as soon as the latter materializes, thus generating a hump-shaped net duration dependence profile reminiscent of DellaVigna et al. (2022).

finding probability for a worker of type x at duration τ writes $O(x,\tau) = a(x,\tau)\ o(x,\tau)$, duration dependence in $O(x,\tau)$ can be decomposed into a net duration effect and a compositional change:

$$\mathbb{E}_\tau\big[O(x,\tau)\big] - \mathbb{E}_0\big[O(x,0)\big] = \underbrace{\mathbb{E}_\tau\big[a(x,\tau)\ o(x,\tau) - a(x,0)\ o(x,0)\big]}_{\text{Net duration effect}} + \underbrace{\mathbb{E}_\tau\big[a(x,0)\ o(x,0)\big] - \mathbb{E}_0\big[a(x,0)\ o(x,0)\big]}_{\text{Compositional change}} \tag{6.18}$$

where $\mathbb{E}_\tau[\cdot]$ denotes the expectation with respect to the conditional density in equation (6.17). Again, the job offer probability can be decomposed into two stages as $o(x,\tau) \equiv c(x,\tau) \cdot o(x,\tau)|c(x,\tau)$. Following the steps in equation (3.3), we further write

$$\begin{aligned}\mathbb{E}_\tau\left[O(x,\tau)\right] - \mathbb{E}_0[O(x,0)] = &\ \mathbb{E}_\tau\big[\big(a(x,\tau) - a(x,0)\big)\ o(x,\tau)\big] \\ &+ \mathbb{E}_\tau\big[a(x,0)\ \big(o(x,\tau) - o(x,0)\big)\big] \\ &+ \mathbb{E}_\tau\big[a(x,0)\ o(x,0)\big] - \mathbb{E}_0\big[a(x,0)\ o(x,0)\big].\end{aligned} \tag{6.19}$$

Just like in our empirical exercise, the decline in job offers and in the job finding rate are explained in part by a compositional change in the pool of unemployed and in part by the net effect of duration. The negative net duration effect can further be decomposed into a reduction of the job offer probability, driven by the decline in the callback probability, and a reduction in the number of applications sent out by unemployed.

6.2.3 Estimation Strategy

Functional Forms

Following Jarosch and Pilossoph (2019), we assume that worker ability follows a Beta distribution on the unit interval and job vacancy productivity follows an uniform distribution on the unit interval with a mass point at 0, whose density $F(0)$ is a parameter to be estimated. Formally,

$$x \sim \mathcal{L}(x) = \text{Beta}(x; B_1, B_2),\ \ \text{supp}(x) = [0,1] \tag{6.20}$$

$$y \sim F(y) = F(0) + y\left(1 - F(0)\right),\ \ \text{supp}(y) = [0,1] \tag{6.21}$$

We assume that worker search efficiency $\epsilon(x)$ is a linear function of ability in production with the search efficiency of the lowest-ability workers being normalized to 1, that is:

$$\epsilon(x) = 1 + \phi x \tag{6.22}$$

Following the literature, we adopt an isoelastic search effort function, that is increasing and convex:

$$\sigma(s) = \psi \frac{s^{1+\eta}}{1+\eta} = \psi \frac{(\epsilon a)^{1+\eta}}{1+\eta} \tag{6.23}$$

where $\eta > 0$. As a result, optimal application intensity solves:

$$a(x,\tau) = \left[\beta \frac{o(x,\tau)}{\psi \epsilon(x)^{1+\eta}} \left[W(x) - U(x,\tau+1) \right] \right]^{\frac{1}{\eta}} \tag{6.24}$$

Structural estimation

We structurally estimate the model to assess its quantitative fit to the data. We estimate the model at monthly frequency for unemployment duration $\tau = 1, \ldots, \tilde{\tau}$, where $\tilde{\tau} = 17$. The estimation strategy is carried out in two steps. We first pin down a set of parameters that have direct empirical counterparts from external sources. Then, we estimate the remaining moments internally via indirect inference. Table 6.1 reports the externally chosen parameters.

Table 6.1: Externally chosen parameters

Parameter	Description	Value	Source
β	Discount factor	0.992	9% annual interest rate*
δ_L	Separation rate (workers)	0.0087	Monthly EU rate*
δ_H	Separation rate (firms)	0.0192	Monthly EN+EU rate*
κ	Interview cost	0.10	Hiring costs in Silva and Toledo (2009); Barron et al. (1997)*
ω	Wage rate	0.991	Job value in Hagedorn and Manovskii (2008)
b	Value of leisure	0.910	Avg flow value of leisure in Hagedorn and Manovskii (2008) and Shimer (2005a)

Targets denoted by * are the same as in Jarosch and Pilossoph (2019).
Numeraire: cross-sectional avg monthly output.

The estimation strategy for the common externally chosen parameters largely follows Jarosch and Pilossoph (2019)'s. We directly pin down the two separation rates by measuring the EU rate and EE rate in our sample from Swiss social security data. For the remaining parameters, we set the wage rate to 0.991 to induce an average value of a job equal to 33% of average monthly output, as in Hagedorn and Manovskii (2008). The flow value of leisure is set to 0.91 in order to generate a flow value of unemployment of 70% of average monthly output, which lies midway between Shimer (2005a) and Hagedorn and Manovskii (2008)'s popular calibrations.

We then estimate the remaining set of parameters via indirect inference through the simulated method of moments. Each parameter conceptually relates to some moment in the data through the equilibrium conditions of the model. Formally, let Θ be the vector of parameters still to be determined: $\Theta = \left\{B_1, B_2, \lambda, F(0), \psi, \phi, \eta\right\}$. We choose parameter values that minimize the sum of weighted squared percentage deviations between a set of moments estimated in actual and simulated data:

$$\Theta^* = \underset{\mu \in \mathcal{M}}{\arg\min} \left(\frac{\mu^M(\Theta) - \mu^E}{\mu^E}\right)^2,$$

where μ^E is a vector of empirical moments and $\mu^E(\Theta)$ is the corresponding vector of model-generated moments. Table (6.2) reports the internally chosen parameters, along with the respective targeted moments.

Table 6.2: Estimated parameters

Parameter	Description	Value	Target	Data	Model
B_1	1^{st} shape parameter Beta distr.	0.0176	$\hat{\beta}_{\ln c,\tau}$: net duration dependence in callback rate*	−0.0192	−0.0198
B_2	2^{nd} shape parameter Beta distr.	0.0775	$\hat{\beta}_{\ln o\|c,\tau}$: net duration dependence in conversion rate	0.0188	0.0174
λ	Contact rate	0.0254	$\mathbb{E}[c(x,\tau)]$: avg callback rate	0.04013	0.0385
$F(0)$	Share of lowest prod. firms	0.8762	$\mathbb{E}[c(x,\tilde{\tau})]$: long-run avg callback rate*	0.0255	0.0298
η	Convexity search effort cost	0.1171	$\hat{\beta}_{\ln A,\tau}$: net duration dependence in applications	−0.0200	−0.0129
ψ	Scalar search effort cost	0.0595	$\mathbb{E}[O(x,\tau)]$: avg job finding rate	0.0611	0.0630
ϕ	Ability-gradient search efficiency	7.9541	$\hat{\beta}^{\text{emp}}_{\ln A,\tau}$: emp. duration dependence in applications	−0.0072	−0.0077
V	Mass of vacancies	0.0248	$\hat{\beta}^{\text{emp}}_{\ln O,\tau}$: emp. duration dependence in job finding rate*	−0.0240	−0.0333

Targets denoted by * are the same as in Jarosch and Pilossoph (2019). All duration dependence coefficients are expressed as semi-elasticities. Numeraire: cross-sectional avg monthly output.

The shape parameters of the Beta distribution, B_1 and B_2, jointly govern the variance of worker ability. These are the crucial parameters controlling the extent of worker heterogeneity in the labor market, which underlies firms' use of unemployment duration as screening device. The higher the variance of worker ability, the stronger negative dynamic selection of workers and, therefore, the more informative unemployment duration is. As a result, both the negative net duration profile in the callback rate and positive duration profile in the job offer conversion rate will be steeper. To inform such shape parameters, we therefore target the net duration dependence in both the callback rate and the conversion rate. In practice, we run the following regressions in the model:

$$\ln c = X\delta_c + \beta_c \tau + \epsilon_c \tag{6.25}$$

$$\ln(o|c) = X\delta_o + \beta_{o|c}\tau + \epsilon_{o|c} \tag{6.26}$$

where X is the vector of (discretized) worker ability types (individual fixed effects). The two estimates, $\hat{\beta}_c$ and $\hat{\beta}_{o|c}$, represent the semi-elasticities of the net duration dependence in callback rate and conversion rate, respectively. Therefore, we use our estimates from the empirical section as targets for indirect inference[35]. Slightly departing from Jarosch and Pilossoph (2019), in our model meeting frictions kick in at the stage where workers' applications and firms' vacancies come together, thus entering the callback rate. Therefore, the extent of meeting frictions, as subsumed by the contact rate λ, governs the average callback rate observed in our sample (pooling together all worker types at any unemployment duration). Following Jarosch and Pilossoph (2019), we pin down the share of lowest productive firms, *i.e.* those firms which are willing to hire any worker, $F(0)$, by targeting the long-run average callback rate in our last observed month, *i.e.* at $\tilde{\tau} = 17$. Intuitively, the conditional distribution of worker ability types at such a long duration will be so tilted towards low abilities that only firms with no ability requirement will be willing to call back someone. The scalar of the search effort cost function, ψ, directly relates to the average search effort which, in turn, shapes the average job finding rate. Since the former is partly unobservable, we choose to target the latter. Then, we observe that the convexity of the search effort cost function, η, governs the degree of pass-through of variations in the job offer rate into optimal application intensity, thus controlling the magnitude of the reduction in application intensity induced by the decline in the job offer rate over the unemployment spell. We therefore target the semi-elasticity of the net duration dependence in the number of applications. In practice, we run the following regression in the model:

$$\ln a = X\delta_a + \beta_a \tau + \epsilon_a \tag{6.27}$$

where $\hat{\beta}_a$ represents the net duration dependence in application intensity in log points, which allows us to directly compare it to our estimate in the empirical section. Then, we notice that the ability gradient in search efficiency, ϕ, governs the positive dynamic selection in application intensity. The higher the gradient, the more costly it is for high-ability workers to exert application intensity, who are therefore expected to apply less intensely than lower-ability ones at any unemployment duration. Thus, we target the empirical/unconditional duration dependence in the number of applications – on top of the net duration dependence from above – to discipline the ability gradient in search efficiency. In practice, we run the following regression in the model:

$$\ln a = \delta_{a^e} + \beta_{a^e} \tau + \epsilon_{a^e} \tag{6.28}$$

where $\hat{\beta}_{a^e}$ represents the empirical duration dependence in search effort in percentage terms, which allows us to directly compare it to our estimate in the empirical section. Finally, the mass of vacancies, V, governs the extent of duration dependence in the job finding rate induced by coordination frictions. We therefore target the empirical duration dependence in the job finding rate. In practice, we run the following regression in the

[35] Here we are working under the assumption that our control for ex-ante propensity of success in the empirical specification is a good proxy for individual (unobserved) ability.

model:

$$\ln O = \delta_{O^e} + \beta_{O^e}\tau + \epsilon_{O^e} \tag{6.29}$$

where $\hat{\beta}_a$ represents the empirical duration dependence in the job finding rate in log points.

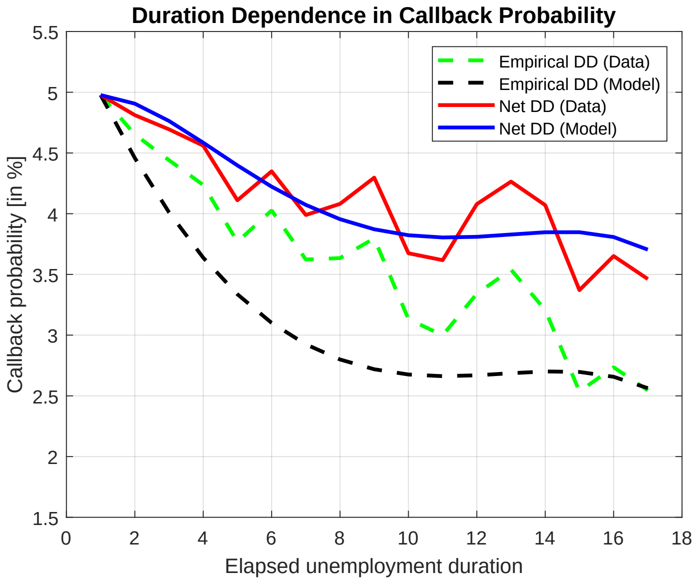
Model Fit

The estimated model is successful in replicating the patterns of duration dependence and dynamic selection in all the relevant variables, while being consistent with workers' flows. On the firm side, the model-implied duration profiles in callback probability and job offer conversion probability are extremely accurate, as reported in Figure 6.1. On the one hand, the model proves able to replicate the targeted net duration dependence of both variables almost perfectly. On the other hand, it also fits well their empirical duration profiles, which are untargeted. Therefore, the Jarosch and Pilossoph (2019)'s framework seems to catch important drivers of firms' decisions during the hiring process. On the worker side, the model exactly replicates the targeted empirical duration profile of the number of applications and goes a long way in accounting for its net duration dependence, as well. Indeed, as reported in Figure 6.2, the model reproduces the net duration dependence in applications almost perfectly up until the 10^{th} month of unemployment duration but misses its further decline afterwards, which accounts for the slight underestimation of the linear coefficient in Table 6.2. Moreover, the model gives rise to the positive dynamic selection in job applications observed in the data through a negative ability-gradient in application intensity – a novel channel that, to the best of our knowledge, we are the first to stress in the duration dependence literature. Importantly, these patterns of duration dependence and dynamic selection are accommodated within an equilibrium framework which is consistent with the observed job finding and separation probabilities, which grants empirical discipline to the pace of dynamic selection.

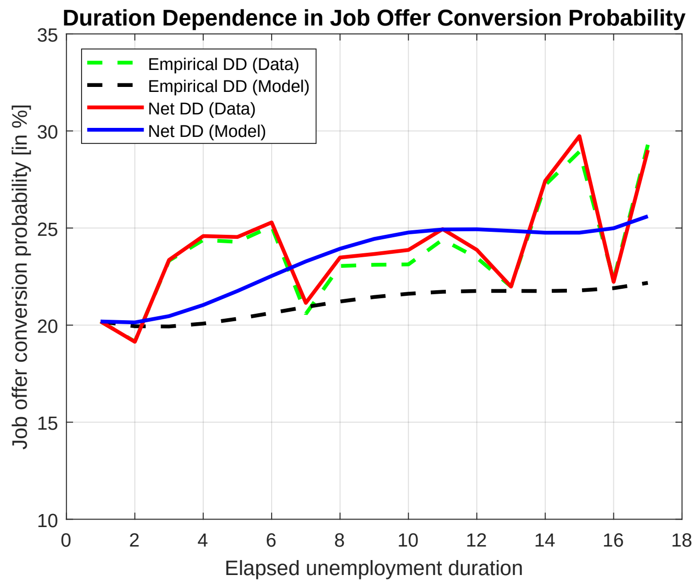
As far as the economy's structure of the estimated model is concerned, the worker ability distribution looks close to bimodal, as in Jarosch and Pilossoph (2019), with more than 90% of workers being either qualified for any job or only for jobs with no ability requirements. This sketches a picture of the labor market as populated by essentially two types of workers – high-ability and low-ability – with the share of low-ability workers increasing with unemployment duration. On the firm side, it turns out that as much as 85% of job openings comes with no ability requirements, which is a higher figure than in Jarosch and Pilossoph (2019) (64%) but consistent with the higher share of low-ability workers that are estimated to populate our labor market. The highest-ability workers are estimated to be 9 times more efficient in search than the lowest-ability ones, which is a measure of the relative likelihood of getting a callback by applying only through the best application channel vis-à-vis the worst. Finally, the search effort cost function is estimated to exhibit only a mild amount of convexity, which maps into a high elasticity of application intensity

Figure 6.1: Duration dependence in firms' responses, model vs data

(A) Callback probability



(B) Job offer conversion probability



Note: This figure contrasts the duration dependence profiles in the callback probability (Panel A) and job offer conversion probability (Panel B) detected in the data (5.3) with those implied by the estimated model. The model-implied duration profiles are computed by fitting a 4^{th}-order polynomial regression in unemployment duration.

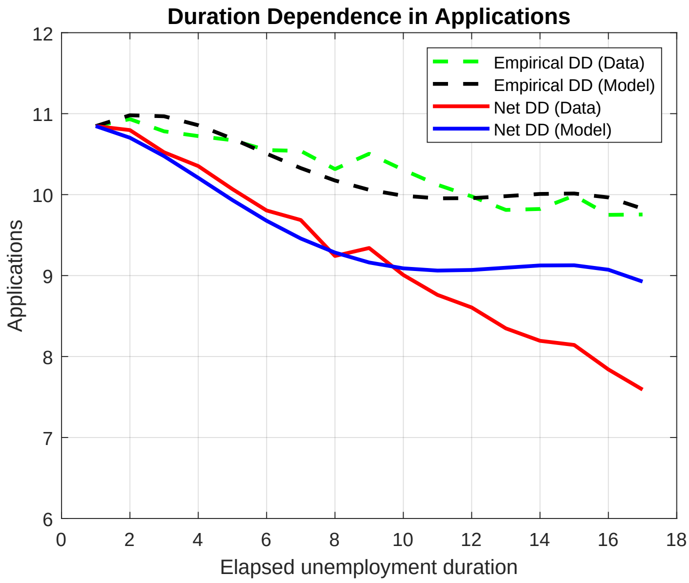
to varying job offer probability.

6.3 Competing explanations

Our structural model presents one possible explanation for the net duration patterns we observe in the data. Nevertheless, some of the dynamics we observe empirically might be due to other mechanisms, which we discuss in the following.

On the job seeker's side, a first alternative explanation for the downwards-sloping net

Figure 6.2: Duration dependence in application effort, model vs data



Note: This figure contrasts the duration dependence profile in the number of applications detected in the data (4.2) with that implied by the estimated model. The model-implied duration profile is computed by fitting a 4^{th}-order polynomial regression in unemployment duration.

duration profile in application effort lies in stock-flow sampling (Salop, 1973; Ebrahimy and Shimer, 2010). The basic idea behind this theory is that suitable jobs to which a job seeker might apply originate both from the initial stock of vacancies and the inflow of new vacancies in each period. In this setup, the number of applications is decreasing over the unemployment spell because workers initially apply to the stock of existing vacancies, before applying to the inflow of new vacancies in the subsequent periods. This mechanism entails a non-gradual decline in application effort with respect to elapsed unemployment duration. In our context, we find that application effort decreases gradually and linearly over time, which tends to contradict the stock-flow sampling hypothesis. [36] Moreover, this hypothesis can directly be tested by estimating the duration dependence profile in application effort, controlling for the stock and flow of vacancies in the relevant labor market. If the stock-flow mechanism prevails, the net duration profile estimated by this augmented model should be flat. This approach is not applicable in our context given that we have no access to job vacancies data, but it has been followed by Faberman and Kudlyak (2019), who do not find supportive evidence for the stock-flow hypothesis.

Another competing hypothesis for the decline in application effort relates to the depletion of job seeker's personal network, which has been shown to play an important role in job

[36] In the most stylized framework, job seekers apply to the stock of vacancies only in the first month of unemployment. This results in a large discrete jump from the first period to the subsequent ones. In a more refined version of the model, this discontinuity can be smoothed out by assuming convex application costs, which would make it optimal for the job seekers not to exhaust the stock of existing vacancies in the first period. However, if stock-flow sampling were to prevail, we would still expect a larger decline in application effort in the early periods of unemployment, compared to latter ones.

finding (Beaman and Magruder, 2012; Burks et al., 2015; Hensvik and Skans, 2016). This mechanism can be seen as a form of personal stock-flow sampling, where the decline in total application effort is entailed by the exhaustion of job seekers' personal contacts. In contrast, applications sent out through other channels ought to remain constant, throughout the unemployment spell. We assess this alternative explanation by estimating equation (4.1) for three application effort measures, corresponding to the three application channels (personal, phone, written). Corresponding results are reported in Table 6.3. They show that the number of applications sent out in person, per phone and in writing all decrease with respect to elapsed unemployment, hence providing little support to the personal contacts exhaustion mechanism .

On the firm's side, several alternative stories might explain the empirical net decline in

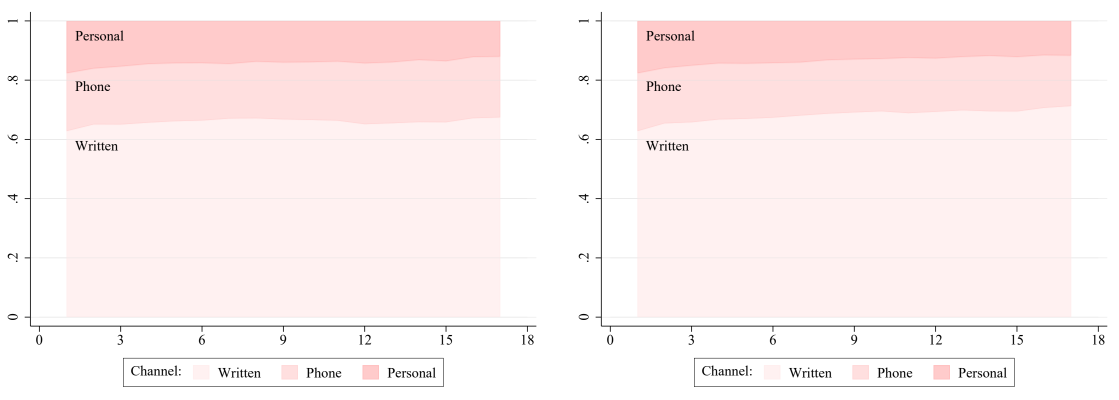
Table 6.3: Duration dependence in application effort per channel

	Written		Phone		Personal	
	(1)	(2)	(3)	(4)	(5)	(6)
Elapsed unemployment duration	-0.037***	-0.132***	-0.003	-0.046***	-0.038***	-0.075***
	(0.009)	(0.020)	(0.006)	(0.012)	(0.005)	(0.012)
	[-0.535%]	[-1.899%]	[-0.146%]	[-2.278%]	[-2.034%]	[-4.034%]
Constant	7.224***		2.025***		1.771***	
	(0.071)		(0.039)		(0.039)	
Individual controls	No	Yes	No	Yes	No	Yes
Policy controls	No	Yes	No	Yes	No	Yes
LLMC	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes
adj.-R^2	0.001	0.631	0.000	0.614	0.003	0.615
N. observations	58755	58755	58755	58755	58755	58755

Note: This table reports empirical estimates of equation (4.1) using OLS, where the parametric duration function $f^A(t; \phi^A)$ is specified linearly. The dependent variables are the number of applications sent out through the written (columns 1-2), phone (columns 3-4) and personal channel (columns 5-6). For each dependent variable, we report estimation results from a simple binary regression (on duration only) and from the full specification described in equation (4.1). Errors are clustered at the individual level and reported in parentheses. Coefficients in relative terms (with respect to the average in the first month of unemployment) are indicated in squared brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Figure 6.3: Changes in the shares of application channels

(A) No control for individual heterogeneity (B) Control for individual heterogeneity



Note: This figure represents the share of applications sent out through the written, phone and personal channels, per month of elapsed unemployment. Panel A corresponds to the patterns in the raw data, without accounting for changes in the pool of applicants. Panel B corresponds to the results of a fixed effects regression, that accounts for the evolution of the pool of applicants.

the callback probability. A first candidate explanation relates to changes in application quality over time: part of the downwards-sloping duration profile in firms' callback probability could be due to the gradual downgrading of job applications characteristics. In our context, we observe an important qualitative aspect of applications: the channel used when contacting firms. As seen in section 5, this characteristic is strongly predictive of applications' success at the callback stage, and captures an important dimension of applications' quality (Beaman and Magruder, 2012; Burks et al., 2015; Hensvik and Skans, 2016).[37] Even though we control for this characteristic in our regressions, we still find evidence of a marked net decline in callback chances, which is unrelated to changes in applications quality. As shown in Figure 6.3, this is because the relative share of each channel in the pool of applications is relatively constant over time, even when controlling for individual heterogeneity. Changes in applications' quality, and more precisely in application channels, are hence unlikely to represent the main driver of our results.[38]

Another potential explanation for the decline in callback chances lies in applications targeting (Galenianos and Kircher, 2009; Wright et al., 2021; Lehmann, 2023). Initially, job seekers might target a specific occupation, before starting to search broader and apply to a wider set of job ads, as spell duration increases. This may reduce callback chances, as job seekers are potentially less suited to the positions they newly apply to. If this mechanism is at play, we should observe adjustments in job search targets over time. We assess this point by studying how occupational targeting changes over time in the *Auxiliary sample*, for which information on occupations is available. Specifically, we construct two measures that characterize the types of occupations job seekers target: a binary variable indicating whether the targeted occupation is the same as the occupation desired by the job seeker, and a measure of net cognitive requirements of targeted occupations.[39] As depicted in Figure 6.4A, we find very little change in occupation search breadth, as measured by the same-occupation indicator. This result is robust to control for heterogeneity through individual fixed effects. Regarding skills requirements, Figure 6.4B shows that the average value of our net cognitive requirements measure decreases substantially along unemployment, from 0.18 to 0.14 over seventeen months. However, this decline is strongly attenuated when job seekers' fixed effects are added. This suggests that the above-mentioned change is

[37] See Table C1 in the Appendix for the role of channels in callback and job offer conversion chances.

[38] If any, we would expect (unobserved) changes in applications' quality to be actually increasing overt time, as job seekers learn how to write better applications over time. Such omitted factor would entail an upward bias in the net duration profile we estimate, meaning that the true net duration dependence in the callback probability would actually be more negative.

[39] In our data, occupations are categorized according to the *Swiss Standard Classification of Occupations 2000* (SSCO 2000). This job nomenclature follows a hierarchical structure, and presents 5 different levels of occupational groups. The binary indicator for occupational similarity between the desired occupation (at the spell level) and targeted occupation (at the application level) can be constructed for the different levels of the SSCO 2000. As for the net cognitive requirements measure, we use *O*Net* skill and ability requirements for each occupation. *O*Net* provides 52 abilities and skills, grouped into cognitive and physical. Our net cognitive measure is based on the difference between weighted importance of cognitive skills requirements and physical requirements.

largely due to a compositional change, and not to a change in application targeting within spells. Altogether, these evidence point towards a limited role of application targeting in the decline of callbacks and job finding chances.

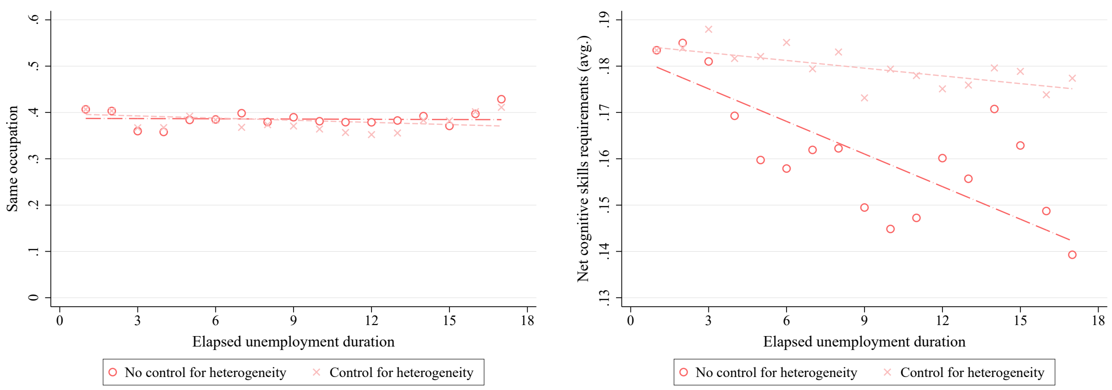
Finally, the net decline in callback chances might be due not to statistical discrimination, but rather to taste-based discrimination. In that case, firms would discriminate against long-term unemployed for preference motives rather than because of statistical inference. Such mechanism is typically formalized in models with multiple applications per job opening, which gives rise to coordination frictions. This requires firms to select a tie-breaking rule when calling back *ex-ante* homogeneous workers. In this framework, negative duration dependence in the callback probability would thus arise in the absence of screening motives, as long as firms call back applicants with lower unemployment duration first (Blanchard and Diamond, 1994). In our context, taste-based discrimination would imply a flat duration profile in the average *ex-ante* probabilities of applications to end up in callbacks, since duration is not statistically related to job seekers' productivity. This hypothetical pattern is however at odds with our empirical observation of dynamic selection in the callback phase and negative duration dependence in the *ex-ante* callback probability (see Figure 5.2A), hence contradicting the taste-based discrimination hypothesis.

7. Conclusion

The decline in job finding chances due to prolonged unemployment has for long been documented in the job search literature. The reasons behind this decline remain relatively misunderstood though. Recent studies have highlighted individual heterogeneity and dynamic selection as key drivers of this negative duration dependence pattern. However, those usually focus on the ultimate outcome of job search, and tend to overlook that job

Figure 6.4: Changes in application targeting

(A) Same occupation (B) Skills requirements



Note: This figure describes the evolution of applications characteristics with respect to elapsed unemployment duration. The two panels are based on the *Auxiliary sample*. Panel A shows results for the share of targeted positions that are the same as occupations desired by the job seekers. Panel B reports evidence for the net-cognitive skills requirements of targeted occupations. Both panels show evidence based on the raw data (circle) and evidence controlling for individual heterogeneity, through individual fixed effects (x-cross).

search is a multi-step process, encompassing sequential decisions taken by job seekers and firms. Moreover, these studies are somewhat at odds with related work, that shows that elapsed unemployment duration itself has a marked net effect on job seekers' and firms' behaviors.

In this paper, we use a unique empirical data source to shed light on how heterogeneity and unemployment duration affect the dynamics of the different phases of the job search process. We collect longitudinal granular information on Swiss unemployed job search activity, stemming from job search diaries filled in at PES. These documents contain information on all applications sent out by a job seeker in each month of her unemployment spell. Specifically, we know for each application whether the contacted firm calls back the applicant, and eventually makes her a job offer.

We examine the dynamics of job seekers' behavior using the monthly number of job applications as a search effort proxy. We document a slight gradual decrease in application effort over the course of unemployment in the raw data. Accounting for individual heterogeneity through individual fixed effects, we find evidence of a much sharper decline in our measure of search effort. This steepening of the duration profile in job seekers' behavior is due to positive dynamic selection: job seekers who experience longer unemployment spells send systematically more applications at any duration.

We study firms' responses to job applications exploiting our rich dataset at its most granular level, *i.e.* at the application level. We show descriptively that the (application-level) callback probability is strongly decreasing over time, whereas the rate at which interviews are converted into job offers, *i.e.* the job offer conversion probability, exhibits slight positive duration dependence. To disentangle the contribution of heterogeneity and duration to these patterns, we use an alternative identification strategy. For each application, we compute its *ex-ante* chance of getting a positive response from firms, based on firms' responses in the very early periods of unemployment, and conditioning on all information that is relevant to firms when they make callback decisions. Controlling for heterogeneity through these *ex-ante* chances, we find that dynamic selection is negative at the callback stage, hence accentuating the duration profile of the callback probability in the raw data. In contrast, our conditioning approach has little effect at the job offer conversion stage, whose duration profile remains slightly positive. These findings are consistent with our intuition that observed job seekers' characteristics are mostly used in the first phase of firms' screening process.

Building on our empirical evidence of duration dependence in job seekers' and firms' behaviors, we develop a job search model with informational frictions and statistical discrimination à la Jarosch and Pilossoph (2019). We expand their baseline model by adding an application phase, in which heterogeneous job seekers choose the optimal level of search effort to exert when contacting heterogeneous firms. Upon receiving an application, a firm decides whether to call back the applicant for a costly job interview. As job seeker's type is unknown to the firm in the callback phase, its callback decision is based on the observed time the job seeker has spent unemployed, which conveys a signal about her productivity. During the interview, the firm discovers the type of the candidate, and decides whether to hire her or not. Statistical discrimination by firms towards long-term unemployed generates negative net duration dependence in the callback probability, as well as non-negative duration dependence in the job offer conversion probability, due to the pool of interviewees getting more homogeneous. The overall reduction in job finding chances entails in turn an endogenous net decline in search effort on the job seeker's side, due to the reduction in the marginal benefit from applying.

Our study enriches our understanding of the dynamics of the job search process, by providing granular and comprehensive evidence on how job seekers' and firms' behaviors evolve along unemployment. Our results corroborate the previous finding that individual heterogeneity is a major driver of these dynamics. However, they also highlight that the role of heterogeneity is not uni-dimensional: dynamic selection is either positive or negative, depending on which side of the labor market we consider. In particular, job seekers with different employment prospects might choose to exert different levels of search effort endogenously, hence generating complex dynamics in the pool of unemployed that are observed all along the duration of unemployment.

Furthermore, our study shows that dynamic selection does not account for the whole story: elapsed unemployment duration itself directly affects agents' behaviors in the labor market. Specifically, the net effects of duration on job seekers' and firms' behaviors tend to further dampen the chances that a match between labor supply and labor demand materializes over time. In light of our structural model, these net duration effects are rooted in firms' statistical discrimination against long-term unemployed, who use the time a job seeker has spent unemployed as a key information to infer her true productivity. If this signal is of primary importance in firms' screening process, prolonged unemployment might have detrimental implications for job seekers' employment prospects, not only in terms of successfully getting through firms' recruiting process, but also with respect to their provision of search effort.

Our work points towards clear policy recommendations for reducing informational frictions in the labor market, already in the early phases of the job search process. The provision of detailed information on workers' productivity, skills or labor market history to firms, already at the moment when they make callback decisions, might reduce the weight put on the negative signal conveyed by prolonged unemployment. Such attenuation of informational frictions would not only makes firms' recruiting decisions more accurate, but would also prevent negative endogenous responses by job seekers, faced with declining job finding chances.

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Appendix

A. Data and empirical measurements

Figure A1: Pre-defined job search forms

Assurance-chômage

Preuves des recherches personnelles effectuées en vue de trouver un emploi

A remettre à l'ORP
au plus tard le 5 du mois suivant

Date de réception / du timbre postal

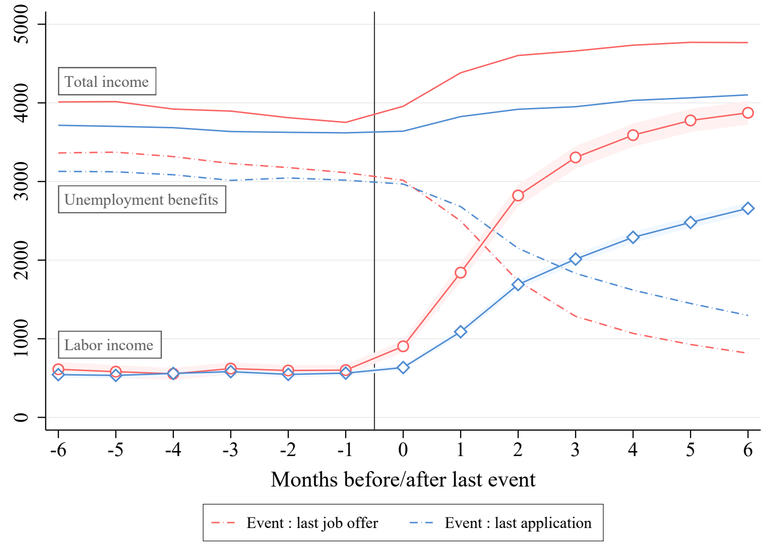
Nom et prénoms	No AVS	Mois et année

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

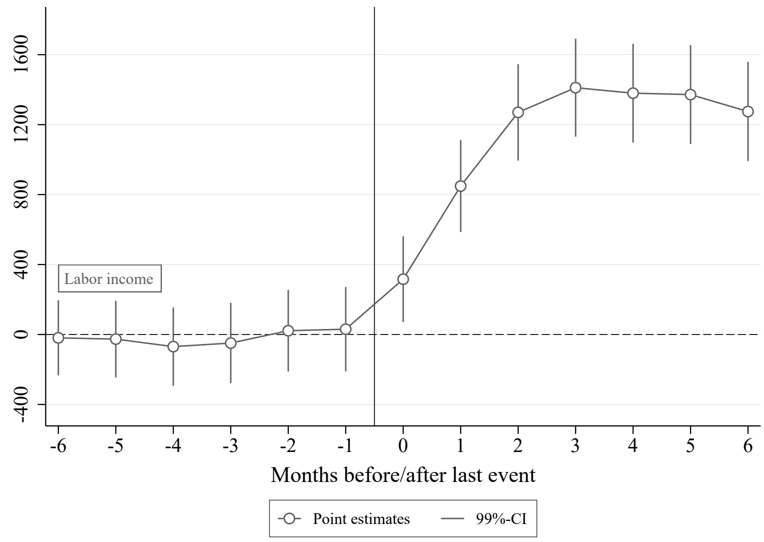
Note: This figure presents the pre-defined job search diary form, in which unemployed record their job search activity.

Figure A2: Job offers and income trajectories

(A) Observed average income trajectories

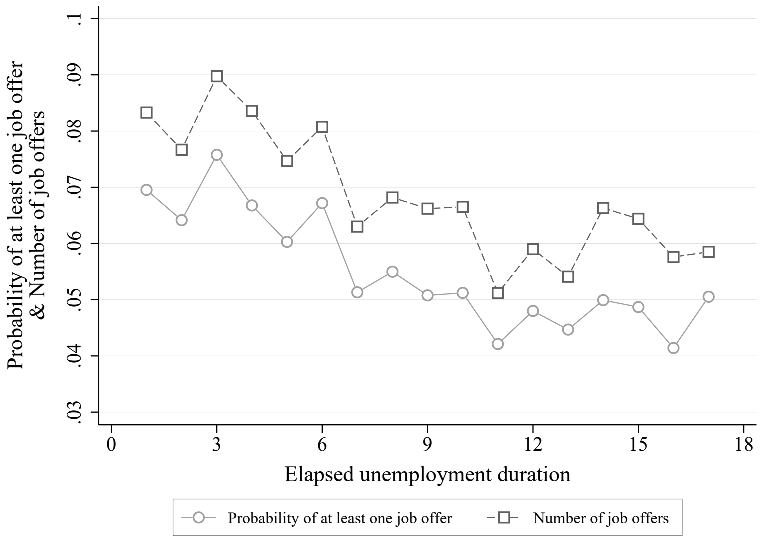


(B) Δ in labor income trajectories (accounting for heterogeneity)



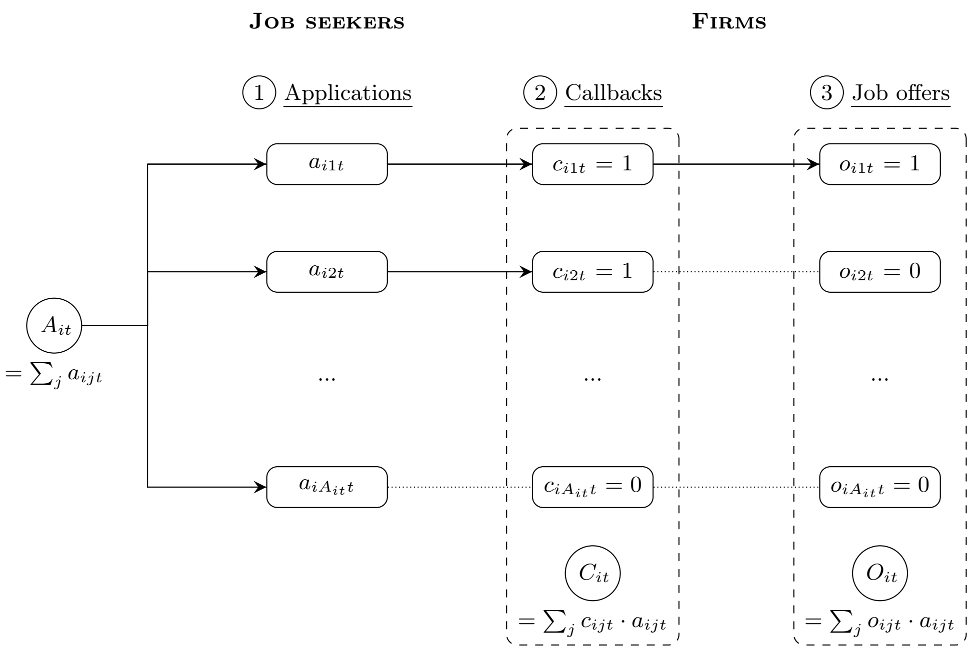
Note: This figure presents an event-study analysis, crossing information from the search diaries and the social security data. It highlights the informational content of the diaries data. Panel A shows the average evolution of total income, labor income and unemployment benefits in months before and after individual-specific events. For each individual, the event is either the last month when a job offer is recorded (in red, if at least one job offer is recorded in the observed data) or the last month when search diaries are collected (in blue, in the absence of job offer recorded). Panel B presents the results of a two-way fixed effects specification, to measure the differences in the labor income trajectories of the two above mentioned groups.

Figure A3: Monthly probability of at least one job offer and number of job offers



Note: This figure plots the average monthly probability of obtaining at least one job offer ($\mathbb{1}(O_{it} > 0)$, solid line) together with the average monthly number of job offers (O_{it}, dashed line).

Figure A4: Conceptual job search framework and empirical measurements of job search



Note: This figure presents our conceptual job search framework, together with data measurements from job search diaries.

Table A1: Job seekers' observed characteristics

	Main sample			***Auxiliary sample***		
	Mean	SDV	N	Mean	SDV	N
Individual characteristics						
Age	39.372	11.898	14798	39.307	10.651	655
1 = Female	0.458	0.498	14798	0.487	0.500	655
1 = Swiss	0.545	0.498	14798	0.539	0.499	655
1 = Primary education	0.269	0.444	14798	0.351	0.478	655
1 = Secondary education	0.588	0.492	14798	0.377	0.485	655
1 = Tertiary education	0.143	0.350	14798	0.189	0.392	655
1 = Manager	0.054	0.225	14798	0.092	0.289	655
1 = Specialist	0.598	0.490	14798	0.475	0.500	655
1 = Auxiliary	0.331	0.471	14798	0.423	0.494	655

Note: This table reports descriptive statistics on job seekers' socio-demographic characteristics, for the *Main sample* and *Auxiliary sample* of study.

Table A2: Descriptive statistics, *Auxiliary sample*

	Mean	SDV	Min	Median	Max	N
A. By application						
$\mathbb{P}(c_{ijt} = 1)$, callback prob. [in %]	7.396	26.171	0.000	0.000	100.000	24770
$\mathbb{P}(o_{ijt} = 1)$, job offer prob. [in %]	1.514	12.213	0.000	0.000	100.000	24770
$\mathbb{P}(o_{ijt} = 1 \mid c_{ijt} = 1)$, job offer conversion prob. [in %]	20.567	40.432	0.000	0.000	100.000	1559
B. By monthly-individual						
A_{it}, nbr. applications	8.900	4.597	1.000	9.000	36.000	2783
C_{it}, nbr. callbacks	0.560	1.259	0.000	0.000	21.000	2783
O_{it}, nbr. job offers	0.089	0.330	0.000	0.000	3.000	2783
$\mathbb{P}(C_{it} > 0)$, prob. a.l. one interview [in %]	28.926	45.350	0.000	0.000	100.000	2783
$\mathbb{P}(O_{it} > 0)$, prob. a.l. one job offer [in %]	7.833	26.874	0.000	0.000	100.000	2783
C. Sample structure						
Time-period			04.2012 - 03.2013			
Region			ZH			
Nbr. applications			24770			
Nbr. monthly-individual			2699			
Nbr. individuals			655			

Note: This table reports descriptive statistics about our *Auxiliary sample* of study. Panels A and B report descriptives on application-level and monthly-individual-level job search outcomes respectively. Panel C provides information about the sample structure.

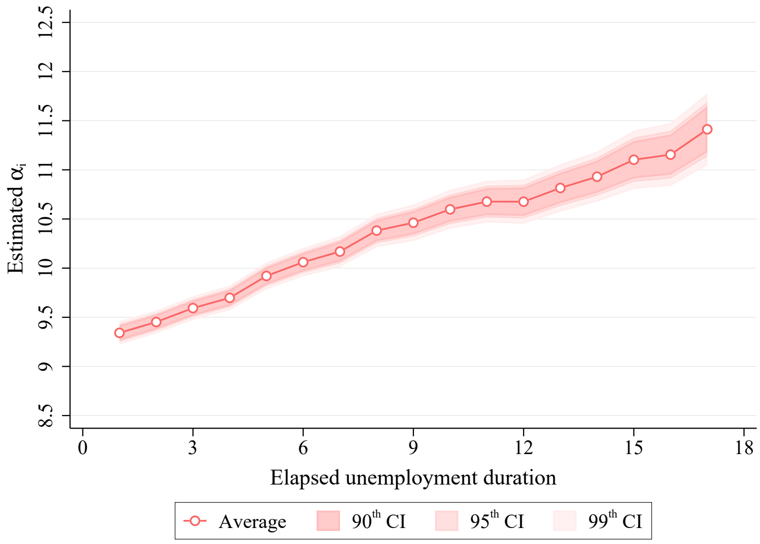
Table A3: Job search diaries, information coding

			Callback	Still open	Job offer	Negative	Freq.	%	Cum. %
Application	Callback	Job offer	☑	☑	☑	☑	93	0.015	0.015
			☑	☑	☑	☐	557	0.093	0.108
			☑	☐	☑	☑	55	0.009	0.117
			☑	☐	☑	☐	958	0.160	0.277
			☐	☑	☑	☑	78	0.013	0.290
			☐	☐	☑	☑	540	0.090	0.380
			☐	☑	☑	☐	500	0.083	0.463
			☐	☐	☑	☐	1506	0.251	0.714
		No job offer	☑	☑	☐	☑	3772	0.628	1.342
			☑	☐	☐	☑	5727	0.954	2.296
			☑	☑	☐	☐	4670	0.778	3.074
			☑	☐	☐	☐	3966	0.661	3.735
	No callback		☐	☑	☐	☑	125234	20.861	24.596
			☐	☐	☐	☑	277523	46.229	70.825
			☐	☑	☐	☐	141224	23.525	94.350
			☐	☐	☐	☐	33920	5.650	100.000
Total							600323	100.000	

Note: This table reports the distribution of the "types" of applications that are recorded in the job search diaries data, based on information contained in the 4 tick-boxes *Interview*, *Still open*, *Job offer* and *Negative*. Given the sequential decisions made by the firm (callbacks first, and then job offers), we impute a job interview for each application that records a job offer.

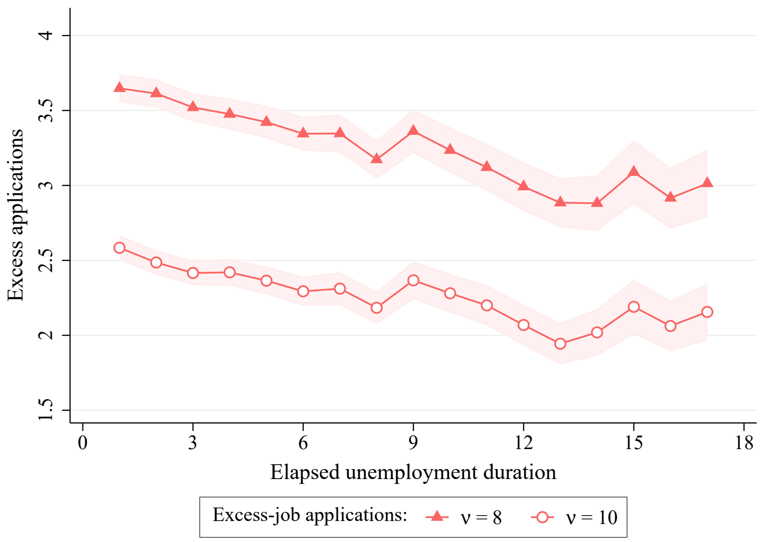
B. Job seekers: job applications

Figure B1: Dynamic selection with respect to application effort



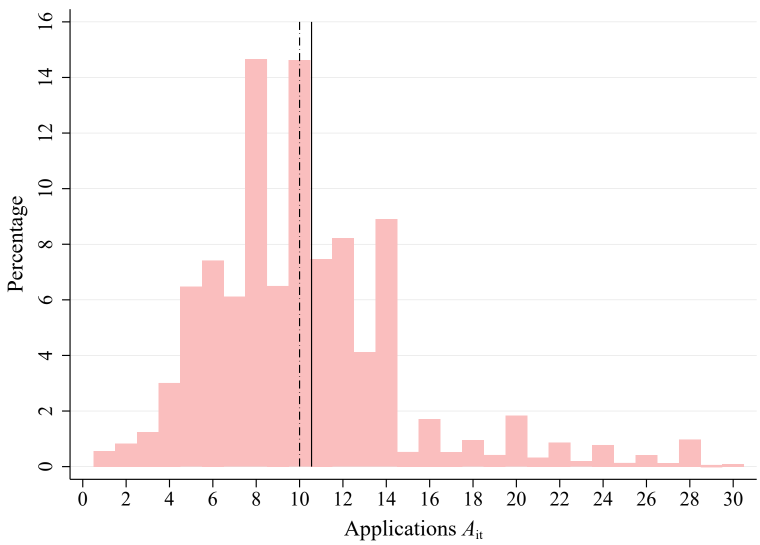
Note: This figure reports evidence on positive dynamic selection with respect to application effort. It plots the average estimated α_i from equation (4.1), per month of elapsed unemployment. For each month, only individuals that are observed in the raw data are considered when computing the average α_i.

Figure B2: Empirical duration dependence in excess application effort



Note: This figure reports empirical evidence of duration dependence in our excess application effort measures.

Figure B3: Empirical distribution of application effort



Note: This figure shows the empirical distribution of application effort, as measured by the number of applications sent out per month.

Table B1: Partial correlations between estimated α_i and observed characteristics

	(1)		(2)		(3)	
Dependent variable: estimated α_i						
Age						
$25-30$	0.021	(0.148)	0.020	(0.147)	-0.002	(0.146)
$30-35$	-0.106	(0.148)	-0.150	(0.148)	-0.147	(0.145)
$35-40$	-0.231	(0.153)	-0.271*	(0.152)	-0.253*	(0.150)
$40-45$	-0.285*	(0.153)	-0.329**	(0.151)	-0.332**	(0.149)
$45-50$	-0.302*	(0.154)	-0.298*	(0.153)	-0.259*	(0.153)
$50-55$	-0.382**	(0.157)	-0.385**	(0.155)	-0.388**	(0.155)
$55-60$	-0.688***	(0.168)	-0.685***	(0.167)	-0.661***	(0.166)
> 60	-2.496***	(0.194)	-2.518***	(0.192)	-2.478***	(0.191)
Residential status						
C-permit	0.479***	(0.093)	0.442***	(0.092)	0.446***	(0.092)
B-permit	0.505***	(0.110)	0.477***	(0.109)	0.467***	(0.108)
Other permit	0.242	(0.235)	0.188	(0.232)	0.320	(0.230)
Education						
Apprentice.	0.134	(0.093)	0.106	(0.092)	0.099	(0.091)
High school	0.453**	(0.185)	0.357*	(0.186)	0.345*	(0.183)
Professional mat.	-0.050	(0.173)	-0.054	(0.171)	-0.007	(0.172)
UAS	-0.125	(0.220)	-0.237	(0.220)	-0.198	(0.224)
University	-0.491***	(0.158)	-0.665***	(0.162)	-0.664***	(0.160)
Female	0.175**	(0.082)	0.177**	(0.081)	0.109	(0.082)
Labor market history						
ln(previous wage)	0.379***	(0.069)	0.378***	(0.069)	0.312***	(0.068)
Unemployment history	-0.495*	(0.268)	-0.486*	(0.266)	-0.502*	(0.267)
Occupation						
Industry & Craft	-2.235***	(0.284)	-2.190***	(0.283)	-2.271***	(0.282)
IT	-2.730***	(0.311)	-2.691***	(0.310)	-2.815***	(0.310)
Construction	-1.580***	(0.296)	-1.565***	(0.295)	-1.526***	(0.294)
Commercial	-1.181***	(0.282)	-1.162***	(0.281)	-1.310***	(0.282)
Hotelling	-1.224***	(0.282)	-1.275***	(0.281)	-1.361***	(0.284)
Administrative	-1.231***	(0.290)	-1.215***	(0.289)	-1.403***	(0.289)
Health & Educ.	-2.599***	(0.293)	-2.608***	(0.293)	-2.573***	(0.294)
Other	-2.451***	(0.300)	-2.435***	(0.298)	-2.578***	(0.298)
Canton						
SG	-2.460***	(0.093)				
VD	2.349***	(0.132)				
ZG	1.305***	(0.137)				
ZH	0.623***	(0.094)				
Constant	7.851***	(0.614)	7.891***	(0.633)	6.183***	(0.761)
Instituitions	Canton		PES		CW	
F-stat. instituitons	709.821		135.287		11.049	
p-value instituitons	0.000		0.000		0.000	
Observations	14798		14798		14798	
Adj-R^2	0.173		0.187		0.227	

Note: This table reports estimates of a multivariate linear regression, where we regress the estimated α_i from equation (4.1) on observed individual characteristics. Three models are reported, differing with respect to the policy controls included as regressors (cantons, PES offices or caseworkers fixed effects).

Table B2: Duration dependence in application effort, Poisson pseudo maximum likelihood

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: application effort A_{it}						
Elapsed unemployment duration	-0.009***	-0.006***	-0.004***	-0.004***	-0.020***	-0.021***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
	[-0.097]	[-0.069]	[-0.048]	[-0.050]	[-0.226]	[-0.230]
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
Mean outcome 1^{st} month	11.107	11.107	11.107	11.107	11.107	11.107
Pseudo-R^2	0.002	0.014	0.066	0.071	0.201	0.206
N. observations	55559	55559	55559	55559	55559	55559

Note: This table reports empirical estimates of equation (4.1) using a Poisson pseudo maximum likelihood estimator, where the parametric duration function $f^A(t;\phi^A)$ is specified linearly. Models are estimated on a restricted sample, that discards individuals who do not exhibit within-variation in application effort. Each column sequentially adds a set of controls or FE. Errors are clustered at the individual level and are reported in parentheses. Absolute coefficients (measuring the monthly decrease in application effort) are indicated in squared brackets and are directly comparable to our OLS baseline estimates. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Table B3: Duration dependence in application effort, alternative application effort measures

	Excess applications				Private applications	
	$\underline{A}=8$		$\underline{A}=10$			
	(1)	(2)	(3)	(4)	(5)	(6)
A. OLS						
Elapsed unemployment duration	-0.069***	-0.201***	-0.058***	-0.179***	-0.099***	-0.202***
	(0.008)	(0.022)	(0.007)	(0.022)	(0.009)	(0.022)
Individual controls	No	Yes	No	Yes	No	Yes
Policy controls	No	Yes	No	Yes	No	Yes
LLMC	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes
Mean outcome 1^{st} month	3.707	3.707	2.754	2.754	10.452	10.452
Adjusted-R^2	0.005	0.393	0.004	0.338	0.008	0.468
N. observations	45901	45901	39563	39563	51305	51305
B. Poisson						
Elapsed unemployment duration	-0.019***	-0.057***	-0.022***	-0.070***	-0.010***	-0.020***
	(0.002)	(0.006)	(0.003)	(0.008)	(0.001)	(0.002)
	[-0.071]	[-0.213]	[-0.060]	[-0.193]	[-0.101]	[-0.205]
Individual controls	No	Yes	No	Yes	No	Yes
Policy controls	No	Yes	No	Yes	No	Yes
LLMC	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes
Mean outcome 1^{st} month	3.707	3.707	2.754	2.754	10.452	10.452
Pseudo-R^2	0.004	0.328	0.004	0.334	0.003	0.200
N. observations	45901	45901	39563	39563	51305	51305

Note: This table reports empirical estimates of equation (4.1) for our alternative job search effort measures (excess application effort and private applications), where the parametric duration function $f^A(t;\phi^A)$ is specified linearly. Models are estimated using OLS (panel A) or Poisson pseudo maximum likelihood (panel B). For each independent variable, we consider either a bivariate model or the full specification. Errors are clustered at the individual level and are reported in parentheses. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

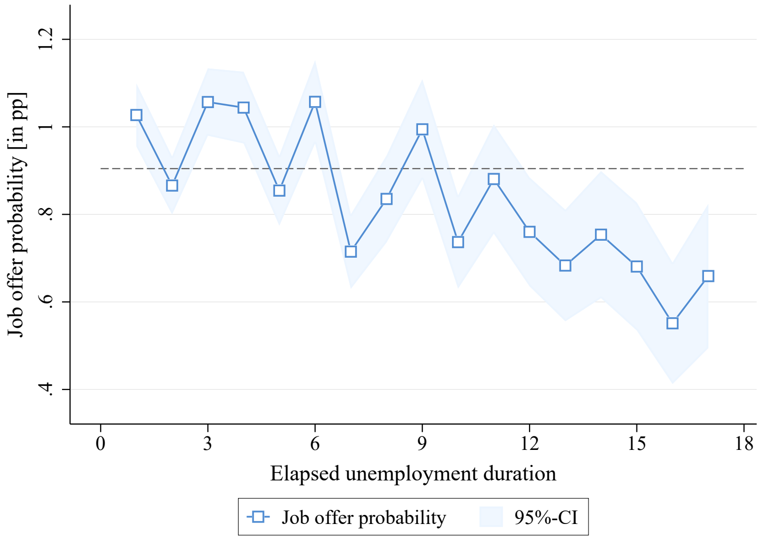
Table B4: Duration dependence in application effort, no exit months

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable : application effort A_{it}						
Elapsed unemployment duration	-0.082***	-0.056***	-0.037***	-0.041***	-0.190***	-0.215***
	(0.008)	(0.008)	(0.007)	(0.007)	(0.010)	(0.021)
	[-0.750%]	[-0.518%]	[-0.343%]	[-0.378%]	[-1.747%]	[-1.975%]
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
Mean outcome 1$^{\text{st}}$ month	10.846	10.846	10.846	10.846	10.846	10.846
adj.-R^2	0.006	0.035	0.179	0.193	0.495	0.502
N. observations	56646	56646	56646	56646	56646	56646

Note: This table reports empirical estimates of equation (4.1), where the parametric duration function $f^A(t;\phi^A)$ is specified linearly. Models are estimated on a restricted sample, that discards individual-monthly observations when an unemployment exit is observed. Each column sequentially adds a set of controls or FE. Errors are clustered at the individual level and reported in parentheses. Coefficients in relative terms (with respect to the average in the first month of unemployment) are indicated in squared brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

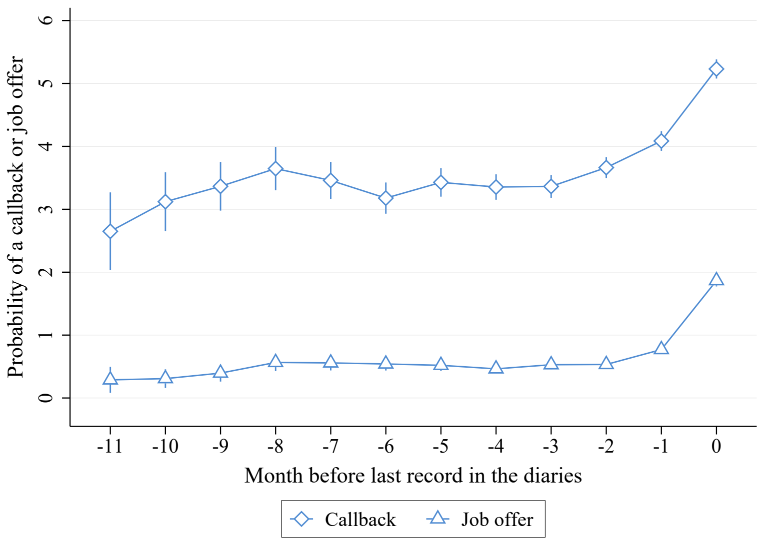
C. Firms' responses: callbacks and job offers

Figure C1: Duration dependence in the job offer probability



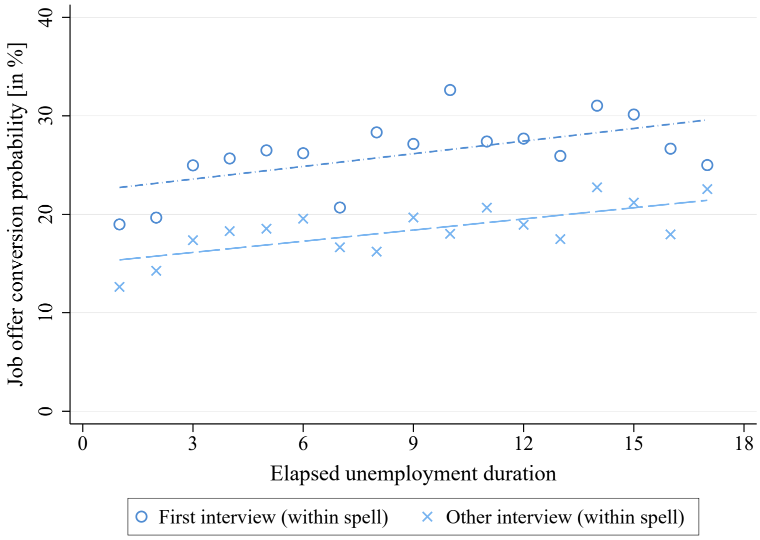
Note: This figure plots the average job offer probability, *i.e.* the probability that an application leads to a job offer, against elapsed unemployment duration. Application-level observations are weighted by the inverse of the monthly number of applications sent out by individual i in month t, so as to put equal weight on all monthly-individual observations.

Figure C2: Concentration of callbacks and job offers at the end of the spell



Note: This figure plots the average probability of a callback and a job offer (computed on all applications), for each month prior to the last month of record in the job search diaries. Application-level observations are weighted by the inverse of the monthly number of applications sent out by individual i in month t, so as to put equal weight on all monthly-individual observations. 95% confidence intervals for the average probabilities are reported.

Figure C3: Duration dependence in job offer conversion probability
First interview vs. Second and more interviews

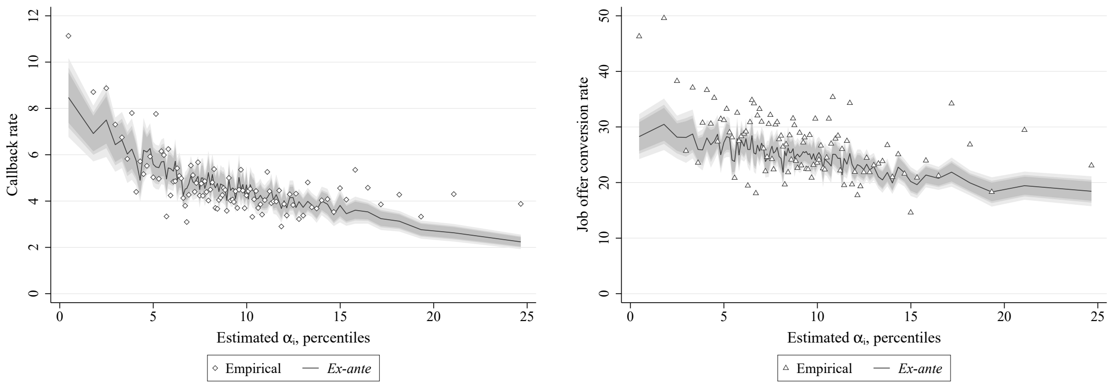


Note: This figure plots the average job offer conversion probability, distinguishing between the first interview recorded per unemployment spell, and all subsequent interviews.

Figure C4: Job seekers' heterogeneity
Application effort and *ex-ante* chances of positive replies by firms

(A) Callback probability

(B) Job offer conversions probability



Note: This figure reports evidence on the relationship between (i) the estimated application effort fixed effects α_i and (ii) job seekers' average chances of getting a positive response from firms. The latter are computed for the callback (panel A) and job offer conversion (panel B) probabilities, by averaging application-level information across all applications sent by a job seeker (only those which led to a callback for panel B). Those job seekers' average chances of a callback or job offer conversion are based either on firms' responses that are directly observed in the data (empirical), or on their *ex-ante* counterparts (*ex-ante*).

Table C1: *Ex-ante* probabilities, estimation in the reference month

	Callback probability		**Job offer conversion probability**	
	Marginal effects	SE	Marginal effects	SE
Age				
$25-30$	-0.158	(0.469)	3.739*	(2.095)
$30-35$	-0.812*	(0.447)	2.052	(2.068)
$35-40$	-0.561	(0.474)	0.841	(2.145)
$40-45$	-0.997**	(0.455)	-1.084	(2.113)
$45-50$	-0.889*	(0.458)	1.113	(2.144)
$50-55$	-1.241***	(0.466)	-0.189	(2.268)
$55-60$	-2.241***	(0.513)	3.656	(2.588)
> 60	-3.693***	(0.494)	5.189	(3.605)
Residential status				
C-permit	-1.164***	(0.270)	-1.548	(1.340)
B-permit	-1.260***	(0.292)	1.624	(1.617)
Other permit	-1.293*	(0.765)	-2.316	(3.820)
Education				
Apprentice.	2.313***	(0.249)	-4.904***	(1.618)
High school	1.571***	(0.508)	-6.619**	(2.934)
Professional mat.	3.786***	(0.517)	-5.035**	(2.457)
UAS	3.784***	(0.612)	-5.054*	(2.714)
University	3.326***	(0.486)	-11.269***	(2.201)
Female	0.360	(0.234)	-0.569	(1.171)
Labor market history				
ln(previous wage)	1.225***	(0.207)	-2.459**	(0.982)
Unemployment history	-3.471***	(0.822)	2.117	(4.179)
Application process				
Phone	-0.044	(0.215)	6.177***	(1.513)
Personal	7.580***	(0.429)	6.900***	(1.202)
CW referral	3.670***	(0.383)	1.068	(2.180)
Search effort α_i	-0.269***	(0.041)	-0.205	(0.154)
Policy controls	CW		PES	
LLMC	Yes		Yes	
Observations	153316		12060	
Pseudo-R^2	0.107		0.057	

Note: This table reports the empirical estimates of equations (5.2a) and (5.2b), in the references months τ_i^A and τ_i^C. Coefficients are reported as average marginal effects (in pp). Errors are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Table C2: *Ex-ante* probabilities with non-CV characteristics, estimation in the reference month

	Callback probability		**Job offer conversion probability**	
	Marginal effects	SE	Marginal effects	SE
Age				
$25-30$	0.086	(0.444)	3.914*	(2.057)
$30-35$	-0.573	(0.423)	2.265	(2.033)
$35-40$	-0.229	(0.453)	1.362	(2.111)
$40-45$	-0.604	(0.435)	-0.605	(2.077)
$45-50$	-0.441	(0.441)	1.994	(2.117)
$50-55$	-0.718	(0.455)	0.622	(2.236)
$55-60$	-1.652***	(0.516)	5.181**	(2.605)
>60	-2.935***	(0.517)	7.413**	(3.721)
Residential status				
C-permit	-1.118***	(0.269)	-1.091	(1.344)
B-permit	-1.224***	(0.290)	1.978	(1.616)
Other permit	-1.287*	(0.755)	-2.622	(3.778)
Education				
Apprentice.	2.190***	(0.253)	-5.283***	(1.618)
High school	1.487***	(0.502)	-7.147**	(2.914)
Professional mat.	3.657***	(0.511)	-5.344**	(2.442)
UAS	3.598***	(0.610)	-5.254*	(2.695)
University	3.033***	(0.472)	-11.134***	(2.215)
Female	0.339	(0.234)	-0.707	(1.169)
Labor market history				
ln(previous wage)	1.122***	(0.204)	-2.173**	(0.982)
Unemployment history	-3.576***	(0.820)	2.076	(4.188)
Application process				
Phone	-0.003	(0.215)	6.317***	(1.513)
Personal	7.687***	(0.426)	6.829***	(1.194)
CW referral	3.597***	(0.383)	1.387	(2.164)
Search effort α_i	-0.261***	(0.040)	-0.186	(0.151)
Non-CV characteristics				
Employability grade CW	0.977***	(0.245)	0.512	(1.137)
1 = Experienced sickness	-1.817***	(0.245)	-8.432***	(1.179)
Mobility degree				
Daily commute	-6.945	(5.489)	10.017	(8.214)
Part of the country	-6.367	(5.506)	10.830	(8.771)
Whole country	-5.613	(5.560)	5.499	(9.178)
International	-3.217	(5.720)	-3.506	(9.095)
Policy controls	CW		PES	
LLMC	Yes		Yes	
Observations	153316		12060	
Pseudo-R^2	0.112		0.065	

Note: This table reports the empirical estimates of equations (5.2a) and (5.2b), in the references months τ_i^A and τ_i^C, adding characteristics that are not observed on the CV. Coefficients are reported as average marginal effects (in pp). Errors are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

D. Model Derivations

We assume that matching frictions are subsumed by an urn-ball matching function, such that each period λa successful applications (balls) sort into V vacancies (urns). We scale the measure of applications a by the extent of meeting frictions λ faced by workers to obtain successful applications.

The measure of search effort crowding out a job seeker with ability x and unemployment duration τ in contact with a job of productivity y at the callback stage reads:

$$z^c(x,y,\tau) \equiv \lambda \sum_{t=0}^{\tau} \left(1 - \frac{1}{2}\mathbb{1}\{t=\tau\}\right) \int \mathbb{1}\{\bar{\tau}(x',y) < \tau\} \left(1 - \frac{1}{2}\mathbb{1}\{x'=x\}\right) s(x',t)u(x',t)\ d\mathcal{L}(x') \tag{D.1}$$

where $\bar{\tau}(x',y)$ denotes the highest duration τ such that (6.10) holds.

The measure of search effort crowding out a job seeker with ability x and unemployment duration τ in contact with a job of productivity y in hiring reads:

$$z(x,y,\tau) \equiv \lambda \sum_{t=0}^{\tau} \left(1 - \frac{1}{2}\mathbb{1}\{t=\tau\}\right) \int \mathbb{1}\left\{\left(\bar{\tau}(x',y) < \tau\right) \cup \left(\bar{\tau}(x',y) \geq \tau, x' \geq x\right)\right\} \left(1 - \frac{1}{2}\mathbb{1}\{x'=x\}\right) \tag{D.2}$$

$$s(x',t)u(x',t)\ d\mathcal{L}(x') + \sum_{t=\tau}^{\bar{\tau}(x',y)} \left(1 - \frac{1}{2}\mathbb{1}\{t=\tau\}\right) \int \mathbb{1}\{x' \geq x\} \left(1 - \frac{1}{2}\mathbb{1}\{x'=x\}\right) s(x',t)u(x',t)\ d\mathcal{L}(x')$$

The measure of search effort crowding out a job seeker with ability x absent discrimination reads:

$$z^{ND}(x) \equiv \lambda \int \mathbb{1}\{x' \geq x\} \left(1 - \frac{1}{2}\mathbb{1}\{x'=x\}\right) s(x',t)u(x',t)\ d\mathcal{L}(x') \tag{D.3}$$

Proof Lemma 1. Let $q(x,\tau{+}1) \equiv \int \left[\mathcal{C}(y,\tau)\exp\left\{-\frac{z^c(x,\tau,y)}{V}\right\} - \mathcal{C}(y,\tau+1)\exp\left\{-\frac{z^c(x,\tau+1,y)}{V}\right\}\right]$. Since $z^c(x,\tau,y) < z(x,\tau,y)\ \forall\tau$, then

$$o(x,\tau+1)|c(x,\tau+1) \geq \frac{\int \mathcal{O}(x,y,\tau)\exp\left\{-\frac{z(x,y,\tau)}{V}\right\}\ dF(y) - \alpha(x,\tau+1)q(x,\tau+1)}{\int \mathcal{C}(y,\tau)\exp\left\{-\frac{z^c(x,y,\tau)}{V}\right\}\ dF(y) - q(x,\tau+1)}.$$

It follows that if $\alpha(x,\tau{+}1) < o(x,\tau)|c(x,\tau)\ \forall\tau$, then $o(x,\tau{+}1)|c(x,\tau{+}1) > o(x,\tau)|c(x,\tau)\ \forall\tau$. □

Table D1: Wealth effect and job search effort provision, permanent income proxy

	Dependent income		**Labor income**		**Total income**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: permanent income proxy						
A. Average past income						
Avg. past income [in kCHF]	0.030**	0.061***	0.028**	0.062***	0.027**	0.065***
	(0.013)	(0.017)	(0.013)	(0.017)	(0.013)	(0.018)
Individual controls	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.000	0.093	0.000	0.093	0.000	0.093
N. observations	14798	14798	14798	14798	14798	14798
B. log-average past income						
ln (Avg. past income [in CHF])	0.132**	0.307***	0.123**	0.320***	0.114*	0.349***
	(0.054)	(0.066)	(0.054)	(0.067)	(0.059)	(0.077)
Individual controls	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.000	0.094	0.000	0.094	0.000	0.093
N. observations	14798	14798	14798	14798	14798	14798

Note: This table reports evidence of the wealth effect on job search effort provision. It reports (partial) correlation coefficients between a permanent income proxy (dependent, labor or total) and the estimated α_i from equation (4.1) measuring individual-specific search effort. Accumulated income is computed based on all income flows from 01.2005 up to the starting month of the unemployment spell, for the three different types of income. Panel A considers accumulated income as regressor, panel B log-accumulated income. Odd columns correspond to bi-variate regressions, whereas even columns additionally control for occupational sectors fixed effects. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Table D2: Wealth effect and job search effort provision, accumulated income

	Dependent income		**Labor income**		**Total income**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: accumulated income						
A. Accumulated income						
Accumulated income [in mmCHF]	-0.421***	-0.027	-0.435***	-0.029	-0.455***	-0.054
	(0.150)	(0.189)	(0.150)	(0.190)	(0.148)	(0.193)
Individual controls	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.001	0.092	0.001	0.092	0.001	0.092
N. observations	14798	14798	14798	14798	14798	14798
B. log-accumulated income						
ln (Accumulated income [in CHF])	-0.105***	0.053	-0.111***	0.053	-0.130***	0.028
	(0.038)	(0.050)	(0.038)	(0.050)	(0.039)	(0.053)
Individual controls	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.000	0.092	0.001	0.092	0.001	0.092
N. observations	14798	14798	14798	14798	14798	14798

Note: This table reports evidence of the wealth effect on job search effort provision. It reports (partial) correlation coefficients between accumulated income (dependent, labor or total) and the estimated α_i from equation (4.1) measuring individual-specific search effort. Accumulated income is computed based on all income flows from 01.2005 up to the starting month of the unemployment spell, for the three different types of income. Panel A considers accumulated income as regressor, panel B log-accumulated income. Odd columns correspond to bi-variate regressions, whereas even columns additionally control for occupational sectors fixed effects. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Table D3: Job search effort provision and appliction channels' shares

	Written channel		**Phone channel**		**Personal channel**	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: estimated α_i						
Application channel's share	0.568***	0.624***	-0.664***	-0.437***	-0.483***	-0.807***
	(0.107)	(0.111)	(0.146)	(0.146)	(0.162)	(0.165)
Individual controls	No	Yes	No	Yes	No	Yes
Adjusted R^2	0.002	0.099	0.001	0.098	0.001	0.099
N. observations	14798	14798	14798	14798	14798	14798

Note: This table reports evidence of the correlation between job search effort provision and the use of application channels. Each column reports the partial correlation between the estimated α_i from equation (4.1) and the share of each channel (written, phone, personal) in all applications sent by job seeker i (aggregated at the individual level). Odd columns correspond to bi-variate regressions, whereas even columns additionally control for job seekers' characteristics. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.