I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16602

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

Jeremy Zuchuat
Rafael Lalive
Aderonke Osikominu
Lorenzo Pesaresi
Josef Zweimüller

NOVEMBER 2023

I Z A Institute
of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 16602

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

Jeremy Zuchuat
University of Lausanne

Rafael Lalive
University of Lausanne and IZA

Aderonke Osikominu
University of Hohenheim and IZA

Lorenzo Pesaresi
University of Zürich

Josef Zweimüller
University of Zürich and IZA

NOVEMBER 2023

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

The job finding rate declines with the duration of unemployment. While this is a well established fact, the reasons are still disputed. We use monthly search diaries from Swiss public employment offices to shed new light on this issue. Search diaries record all applications sent by job seekers, including the outcome of each application – whether the employer followed up with a job interview and a job offer. Based on more than 600,000 applications sent by 15,000 job seekers, we find that job applications and job interviews decrease, but job offers (after an interview) increase with duration. A model with statistical discrimination by firms and learning from search outcomes by workers replicates these empirical duration patterns closely. The structurally estimated model predicts that 55 percent of the decline in the job finding rate is due to "true" duration dependence, while the remaining 45 percent is due to dynamic selection of the unemployment pool. We also discuss further drivers of the observed duration patterns, such as human capital depreciation, stock-flow matching, depletion of one's personal network, and changes in application targeting or quality.

JEL Classification: J24, J64

Keywords: job search, job finding, duration dependence, dynamic selection, search effort, job application, callback, job interview, job offer

Corresponding author:
Rafael Lalive
Department of Economics
HEC University of Lausanne
CH-1015 Lausanne
Switzerland
E-mail: Rafael.Lalive@unil.ch

* We are grateful to seminar audiences in Austin, Basel, Bergen, Berkeley, Berlin, Bonn, Cornell, Georgetown, Madrid, Rome, Salzburg, Stockholm, Tel Aviv, Tilburg, Uppsala, and Vienna, and especially to David Card, Pierre Cahuc, Stefano DellaVigna, Gregor Jarosch, Philipp Kircher, Pat Kline, Attila Lindner, Enrico Moretti, Andreas Mueller, Laura Pilossoph, Benjamin Schoefer and Simon Trenkle. Rafael Lalive acknowledges financial support through Swiss National Science Foun- dation Grant No. 100018_204575.

1. Introduction

The rate at which unemployed workers find new regular jobs decreases with the duration of unemployment. While this is a well established empirical fact, the reasons are still disputed. As often, the debate is about causation versus correlation. Does the falling job finding rate reflect a causal effect of unemployment duration on the chances to find a new job? Or does it reveal negative dynamic selection, so that the long-term unemployed had weak employment prospects to begin with? Answers to these questions are crucial because they lead to quite different policy responses. If low job finding rates are caused by duration, avoiding long-term unemployment calls for early intervention programs such as job search assistance and close monitoring of job search. Instead, if the long-term unemployed are a negatively selected group, training programs upgrading their skills are the principal measure to improve their job prospects.

This paper sheds new light on the falling job finding rate by using *monthly search diaries* from the Swiss public employment offices. In Switzerland, job seekers drawing unemployment insurance (UI) benefits have to document their search activities in search diaries. Search diaries do not only list each single application, they also indicate whether the employer followed up with an invitation to a job interview and, if so, whether the interview eventually resulted in a job offer. Search diaries are an important monitoring tool providing high-quality information on unemployed workers' search effort as well as the outcome of their search activities.

Our paper contributes to the literature in two respects. On the *empirical* side, we digitized 58,000 search diaries containing 600,000 job applications sent by 15,000 job seekers. These data allow us to dig deeper into the various steps of the job finding process and provide novel evidence on how job applications, interviews, and job offers change with the duration of unemployment. In this respect, our comprehensive approach extends the existing literature which has either looked at the effect of duration on search effort or the effect of duration on employer callbacks (but not on both jointly). To the best of our knowledge, our study is the first one exploring how the probability to obtain a job offer after an interview changes with unemployment duration.

On the *theoretical* side, we develop a unifying framework that makes precise how duration dependence in applications, interviews and job offers eventually translates into "true" duration dependence in the job finding rate.[1] Our framework combines a model of statistical discrimination against the long-term unemployed with a model in which job seekers have imperfect information about their ability and learn from search outcomes during the unemployment spell.[2] It delivers predictions about job applications, interviews and job offers – and how they change with duration – that are qualitatively consistent with what we observe in our search diary data. Structurally estimating this model not only allows us to decompose the empirically observed decline in the job finding rate into duration dependence and dynamic selection. It also enables us to quantify the extent to which duration dependence is driven by search behavior of workers and by interview/hiring choices of recruiters.

In our empirical analysis, we start by exploring how *job applications* change with the duration of unemployment. The average job seeker makes 11 applications in month 1 of the unemployment spell, which decreases to slightly less than 10 in months 12-15. Because applications are repeatedly observed for each job seeker, a fixed-effect model can tease out duration dependence. It turns out that there is a strong within-individual decline from 11 applications in month 1 to 8 applications in months 12-15. Since, in the cross-section, the number of applications decreases only slightly, this implies there is *positive* dynamic selection: job seekers who eventually become long-term unemployed search harder at all durations.

We proceed by analyzing job interviews and job offers. The probability of a *job interview* shows a marked decline from 5 percent for applications sent in month 1 to 2.5 percent for those sent in months 12-15, very similar to Kroft, Lange, and Notowidigdo (2013) for fictitious job applicants in the U.S. Interestingly, and perhaps surprisingly, the probability to get a *job offer* (conditional on a job interview) *increases* with duration, from 20 percent in month 1 of the spell to 25 percent or more in months 12-15.

Disentangling duration dependence from dynamic selection in interviews and job offers is more complicated than for applications. Unlike job applications, which are repeatedly

[1] Throughout the paper, when we refer to duration dependence, we always mean "true", "structural" or "within-individual" duration dependence: a duration profile of the respective variable that is not driven by a change in the composition in the unemployment pool but purely by duration.

[2] Our model of statistical discrimination builds upon Jarosch and Pilossoph (2019) which explores how an applicants' duration of unemployment affects recruiters' choice to invite her to a costly job interview. For models emphasizing how search outcomes affect search effort along the unemployment spell, see Burdett and Vishwanath (1988), Gonzalez and Shi (2010) and He and Kircher (2023).

observed and occur throughout the unemployment spell, job interviews and job offers are rare events that that are concentrated at the end of the spell. For this reason, the fixed-effect model does not work. Instead, we use a "prediction model" similar in spirit to Mueller and Spinnewijn (2023)'s. Using this model, which holds the composition of *observable* characteristics constant, we find that the interview probability reduces from 5 percent in month 1 to 3.5 percent in months 12-15, a decline that is smaller than empirically observed because of negative dynamic selection on observables. Using the same procedure for job offers (after an interview), we find that observable characteristics cannot account for the upward sloping job offer probability.

In sum, we find negative duration dependence (and positive dynamic selection) in the number of job applications; and we find negative dynamic selection on observables for job interviews and no selection on observables for job offers. However, it remains unclear whether the remaining downward sloping duration profile for interviews and upward sloping profile for job offers are due to duration dependence or dynamic selection on *unobservables*. To answer this question we need a theoretical framework.

Our theoretical framework combines the model of Jarosch and Pilossoph (2019), where employers statistically discriminate against the long-term unemployed, with a model of search under incomplete information, where workers learn from search outcomes according to Burdett and Vishwanath (1988)'s negative selection mechanism. This combined framework captures the empirically estimated duration patterns in applications, interviews, and job offers. First, it predicts that the *interview* probability falls with duration. Job seekers differ in (unobserved) ability and firms differ in ability requirements. Because high-ability workers find jobs more quickly, the expected average ability of a job seeker is lower the longer her unemployment duration. This induces firms to use unemployment duration as a screening device. In particular, firms with high ability requirements will refrain from calling back long-term unemployed job seekers for an interview.

Second, the model predicts negative duration dependence in *job applications*. This happens for two reasons. On the one hand, since job seekers do not exactly know their own ability, negative search outcomes induce them to revise beliefs about own job prospects downward. The resulting lower expected value of search discourages search at longer durations. On the other hand, job search is further discouraged because the long-term unemployed are aware that employers will discriminate against them in equilibrium.

Finally, the model predicts that the *job offer* probability (conditional on an interview) increases with duration. For recruiters, a short duration provides only a weak signal about the applicant's ability because the short-term unemployment pool consists of both high- and low-ability workers. Most firms will interview but firms with high ability-requirements will reject many applicants. In other words, for applicants with at short durations the interview probability is high, but the job offer probability is low. In contrast, a long unemployment duration provides a strong signal for recruiters as mostly low-ability workers are left in the long-term unemployment pool. Few firms will interview but those who do are likely making an offer.

Structurally estimating this model helps us to decompose the decrease in the job finding rate into duration dependence and dynamic selection on unobservables. The decomposition exercise reveals that the decrease in the observed job finding rate (from 7 percent in month 1 to 4.5 percent in months 12-15 of the unemployment spell) is to a large extent driven by duration dependence (55 percent of the decrease), though also dynamic selection (45 percent) explains an important part.[3] According to our estimates, duration dependence comes about mainly from reduced search effort by job seekers (45 percentage points of the 55 percent), while employer behavior (interviews, job offers) is quantitatively less important (10 percentage points of the 55 percent).[4]

Our model emphasizes limited information and disregards potentially important other channels that might explain why unemployment duration has an impact on the job finding rate, such as skill depreciation during unemployment (Ljungqvist and Sargent, 1998), falling job opportunities (e.g. due to stock-flow matching), depletion of private networks, falling quality of applications and increasing (regional or occupational) search radius. At the end of the paper we discuss the potential relevance of these other channels and provide selective additional evidence where data permit.

The remainder of the paper is organized as follows. In Section 2 we discuss related literature. Section 3 describes the institutional context and the data we use for our

[3]The decomposition exercise uses our empirical analysis to account for the role of observable characteristics and the theoretical analysis (and the structurally estimated parameters) to decompose the remaining duration profiles after controlling for observables into selection on unobservables and duration dependence.

[4]This latter result echoes the findings of Jarosch and Pilossoph (2019) in the US context, according to which only about 10 percent of the decrease in the job finding rate can be attributed to structural duration dependence originating in employers' interview choices.

empirical analysis. Section 4 studies duration dependence in applications, interviews and job offers based on the search diary data. In Section 5 we develop our theoretical framework and Section 6 structurally estimates this model. Section 7 highlights crucial assumptions and limitations of our analysis and discusses alternative mechanisms that might explain our findings. Section 8 concludes.

2. Related literature

Our paper is related to an old literature, dating back to Lancaster (1979), Heckman and Singer (1984), and Van den Berg and Van Ours (1996), that developed appropriate econometric models to disentangle duration dependence from dynamic selection. Recent papers that have extended these approaches include Ahn and Hamilton (2020), Alvarez, Borovičková, and Shimer (2022) and Mueller and Spinnewijn (2023). These more recent papers point to heterogeneity as the most important driver behind the falling job finding rate and the dynamics of labor markets more generally (Ahn, Hobijn, and Şahin, 2023).

Another related strand of literature focuses on how search effort varies with the duration of unemployment, with several studies based on repeated surveys (Krueger, Mueller, Davis, and Şahin, 2011; Mueller, Spinnewijn, and Topa, 2021; DellaVigna, Heining, Schmieder, and Trenkle, 2022) or data from online job boards (Faberman and Kudlyak, 2019; Fluchtmann, Glenny, Harmon, and Maibom, 2021). Many (though not all) of these studies find a limited role of unemployment duration on search effort of workers. Several recent paper have documented that search effort varies systematically around exhaustion of UI benefits (Marinescu and Skandalis, 2021; DellaVigna, Lindner, Reizer, and Schmieder, 2017; DellaVigna, Heining, Schmieder, and Trenkle, 2022). Other papers have explored how changes in search strategies along the duration of unemployment affect the job finding rate (Belot, Kircher, and Muller, 2018).

Correspondence testing studies have investigated whether callback rates are lower for long-term unemployed workers. Kroft, Lange, and Notowidigdo (2013), Oberholzer-Gee (2008), Eriksson and Rooth (2014) and Nüß (2018) find evidence in favor of that hypothesis for the US, Switzerland, Sweden and Germany, respectively. However, Farber, Silverman, and Von Wachter (2016) do not find an impact of duration on the callback rate.

On the theoretical side, our paper relates to two main strands of literature. First, we speak to the structural literature on duration dependence in hiring. Duration dependence in hiring has been explained by models of skill depreciation during unemployment (Ljungqvist and Sargent, 1998, 2008), ranking by unemployment duration among multiple applicants (Blanchard and Diamond, 1994; Fernández-Blanco and Preugschat, 2018), and statistical discrimination against long-term unemployed (Vishwanath, 1989; Lockwood, 1991; Jarosch and Pilossoph, 2019). Our model of firms' behavior builds on Jarosch and Pilossoph (2019)'s framework and encompasses both statistical discrimination and ranking among multiple applicants as sources of duration dependence.

Second, we contribute to the literature on job seekers' learning from search. To explain declining reservation wages over an unemployment spell, Burdett and Vishwanath (1988) proposes a model in which job seekers learn about their individual job prospects. Specifically, job seekers revise their beliefs about their prospects downward after unsuccessful search outcomes. Falk, Huffman, and Sunde (2006) applies the same logic to labor market participation decisions. Gonzalez and Shi (2010) and Doppelt (2016) develop search models with incomplete information and lifetime learning from labor market outcomes to explain negative duration dependence in reemployment wages. In a contemporaneous work, He and Kircher (2023) explores the implications of biased beliefs for the dynamics of the individual perceived job finding rate, hinting at significant implications for job seekers' search effort. We contribute to this literature by proposing a novel model of learning from search that applies Burdett and Vishwanath (1988)'s negative selection mechanism to application decisions, as well as featuring empirically-relevant heterogeneity in search efficiency across job seekers. To the best of our knowledge, we are the first to investigate how duration dependence in the job finding rate is shaped by the interaction between statistical discrimination by firms and learning from search by workers.

3. Institutional context and data

The context of our analysis are job seekers in Switzerland drawing unemployment insurance (UI) benefits. Like in most unemployment insurance (UI) systems, job seekers in Switzerland who receive UI benefits are obliged to actively search for new jobs. Compliance with Swiss UI rules implies that job seekers have to document their search effort in monthly search diaries.[5] In meetings with the caseworker, search diaries are discussed and updated (to keep track of application outcomes in the current and previous unemployment-months). To check the correctness of the information, caseworkers review copies of the resumes and check on a random basis with employers whether the application has indeed been sent, or whether an applicant has shown up for a job interview. Non-compliance with these obligations may lead to a benefit sanction – a temporary benefit reduction or even a removal of UI benefit payments. This means that unemployed workers have a strong incentive to provide correct information in search diaries.

The Swiss UI system is rather generous. UI benefits are 70% of previous earnings or 80% for low income earners or job seekers with dependents. The maximum duration of UI benefits is 18 months. In what follows, we will truncate the analysis at 17 months. The main reason is the lack of statistical power at longer durations. This also means that the observed duration profiles are not determined by changes in UI benefits over time, as all job seekers are entitled to regular UI benefits throughout when their outcomes – applications, interviews, and job offers – are observed.

The search diary data used for this study were collected between April 2012 and March 2013 in five Swiss cantons (Zürich, Bern, Vaud, Zug and St-Gallen).[6] All workers who were unemployed in April 2012 and all who entered unemployment between April 2012 and March 2013 are included in the analysis (combined stock-flow sample). Search diary forms contain detailed information on the number of applications made by the job seeker in each month of the unemployment spell (one diary per month). Importantly for our analysis, search diaries report information on each application's outcomes (job interview, job offer, negative or still open).[7]

We digitized more than 58,000 monthly search diaries filled out by 15,000 job seekers. These diaries document more than 600,000 job applications and their outcomes (job interview, job offer). A particular advantage is that the search diary data can be linked to the Swiss unemployment insurance register (reporting job seekers' socio-economic and demographic characteristics) and to the Swiss social security register (providing informa-

[5]The monthly search diary is a standardized form that job seekers have to fill out. For the design of this form, see Appendix, in Figure A1.

[6]Around 47% of the Swiss population live in one of these five cantons.

[7]Search diaries also include information on application dates, application channels (written, personal or by phone), the work-time percentage of targeted positions (full-time or part-time).

tion on workers' previous and subsequent earnings- and employment history). Another advantage is that search diaries report the behavior of both job seekers and recruiters, thus allowing us to quantify the relative importance of supply and demand forces as drivers of the job finding rate.[8]

We restrict our analysis samples to those job applications made in months during which a job seeker receives UI benefits. This is motivated by data reliability: only job seekers drawing unemployment benefits have the legal obligation to fill in search diaries, and the recorded information is checked by caseworkers. Additionally, we focus on individuals for whom information on socio-demographic characteristics and the employment history is non-missing, these pieces of information playing an important role in our identification strategy. We remove job seekers who return to the previous employer, as job search after a temporary layoff substantially differs job search after a permanent layoff (Nekoei and Weber, 2020).

A possible limitation of the search diary data is that some applications remain right-censored, meaning that the outcome of the job application remains unknown. However, since right-censoring in applications does not vary with unemployment duration (see Figure B4 in the Appendix), it is unlikely that the estimated duration profiles are systematically biased. Moreover, we show below that the number of job offers we actually observe is very much in line with the number of people leaving unemployment (Figure 1), suggesting that right-censored applications would typically not have resulted in a job offer. For these reasons, we integrated right-censored job applications into the baseline analysis and code the response to right-censored job applications the same way as a rejection to the application. Our results are not sensitive to treating right-censored applications as rejections or to removing them from the pool of applications (see Figures B5 to B7 in the Appendix).[9]

---

[8]When interpreting applications as workers' search behavior and interviews and job offers as firms' decisions, one should keep in mind the caveats to this interpretation. The number of applications sent is partly driven by UI compliance rules. For instance, some applications may be merely sent to fulfill search requirements or because of an assignment by the caseworkers. An employer's response to an application will be influenced by the quality of the application and a worker's behavior during the job interviews. We argue that, to the extent these confounders do not vary in a systematic way with duration, they should not bias the estimated contribution of supply- and demand factors to the falling job finding rate.

[9]The search diary data do not provide information on the characteristics of the vacancies to which job seekers apply. In an auxiliary but smaller data set we can observe certain vacancy characteristics. Appendix Table A1 provides descriptive statistics of this auxiliary sample and compares it to the main sample. We use the vacancy information in the auxiliary data to discuss the relevance of changes in

The outcome of main interest is the *job finding rate* – as measured by the probability of at least one job offer from applications sent during a given month. Notice that the job finding rate is purely based on search diaries and relates the job finding event to the month when the application was made. Table 1 reports descriptive statistics on the job finding rate, and on applications, job interviews, and job offers. The average monthly job finding rate is 6.1 percent. These job offers are the result of job seekers applying to jobs and firms responding to these job offers. Job seekers report about 10.5 applications on a typical search diary. Firms invite applicants to an interview with a 4.0 percent probability, and interviewees receive a job offer with a 22.5 percent probability. The probability that an application yields an interview and a job offer is 0.9 percent. This means that job seekers need to make more than 100 applications to receive one job offer.

Figure 1 shows that the job finding rate decreases with the duration of unemployment (bold line). The job finding rate is around 7 percent in the first three months in unemployment and falls below 5 percent later in the unemployment spell. (Recall that our measurement of the job finding rate is purely based on search diaries and refers to the month when the application was sent.) We validate the information content of search diaries in two ways. First, we compare the duration profile of the job finding rate as measured in the search diary to the transition rate from unemployment to employment as observed in the social security data (Figure 1). Because search diary data can be linked to the social security data at the individual level, both graphs are conceptually similar and based on the same population at risk.[10] Figure 1 shows that the two graphs

Table 1: Main outcome variables, mean (std. dev.)

A. Person-month level (search-diary level)		
Job finding rate (per month)	0.061	(0.239)
Number of applications (per month)	10.553	(4.698)
B. Application level		
Interview probability (per application)	0.040	(0.196)
Job offer probability (conditional on interview)	0.225	(0.418)
Unconditional job offer probability (per application)	0.009	(0.095)

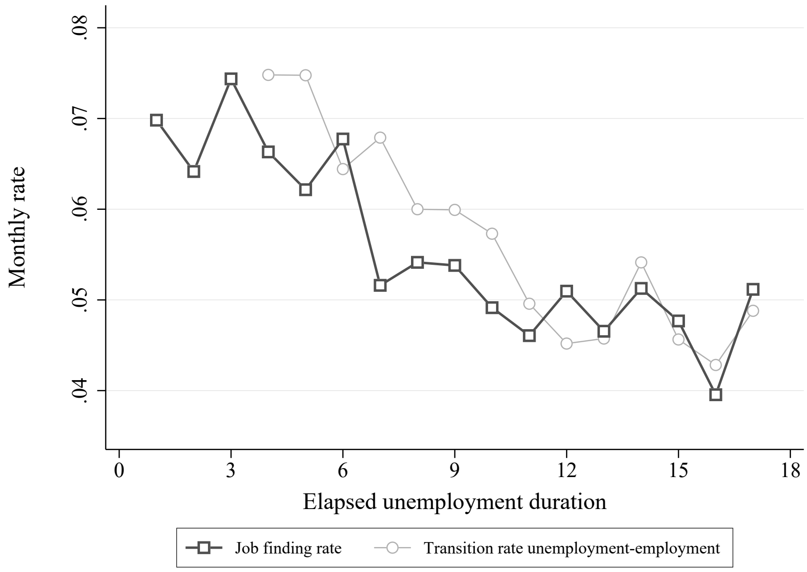
Note: This table reports descriptive statistics on the job finding rate, applications, interviews, and job offers. The interview probability is the probability of at last one interview for all applications in a search diary.

targeting of search in Section 7, see also Appendix B.4.

[10] In our definition of the job finding rate, the population at risk includes individuals sending applications during duration month t; for the transition rate from unemployment to employment, the population at risk comprises all individuals with an elapsed duration of unemployment of t months.

have similar slopes, though the transition rate is located to the right of the job finding rate. The reason is that the job finding rate (as defined here) refers to the month when the application was sent, while the transition rate from unemployment to employment refers to the month when a job was actually started.[11]

Figure 1: Monthly job finding and unemployment-to-employment transition rates



Note: This figure depicts the empirical duration dependence in the job finding rate (computed from search diaries data) and the monthly unemployment-to-employment transition rate (computed from social security data).

Our second validation of the information content of the search diaries is based on income trajectories observed in the social security data after the last job offer observed in the search diary data. Appendix Figure A2 shows that, indeed, labor earnings are close to zero during the months before the job offer and increase sharply in the 2-3 months after the last job offer. This makes us confident that the information on job finding in the search diaries is indeed predictive of taking up a regular job.

Figure 2 shows the empirical (cross-sectional) duration profiles of the number of job applications, the probability (per application) of a job interview and a job offer (condi-

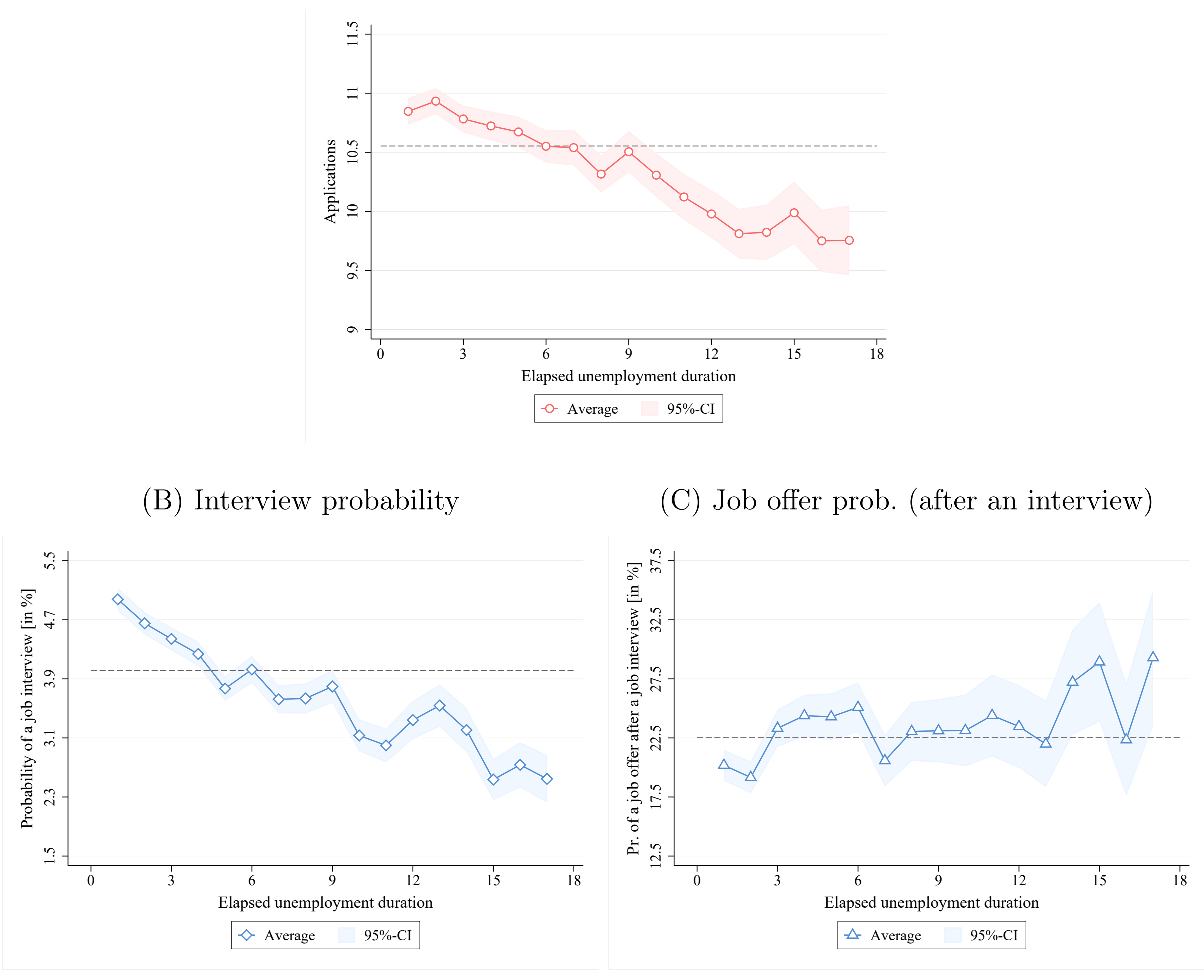
[11] Search diaries contain information on the month when the application was made, but not on the month when the interview took place nor the month when the job was offered or started. Hence we assign interviews and job offers to the month when the eventually successful application was made. The job finding rate would be identical to the latter only under two conditions. First, a job seeker who obtains at least one job offer during month t always accepts an offered job. This condition is mostly met, since job search requirements oblige job seekers to accept job offers. Second, if the successful application was made in month t of the unemployment spell, the start of the new job needs to be in the same month. This is usually not the case. Because recruitment decisions take time, the month when the application was made usually precedes the month when the job is started. We do not know the identity of the recruiter in the search diary, we cannot directly check whether the new firm as observed in the social security data is identical to the employer who made a job offer to the job seeker.

Figure 2: Empirical duration profiles

(A) Applications

(B) Interview probability

(C) Job offer prob. (after an interview)



Note: This figure depicts the empirical duration profiles in the number of job applications made per month (Panel A), the application-level probability of a job interview (Panel B) and the application-level probability of a job offer conditional on an interview (Panel C). Dashed horizontal lines indicate sample average.

tional on an interview). Panel A shows that applications decrease from close to 11 in the first months of the unemployment spell to slightly less than 10 after 12 months or more. Panel B shows that the probability that an application receives an invitation to a job interview declines from about 5 percent to only 2.5 percent after 15 months or more. Interestingly, and perhaps surprisingly, the probability that an application results in a job offer – conditional on a job interview – *increases* with duration (Panel C). Early in the unemployment spell this probability is around 20 percent, increasing up to 30 percent at long durations.

It is worth noting at this stage that, with respect to job applications and job interviews, the descriptive evidence is in the ballpark of what other studies have documented in different contexts. For instance Faberman and Kudlyak (2019) found a decreasing profile of job applications in online job board data. The correspondence testing study of Kroft, Lange, and Notowidigdo (2013) found callback rates of a very similar order of magnitude and a strong downward sloping duration profile. To our knowledge there is no other paper that would have documented how the probability of a job offer after an interview changes with duration.

4. Applications, interviews and job offers

We now exploit our search diary data to study in detail how (i) the number of job applications, (ii) the probability of an interview and (iii) the probability of a job offer (after an interview) change with the duration of unemployment.

Job applications. To disentangle duration dependence from dynamic selection in the number of applications, we take advantage of the fact that, for a given job seeker, the number of applications can be repeatedly observed. A fixed-effect approach can account for time-constant individual heterogeneity. Our baseline specification is

$$A_{it} = \alpha_i + f^A(t;\phi^A) + X_{it}\beta^A + \delta^A_{mk} + \varepsilon^A_{it}, \tag{1}$$

where A_{it} denotes the number applications made by individual i at duration-month t, α_i is the individual fixed effect, X_{it} a vector of observed characteristics, δ^A_{mk} a fixed effect capturing changing local labor market conditions (in occupational sector m and calendar quarter k), and ε^A_{it} an idiosyncratic error term. The function $f^A(t;\phi^A)$ captures duration dependence in the number of applications net of individual observed and unobserved characteristics, X_{it} and α_i, as well as changing local labor market conditions.[12]

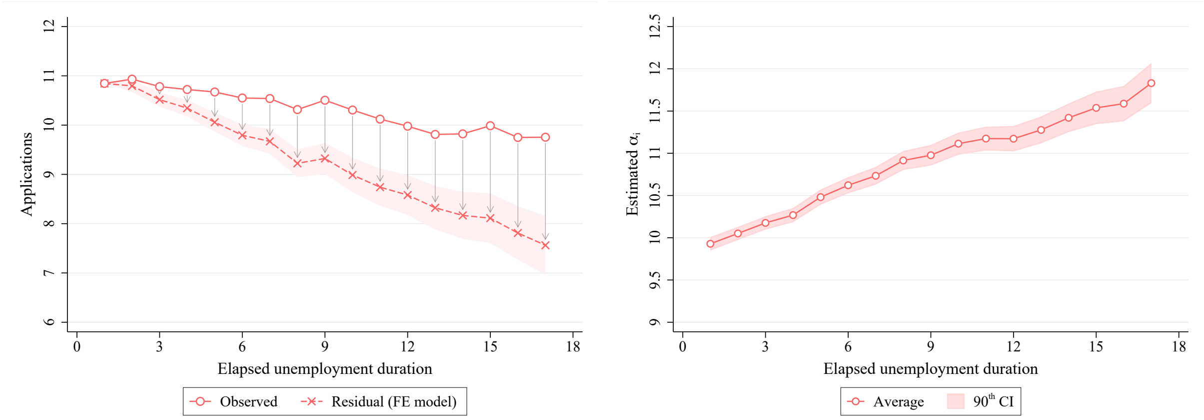
In Figure 3A we compare the cross-sectional duration profile in the number of job applications with the one obtained when we net out both observed and unobserved heterogeneity (true duration dependence), that is after controlling for individual fixed effects and the time-varying covariates. The function $f^A(t;\phi^A)$ is specified with one dummy for every unemployment month. The duration-dependence graph is drawn such that the duration profile coincides with the empirical duration profile in month 1. In other words,

[12] This approach has also been applied in other recent work studying application effort (Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021; Fluchtmann, Glenny, Harmon, and Maibom, 2021). It delivers reliable estimates of duration dependence when the dependent variable is not directly related to exits from the sample (Zuchuat, 2023).

Figure 3: Duration profile of applications

(A) Empirical and residual duration profile

(B) Average individual fixed effect by elapsed unemployment duration



Note: Panel A depicts the empirical duration profile of the number of job applications (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity and individual fixed effects (dashed line), with function $f^A(t;\phi^A)$ in equation (1) modeled as a step function with one dummy for each unemployment month. The shaded area around the estimated duration dependence corresponds to the 95% confidence interval. Panel B depicts the average of the estimated individual fixed effects, α_i in equation (1), by month of elapsed unemployment. That is, the average is computed based on those individuals who are still unemployed at the respective unemployment month. Confidence intervals (shaded areas) are based on standard errors clustered at the individual level.

the graph draws the application profile that would have emerged had the unemployment pool in any month t consisted of the same types of job seekers as the pool in month 1.

Panel A of the figure reveals that the profile for true duration dependence decreases much more strongly than the cross-sectional duration profile. Since the number of applications falls much more strongly when the composition is kept constant this means there is positive dynamic selection in application effort: those who eventually remain unemployed for long make more applications at all durations. Figure 3B shows the average of the estimated individual fixed effects of those job seekers who are still unemployed in the respective unemployment month. Those still in unemployment at high elapsed durations have a higher fixed effect α_i than those who leave unemployment quickly.

In Table B1 in Appendix B, we present additional estimation results for equation (1) based on alternative specifications for the function $f^A(t;\phi^A)$ and varying the set of controls. In addition, we verify the robustness of the duration patterns documented. For instance, we replace the total number of applications by the number of applications that exceed the required minimum (usually 8 or 10 applications per month). The idea is that this way of measuring application effort reflects more closely a job seeker's intrinsic motivation. It turns out that the results do not change much across specifications. We conclude that there is strong negative duration dependence and strong positive dynamic selection in the number job applications.

We have also estimated models that allow for heterogeneity in the duration dependence of applications with respect to observables, e.g. age, education or nationality (see Figure B3 in the Appendix). With few exceptions, we find that the decline in job applications, as spells lengthen, is homogeneous across age groups, education levels, and for people with different nationality, whether we look at it in the raw data or allow for job seeker fixed effects.

Job interviews and job offers (conditional on an interview). Decomposing the falling interview- and the rising job-offer probabilites (Figures 2B and 2C) into dynamic selection and duration dependence is more tricky. Unlike job applications, which occur frequently throughout the unemployment spell, job interviews are rare events concentrated at the end of the spell. Job offers, in most cases, occur only once, as job seekers typically accept the first offer they get. As a result, the fixed-effect approach does not work to recover duration dependence for these outcomes (Zuchuat, 2023).

Our alternative strategy is based on a "prediction model", inspired by Mueller and Spinnewijn (2023). (They use such a model to predict the risk of long-term unemployment, while we use it to predict the chances of a job interview and a job offer, respectively, along the unemployment spell.) We first compute the *ex-ante* probability that an application receives a positive response (an interview or a job offer). We exploit our detailed data to create a set of variables capturing the information a recruiter can extract from an application. We then regress the predicted *ex-ante* probability on the respective actual outcome. If *ex-ante* chances are a perfect predictor of actual outcomes later in the spell, we can conclude that the empirical (cross-sectional) duration profile is entirely due to selection on observables. In contrast, if *ex-ante* chances do not predict actual outcomes, the empirical duration profile is due either to duration dependence, to selection on unobservables or a combination of the two.

In the first step, we estimate the conditional *ex-ante* probabilities of an interview and a job offer. By *ex ante*, we mean early in the unemployment spell, before dynamic selection has affected the unemployment pool. We estimate these probabilities in the first month of a job seeker's unemployment spell.[13] We rely on information that is typically available

[13] For left-censored unemployment spells, we do not observe outcomes in $t = 1$. For these observations, we use the outcomes of the first unemployment-month observed in the data.

in a job seeker's CV and the application itself, e.g. gender, age, education, previous work history, etc. The conditional *ex-ante* probability for outcome y ($y = c$ in the case of a job interview and $y = o$ in the case of a job offer) of application j made by individual i in the reference month is:

$$\gamma^y(X_{ij1}) \equiv \mathbb{P}(y_{ij1} = 1 \mid X_{ij1}, \hat{\alpha}_i, \delta^y_{mk}, z_{ij1} = 1) \tag{2}$$

where $\hat{\alpha}_i$ is the estimated individual fixed effect from equation equation (1), and δ^y_{mk} a fixed effect capturing changing local labor market conditions (analogously to equation (1) for applications).[14] The variable z_{ij1} is a dummy indicating the preceding event in the job finding process, *i.e* an application when the outcome is a job interview and a job interview when the outcome is a job offer. We estimate equation (2) separately for interviews and job offers using logit models.[15] Then we use the parameter estimates to predict the conditional *ex-ante* probabilities for all months t, which yields $\widehat{\gamma}^c(X_{ijt})$ for job interviews and $\widehat{\gamma}^o(X_{ijt})$ for job offers. The predicted *ex-ante* probabilities capture the propensity with which a job seeker's application made in unemployment month t receives a positive response from a firm, if the firm's behavior was kept as in the first month.

In the second step, we include the predicted *ex-ante* probability as a control to net out dynamic selection on observables in the the probability of an interview or a job offer, respectively. This is in the spirit of a control function approach (Matzkin, 2003). Specifically, we estimate two binary outcome models, one for job interviews ($y = c$) and one job offers ($y = o$), using the applications made in all months $t \geq 1$:

$$\mathbb{P}(y_{ijt} = 1 \mid \widehat{\gamma}^y_{ijt}, z_{ijt} = 1) = \mathbb{P}\Big(\alpha^y + f^y(t; \phi^y) + \beta^y \ln(\widehat{\gamma}^y_{ijt}) > \varepsilon^y_{ijt} \,|\, z_{ijt} = 1\Big) \tag{3}$$

where $\beta^y \ln(\widehat{\gamma}^y_{ijt})$ controls for dynamic selection, whereas $f^y(t; \phi^y)$ captures the effect of duration after controlling for observables for outcome $y \in \{c, o\}$. The variable ε^y_{ijt} represents an idiosyncratic error term. In the results shown in the main text, the functions $f^c(t; \phi^c)$ and $f^o(t; \phi^o)$ are specified as step functions with one dummy for every month of elapsed unemployment duration. In Appendix B, we also report estimates from linear

[14] See Table B6 in Appendix B for the list of control variables included.

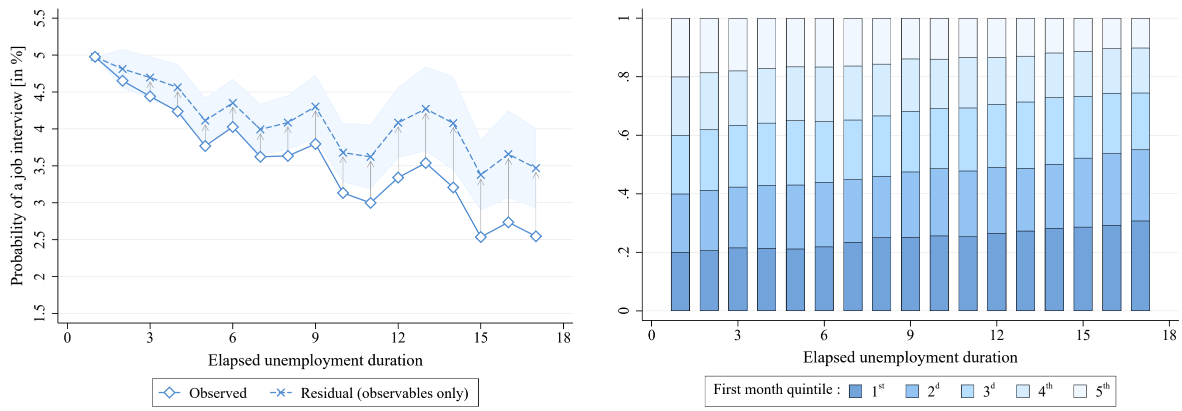
[15] We report the estimation results for the *ex-ante* probabilities in Table B6 and more details on the empirical approach in Appendix B.2.1.

specifications for duration dependence conditional on variables observable to the recruiter when the application is made (see Table B7). Notice that the prediction model controls for the heterogeneity observable to the recruiting firm when it receives the application.[16] It helps us to understand how firms process the information on an applicant's unemployment duration. We uncover the relevant effect of duration on the interview probability under the assumption that we observe all the information relevant to the recruiting firm when it evaluates a job seeker's application (i.e. under a conditional independence assumption). Like Mueller and Spinnewijn (2023) our prediction models are based on rich administrative data that help predicting the success of applications later in the spell.[17]

Figure 4: Duration profile of job interviews

(A) Empirical and residual duration profile

(B) Distribution of the *ex-ante* probability by elapsed unemployment duration



Note: Panel A depicts the empirical duration profile of the interview probability (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity (dashed line), with function $f^c(t;\phi^c)$ in equation (3) modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 90% confidence interval. Panel B depicts the change in the composition of the unemployment pool. By construction, each quintile comprises 20 percent of the unemployment pool in month 1. In later months, the unemployment pool consists more and more of individuals with low ex-ante chances: The lower quintiles in the distribution of *ex-ante* chances gain weight at the expense of the higher quintiles.

Figure 4A summarizes the estimation results for the probability of a job interview, contrasting the profile of the empirical probability with the estimated one based on equation (3) that nets out dynamic selection based on observables. The figure shows that the empirical interview probability decreases from 5 percent in month one to 2.5 percent in month 15 of unemployment. In contrast, the decline in the interview probability ad-

[16]We also control for the estimated fixed effect in applications, which we think of as a control for quality of the applications.

[17]In Appendix B, we substantiate the robustness of our results to changes in the way we account for the observable heterogeneity of job seekers and their applications. In one robustness check, for instance, we directly control for observable characteristics in equation (3) instead of the log predicted *ex-ante* probability, $\ln(\widehat{\gamma}^y_{ijt})$ (see Table B7), see column (2) of Table B7.

justed for observed heterogeneity is substantially lower and decreases from 5 to only 3.5 percent, *i.e* by 0.1 percentage points every month (see also Table B7 in Appendix B). These numbers suggest that 40 percent of the reduction in the interview probability can be attributed to dynamic selection on observables.

Our estimates of the decrease in the interview probability after controlling for observables are surprisingly similar to those of Kroft, Lange, and Notowidigdo (2013), who document a 3.7 percentage points decline in the callback probability over a period of 36 months of unemployment, roughly 0.1 percentage point every month.[18] Note, however, that the falling interview probability need not be driven by duration dependence. Rather it may reflect the firm's reaction to additional heterogeneity in job seeker quality that is still unobserved at the point when the firm decides to call the job seeker back. This point was first stressed by Jarosch and Pilossoph (2019), and we will elaborate this further in the theoretical part (Section 5).

Figure 4B illustrates the extent to which the composition of the unemployment pool changes with duration. The composition is measured by the quintiles of the distribution of the ex-ante chances to receive an invitation to a job interview. By construction, each quintile has equal size in month 1. The figure shows that, later in the spell, applications from the highest (lowest) quintile make up a smaller (larger) share of the unemployment pool. In other words, the unemployment pool becomes more homogeneous over time as applications with a high ex-ante chance disappear more quickly from unemployment, while individuals with low ex-ante chances are more likely to become long-term unemployed.

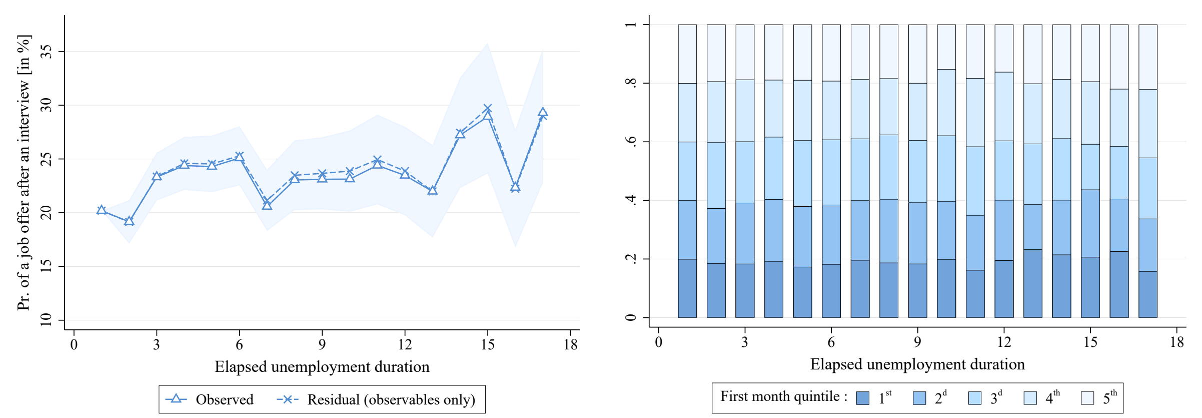
The probability of a job offer after an interview increases with unemployment duration (Figure 5A) by around 0.35 percentage points per month (see also Table B7 in Appendix B). Adjusting for dynamic selection in terms of characteristics observable to the firm when the application is made hardly affects the duration profile: the cross-section duration profile of job offers and the duration profile that nets out observables nearly coincide. There are two reasons for this. First, job seeker and application characteristics explain less of the variation in the *ex-ante* probability of a job offer than they do in predicting interviews (Table B6 in the Appendix, pseudo-R^2s 0.06 for interviews, and 0.11

[18] Eriksson and Rooth (2014) report a callback rate of 25 percent, for fictitious job applicants in Sweden. The callback rate is high because applications were sent to high skilled jobs, and applications had excellent fit for the job.

Figure 5: Duration profile of job offers after an interview

(A) Empirical and residual duration profile

(B) Distribution of the *ex-ante* probability by elapsed unemployment duration



Note: Panel A depicts the empirical duration profile in the job offer probability (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity (dashed line), with function $f^o(t;\phi^o)$ in equation (3) modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 90% confidence interval. Panel B depicts the change in the composition of the unemployment pool. By construction, each quintile comprises 20 percent of the unemployment pool in month 1. In later months, the composition of the unemployment pool does not change very much.

for job offers). Second, the predicted *ex-ante* probability of a job offer does not move systematically down (or up) with duration (Figure 5B) whereas the predicted *ex-ante* probability of an interview falls (Figure 4B).

Information on job seeker- and application characteristics plays only a limited role at the job offer stage of the recruitment process. Given that a firm has decided to interview a job seeker, the decision whether to hire them is based on information newly revealed during the interview that is orthogonal to the information already contained in the job seeker's application. This reflects the rationality of firms' behavior: if firms could infer perfectly already from an application whether a job seeker would be a good fit, costly job interviews would be unnecessary. The information on a job seeker revealed during the interview is largely unobserved to us. Nonetheless, our finding of positive duration profile in the empirical job offer probability controlling for observables is still strongly suggestive of positive duration dependence in job offers because, if anything, dynamic selection on unobservables among the interviewees should be negative. This implies that not accounting sufficiently for it will downward bias the estimated net effect of unemployment duration on firms' job offer decisions. In fact, positive duration dependence in the probability of a job offer reflects the fact that the composition of the pool of interviewees becomes more and more homogeneous as unemployment continues. We will illuminate the mechanisms further in the theory section.

Our analysis so far assumes that the set of control variables contain all relevant information for firms to decide on a job interview. In a robustness check, we add variables to the original conditioning set that reflect the assessment of the employment chances by the caseworker during the first meeting at the PES as well as variables on the job seeker's health. While the information contained in these additional variables should be unobserved to the recruiter when they receive the application, these variables could nevertheless be correlated with observable information (to the recruiter) that we may have missed in the main specification. Estimates of duration effects in interviews conditional on observables are robust to including this additional information, even though this information is valuable to recruiters in the job offer decisions (see Table B8). These analyses suggest that we can recover the effect of duration on the probability of a job interview after controlling for observed heterogeneity (from the viewpoint of the recruiter at the time when the application is made).

In sum, the results on job interviews and job offers highlight two interesting insights: keeping constant observable heterogeneity (at the point when the application is made), the duration of unemployment negatively affects the probability of a job interview, as emphasized by audit studies (Oberholzer-Gee, 2008; Kroft, Lange, and Notowidigdo, 2013; Eriksson and Rooth, 2014; Nüß, 2018). In contrast, it does not reduce the probability of a job offer after an interview. As pointed out by Jarosch and Pilossoph (2019), job seekers lose out on some interviews through negative duration dependence in the interview probability (after accounting for observable heterogeneity at the point when the application is made), but the long-term unemployed are not discriminated against further when firms make their job offer decisions. Overall, our results are coherent with a statistical learning approach to the labor market, which we explore in detail in the next section.

5. A theory of statistical discrimination and learning from search

In this section, we develop a model of statistical discrimination and learning from search that provides a consistent explanation for our empirical findings. The model builds upon Jarosch and Pilossoph (2019) which explores how the duration of unemployment affects the probability to receive an invitation to a job interview.[19] We extend Jarosch and

[19]Specifically, Jarosch and Pilossoph (2019) explores why the callback rate controlling for observables falls with duration. Their theoretical analysis shows that a falling callback rate does not necessarily indicate duration dependence in the job finding rate. Their quantitative analysis – in the US context

Pilossoph (2019)'s analysis for a job search process under incomplete information, which is modelled in the spirit of Burdett and Vishwanath (1988). This extended framework delivers predictions about duration dependence in search effort, interviews and job offers, and makes precise to which extent duration dependence along these dimensions translates into duration dependence in the job finding rate.

We consider a frictional labor market where workers differ in ability and search efficiency and firms differ in ability requirements. As in our empirical setting, the job finding process comprises three stages: applications, job interviews and job offers. Unemployed workers decide in each period how many applications to send. Firms receive applications, decide whether to invite a candidate to a costly interview and, if so, whether to make her a job offer. Ability is not perfectly observable. Firms cannot infer a worker's ability from the resume and unemployed workers do not know how valuable their ability is on the labor market. The job interview perfectly reveals the worker's ability to the firm. As long as a worker remains unemployed, she does not observe her true ability but holds beliefs which are revised downward after a negative search outcome.[20]

Environment. We consider a discrete-time economy populated by a unit mass of workers, who differ in their search efficiency type $\epsilon \sim \mathcal{L}(\epsilon),\ \epsilon \in (\underline{\epsilon}, \overline{\epsilon})$, and a continuum of firms differing in their productivity $y \sim G(y),\ y \in \big(\underline{y}, \overline{y}\big)$.[21]

Search efficiency is an unobservable characteristic measuring how effective a worker is in overcoming meeting frictions: the higher the search efficiency, the fewer applications are needed to meet a vacancy with a given probability. Every time a worker of type ϵ separates from a job, nature draws a new ability x from an exogenous distribution $\mathcal{H}(x|\epsilon, \tau = 0)$, where $\tau \in \mathbb{N}$ stands for elapsed unemployment duration, and $\mathbb{E}[x|\epsilon] > 0$.[22]

– actually leads to the conclusion that the falling job finding rate is primarily due to negative dynamic selection on unobservables rather than duration dependence.

[20] More precisely, the assumption is that the firm perfectly observes a job seeker's ability after the interview, while job seekers never observe their ability perfectly, though they update their beliefs based on elapsed unemployment duration. A longer elapsed unemployment duration signals a lower ability to the job seekers. Since the model abstracts from on-the-job search, beliefs of the employed do not affect labor market outcomes.

[21] In the model workers differ only in unobservable characteristics. As a result, the labor market in our model economy is conceptually defined by the common observable characteristics across all the workers populating it, as well as fully segmented from others.

[22] New ability draws following job separations are meant to capture stochastic evolution in one worker's breadth of qualification for jobs in the marketplace. In the model, this implies that past labor market experience is not informative about worker's ability in her current spell.

Information is incomplete: workers do not observe their own ability draw. However, the underlying distribution $\mathcal{H}(x|\epsilon, \tau = 0)$ is common knowledge.

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 sequential random search protocol. Search-and-matching frictions are represented by an exogenous separation rate δ_H and the endogenously determined job finding rate $f(\epsilon, \tau, x)$. The exogenous separation rate δ_H comprises both quits to unemployment with probability δ_L and job-to-job transitions towards other identical firms with complementary probability $\delta_H - \delta_L$.

Job seekers can increase their chances to find a job by exerting search effort. Search effort s is made up by the product between search efficiency ϵ and application effort a, *i.e.* $s(\epsilon, \tau) \equiv \epsilon a(\epsilon, \tau)$.[23] A job seeker's job finding chances are higher either if she makes more applications (higher a) or *better* applications (higher ϵ).

Job finding comes as the result of a three-stage hiring process. First, job seekers decide how much application effort a to exert, subject to an increasing and convex search cost function $\sigma\left(s(a)\right),\ \sigma'(.) > 0,\ \sigma''(.) > 0$ (Pissarides, 2000).[24] Second, job seekers come together with vacancies through a constant-return-to-scale meeting function $\mathcal{M}(S, V)$, where S denotes aggregate search effort and V the mass of outstanding vacancies. As a result, a job seeker exerting search effort s meets a vacancy with probability $s\lambda(\theta)$, where $\lambda(\theta) \equiv \frac{\mathcal{M}(\mathcal{S},\mathcal{V})}{S} = \mathcal{M}(1, \theta)$ and $\theta \equiv \frac{V}{S}$ represents labor market tightness.

Upon meeting, the only relevant information released to firms is the length of the job seeker's unemployment spell. Based on this information only, firms decide whether to call the job seeker back for a job interview at cost $\kappa > 0$. Finally, conditional on interviewing the job seeker, the firm gets to know her true ability x and decides whether to offer her

[23] Application effort relates to the number of applications sent out by a job seeker in a given month, but the two concepts do not fully coincide. This is due to the sequential search protocol adopted in the model that allows for at most one worker-vacancy meeting in any period and does not restrict applications to integer numbers (thus preventing an application-level analysis). We discuss the alternative simultaneous search protocol in Section 7.

[24] Notice that the cost depends on the total search effort exerted – not only on application effort. As a result, higher search efficiency entails that the marginal cost of any application is higher, as well. In Appendix C.1 we provide a microfoundation for this functional form assumption based on an optimal time allocation model where workers value social leisure and face a unitary time constraint. As long as the marginal utility of social leisure is positively correlated with search efficiency, *e.g.* because more outgoing workers have a larger personal network allowing them to overcome meeting frictions more easily, our search effort cost function is generated by such an optimal time allocation model under a suitable parametrization.

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:[25]

$$p(x,y) = \begin{cases} x+y & \text{if } x \geq y \\ 0 & \text{else} \end{cases} \tag{4}$$

A worker is thus qualified for a job if her ability x exceeds the firm's productivity y, meaning that higher-ability job seekers enjoy a higher unconditional job offer probability per unit of search effort. For any (x,y) pair, let $\mathcal{Q}$ be a qualification indicator such that $\mathcal{Q}(x,y) = \mathbb{1}\{x \geq y\}$.

Workers enjoy a flow value of leisure b while unemployed. Following Hall (2005), wages are rigid and fixed at $\omega \in (b, p(\underline{x}, \underline{y}))$ for the entire duration of the match.[26]

Workers. Workers are either matched to a firm (employed) or job seekers (unemployed). Job seekers choose how much application effort 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:

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

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

where $\hat{o}(\epsilon,\tau) = \int o(x,\tau)\ d\hat{\mathcal{H}}(x|\epsilon,\tau)$ denotes the expected unconditional job offer probability per unit of search effort for a job seeker of search efficiency ϵ at duration τ according to the belief function $\hat{\mathcal{H}}(x|\epsilon,\tau)$. Accordingly, the expected job finding rate is defined as $\hat{f}(\epsilon,\tau) \equiv s(\epsilon,\tau)\ \hat{o}(\epsilon,\tau)$.

[25]We adopt the modified Albrecht and Vroman (2002)'s production function proposed by Jarosch and Pilossoph (2019) as it grants an intuitive notion of a worker's qualification for a job, on top of being consistent with the production function estimation of Lise and Robin (2017). Our results extend to any alternative specification giving rise to positive assortative matching.

[26]As in Jarosch and Pilossoph (2019), assuming rigid wages allows us to focus on sources of duration dependence unrelated to changes in the individual reservation wage, as well as to simplify the model significantly. However, our results would go through more sophisticated wage setting protocols giving rise to compressed wage structures, *i.e.* as long as reservation wages do not adjust so much that firms are indifferent between workers of different abilities, or prefer lower-ability ones.

Optimal application effort balances the marginal cost of exerting higher application effort to the expected marginal benefit of meeting a vacancy, *i.e.* the marginal increase in the expected job finding rate weighted by the discounted capital gain upon employment:

$$a(\epsilon,\tau): \underbrace{\frac{\partial\sigma(s(a))}{\partial s}}_{\text{marginal cost}} = \underbrace{\beta\ \hat{o}(\epsilon,\tau)\ \Big[W(\epsilon) - U(\epsilon,\tau+1)\Big]}_{\text{marginal benefit}} \tag{5}$$

Notice that job seekers with higher search efficiency have both higher marginal benefit (because search efficiency is positively related to ability) and higher marginal cost of exerting application effort (because each unit of application effort is more costly). As a result, whether higher-search-efficiency job seekers exert more or less application effort is qualitatively ambiguous as it depends on which of the two opposing forces dominates.

Firms. Firms can either be matched with one worker or not. Unmatched firms pay a vacancy posting cost κ_v to draw a productivity y, which allows them to meet a job seeker in the next period with probability $\lambda(\theta)/\theta$. Free entry into the labor market dictates that, in equilibrium, the labor market tightness adjusts to arbitrage out any pure profit from vacancy creation:

$$-\kappa_v + \beta\ \frac{\lambda(\theta)}{\theta} \int \Pi(y)dG(y) = 0 \tag{6}$$

where $\Pi(y)$ denotes expected profits of a firm with productivity y upon meeting a job seeker (derived below). The value of a filled job is given by the present discounted value of flow profits, *i.e.* $J(x,y) = \frac{p(x,y)-\omega}{1-\beta(1-\delta_H)}$.

The hiring process. Upon meeting a job seeker, the firm decides whether to call her back for a job interview at cost κ, based on her elapsed unemployment duration τ only. For any (y,τ) pair, let $\mathcal{C}$ denote a callback indicator such that:

$$\mathcal{C}(y,\tau) = \mathbb{1}\left\{\int \max\Big\{J(x,y),0\Big\}\ \mu(x|\tau)\ dx \geq \kappa\right\} \tag{7}$$

where $\mu(x|\tau)$ is the search-effort-weighted density of job seekers' ability at unemployment duration τ – the key equilibrium object driving statistical discrimination. In words, a firm of productivity y calls back a job seeker with elapsed unemployment duration τ if the expected value of matching to a job seeker of that unemployment duration exceeds the interview cost κ. On the job seeker's side, this implies that the interview probability per unit of search effort only depends on unemployment duration τ:

$$c(\tau) = \lambda(\theta) \int \mathcal{C}(y, \tau)\ dG(y) \tag{8}$$

It follows that the *interview rate*, the probability that a job seeker exerting optimal search effort receives an interview at duration month τ equals $c(\epsilon, \tau, x) = s(\epsilon, \tau)\ c(\tau)$.

After the interview takes place, the firm gets to know job seeker's ability x and makes her a job offer as long as she is qualified for its production technology (4), regardless of unemployment duration. For any (x, y, τ) triple, let $\mathcal{O}$ denote a job offer indicator such that:

$$\mathcal{O}(x, y, \tau) = \mathcal{C}(y, \tau)\mathcal{Q}(x, y) \tag{9}$$

In words, a firm of productivity y which meets a job seeker of ability x at duration τ offers her a job if her unemployment duration makes it profitable to interview her and she is qualified for its production technology. On the job seeker's side, this implies that the conditional job offer probability writes:

$$o|c(x, \tau) = \frac{\int \mathcal{O}(x, y, \tau)\ dG(y)}{\int \mathcal{C}(y, \tau)\ dG(y)} \tag{10}$$

As a result of this two-stage recruitment process, expected profits of a firm with productivity y upon meeting a job seeker equal $\Pi(y) = \sum_{\tau=0}^{\infty} r(\tau)\big(\int J(x, y)\mathcal{Q}(x, y)$ $\mu(x|\tau)dx - \kappa\big)\mathcal{C}(y, \tau)$, where $r(\tau)$ equals the probability of meeting a job seeker with unemployment duration τ.

The unconditional job offer probability for a job seeker of ability x at duration τ is given by:[27]

$$o(x, \tau) \equiv c(\tau)\ o|c(x, \tau) = \lambda(\theta) \int \mathcal{O}(x, y, \tau)\ dG(y) \tag{11}$$

[27] Absent statistical discrimination, *i.e.* if $\kappa = 0$, the unconditional job offer probability would read $o^{ND}(x) = \lambda(\theta) \int \mathcal{Q}(x, y)\ dG(y)$. Contrasting it with equation (11), we notice that statistical discrimination by firm y affects a job seeker's unconditional job offer probability if and only if $\mathcal{Q}(x, y) = 1$, that is, if the job seeker is denied an interview for a job she would have been qualified for.

Finally, the individual *job finding rate* at duration τ reads:

$$f(\epsilon, \tau, x) = s(\epsilon, \tau)\ o(x, \tau) \tag{12}$$

Stationary equilibrium. Closing the model requires to specify the equilibrium conditions for the measure of unemployed of each type and duration. To do so, we solve the model in stationary equilibrium by imposing balance of flows:[28]

$$u(\epsilon, \tau) = \begin{cases} \delta_L\big(1 - \sum_{t=0}^{\infty} u(\epsilon, t)\big) & \text{if } \tau = 0 \\ u(\epsilon, \tau - 1)\big[1 - f(\epsilon, \tau - 1)\big] & \text{if } \tau > 0 \end{cases} \tag{13}$$

where $1 - \sum_{t=0}^{\infty} u(\epsilon, t)$ denotes the type-specific employment rate.

The key equilibrium objects of the model are the belief function about job seeker's ability, $\hat{h}(x|\epsilon, \tau) = \hat{\mathcal{H}}'(x|\epsilon, \tau)$, which drives job seekers' application decisions, and the search-effort-weighted density of job seekers' ability at each duration, $\mu(x|\tau)$, which drives firms' callback decisions. For given $\hat{h}(x|\epsilon, 0) = h(x|\epsilon, 0)$, the belief function about job seeker's ability evolves according to Bayesian updating:

$$\hat{h}(x|\epsilon, \tau) = \frac{(1 - f(\epsilon, \tau, x))\, \hat{h}(x|\epsilon, \tau - 1)}{\int (1 - f(\epsilon, \tau, x))\ d\hat{\mathcal{H}}(x|\epsilon, \tau - 1)} \quad \forall \tau > 0 \tag{14}$$

Intuitively, job seekers adjust their belief about their own ability as unemployment duration lengthens, by assigning increasingly higher density to ability levels with a lower-than-average job finding rate.

In equilibrium, job seekers' belief function about own ability equals the type-specific ability distribution at each duration, *i.e.* $\mathcal{H}(x|\epsilon, \tau) = \hat{\mathcal{H}}(x|\epsilon, \tau)$.

The search-effort-weighted density of job seeker's ability at each duration reads:

$$\mu(x|\tau) = \frac{\int s(\epsilon, \tau)\ u(\epsilon, \tau)\ h(x|\epsilon, \tau)\ d\mathcal{L}(\epsilon)}{\int s(\epsilon, \tau)\ u(\epsilon, \tau)\ d\mathcal{L}(\epsilon)} \tag{15}$$

Definition 1. *A stationary equilibrium of the economy is a tuple* $\big\{a(\epsilon, \tau), o(x, \tau), \hat{h}(x|\epsilon, \tau), u(\epsilon, \tau), \theta\big\}$*, where application effort satisfies equation (5), the unconditional job offer prob-*

[28] Intuitively, the stationary measure of unemployed at $\tau = 0$ equals the measure of employed that separate from their employer. In turn, the stationary measure of unemployed at longer durations equals the share of unemployed who have not found a job in the previous period.

ability satisfies equation (11), the belief function satisfies equation (14) for given $\mathcal{H}(x|\epsilon, 0)$, the unemployment rate satisfies equation (13), and the labor market tightness is pinned down by equation (6).

Equilibrium characterization. We are now in the position to discuss the mechanisms behind the duration profiles observed in the data through the lens of our structural model. Upon meeting a job seeker with unemployment duration τ, firms form an expectation about her ability based on $\mu(x|\tau)$. Since job seekers with high ability x match more easily according to the production technology (4), the density $\mu(x|\tau)$ features negative dynamic selection, with low-ability job seekers being over-represented at longer unemployment durations. This generates negative duration dependence in the interview probability according to equation (8), as firms use elapsed unemployment duration as a screening device when choosing whether to call back a job seeker for an interview. Proposition 1 provides a sufficient condition for the interview probability to exhibit negative duration dependence.[29]

Proposition 1. *If $\int \max\{J(x,y), 0\}\, \mu(x|0)\, dx > \kappa\ \forall y$ and $G(y \in \mathcal{Y} : J(\underline{x}, y) < \kappa) > 0$, then the interview probability exhibits negative duration dependence, i.e. $dc(\tau)/d\tau \leq 0\ \forall \tau$ and $\exists \hat{\tau} : dc(\hat{\tau})/d\tau < 0$.*

Proof. See Jarosch and Pilossoph (2019). □

Negative dynamic selection in job seeker's ability further entails that the pool of job seekers becomes increasingly more homogeneous as unemployment duration lengthens, with low-ability ones accounting for a progressively larger share. As a result, the signal embedded in unemployment duration becomes more and more informative about job seekers's ability, thus making firms' callbacks more targeted. This induces positive duration dependence in the conditional job offer probability.[30] Proposition 2 spells out the

[29]Notice that the right model counterpart of the interview probability analyzed in Figure 4A is per unit of application effort, *i.e.* $\epsilon c(\tau)$. Given that search efficiency is time-invariant, the duration profiles of the two variables coincide.

[30]To see why this is the case, suppose that the pool of job seekers resembles the population ability distribution at short unemployment duration. Under the assumptions in Proposition 1, all the firms will call back any job seeker at that duration and reject the unqualified ones at the interview stage. The conditional job offer probability will then approach the probability that a worker is qualified for the firm's job. Now suppose that the pool of job seekers is composed almost entirely by low-ability workers at long unemployment duration. Most of the firms will find it unprofitable to call back a job seeker at such duration according to equation (7). As a result, only firms that are willing to hire a

regularity conditions under which the conditional job offer probability exhibits positive duration dependence.

Proposition 2. *If the callback indicator $\mathcal{C}(y, \tau)$ is monotonically decreasing in y and τ, then the conditional job offer probability exhibits positive duration dependence, i.e.* $do|c(x,\tau)/d\tau \geq 0 \; \forall (x,\tau)$ *and* $\exists \hat{\tau} : do|c(x,\hat{\tau})/d\tau > 0$ *for some* x.

Proof. See Appendix C.2. $\square$

Even though the interview probability and the conditional job offer probability move in opposite directions, Proposition 3 in Appendix C.2 proves that the unconditional job offer probability as defined in equation (11) exhibits negative duration dependence. Intuitively, the unconditional job offer probability is determined by the share of firms for which a job seeker is qualified *and* which call back job seekers of her unemployment duration. Since the pool of firms satisfying such requirements shrinks with duration (due to statistical discrimination), the unconditional job offer probability needs to decline, as well. Formally, the job offer indicator (9) is monotonically decreasing in τ.

In equilibrium, job seekers optimally respond to negative duration dependence in their expected unconditional job offer probability by scaling down their application effort over the unemployment spell according to equation (5).[31] Negative duration dependence in job seekers' application effort results from both firms' statistical discrimination and learning. First, for given belief about own ability, firms' statistical discrimination induces negative duration dependence in the *true* unconditional job offer probability. Second, for given unconditional job offer probability per ability level, negative dynamic selection induces job seekers to revise their beliefs about own ability downward, which results in a lower expected unconditional job offer probability due to changing probability weights attached to each ability level.

low-ability worker will call back job seekers at that duration. The conditional job offer probability will therefore approach 1.

[31]The necessary and sufficient condition for negative duration dependence in application effort to arise at any duration τ is that the reduction in the expected unconditional job offer probability, *i.e.* $d\hat{o}(\epsilon,\tau)/d\tau < 0$, dominates the capital gain increase upon employment due to the depletion of the value of unemployment at longer durations, *i.e.* $U(\epsilon,\tau+1) < U(\epsilon,\tau)$. This happens whenever the reduction in the expected unconditional job offer probability is *smooth enough*. Indeed, if it exhibited discrete jumps, job seekers would find it optimal to anticipate such future drops in the value of unemployment and would apply increasingly more intensely as they approach.

6. Quantitative analysis

To make the model amenable for quantification, we enrich the framework outlined in the previous section with two additional components. First, following Blanchard and Diamond (1994) and Shimer (2005a), we allow for coordination frictions in the form of multiple job seekers per vacancy. Coordination frictions are a standard assumption in the existing literature as, in their presence, firms need to sort potentially multiple job seekers. As long as firms sort job seekers by unemployment duration (interviewing those with shorter duration first), coordination frictions induce negative duration dependence in the interview probability.[32] We introduce coordination frictions to smooth out the duration profile of the unconditional job offer probability for given ability, which makes sure that application effort is monotonically decreasing in unemployment duration. Second, we assume that qualified job seekers get offered a job after an interview with probability $q \in (0, 1)$. This assumption catches idiosyncratic matching frictions as in models of stochastic match quality (Pissarides, 2000; Menzio and Shi, 2011; Wright, Kircher, Julien, and Guerrieri, 2021) and allows us to replicate the scale of the conditional job offer probability observed in the data. Appendix C.3 develops the extended model.

Functional forms. Following Jarosch and Pilossoph (2019), we assume that worker ability x and firm productivity y lie in the unit interval, *i.e.* $\text{supp}(x) = \text{supp}(y) = [0, 1]$. Worker search efficiency and firm productivity follow flexible (shifted) Beta distributions. Formally,

$$\epsilon \sim \mathcal{L}(\epsilon) = 1 + \phi \text{Beta}(B_1, B_2), \ \text{supp}(\epsilon) = [1, 1 + \phi]$$
$$y \sim G(y) = \text{Beta}(G_1, G_2), \ \text{supp}(y) = [0, 1]$$

We then proceed by discretizing worker ability and firm productivity on an equally-spaced grid with N grid points. Similarly, we discretize search efficiency on N grid points defined by $\epsilon_j = 1 + \phi x_j, \ \forall j = 1, \ldots, N$. We then posit that the initial discretized density of job

[32]Unlike in models of taste-based discrimination such as Blanchard and Diamond (1994), in our model job seekers with different unemployment duration are on average not equally productive for firms, due to negative dynamic selection in job seekers' ability. As a result, coordination frictions do not give rise to an additional source of duration dependence in the interview probability but simply amplify the impact of statistical discrimination.

seekers' ability for given search efficiency is given by:

$$h(x_j|\epsilon, \tau = 0) = \begin{cases} \rho & \text{if } \epsilon = \epsilon_j \\ \frac{1-\rho}{N-1} & \text{else} \end{cases}$$

The parameter ρ governs the correlation between ability and search efficiency values which are equally ranked. This is a parsimonious way to get a positive correlation between ability and search efficiency through a single parameter.

Since our model is cast in discrete time, we adopt the meeting function of Ramey, den Haan, and Watson (2000), $\mathcal{M}(V, S) = \left(V^{-\xi} + S^{-\xi}\right)^{-\frac{1}{\xi}}$, which makes sure that contact probabilities lie in the unit interval. Following the literature, we adopt an isoelastic search effort function, *i.e.* $\sigma(s) = \psi \frac{s^{1+\eta}}{1+\eta} = \psi \frac{(\epsilon a)^{1+\eta}}{1+\eta}$, that is increasing and convex ($\eta > 0$).

Structural estimation. We structurally estimate the model at monthly frequency for unemployment duration $\tau = 0, \ldots, \tilde{\tau}$. We set the grid size to $N = 25$ and $\tilde{\tau} = 16$. The estimation is carried out in two steps. First, we 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 2 reports the externally chosen parameters.

Following Davis and von Wachter (2011), we set the discount factor to 0.996 to replicate a 5% annual interest rate. We then directly pin down the two separation rates from the EU rate and EE rate measured in our Swiss social security data. As in Jarosch and Pilossoph (2019), we set the interview cost to 10% of average monthly output to replicate the hiring cost estimate reported in Silva and Toledo (2009).[33] We set the wage rate to 0.985 to induce an average value of a job equal to 65% of average monthly output, as per Jarosch and Pilossoph (2019)'s proposed average across standard calibrations. We follow the same strategy for setting the flow value of leisure to 0.678.

We then estimate the remaining set of parameters via indirect inference through the simulated method of moments. Each such parameters conceptually relates to some mo-

[33] Since only a fraction q of job interviews is successful, we scale the interview cost κ by q to get closer to our hiring cost target. As in Jarosch and Pilossoph (2019), the fact that job interviews fail when the job seeker is unqualified, may lead to an overestimation of interview costs. However, Silva and Toledo (2009)'s hiring cost estimate is relatively low in comparison with the literature (Gavazza, Mongey, and Violante, 2018), which alleviates this concern.

Table 2: Externally chosen parameters

Parameter	Description	Value	Source
β	Discount factor	0.996	5% annual interest rate in Davis and von Wachter (2011)
δ_L	Separation rate (workers)	0.009	Monthly EU rate
δ_H	Separation rate (firms)	0.019	Monthly EE+EU rate
κ	Interview cost	0.100	Hiring costs in Silva and Toledo (2009), Barron et al. (1997)
ω	Wage rate	0.985	Avg job value in Shimer (2005b), Hagedorn and Manovskii (2008), and Gertler and Trigari (2009)
b	Value of leisure	0.678	Avg flow value of leisure in Shimer (2005b), Hagedorn and Manovskii (2008), and Gertler and Trigari (2009)

Numeraire: cross-sectional avg monthly output.

ment in the data through the equilibrium conditions of the model. Formally, let Θ be the vector of parameters still to be determined: $\Theta = \Big\{B_1, B_2, G_1, G_2, \xi, \eta, \psi, \phi, \kappa_v, q, \rho\Big\}$. We choose parameter values that minimize the sum of weighted squared percentage deviations between a set of empirical moments (μ) and model-generated moments ($\hat{\mu}$):

$$\Theta^* = \arg\min_{\Theta \in \mathcal{P}} \sum_{m \in \mathcal{M}} w_m \left(\frac{\hat{\mu}_m(\Theta) - \mu_m}{\mu_m} \right)^2$$

where $\mathcal{P}$ denotes the parameter space, $\mathcal{M}$ the set of targeted moments, and w some weighting factor. Table (3) reports the internally chosen parameters, along with the respective targeted moments. In Appendix C.5 we explain the rationale behind our choice of the targeted moments and comment our estimation results.

Table 3: Estimated parameters

Parameter	Description	Value	Target	Data	Model
B_1	1^{st} shape param. Beta distr. search eff.	0.158	$\hat{\beta}_{\ln c(\epsilon,\tau,x),\tau}$: duration effect interview rate, residual (obs.)	-0.023	-0.022
B_2	2^{nd} shape param. Beta distr. search eff.	0.454	$\mathbb{E}[c(\epsilon,\tilde{\tau},x)]$: long-term avg interview rate	0.178	0.184
G_1	1^{st} shape param. Beta distr. prod.	0.168	$\hat{\beta}_{\ln f(\epsilon,\tau,x)),\tau}$: duration effect job finding rate, residual (obs.)	-0.017	-0.019
G_2	2^{nd} shape param. Beta distr. prod.	0.434	$\mathbb{E}[f(\epsilon,\tilde{\tau},x))]$: long-term avg job finding rate	0.051	0.057
ξ	Subst. param. meeting function	0.176	$\mathbb{E}[c(\epsilon,\tau,x))]$: avg interview rate	0.228	0.226
η	Convexity search effort cost	0.228	$\hat{\beta}_{\ln a(\epsilon,\tau),\tau\mid\epsilon}$: duration effect applications, residual (FE)	-0.020	-0.013
ψ	Scalar search effort cost	0.016	$\mathbb{E}[a(\epsilon,\tau)]$: avg applications	10.75	8.98
ϕ	Search efficiency dispersion param.	19.47	$\sigma(\epsilon)$: std. dev. application fixed effects	4.120	5.074
κ_v	Vacancy posting cost	0.005	$\mathbb{E}[f(\epsilon,\tau,x))]$: avg job finding rate	0.062	0.068
q	Cond. job offer prob. qualified job seeker	0.409	$\mathbb{E}[a(\epsilon,\tilde{\tau})]$: long-term avg applications	10.41	8.660
ρ	Equally ranked ability-eff. correlation	0.588	$\hat{\beta}_{\ln a(\epsilon,\tau),\tau}$: duration effect applications, residual (obs.)	-0.004	-0.005

Note: All duration effects are computed from a linear model and expressed as semi-elasticities. All averages are computed with respect to the distribution of observables at $\tau = 0$. Numeraire: cross-sectional avg monthly output.

Model fit. The estimated model is able to replicate the duration profiles of the outcome variables, while being consistent with observed workers' flows.

On the workers' side, the model replicates the duration profiles of the number of applications quite closely. Figure 6A compares the empirical duration profile of applications after controlling for observables with the average application effort predicted by the model, $\mathbb{E}_\tau[\hat{a}(\epsilon, \tau)]$. Figure 6B compares the duration profile of applications after controlling for individual fixed effects with the duration profile predicted by the model when the composition of the unemployment pool is kept constant, $\mathbb{E}_0[\hat{a}(\epsilon, \tau)]$. Comparison across panels reveals that, quantitatively, the divergence between the two duration profiles is slightly lower in the model than in the data (as also apparent from the respective linear coefficients in Table 3), though the discrepancy is small. Importantly, the model delivers the positive dynamic selection in job applications highlighted in Figure 3B (see Figure D1 for the model counterpart). In the model, job seekers with higher search efficiency exert lower application effort in equilibrium. Since ability and search efficiency are positively correlated, job seekers who exert higher application effort at every duration are therefore more likely to experience longer unemployment spells.

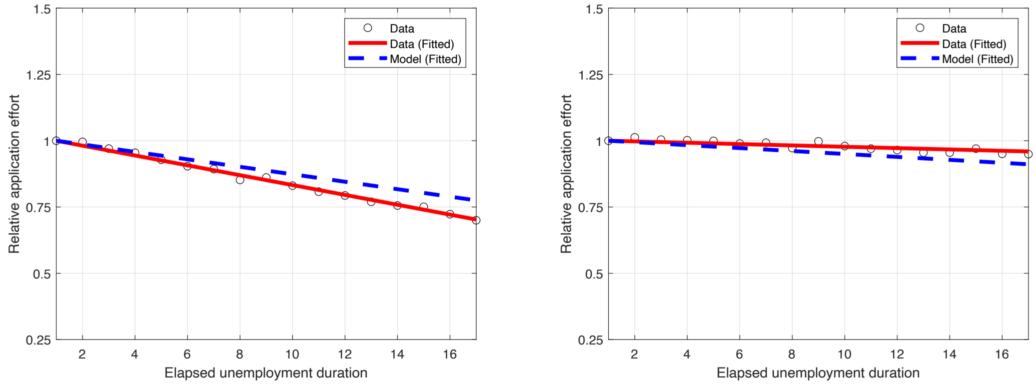
On the firms' side, the model-based duration profiles of the interview rate and job finding rate (controlling for observables) are replicated accurately. Figure 7A displays the *interview rate*, $\mathbb{E}_\tau[\hat{c}(\epsilon, \tau, x)]$, while Figure 7B shows the *job finding rate*, $\mathbb{E}_\tau[\hat{f}(\epsilon, \tau, x)]$. Notice that the duration profile of the interview rate is steeper than that of the job finding rate. This implies that the conditional job offer probability increases with duration, as observed in our data (see Figure 5A). This is a remarkable result as, in the model, the duration profile of the conditional job offer probability is qualitatively ambiguous due to the countervailing effects of positive duration dependence (see Proposition 2) and negative dynamic selection on unobservables.

Notably, our estimated model is able to replicate all the duration profiles not only in relative terms but also in levels. It follows that the observed job finding rate and separation rate pin down the pace of dynamic selection.

Duration dependence versus dynamic selection. We now use our model as an accounting framework to break down the decrease of the observed job finding rate into

Figure 6: Duration profile of application effort, model vs data

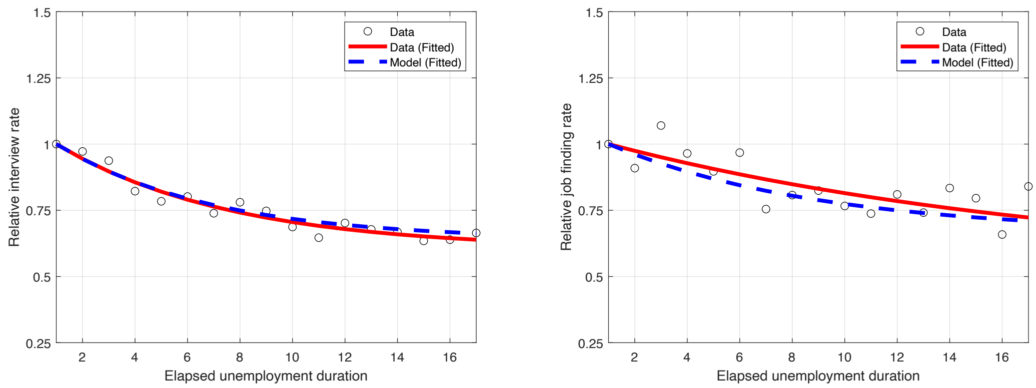
(A) Application effort, residual (FE) (B) Application effort, residual (obs.)



Note: This figure contrasts the duration profiles comntrolling for individual fixed effects (Panel A) and for observables (Panel B) of application effort in the data (solid red) with those implied by the estimated model (dashed blue). Both the duration profiles in the data and in the model are derived by estimating individual fixed effects and duration effects from a saturated regression, computing the expected values of application effort at any unemployment duration, and normalizing them with respect to the first month of unemployment. For the duration profile controlling for individual fixed effects, expected values are computed with respect to workers' search efficiency distribution in the first month of unemployment, *i.e.* $\mathbb{E}_0[\hat{a}(\epsilon,\tau)]$; for the duration profile controlling for observables, expected values are computed with respect to workers' search efficiency distribution in the contemporaneous period of unemployment, *i.e.* $\mathbb{E}_\tau[\hat{a}(\epsilon,\tau)]$. The distribution of observables across unemployment durations is kept the same as in the first month of unemployment in both specifications. Finally, both the data- and the model-implied duration profiles are fitted by a linear function.

Figure 7: Duration profile of interview rate and job finding rate, model vs data

(A) Interview rate, residual (obs.) (B) Job finding rate, residual (obs.)



Note: This figure contrasts the duration profiles controlling for observables of the interview rate (Panel A) and job finding rate (Panel B) detected in the data (solid red) with those implied by the estimated model (dashed blue). Both the duration profiles in the data and in the model are derived by estimating individual fixed effects and duration effects from a saturated regression, computing the expected values of the interview rate and job finding rate at any unemployment duration, and normalizing them with respect to the first month of unemployment. Expected values are computed with respect to the joint distribution of workers' search efficiency and ability in the contemporaneous period of unemployment, *i.e.* $\mathbb{E}_\tau[\hat{c}(\epsilon,\tau,x)]$ and $\mathbb{E}_\tau[\hat{f}(\epsilon,\tau,x)]$.The distribution of observables across unemployment durations is kept the same as in the first month of unemployment. Finally, both the data- and the model-implied duration profiles are fitted by a negative exponential function estimated via weighted nonlinear least squares.

duration dependence and dynamic selection. In addition, our model allows us to separate duration dependence due to workers from that due to firms. On the workers' side, the estimated model allows us to quantify the extent of dynamic selection on unobservables affecting total search effort – not only application effort as in Section 4. On the firms' side, the estimated model provides a structural decomposition of the duration profile of the unconditional job offer probability controlling for observables into duration dependence and dynamic selection on unobservables, which complements our empirical assessment of the role of observables at the interview and job offer stage.

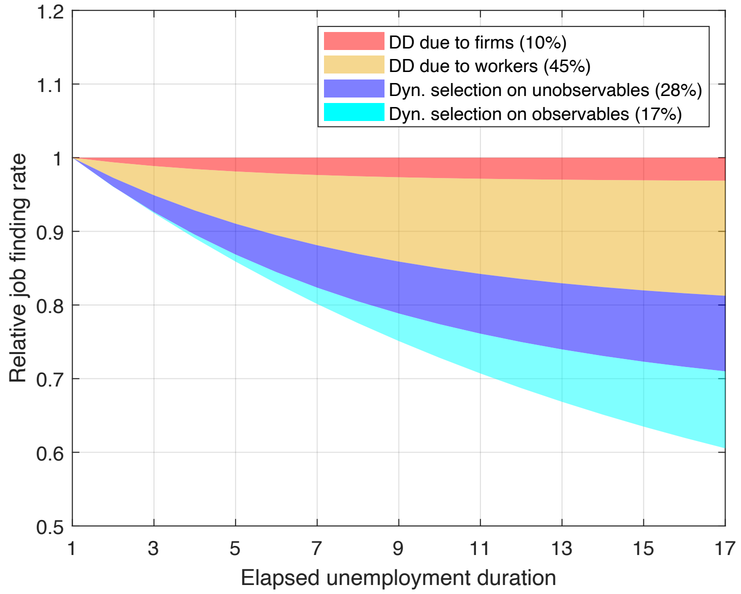
Recall from equation (12) that the job finding rate at duration τ is shaped both by workers' behavior (search effort) and firms' behavior (job offers), *i.e.* $f(\epsilon, \tau, x) = s(\epsilon, \tau)\ o(x, \tau)$. We decompose the decline in the job finding rate after netting out dynamic selection on observables into duration dependence – separating the components due to workers and firms – and dynamic selection on unobservables, as follows:

$$\begin{aligned}\underbrace{\mathbb{E}_\tau\left[f(\epsilon,\tau,x)\right]-\mathbb{E}_0[f(\epsilon,0,x)]}_{\text{Duration profile controlling for obs.}} = &\ \underbrace{\mathbb{E}_\tau\Big[s(\epsilon,0)\ \big(o(x,\tau)-o(x,0)\big)\Big]}_{\text{DD due to firms}} \\ &+ \underbrace{\mathbb{E}_\tau\Big[\big(s(\epsilon,\tau)-s(\epsilon,0)\big)\ o(x,\tau)\Big]}_{\text{DD due to workers}} \\ &+ \underbrace{\mathbb{E}_\tau\Big[s(\epsilon,0)\ o(x,0)\Big]-\mathbb{E}_0\Big[s(\epsilon,0)\ o(x,0)\Big]}_{\text{Dynamic selection on unobservables}}\end{aligned} \tag{16}$$

where $\mathbb{E}_t[.]$ denotes the expectation with respect to the distribution of workers' unobservable characteristics, *i.e.* type ϵ and ability x, at duration t. "Duration dependence due to firms" captures the extent to which the reduction in the true unconditional job offer probability affects the job finding rate directly, while "duration dependence due to workers" captures by how much the change in application effort contributes to a reduction in the job finding rate. The dynamic selection component reflects to what extent job seekers still unemployed in month τ differ from those in the first month of the unemployment spell in terms of unobservable characteristics.

We notice that our model assumes that workers are homogeneous in terms of observable characteristics in a given labor market. Accordingly, when estimating the model, we target the duration profile of the job finding rate controlling for observables. This amounts to positing that the distribution of observables at any unemployment duration is the same as in the first month of unemployment. Let X be a vector of observable characteristics. Hence, $\mathbb{E}_t[f(\epsilon,\tau,x)] \equiv \tilde{\mathbb{E}}_0\left[\mathbb{E}_t[f(\epsilon,\tau,x)|X]\right]$, where $\tilde{\mathbb{E}}_t[\cdot]$ denotes the expectation with respect to the distribution of workers' observable characteristics at duration t. To complete the decomposition of the observed duration profile of the job finding rate, we therefore put together the model-based assessment of duration dependence vs. dynamic selection on unobservables with our empirical estimate of the importance of dynamic se-

Figure 8: Duration profile of the job finding rate, decomposition



Note: This figure reports the decomposition of the duration profile of the job finding rate into the different sources of duration dependence and dynamic selection derived in equation (16) and equation (17). The model-based duration profiles of the components of the job finding rate reported in reported in equation (16) are derived by estimating individual fixed effects and duration effects from a saturated regression, computing the expected values of each component at any unemployment duration, and normalizing them with respect to the first month of unemployment. Expected values are computed with respect to the joint distribution of workers' search efficiency and ability in the contemporaneous period of unemployment. The distribution of observables across unemployment durations is kept the same as in the first month of unemployment. According to equation (17), the duration profiles of the component due to dynamic selection on observables is computed as the difference between the observed duration profile of the job finding rate and the duration profile controlling for observables (see Figure B12). Finally, all duration profiles are fitted by a negative exponential function estimated via weighted nonlinear least squares. The reported shares are the frequency-weighted average shares of the respective raw components over the entire unemployment spell.

lection on observables reported in Figure B12. The observed duration profile of the job finding rate can be decomposed as follows:

$$\underbrace{\hat{\mathbb{E}}_\tau \left[f(\epsilon,\tau,x,X) \right] - \hat{\mathbb{E}}_0 \left[f(\epsilon,0,x,X) \right]}_{\text{Observed duration profile}} = \underbrace{\mathbb{E}_\tau \left[f(\epsilon,\tau,x) \right] - \mathbb{E}_0 \left[f(\epsilon,0,x) \right]}_{\text{Duration profile controlling for obs.}} + \underbrace{\hat{\mathbb{E}}_\tau \left[f(\epsilon,\tau,x,X) \right] - \mathbb{E}_\tau \left[f(\epsilon,\tau,x) \right]}_{\text{Dynamic selection on observables}} \tag{17}$$

where $\hat{\mathbb{E}}_t[\cdot]$ denotes the expectation with respect to the joint distribution of job seekers' unobservable characteristics (ϵ, x) *and* observable characteristics X at duration t, which we read off the data.

Figure 8 shows the decomposition graphically. According to our model, 55% of the observed decline the job finding rate is attributable to duration dependence and 45% to dynamic selection. More specifically, duration dependence is mainly driven by workers' search behavior, which accounts on average for 45% of the observed decline of the job finding rate, and largely outweighs the role of firms' hiring behavior (10%).[34] Dynamic selection happens primarily on unobservables, which accounts for 28% of the observed decline, even though the role of observables is also significant (17%).

On the one hand, our model-based assessment of the (limited) importance of duration dependence due to firms' statistical discrimination is in line with Jarosch and Pilossoph (2019)'s, with the caveat that in our framework firms' statistical discrimination exerts an additional indirect effect on the job finding rate via induced workers' discouragement.[35]

On the other hand, our results stand in contrast with much of the existing literature as far as the relative importance of duration dependence vis-à-vis dynamic selection is concerned.[36] Indeed, we show that duration dependence is at least as important as dynamic selection – and actually even more – in explaining the observed decline in the job finding rate. This is by and largely driven by workers' sizable reduction in application effort over an unemployment spell, which results both from discouragement due to firms' statistical discrimination and learning.[37] Therefore, our results stress the importance of analyzing workers' application behavior and firms' hiring policy jointly to study the drivers of duration dependence in the job finding rate.

The role of labor market frictions. We use the estimated model as a laboratory to highlight the role of different labor market frictions in generating negative duration dependence in the job finding rate and (long-term) unemployment. In particular, our structural model allows us to draw a causal link between negative dynamic selection in

[34] We check that our results are robust to allowing for arbitrary nonlinearity in the relationship between application effort and individual job finding rate and re-estimating the model accordingly. To guard against potential under-identification of the model parameters, we maintain the standard assumption of linearity, though.

[35] Jarosch and Pilossoph (2019) reports the same decomposition for the duration profile controlling for observables only, based on their baseline model without coordination frictions. According to Jarosch and Pilossoph (2019)'s estimates, duration dependence due to firms account for slightly less than 10%. The inclusion of coordination frictions in the extended model necessarily increases their importance.

[36] Using administrative data from Sweden, Mueller and Spinnewijn (2023) estimates a prediction model for the probability of finding a job within 6 months based on observables. According to their results, dynamic selection on unobservables explains (at least) 49% of the observed decline of the 6-month job finding rate in the first 6 months and 36% in the successive 6 months. According to our results, dynamic selection on observables accounts on average for 17%, which is less than in their decomposition. But note that Mueller and Spinnewijn (2023) focuses on the cumulative job finding rate over a 6-month horizon, while we provide a decomposition of the monthly job finding rate, so the two empirical approaches differ substantially with respect to time aggregation.

[37] In Appendix C.6 we show that firms' statistical discrimination and learning affect duration dependence due to workers in almost equal proportions.

worker ability, *i.e.* $d\mathbb{E}[x|\tau]/d\tau < 0$, and negative duration dependence in the job finding rate. This causal link is mediated by firms' statistical discrimination against unemployment duration in their callback policy and workers' learning from search in their application decisions. Crucially, the reason why duration dependence arises is the presence of search costs, namely interview costs and application costs. As a result, government policies aimed at minimizing these costs should mitigate duration dependence and reduce (long-term) unemployment. To assess the relative potential of such policies, we run two counterfactual experiments in our model by letting application costs (ψ) and interview costs (κ) approach zero, respectively.

Figure C4 compares the cumulative measure of unemployed at each duration in our baseline and in the two counterfactual economies. Removing application costs results in the highest reduction in the unemployment rate, which collapses from 12% to 3%, with long-term unemployment being virtually zeroed out.[38] This is a useful benchmark since removing application costs allows overcoming meeting frictions altogether – the main reason why unemployment exists in the first place. On the other hand, removing interview costs entails a significant drop in the unemployment rate by 4pp, which is largely driven by a reduction in the long-term unemployment rate. Overall, the main normative implication we draw from our counterfactual exercises is that governments should consider widening their toolkit of policies aimed at reducing (long-term) unemployment by devising search assistance programs aimed at firms – as well as workers – in order to minimize their interview costs. This would reduce both the aggregate unemployment rate (by stimulating firm entry) and long-term unemployment (by alleviating statistical discrimination). Appendix C.7 provides further details on our counterfactual exercises.

7. Discussion and alternative explanations

Our structural model encompasses potential mechanisms rationalizing our empirical findings. In this section we discuss our modelling choices in the light of alternative approaches proposed in the existing literature. We also discuss – and, where data permit, provide some additional evidence – mechanisms that are not directly captured in our structural model.

[38] Long-term unemployment is defined as the population share of unemployed for more than 1 year according to the OECD definition.

Workers' search behavior. To rationalize negative duration dependence in application effort, we propose a model of job seekers' learning from search about own ability. The intuition is simple: if job seekers do not know their own ability at the start of the unemployment spell, they find it optimal to form their beliefs based on the *average* job finding rate. Since the average job finding rate declines smoothly with unemployment duration, so does the expected job offer probability and, as a result, application effort.[39] This mechanism represents the conceptual counterpart of our model of firms' behavior and is close to He and Kircher (2023)'s, up to the specification of the belief function. DellaVigna, Heining, Schmieder, and Trenkle (2022) and DellaVigna, Lindner, Reizer, and Schmieder (2017) show that the duration profile of job seekers' search effort (proxied by hours spent searching) is well approximated by models of reference dependence in consumption, which deliver spikes in search effort corresponding to times when consumption changes. Early in the unemployment spell, reference dependence provides an observationally equivalent mechanism to learning from search to explain the decline in application effort. At longer durations, reference-dependent job seekers are expected to scale up application effort as UI benefits approach exhaustion, to then decrease it again. Since we lack statistical power to document search behavior around UI benefit exhaustion reliably, we are unable to provide a definitive test for reference dependence.

We model positive dynamic selection in application effort as the result of heterogeneous search efficiency across workers (Gregory, Menzio, and Wiczer, 2021; Lafuente, 2023). Workers with higher search efficiency have a higher probability of meeting a vacancy per application, but face higher marginal application costs as well.[40] Positive dynamic selection in application effort arises because search efficiency and ability are positively correlated. Alternatively, positive dynamic selection in job seekers' application effort can be captured by models where search effort is a strategic substitute for the unconditional

[39] A simple, perfect-information model is unable to replicate the duration profile controlling for observables of the job finding rate and the duration dependence in application effort jointly. Since individual applications declines by twice as much the unconditional job offer probability controlling for observables (which pools duration dependence and dynamic selection on unobservables), the elasticity of applications to the unconditional job offer probability should be extremely high in such a model. Since job seekers respond with the same elasticity to the unconditional job offer probability and capital gain upon employment, applications would be expected to *increase* markedly in anticipation of future declines in job prospects, to then drop when the latter materialize – not to decrease linearly.

[40] Appendix C.1 shows that this result obtains in any model where the unconditional job offer probability per application is positively correlated with the marginal utility of social leisure in the presence of a time constraint.

job offer probability, *e.g.* by models of simultaneous search (Kircher, 2009; Galenianos and Kircher, 2009; Birinci, See, and Wee, 2023; Wolthoff, 2018) or with a generalized matching function (Mukoyama, Patterson, and Şahin, 2018; Faberman and Kudlyak, 2019).[41] In these models, application effort is *decreasing* in the unconditional job offer probability, which entails that low-ability job seekers apply more than high-ability ones – absent any difference in search efficiency. To disentangle the role of strategic substitution as opposed to heterogeneous search efficiency in the cross section, we plot in Figure B8 the *ex ante* interview probability, *i.e.* controlling for observables, against the application fixed effects for given unemployment durations. If search efficiency was constant across workers, the relationship would look flat, since by construction job seekers are observationally equivalent to firms. On the contrary, we detect a significantly negative gradient at any unemployment duration, which points to substantial heterogeneity in search efficiency.[42] Moreover, by the same logic of strategic substitution, job seekers should scale *up* their application effort over an unemployment spell as their unconditional job offer probability reduces, which is inconsistent with the strongly negative duration dependence we detect empirically.

Human capital depreciation. Human capital depreciation over the course of unemployment as, for instance, in Ljungqvist and Sargent (1998) represents the main alternative (or complementary) explanation for negative dynamic selection on ability and negative duration dependence in application effort. On the one hand, even absent any cross-sectional heterogeneity in ability at the start of the unemployment spell, firms would statistically discriminate against long unemployment durations to the extent that a job seeker's ability deteriorates with the duration of unemployment. Note, however, that in our data substantial heterogeneity in the unconditional job offer probability (and application effort) remains after controlling for observed characteristics. This suggests that ability depreciation is unlikely to be the only determinant of dynamic selection.[43] On the

[41] In principle, models of simultaneous search can accommodate both strategic complementarity and substitutability between application effort and the unconditional job offer probability.

[42] Positive dynamic selection in application effort may also arise if workers are risk-averse through a dominant wealth effect in search effort, as alluded by Faberman and Kudlyak (2019). However, wealth effects are equally unable to generate the negative gradient between the individual *ex ante* interview probability and the application fixed effects by themselves, either.

[43] Jarosch and Pilossoph (2019) estimates a model putting together both ability depreciation and cross-sectional heterogeneity as sources of dynamic selection and finds that ability should depreciate very

other hand, job seekers would scale down application effort over the unemployment spell due to both firms' statistical discrimination for given individual ability and progressive ability downgrading. Hence, human capital depreciation generates negative duration dependence in application effort in a qualitatively similar way to our model of learning from search (how quickly the unconditional job offer probability declines would depend on the exogenous depreciation process rather than the endogenous job finding process). Our takeaway is that, while our model generates a duration profile of application effort that is able to replicate the empirical evidence, the precise reasons why job seekers get increasingly discouraged are still unclear. We conclude that the extent to which human capital depreciation drives workers' search behavior remains an open question. Also the recent empirical literature remains inconclusive on this issue (Cohen, Johnston, and Lindner, 2023; Dinerstein, Megalokonomou, and Yannelis, 2022; Arellano-Bover, 2022).

Stock-flow matching. Negative duration dependence in application effort can stem from stock-flow sampling of vacancies (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. Accordingly, the number of applications is decreasing over the unemployment spell because workers initially apply to the large stock of existing vacancies and in subsequent periods to the smaller inflow of new vacancies. This mechanism entails a non-gradual decline in application effort with elapsed unemployment duration. In our context, we find that application effort decreases gradually and linearly over time, which is not in line with the stock-flow sampling hypothesis.[44]

Depletion of personal networks. Negative duration dependence in application effort may be related to the depletion of a job seeker's personal network, which has been shown to play an important role in job finding (Beaman and Magruder, 2012; Burks

slowly to be consistent with the observed decline in the interview rate.

[44] In the most stylized framework, job seekers apply to the stock of vacancies in the first month of unemployment only. This results in a large discontinuous drop from the first to subsequent periods. The hypothesis can directly be tested by estimating the duration profile in application effort controlling for the stock and flow of vacancies in the relevant labor market. If the stock-flow mechanism prevails, duration dependence estimated by this augmented model should be zero. This approach is not feasible in our context because we do not have access to data on job vacancies. However, Faberman and Kudlyak (2019) do not find supporting evidence for the stock-flow hypothesis.

et al., 2015; Hensvik and Nordström Skans, 2016). This mechanism can be seen as a form of personal stock-flow sampling, where the decline in total application effort is caused by the exhaustion of the job seeker's personal contacts. In contrast, applications made through other channels ought to remain constant throughout the unemployment spell. We assess this alternative explanation by estimating equation (1) distinguishing between three different application channels (personal, phone, written). We find that the number of applications made in person, per phone and in writing all decrease with elapsed unemployment duration, hence providing little support for exhaustion of personal contacts (Appendix Table B10).

Firms' hiring behavior. The negative duration profile of the interview probability after netting out observable heterogeneity can stem from firms' discrimination against duration and/or negative dynamic selection on unobservable characteristics of workers. Our empirical finding of a positive duration profile for the probability of a job offer after an interview (controlling for observables) supports statistical discrimination, while being inconsistent with both pure taste-based discrimination (Blanchard and Diamond, 1994) and pure dynamic selection on unobservables (Mueller, Spinnewijn, and Topa, 2021). Pure taste-based discrimination assumes that job seekers are all equally productive but firms, faced with multiple applicants, rank them by duration. Hence, job seekers with a longer unemployment duration face a lower interview probability, but the job offer probability after an interview does not change with duration. Pure dynamic selection on unobservables assumes that job seekers face a constant unconditional job offer probability throughout the entire unemployment spell corresponding to their unobserved type. Absent interview costs, firms would call back applicants of any duration and make a job offer to the best of them based on their interviews. Since dynamic selection on unobservables is negative, the job offer probability after an interview should decline with duration. As per Proposition 2, our statistical discrimination framework – just as in Jarosch and Pilossoph (2019) – generates positive duration dependence in the job offer probability after an interview. As long as such positive duration dependence outweighs negative dynamic selection on unobservables, the job offer probability after an interview (controlling for observables) exhibits a positive duration profile.

Changes in application quality. The observed decline in the interview probability may relate to changes in application quality over time: (part of) the downward-sloping duration profile in the interview probability could reflect a gradual downgrading of job application characteristics. In our context, we observe an important dimension of application quality: the channel used to contact the firm (Beaman and Magruder, 2012; Burks, Cowgill, Hoffman, and Housman, 2015; Hensvik and Nordström Skans, 2016). As we show in Appendix B.4, Figure B9, the application channel is strongly predictive of an application's success at the interview stage, with personal applications being more successful than written resumes or phone applications.[45] However, changes in application quality as captured by the application channel seem unlikely to represent the main driver of the effect of our duration results. On the one hand, the relative importance of each channel remains constant with duration, even after controlling for individual heterogeneity (see Figure B9). On the other hand, we still find evidence of a marked decline in the interview probability after controlling for the application channel in our regressions.[46]

Increasing the search radius. Another potential explanation for the decline in the interview probability lies in application targeting (Galenianos and Kircher, 2009; Wright, Kircher, Julien, and Guerrieri, 2021; Lehmann, 2023). Initially, job seekers might target a specific occupation, before starting to search more broadly and to apply to a wider set of job ads as unemployment 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 we have information on the occupation of the vacancies reported in the search diary. 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

[45]See Table B6 in the Appendix for regression results on the effect of application channel on the probabilities of a job interview and job offer (after an interview).

[46]If anything, we would expect (unobserved determinants of) application quality to be actually increasing over time, as job seekers learn how to make better applications over time. Such omitted determinants would induce an upward bias in the estimated duration profile that controls for observable characteristics, implying that the true duration dependence in the interview probability would actually be more negative.

net cognitive requirements of targeted occupations.[47] The range of occupations for which job seekers apply, as measured by the same-occupation indicator (Figure B10A), hardly changes with unemployment duration, regardless of whether we control for job seeker fixed effects or not. At short unemployment durations, job seekers apply to occupations that have on average higher cognitive requirements than physical requirements, whereas job applications later in the spell target less cognitively intense occupations. However, the decline in cognitive intensity of target occupations is strongly attenuated once job seeker fixed effects are added (Figure B10B). This suggests that the decline in cognitive intensity is largely driven by the changing composition of the pool of unemployed rather than by a change application targeting within individuals. Altogether, these pieces of evidence point towards a limited role of application targeting in the decline of the interview probability.

8. Conclusions

We use monthly search diary data from the Swiss unemployment insurance system to shed new light on the long-standing question why the job finding rate decreases with the duration of unemployment. Empirical evidence from search diaries shows that, as the unemployment spell progresses, job seekers send fewer applications, have lower chances to be invited to a job interview but higher chances to get a job offer conditional on a job interview.

We develop a model in which firms statistically discriminate against the long-term unemployed and in which job seekers learn from their search outcomes along the unemployment spell. This model captures our empirical findings closely and allows us to explore in more depth the driving forces behind the observed decrease in the job finding rate. According to our framework, duration dependence contributes 55 percent to the observed decrease in the job finding rate, while the remaining 45 percent is due to dynamic selection. Duration dependence arises mainly because job seekers get increasingly discouraged and send fewer applications at longer durations. As in Jarosch and Pilos-

[47] 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 skill requirements and physical requirements.

soph (2019) statistical discrimination of firms against the long-term unemployed does only weakly decrease a job seeker's job prospects (because most lost interviews would not have resulted in a job offer anyway).

The reasons for job seekers' discouragement are less clear. Our model emphasizes that negative search outcomes make job seekers more pessimistic about their own labor market prospects. However, other mechanisms such as human capital depreciation, running out of job opportunities or a loss of attachment to the labor market (and social capital and motivation) may also explain the reduction in a job seeker's search effort. It could also be that the long-term unemployed widen their (occupational and regional) search radius and end up applying to jobs that are less likely providing a good fit. Exploring the relative importance of these channels in more detail is a fruitful direction for future research.

References

Abbring, J. H. and Van den Berg, G. J. The nonparametric identification of treatment effects in duration models. *Econometrica*, 71(5):1491–1517, 2003.

Ahn, H. J., Hobijn, B., and Şahin, A. The dual u.s. labor market uncovered. *NBER Working Paper no 31241*, 2023.

Ahn, H. J. and Hamilton, J. D. Heterogeneity and unemployment dynamics. *Journal of Business & Economic Statistics*, 38(3):554–569, 2020.

Albrecht, J. and Vroman, S. A matching model with endogenous skill requirements. *International Economic Review*, 43(1):283–305, 2002.

Alvarez, F. E., Borovičková, K., and Shimer, R. Decomposing duration dependence in a stopping time model. Technical report, National Bureau of Economic Research, 2022.

Arellano-Bover, J. The Effect of Labor Market Conditions at Entry on Workers' Long-Term Skills. *The Review of Economics and Statistics*, 104(5):1028–1045, December 2022.

Arni, P. and Schiprowski, A. Job search requirements, effort provision and labor market outcomes. *Journal of Public Economics*, 169:65–88, 2019.

Barron, J., Berger, M., and Black, D. How well do we measure training? *Journal of Labor Economics*, 15(3):507–28, 1997.

Beaman, L. and Magruder, J. Who gets the job referral? Evidence from a social networks experiment. *American Economic Review*, 102(7):3574–93, 2012.

Behncke, S., Frölich, M., and Lechner, M. A caseworker like me - Does the similarity between the unemployed and their caseworkers increase job placements? *The Economic Journal*, 120(549):1430–1459, 2010.

Belot, M., Kircher, P., and Muller, P. Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice. *The Review of Economic Studies*, 86(4): 1411–1447, 10 2018.

Birinci, S., See, K., and Wee, S. L. Job Applications and Labour Market Flows. Staff Working Papers 21-49, Bank of Canada, October 2023.

Blanchard, O. J. and Diamond, P. Ranking, unemployment duration, and wages. *The Review of Economic Studies*, 61(3):417–434, 1994.

Burdett, K. and Vishwanath, T. Declining reservation wages and learning. *The Review of Economic Studies*, 55(4):655–665, 10 1988.

Burks, S. V., Cowgill, B., Hoffman, M., and Housman, M. The value of hiring through employee referrals. *The Quarterly Journal of Economics*, 130(2):805–839, 2015.

Choudhury, J. B. Non-parametric confidence interval estimation for competing risks analysis: application to contraceptive data. *Statistics in medicine*, 21(8):1129–1144, 2002.

Christensen, B. J., Lentz, R., Mortensen, D., Neumann, G. R., and Werwatz, A. On-the-job search and the wage distribution. *Journal of Labor Economics*, 23(1):31–58, 2005.

Cohen, J., Johnston, A. C., and Lindner, A. Skill depreciation during unemployment: Evidence form panel data. *Working paper*, 2023.

Davis, S. J. and von Wachter, T. Recessions and the Costs of Job Loss. *Brookings Papers on Economic Activity*, 42(2 (Fall)):1–72, 2011.

DellaVigna, S., Lindner, A., Reizer, B., and Schmieder, J. Reference-dependent job search: Evidence from hungary. *The Quarterly Journal of Economics*, 132, 05 2017.

DellaVigna, S., Heining, J., Schmieder, J. F., and Trenkle, S. Evidence on job search models from a survey of unemployed workers in germany. *The Quarterly Journal of Economics*, 137(2):1181–1232, 2022.

Dinerstein, M., Megalokonomou, R., and Yannelis, C. Human capital depreciation and returns to experience. *American Economic Review*, 112(11):3725–62, November 2022.

Doppelt, R. The hazards of unemployment: A macroeconomic model of job search and résumé dynamics. *Working Paper*, 2016.

Ebrahimy, E. and Shimer, R. Stock–flow matching. *Journal of Economic Theory*, 145 (4):1325–1353, 2010. ISSN 0022-0531. Search Theory and Applications.

Elbers, C. and Ridder, G. True and spurious duration dependence: The identifiability of the proportional hazard model. *The Review of Economic Studies*, 49(3):403–409, 1982.

Eriksson, S. and Rooth, D.-O. Do employers use unemployment as a sorting criterion when hiring? evidence from a field experiment. *American Economic Review*, 104(3): 1014–39, 2014.

Faberman, R. J. and Kudlyak, M. The intensity of job search and search duration. *American Economic Journal: Macroeconomics*, 11(3):327–57, 2019.

Falk, A., Huffman, D., and Sunde, U. Self-confidence and search. IZA Discussion Papers 2525, Institute of Labor Economics (IZA), 2006.

Farber, H. S., Silverman, D., and Von Wachter, T. Determinants of callbacks to job applications: An audit study. *American Economic Review*, 106(5):314–18, 2016.

Fernández-Blanco, J. and Preugschat, E. On the effects of ranking by unemployment duration. *European Economic Review*, 104:92–110, 2018. ISSN 0014-2921.

Fluchtmann, J., Glenny, A. M., Harmon, N., and Maibom, J. The dynamics of job search in unemployment: Beyond search effort and reservation wages. *Working Paper*, 2021.

Galenianos, M. and Kircher, P. Directed search with multiple job applications. *Journal of economic theory*, 144(2):445–471, 2009.

Gavazza, A., Mongey, S., and Violante, G. L. Aggregate recruiting intensity. *American Economic Review*, 108(8):2088–2127, August 2018.

Gertler, M. and Trigari, A. Unemployment fluctuations with staggered nash wage bargaining. *Journal of Political Economy*, 117(1):38–86, 2009.

Gonzalez, F. M. and Shi, S. An equilibrium theory of learning, search, and wages. *Econometrica*, 78(2):509–537, 2010.

Gourieroux, C., Monfort, A., and Trognon, A. Pseudo maximum likelihood methods: Applications to poisson models. *Econometrica: Journal of the Econometric Society*, pages 701–720, 1984.

Gregory, V., Menzio, G., and Wiczer, D. G. The alpha beta gamma of the labor market. Working Paper 28663, National Bureau of Economic Research, April 2021.

Hagedorn, M. and Manovskii, I. The cyclical behavior of equilibrium unemployment and vacancies revisited. *American Economic Review*, 98(4):1692–1706, September 2008.

Hall, R. E. Employment fluctuations with equilibrium wage stickiness. *American Economic Review*, 95(1):50–65, March 2005.

He, Q. and Kircher, P. Updating about yourself by learning about the market: The dynamics of beliefs and expectations in job search. *Working Paper*, 2023.

Heckman, J. and Singer, B. A method for minimizing the impact of distributional assumptions in econometric models for duration data. *Econometrica*, 95(2):50–65, March 1984.

Hensvik, L. and Nordström Skans, O. Social networks, employee selection, and labor market outcomes. *Journal of Labor Economics*, 34(4):825–867, 2016.

Jarosch, G. and Pilossoph, L. Statistical discrimination and duration dependence in the job finding rate. *The Review of Economic Studies*, 86(4):1631–1665, 2019.

Kircher, P. Efficiency of Simultaneous Search. *Journal of Political Economy*, 117(5): 861–913, October 2009.

Kroft, K., Lange, F., and Notowidigdo, M. J. Duration dependence and labor market conditions: Evidence from a field experiment. *The Quarterly Journal of Economics*, 128(3):1123–1167, 2013.

Krueger, A. B., Mueller, A., Davis, S. J., and Şahin, A. Job search, emotional well-being, and job finding in a period of mass unemployment: Evidence from high frequency longitudinal data. *Brookings Papers on Economic Activity*, pages 1–81, 2011.

Lafuente, C. Hysteresis for the young: Search capital and unemployment. *Working Paper*, 2023.

Lancaster, T. Econometric methods for the duration of unemployment. *Econometrica: Journal of the Econometric Society*, pages 939–956, 1979.

Leduc, S. and Liu, Z. The weak job recovery in a macro model of search and recruiting intensity. *American Economic Journal: Macroeconomics*, 12(1):310–43, January 2020.

Lehmann, T. How directed is search in the labor market? Evidence from an online job board. *Working paper*, 2023.

Lise, J. On-the-Job Search and Precautionary Savings. *Review of Economic Studies*, 80 (3):1086–1113, 2013.

Lise, J. and Robin, J.-M. The macrodynamics of sorting between workers and firms. *American Economic Review*, 107(4):1104–35, April 2017.

Ljungqvist, L. and Sargent, T. J. The European Unemployment Dilemma. *Journal of Political Economy*, 106(3):514–550, June 1998.

Ljungqvist, L. and Sargent, T. J. Two Questions about European Unemployment. *Econometrica*, 76(1):1–29, January 2008.

Lockwood, B. Information externalities in the labour market and the duration of unemployment. *The Review of Economic Studies*, 58(4):733–753, 1991.

Marinescu, I. and Skandalis, D. Unemployment insurance and job search behavior. *The Quarterly Journal of Economics*, 136(2):887–931, 2021.

Matzkin, R. L. Nonparametric estimation of nonadditive random functions. *Econometrica*, 71(5):1339–1375, 2003.

McCall, J. J. Economics of information and job search. *The Quarterly Journal of Economics*, pages 113–126, 1970.

Menzio, G. and Shi, S. Efficient Search on the Job and the Business Cycle. *Journal of Political Economy*, 119(3):468–510, 2011.

Mueller, A. I. and Spinnewijn, J. Predicting long-term unemployment risk. *Working paper*, 2023.

Mueller, A. I., Spinnewijn, J., and Topa, G. Job seekers' perceptions and employment prospects: Heterogeneity, duration dependence, and bias. *American Economic Review*, 111(1):324–63, 2021.

Mukoyama, T., Patterson, C., and Şahin, A. Job search behavior over the business cycle. *American Economic Journal: Macroeconomics*, 10(1):190–215, January 2018.

Nekoei, A. and Weber, A. Seven Facts about Temporary Layoffs. CEPR Discussion Papers 14845, C.E.P.R. Discussion Papers, June 2020.

Nüß, P. Duration dependence as an unemployment stigma: Evidence from a field experiment in germany. Technical report, Economics Working Paper, 2018.

Oberholzer-Gee, F. Nonemployment stigma as rational herding: A field experiment. *Journal of Economic Behavior & Organization*, 65(1):30–40, 2008.

Pissarides, C. A. *Equilibrium Unemployment Theory, 2nd Edition*, volume 1 of *MIT Press Books*. The MIT Press, February 2000.

Ramey, G., den Haan, W. J., and Watson, J. Job destruction and propagation of shocks. *American Economic Review*, 90(3):482–498, June 2000.

Salop, S. C. Systematic job search and unemployment. *The Review of Economic Studies*, 40(2):191–201, 1973.

Shimer, R. The Assignment of Workers to Jobs in an Economy with Coordination Frictions. *Journal of Political Economy*, 113(5):996–1025, 2005a.

Shimer, R. The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, 95(1):25–49, March 2005b.

Silva, J. and Toledo, M. Labor turnover costs and the cyclical behavior of vacancies and unemployment. *Macroeconomic Dynamics*, 13:76–96, 05 2009.

Spinnewijn, J. Unemployed but optimistic: Optimal insurance design with biased beliefs. *Journal of the European Economic Association*, 13(1):130–167, 2015.

Van den Berg, G. J. Nonstationarity in job search theory. *The Review of Economic Studies*, 57(2):255–277, 1990.

Van den Berg, G. J. and Van Ours, J. C. Unemployment dynamics and duration dependence. *Journal of Labor Economics*, 14(1):100–125, 1996.

Vishwanath, T. Job search, stigma effect, and escape rate from unemployment. *Journal of Labor Economics*, 7(4):487–502, 1989.

Wolthoff, R. Applications and Interviews: Firms' Recruiting Decisions in a Frictional Labour Market. *Review of Economic Studies*, 85(2):1314–1351, 2018.

Wright, R., Kircher, P., Julien, B., and Guerrieri, V. Directed search and competitive search equilibrium: A guided tour. *Journal of Economic Literature*, 59(1):90–148, 2021.

Yashiv, E. The determinants of equilibrium unemployment. *American Economic Review*, 90(5):1297–1322, December 2000.

Zuchuat, J. Estimating duration dependence in job search: the within estimation duration bias. *Working paper*, 2023.

Appendix

Table of Contents

A Data and empirical measurements **50**

B Details of the empirical analysis and further empirical results **54**

B.1 Job applications 54

B.2 Job interviews and job offers (after an interview) 60

B.3 Incidence of right censoring and estimation results from non-right-censored data 66

B.4 Evidence to evaluate complementary explanations 69

B.5 Job interviews and job finding at the person-month level 71

C Details of the structural model **74**

C.1 Microfoundation of search effort cost function 74

C.2 Additional propositions and proofs 75

C.3 Quantitative model 77

C.4 Model derivations 79

C.5 Details of structural estimation 81

C.6 Expanded decomposition duration profile of the job finding rate 85

C.7 Counterfactuals 87

D Additional Graphs & Tables **93**

A. Data and empirical measurements

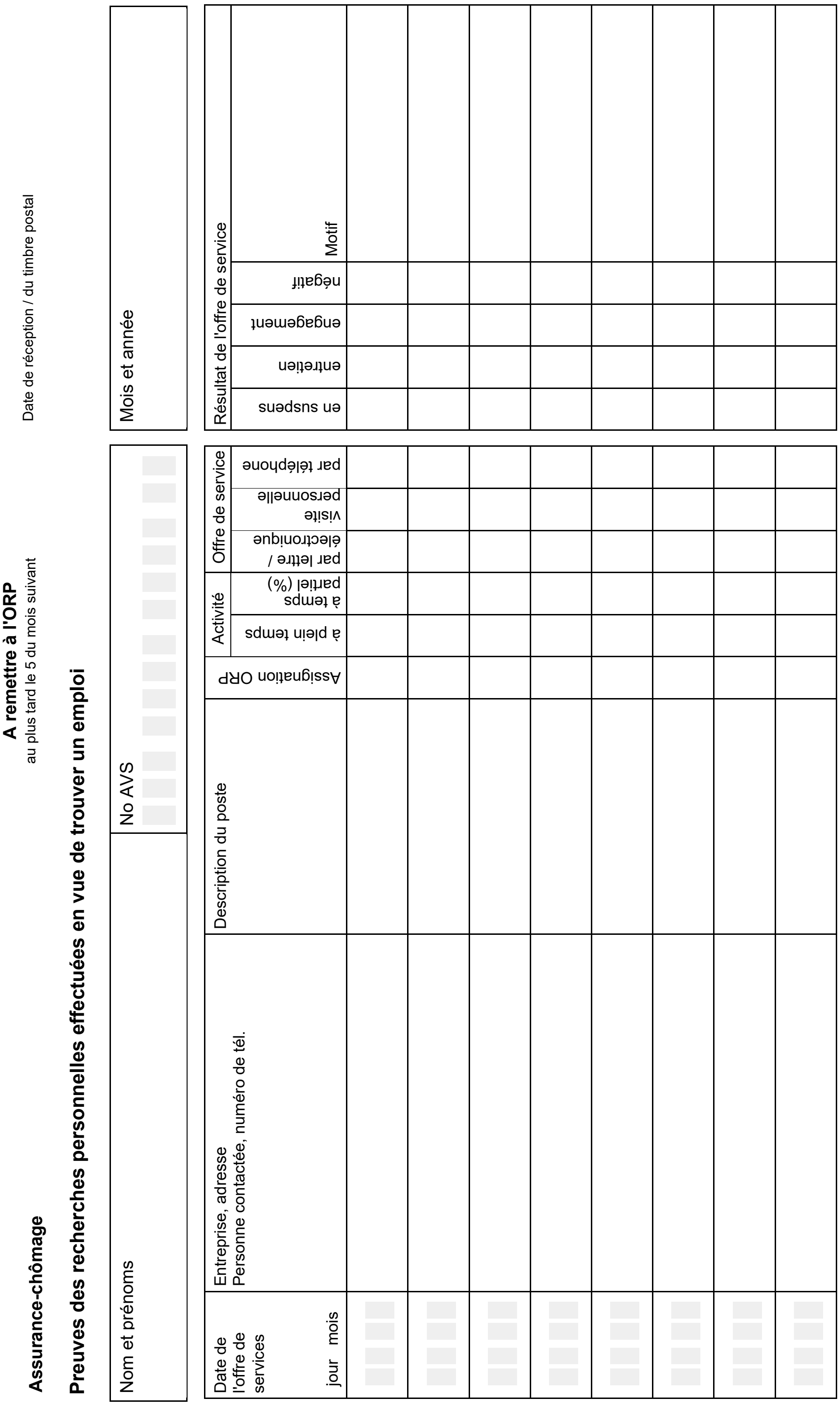
In this Section, we provide further details on the contents of our main search diary data, that includes information from the cantons Bern (BE), St. Gallen (SG), Vaud (VD), Zug (ZG), and Zurich (ZH), as well as of the auxiliary data, that includes information from one employment office in Zurich.

Table A1: Job seekers' outcomes and observed characteristics, *main* and *auxiliary samples*

	Main sample			***Auxiliary sample***		
	Mean	St. Dev.	N	Mean	St. Dev.	N
A. Outcomes						
Person-month level (search-diary level)						
Job finding rate	0.061	(0.239)	58755	0.078	(0.269)	2783
Number of applications	10.553	(4.698)	58755	8.900	(4.597)	2783
Job interview rate	0.226	(0.418)	58755	0.289	(0.453)	2783
Application-level						
Interview Probability	0.040	(0.196)	600323	0.074	(0.262)	24770
Conditional Job Offer Probability	0.225	(0.418)	22422	0.206	(0.404)	1559
Unconditional Job Offer Probability	0.009	(0.095)	600323	0.015	(0.122)	24770
B. 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
C. Sample structure						
Time-period		04.2012 - 03.2013			07.2007 - 03.2008	
Region		BE, SG, VD, ZG, ZH			ZH	
Number of applications		600323			24770	
Person-month observations		58755			2699	
Number of individuals		14798			655	

Note: This table reports means and standard deviations on job seekers' outcomes, socio-demographic characteristics and sample information, for the *main sample* and *auxiliary sample*.

Figure A1: Job search diaries



Assurance-chômage

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

Date de réception / du timbre postal

Preuves des recherches personnelles effectuées en vue de trouver un emploi

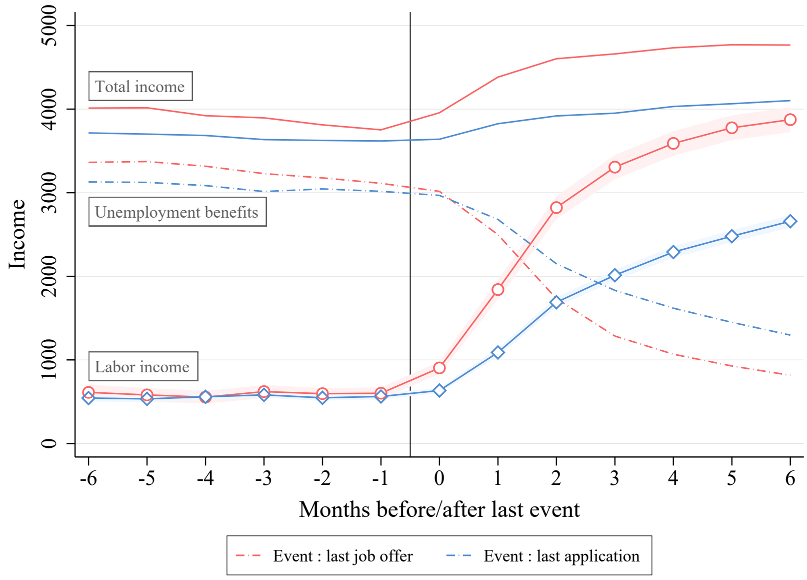
Nom et prénoms	No AVS	Mois et année

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

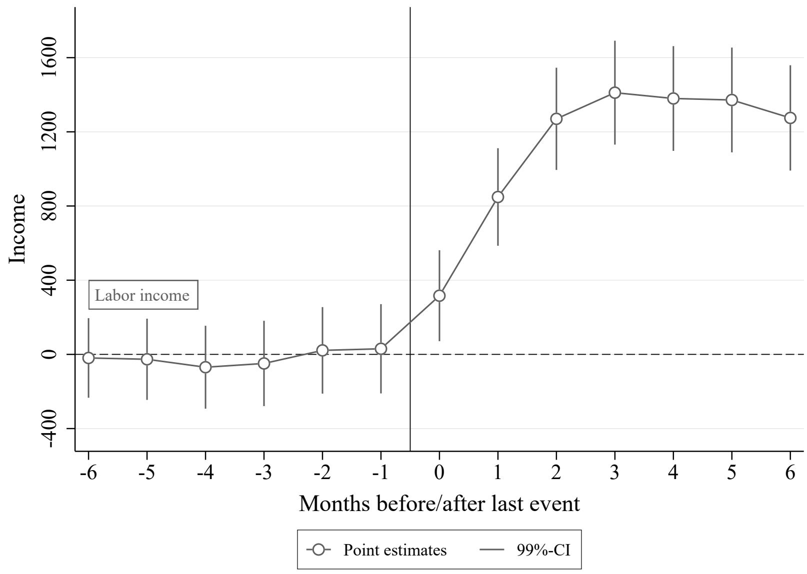
Note: This figure presents the job search diary form that job seekers have to use to document their search activities.

Figure A2: Job offers and income trajectories

(A) Observed average income trajectories

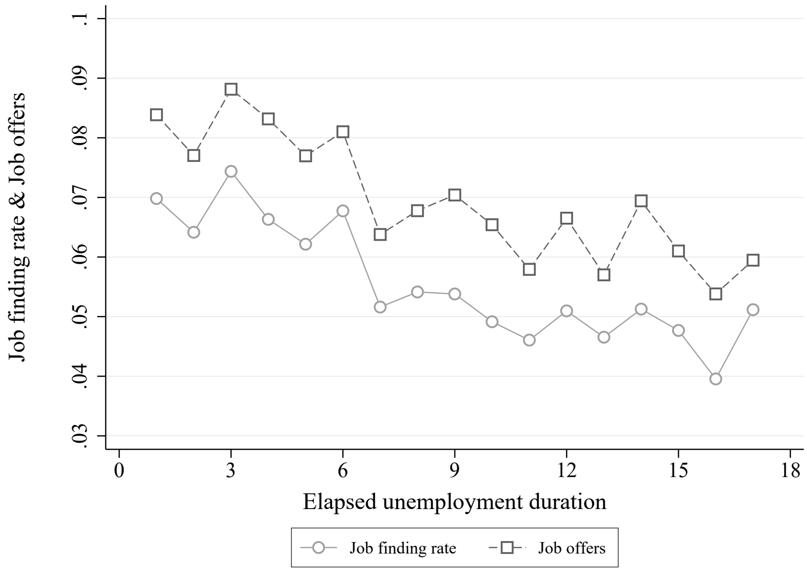


(B) Δ in labor income trajectories (accounting for heterogeneity)



Note: This figure presents an event-study analysis, contrasting information from the search diary data and the social security data. It highlights the informational content of the search diaries. 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 reported (in blue, if no job offer is 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 job finding rate and number of job offers



Note: This figure plots the average monthly probability of a job offer together with the average monthly number of job offers.

B. Details of the empirical analysis and further empirical results

B.1 Job applications

B.1.1 Detailed estimation results

In Table B1, we report step-by-step OLS estimates of equation (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 square brackets.

Table B1: Duration dependence in application effort, linear specification

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable : Applications						
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
Local labor market conditions	No	No	No	Yes	No	Yes
Individual FE	No	No	No	No	Yes	Yes
Mean outcome 1st month	10.846	10.846	10.846	10.846	10.846	10.846
Adjusted-R^2	0.005	0.038	0.179	0.192	0.486	0.498
Observations	58755	58755	58755	58755	58755	58755

Note: This table reports estimates of equation (1) using OLS, where the duration function $f^A(t;\phi^A)$ is specified linearly. Each column sequentially adds a set of control variables or fixed effects. Standard 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 reported in square brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

In Figure B1, we report equivalent results for the saturated specification of equation (1), distinguishing between the effect of elapsed unemployment duration on application effort as observed in the data, the effect of duration net of observable heterogeneity and the effect of duration after controlling for observable heterogeneity and individual fixed effects.

To better understand what characterizes job seekers with higher values of the individual fixed effect, we regress the estimated $\hat{\alpha}_i$ on observed individual characteristics. Partial correlation coefficients are reported in Table B2.

B.1.2 Robustness Checks

We perform several robustness checks to assess the validity of our finding that unemployment duration affects application effort negatively.

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

Table B2: Partial correlations between estimated α_i and observed characteristics

	(1)		(2)		(3)	
Dependent variable: estimated α_i						
Age : ref. < 25						
$25 - 30$	0.003	(0.148)	0.001	(0.147)	-0.020	(0.146)
$30 - 35$	0.572***	(0.148)	0.527***	(0.148)	0.530***	(0.145)
$35 - 40$	-0.674***	(0.153)	-0.715***	(0.152)	-0.697***	(0.150)
$40 - 45$	-0.482***	(0.153)	-0.527***	(0.151)	-0.530***	(0.149)
$45 - 50$	-1.321***	(0.154)	-1.318***	(0.153)	-1.281***	(0.153)
$50 - 55$	-1.242***	(0.157)	-1.245***	(0.155)	-1.249***	(0.155)
$55 - 60$	-1.178***	(0.168)	-1.176***	(0.167)	-1.153***	(0.166)
> 60	-3.382***	(0.194)	-3.404***	(0.192)	-3.364***	(0.191)
Residential status : ref. CH resident						
C-permit	0.495***	(0.093)	0.457***	(0.092)	0.461***	(0.092)
B-permit	0.659***	(0.110)	0.631***	(0.110)	0.621***	(0.109)
Other permit	-0.751***	(0.235)	-0.805***	(0.232)	-0.673***	(0.230)
Education : ref. Primary						
Apprenticeship	-0.362***	(0.093)	-0.390***	(0.092)	-0.397***	(0.091)
High school	-0.986***	(0.186)	-1.082***	(0.187)	-1.094***	(0.183)
Prof. maturity	-0.422**	(0.173)	-0.427**	(0.171)	-0.381**	(0.172)
University of appl. science	-2.826***	(0.221)	-2.938***	(0.220)	-2.898***	(0.225)
University	-0.458***	(0.158)	-0.633***	(0.162)	-0.632***	(0.160)
Female	0.179**	(0.082)	0.181**	(0.081)	0.113	(0.082)
ln(previous wage)	0.373***	(0.069)	0.371***	(0.069)	0.306***	(0.068)
Unemployment history	-0.489*	(0.269)	-0.480*	(0.266)	-0.496*	(0.267)
Occupation : ref. Agriculture						
Industry & Craft	-2.211***	(0.284)	-2.167***	(0.283)	-2.250***	(0.281)
IT	-2.664***	(0.311)	-2.625***	(0.310)	-2.751***	(0.309)
Construction	-1.604***	(0.296)	-1.589***	(0.295)	-1.552***	(0.293)
Commercial	-1.156***	(0.282)	-1.138***	(0.281)	-1.287***	(0.282)
Hotelling	-1.215***	(0.281)	-1.266***	(0.280)	-1.359***	(0.284)
Administrative	-1.201***	(0.290)	-1.187***	(0.289)	-1.376***	(0.289)
Health & Educ.	-2.627***	(0.293)	-2.636***	(0.293)	-2.609***	(0.294)
Other	-2.428***	(0.299)	-2.412***	(0.298)	-2.558***	(0.297)
Canton : ref. BE						
SG	-2.463***	(0.093)				
VD	2.345***	(0.132)				
ZG	1.303***	(0.138)				
ZH	0.621***	(0.094)				
Constant	9.165***	(0.613)	9.207***	(0.632)	7.487***	(0.762)
Instituitions	Canton		PES		Casew.	
F-stat. instituitons	708.153		134.969		11.026	
p-value instituitons	0.000		0.000		0.000	
Mean outcome	10.224		10.224		10.224	
Adj-R^2	0.217		0.231		0.269	
Observations	14798		14798		14798	

Note: This table reports estimates of an OLS regression that regresse the estimated α_i from equation (1) on observed individual characteristics. Three models are reported, differing with respect to the control variables included.

fixed effects. The corresponding results are reported in Table B3 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. This robustness check

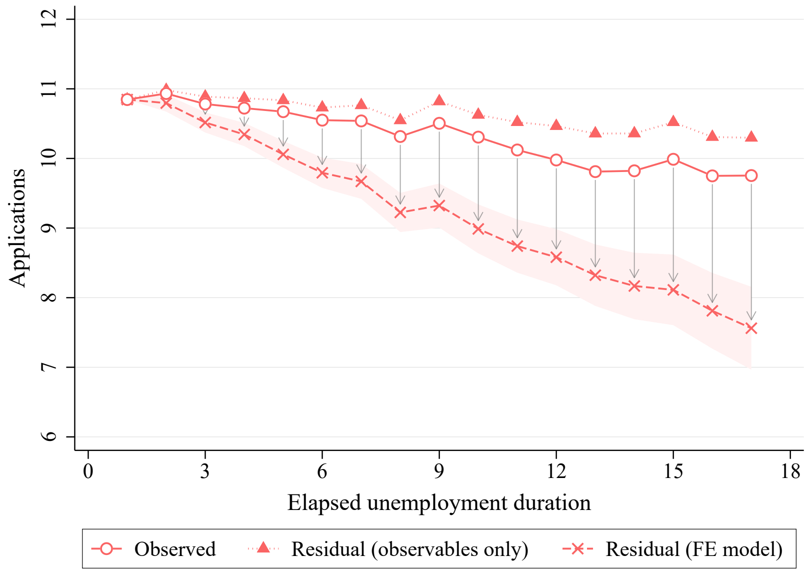
Table B3: Duration dependence in application effort, Poisson pseudo maximum likelihood

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Applications						
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
Local labor market conditions	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
Observations	55559	55559	55559	55559	55559	55559

Note: This table reports estimates of equation (1) using a Poisson pseudo maximum likelihood estimator, where the duration function $f^A(t;\phi^A)$ is specified linearly. Models are estimated on a restricted sample that discards individuals whose application effort does not vary over time. Each column sequentially adds a set of controls or fixed effects. Standard errors clustered at the individual level are reported in parentheses. Absolute coefficients (measuring the monthly decrease in application effort) are indicated in square brackets and are directly comparable to the OLS estimates. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

is motivated by the following two observations. Caseworkers set a minimum search requirement for every job seeker which specifies the minimal number of job applications that a job seeker has to make every month. As a result, we observe in the search diary data some bunching at common values for minimum search requirements, i.e. $\underline{A} = 8, 10$. In addition, not all applications directly result from the job seeker's own initiative, but some occur in response to a suggestion by the caseworker. For instance, caseworkers may refer job seekers to apply to jobs Therefore, one might argue that the total number of

Figure B1: Duration profile of application effort, alternative prediction models



Note: This figure depicts the empirical profile of duration dependence in the number of job applications (solid line) and the estimated duration dependence that controls observable heterogeneity and fixed effects (dashed line), where function $f^A(t;\phi^A)$ in equation (1) is modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 95% confidence interval.

applications made in a given month, A_{it}, does not capture application effort accurately enough. As a robustness check, we re-estimate our model using alternative search effort measures as dependent variables: In one specification, we use the excess application effort defined as the number of applications exceeding the standard minimum search requirement, $\bar{A}_{it} = \max(0, A_{it} - \underline{A})$, where $\underline{A} = 8, 10$ (see Figure B2 for descriptive evidence). In another specification, we consider the monthly number of applications that are not a response to a referral. The corresponding estimates are reported in Table B4 and are very much in line with our baseline findings.

Table B4: Duration dependence in application effort, alternative application effort measures

Dependent variables:	Excess applications				Applications on own initiative	
	$\underline{A} = 8$		$\underline{A} = 10$			
	(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
Local labor market conditions	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes
Mean outcome 1st month	4.274	4.274	3.316	3.316	11.055	11.055
Adjusted-R^2	0.005	0.393	0.004	0.338	0.008	0.468
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)
	[-0.082]	[-0.245]	[-0.072]	[-0.232]	[-0.107]	[-0.217]
Individual controls	No	Yes	No	Yes	No	Yes
Policy controls	No	Yes	No	Yes	No	Yes
Local labor market conditions	No	Yes	No	Yes	No	Yes
Individual FE	No	Yes	No	Yes	No	Yes
Mean outcome 1st month	4.274	4.274	3.316	3.316	11.055	11.055
Pseudo-R^2	0.004	0.328	0.004	0.334	0.003	0.200
Observations	45901	45901	39563	39563	51305	51305

Note: This table reports estimates of equation (1) for our alternative measures of application effort (excess applications and applications on own initiative), where the 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. Standard errors clustered at the individual level are reported in parentheses. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

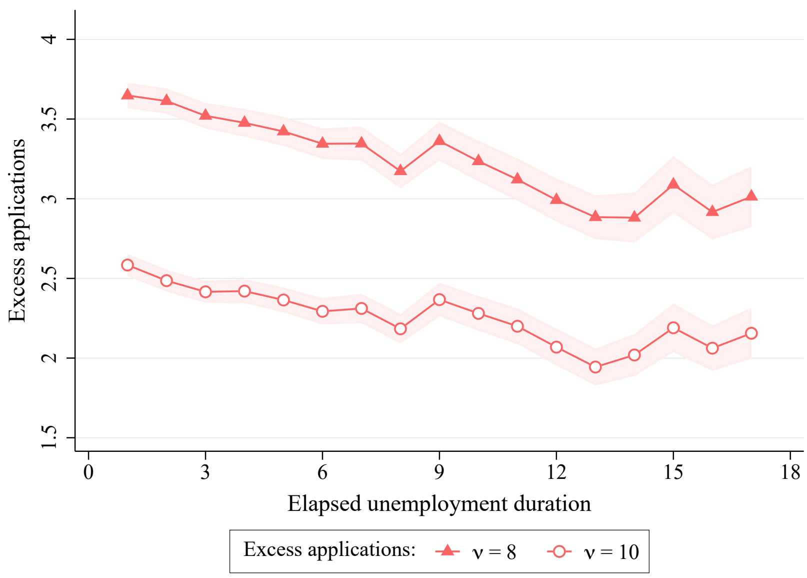
Third, we discuss the existence of a potential within-estimation bias of duration effects in our baseline estimates. As shown in Zuchuat (2023), using fixed effects models to estimate duration dependence profiles from data subject to attrition might entail a strong bias in the estimated duration effects. This is notably the case if the dependent variable is closely related to the attrition mechanism, as this mechanically generates a correlation between the within-variation of the regressor and the error term. In our context, applications are observed repeatedly within an unemployment spell and do not directly translate into exits from unemployment. As an additional check, we re-estimate our baseline specification on a subsample that excludes the last observation of each non-right-censored spell, *i.e.* using only those observations at the person-month level that are not contemporaneous to an unemployment exit. The corresponding estimation results are reported in Table B5 and turn out to be highly similar to our baseline estimates.

Table B5: Duration dependence in application effort, dropping exit months

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: Applications						
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
Local labor market conditions	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
Adjusted-R^2	0.006	0.035	0.179	0.193	0.495	0.502
Observations	56646	56646	56646	56646	56646	56646

Note: This table reports estimates of equation (1), where the duration function $f^A(t;\phi^A)$ is specified linearly. Models are estimated on a restricted sample, that discards those observations at the person-month level in which an unemployment exit is observed. Each column sequentially adds a set of controls or fixed effects. Standard 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 square brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

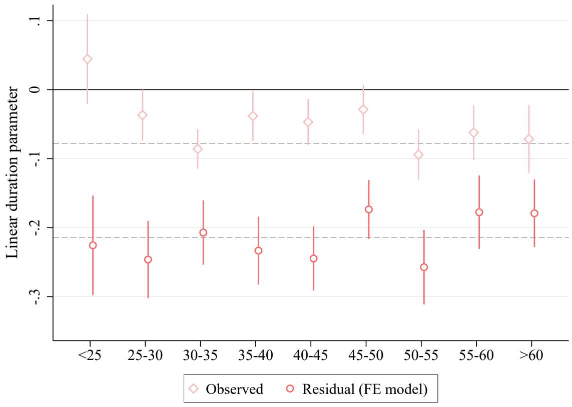
Figure B2: Empirical duration dependence in excess application effort



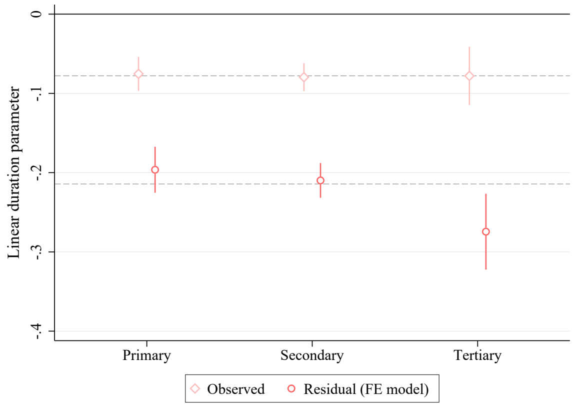
Note: This figure reports the empirical duration profiles of excess applications using two different values for the minimum search requirement.

Figure B3: Heterogeneity in the effect of duration on application effort

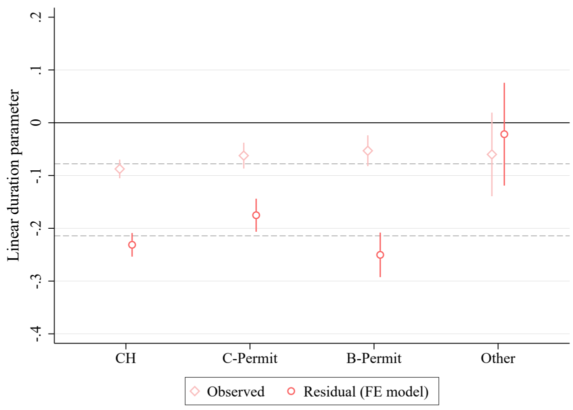
(A) Age



(B) Education



(C) Nationality/Residential status



Note: This figure depicts the estimation results of Equation (1) on sub-samples based on various observables, where the $f(t;\phi^A)$ is specified linearly. The estimated coefficient is reported together with 90% confidence intervals.

B.2 Job interviews and job offers (after an interview)

B.2.1 Details of the empirical strategy

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 and the corresponding response of the firm (job interview or job offer) is documented in the data. For simplicity we denote this reference month as $t = 1$.[48] We estimate a binary outcome model for the application-level probability of obtaining a job interview or a job offer (after an interview) in the corresponding reference month. We model the latent propensity, $\tilde{y}_{ij1}$, $y = c, o$, in the reference month as

$$\tilde{y}_{ij1} = \vartheta_0^y + X_{i1}^1 \vartheta_1^y + X_{ij1}^2 \vartheta_2^y + \delta_{mk}^y - \nu_{ij1}^y \tag{B.1}$$

The row vector X_{i1}^1 contains the individual-level characteristics, the row vector X_{ij1}^2 the application-level characteristics, δ_{mk}^y are fixed effects capturing the conditions in local labor market m in calendar quarter k, ν_{ij1}^y is an idiosyncratic error term. The conditional *ex-ante* probabilities of obtaining a job interview and a job offer (after an interview) in the reference month are given by

$$\begin{aligned} \gamma^y(X_{ji1}) &= \mathbb{P}(y_{ij1} = 1 \mid X_{ij1}, z_{ij1} = 1) \\ &= \mathbb{P}(\vartheta_0^y + X_{i1}^1 \vartheta_1^y + X_{ij1}^2 \vartheta_2^y + \delta_{mk}^y > \nu_{ij1}^y \mid z_{ij1} = 1) \end{aligned} \tag{B.2}$$

where $X_{ij1} = (X_{i1}^1, X_{ij1}^2, \delta_{mk}^y)$, with $y = c, o$, and z_{ij1} denotes a dummy indicating the preceding event in the job finding process, *i.e*, an application or an interview. After estimating equation (B.2) using logit models, we retrieve the estimated parameters and predict the conditional *ex-ante* probabilities for all months t. As outlined in Section 4, we then estimate the effect of duration on firms' responses using the logarithm of the *ex-ante* probabilities to control for dynamic selection based on observables (see equation (3)).

[48]To be precise, the reference month differs from the first unemployment month in those cases in which we do not observe a search diary in the first unemployment month. Moreover, for a given job seeker, we may use a different reference month for job interviews and job offers because, at this step of the analysis, we only retain those applications for which the corresponding outcome is known. For the sake of readability, we abstract from this in the notation.

B.2.2 Detailed estimation results

We report logit estimates for the *ex-ante* interview and job offer probabilities defined in equation (B.2) in Table B6. Observed characteristics are found to predict the *ex-ante* probability of a job interview significantly, with older job seekers and those writing many applications having a lower *ex-ante* probability to be invited, while those with high education, and a high wage are invited with a higher probability. Applications in person, and those referred by caseworkers are more likely to lead to a job interview. Concerning the variables that predict the *ex-ante* probability of a job offer (after an interview) age or residence permit turn out insignificant, but a higher education and a high previous wage have a significantly negative effect.

Table B6: Estimates of *ex-ante* probabilities in the reference month

	Job interview		**Job offer after an interview**	
	Marginal effects	SE	Marginal effects	SE
Dependent variable: Estimated α_i				
Age : ref. < 25				
$25-30$	-0.165	(0.476)	3.737*	(2.098)
$30-35$	-0.630	(0.459)	2.195	(2.080)
$35-40$	-0.703	(0.478)	0.756	(2.147)
$40-45$	-1.069**	(0.461)	-1.123	(2.115)
$45-50$	-1.184**	(0.461)	0.912	(2.148)
$50-55$	-1.484***	(0.469)	-0.355	(2.266)
$55-60$	-2.380***	(0.516)	3.557	(2.589)
> 60	-3.870***	(0.497)	5.009	(3.607)
Residential status : ref. CH resident				
C-permit	-1.159***	(0.270)	-1.546	(1.340)
B-permit	-1.222***	(0.294)	1.653	(1.619)
Other permit	-1.512**	(0.728)	-2.507	(3.797)
Education : ref. Primary				
Apprenticeship	2.229***	(0.252)	-5.018***	(1.621)
High school	1.260**	(0.490)	-6.911**	(2.929)
Prof. maturity	3.743***	(0.521)	-5.121**	(2.462)
University of appl. science	2.947***	(0.580)	-5.609**	(2.730)
University	3.419***	(0.498)	-11.293***	(2.209)
Female	0.361	(0.234)	-0.568	(1.171)
ln(previous wage)	1.223***	(0.207)	-2.461**	(0.982)
Unemployment history	-3.467***	(0.822)	2.119	(4.179)
Application channel : ref. Written				
Phone	-0.044	(0.215)	6.176***	(1.513)
Personal	7.580***	(0.429)	6.901***	(1.202)
Caseworker referral	3.673***	(0.383)	1.066	(2.180)
Search effort α_i	-0.270***	(0.041)	-0.201	(0.154)
Policy controls	Yes		Yes	
Local labor market conditions	Yes		Yes	
Mean outcome	4.832		23.749	
Pseudo-R^2	0.107		0.057	
Observations	153316		12060	

Note: This table reports the empirical estimates of equation (B.2) in the reference month. Point estimates correspond to average marginal effects (in percentage points). Standard errors (SE) are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Table B7: Duration dependence in firms' responses, linear specification

Dependent variables:	Job interview			Job offer after an interview		
	(1)	(2)	(3)	(4)	(5)	(6)
Elapsed unemp. duration	-0.155***	-0.097***	-0.095***	0.350***	0.430***	0.381***
	(0.015)	(0.015)	(0.015)	(0.099)	(0.097)	(0.094)
	[-3.117%]	[-1.941%]	[-1.912%]	[1.736%]	[2.132%]	[1.889%]
ln(Ex-ante chance)			3.364***			18.826***
			(0.094)			(0.868)
Individual controls	No	Yes	No	No	Yes	No
Policy controls	No	Yes	No	No	Yes	No
Local labor market conditions	No	Yes	No	No	Yes	No
Control for ex-ante pr.	No	No	Yes	No	No	Yes
Mean outcome 1^{st} month	4.977	4.977	4.977	20.187	20.187	20.187
Pseudo R^2	0.003	0.094	0.075	0.001	0.050	0.044
Observations	600323	600323	600323	22422	22422	22422

Note: This table reports estimates of duration effects on the probability of a job interview and a job offer according to equation (3). Columns (1)-(3) report estimates for job interviews and columns (4)-(6) for job offers. Application-level observations are weighted by the inverse of the monthly number of applications made by individual i in month t, so as to put equal weight on all person-month observations. Point estimates correspond to average marginal effects (in percentage points). Standard errors (in parentheses) are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

We next provide estimates of the effects of duration on the probability of a job interview or a job offer (after an interview), formalized in equation (3), after controlling for observable heterogeneity. Table B7 presents estimates for a linear specification of the duration effects. Columns (1)-(3) report results for job interviews, while columns (4)-(6) focus on job offers.

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

Turning to the results for the conversion of interviews into job offers, we find a significantly positive linear effect of duration in the raw data, consistent with our descriptive evidence. Column (4) of Table B7 shows that the job offer probability increases by 0.35 percentage points per month spent unemployed. Directly controlling for observed heterogeneity slightly increases the duration dependence parameter in column (5), whereas controlling for *ex-ante* job offer chances does not affect it in column (6).

B.2.3 Robustness checks

Our identification of the effect of duration on firms' responses conditional on observed heterogeneity is based on a conditional independence assumption: we suppose we observe all relevant information to the recruiting firm at the time when it evaluates the application. To further assess the relevance and predictability of our conditioning variables, we re-estimate equation (3) using additional controls from our administrative data, which are supposedly unobserved to recruiters 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 duration dependence in the probability of

Table B8: Duration dependence in firms' responses, control for non-CV information

	(1)	(2)	(3)	(4)
A. Probability of a job interview				
Elapsed unemp. duration	-0.097***	-0.094***	-0.095***	-0.091***
	(0.015)	(0.015)	(0.015)	(0.014)
ln(Ex-ante chance)			3.364***	3.371***
			(0.094)	(0.092)
Individual controls	Yes	Yes	No	No
Policy controls	Yes	Yes	No	No
Local labor market conditions	Yes	Yes	No	No
Control for ex-ante pr.	No	No	Yes	Yes
Information not on CV	No	Yes	No	Yes
Mean outcome 1st month	4.977	4.977	4.977	4.977
Pseudo R^2	0.094	0.099	0.075	0.079
Observations	600323	600323	600323	600323
B. Probability of a job offer after a job interview				
Elapsed unemp. duration	0.430***	0.407***	0.381***	0.361***
	(0.097)	(0.097)	(0.094)	(0.094)
ln(Ex-ante chance)			18.826***	19.634***
			(0.868)	(0.810)
Individual controls	Yes	Yes	No	No
Policy controls	Yes	Yes	No	No
Local labor market conditions	Yes	Yes	No	No
Control for ex-ante pr.	No	No	Yes	Yes
Information not on CV	No	Yes	No	Yes
Mean outcome 1st month	20.187	20.187	20.187	20.187
Pseudo R^2	0.050	0.060	0.044	0.054
Observations	22422	22422	22422	22422

Note: This table reports estimates of the effect of duration on the interview and job offer 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 the probability of a job interview, whereas panel B reports estimates for the probability of a job offer (after an interview). Application-level observations are weighted by the inverse of the monthly number of applications made by individual i in month t, so as to put equal weight on all person-month observations. Point estimates correspond to average marginal effects (in percentage points). Standard errors (in parentheses) are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

a job interview. In contrast, their role is possibly greater when estimating the duration profile in the probability of job offer (after an interview), 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 B8.[49] As expected, adding these controls leads to a more marked change in the pseudo-R^2 for the probability of a job offer after an interview (+20%) compared to the probability of an interview (+5%). This can also be seen through the parameter associated with the *ex-ante* probability, which increases more markedly for the probability of a job offer than the probability of a job interview (in columns 3 and 4). Consequently, the change in the estimated duration effect is virtually zero for the probability of a job interview, while it is slightly larger for the probability of a job offer after an interview (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 effect of duration on the probability of a job interview after controlling for job seekers and application characteristics that are observable to the recruiting firm at the time when it decides to interview the job seeker. They also support the hypothesis that additional information is revealed during the job interview which might affect a firm's job offer decisions.

[49] Table B9 shows the estimation results of the corresponding *ex-ante* probabilities.

Table B9: Estimates of *ex-ante* probabilities with non-CV charac. in the reference month

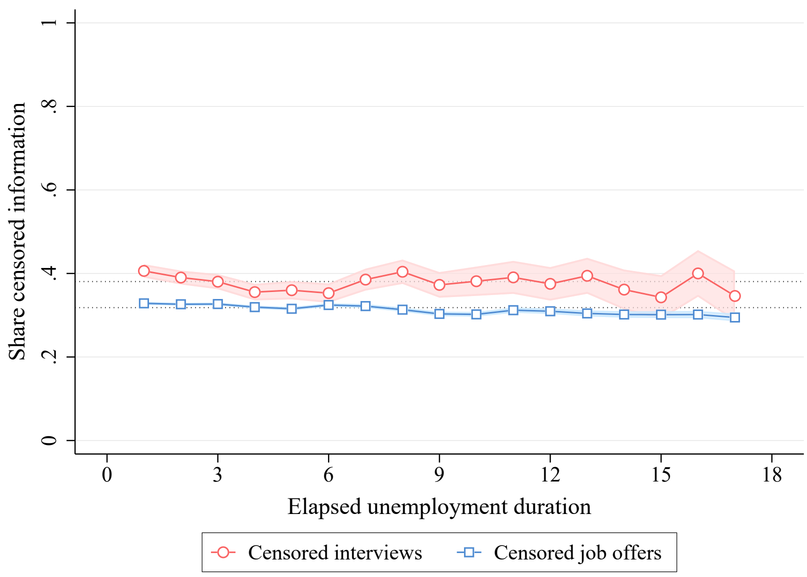
	Job interview		**Job offer after an interview**	
	Marginal effects	SE	Marginal effects	SE
Dependent variable: Estimated α_i				
Age : ref. < 25				
$25-30$	0.083	(0.451)	3.913*	(2.060)
$30-35$	-0.399	(0.434)	2.394	(2.045)
$35-40$	-0.360	(0.456)	1.286	(2.112)
$40-45$	-0.666	(0.440)	-0.639	(2.079)
$45-50$	-0.722	(0.442)	1.812	(2.123)
$50-55$	-0.950**	(0.457)	0.473	(2.236)
$55-60$	-1.781***	(0.517)	5.092*	(2.607)
> 60	-3.109***	(0.516)	7.248*	(3.724)
Residential status : ref. CH resident				
C-permit	-1.113***	(0.269)	-1.089	(1.344)
B-permit	-1.187***	(0.292)	2.003	(1.618)
Other permit	-1.500**	(0.719)	-2.792	(3.758)
Education : ref. Primary				
Apprenticeship	2.106***	(0.256)	-5.385***	(1.621)
High school	1.182**	(0.485)	-7.410**	(2.910)
Prof. maturity	3.613***	(0.515)	-5.422**	(2.447)
University of appl. science	2.794***	(0.580)	-5.755**	(2.711)
University	3.116***	(0.483)	-11.155***	(2.223)
Female	0.340	(0.234)	-0.706	(1.169)
ln(previous wage)	1.121***	(0.204)	-2.176**	(0.982)
Unemployment history	-3.573***	(0.820)	2.078	(4.188)
Application channel : ref. Written				
Phone	-0.003	(0.215)	6.317***	(1.513)
Personal	7.686***	(0.426)	6.830***	(1.194)
Caseworker referral	3.599***	(0.383)	1.385	(2.164)
Search effort α_i	-0.262***	(0.040)	-0.181	(0.150)
Non-CV characteristics				
Employability grade	0.977***	(0.245)	0.512	(1.137)
1 = Experienced sickness	-1.816***	(0.245)	-8.433***	(1.179)
Mobility degree : ref. Not mobile				
Daily commute	-6.939	(5.489)	10.013	(8.215)
Part of the country	-6.358	(5.505)	10.827	(8.772)
Whole country	-5.609	(5.559)	5.492	(9.178)
International	-3.214	(5.719)	-3.509	(9.097)
Policy controls	Yes		Yes	
Local labor market conditions	Yes		Yes	
Mean outcome	4.832		23.749	
Pseudo-R^2	0.112		0.065	
Observations	153316		12060	

Note: This table reports the empirical estimates of equation (B.2) in the reference month adding characteristics that are not observable to the recruiter when the application is made. Point estimates correspond to average marginal effects (in percentage points). Standard errors (SE) are clustered at the individual level. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

B.3 Incidence of right censoring and estimation results from non-right-censored data

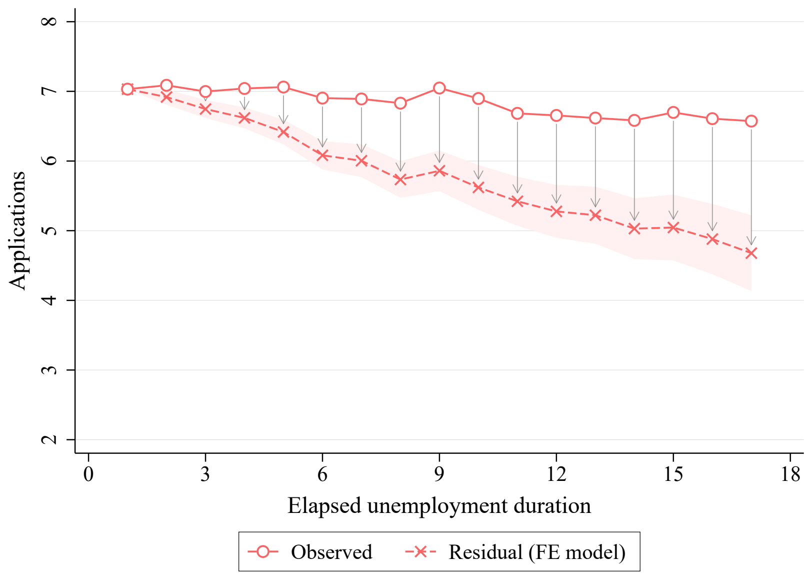
In this subsection, we provide information on the incidence of right censoring by elapsed unemployment duration and show versions of our main empirical results estimated from non-right-censored data. In sum, the incidence of right censoring does not change with unemployment duration (Figure B4), and the duration profiles of applications, job interviews and job offers computed from non-right-censored data shown in Figures B5 to B7 look qualitatively very similar to those computed from the censored data shown in the main text (Figures 3A, 4A and 5A).

Figure B4: Incidence of right censoring by elapsed unemployment duration



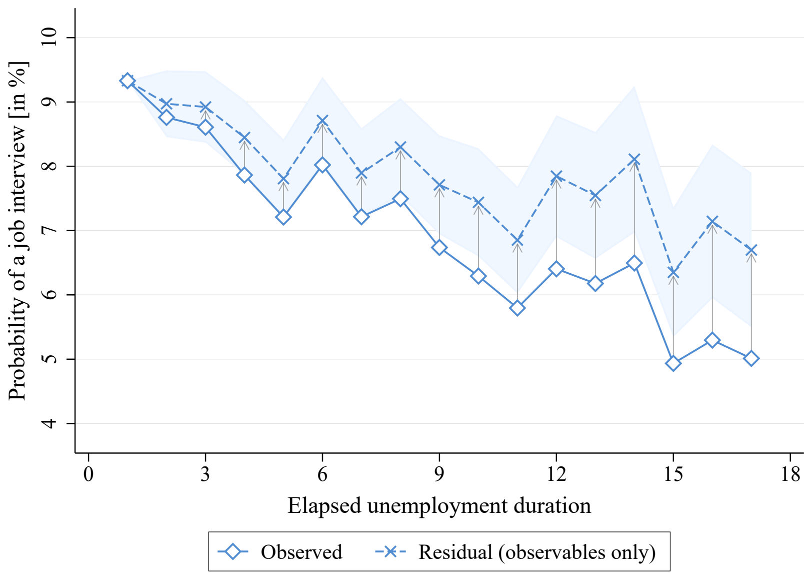
Note: This figure depicts the incidence of right censoring of (i) interviews (out of all applications) and (ii) job offers (out of all interviews) by elapsed duration of unemployment. 95% confidence intervals for the (conditional) means are reported.

Figure B5: Duration profile of applications, non-censored applications only



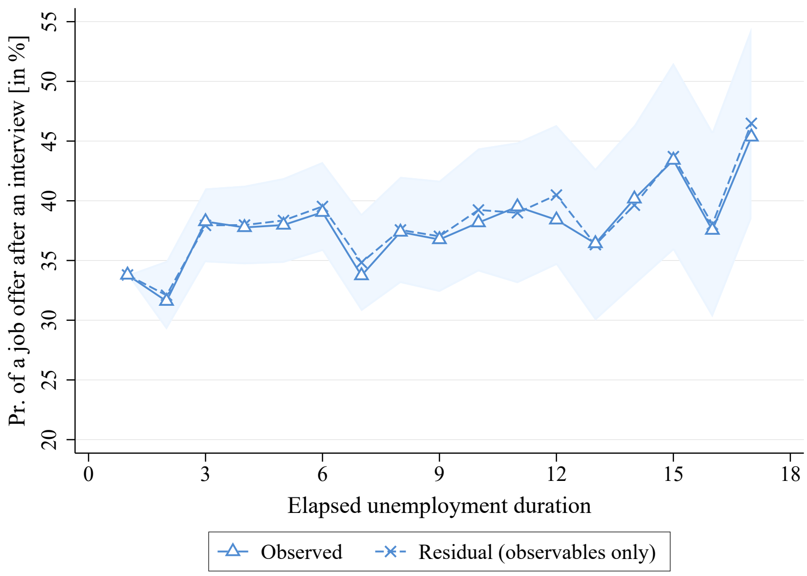
Note: This Figure depicts the empirical duration dependence in the number of job applications (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity and individual fixed effects (dashed line), with function $f^A(t;\phi^A)$ in equation (1) modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 95% confidence interval. Only non-censored applications are considered.

Figure B6: Duration profile of job interviews, applications with known interview outcome only



Note: This figure depicts the empirical duration dependence in the probability of a job interview (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity (dashed line), with function $f^c(t;\phi^c)$ in equation (3) modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 90% confidence interval. Only non-censored applications are considered.

Figure B7: Duration profile of job offers, applications with known job offer outcome only



Note: This figure depicts the empirical duration dependence in the job offer probability (solid line) and the estimated duration dependence obtained after controlling for observable heterogeneity (dashed line), with function $f^o(t;\phi^o)$ in equation (3) modeled as a step function with one dummy for each month of elapsed unemployment duration. The shaded area around the estimated duration dependence corresponds to the 90% confidence interval. Only non-censored applications are considered.

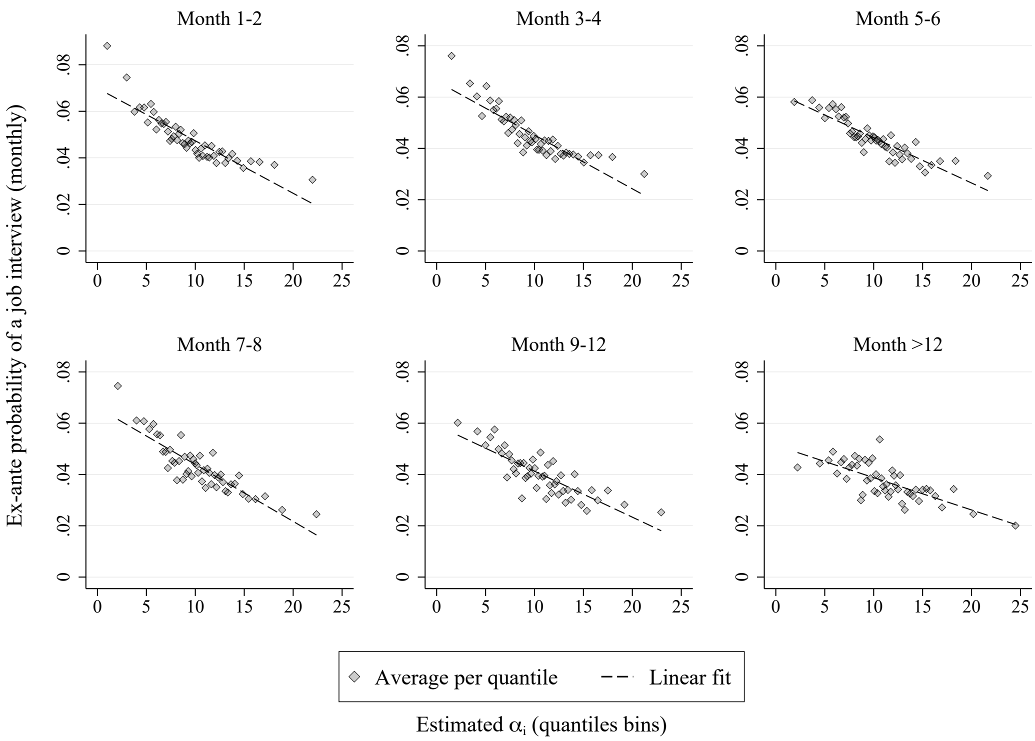
B.4 Evidence to evaluate complementary explanations

Table B10: Duration profile of applications by channel

Dependent variables:	**In writing**		**By phone**		**In person**	
	(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
Mean outcome 1st month	6.962	6.962	2.035	2.035	1.849	1.849
adj.-R^2	0.001	0.631	0.000	0.614	0.003	0.615
Observations	58755	58755	58755	58755	58755	58755

Note: This table reports empirical estimates of equation (1) using OLS, where the parametric duration function $f^A(t;\phi^A)$ is specified linearly. The dependent variables are the number of applications made in writing (columns 1-2), by phone (columns 3-4) and in person (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 (1). Standard 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 square brackets. Stars indicate the following significance levels: * 0.1, ** 0.05 and *** 0.01.

Figure B8: Heterogeneous search efficiency:
Application fixed effects and *ex-ante* interview probability

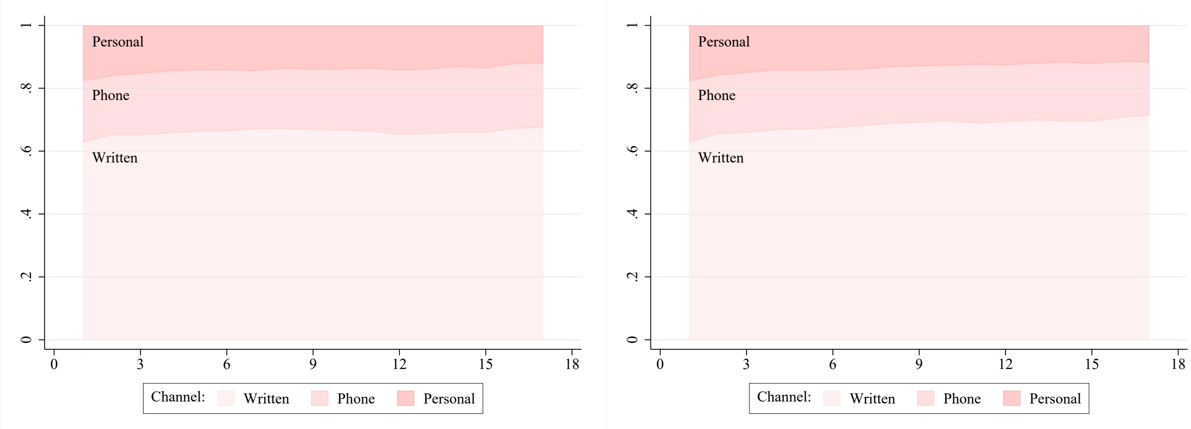


Note: This figure reports evidence on the relationship between the estimated application fixed effects α_i and the *ex-ante* interview probability conditional on unemployment duration.

Figure B9: Changes in the shares of application channels

(A) Observed

(B) Fixed effects

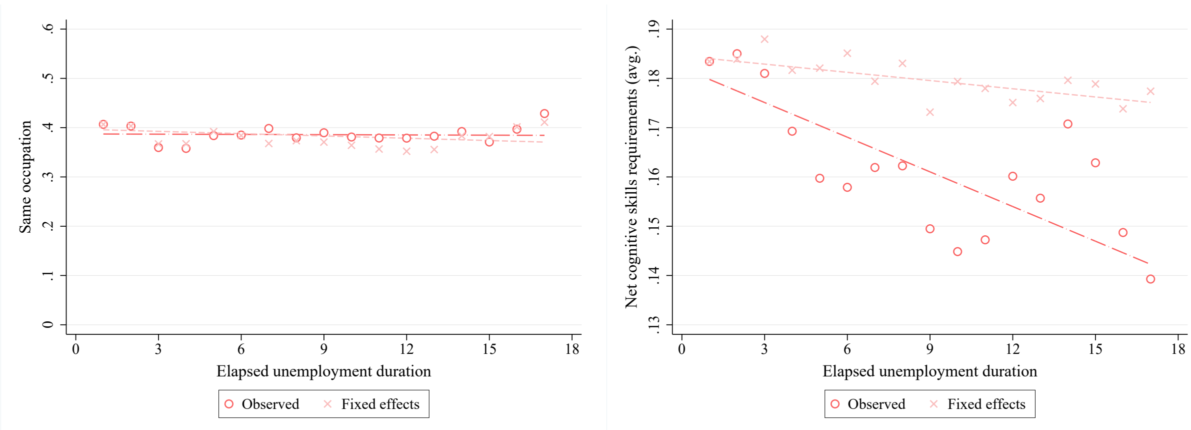


Note: This figure represents the share of applications sent out through the written, phone and personal channels, per month of elapsed unemployment. Panel A corresponds to the patterns in the raw data, without accounting for changes in the pool of applicants. Panel B corresponds to the results of a fixed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

Figure B10: Changes in application targeting

(A) Same occupation

(B) Skills requirements



Note: This figure describes the evolution of application 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 skill 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).

B.5 Job interviews and job finding at the person-month level

In this section we report evidence on the job interview rate and job finding rate at the person-month level that are used as targets in the structural estimation (see Section C.5). For this purpose, we aggregate the application-level information to the person×month (or search diary) level (see Panel A of Table A1 for descriptive statistics). In contrast, the evidence discussed in Section 4 and Appendix B is based on data at the application level.

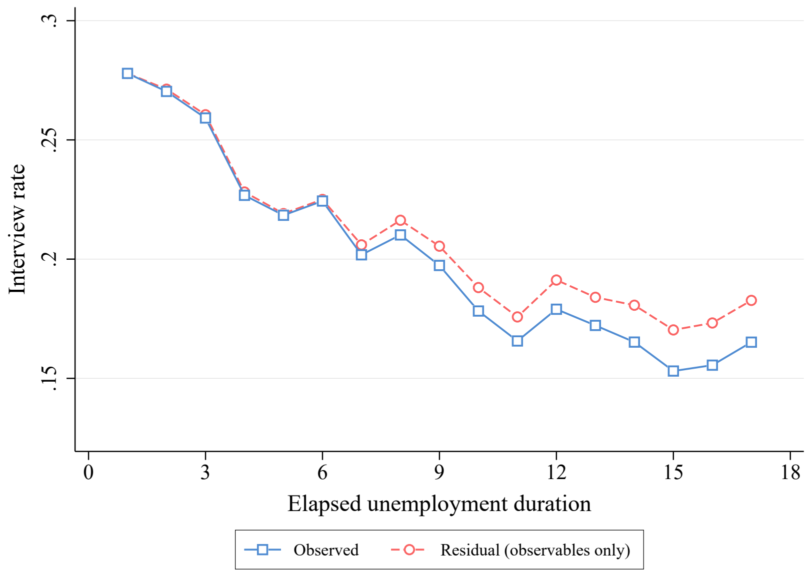
In Figure B11 and Figure B12, the blue line refers to the empirical duration profile, while the red line refers to the duration profile obtained from a regression that controls for those job seeker characteristics that are observable to the recruiting firm at the time when the application is made. Specifically, we estimate two binary outcome models, one for the outcome job interview ($y = I$) and one for job finding ($y = F$), for individual i in month t of unemployment:

$$\mathbb{P}(y_{it} = 1 \mid X_{it}) = \mathbb{P}\Big(\alpha^y + f^y(t; \phi^y) + X_{it}\beta^y > \varepsilon^y_{it}\Big) \tag{B.3}$$

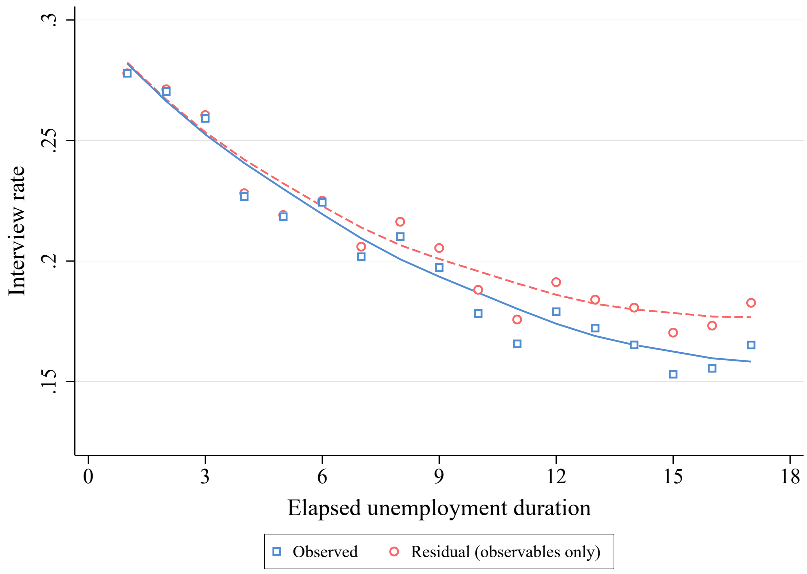
where $X_{it}\beta^y$ controls for dynamic selection on observable job seeker characteristics and $f^y(t; \phi^y)$ captures the effect of duration after controlling for observables. The latter is specified as a step function with one dummy for every month of elapsed unemployment duration. The variable ε^y_{it} represents an idiosyncratic error term.

Figure B11: Interview rate, observed and controlling for observables

(A) Base version



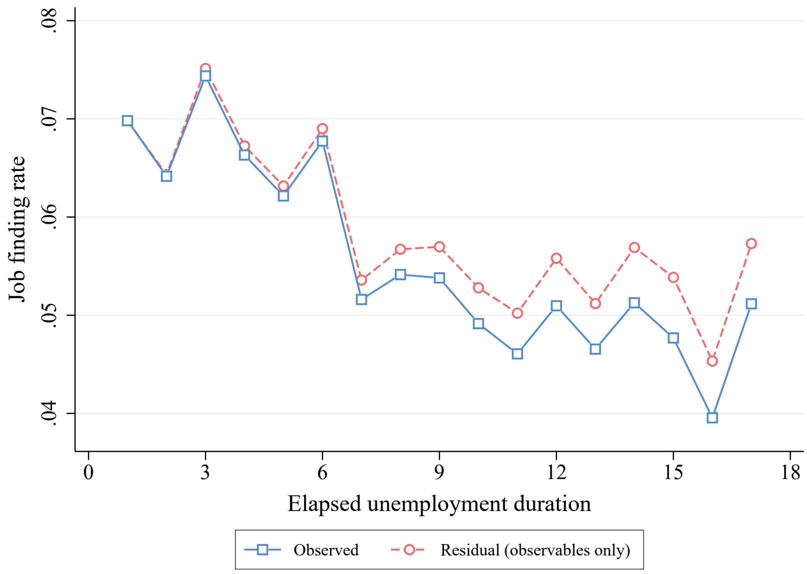
(B) Smoothed version



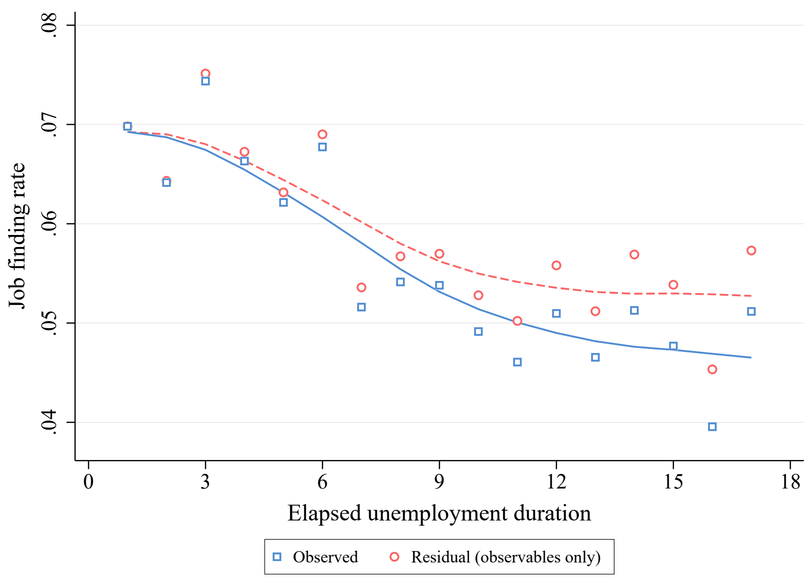
Note: This figure reports the empirical duration dependence in the job interview rate (probability of at least one job interview in a month) and the estimated duration dependence obtained after controlling for observable heterogeneity. In the latter case, the control variables enter directly in the regression equation. Panel (A) reports the point estimates, while panel (B) reports a smoothed version.

Figure B12: Job finding rate, observed and controlling for observables

(A) Base version



(B) Smoothed version



Note: This figure reports the empirical duration dependence in the job finding rate (probability of at least one job offer in a month) and the estimated duration dependence obtained after controlling for observable heterogeneity. In the latter case, the control variables enter directly in the regression equation. Panel (A) reports the point estimates, while panel (B) reports a smoothed version.

C. Details of the structural model

C.1 Microfoundation of search effort cost function

In this section, we review a common microfoundation of the search effort cost function adopted in standard models of endogenous search effort (Pissarides, 2000) and extend it to our specific framework.

Consider the problem of a job seeker who gains utility from consumption and social leisure in an additively separable fashion. The job seeker is endowed with one unit of time each period, which can be spent either exerting search effort s or in social activities. Formally,

$$\max_{s,\ell} u(b) + \nu(\ell) + \beta so(W - U)$$
$$\text{s.t. } h(s) + \ell = 1$$

where $h(s)$ denotes the hours it takes to exert s units of search effort (normalized by the unitary amount of total hours) and o represents the job offer probability per unit of search effort. Optimal time allocation trades off higher current utility from social leisure against higher expected discounted utility from finding a job:

$$\nu'(\ell)h'(s) = \beta o(W - U)$$

By assuming linear utility from social leisure, *i.e.*, $\nu(\ell) = \zeta\ell$ and convex and isoelastic search effort hours function, *i.e.* $h(s) = \psi\frac{s^{1+\eta}}{1+\eta}$, this time allocation model is isomorphic to standard models of endogenous search effort subject to convex costs, with cost function $\sigma(s) = \nu'(\ell)h(s)$.

Our main innovation with respect to standard models of endogenous search effort is modelling search effort as the product between individual search efficiency ϵ and endogenous application effort a. In what follows, we extend the previous microfoundation to a model where job seekers are heterogeneous in their character, which determines both how much they value social leisure and their search efficiency.

Assume that workers differ in their character, which ranges from introverted to outgoing. Outgoing workers draw higher utility from spending time in social relations and therefore have a larger personal network which allows them to overcome meeting frictions more easily when looking for a job. Formally, we identify a worker's character as the marginal utility she gains from social leisure ζ. It follows that workers of character ζ have search efficiency $\epsilon = \epsilon(\zeta)$, where $\epsilon' > 0$.

We are interested in the time allocation decisions made by job seekers of different character ζ. Optimal application effort solves the following utility-maximization problem:

$$\begin{aligned} &\max_{a,\ell} u(b) + \nu_\zeta(\ell) + \beta\epsilon(\zeta)ao(W-U) \\ &\text{s.t. } h(a) + \ell = 1 \end{aligned}$$

Notice that, differently from the previous case, $h(a)$ denotes the hours it takes to exert a units of application effort – not of total search effort. Taking the first-order condition with respect to a yields:

$$\nu'(\ell)h'(a) = \epsilon\beta o(W-U) \iff \frac{\zeta}{\epsilon(\zeta)}h'(a) = \beta o(W-U)$$

Following the same argument as before, we assume convex and isoelastic application effort hours function, *i.e.* $h(a) = \psi\frac{a^{1+\eta}}{1+\eta}$, and define $\epsilon(\zeta) \equiv \zeta^{\frac{1}{1+\eta}}$. Under this functional form assumptions, this time allocation model is isomorphic to the model of endogenous application effort adopted in the main text with cost function $\sigma(s) = h(s)$.

C.2 Additional propositions and proofs

Proof Proposition 2. Since the callback indicator is monotonically decreasing in y, one can define as $y^*(\tau)$ the productivity of the firm that is just indifferent between calling back a job seeker with duration τ or not. Formally,

$$y^*(\tau) : \int \max\{J\left(x, y^*(\tau)\right), 0\}\mu(x|\tau)dx = \kappa$$

Therefore, the interview probability reads:

$$c(\tau) \equiv \lambda(\theta)\mathbb{P}\left(y \le y^*(\tau)\right) = \lambda(\theta)G(y^*(\tau))$$

In turn, the conditional job offer probability defined in equation (10) is given by:

$$o|c(x,\tau) \equiv \frac{\mathbb{P}\left(y \leq \min\{x, y^*(\tau)\}\right)}{\mathbb{P}\left(y \leq y^*(\tau)\right)} = \frac{G(\min\{x, y^*(\tau)\})}{G(y^*(\tau))}$$

The duration profile of the conditional job offer probability obeys:

$$\frac{do|c(x,\tau)}{d\tau} = \frac{1}{G\left(y^*(\tau)\right)}\left[\frac{dG\left(\min\{x, y^*(\tau)\}\right)}{d\tau} - \frac{G\left(\min\{x, y^*(\tau-1)\}\right)}{G\left(y^*(\tau-1)\right)}\frac{dG\left(y^*(\tau)\right)}{d\tau}\right] \quad \text{(C.1)}$$

where $dG\left(\min\{x, y^*(\tau)\}\right)/d\tau \equiv G\left(\min\{x, y^*(\tau)\}\right) - G\left(\min\{x, y^*(\tau-1)\}\right)$. In order to pin down the sign of equation (C.1), we distinguish two cases.

$$\text{CASE 1}: \ x \geq y^*(0) \iff \min\{x, y^*(\tau)\} = y^*(\tau)$$

$$\implies \frac{do|c(x,\tau)}{d\tau} = 0$$

$$\text{CASE 2}: \ x < y^*(0)$$

$$\text{Monotonicity of } \mathcal{C}(y,\tau) \text{ in } \tau \text{ entails that } x \begin{cases} < y^*(\tau) & \text{if } \tau < T \\ \geq y^*(\tau) & \text{if } \tau \geq T \end{cases} \quad \text{for some } T < \infty$$

$$\text{For } \tau < T, \ \min\{x, y^*(\tau)\} = x$$

$$\implies \frac{do|c(x,\tau)}{d\tau} \propto -\frac{dG\left(y^*(\tau)\right)}{d\tau} \geq 0$$

$$\text{For } \tau = T, \ \min\{x, y^*(\tau)\} = y^*(\tau), \ \min\{x, y^*(\tau-1)\} = x$$

$$\implies \frac{do|c(x,\tau)}{d\tau} \propto -\left[G(y^*(\tau-1)) - G(x)\right] > 0$$

$$\text{For } \tau \geq \tilde{\tau}, \ \min\{x, y^*(\tau)\} = y^*(\tau)$$

$$\implies \frac{do|c(x,\tau)}{d\tau} = 0$$

Hence, we conclude that the conditional job offer probability is nondecreasing in unemployment duration. □

Proposition 3. *If* $\int \max\left\{J(x,y), 0\right\}\mu(x|0)\ dx > \kappa\ \forall y$ *and* $G(y \in \mathcal{Y} : J(\underline{x}, y) < \kappa) > 0$, *then the unconditional job offer probability exhibits negative duration dependence, i.e.*

$do(x,\tau)/d\tau \leq 0 \ \forall \tau$ *and* $\exists \hat{\tau} : do(x,\hat{\tau})/d\tau < 0.$

Proof. Consider a job seeker of ability x, whose unconditional job offer probability is given by equation (11). As shown in Proposition 1, the callback indicator $\mathcal{C}(y,\tau)$ is monotonically decreasing in τ. Hence, $\exists \hat{x}$: for $x \geq \hat{x}, \exists$ at least one unemployment duration $\hat{\tau}$ s.t.

$$\begin{cases} \mathcal{C}(y,\hat{\tau}-1)\mathcal{Q}(x,y) = 1 \\ \mathcal{C}(y,\hat{\tau})\mathcal{Q}(x,y) = 0 \end{cases} \iff o(x,\hat{\tau}) < o(x,\hat{\tau}-1)$$

For $x < \hat{x}$, $o(x,\tau) = o(x,0) \ \forall \tau$.

Hence, we conclude that the unconditional job offer probability is nonincreasing in unemployment duration. □

C.3 Quantitative model

In this section we describe the quantitative model used for structural estimation. The quantitative model extends the baseline model outlined in Section 5 along two dimensions. First, job seekers and firms/vacancies are assumed to get together through an urn-ball meeting process generating coordination frictions.[50] Second, qualified job seekers get offered a job after an interview with probability $q \in (0,1)$.

The hiring process has the following timing: (1) upon meeting at least one job seeker, the firm decides whether to call back a job seeker at cost κq; (2) conditional on calling back a job seeker, the firm gets to know her ability x and, based on that, decides whether to interview another job seeker; (3) if any of the interviewees is qualified, the firm offers a job to the highest-ability one with probability q.

In the presence of coordination frictions, firms need to sort potentially multiple job seekers. Since average job seeker's ability is decreasing with duration, when faced with multiple job seekers, firms find it optimal to rank them according to their unemployment duration starting with the shortest. Upon calling back the shortest-duration job seeker (as long as it is profitable according to equation (7)), the firm calls back the next job

[50] The urn-ball meeting process gives rise to a distribution of the number of job seekers that each firm meets in each period, being the average number of such meetings still determined by the meeting function.

seeker, as well, if:[51]

$$\int \max\left\{J(x,y) - J(\hat{x},y), 0\right\} \mu(x|\tau)\ dx \geq \kappa \tag{C.2}$$

where $\hat{x}$ represents the ability of the previous job seeker, which is revealed at the interview stage. Denoting as $z^c(x,y,\tau)$ the search-effort-weighted measure of job seekers crowding out a job seeker with ability x and unemployment duration τ in contact with a firm of productivity y at the callback stage (derived in Appendix C.4), the interview probability writes:

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

where $\exp\left\{-\frac{z^c(x,y,\tau)}{V}\right\}$ equals the probability that firm y is not in contact with any job seeker with shorter duration than τ that does not warrant an interview to a $(x,\tau)-$job seeker in the sense of equation (C.2).

Denoting as $z(x,y,\tau)$ the search-effort-weighted measure of job seekers crowding out a job seeker with ability x and unemployment duration τ in contact with a firm of productivity y in hiring (derived in Appendix C.4), the conditional job offer probability writes:

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

In words, with probability q, a firm makes a job offer to the highest-ability job seeker that grants it positive flow profits, conditional on discovering her ability type during the interview. Hence, the unconditional job offer probability is defined as:

$$o(x,\tau) \equiv c(x,\tau) \cdot o|c(x,\tau) = \lambda(\theta) q \int \mathcal{O}(x,y,\tau) \exp\left\{-\frac{z(x,y,\tau)}{V}\right\}\ dG(y)$$

[51]Following Jarosch and Pilossoph (2019), we assume that by interviewing another candidate the firm does not lose the option of hiring any of the previous interviewees.

For given labor market tightness, expected profits upon drawing productivity y read:

$$\begin{aligned}\mathbb{E}[\Pi(y)|\theta] = q \sum_{m=1}^{\infty} \mathbb{P}(N=m|\theta) \sum_{\tau_1=0}^{\infty} \mathbb{P}\left(\underline{\mathbf{t}}_{1,N}=\tau_1\right) \sum_{\tau_2=\tau_1}^{\infty} \mathbb{P}\left(\underline{\mathbf{t}}_{2,N}=\tau_2|\underline{\mathbf{t}}_{1,N}=\tau_1\right)\ldots \\ \sum_{\tau_N=\tau_{N-1}}^{\infty} \mathbb{P}\left(\tau_N=\tau_N|\underline{\mathbf{t}}_{N-1,N}=\tau_{N-1}\right) \int\cdots\int \Big[\sum_{k=1}^{N}\big(J(x,y)\mathcal{Q}(x,y) \\ \mu(\bar{\mathbf{x}}_{1,k}=x|\mathbf{t}_{1,k})-k\kappa\big)\mathbb{1}\{t_{k+1}>\bar{\tau}(\bar{\mathbf{x}}_{1,k},y)\ \&\ t_s\leq\bar{\tau}(\bar{\mathbf{x}}_{1,s-1},y)\ \forall s\leq k\}\Big] \\ dx_1\ldots dx_N\ \mathcal{C}(y,\tau_1)\end{aligned}$$

where $\mathbb{P}(N=m|\theta)=\left(\frac{\lambda(\theta)S}{V}\right)^m \frac{1}{m!}\exp\left\{-\frac{\lambda(\theta)S}{V}\right\}$ and $\underline{\mathbf{t}}_{n_1,n_2}\equiv\min\{t_{n_1},\ldots,t_{n_2}\}$ and $\bar{\mathbf{x}}_{1,k}\equiv\max\{x_1,\ldots,x_k\}$. In the presence of coordination frictions, the number of job seekers N met by a firm in each period is not restricted to $\{0,1\}$ (as in the baseline model) but follows a Poisson distribution. As discussed above, the firm finds it optimal to rank such N job seekers by unemployment duration, with τ_1 denoting the shortest and τ_N the longest. If the duration of the first job seeker warrants a job interview, *i.e.* $\mathcal{C}(y,\tau_1)=1$, the firm calls back as many job seekers n as warranted by equation (C.2) at cost κq each. Upon selecting the highest-ability job seeker among them (as long as she is qualified, *i.e.* $\mathcal{Q}(\bar{\mathbf{x}}_{1,n},y)=1$), the firm offers her a job with probability q – the job seekers' selection process being therefore independent of the latter.

Finally, the free entry condition pins down the labor market tightness θ such that vacancy posting costs equalize discounted *ex ante* expected profits as per equation (6):

$$\kappa_v = \beta \int \mathbb{E}[\Pi(y)|\theta]\ dG(y)$$

C.4 Model derivations

According to the urn-ball meeting process between job seekers and vacancies, each period $\lambda(\theta)S$ job seekers (balls) sort into V vacancies (urns). Following Jarosch and Pilossoph (2019), we scale the measure of aggregate search effort $S\equiv\sum_{\tau=0}^{\infty}\int s(\epsilon,\tau)u(\epsilon,\tau)\,d\mathcal{L}(\epsilon)$ by the extent of meeting frictions $\lambda(\theta)$ faced by job seekers to obtain effective applications, *i.e.* the measure of job seekers' search effort that does not get lost because of meeting frictions (or the output of the meeting function). Since we consider a continuum of job seekers and vacancies, the binomial distribution of effective applications at a given vacancy converges to a Poisson distribution (Blanchard and Diamond, 1994). As a result, each vacancy receives zero effective applications with probability $\exp\{-\frac{\lambda(\theta)S}{V}\}$. Throughout, we assume that firms, whenever faced with equivalent job seekers at each stage of the hiring process, randomize among them.

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

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

where $\bar{\tau}(x',y)$ denotes the highest duration τ such that equation (C.2) holds. Intuitively, a job seeker with ability x and unemployment duration τ is not interviewed by a firm she is in contact with if there is at least another job candidate with shorter unemployment duration whose interview is successful and has ability high enough to make interviewing a $(x,\tau)-$job seeker unprofitable.

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

$$z(x,y,\tau) \equiv \lambda(\theta) \Bigg(\sum_{t=0}^{\tau} \left(1 - \frac{1}{2}\mathbb{1}\{t=\tau\}\right) \int\int \mathbb{1}\left\{(\bar{\tau}(x',y) < \tau) \cup (\bar{\tau}(x',y) \geq \tau, x' \geq x)\right\}$$
$$\left(1 - \frac{1}{2}\mathbb{1}\{\bar{\tau}(x',y) \geq \tau, x' \geq x\}\right) s(\epsilon,t)u(\epsilon,t)\ d\mathcal{H}(x'|\epsilon,t)\ d\mathcal{L}(\epsilon) + \int\int \sum_{t=\tau}^{\bar{\tau}(x',y)}$$
$$\left(1 - \frac{1}{2}\mathbb{1}\{t=\tau\}\right) \mathbb{1}\{x' \geq x\} \left(1 - \frac{1}{2}\mathbb{1}\{x'=x\}\right) s(\epsilon,t)u(\epsilon,t)\ d\mathcal{H}(x'|\epsilon,t)\ d\mathcal{L}(\epsilon) \Bigg)$$

Intuitively, a job seeker with ability x and unemployment duration τ is not hired by a firm she is in contact with for two main reasons. First, she will not be hired if there is at least another job candidate with shorter unemployment duration whose interview is successful and either has ability high enough to make interviewing a $(x,\tau)-$job seeker unprofitable or is of higher ability than x (first summation). Second, she will not be hired if there is at least another job candidate with unemployment duration between hers and the longest unemployment duration such that another candidate is interviewed after her who has higher ability than hers (second summation).

C.5 Details of structural estimation

In this section we discuss our model estimation strategy and comment the estimation results.

Moments selection. Since workers in the model differ in unobservable characteristics only, we first notice that the correct counterparts of the unconditional duration profiles in the model are the duration profiles controlling for observables in the data. Moreover, the sequential search protocol of our model requires to select individual-level targets – rather than application-level ones – from search diaries (see Table A1 for the respective descriptive statistics). Even though all the parameters are estimated jointly, in what follows we discuss how the empirical moments we select relate to the identification of each parameter.

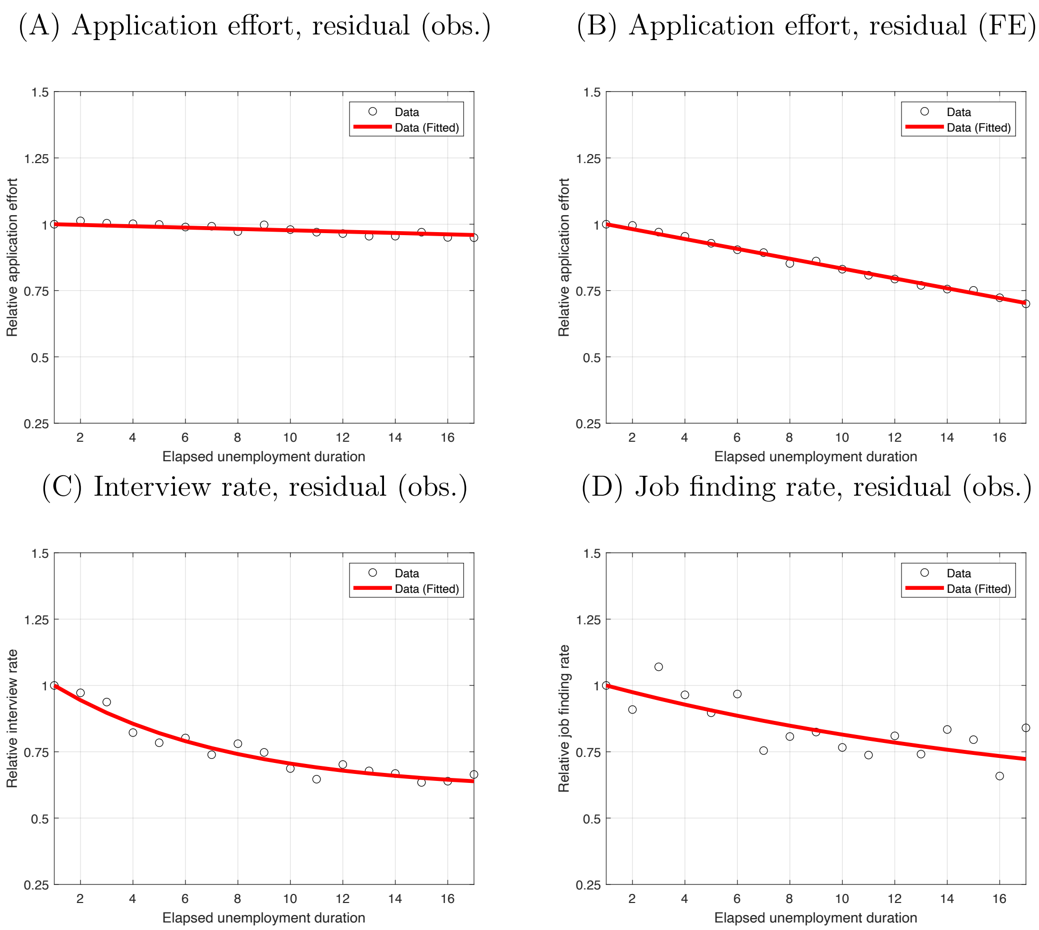
The Beta shape parameters of the search efficiency and productivity distributions, $[B_1, B_2, G_1, G_2]$, govern the variance and skewness of job seekers' ability and firms' productivity, respectively. As in Jarosch and Pilossoph (2019), the higher the variance in ability and productivity, the higher the scope for negative dynamic selection, which determines the steepness of the duration profiles of the interview rate and job finding rate. In turn, the higher the skewness in ability and productivity, the faster dynamic selection occurs, which determines the convexity of such duration profiles and, as a result, the levels at which the interview rate and job finding rate eventually plateau. We therefore target the duration profiles controlling for observables of the interview rate (Figure B11) and job finding rate (Figure B12), as well as their long-term averages, to identify such parameters.

The substitution parameter of the meeting function, ξ, controls the job seekers' meeting probability per unit of search effort for given labor market tightness, thus being identified by the average interview rate. The convexity of the search effort cost function, η, is the reciprocal of the elasticity of application effort to the expected unconditional job offer probability, which makes the duration profile of application effort controlling for individual fixed effects (Figure 3A) its natural target. The scalar of the search effort cost function, ψ, determines the level of application effort, thereby being identified by average application effort. The dispersion parameter of search efficiency, ϕ, governs the cross-sectional variance in application effort for given unemployment duration. Thus, we identify it by targeting the standard deviation of the application fixed effects. As standard in the literature, the vacancy posting cost, κ_v, is identified by the average job finding rate, given that it determines the labor market tightness. The conditional job offer probability of qualified job seekers, q, relates to the long-term unconditional job offer probability and, as such, informs the application decisions of long-term unemployed. We therefore target long-term average application effort to identify it. Finally, the correlation between equally-ranked ability and search efficiency grid points, ρ, affects the scope for learning from search and the ensuing reduction in application effort over an unemployment spell. Its identification is obtained by targeting the duration profile of application effort net of observable heterogeneity (see Figure B1).

Details of estimation strategy. Our treatment of the duration profiles follows closely Jarosch and Pilossoph (2019)'s. In particular, we first make functional form assumptions on the duration profile of each variable normalized with respect to the first period of unemployment. As in Jarosch and Pilossoph (2019) and Kroft, Lange, and Notowidigdo (2013), we estimate a negative exponential relationship for the duration profiles controlling for observables of the interview rate and job finding rate via weighted nonlinear least squares. Guided by our empirical results, we then estimate a linear relationship for the duration profiles controlling for observables and for individual fixed effects of application effort. Figure C1 reports the fitted duration profiles along with the raw data. For the sake of our indirect inference exercise, we treat the duration profiles implied by the model exactly as those in the data, by repeating the same steps outlined above. Following Jarosch and Pilossoph (2019), we choose as targets the entire duration profiles of each normalized variable rather than just its linear trend. In practice, each duration-related target is a vector of equally-weighted values for each duration $\tau = 1, \ldots, 17$. Given our main focus on duration dependence, we assign weight $w_1 = 10$ to the 4 duration-related moments and weight $w_2 = 1$ to the remaining 7 moments.

Estimation results. Our estimation results provide some useful insights into the structure of the Swiss labor market. First of all, we notice that the firm productivity distribution $G(y)$ displays a spike at $y = 0$, where almost half of the mass is concen-

Figure C1: Goodness of fit, functional forms



(A) Application effort, residual (obs.)

(B) Application effort, residual (FE)

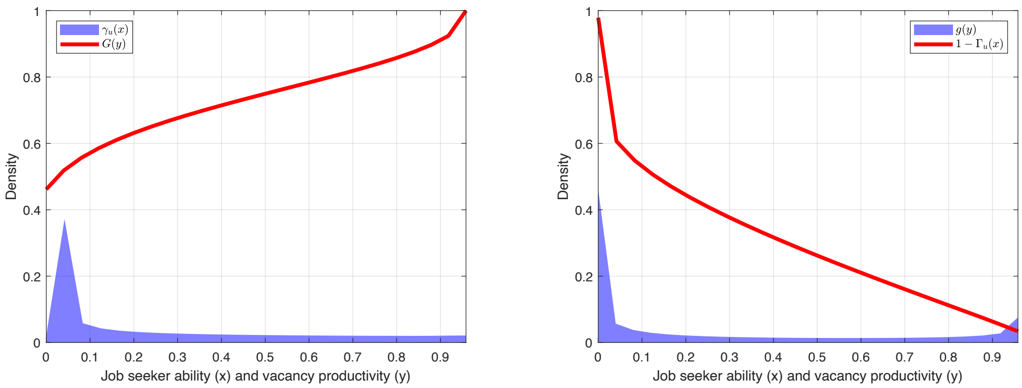
(C) Interview rate, residual (obs.)

(D) Job finding rate, residual (obs.)

Note: This figure reports the fitted and raw duration profiles controlling for observables of application effort (Panel A), interview rate (Panel C), and job finding rate (Panel D), as well as the duration profile controlling for individual fixed effects of application effort (Panel B). The fitted duration profiles of applications are estimated through a linear relationship, those of the interview rate and job finding rate through a negative exponential relationship via weighted nonlinear least squares.

Figure C2: Matching frictions, estimated model

(A) Matching probability, job seekers (B) Matching probability, vacancies



Note: This figure reports the after-meeting matching probability faced by job seekers across the ability distribution (Panel A) and by firms across the vacancy productivity distribution (Panel B). The red solid line represent the probability that a worker meets a firm she is qualified for conditional on meeting one (Panel A) and the probability that a firm meets a qualified worker conditional on meeting one (Panel B); the blue areas display the density of the job seeker ability distribution $\gamma_u(x)$ (Panel A) and the density of the vacancy productivity distribution $g(y)$ (Panel B).

trated.[52] This is perfectly in line with Jarosch and Pilossoph (2019), which finds the same spike with density ranging from 40% to 64% across different model specifications. Instead of the uniform pattern imposed by Jarosch and Pilossoph (2019) for the rest of the distribution, we estimate a U-shaped density with more than 10% of the mass being concentrated in the two highest values.[53] Similarly, the equilibrium job seeker ability distribution displays a spike at the lowest positive grid point accounting for 30% of the total mass. The rest of the distribution is instead relatively close to uniform.

The relative shape of the ability and productivity distribution is informative of the extent of matching frictions faced by searching agents. Figure C2A plots the matching probability faced by job seekers across the ability distribution, *i.e.* the probability of meeting a firm they are qualified for (conditional on meeting one). As a result of the production technology (4), such matching probability is increasing in ability. Figure C2B reports the same graph under the firms' perspective. Unlike for workers, firms' matching probability is decreasing in productivity, with the highest-productivity firms being the most selective.

The substitution parameter of the meeting function, ξ, is estimated to be 0.18, which

[52] For comparability with Jarosch and Pilossoph (2019), we shift each discretized y value leftward by one discretization step in order to allow for a positive mass at $y = 0$.

[53] Allowing for a flexible productivity distribution is critical for our results because the thickness of the right tail of the distribution is directly related to the extent of duration dependence in the interview rate, being high-productivity firms the most prone to statistical discrimination.

entails a moderate amount of complementarity between aggregate search effort and vacancies. As a result, our estimated meeting function looks closer to the standard Cobb-Douglas specification ($\xi = 0$) than to that estimated by Ramey, den Haan, and Watson (2000) ($\xi = 1.27$). According to our results, the search effort cost function displays a mild convexity ($\eta = 0.23$), which implies a sizable elasticity of application effort to the expected unconditional job offer probability of more than 4. It follows that our estimated implied elasticity is markedly higher than the unitary elasticity implied by the quadratic search cost function commonly used in the literature (Yashiv, 2000; Christensen, Lentz, Mortensen, Neumann, and Werwatz, 2005), but remarkably close to that estimated by Lise (2013).[54] The search efficiency dispersion parameter ϕ is estimated to be around 20, meaning that the highest-efficiency workers are 10 times more likely to get a callback than lowest-efficiency ones for given application effort. Such significant cross-sectional heterogeneity in search efficiency is the reason why our estimated model is able to replicate the simultaneous patterns of positive dynamic selection and negative duration dependence in application effort detected in the data, since job seekers with higher search efficiency (and ability) find it optimal to exert less application effort in equilibrium. Importantly, we tie our hands tightly in terms of admissible dispersion in search efficiency by targeting the empirical standard deviation of application fixed effects for the sake of identification. The estimated vacancy posting cost, κ_v, equals just 0.5% of average monthly output, consistently with the reasonable notion that most of hiring costs arises from interview costs rather than entry costs. The conditional job offer probability of qualified applicants equals 40%, supporting an important role of idiosyncratic matching frictions (unrelated to workers' qualification) in the hiring process. Finally, we estimate a correlation between equally-ranked ability and search efficiency grid points, ρ, of almost 60%, according to which short-term unemployed are expected to place on average a three-fifths probability on their true ability – the rest being equally split across other ability levels by construction.

C.6 Expanded decomposition duration profile of the job finding rate

In this section we expand our decomposition exercise carried out in Section 6. Our goal is to quantify the indirect effect of firms' statistical discrimination on workers' search

[54] This is the mirror image of our empirical finding of a significantly higher duration dependence in application effort than commonly thought.

effort. In practice, we aim to further decompose the share of duration dependence due to workers into two distinct components: a component due to changes in the true unconditional job offer probability (driven by firms' statistical discrimination) and a component due to learning (driven by incomplete information).

With this goal in mind, we proceed by defining the counterfactual search effort under perfect information, $s(\epsilon, \tau, x)$, as follows:

$$s(\epsilon, \tau, x) = \sigma^{-1}\big(\beta\ o(x, \tau)\ [W(\epsilon, x) - U(\epsilon, \tau + 1, x)]\big) \tag{C.3}$$

Intuitively, $s(\epsilon, \tau, x)$ equals the amount of search effort that would be exerted by a job seekers of type ϵ and ability x at duration τ if ability x were known. Unlike actual search effort (5), search effort under perfect information depends on the current *true* unconditional job offer probability, as well as its full forward-looking sequence via the capital gain upon employment, which move in response to firms' hiring policy. Hence, changes in $s(\epsilon, \tau, x)$ identify the role of firm-worker interaction.

In turn, the wedge between actual search effort and search effort under perfect information captures the differential amount of search effort induced by incomplete information, which we denote as $\Delta(\epsilon, \tau, x)$ and compute residually as follows:

$$\Delta(\epsilon, \tau, x) \equiv s(\epsilon, \tau) - s(\epsilon, \tau, x) \tag{C.4}$$

Intuitively, $\Delta(\epsilon, \tau, x)$ moves in response to learning: the closer the expected unconditional job offer probability approaches the true unconditional job offer probability, the lower the wedge is.

We then revisit the decomposition of the decline in the job finding rate controlling for observables provided in equation (16) by explicitly distinguishing duration dependence due to firm-worker interaction and due to workers' learning as follows:

$$\begin{aligned}
\underbrace{\mathbb{E}_\tau\left[f(\epsilon,\tau,x)\right]-\mathbb{E}_0[f(\epsilon,0,x)]}_{\text{Duration profile controlling for obs.}} = \; & \underbrace{\mathbb{E}_\tau\big[s(\epsilon,0)\;\big(o(x,\tau)-o(x,0)\big)\big]}_{\text{DD due to firms}} \\
& + \underbrace{\mathbb{E}_\tau\big[\big(s(\epsilon,\tau,x)-s(\epsilon,0,x)\big)\;o(x,\tau)\big]}_{\text{DD due to firm-worker interaction}} \\
& + \underbrace{\mathbb{E}_\tau\big[\big(\Delta(\epsilon,\tau,x)-\Delta(\epsilon,0,x)\big)\;o(x,\tau)\big]}_{\text{DD due to workers' learning}} \\
& + \underbrace{\mathbb{E}_\tau\big[s(\epsilon,0)\;o(x,0)\big]-\mathbb{E}_0\big[s(\epsilon,0)\;o(x,0)\big]}_{\text{Dynamic selection on unobservables}}
\end{aligned} \tag{C.5}$$

where $\mathbb{E}_t[.]$ denotes the expectation with respect to the distribution of workers' unobservable characteristics, *i.e.* type ϵ and ability x, at duration t. "Duration dependence due to firm-worker interaction" captures the indirect effect of the reduction in the true unconditional job offer probability on the job finding rate through the induced workers' discouragement, while "duration dependence due to worker learning" captures by how much the change in application effort due to learning contributes to a reduction in the job finding rate.

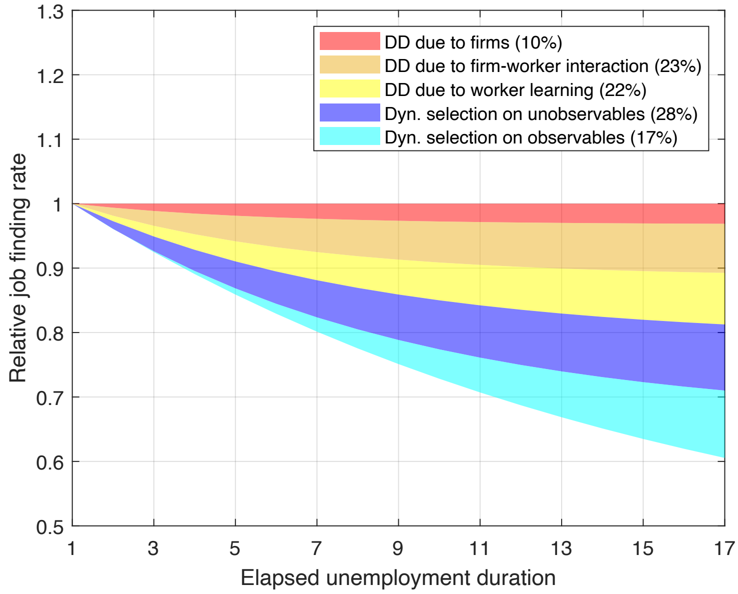
Upon integrating equation (C.5) with equation (17), Figure C3 shows the expanded decomposition of the observed decline of the job finding rate graphically. According to our estimates, "duration dependence due to workers" (as defined in equation (16)) is driven by workers' equilibrium response to firms' statistical discrimination (worker-firm interaction) and by workers' learning in almost equal proportions.

C.7 Counterfactuals

In this section we present the counterfactual exercises we run in our estimated model. Motivated by the crucial importance of duration dependence in explaining the negative duration profile of the job finding rate, we make use of the estimated model as a laboratory to single out the role of different labor market frictions in generating (long-term) unemployment. In doing so, we aim to quantify the maximum unemployment-reduction potential of public policies.

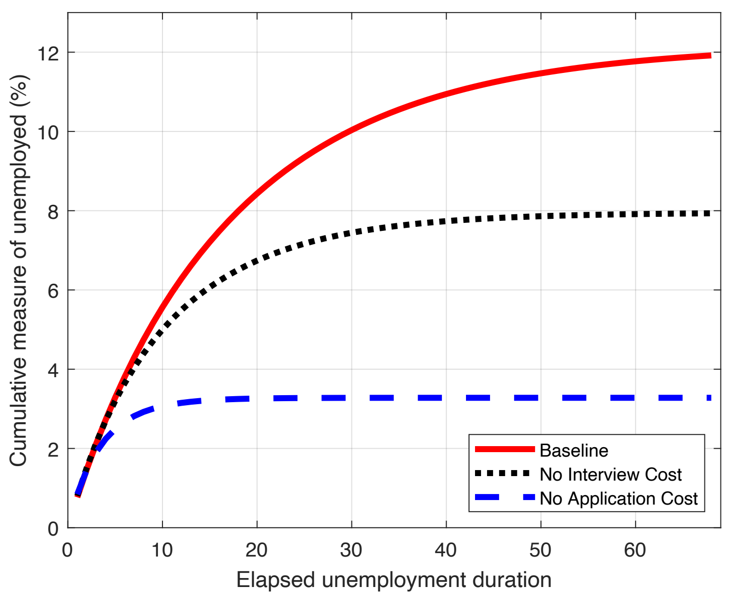
No application costs. As a first benchmark, we run a comparative statics exercise by letting application costs vanish, *i.e.* $\psi \to 0$. In this counterfactual economy, all the

Figure C3: Duration profile of the job finding rate, expanded decomposition



Note: This figure reports the decomposition of the duration profile of the job finding rate into the different sources of duration dependence and dynamic selection derived in equation (C.5) and equation (17). The model-based duration profiles of the job finding rate components reported in equation (C.5) are derived by estimating individual fixed effects and duration effects from a saturated regression, computing the expected values of each component at any unemployment duration, and normalizing them with respect to the first month of unemployment. Expected values are computed with respect to the joint distribution of workers' search efficiency and ability in the contemporaneous period of unemployment. The distribution of observables across unemployment durations is kept the same as in the first month of unemployment. According to equation (17), the duration profile of the component due to dynamic selection on observables is computed as the difference between the observed duration profile of the job finding rate and its duration profile controlling for observables (see Figure B12). Finally, all duration profiles are fitted by a negative exponential function estimated via weighted nonlinear least squares. The reported shares are the frequency-weighted average shares of the respective raw components over the entire unemployment spell.

Figure C4: Unemployment distribution, counterfactuals



Note: This figure compares compares the cumulative measure of unemployed at each duration in our baseline (in solid red) to that in the two counterfactual economies with no interview costs (in dotted black) and no application costs (in dashed blue).

job seekers find it optimal to send out infinite applications. As a result, meeting frictions are fully overcome by infinite search effort and the meeting function collapses to:[55]

$$\lim_{S\to\infty} \mathcal{M}(S,V) = \min\{u, V\}$$

The individual average meeting probabilities are therefore equal to $s\lambda(\theta) = \min\{1,\theta\}$ for workers and $s\lambda(\theta)/\theta = \min\{1,\theta\}/\theta$ for firms.

Table C1: Baseline vs No application cost, counterfactual

	Baseline	No application cost
avg interview rate	0.226	0.844
long-term avg interview rate	0.184	0.646
avg job finding rate	0.068	0.259
long-term avg job finding rate	0.057	0.217
unemployment rate	0.122	0.033
long-term unemployment rate	0.059	0.001

Table C1 compares our baseline economy to the counterfactual with no application costs. Both the interview rate and the job finding rate would be almost four times as large by removing application costs, leading to a similarly four-fold reduction in the unemployment rate. Long-term unemployment rate would be virtually zeroed out. We therefore conclude that meeting frictions account for three-quarters of the aggregate unemployment rate, thus hinting at a vast unemployment-reduction potential of job search assistance programs to workers.[56]

No interview costs. We now assess the role of interview costs by running a comparative statics exercise where job interviews are assumed to be free, *i.e.* $\kappa \to 0$.

In spite of a modest direct effect of duration dependence due to statistical discrimination detected in Figure 8, removing interview costs would bring about a significant

[55]Since we work in discrete time, we assume that $\mathcal{M}(S,V) \leq \min\{S,V\}$. Since the search protocol is sequential, we further impose that $\mathcal{M}(S,V) \leq \min\{u,V\}$, where u is the measure of unemployed.

[56]Removing meeting frictions without setting application costs to zero, *i.e.* assuming that $\mathcal{M}(S,V) = \min\{S,V,u\}$, would be isomorphic to the case without application costs, up to the fact that the workers' welfare would be lower. This is the case because in our estimated model expected profits from entry would exceed vacancy posting costs if firms' meeting probability were unitary, and wages are fixed. In equilibrium, the mass of vacancies needs therefore to exceed the measure of unemployed. In turn, job seekers find it optimal to scale down their search effort to 1 whenever their meeting probability is unitary.

Table C2: Baseline vs No interview cost, counterfactual

	Baseline	No interview cost
avg application effort	8.980	11.13
long-term avg application effort	8.656	11.00
avg callback prob.	0.226	0.391
long-term avg interview rate	0.184	0.344
avg job finding rate	0.068	0.105
long-term avg job finding rate	0.057	0.086
unemployment rate	0.122	0.080
long-term unemployment rate	0.059	0.025

drop in the unemployment rate by more than 4pp, which is largely driven by a reduction in long-term unemployment. Motivated by the rise in the average job finding rate beyond what would be warranted by simply alleviating statistical discrimination against long-term unemployed, we investigate the role of firm entry, *i.e.* the extensive margin adjustment, in driving the results. To do so, we repeat the same comparative statics exercise of letting interview costs approach zero in a model of exogenous job creation, by keeping the mass of vacancies fixed at its baseline level.

Table C3: No interview cost: exogenous vs endogenous job creation, counterfactual

	Baseline	No interview cost (fixed V)	No interview cost
avg application effort	8.980	8.821	11.13
long-term avg application effort	8.656	8.741	11.00
avg interview rate	0.226	0.247	0.391
long-term avg interview rate	0.184	0.224	0.344
avg job finding rate	0.068	0.067	0.105
long-term avg job finding rate	0.057	0.058	0.086
unemployment rate	0.122	0.121	0.080
long-term unemployment rate	0.059	0.058	0.025

Table C3 reports the results of our intensive vs extensive margin decomposition. We find that virtually all the reduction in (long-term) unemployment is accounted for by an increase in firm entry (extensive margin), as opposed to higher job offer probability by incumbent firms (intensive margin). Hence, our results align with Jarosch and Pilossoph (2019)'s, as far as the (limited) importance of interview costs for long-term unemployment in models of exogenous job creation is concerned.[57] Interestingly, in the face of a muted

[57] Jarosch and Pilossoph (2019) assumes exogenous contact rates, *i.e.* fixed λ, rather than exogenous job

effect on the unemployment rate, the model with exogenous job creation still foresees a reduction in the duration dependence of the job finding rate by 30% with respect to the baseline. The reason why this (apparently counterintuitive) result obtains is that duration dependence is *not* directly linked to (long-term) uenmployment in models of endogenous (and costly) search effort: since eliminating interview costs makes the duration profile of expected unconditional job offer probability flatter, job seekers react by sending out fewer applications in early months of unemployment, which reduces their job finding rate at such early durations.[58]

Nevertheless, we refrain from concluding that removing interview costs is akin to any other policy stimulating firm entry, *e.g.* entry cost or hiring subsidies. The reason is that the tighter the labor market becomes, the faster negative dynamic selection occurs and, therefore, the larger the pool of firms that find it optimal to statistically discriminate against relatively short unemployment durations – a mechanism empirically documented by Kroft et al. (2013). As a result, policies aimed at lowering interview costs are expected to have a stronger *multiplier* in terms of unemployment reduction than other policies promoting firm entry. Accordingly, search assistance programs aimed at firms could represent effective policies to cope with labor market slackness.

No coordination frictions. Finally, we assess the role of coordination frictions by assuming a one-to-one meeting process rather than an urn-ball one. In doing so, we quantify the role of ranking by unemployment duration in generating negative duration dependence in the job finding rate and long-term unemployment, as conceptualized by Blanchard and Diamond (1994).

Table C4 supports the small – albeit non-negligible – role played by coordination frictions in generating long-term unemployment. Indeed, removing multiple applications per vacancy would reduce the unemployment rate by 0.5pp – all of such reduction being concentrated among long-term unemployed.

creation, *i.e.* fixed V. The same (ir)relevance result of interview costs on long-term unemployment holds *a fortiori* in our model with exogenous contact rates.

[58] A similar argument is developed in He and Kircher (2023) with respect to the relationships between biased beliefs about own job finding rate and unemployment.

Table C4: No coordination frictions, counterfactual

	Baseline	No coordination frictions
avg application effort	8.980	8.975
long-term avg application effort	8.656	8.950
avg interview rate	0.226	0.230
long-term avg interview rate	0.184	0.197
avg job finding rate	0.068	0.070
long-term avg job finding rate	0.057	0.061
unemployment rate	0.122	0.117
long-term unemployment rate	0.059	0.054

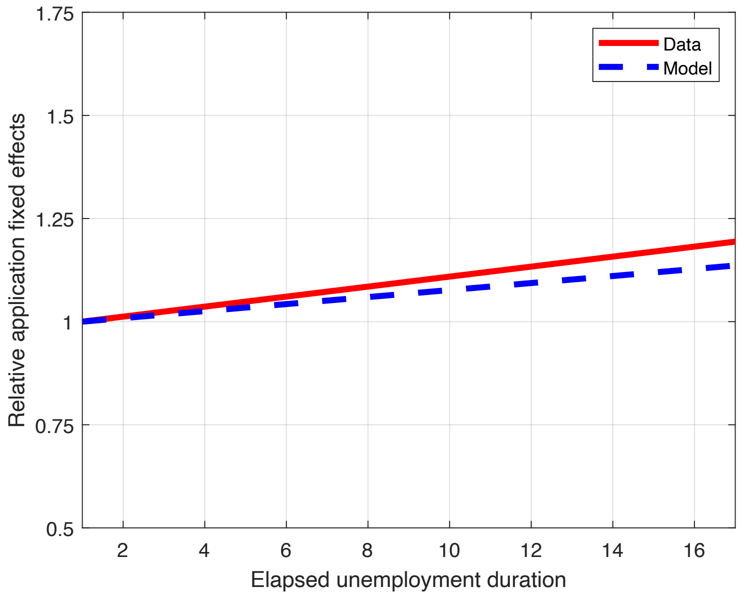
D. Additional Graphs & Tables

Table D1: Job search effort provision and application channels' shares

	Written channel		Phone channel		Personal channel	
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable: estimated α_i						
Application channel's share	0.569***	0.857***	-0.863***	-0.662***	-0.251	-0.973***
	(0.123)	(0.126)	(0.169)	(0.165)	(0.184)	(0.186)
Individual controls	No	Yes	No	Yes	No	Yes
Mean outcome	10.224	10.224	10.224	10.224	10.224	10.224
Adjusted R^2	0.002	0.156	0.002	0.153	0.000	0.154
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 (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.

Figure D1: Application fixed effects, residual (obs.)



Note: This figure contrasts the duration profiles controlling for individual fixed effects (Panel A) and for observables (Panel B) of application effort fixed effects in the data (solid red) with those implied by the estimated model (dashed blue). Both the duration profiles in the data and in the model are derived by estimating individual fixed effects and duration effects from a saturated regression, computing the expected values of application effort fixed effects at any unemployment duration, and normalizing them with respect to the first month of unemployment. Expected values are computed with respect to workers' search efficiency distribution in the first month of unemployment, *i.e.* $\mathbb{E}_0[\hat{\alpha}(\epsilon, \tau)]$. The distribution of observables across unemployment durations is kept the same as in the first month of unemployment. Finally, both the data- and the model-implied duration profiles are fitted by a linear function.