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BIASED BELIEFS, JOB SEARCH, AND WELFARE: A STRUCTURAL ANALYSIS OF COACHING AND COUNSELING

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Biased Beliefs, Job Search, and Welfare: A Structural Analysis of Coaching and Counseling

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Abstract

How do unemployed workers form beliefs about their labor-market prospects, and how do these beliefs affect behavior, policy effectiveness, and welfare? We develop and estimate a structural job-search model with quasi-Bayesian updating, combining Swiss panel data on beliefs and job-search behavior with a randomized counseling-and-coaching intervention. Job seekers enter unemployment with overly optimistic beliefs about interview arrivals, but gradually become pessimistic as past signals fade from memory. The estimated updating process combines features consistent with both motivated beliefs and recency-weighted information processing. The model replicates the observed dynamics of applications, interviews, wages, and job finding, while decomposing treatment effects into changes in search efficiency, search costs, and beliefs. We find that belief formation is the principal channel through which the intervention accelerates transitions into employment. However, despite increasing job finding, the intervention reduces participant welfare because it operates primarily through lower reservation wages.

Keywords: Job search, biased beliefs, expectations, quasi-Bayesian learning, randomized control trial, structural econometric estimation, evaluation, active labor market policies.

JEL classification codes: C41, C51, C93, D04, D83, J64, J68

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1 Introduction

Beliefs play a central role in economic decision-making because they shape motivation, behavior, and welfare. A growing theoretical literature argues that beliefs may depart systematically from Bayesian benchmarks. In models of motivated beliefs (Bénabou and Tirole, 2002, 2004, 2016), favorable expectations generate psychological and motivational benefits, making individuals less responsive to information that threatens desirable views of themselves or their prospects and thereby contributing to persistently optimistic beliefs. Departures from Bayesian learning need not, however, arise solely from motivated cognition. Recent theories show that cognitive constraints can distort the processing of information by assigning disproportionate weight to recent signals relative to past information (Malmendier, 2022; Afrouzi et al., 2023; Azereido Da Silveira et al., 2024). While these theories have generated important insights, evidence linking these belief-formation mechanisms to consequential economic decisions remains scarce.

Unemployment provides a particularly useful setting for studying these mechanisms because job seekers repeatedly receive information about their labor-market prospects through interviews and job offers, creating opportunities to learn and update expectations. At the same time, consistent with theories of motivated beliefs, there is extensive evidence that unemployed workers remain overly optimistic about job-finding prospects[1] and frequently expect higher wage offers than they ultimately receive.[2] However, there is little evidence on how these beliefs evolve over the unemployment spell and, in particular, how updating of beliefs relates to recent theories of expectation formation. A main objective of this paper is to develop a framework that allows us to characterize how belief updating departs from Bayesian learning and to assess whether the resulting belief dynamics are consistent with these theories.

Understanding belief formation is particularly important when beliefs affect economic behavior. In the context of unemployment, expectations determine both search effort and reservation wages, making them a potentially important driver of job-finding outcomes. We therefore integrate the theoretical framework about belief formation into a standard job search model and then estimate this model using data on older entrants into unemployment in Switzerland. This enables us to characterize how changing beliefs can generate complex,

[1] This optimism bias is documented not only among job seekers in developed countries (Spinnewijn, 2015; Arni, 2015; Conlon et al., 2018; Potter, 2021; Mueller et al., 2021; Balleer et al., 2026a,b; Harmon et al., 2026), but also in developing countries (Alfonsi et al., 2020; Banerjee and Sequeira, 2023; Bandiera et al., 2025; Abebe et al., 2025). See Mueller and Spinnewijn (2023) for a survey.

[2] See Krueger and Mueller (2016); Arni (2015); Drahs et al. (2018); Caliendo et al. (2024).

nonmonotonic behavioral reactions, and ultimately job finding over the unemployment spell, which is not possible in standard job search models with complete information about the job arrival rate. Moreover, the framework allows us to quantify the welfare consequences of the departures from Bayesian learning and to evaluate the welfare effects of policy interventions.

If beliefs are an important determinant of behavior, a natural policy question is whether labor-market interventions can improve outcomes by changing expectations. Identifying such effects is challenging because interventions may simultaneously affect other determinants of job finding, including search costs and search efficiency. We therefore develop a methodology that disentangles these channels and isolates the role of belief formation. We do this by relating the different channels to the main structural parameters of our job-search model, which we then identify through the imposed theoretical structure and the random assignment of a subsample of Swiss job seekers to a job-search assistance program. Taken together, these elements allow us to trace the entire causal chain from information and expectation formation to behavior, job finding, policy effectiveness, and welfare.

To address these questions, we develop and estimate a discrete-time structural non-stationary job search model. In the model, workers hold biased beliefs about the arrival of job interviews–and thus about job offers, while maintaining an unbiased perception of the wage-offer distribution. Belief distortions arise from misperceptions of information, specifically of the number of interviews received. These distortions may evolve over the unemployment spell, including becoming pessimistic through memory-driven distortions as in Azereido Da Silveira et al. (2024). Workers update beliefs using Bayesian reasoning within a misspecified model: they behave as *quasi-Bayesian* agents in the sense of Rabin (2013).[3] Although we estimate the model on a very specific sample, it is sufficiently general to provide a useful framework for estimation on other data.

We estimate the model using rich panel data on older entrants into unemployment in Switzerland. The data track job search effort, acceptance behavior, and job finding over the unemployment spell, and contain repeated elicitations of beliefs concerning interview prospects at six points in time. In addition, a randomly selected subset of workers was offered participation in an intensive coaching-and-counseling program. The randomized assignment provides exogenous variation in information and guidance, allowing us to study whether interventions affect belief formation and to identify the channels through which they influence job finding.

[3] Rabin (2013) defines quasi-Bayesian agents as individuals who hold an incorrect model of the world but update beliefs using Bayes' rule within that model (Benjamin, 2019; Ortoleva, 2024).

We obtain four main findings. First, unemployed workers enter unemployment with overly optimistic expectations about interview arrivals. During the first period of 40 days these expectations first increase further, but as from the second period decline monotonically during the unemployment spell and eventually become pessimistic. Second, estimated belief updating departs from Bayesian learning by placing disproportionate weight on recent realizations. The estimated updating process combines features that are consistent with both motivated beliefs and recent theories emphasizing recency-weighted information processing. Third, the intervention accelerates job finding primarily through altered expectations. Coaching initially raises optimism by strengthening search effectiveness and self-confidence, echoing evidence that training can increase perceived job prospects (Bandiera et al., 2025). However, subsequently it accelerates the downward belief adjustment, consistent with the coaching component aimed at forming more realistic beliefs. These expectation shifts reduce selectivity and raise job finding, while leaving search effort and interview arrival largely unchanged. Although counseling also improves search efficiency (more interviews per unit of search) and intensified counseling reduces the marginal cost of applications, these channels do not translate into higher job finding because reservation wages rise at the same time, offsetting gains on the offer-arrival margin. A final finding is that information frictions have economically meaningful welfare consequences. The cost of biased initial beliefs and of quasi-Bayesian updating relative to unbiased initial beliefs and Bayesian updating amounts to 2,426 Swiss Francs (CHF). In other words, if the unemployed could evaluate their welfare based on the actual job finding hazards, they would be indifferent between sacrificing half of the first month's benefit payment and removing bias from beliefs until the end of unemployment. Furthermore, although the intervention accelerated exit from unemployment, it reduced participants' welfare by CHF 2,754, essentially because the higher exit rate was driven by a lower reservation wage.

This paper contributes to three literatures. First, we contribute to the literature on belief formation and learning from experience by studying expectation dynamics in job search, a high-stakes economic environment with a long horizon and infrequent arrival of information. We document substantial optimism at the start of unemployment and show that belief revisions depart systematically from Bayesian learning. Our estimates reveal updating patterns that share important features with both theories of motivated beliefs and recency-weighted information processing.

The theory of *motivated beliefs* emphasizes that individuals may derive utility or motivation from optimism and may discount or forget unfavorable information (Bénabou and Tirole, 2002, 2004, 2016; Zimmermann, 2020; Huffman et al., 2022). This perspective helps

explain why job seekers tend to be overly optimistic about both job-finding prospects and wage offers (Mueller et al., 2021; Krueger and Mueller, 2016; Caliendo et al., 2024). At the same time, there is a body of research that documents that expectations may react excessively to new information relative to the Bayesian benchmarks.[4] In particular, grounded in cognitive neuroscience, Azereido Da Silveira et al. (2024) show that such overreaction to recent information can be rational when storing and retrieving past information is costly, while Sung (2026) argues that such mechanisms are particularly relevant in contexts with a long horizon and infrequent arrival of new information. He and Kircher (2026) show that overreaction to recent news about improvements in aggregate labor market conditions can mask declining expectations at the individual level, suggesting that the reported persistence in optimism may be partially spurious. We propose a parsimonious specification of quasi-Bayesian belief formation that can accommodate both motivated-beliefs mechanisms and memory-based overreaction, and find evidence consistent with both. In line with He and Kircher (2026) and recent evidence from developing-country settings discussed below, our empirical analysis further shows that job seekers gradually revise their expectations downward over the unemployment spell.

Second, we contribute to the literature on expectations and job-search behavior by developing a framework that links expectation formation to search effort, reservation wages, job finding, and welfare.[5] While previous studies have documented the presence of biased beliefs among job seekers, much less is known about how the evolution of these beliefs shapes behavior over the unemployment spell.[6] By embedding expectation formation within a structural search model, we show how belief dynamics translate into labor-market outcomes.

Methodologically, our paper extends Conlon et al. (2018) and Potter (2021). Compared with Conlon et al. (2018), we focus on interview arrivals rather than job offers, allow for both search effort and acceptance decisions, and explicitly model departures from Bayesian learning.[7] Potter (2021) estimates a related model with biased beliefs about job offers un-

[4]See, e.g., Malmendier and Nagel (2011, 2016); Bordalo et al. (2020); Malmendier (2022); Nagel and Xu (2022); Afrouzi et al. (2023) and Conlon et al. (2018) in the context of job search.

[5]More generally, this paper contributes to the growing literature that examines the job search process through the lens of behavioral economics. In addition to research of the impact of over-optimism (Spinnewijn, 2015; Mueller et al., 2021), scholars have explored the role of locus of control (Caliendo et al., 2015), information and motivation (Altmann et al., 2018; Belot et al., 2019), hyperbolic time preferences (DellaVigna and Paserman, 2005), and reference dependent preferences (DellaVigna et al., 2017, 2022).

[6]Most of the existing studies focus on developing countries discussed below in our contribution to the literature on active labor market policies (ALMP).

[7]Drahs et al. (2018) estimate a structural search model with over-optimism about wage offers but assume

der Bayesian updating using data on search decisions and outcomes alone. We extend by exploiting repeated elicitation of beliefs at six points during unemployment. These richer expectation data allow us to model quasi-Bayesian updating (Rabin, 2013),[8] distinguish perceived from objective information, and incorporate memory-related distortions as in Azereido Da Silveira et al. (2024).This richer information set allows us to identify relationships between beliefs and behavior that cannot be recovered from observed search decisions and labor-market outcomes alone.

One key insight made possible by these richer expectation data is that belief dynamics and job-search behavior can evolve in a highly heterogeneous and non-monotonic manner over the unemployment spell. Because job seekers receive different interview signals and process these signals through quasi-Bayesian updating, workers with identical initial conditions may follow markedly different trajectories of beliefs, reservation wages, and job-finding prospects. Similar conclusions regarding the evolution of job-search behavior have been obtained by Potter (2021) under Bayesian learning. However, the expectations data collected in our study indicate that standard Bayesian updating is unable to reproduce the observed dynamics of beliefs. By contrast, the quasi-Bayesian updating process proposed here generates belief trajectories that are both more persistent and more heterogeneous, thereby producing richer patterns of job-search behavior. More broadly, these findings illustrate why understanding belief formation is essential for interpreting observed job-search behavior and evaluating policies that seek to influence it.

Third, we contribute to the literature on active labor market policies (ALMPs). Existing evidence suggests that policy interventions frequently affect expectations, but it remains difficult to separate the role of belief changes from other channels such as lower search costs or higher matching efficiency. Our framework provides such a decomposition. Applying it to a randomized counseling-and-coaching intervention, we show that changes in expectations are the dominant net driver of the treatment effect on job finding.

Existing evidence, primarily from developing-country settings, shows that interventions can reshape expectations with important behavioral consequences. In South Africa, increased exposure to job search opportunities triggered by a transport subsidy leads to downward belief revisions and, after an initial boost in search effort, lower reservation

all offers are accepted, so job finding identifies search effort. Their data do not include rejected offers, limiting what can be learned about how expectations respond to new information.

[8]In the special case of Bayesian updating, our model is closely related to that of Potter (2021). The main differences are that we measure search effort by the number of applications rather than by search time, and that workers may receive multiple job offers within a period, one for each interview, rather than at most one offer per period.

wages and worse labor market outcomes (Banerjee and Sequeira, 2023). In Uganda, vocational training can raise expectations and search effort, while additional matching with employers can reverse those expectations and affect job quality (Bandiera et al., 2025). While these findings suggest that interventions correcting overly optimistic beliefs risk may backfire and worsen job outcomes, Abebe et al. (2025) show that job fairs can moderate optimism while boosting search effort on both sides of the market, thereby improving employment prospects. However, interventions that facilitate information exchange may also be counterproductive when participants hold overly high expectations about the job quality that such exchange can deliver (Kelley et al., 2024). These findings suggest that ALMPs may be more effective when paired with information that helps calibrate beliefs. Jones and Santos (2022) find that SMS messages about market wages accelerate the downward revision of wage expectations. Harmon et al. (2026) show that an online message informing a subset of UI recipients in Denmark that they face a high risk of long-term unemployment accelerates exits from unemployment. While these exits are more pronounced among overly optimistic job seekers, suggesting that the message successfully corrected biased beliefs, they did not improve job finding for all unemployed workers: 40% abandon job search altogether and enter passive income-support programs that do not require active job search. Alfonsi et al. (2025) show that more personalized and tailored information delivered through mentoring can be more effective than online messages.

We contribute to this literature in three ways. First, we study an affluent-country setting and focus on older workers, a population that has received comparatively little attention. Second, we provide a structural decomposition of treatment effects into changes in search costs, search efficiency, and expectation formation. Third, we show that an intervention can simultaneously increase job finding and reduce participant welfare because its effects operate primarily through lower reservation wages rather than improved employment opportunities. This distinction between employment effects and welfare effects is difficult to uncover in reduced-form evaluations but is crucial for assessing the consequences of information-based policy interventions.

The remainder of the paper is organized as follows. We first describe the institutional context, the field experiment, and the data. Section 3 presents the structural model with biased beliefs, first abstracting from the intervention and then incorporating it. Section 4 discusses the specification, identification and structural estimation. Section 5 reports the estimation results and assesses model fit. Section 6 presents counterfactual simulations that clarify the roles of quasi-Bayesian updating and of the intervention's different components in shaping belief formation, search behavior, and labor market outcomes.

Section 7 briefly summarizes the welfare implications of quasi-Bayesian updating and the intervention. The final section concludes.

2 Institutional Setting, Field Experiment, and Data

This study draws on a random sample of 327 older job seekers, aged between 45 and 61.5 years, who entered unemployment between December 2007 and December 2008 at one of two Public Employment Service (PES) agencies in the Zurich metropolitan area. The first subsection briefly describes the institutional context in which these workers search for jobs. We then present details of the field experiment, which randomly assigned 60 percent of the sample to an ALMP. Finally, we describe the data used in the analysis, and report descriptive statistics.

2.1 Institutional Context

The Swiss UI system is broadly representative of UI systems across OECD countries.[9] Its structural features and labor market policy design are therefore highly comparable to most other OECD systems (see, e.g., OECD Employment Outlooks). The standard maximum duration of unemployment benefits in the Swiss UI system is eighteen months (400 benefit days) for individuals who meet the eligibility requirements. This duration increases by six months (120 benefit days) at age 55 and again at age 62, although the latter age group is excluded from the analysis. The replacement rate ranges from 70 to 80 percent, depending on income, with a cap of CHF10,500 (€7,000). After benefits expire, job seekers are eligible for welfare benefits at a replacement rate of roughly 76 percent of the unemployment benefit.

Job seekers meet with their caseworker monthly. During these meetings, caseworkers may provide job search assistance and verify compliance with eligibility criteria. To remain eligible, workers must apply to at least 6 to 10 vacancies per month, although caseworkers have some discretion to adjust this target. They must also participate in ALMPs proposed by their caseworker, typically a short job search assistance program lasting three to seven working days after three to four months of unemployment. Non-compliance results in full withdrawal of benefits for 1 to 60 days, with most sanctions ranging from five to ten days (Arni et al., 2013). Because these requirements are strictly enforced in Switzerland, compliance rates are very high.

[9] See Appendix A in Arni (2015) and Arni et al. (2013) for details.

2.2 Field Experiment

We use data collected by Arni (2015), who implemented a field experiment to evaluate the effects of an intervention combining intensified counseling with coaching on various outcomes. The intervention targeted older workers who were expected to benefit from the program based on information collected at registration prior to the first meeting with their caseworker. Highly employable workers, top managers, those who had found a temporary subsidized job, and individuals with insufficient language skills to follow the coaching were excluded. This target group was then randomly assigned to a treatment group (60 percent) and a control group (40 percent). Participation in the assigned ALMP was mandatory for all selected participants.

The control group received *business as usual*, whereas the treatment group was assigned to two interventions. First, beginning at unemployment entry, meetings with the caseworker were held every two weeks rather than once a month during the first four months of unemployment. The purpose of this increased meeting frequency was to provide additional job-search assistance rather than stricter monitoring.

Second, after a median duration of 50 days, members of the treatment group began a coaching program in groups of 10 to 15 participants. The program required attendance for approximately three working days per week, plus additional homework, over 54 calendar days. The coaching program pursued two main objectives: (1) enhancing skills to improve job search efficiency and (2) making labor market expectations more realistic. The curriculum comprised five core tasks:

1. *Self-profiling and its implications for optimizing search strategy*: Detailed collection and analysis of personal strengths and weaknesses; how to communicate them positively; highlighting the right ones on the CV. Based on the clarified profile, participants worked on optimizing their search strategy, including where and how to search, with particular focus on assessing the potential for reorientation (e.g., expanding search to other industries, regions, contract types, and working times).
2. *Realistic self-assessment*: Contrasting self-perception with external perception; determining realistic requirements and expectations; setting realistic wage demands (at age 45+); assessing feasibility of further training or skill upgrading; understanding the risk of long-term unemployment and benefit exhaustion.
3. *Improvement of job application skills*: Interview training and feedback; role plays; use of electronic applications; unsolicited telephone applications (including practical training).

4. *Job-search efficiency*: Directed search; guidance and lists of where to search (with focus on online resources); use of alternative search channels such as spontaneous applications; general search coaching.
5. *Self-marketing*: Learning how to present oneself effectively (including practical training); motivating participants to engage in more self-marketing.

2.3 Data

Our data combine administrative records with repeated surveys of job seekers and caseworkers. Surveys were scheduled for months 1, 2, 3, 4, 9, and 12 after registration for UI, typically just prior to meetings with the caseworker, as well as an exit survey approximately three months after leaving unemployment. Actual timing deviated somewhat from this plan: the median realized duration between consecutive survey interviews was 40 days. Accordingly, we group time into 40-day intervals and assign survey information to the interval whose endpoint is closest to the survey date. If no survey falls within a symmetric 40-day window around the endpoint, then the survey information regarding this interval is coded as missing.

Administrative records include daily information on exits to employment and subsequent reentries into UI, individual characteristics, and UI and wage history. The surveys elicit information on (i) search behavior (number of applications, interviews, search channels, and reservation wage); (ii) subjective attitudes (motivation, reliability, and self-confidence); and (iii) beliefs about job finding (expected interview arrivals and wage expectations relative to the previous job).

For the purposes of the structural analysis, we focus on survey measures most relevant to our framework. Caseworker surveys report the number of applications and interviews realized in each period, while job seeker surveys elicit the expected number of interviews. The relevant survey questions are:

1. *How many applications did the job seeker send out in the last 4 weeks?*
2. *How many interviews did the job seeker have in the last four weeks?*
3. *Based on the applications that I sent out in the last four weeks, I believe that I will be invited to the following number of interviews.*

While survey questions refer to four-week periods, we group data into 40-day intervals and scale responses by a factor 40/28.

2.4 Descriptive Statistics

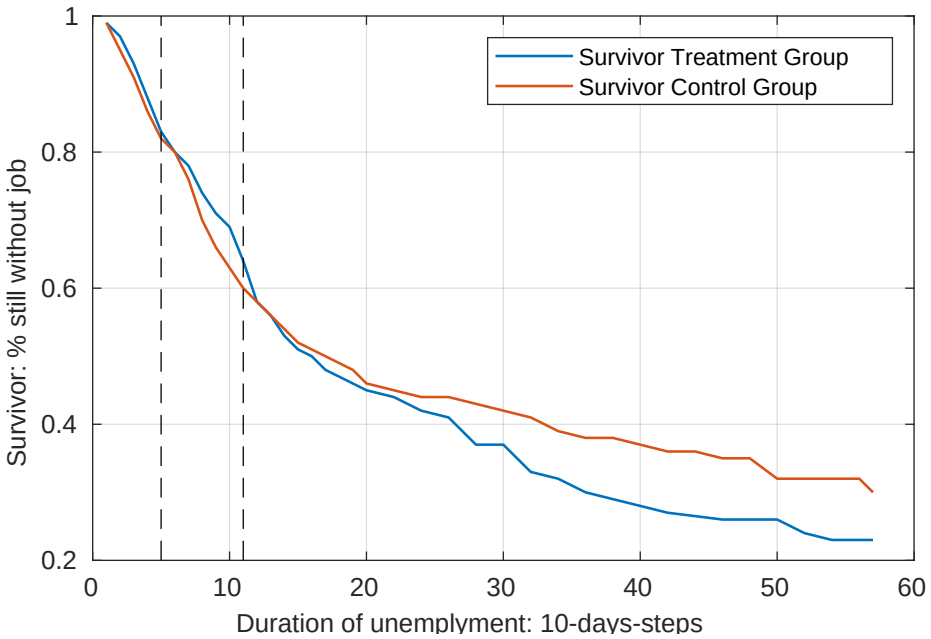
Table 1 reports descriptive statistics by treatment group and indicates that these characteristics are well balanced across groups. Figure 1 illustrates the estimated causal effect of the ALMP on the unemployment survival rate. The intervention generates a locking-in effect until approximately the end of the coaching period (indicated by the vertical lines in the figure): during this time, the survival rate of the treatment group exceeds that of the control group. Immediately after the coaching ends, the survival rate of the treatment group converges to that of the control group and subsequently declines below it, remaining lower after roughly seven months of unemployment. Arni (2015) shows that these opposing effects result in a 9-percentage-point increase in the proportion of individuals who found a job: 72 percent in the treated group compared with 63 percent in the control group (p-value = 0.09).

Table 1: Balancing Table by Treatment Group

	Treatment Group	Control Group	p-Value
Gender: Female	44.1%	43.3%	0.882
Married	56.4%	49.7%	0.224
Age in years	52.5	51.9	0.305
Nationality (Swiss)	84.4%	85.1%	0.862
Qualification: (Semi-)skilled[1]	96.2%	95.7%	0.824
Employability: middle (3) / low (4)	77.4% / 21.5%	78.0% / 21.3%	0.898 / 0.960
Knowledge of at least one foreign language	55.4%	53.2%	0.696
Working time in last job < 100%	17.7%	17.7%	0.998
PES agency # 2[2]	14.5%	10.6%	0.292
Daily benefit, CHF: mean / std.dev.	188.7 / 73.3	198.5 / 76.9	0.247 / 0.326
Salary in the last job, CHF: mean / std.dev.	5,727 / 1,958	5,810 / 2,086	0.345 / 0.203
Observations	186 (56.9%)	141 (43.1%)	

Notes: [1] Job seekers are classified as semi-skilled or skilled if they have completed any form of professional education.
[2] The field experiment was implemented in two PES agencies, the first of which was the largest of the two.
Reported p-values are from Welch's unpaired t-test for equality of means (Welch, 1947) and the Brown–Forsythe test for equality of variances around the mean (Brown and Forsythe, 1974).

Figure 1: Treatment Effect on the Survival in Unemployment



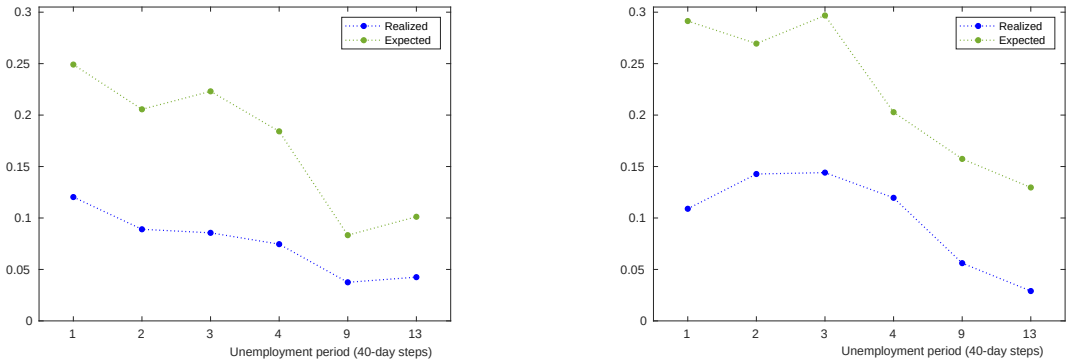
Note: The coaching period is scheduled between the first two vertical lines.

Figure 2 displays the evolution of the expected and realized interview rates at the six survey points for the control group (left panel) and the treated group (right panel). The figure suggests that at the start of unemployment, job seekers are overly optimistic about their interview prospects, but gradually revise their expectations downward and bring them closer to realized outcomes. This interpretation should, however, be treated with some caution because of the relatively small sample size at later survey waves, due to cumulative exits from unemployment and survey nonresponse. At longer unemployment durations, the smaller sample sizes imply that the model's structural restrictions linking expectation formation to past behavior become increasingly important for identifying the direction of expectation bias.

3 Structural Job Search Model with Biased Beliefs

We extend a standard non-stationary discrete-time search model with multiple interviews per period by allowing unemployed job seekers to hold biased initial beliefs about the arrival

Figure 2: Evolution of the Expected and Realized Interview Rates: Control Group (Left) and Treated Group (Right)



Note: The realized interview rate is computed as the average, within each period, of the ratio of the reported number of interviews to the number of applications. The expected interview rate is constructed analogously, replacing the actual number of interviews in the numerator with the expected number.

rate of interviews and to update this expectation each period based on their search effort and the *perceived* number of interviews they received in the preceding period. Because workers are assumed to update their beliefs rationally using *perceived* rather than *actual* interviews, they behave as *quasi*-Bayesian learners (Rabin, 2013). Because the data contain no information on job offers, we assume that each interview results in a job offer, possibly at a very low wage. For simplicity, we also assume that employment is an absorbing state. We first develop the model for workers in the control group and then show how the ALMP affects beliefs and job-search behavior through the model's structural parameters.

We begin by describing the timing of decisions, events and belief formation. We then formulate and solve the worker's optimization problem before showing how the ALMP is incorporated into the framework.

3.1 The Timing of Actions and Events

We assume the following sequence of actions and events within each time period t, starting from $t = 1$:

1. **Prior beliefs**. At the start of each period t, workers hold a (possibly biased) *prior* belief $\boldsymbol{\iota}$ about the interview arrival rate per job application,[10] based on their realized

[10]Random variables are denoted in boldface; their realizations in plain type.

search behavior and *perceived* interview history up to period $t-1$, i.e., $\tilde{\mathcal{H}}_1^{t-1} \equiv \{s_\tau^*, \tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau)\}_{\tau=1}^{t-1}$ for $t > 1$ and $\tilde{\mathcal{H}}_1^0 \equiv \emptyset$ in the first period $t = 1$, where $\emptyset$ denotes the empty set. As discussed in Section 3.2.2, individuals may hold perceptions of the number of past ($\tau < t$) interviews that may differ from the actual realizations, i.e., $\tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau) \neq \hat{\imath}_\tau$. These perceptions may depend on the time $t+1-\tau$ elapsed since the interview took place.

2. **Search and reservation wage choices**. Based on this prior belief, they choose search effort s_t^*[11] and a reservation wage r_t^*.

3. **Interview arrivals**. Interviews arrive at the *true* Poisson rate $\mu_t^* \equiv \iota s_t^*$. All interviews result in job offers.

4. **End-of-period decisions**. At the end of period t, workers observe the actual number of interviews and, hence, job offers received, $\hat{\imath}_t$, and choose between employment and continued search:

   (i) If the highest offer exceeds the reservation wage r_t^*, workers accept the offer and transition permanently into employment.

   (ii) If no interview occurs or if all offers fall below r_t^*, workers update their job-search history and *perceived* interview history to $\tilde{\mathcal{H}}_1^t$ and form a posterior belief based on this updated history.

5. **Transition to the next period**. Period $t+1$ begins. Workers who remain unemployed return to step 1, with $t+1$ replacing t and the *posterior* belief becoming the new *prior*.

3.2 Belief Formation and Quasi-Bayesian Learning

In this subsection, we first describe how workers in our model form subjective beliefs about the arrival rate of interviews and how these beliefs are updated over time. We then justify our modeling assumptions by relating them to the literature on belief formation.

3.2.1 Belief Formation

Unlike a standard job-search model in which unemployed workers know the *true* interview-arrival rate (and job-offer arrival rate) ι per application, this rate $\boldsymbol{\iota}$ is, in our framework, an unknown random variable about which they form a belief. At the start of unemployment,

[11] s_t measures search effort, normalized such that one unit corresponds to one application sent.

the initial belief about $\boldsymbol{\iota}$ is assumed to follow a Gamma distribution with shape and rate parameters $\tilde{A}_0 \equiv \tilde{\alpha}$ and $\tilde{B}_0 \equiv \tilde{\alpha}/\tilde{\iota}$ such that $\boldsymbol{\iota} \sim \mathcal{G}\left(\tilde{A}_0, \tilde{B}_0\right)$. Because multiplying a Gamma-distributed random variable by a positive constant s_1^* divides its rate parameter by that constant, the induced prior belief about the expected number of interviews in period 1, conditional on the chosen search effort, satisfies $\boldsymbol{\mu}_1^* | s_1^* \equiv (\boldsymbol{\iota} s_1^*) | s_1^* \sim \mathcal{G}\left(\tilde{A}_0, \tilde{B}_0/s_1^*\right)$. The conditional mean of this belief is:

$$E\left(\boldsymbol{\mu}_1^* | s_1^*\right) = \frac{\tilde{A}_0}{\tilde{B}_0/s_1^*} \equiv \tilde{\iota} s_1^* \equiv \tilde{\mu}_1^0 \tag{1}$$

Equation (1) implies that job seekers are overly optimistic at the start of the unemployment spell if the subjective expected number of interviews exceeds the objective Poisson arrival rate of interviews, $\tilde{\mu}_1^0 > \mu_1^*$, or, equivalently, if $\tilde{\iota} > \iota$.[12] $\tilde{A}_0 \equiv \tilde{\alpha}$ is a measure of relative precision of the initial belief.[13]

Starting from this prior belief, workers update their beliefs about the interview-arrival rate at the end of each period. They learn as Bayesian agents, but they misperceive the data used to form the posterior belief. Instead of combining the Gamma prior with the Poisson likelihood of the realized interviews $\hat{\imath}_1$ conditional on the unknown mean μ, they replace $\hat{\imath}_1$ with the *perceived* number of interviews, $\tilde{\Psi}_1(\hat{\imath}_1)$. Because the Gamma distribution is a conjugate prior for data generated by a Poisson process with unknown mean, this updating rule yields a posterior distribution for $\boldsymbol{\iota}$ that is also Gamma-distributed: $\boldsymbol{\iota} \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_1(\hat{\imath}_1), \tilde{B}_0 + s_1^*\right)$ (see Appendix B.1 for a derivation).[14] This posterior then becomes the prior at the start of the second period.

In Appendix B.1, we show that repeatedly using the posterior distribution of the previous period as the prior distribution of the subsequent period and combining this prior with the Poisson likelihood evaluated at the perceived number of interviews yields the following Gamma posterior distribution for the unknown arrival rate of interviews per application at the end of period t (which serves as the prior distribution in period $t+1$):

[12] Spinnewijn (2015) distinguishes between *baseline* bias (a difference between subjective and objective job finding probabilities) and *control* bias (a difference between subjective and objective returns to search effort). Under our parameterization, both biases have the same sign. We also explored a specification that allows the biases to have opposite signs, $\tilde{B}_0 = \frac{\tilde{\alpha} s_1}{\tilde{\iota}(\tilde{\theta}+s_1)}$, but the available data lacked sufficient variation to separately identify $\tilde{\iota}$ and $\tilde{\theta}$.

[13] $Var\left(\boldsymbol{\mu}_1^* | s_1^*\right) = \frac{\tilde{A}_0}{\tilde{B}_0^2/s_1^{*2}} = \frac{\left(\tilde{\mu}_1^0\right)^2}{\tilde{\alpha}}$. It follows that the coefficient of variation is $CV = \frac{\tilde{\mu}_1^0}{\sqrt{\tilde{\alpha}}} \Big/ \tilde{\mu}_1^0 = 1/\sqrt{\tilde{\alpha}}$.

[14] This conjugacy property makes Bayesian updating analytically tractable, which in turn facilitates an estimation procedure that is already computationally demanding.

$\boldsymbol{\iota}|\tilde{\mathcal{H}}_1^t \sim \mathcal{G}\left(\tilde{A}_t, \tilde{B}_t\right)$, where

$$\tilde{A}_t \equiv \tilde{A}_0 + \sum_{\tau=1}^{t} \tilde{\Psi}_{(t+1-\tau)}(\hat{\imath}_\tau) \qquad \text{and} \tag{2}$$

$$\tilde{B}_t \equiv \tilde{B}_0 + \sum_{\tau=1}^{t} s_\tau^* \tag{3}$$

Furthermore, the subjective expected interview rate formed at the end of time period t, conditional on the history $\tilde{\mathcal{H}}_1^t$, is

$$\tilde{\imath}_{t+1}^t \equiv E\left[\boldsymbol{\iota}\middle|\tilde{\mathcal{H}}_1^t\right] = \frac{\tilde{A}_t}{\tilde{B}_t} \equiv \frac{\tilde{\alpha} + \sum_{\tau=1}^{t} \tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau)}{\tilde{\alpha}/\tilde{\imath} + \sum_{\tau=1}^{t} s_\tau^*} \tag{4a}$$

$$= (1-\omega_t)\,\tilde{\imath}_t^{t-1} + \omega_t \frac{\tilde{\Psi}_1(\hat{\imath}_t)}{s_t^*} + \frac{\sum_{\tau=1}^{t-1}\left[\tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau) - \tilde{\Psi}_{t+1-\tau-1}(\hat{\imath}_\tau)\right]}{\tilde{B}_t} \tag{4b}$$

where

$$\omega_t \equiv \frac{\hat{\tau}_t}{\hat{\tau}_t + \tilde{\tau}_t}. \tag{5}$$

Here $\hat{\tau}_t$ and $\tilde{\tau}_t$ denote, respectively, the precision of the most recent interview-arrival-rate signal and of the prior expected interview rate. Specifically, $\hat{\tau}_t$ is defined as the inverse of the expected conditional sampling variance of the interview-arrival-rate signal, while $\tilde{\tau}_t$ is defined as the inverse of the posterior variance of $\boldsymbol{\iota}$ at the end of period $t-1$. Appendix B.1 provides further details and derives the equality in (4b).

Equations (4a) and (4b) have familiar intuitive interpretations when $\tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau) = \hat{\imath}_\tau$, i.e., when updating reduces to standard Bayesian updating. First, if we ignore the first terms in the numerator and denominator, $\tilde{A}_0$ and $\tilde{B}_0$, which reflect the prior belief before any information has been gathered, then $\tilde{A}_t/\tilde{B}_t$ is simply the ratio of the total number of interviews to the total number of applications up to time t, a natural estimator of ι. Equation (4b) then shows that the expected posterior interview arrival rate per application is a weighted average of the prior expected interview arrival rate and the signal received in period t, where weights are determined by the relative precision of these components.

When $\tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau) \neq \hat{\imath}_\tau$, the contemporaneous signal is distorted, causing the job seeker to perceive an interview-arrival rate that differs from the one actually realized. When the unemployed worker is overly optimistic, belief updating proceeds as if the realized arrival of interviews were more favorable than a Bayesian agent would perceive. However, under quasi-Bayesian updating, Bayes' rule itself remains unchanged; only the perceived data

entering the updating process are distorted (Rabin, 2013). If contemporaneous signals are systematically perceived too favorably, beliefs may remain persistently optimistic. As explained in Subsection 3.2.2, this can be justified by *theories of motivated beliefs*. The additional correction term in (4b) allows perceptions of interview realizations from earlier periods to evolve over time. This term may capture memory decay, which can attenuate and even reverse the persistent optimism.

Workers choose in each period t the level of search effort s_t^* and the reservation wage r_t^* based on their subjective beliefs about the number of interviews $\boldsymbol{\imath}_t$ they will receive, conditional on current search effort s_t and the history $\tilde{\mathcal{H}}_1^{t-1}$. This conditional subjective probability distribution, $\tilde{P}_t^{t-1}\left(\boldsymbol{\imath}_t \middle| s_t; \tilde{\mathcal{H}}_1^{t-1}\right)$, is obtained by integrating the Poisson distribution over the unknown arrival rate $\boldsymbol{\mu}$ at the start of period t: $\boldsymbol{\mu} \middle| s_t; \tilde{\mathcal{H}}_1^{t-1} \sim \mathcal{G}\left(\tilde{A}_{t-1}, \tilde{B}_{t-1}/s_t\right)$.[15] Appendix B.2 shows that this implies that the worker's subjective predictive distribution of the number of interviews is Negative Binomial: $\boldsymbol{\imath}_t \middle| s_t; \tilde{\mathcal{H}}_1^{t-1} \sim \tilde{P}_t^{t-1}\left(\boldsymbol{\imath}_t \middle| s_t; \tilde{\mathcal{H}}_1^{t-1}\right)$, where

$$\tilde{P}_t^{t-1}\left(\boldsymbol{\imath}_t \middle| s_t; \tilde{\mathcal{H}}_1^{t-1}\right) = \frac{\Gamma\left(\tilde{A}_{t-1} + i_t\right)}{\Gamma\left(\tilde{A}_{t-1}\right)\Gamma\left(i_t + 1\right)} \left[\frac{\tilde{A}_{t-1}}{\tilde{A}_{t-1} + \tilde{\mu}_t^{t-1}}\right]^{\tilde{A}_{t-1}} \left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i_t}, \tag{6}$$

and where $\tilde{\mu}_t^{t-1} \equiv \tilde{\iota}_t^{t-1} s_t$ denotes the expected number of interviews in period t formed at the end of period $t-1$, with $\tilde{\iota}_t^{t-1}$ defined in (4a) and (4b).

3.2.2 Perceived Interview Invitations as Signals in Updating

In Section 3.1, we allowed individuals to update their expectations about the arrival of interviews based on their perception, rather than actual, number of interviews. We take this approach because the observed dynamics of expectations are empirically difficult to reconcile with standard Bayesian updating, in which the realized interview counts constitute the signals used for learning. Instead, we propose that individuals update rationally based on perceived signals $\tilde{\Psi}_{t+1-\tau}(\hat{\imath}_\tau)$ and act as *quasi-Bayesian* agents in the sense of Rabin (2013). We specify perceptions so that the resulting learning dynamics are compatible with at least two prominent theories in the broader literature on belief formation and learning from experience, and with existing studies within the job search literature: theories of *motivated beliefs* (Bénabou and Tirole, 2002, 2004, 2016; Zimmermann, 2020; Huffman et al., 2022) and theories that explain individuals' overreaction to recent signals

[15] This follows from $\boldsymbol{\iota} \sim \mathcal{G}\left(\tilde{A}_{t-1}, \tilde{B}_{t-1}\right)$ at the start of period t and the property that multiplying a Gamma-distributed random variable by a positive constant s_t^* divides its rate parameter by the same constant.

(Azereido Da Silveira et al., 2024; Sung, 2026). This leads us to specify the perception as follows:

$$\tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau) = \tilde{\psi}_0 \tilde{\psi}_1^{(t-\tau)} \hat{i}_\tau \qquad \text{for } \tilde{\psi}_0 \geq 0,\ \tilde{\psi}_1 \geq 0,\ t \geq 1 \text{ and } 1 \geq \tau \geq t. \tag{7}$$

$\tilde{\psi}_0 \tilde{\psi}_1^{(t-\tau)}$ is the importance weight of the realized signal $\hat{i}_\tau$. It implies geometric decay if $\tilde{\psi}_1 < 1$.

In an influential contribution, Mueller et al. (2021) show that job seekers are overly optimistic about their job finding probability from the moment they enter unemployment and show that this belief is persistent. Other researchers also document persistent overoptimism in wage expectations (Krueger and Mueller, 2016; Caliendo et al., 2024). *Theories of motivated beliefs* offer a plausible explanation for these observations: workers are *overconfident* about their ability to find a job that pays well. These theories argue that such overconfidence arises either because workers derive utility from optimistic beliefs (Brunnermeier and Parker, 2005; Köszegi, 2006) or because optimistic beliefs help present-biased agents to overcome self-control problems and motivate them to exert search effort (Bénabou and Tirole, 2002). Under our current modeling assumptions—which ignore present bias and imply both baseline and control optimism—the second rationale is not relevant, as overly optimistic beliefs would then induce lower search effort and/or higher reservation wages.

Theories of motivated beliefs also explain why overconfidence persists in the presence of feedback: individuals exhibit *selective recall*. They retain overly positive memories of past good performance (such as invitations to job interviews), whereas memories of poor performance (such as the absence of such invitations) fade more quickly (Zimmermann, 2020; Huffman et al., 2022). In our specification, this corresponds to choosing parameters in (7) such that $\tilde{\psi}_0 > 1$. Complete persistence of positive memories corresponds to $\tilde{\psi}_1 = 1$, whereas values below one allow for memory decay. Motivated-belief theories would therefore lead one to expect $\tilde{\psi}_1$ to be relatively close to one.

At the same time, a growing literature shows that job seekers do adjust their beliefs in response to labor-market feedback, particularly when they repeatedly fail to find a job.[16] He and Kircher (2026) reconcile these findings with the persistent optimism documented by Mueller et al. (2021) by showing that the latter may be driven by improvements in aggregate labor market conditions, to which workers overreact. Researchers have also found

[16] See, e.g., Jones and Santos (2022); Banerjee and Sequeira (2023); Bandiera et al. (2025); Abebe et al. (2025); Alfonsi et al. (2025).

that individuals tend to overreact to individual-level news in various contexts,[17] especially in environments characterized by a long horizon and infrequent feedback (Sung, 2026), such as job search. Consistent with this, Conlon et al. (2018) report that, upon receiving new information embedded in wage offers, job seekers revise their wage expectations too strongly relative to a Bayesian agent.

Nagel and Xu (2022) justify such overreaction by *fading memory*, which Azereido Da Silveira et al. (2024) show can arise from rational behavior once the retrieval of information from memory is recognized to be costly. In our model, this corresponds to choosing parameters in (7) such that $\tilde{\psi}_1 < 1$, while maintaining $\tilde{\psi}_0 \geq 1$. As a consequence, more recent interview realizations receive greater weight in belief updating, while the influence of earlier realizations decays geometrically with elapsed duration $t - \tau$. This generates fading memory from period two onward and gives rise to the negative correction term in (4b) (see Appendix B.1).[18]

3.3 The Optimization Problem of the Worker

3.3.1 Wage Offers

We assume that each interview generates a wage offer. Wage offers received within the same period can be compared, implying that only the highest offer matters. Let $F(w)$ denote the distribution function of a single wage offer and $f(w)$ the corresponding density function. Assuming that wage-offer draws are i.i.d. across interviews, the distribution of the maximum of i offers is given by $F^{[i]}(w) \equiv [F(w)]^i$, with corresponding density $f^{[i]}(w) \equiv i\,[F(w)]^{i-1} f(w)$.

3.3.2 Value Functions

Workers are risk-neutral, have an infinite time horizon, and discount future income using the discount factor $\beta \in (0, 1)$. They are either unemployed or employed. When employed,

[17] See, e.g., Malmendier and Nagel (2011, 2016); Bordalo et al. (2020); Malmendier (2022); Afrouzi et al. (2023).

[18] Note that, although the qualitative predictions are similar over our period of analysis, our specification deviates from those proposed by the aforementioned authors. They model fading memory by raising the likelihood of new information to a power less than one, following earlier work by Ibrahim and Chen (2000), Ibrahim et al. (2003), and Prat-Carrabin et al. (2021). Such a specification generates fluctuating bias, which ours does not. However, our observation period is too short to determine whether the long-term unemployed would eventually revert to overoptimism and continue to cycle between overoptimism and pessimism. Moreover, analytical tractability prevents us from implementing their learning model directly, as raising the likelihood to a power would break the Gamma–Poisson conjugacy and thereby eliminate the closed-form updating expressions.

they earn in each period a constant wage w forever, so the value of employment is

$$W(w) = \frac{w}{1-\beta} \tag{8}$$

When unemployed, workers receive in each period t an allowance $b_t = b_{UI}$ proportional to past earnings. Once their entitlement to UI expires at $t = T$, they receive a lower welfare allowance $b_T = b_W$ proportional to the UI benefit. When searching for a job, they incur a search cost $c(s_t)$ in each period, which is increasing and convex in effort: $c^{'}(s_t) > 0$ and $c^{''}(s_t) > 0$. Given their search effort, workers may receive an interview and therefore a wage offer that exceeds their reservation wage r_t. If an acceptable offer arrives, they transition to employment in the following period; if not, they remain unemployed and continue searching.

Unemployed workers choose search effort s_t and reservation wage r_t in each period to maximize their (possibly biased) subjective expected value of unemployment, $\tilde{U}_t^{t-1}$, given the available information at the end of period $t-1$:[19]

$$\tilde{U}_t^{t-1} = \max_{\{r_t,\, s_t\}} \left\{ \begin{array}{l} b_t - c\left(s_t\right) + \beta \left[\left(1 - \tilde{h}_t^{t-1}\left(s_t, r_t\right)\right) \tilde{U}_{t+1}^{t-1} \right. \\ \left. + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}\left(i \,|s_t, r_t\right) E_w^{[i]}\left[W(w) | w \geq r_t\right] \right], \end{array} \right\} \tag{9}$$

for $t = 1, 2, \ldots, T-1$. Here,

$$\tilde{h}_t^{t-1}\left(i \,|s_t, r_t\right) \equiv \tilde{P}_t^{t-1}\left(i \,\middle|\, s_t; \tilde{\mathcal{H}}_1^{t-1}\right) \left[\left(1 - F^{[i]}\left(r_t\right)\right)\right] \tag{10}$$

is the subjective probability, formed at $t-1$, that exactly i interviews arrive in period t and that unemployment is exited, i.e., that at least one of the resulting wage offers exceeds r_t. The subjectively perceived job-finding hazard in period t is

$$\tilde{h}_t^{t-1}\left(s_t, r_t\right) \equiv \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}\left(i \,|s_t, r_t\right), \tag{11}$$

i.e., the subjective probability that at least one interview results in an acceptable offer. $E_w^{[i]}\left[W(w)|\ \ w \geq r_t\right] \equiv \int_{r_t}^{\infty} W(w) \frac{f^{[i]}(w)}{1-F^{[i]}(r_t)} dw$ is the expected value of employment conditional on the maximum of the i wage offers in period t being acceptable.

Because the optimization problem becomes stationary after UI benefits expire at T, the value function for the optimal choices $\{s_\tau, r_\tau\}_{\tau=T}^{\infty}$ is obtained by imposing as termi-

[19] Details on the derivation of the value function are provided in Appendix C.

nal condition the solution to the stationary problem faced upon entry into welfare after expiration:

$$\tilde{U}_T^{T-1} = \max_{\{r_T,\, s_T\}} \frac{b_T - c(s_T) + \sum_{i=1}^{\infty} \tilde{h}_T^{T-1}\left(i \,|s_T, r_T\right) E_w^{[i]}\left[W(w)|w \geq r_T\right]}{\beta\left((1-\beta)/\beta + \tilde{h}_t^{t-1}\left(s_T, r_T\right)\right)} \tag{12}$$

where $(1-\beta)/\beta$ is the discount rate.

The value function of unemployment is indexed by the superscript $t-1$, which denotes the time of the most recent signal and the moment at which posterior belief is formed. Because the Bellman equation (9) is solved by backward induction, the optimal choice at time t can only be determined by solving the full sequence of optimal decisions from the terminal state at time T back to time t. Because interview arrivals alter workers' subjective beliefs in every period, the non-stationary optimization problem must be solved repeatedly—with updated beliefs in each period—rather than only once at the onset of unemployment.

3.3.3 First-Order Conditions

Derivations of the first-order conditions are provided in Appendix D. The optimal reservation wage satisfies

$$r_t^* + c\left(s_{t+1}^*\right) = b_{t+1} + \beta\left\{\sum_{i=1}^{\infty} \tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*) E_w^{[i]}\left[\frac{w - r_{t+1}^*}{1-\beta}\middle| w \geq r_{t+1}^*\right] + \Delta\tilde{U}_{t+1}^{t-1}\right\} \tag{13}$$

where

$$\Delta\tilde{U}_{t+1}^{t-1} \equiv \tilde{U}_{t+2}^{t-1} - \tilde{U}_{t+1}^{t-1} = \frac{r_{t+1}^* - r_t^*}{1-\beta} \tag{14}$$

The interpretation is standard (see, e.g., van den Berg, 1990; Cockx et al., 2018), except that the objective job-finding hazard in period $t+1$, $h_{t+1}(i|s_{t+1}^*, r_{t+1}^*)$, is replaced by its subjectively perceived counterpart, $\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)$. The left-hand side of (13) captures the cost of continuing to search in period $t+1$: the opportunity cost of not accepting a job offer in period t at reservation wage r_t^*, plus the search cost $c(s_{t+1}^*)$. At the optimum, these costs must equal the benefits of rejecting the offer and continuing to search. These benefits, shown on the right-hand side, consist of three components: (i) the unemployment benefit b_{t+1}; (ii) the subjectively perceived probability of receiving at least one acceptable offer in $t+1$ multiplied by the expected discounted lifetime wage gain from delaying acceptance at wage r_t^*; and (iii) the rate of appreciation (or depreciation, if negative) of the asset value

of unemployment.

Observe that, when job seekers are overly optimistic, the perceived benefit of continued search increases for any given effort and reservation wages. As a result, overly optimistic beliefs lead to a higher reservation wage.

The optimal search effort satisfies

$$c'\left(s_t^*\right) = \frac{\beta}{1-\beta} \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t^*} E_w^{[i]}\left[w - r_t^* \middle| w \geq r_t^*\right] \tag{15}$$

where

$$\frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t^*} = \frac{\tilde{A}_{t-1}}{\left(\tilde{A}_{t-1} + \tilde{\mu}_t^{t-1}\right)} \left(i - \tilde{\mu}_t^{t-1}\right) \frac{\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{s_t^*} \tag{16}$$

Equation (15) generalizes the familiar condition that the marginal cost of search must equal its expected marginal return (See, e.g., Mortensen, 1986). The generalization arises because, in our setting, the derivative of the objective hazard to employment with respect to search effort is replaced by the derivative of its subjectively perceived counterpart.

The first-order conditions (13) and (15) form a system of equations that can be solved recursively starting from stationary counterparts which are solutions to the the terminal condition (12). More details can be found in Appendix E.2.

3.4 Modeling Intensified Coaching and Counseling

We now explain how the ALMP affects the three channels emphasized in the introduction: search costs, search effectiveness, and belief formation. Intensified counseling provides additional job-search assistance and is modeled as a permanent reduction in the marginal search cost, $c'(.)$, through this assistance. Coaching, by contrast, permanently affects both search effectiveness and belief formation from the onset of program participation. The increase in effectiveness is modeled as a higher objective interview arrival rate, ι, for any given level of search effort. Moreover, assignment to coaching may alter both the initial belief parameters $(\tilde{\iota}, \tilde{\alpha})$ and the updating process, as reflected in the values of $\left(\tilde{\psi}_0, \tilde{\psi}_1\right)$, which determine how workers process new information when revising their beliefs.[20]

We assume that, upon assignment at the onset of unemployment, participants know that the marginal cost of search will be lower in all future periods, and they take this into

[20] We experimented with a specification allowing these parameters to differ before, during, and after program participation, but the estimation routine did not converge, likely because the time aggregation of the data is too coarse to identify such time dependence.

account when determining their current choice variables by backward induction from the terminal condition at T. By contrast, before entering coaching, typically starting in the second period, assigned workers do not anticipate that their beliefs about the interview-arrival rate will be affected by participation. Beliefs begin to change only once coaching actually starts. Moreover, even if coaching increases the objective interview-arrival rate ι, participants become aware of this only gradually because learning about the program's effect is sequential rather than instantaneous.

4 Specification, Identification, and Structural Estimation

4.1 Specification

The search cost function for the control group is specified as

$$c\left(s_t\right) = \left[e^{\zeta_1 s_t} - 1\right]. \tag{17}$$

where $c(0) = 0$. For this functional form $\zeta_1 = c''(s_t)/c'(s_t) \equiv d\log c'(s_t)/ds_t$, which is the semi-elasticity of the marginal cost with respect to search effort.[21] For the treatment group, the corresponding parameter is specified as $\zeta_1 \exp(\gamma_{\zeta_1})$, so that γ_{ζ_1} measures the proportional deviation from the control-group parameter. More generally, every structural parameter in the treatment group is specified as $\pi \exp(\gamma_\pi)$, where π denotes the control-group value and γ_π the proportional treatment effect on that parameter.

The wage-offer distribution is assumed to be lognormal: $w \sim \mathcal{LN}\left(\mu, \sigma\right)$. Accepted wages w^o are measured with a unit-mean, log-normally distributed multiplicative error: $m \sim \mathcal{LN}\left(-\nu^2/2, \nu\right)$ with density $h(m)$. With these assumptions, the density of observed accepted wages w^o is

$$f_o\left(w^o; r_\tau\right) = \int_0^{w^o/r_\tau} \frac{f\left(w^o/m\right)}{m\bar{F}\left(r_\tau\right)} h\left(m\right) dm \tag{18}$$

where τ denotes the period in which the transition to employment occurs and r_τ is the reservation wage chosen in that period (Christensen and Kiefer, 1994).[22] To ensure a good

[21] We also considered a specification that included a multiplicative constant term, but with the available data this could not be estimated separately from ζ_1, likely due to insufficient variation in observed search effort.

[22] Equation (18) has a closed-form expression. Its derivation is available from the authors upon request.

fit for the accepted-wage distribution and to relax the assumption of common wage-offer distribution for all sampled unemployed workers, we construct a productivity index p_i for each worker i. This index scales the mean of the wage-offer distribution according to $\mu_i = \kappa_0 + \kappa_1 p_i$. The productivity index p_i measures the percentage deviation of the worker i's quintile-average earnings in the previous job from the average earnings in the third quintile of the previous-earnings distribution.

The remaining parameters, $\tilde{\iota}$, $\tilde{\alpha}$, ι, $\tilde{\psi}_0$, and $\tilde{\psi}_1$, govern belief formation and learning and were introduced in previous sections.

4.2 Identification

We first discuss how the model parameters for the no-treatment counterfactual are identified using the control-group data. The corresponding parameters for the treatment counterfactual are identified analogously using the treatment-group data. The discount factor β is estimated outside the model, based on average period interest rates during the survey years. Its value is set to 0.9946, which corresponds to an annual discount rate of approximately 5 percent.

The identification of the wage-offer distribution and the reservation wage follows the standard arguments in the literature (Flinn and Heckman, 1982; Eckstein and van den Berg, 2007). The quantiles of the theoretical accepted-wage distribution are identified by their empirical counterparts, which are estimated using the earnings reported in the exit surveys. The lognormality assumption then allows to recover the complete wage-offer distribution from its truncated counterpart, thereby identifying $\{\mu, \sigma\}$ and through variation in the productivity index p_i, the parameters $\{\kappa_0, \kappa_1\}$. In addition, lognormality and independence of the measurement error relative to the true wage identify the variance of the measurement error, ν^2. Without measurement error, the reservation wages r_t^* could, in principle, be identified from the minimum observed wage in each period. However, this puts high demands on the data, making this approach unreliable in practice. The reservation wages are therefore essentially identified through their first-order conditions (13) for each t.

Survey observations on reported job applications and interviews identify nonparametrically the search effort s_t^* and the *objective* interview-arrival rate $\iota = \mu_t^*/s_t^*$ in periods $t = 1, 2, 3, 4, 9, 13$. Moreover, in these periods s_t^* and ι are overidentified for two reasons. First, conditional on reservation wage r_t, the probability of receiving $\hat{i}_t$ interviews and transitioning to employment, $h_t(\hat{i}|s_t^*, r_t^*)$, recovered from the register data for

each period t, also identifies the *objective* Poisson probability of receiving $\hat{i}_t$ job offers: $\mathcal{P}(\hat{i}|\mu_t^*) = h(\hat{i}|s_t^*, r_t^*)/\left[1 - F^{[\hat{i}](r_t^*)}\right]$. Since this probability uniquely determines the Poisson mean, it follows that $\mu_t^* = \iota s_t^*$ is also identified through the transition rates. Second, the first order condition for search effort, (15), identifies search effort s_t^* in each period. This overidentification is informative because it allows the first-order condition in one period to pin down the search-cost parameter ζ_1.

The sample means of the ratios of expected number of interviews $\hat{\tilde{\mu}}_t^{t-1}$ to search effort s_t^* identify $\tilde{\iota}_t^{t-1} = \tilde{\mu}_t^{t-1}/\hat{s}_t^*$ for $t = 1, 2, 3, 4, 9, 13$. Conditional on the objective search history $\mathcal{H}_{\tau=1}^{t-1} \equiv \left\{s_\tau^*, \hat{i}_\tau\right\}_{\tau=1}^{t-1}$, the expression (4a) for the first four periods t = 1-4 defines a system of four independent equations that identifies the four unknown parameters $\left(\tilde{\iota}, \tilde{\alpha}, \tilde{\psi}_0, \tilde{\psi}_1\right)$. The two additional equations for $t = 9$ and $t = 13$ provide overidentifying restrictions.

4.3 Choice of the Estimator

The identification arguments outlined above naturally suggest a method-of-moments estimation strategy. We therefore estimate the model by minimizing the weighted distance between the theoretical and empirical moments observed in the data (See, e.g., DellaVigna et al., 2017).[23] The moments we match are:

(i) the cumulative hazard rates of unemployment duration in each 40-day period over 16 consecutive periods;

(ii) the average number of applications submitted in each period;

(iii) the average subjective expected number of interviews in each period;

(iv) the average number of realized job interviews in each period; and

(v) nine quantiles [0.1(0.1)0.9] of the wage earnings distribution upon successful transition from unemployment to employment.

Since the number of applications and the realized and expected numbers of interviews are observed only in the survey waves, the corresponding empirical moments are available only in periods 1-4, 9 and 13. This creates a complication because the recursive solution algorithm described in Section 3.3.3 requires uninterrupted observations on the realized number of interviews in every period in order to form the prior expectation of interviews for the subsequent period—beliefs that are essential for determining workers' choices in

[23] DellaVigna et al. (2017) minimize the distance between theoretical and empirical hazard rates using inverted variances of the empirical hazard rates as weights.

those periods. Consequently, it is not possible to construct the theoretical moments corresponding to the empirical moments beyond period 4.

To address this problem, we use the simulated method of moments (Gouriéroux and Monfort, 1997). In this approach, for periods in which survey data are missing, we simulate the number of interviews period by period by drawing from a Poisson distribution with mean $\mu_t^* = \iota s_t^*$. The method requires generating S simulated paths per individual for all periods and then averaging the theoretical moments across the S simulated paths. We set $S = 5$. Appendix E provides details of the implementation of this procedure.

We match the empirical and theoretical moments separately for the control and treatment groups. For each treatment group, we use 16 moments for the cumulative hazards to employment, 6 moments each for job applications, realized interviews, and subjectively expected number of interviews, as well as 9 quantiles of the accepted-wage distribution. In total, this yields 86 moments to match (2×43).

Table 2: Parameter Estimates for Control and Treatment Groups

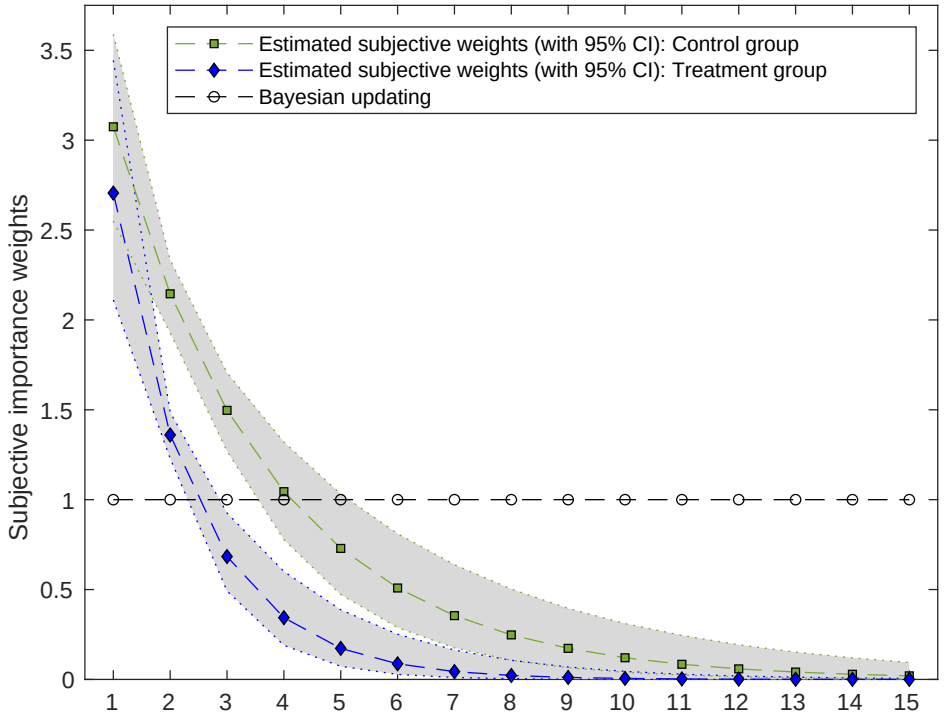
	Model parameters control group					**Treatment effect parameters**			
	coeff.	s.e.	z-stat	p-value		coeff.	s.e.	z-stat	p-value
ζ_1	0.5255	0.0066	79.0861	0.0000	γ_{ζ_1}	-0.0605	0.0163	-3.7120	0.0002
ι	0.0866	0.0011	78.5172	0.0000	γ_{ι}	0.0964	0.0346	2.7879	0.0053
$\tilde{\iota}$	0.2111	0.0024	87.6501	0.0000	$\gamma_{\tilde{\iota}}$	1.1966	0.3183	3.7592	0.0002
$\tilde{\alpha}$	0.0529	0.0054	9.8061	0.0000	$\gamma_{\tilde{\alpha}}$	-0.3997	1.1506	-0.3474	0.7283
$\tilde{\psi}_0$	3.0745	0.2693	11.4176	0.0000	$\gamma_{\tilde{\psi}_0}$	-0.1278	0.1719	-0.7432	0.4573
$\tilde{\psi}_1$	0.6978	0.0465	15.0024	0.0000	$\gamma_{\tilde{\psi}_1}$	-0.3281	0.1643	-1.9970	0.0458
μ:									
_constant (κ_0)	8.6625	0.0422	205.0856	0.0000					
productivity (κ_1)	0.9162	0.5789	1.5828	0.1135		Number of observations:		327	
σ	0.0658	0.0076	8.6230	0.0000		Obj. function:		132.97	
ν	0.2567	0.0009	295.5725	0.0000		S:		5	

5 Estimation Results and Model Fit

5.1 Estimation Results

Table 2 presents the estimated parameters. Apart from $\gamma_{\tilde{\alpha}}$, all parameters are estimated with relatively high precision. We first discuss the point estimates for the control group. Consistent with the descriptive evidence in Figure 2, we find that the initial expectation about the arrival rate of interviews per application, $\tilde{\iota}$, is 21 percent—substantially higher than the estimated objective arrival rate of 9 percent. The estimate of $\tilde{\alpha}$ indicates that workers hold, at the onset of unemployment, a relatively diffuse prior about their expected number of interviews: the estimated value of 0.05 corresponds to a coefficient of variation of 4.3.[24]

Figure 3: Importance Weights $\tilde{\psi}_0\tilde{\psi}_1^{(t-\tau)}$ as a Function of Elapsed Duration $t+1-\tau$ Since the Job Interviews i_τ at Time $\tau \leq t$



In line with previous research, most notably that of Conlon et al. (2018) on the updating of wage expectations, we find that workers place excessive weight on new information when

[24] As shown in footnote 13, the coefficient of variation equals $1/\sqrt{\tilde{\alpha}}$.

revising their beliefs. The estimate $\tilde{\psi}_0 = 3.1$ implies that workers perceive a newly received interview invitation as equivalent to receiving three such invitations. This overweighting of signals is consistent with theories of motivated beliefs, according to which individuals place disproportionate weight on positive news. In our setting, receiving a job interview constitutes positive news, while the absence of job interviews constitutes negative news. However, unlike what these theories typically imply, this excess weight declines rapidly over time: $\tilde{\psi}_1 = 0.7$, which is significantly below one and therefore consistent with fading memory. Figure 3 plots these weights as a function of the time $t + 1 - \tau$ elapsed since the information arrived. After four periods, the weight placed on past interview outcomes falls below the weight that a Bayesian agent would assign, implying, by equation (4a), that these overly optimistic beliefs eventually reverse.

The estimate of ζ_1 implies that the semi-elasticity of the marginal cost of search with respect to search effort is 0.53. Equivalently, each additional application increases the marginal cost of search by roughly 70 percent, since $c'(s+1)/c'(s) - 1 = e^{0.53} - 1 \approxeq 0.7$. The average wage offer for workers whose previous-job earnings equal the average earnings in the third quintile of the previous-earnings distribution is approximately CHF5,782 (= exp(8.6625)) per 40-day period. This is slightly lower than the average unemployment benefit level of CHF6,064 at the onset of unemployment. This small difference reflects our simplifying assumption that *every* interview results in a job offer: many wage offers must therefore be sufficiently low to replicate the outcomes that would arise if some interviews yielded no offer at all. Furthermore, if the previous-job earnings are 10 percent higher (lower) than this reference value, the mean wage offer is about 9 percent higher (lower), because $\hat{\kappa}_1 \times 0.10 \approxeq 0.09$. The standard deviation of the measurement error, ν, is roughly four times that of the wage-offer distribution. However, as shown in the next subsection, this does not imply a poor fit of the wage-offer distribution. This is because σ denotes the standard deviation of the wage-offer distribution *conditional* on the productivity index p_i, which absorbs a substantial amount of heterogeneity, whereas ν reflects the size of the measurement error in observed wages *unconditional* on p_i.

Consider now the estimates of the treatment effects. As expected, intensified counseling reduces the semi-elasticity of the marginal cost of search with respect to search effort by about 6 percent, and coaching increases the search effectiveness, as measured by ι, by roughly 10 percent. Coaching also has a substantial impact on beliefs. First, the precision of the initial belief at the onset of unemployment drops to 67 percent of the control-group level (since $\exp(-0.4) = 0.67$); however, despite its magnitude, the estimate has a large standard error and is not significantly different from zero. In contrast, $\tilde{\iota}$ increases by a

highly significant factor of 3.3 (equal to exp(1.2)). Although this is a large effect and runs counter to the program's objective of moderating expectations, we show in the next section that it has no discernible effect on the expected number of interviews. This is because coaching typically begins only in the second period and, from that point onward, the initial prior receives negligible weight in belief updating. As equation (4a) makes clear, the first term in the denominator ($\tilde{\alpha}/\tilde{\iota} \approxeq .05$) is negligible compared with the second term, s_1^*, which averages around 8.

While coaching has no significant effect on $\tilde{\psi}_0$, it does significantly reduce $\tilde{\psi}_1$ to 72 percent of the control-group value. This is reflected in Figure 3, where already in the third period the importance weights fall below the weights Bayesian agents would assign. This implies that coaching successfully moderates expectations, but only gradually. The simulations presented in the next section make this pattern more transparent.

5.2 Model Fit

In this section we assess model fit by examining the extent to which the predicted model moments fall within the 95 percent confidence intervals of their empirical counterparts. Overall, the fit is excellent: only 8 out of the 86 model moments lie outside these confidence intervals.

Table 3 reports the model fit for job applications, realized interviews, and expected number of interviews. For the control group, the model overpredicts the number of job applications in the first period and underpredicts it in the second period. This pattern is not unexpected, as these are the only two periods in which job search behavior exhibits substantial variation. The lower search effort in the first period may also reflect an adaptation phase during which job seekers familiarize themselves with the job-search requirements. The strict enforcement of these requirements further explains why the number of applications remains stable (slightly above 10 per period), even at long durations. This stability is notable in the light of the recent debate on true versus spurious duration dependence in the literature (Alvarez et al., 2024; Mueller and Spinnewijn, 2025).[25]

[25]Our findings contrast with those of Lalive et al. (2025), who document that applications decrease for a sample of 15,000 job seekers across five Swiss cantons whose search behavior was tracked between April 2012 and March 2013. This difference cannot be attributed to dynamic selection induced by heterogeneity. Such selection would generate *positive* duration dependence in the number of applications, thereby making the pattern observed in our data even more distinct from the one documented by these authors. Rather, it reflects that our specific sample of older workers is not representative of the broader population of unemployed job seekers in

Table 3: Model Fit for Job Applications, Realized Interviews, and Expected Interviews

Control Group						Treatment Group					
Model period		Model moments	Data moments mean	95% CI	obs	Model period		Model moments	Data moments mean	95% CI	obs
Number of job applications						Number of job applications					
1		8.19	6.98	[5.94, 8.01]	129	1	*	8.46	8.22	[7.27, 9.17]	172
2		10.38	13.60	[11.61, 15.58]	87	2	*	10.90	11.23	[10.24, 12.21]	121
3	*	10.58	11.22	[9.54, 12.91]	56	3	*	11.20	10.77	[9.40, 12.13]	78
4	*	10.53	12.24	[10.36, 14.11]	46	4	*	11.49	11.61	[10.08, 13.15]	62
9	*	11.27	10.00	[7.56, 12.44]	15	9	*	11.76	12.91	[10.47, 15.36]	25
13	*	11.36	10.21	[8.65, 11.78]	20	13	*	11.87	11.34	[8.64, 14.04]	16
Number of job interviews realized						Number of job interviews realized					
1	*	0.71	0.68	[0.50, 0.86]	129	1	*	0.74	0.79	[0.57, 1.01]	172
2	*	0.90	1.18	[0.88, 1.49]	87	2		1.00	1.49	[1.19, 1.78]	121
3	*	0.92	0.90	[0.57, 1.22]	59	3	*	1.04	1.04	[0.77, 1.32]	78
4	*	0.91	1.06	[0.61, 1.50]	46	4	*	1.07	1.27	[0.91, 1.63]	62
9		0.98	0.48	[0.03, 0.92]	15	9		1.12	0.69	[0.26, 1.11]	25
13		0.98	0.50	[0.13, 0.87]	20	13		1.10	0.54	[0.06, 1.01]	16
Number of job interviews expected						Number of job interviews expected					
1	*	1.73	1.60	[1.30, 1.91]	130	1	*	2.12	2.01	[1.66, 2.36]	167
2	*	1.94	2.37	[1.92, 2.83]	80	2	*	2.23	2.54	[2.17, 2.90]	116
3	*	2.21	2.03	[1.68, 2.38]	57	3	*	2.78	2.48	[2.08, 2.86]	79
4	*	1.57	2.05	[1.54, 2.55]	44	4	*	2.16	1.95	[1.50, 2.41]	57
9	*	1.31	0.99	[0.34, 1.64]	13	9		1.00	1.76	[1.23, 2.28]	26
13	*	1.04	1.22	[0.36, 2.41]	7	13	*	0.81	1.30	[0.75, 1.85]	22

For the treatment group, the model captures the duration dependence in applications well. The intensified counseling may help job seekers understand the search requirements more quickly, which may explain why the model achieves a good fit already in the early periods of unemployment.

The model tracks the number of realized interviews reasonably well in the first four periods but overpredicts this number in periods 9 and 13 for both the control and treatment groups. The stronger decline observed in the data may reflect that our model does

Switzerland. Consistent with our findings, Lalive et al. (2025) also report that the number of interviews declines with unemployment duration.

not allow for heterogeneity in the *objective* interview-arrival rate per application, ι, and therefore cannot capture the spurious negative duration dependence present in the data. Nevertheless, the model predictions exceed the upper bounds of the confidence intervals only mildly and account for a small share of fit violations. Given the computational complexity associated with incorporating heterogeneity in ι, together with the excellent fit observed in the first four periods, we chose not to introduce this heterogeneity.

With the exception of period 9 for the treatment group, the model predicts the non-monotonic evolution of beliefs remarkably well. This is important, as understanding how unemployed job seekers form and update their beliefs is one of the central objectives of this study. As shown in Appendix A, the model also fits the survival rate in unemployment (Figure A1) and the quantiles of the accepted-wage distribution (Figure A2) almost perfectly. Moreover, Figure A3 shows that the model also captures the non-monotonic evolution of the hazard rate to employment quite closely. The more erratic pattern observed in the empirical hazard is explained by the small sample size.

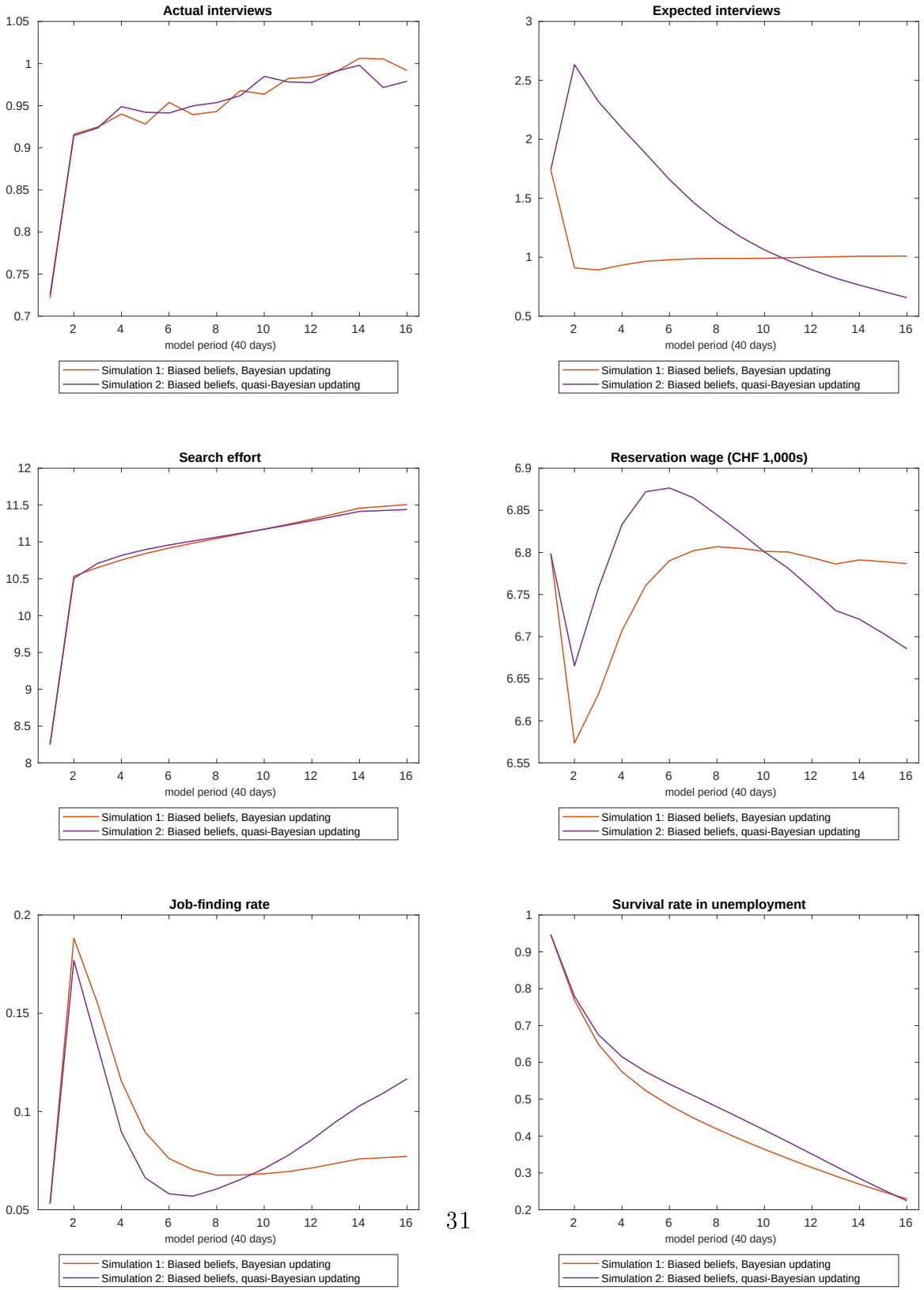
6 Counterfactual Simulations

In this section, we present two sets of counterfactual simulations. The first set aims to provide a better understanding of the impact of quasi-Bayesian updating relative to Bayesian updating. In these simulations we consider an environment without intervention. For each sampled individual, we simulate five trajectories of job-search behavior and outcomes under both updating rules. The second set of simulations disentangles the impact of the different components of the intervention. We first separately evaluate the effects of intensified counseling (operating through search costs) and of coaching (operating through search efficiency and belief updating). In a second step, we further distinguish the two channels through which coaching operates, thereby identifying their distinct effects.

6.1 The Impact of Quasi-Bayesian Updating

To evaluate the effect of quasi-Bayesian updating relative to Bayesian updating, we simulate the behavior of $S = 100$ *twins* of each sampled individual by solving their optimization problem, as defined in Section 3.3, twice. In the first case, we solve the model using the structural parameter estimates for the control group reported in Table 2, which yields the predicted behavior under quasi-Bayesian updating. In the second case, we keep all parameters fixed at these values except for the importance weights, $\tilde{\psi}_0$ and $\tilde{\psi}_1$, both of which are

Figure 4: Comparison of Bayesian (Orange) and Quasi-Bayesian Updating (Purple): Effects on Job-Search Behavior and Outcomes



set to one to impose Bayesian updating. Note that we retain the assumption of an overly optimistic prior belief at the onset of unemployment, namely $\tilde{\iota} = 0.2111 > 0.0866 = \iota$.

To summarize the comparison between these two updating rules, Figure 4 plots the average evolution of six outcomes under the two counterfactual scenarios. A first notable finding is the non-monotonic evolution of the average reservation wage. Such a pattern is difficult to reconcile with a canonical job-search model in which job seekers have complete information about the arrival rate of job opportunities. In such a model, two opposing forces shape the evolution of reservation wages. First, job seekers gradually lower their selectivity in anticipation of benefit exhaustion. However, this effect becomes relevant only as benefit exhaustion approaches and therefore cannot explain the initial decline observed in Figure 4. Second, dynamic sorting increases the average reservation wage among those who remain unemployed. Moreover, as shown in Appendix F, some individuals display (partly) increasing reservation-wage profiles, suggesting that neither of these forces, nor their combined effect, can fully account for the pattern observed in the figure.

The arrival of new information and the way in which it feeds into job seekers' beliefs are therefore key to understanding the observed evolution of reservation wages. Potter (2021) shows that reservation wages move monotonically with beliefs when job seekers update their beliefs according to Bayes' rule. Figure 4 shows that initially overly optimistic Bayesian agents revise their beliefs *on average* downward to a level close to that implied by the constant objective Poisson interview-arrival rate already in the second period, after which beliefs remain closely aligned with this level throughout the spell. The gradual increase in the expected number of interviews beyond period two reflects the gradual increase in search effort induced by the anticipation of benefit exhaustion, while the initial jump in search effort is explained by the lower option value of remaining unemployed resulting from the downward revision of beliefs.[26] In line with Potter's prediction, the reservation wage also declines substantially between the first and the second periods. Thereafter, however, the reservation wage rises much more strongly than the expected number of interviews. This reflects dynamic sorting. Appendix F illustrates that the evolution of reservation wages can differ markedly from the average evolution because it depends on the random, and therefore heterogeneous, timing of job interviews. It also suggests that job seekers with low reservation wages tend to leave unemployment earlier, thereby increasing the average reservation wage among survivors more strongly than the corresponding increase

[26] Potter (2021) demonstrates that, for a Bayesian updater, the effect of deteriorating beliefs on job search effort is ambiguous. The reduced option value stimulates search effort, while the lower expected return may induce a substitution away from search effort. Here, the first effect dominates.

in expectations at the individual level. After about eight months, however, this sorting no longer dominates the downward pressure generated by approaching benefit exhaustion, and the reservation wage begins to decline again mildly.

The time profile of expected interviews differs markedly between quasi-Bayesian and Bayesian updaters. For the average quasi Bayesian updater, the expected number of interviews rises substantially between the first and the second period and then declines monotonically thereafter.[27] The initial increase is driven primarily by the rise in search effort and only to a lesser extent by changes in beliefs. Moreover, the average masks substantial heterogeneity in updating. Only 34 percent of job seekers receive at least one interview during the first period. For these individuals, quasi-Bayesian updating generates a sharp upward revision of expectations because each interview is perceived as substantially more informative than under Bayesian updating. However, the remaining 66 percent receive no interview and therefore revise their expectations downward. As a result, the increase in average expected interviews is driven by a relatively small group of workers experiencing very large upward revisions. The corresponding increase in their reservation wages is insufficient to offset the decline in reservation wages among the majority who receive no interview. Consequently, the average reservation wage initially falls despite the increase in the average expected number of interviews.

From the second period onward, expected number of interviews decline as memory decay gradually erodes optimism. Nevertheless, quasi-Bayesian updaters remain considerably more optimistic than Bayesian updaters during the early stages of unemployment, which explains why their reservation wages initially rise more rapidly. The average reservation wage reaches its peak after six periods and then declines sharply as growing pessimism induced by memory decay increasingly dominates. After period ten, the average reservation wage of quasi-Bayesian updaters falls below that of Bayesian updaters and continues to decline until the end of the observation period.

Because the updating rule has little effect on search effort, and therefore on the actual arrival of interviews, differences in the hazard rate to employment are driven primarily by differences in reservation wages. Accordingly, the job-finding hazard is higher under Bayesian updating up to approximately period 10, after which the ranking reverses. As a result, the unemployment survival rate remains higher for quasi-Bayesian updaters throughout the 16 simulated periods.

[27] This explains why a model imposing Bayesian updating is unable to reproduce the observed expectation dynamics.

6.2 Decomposing the Effects of the Intervention

Figure 1 in Section 2.4 shows that the intervention increases the exit rate to employment. However, the RCT alone cannot reveal the underlying mechanisms: is the treatment effect driven by intensified counseling or by coaching? And, within coaching, does the effect operate through enhanced search efficiency or through changes in belief formation? To answer these questions, we simulate the model and plot the average evolution of six outcomes under a set of counterfactual scenarios that isolate the different channels—reduced search costs, higher search efficiency, and modified belief formation—relative to the no-intervention scenario.

Figure 5 contrasts the impacts of intensified counseling and coaching. Figure 6 further decomposes the coaching effect into its two constituent channels: search efficiency and belief updating.[28] Together, these simulations indicate that the positive effect on job finding is driven entirely by the intervention's impact on belief formation.

In the top-left panel of Figure 5, we see that both coaching (yellow) and counseling (red) increase the number of interviews to which job seekers are invited, and that they do so to a broadly similar extent. However, the panel below shows that this increase is driven by higher search effort only in the case of counseling. This pattern is consistent with expectations: counseling lowers marginal search costs, whereas coaching raises search efficiency per application.

The effects on expectations about interviews (top-right panel of Figure 5) also differ across the two components. Intensified counseling increases search effort and makes job seekers slightly more optimistic about receiving interviews (the red line lies slightly above the blue no-intervention line). By contrast, coaching clearly reduces this optimism (the yellow line lies further below the blue line than the red line lies above it). The top-right panel of Figure 6 shows that the downward adjustment of expectations under coaching is driven entirely by its effect on belief formation (yellow), not by its effect on search efficiency (red): only the yellow curve lies below the blue no-intervention line, whereas the red curve lies slightly above it, suggesting that the effect of coaching through higher search efficiency is similar to the effect of intensified counseling through lower search costs.

The middle-right panels of Figures 5 and 6 show that the enhanced optimism generated

[28] In this decomposition, we remain consistent with our model assumptions, under which intensified counseling operates solely through reduced search costs and coaching affects outcomes only through search efficiency and belief formation. However, because the timing of counseling and coaching largely overlaps, the data alone do not allow us to disentangle the separate impacts of these two program components. The decomposition therefore relies partly on the theoretical restrictions we impose. For example, we cannot entirely rule out that the changes in belief formation are partly induced by intensified counseling.

Figure 5: Decomposing the Treatment Effect in Intensified Counseling and Coaching

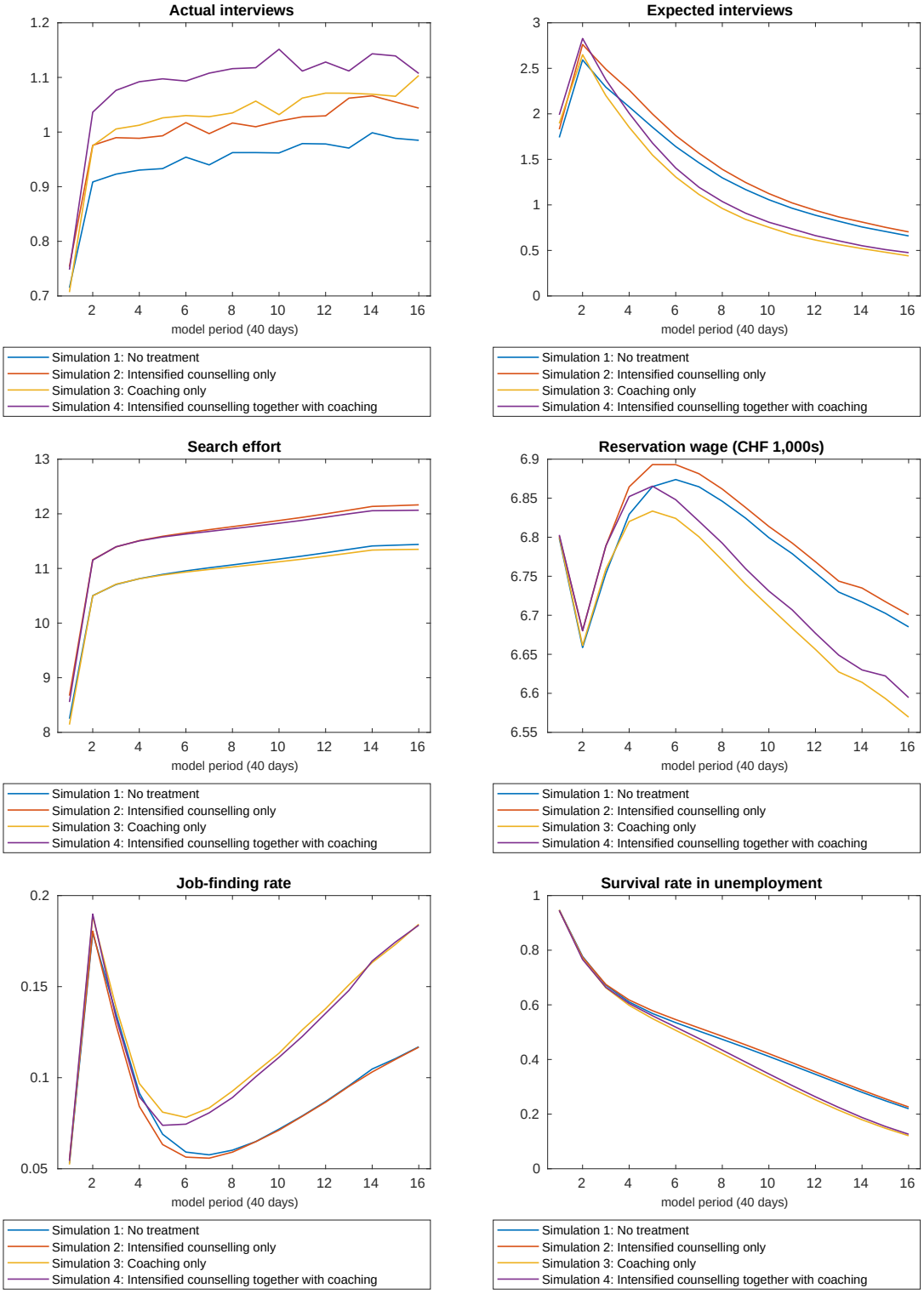
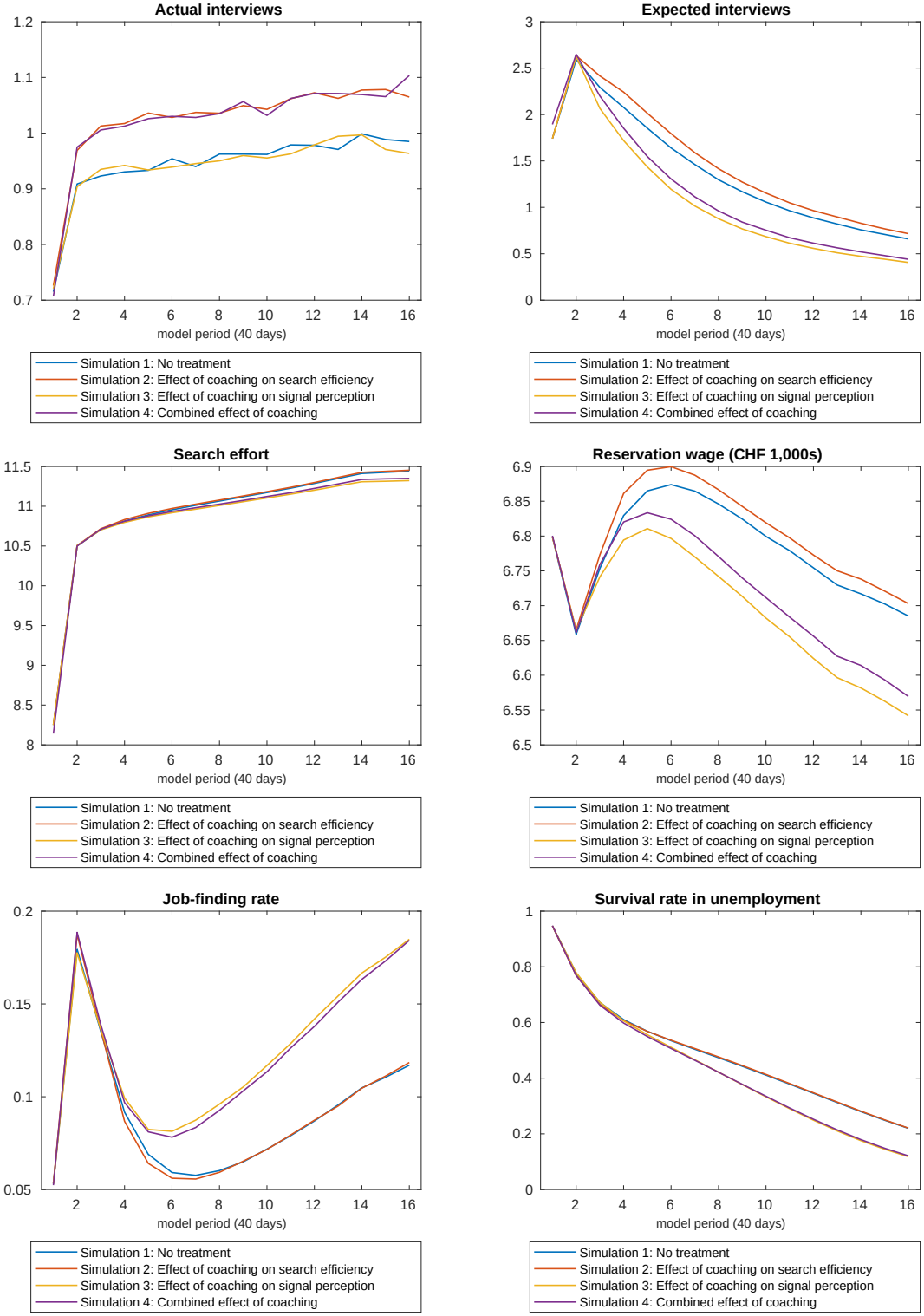


Figure 6: Decomposing the Effect of Coaching into Its Impact on Search Efficiency and Belief Formation



by reduced search costs under intensified counseling and by the higher search efficiency under coaching both raise the reservation wage to a similar extent. As displayed in the bottom panels of these figures, the comparable positive effects of these two channels on job finding, operating through the increased number of actual interviews, are offset by the similarly sized negative effects, operating through the higher reservation wage. These opposing forces cancel each other out, resulting in essentially no net effect on job finding. The yellow curves in these panels indicate that the positive effect on job finding is entirely driven by negative impact that coaching has on the reservation wage through its effect on belief formation. In these simulations, belief formation has virtually no effect on search effort or on the actual number of interviews, implying that its effect on job finding operates almost entirely through reservation wages.

7 Welfare Analysis

In this section, we first quantify the cost of information frictions induced by biased initial beliefs and quasi-Bayesian learning. We then assess the welfare impact of the intervention. The cost of information frictions is computed under the no-treatment counterfactual. At the onset of unemployment, we compare the expected present discounted value of utility along the estimated choice trajectory with the discounted utility that the same individuals would obtain if their initial beliefs were unbiased and had they updated those beliefs according to Bayes' rule.

To compute these welfare costs, we follow Conlon et al. (2018) and replace the *subjectively perceived* job-finding hazards $\tilde{h}_t^{t-1}(.|s_t, r_t)$ and $\tilde{h}_t^{t-1}(s_t, r_t)$ in the value functions defined in equations (9)-(12) with their *objective* counterparts. We then evaluate the welfare associated with each of the two choice trajectories using these *objective* value functions. Concretely, on the right-hand side of equations (10)-(11) $\tilde{P}_t^{t-1}\left(i \left| s_t; \tilde{\mathcal{H}}_1^{t-1}\right.\right)$ is replaced by its objective analogue $P_t^{t-1}\left(i \left| s_t; \tilde{\mathcal{H}}_1^{t-1}\right.\right)$, which denotes the true probability that i interviews arrive for a given search effort s_t. This probability is assumed to follow a Poisson distribution with rate ιs_t. Because the expectations of an unbiased Bayesian learner converge to the true interview-arrival rate whereas those of a quasi-Bayesian learner do not, the estimated discounted welfare under Bayesian learning exceeds that under quasi-Bayesian learning. This results in a welfare cost of biased beliefs at the onset of unemployment amounting to CHF 2,426 per person, i.e., approximately 40 percent of the average per-period unemployment benefit.

Finally, we next calculate the welfare effects of the intervention, i.e., of intensified counseling and coaching, at the onset of unemployment. Interestingly, the intervention *decreases* welfare by CHF 2,754, approximately 45 percent of the average per-period unemployment benefit. This result is expected, because the higher exit rate to employment results from a lower reservation wage, which in turn implies a lower discounted value of continued unemployment. Evaluating this value using *objective* rather than *subjective* expectations does not alter this conclusion. Although these findings raise concerns about the desirability of the intervention from the participants' perspective, the intervention may still be socially desirable if the fiscal savings generated through accelerated re-employment (via lower unemployment and welfare benefit payments) offset both this welfare loss and the operating costs of the program.

8 Conclusion

This paper studies how unemployed workers form beliefs about their labor-market prospects, how these beliefs affect job-search behavior, and how policy interventions influence beliefs and job-search behavior. We develop and estimate a structural job-search model with quasi-Bayesian learning using rich survey data and a randomized counseling-and-coaching intervention among older unemployed workers in Switzerland.

Our findings suggest that belief formation plays a central role in shaping labor-market outcomes. Job seekers enter unemployment with overly optimistic expectations and update these beliefs in a manner inconsistent with Bayesian learning. The resulting belief dynamics affect reservation wages and job finding, while expectation changes emerge as the dominant mechanism through which the intervention operates. Perhaps most strikingly, higher job finding does not necessarily imply higher participant welfare.

We see the framework developed here not as a final model of belief formation during unemployment, but as a first step toward a broader research agenda linking information, beliefs, behavior, policy, and welfare. More generally, we view the framework as a tool for studying these interactions in a broad range of labor-market settings. The quantitative findings reported here are specific to older unemployed workers in Switzerland and to the institutional setting in which the intervention was implemented. However, the modeling framework can readily be applied to other populations, labor-market institutions, and information-based interventions. Understanding how institutional environments shape belief formation and its behavioral consequences remains an important avenue for future research.

Several extensions appear particularly promising. First, our quasi-Bayesian specification is deliberately parsimonious. While it captures empirical patterns consistent with both motivated beliefs and memory-based overreaction, it does not derive these mechanisms from first principles. Second, the model incorporates only limited heterogeneity across workers. Extending the framework to allow for richer forms of observed and unobserved heterogeneity may improve our understanding of how different individuals form beliefs and react to information. Third, our specification imposes a common structure on different sources of belief distortions. In particular, baseline bias and control bias, in the sense of Spinnewijn (2015), are constrained to have the same sign. Although we explored a more flexible specification, the available data did not provide sufficient variation to separately identify these two dimensions of belief formation. Developing empirical settings that allow such a distinction may yield additional insights into how beliefs shape job-search behavior. Finally, the estimated model could be used to explore alternative intervention designs and their implications for both participant and social welfare.

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Conflicts of Interest

The authors have no conflict of interest to declare.

Data and Code Availability

The data underlying this article were provided by two regional Public Employment Services in the Zurich metropolitan area and the Office of Economic Affairs and Labour (AWA) of the Canton of Aargau, Switzerland. Owing to data-sharing restrictions imposed by the data providers, the data are not publicly available but may be accessed with AWA's permission. For further information regarding data access, please contact Patrick Arni at patrick.arni@zhaw.ch. The code used in this study was written in MATLAB and is available upon request from Andrey Launov at a.launov@kent.ac.uk.

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Online Appendix

A Additional Figures

Figure A1: Model Fit of the Survival Rate in Unemployment: Control Group (Left) and Treated Group (Right)

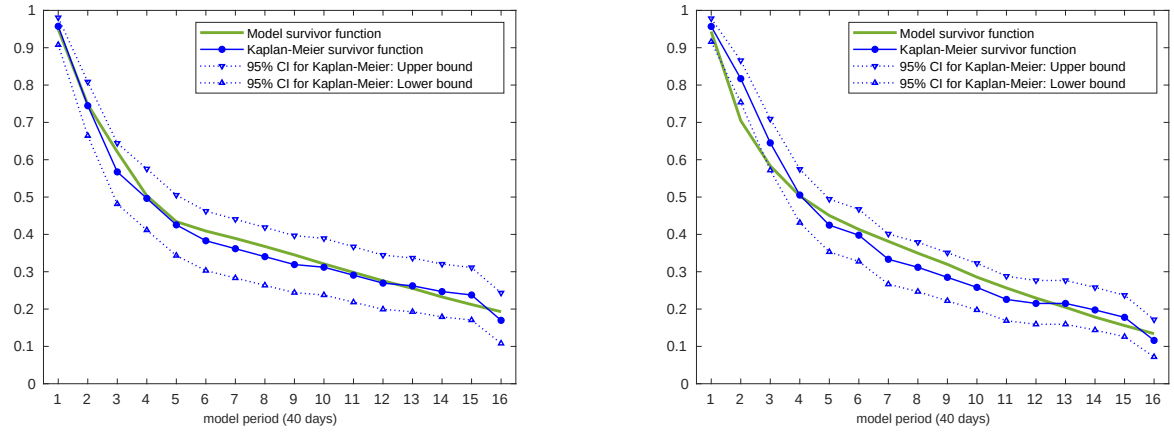


Figure A2: Model Fit of Accepted-Wage Distribution: Control Group (Left) and Treated Group (Right)

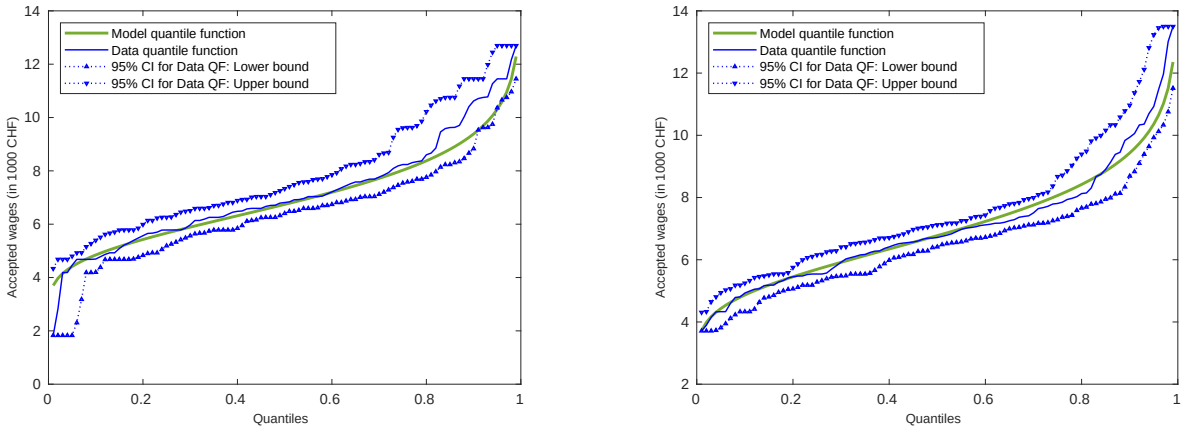
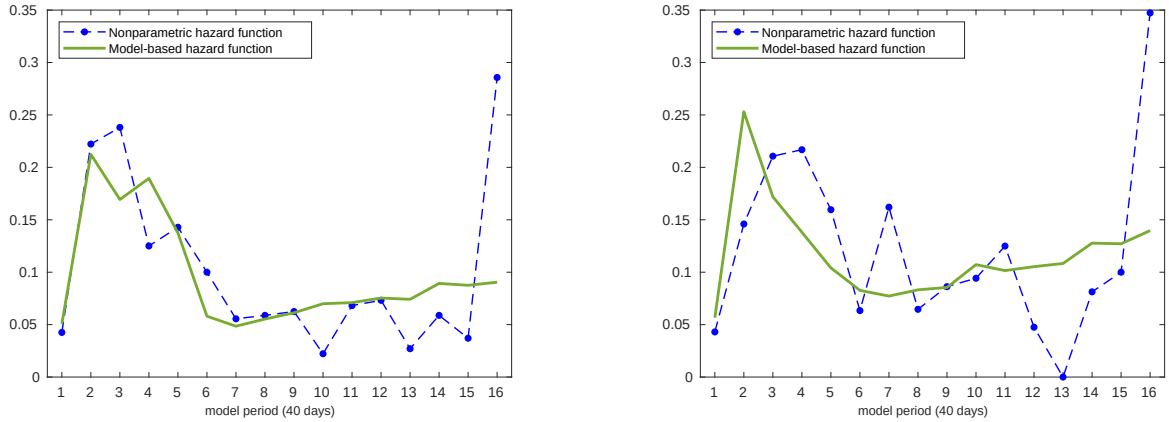


Figure A3: Model Fit of the Hazard Rate to Employment: Control Group (Left) and Treated Group (Right)



B Evolution of Subjective Distributions

B.1 Sequential Updating

- First period

At $t = 1$ an individual enters unemployment with the *subjective* prior distribution of the arrival rate of job interviews $\boldsymbol{\iota} \sim \mathcal{G}\left(\tilde{A}_0, \tilde{B}_0\right)$, where $\tilde{A}_0 = \tilde{\alpha}$ and $\tilde{B}_0 = \tilde{\alpha}/\tilde{\iota}$. Because multiplying a Gamma-distributed random variable by a positive constant s_1^* divides its rate parameter by that constant, choosing the optimal level of search effort s_1^*, the subjective prior distribution of the expected number of interviews becomes $\boldsymbol{\mu}_1^* | s_1^* \sim \mathcal{G}\left(\tilde{A}_0, \tilde{B}_0/s_1^*\right)$, since $\boldsymbol{\mu}_1^* \equiv \boldsymbol{\iota} s_1^*$. A standard Bayesian agent updates this prior belief after observing $\hat{i}_1$ interviews in period $t = 1$. Assuming that the interview arrivals are generated by a Poisson distribution with *true* rate $\mu_1^* \equiv \iota s_1^*$, the posterior is proportional to the product of the Gamma prior and the Poisson likelihood, $\hat{\mathbf{i}}_1 \sim Poi\left(\mu_1^*\right)$. We instead assume that the job seeker is a *quasi-Bayesian* updater who may perceive a different number of interviews, $\tilde{\Psi}_1(\hat{i}_1) \geq 0$, than actually occurred; that is, generally $\tilde{\Psi}_1(\hat{i}_1) \neq \hat{i}_1$. The worker updates beliefs as if $\tilde{\Psi}_1(\hat{i}_1)$ were the realized signal and therefore evaluates the Poisson likelihood at this perceived count. Up to proportionality, this implies the

likelihood $[\mu_1^*]^{\tilde{\Psi}_1(\hat{i}_1)}\, e^{-\mu_1^*}$. Combining this likelihood with the Gamma prior yields the posterior

$$\begin{aligned}\boldsymbol{\mu}_1^* \left| \left\{ s_1^*, \tilde{\Psi}_1(\hat{i}_1) \right\} \right. &\propto \left\{ [\mu_1^*]^{\tilde{A}_0 - 1}\, e^{-\left(\tilde{B}_0/s_1^*\right)\mu_1^*} \right\} \left\{ [\mu_1^*]^{\tilde{\Psi}_1(\hat{i}_1)}\, e^{-\mu_1^*} \right\} \\ &\propto [\mu_1^*]^{\tilde{A}_0 + \tilde{\Psi}_1(\hat{i}_1) - 1} \exp\left\{ -\left(\frac{\tilde{B}_0}{s_1^*} + 1 \right) \mu_1^* \right\},\end{aligned}$$

leading to $\boldsymbol{\mu}_1^* \left| \left\{ s_1^*, \tilde{\Psi}_1(\hat{i}_1) \right\} \right. \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_1(\hat{i}_1), \frac{\tilde{B}_0}{s_1^*} + 1 \right)$. Applying the scaling property of the Gamma distribution to $\iota = \mu_1^*/s_1^*$, the posterior distribution of the interview-arrival rate becomes

$$\boldsymbol{\iota} \left| \left\{ s_1^*, \tilde{\Psi}_1(\hat{i}_1) \right\} \right. \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_1(\hat{i}_1), \tilde{B}_0 + s_1^* \right).$$

- Subsequent periods

The subjective posterior distribution of the interview-arrival rate at the end of period 1 becomes the subjective prior distribution at the beginning of period 2. Job seekers use this prior distribution to determine their optimal search effort s_2^* (and reservation wage r_2^*) in period 2. Since $\boldsymbol{\mu}_2^* \equiv \boldsymbol{\iota} s_2^*$, the prior distribution of the expected number of interviews at the beginning of period 2, used to determine s_2^*, is $\boldsymbol{\mu}_2 \left| s_2^*, \left\{ s_1, \tilde{\Psi}_1(\hat{i}_1) \right\} \right. \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_1(\hat{i}_1), \left(\tilde{B}_0 + s_1 \right)/s_2 \right)$.

At the end of period 2, beliefs are updated in a manner analogous to period 1, but with one important difference. At this point, a quasi-Bayesian agent may perceive the number of interviews received in period 1 differently because perceptions may change over time. For example, recollections of past interviews may fade over time, as discussed in Section 3.2.2. Consequently, in general, $\tilde{\Psi}_2(\hat{i}_1) \neq \tilde{\Psi}_1(\hat{i}_1)$. The subscript $t+1-\tau$ in $\tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau)$ denotes the elapsed unemployment duration between the realization of the interview count $\hat{i}_\tau$ and the moment at which this realization is perceived. Therefore, at the end of period two the prior distribution reads $\boldsymbol{\mu}_2^* \left| s_2^*, \left\{ s_1^*, \tilde{\Psi}_2(\hat{i}_1) \right\} \right. \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_2(\hat{i}_1), \left(\tilde{B}_0 + s_1^* \right)/s_2^* \right)$. Combining the resulting Gamma prior with the Poisson likelihood evaluated at the perceived number of interviews in period 2 yields the following posterior distribution at the end of period 2:

$$\begin{aligned}\boldsymbol{\mu}_2^* \left| \left\{ s_2^*, \tilde{\Psi}_1(\hat{i}_2) \right\}, \left\{ s_1^*, \tilde{\Psi}_2(\hat{i}_1) \right\} \right. &\propto \left\{ [\mu_2^*]^{\tilde{A}_0 + \tilde{\Psi}_2(\hat{i}_1) - 1}\, e^{-\left(\left(\tilde{B}_0 + s_1^*\right)/s_2^*\right)\mu_2^*} \right\} \left\{ [\mu_2^*]^{\tilde{\Psi}_1(\hat{i}_2)}\, e^{-\mu_2^*} \right\} \\ &\propto [\mu_2^*]^{\tilde{A}_0 + \tilde{\Psi}_2(\hat{i}_1) + \tilde{\Psi}_1(\hat{i}_2) - 1} \exp\left\{ -\left(\frac{\tilde{B}_0 + s_1^*}{s_2^*} + 1 \right) \mu_2^* \right\},\end{aligned}$$

leading to $\boldsymbol{\mu}_2^*|\{s_\tau^*, \tilde{\Psi}_{3-\tau}(\hat{i}_\tau)\}_{\tau=1}^2 \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_2(\hat{i}_1) + \tilde{\Psi}_1(\hat{i}_2), \frac{\tilde{B}_0+s_1^*}{s_2^*} + 1\right)$. Applying the scaling property of the Gamma distribution to $\iota = \mu_2^*/s_2^*$, the subjective posterior distribution of the interview-arrival rate becomes

$$\boldsymbol{\iota}|\{s_\tau^*, \tilde{\Psi}_{3-\tau}(\hat{i}_\tau)\}_{\tau=1}^2 \sim \mathcal{G}\left(\tilde{A}_0 + \tilde{\Psi}_2(\hat{i}_1) + \tilde{\Psi}_1(\hat{i}_2), \tilde{B}_0 + s_1^* + s_2^*\right).$$

Iterating these steps yields a Gamma posterior distribution for the unknown interview-arrival rate per application in period t (which serves as the prior in period $t+1$), conditional on the history of search effort and perceived interviews, $\tilde{\mathcal{H}}_1^t \equiv \{s_\tau^*, \tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau)\}_{\tau=1}^{t-1}$: $\boldsymbol{\iota}\left|\tilde{\mathcal{H}}_1^t \sim \mathcal{G}\left(\tilde{A}_t, \tilde{B}_t\right)\right.$, where $\tilde{A}_t$ and $\tilde{B}_t$ are defined in Equations (2) and (3), respectively. Since this posterior is Gamma distributed, its expectation is given by (4a), and its conditional variance equals $Var\left(\boldsymbol{\iota}\left|\tilde{\mathcal{H}}_1^t\right.\right) = \frac{\tilde{A}_t}{\tilde{B}_t^2}$.

- Derivation of Equations (4b) and (5)

First, the definitions of $\tilde{A}_t$ and $\tilde{B}_t$ in (2) and (3) can be rewritten as the following recursive equations:

$$\tilde{A}_t \equiv \tilde{A}_{t-1} + \tilde{\Psi}_1(\hat{i}_t) + \sum_{\tau=1}^{t-1}\left[\tilde{\Psi}_{(t+1-\tau)}(\hat{i}_\tau) - \tilde{\Psi}_{(t-\tau)}(\hat{i}_\tau)\right] \quad \text{and} \tag{B-1}$$

$$\tilde{B}_t \equiv \tilde{B}_{t-1} + s_t^* \tag{B-2}$$

Inserting these expressions in the first right-hand side expression of (4a), and multiplying and dividing the first and second terms, respectively, by $\tilde{B}_{t-1}$ and s_t^* yields

$$\frac{\tilde{A}_t}{\tilde{B}_t} = \frac{\tilde{B}_{t-1}}{\tilde{B}_{t-1}+s_t^*}\frac{\tilde{A}_{t-1}}{\tilde{B}_{t-1}} + \frac{s_t^*}{\tilde{B}_{t-1}+s_t^*}\frac{\tilde{\Psi}_1(\hat{i}_t)}{s_t^*} + \frac{\sum_{\tau=1}^{t-1}\left[\tilde{\Psi}_{(t+1-\tau)}(\hat{i}_\tau) - \tilde{\Psi}_{(t-\tau)}(\hat{i}_\tau)\right]}{\tilde{B}_t}$$

To complete the proof of (4b), it remains to show that

$$\frac{s_t^*}{\tilde{B}_{t-1}+s_t^*} = \frac{\hat{\tau}_t}{\hat{\tau}_t + \tilde{\tau}_t} \equiv \omega_t,$$

where the last definition corresponds to (5), then this proves the equality in (4b). To establish this result, first note that since $\boldsymbol{\iota}|\mathcal{H}_1^{t-1} \sim \mathcal{G}\left(\tilde{A}_{t-1}, \tilde{B}_{t-1}\right)$ the posterior variance of $\boldsymbol{\iota}$ at the end

of period $t-1$ (equivalently, the prior variance at the beginning of period t) is

$$Var\left(\boldsymbol{\iota}|\mathcal{H}_1^{t-1}\right) = \frac{\tilde{A}_{t-1}}{\tilde{B}_{t-1}^2}$$

The precision of the prior belief in period t is defined as the inverse of this variance:

$$\tilde{\tau}_t \equiv \frac{\tilde{B}_{t-1}^2}{\tilde{A}_{t-1}} \tag{B-3}$$

Second, as discussed in the main text, the assumption of quasi-Bayesian updating implies that Bayes' rule continues to govern the updating process. Consequently, the precision of the signal is based on the expected conditional sampling variance of the observed interview-arrival rate $\hat{i}_t/s_t^*$, rather than on its perceived counterpart $\tilde{\Psi}_1(\hat{i}_t)/s_t^*$. Conditional on ι the interview count is Poisson distributed with parameter $\mu_t^* \equiv \iota s_t^*$: $\hat{i}_t|\iota \sim Poi(\iota s_t^*)$. Consequently,

$$Var\left(\frac{\hat{i}_t}{s_t^*}|\iota, \tilde{\mathcal{H}}_1^{t-1}, s_t^*\right) = \frac{\iota}{s_t^*}$$

Taking expectations with respect to the posterior distribution of $\boldsymbol{\iota}$ at time $t-1$ (prior at time t), we obtain

$$E\left[Var\left(\frac{\hat{i}_t}{s_t^*}|\iota, \tilde{\mathcal{H}}_1^{t-1}, s_t^*\right)|\tilde{\mathcal{H}}_1^{t-1}, s_t^*\right] = \frac{\tilde{A}_{t-1}}{s_t^*\tilde{B}_{t-1}}$$

The signal precision is then defined as the inverse of this expected conditional sampling variance:

$$\hat{\tau}_t = \frac{s_t^*\tilde{B}_{t-1}}{\tilde{A}_{t-1}} \tag{B-4}$$

Using the definition (5) of the weight ω_t and inserting in this definition (B-3) and (B-4) yields:

$$\begin{aligned}
\omega_t &\equiv \frac{\hat{\tau}_t}{\hat{\tau}_t + \tilde{\tau}_t} \\
&= \frac{\frac{s_t^*\tilde{B}_{t-1}}{\tilde{A}_{t-1}}}{\frac{s_t^*\tilde{B}_{t-1}}{\tilde{A}_{t-1}} + \frac{\tilde{B}_{t-1}^2}{\tilde{A}_{t-1}}} \\
&= \frac{s_t^*}{s_t^* + \tilde{B}_{t-1}}
\end{aligned} \tag{B-5}$$

where the final equality follows after canceling the common factors $\tilde{A}_{t-1}$ and $\tilde{B}_{t-1}$ in numerator and denominator.

- The correction term in Equation (4b) is negative if the specification for $\tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau)$ is given by (7) and $0 < \tilde{\psi}_1 < 1$.

Insert (7) $\tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau) = \tilde{\psi}_0 \tilde{\psi}_1^{(t-\tau)} \hat{i}_\tau$ into the correction term in (4b) yields:

$$\begin{aligned} \sum_{\tau=1}^{t-1} \left[\tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau) - \tilde{\Psi}_{t-\tau}(\hat{i}_\tau) \right] &= \tilde{\psi}_0 \textstyle\sum_{\tau=1}^{t-1} \left(\tilde{\psi}_1^{t-\tau} - \tilde{\psi}_1^{t-\tau-1} \hat{i}_\tau \right) \\ &= \tilde{\psi}_0 (\tilde{\psi}_1 - 1) \textstyle\sum_{\tau=1}^{t-1} \tilde{\psi}_1^{t-\tau-1} \hat{i}_\tau \end{aligned} \tag{B-6}$$

which is negative for $0 < \tilde{\psi}_1 < 1$.

B.2 Distribution of Interview Invitations

Conditional on μ_t, the interview count is Poisson distributed, $\hat{\boldsymbol{i}}_t | \mu_t \sim Poi(\mu_t)$. Conditional on search effort s_t, the worker's subjective prior distribution of the unknown expected number of interviews in period t is $\boldsymbol{\mu}_t | s_t, \tilde{\mathcal{H}}_1^{t-1} \sim \mathcal{G}(\tilde{A}_{t-1}, \tilde{B}_{t-1}/s_t)$. We derive the worker's subjective predictive distribution of $\hat{i}_t$ by integrating the Poisson distribution over this Gamma prior:

$$\begin{aligned} \tilde{P}_t^{t-1}\left(i_t | s_t, \tilde{\mathcal{H}}_1^{t-1}\right) &= \int_0^\infty \left(\frac{[\mu_t]^{\tilde{A}_{t-1}-1} e^{-(\tilde{B}_{t-1}/s_t)\mu_t} \left[\tilde{B}_{t-1}/s_t\right]^{\tilde{A}_{t-1}}}{\Gamma\left(\tilde{A}_{t-1}\right)} \right) \left(\frac{e^{-\mu_t} [\mu_t]^{i_t}}{i_t!} \right) d\mu_t \\ &= \frac{\left[\tilde{B}_{t-1}/s_t\right]^{\tilde{A}_{t-1}}}{\Gamma\left(\tilde{A}_{t-1}\right) i_t!} \int_0^\infty \left([\mu_t]^{\tilde{A}_{t-1}-1} [\mu_t]^{i_t} \right) \left(e^{-(\tilde{B}_{t-1}/s_t)\mu_t} e^{-\mu_t} \right) d\mu_t \\ &= \frac{\left[\tilde{B}_{t-1}/s_t\right]^{\tilde{A}_{t-1}}}{\Gamma\left(\tilde{A}_{t-1}\right) i_t!} \int_0^\infty [\mu_t]^{i_t+\tilde{A}_{t-1}-1} e^{-(1+\tilde{B}_{t-1}/s_t)\mu_t} d\mu_t \end{aligned}$$

Considering the change of variable

$$y_t = (1 + \tilde{B}_{t-1}/s_t)\mu_t$$

we get

$$\begin{aligned}
\tilde{P}_t^{t-1}\left(i_t|s_t,\tilde{\mathcal{H}}_1^{t-1}\right) &= \frac{\left[\tilde{B}_{t-1}/s_t\right]^{\tilde{A}_{t-1}}}{\Gamma\left(\tilde{A}_{t-1}\right)i_t!}\int_0^\infty\left(\frac{y_t}{(1+\tilde{B}_{t-1}/s_t)}\right)^{i_t+\tilde{A}_{t-1}-1}e^{-y_t}\frac{1}{1+\tilde{B}_{t-1}/s_t}dy_t \\
&= \frac{\left[\tilde{B}_{t-1}/s_t\right]^{\tilde{A}_{t-1}}}{\Gamma\left(\tilde{A}_{t-1}\right)i_t!}\frac{1}{(1+\tilde{B}_{t-1}/s_t)^{i_t+\tilde{A}_{t-1}}}\int_0^\infty y_t^{i_t+\tilde{A}_{t-1}-1}e^{-y_t}dy_t \\
&= \frac{1}{\Gamma\left(\tilde{A}_{t-1}\right)i_t!}\left(\frac{\tilde{B}_{t-1}/s_t}{1+\tilde{B}_{t-1}/s_t}\right)^{\tilde{A}_{t-1}}\frac{1}{(1+\tilde{B}_{t-1}/s_t)^{i_t}}\int_0^\infty y_t^{i_t+\tilde{A}_{t-1}-1}e^{-y_t}dy_t \\
&= \frac{\Gamma\left(i_t+\tilde{A}_{t-1}\right)}{\Gamma\left(\tilde{A}_{t-1}\right)i_t!}\left(\frac{\tilde{B}_{t-1}/s_t}{1+\tilde{B}_{t-1}/s_t}\right)^{\tilde{A}_{t-1}}\frac{1}{(1+\tilde{B}_{t-1}/s_t)^{i_t}}
\end{aligned}$$

where at the last step $\Gamma\left(i_t+\tilde{A}_{t-1}\right) = \int_0^\infty y_t^{i_t+\tilde{A}_{t-1}-1}e^{-y_t}dy_t$ is a complete gamma integral. Using

$$\tilde{\mu}_t^{t-1} = \frac{\tilde{A}_{t-1}}{\tilde{B}_{t-1}}s_t,$$

we obtain

$$1+\frac{\tilde{B}_{t-1}}{s_t} = \frac{\tilde{A}_{t-1}+\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1}}$$

and

$$\frac{\tilde{B}_{t-1}/s_t}{1+\tilde{B}_{t-1}/s_t} = \frac{\tilde{A}_{t-1}}{\tilde{A}_{t-1}+\tilde{\mu}_t^{t-1}}.$$

Substituting these expressions into $\tilde{P}_t^{t-1}\left(i_t|s_t,\tilde{\mathcal{H}}_1^{t-1}\right)$ yields

$$\begin{aligned}
\tilde{P}_t^{t-1}\left(i_t|s_t,\tilde{\mathcal{H}}_1^{t-1}\right) &= \frac{\Gamma\left(i_t+\tilde{A}_{t-1}\right)}{\Gamma\left(\tilde{A}_{t-1}\right)i_t!}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1}+\tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\frac{1}{\left(\frac{1}{\tilde{\mu}_t^{t-1}}\left(\tilde{\mu}_t^{t-1}+\tilde{A}_{t-1}\right)\right)^{i_t}} \\
&= \frac{\Gamma\left(i_t+\tilde{A}_{t-1}\right)}{\Gamma\left(\tilde{A}_{t-1}\right)\Gamma\left(i_t+1\right)}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1}+\tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1}+\tilde{A}_{t-1}}\right)^{i_t},
\end{aligned}$$

thereby establishing Equation (6).

C Value of Unemployment

The unemployed worker chooses search effort s_t and reservation wage r_t in period t to maximize the, possibly biased, subjective expected value of unemployment $\tilde{U}_t^{t-1}$, conditional on the information available at the end of period $t-1$,

$$\tilde{U}_t^{t-1} = \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\tilde{P}_t^{t-1}(0)\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{P}_t^{t-1}(i) E_w^{[i]} \max\left\{ W(w), \tilde{U}_{t+1}^{t-1} \right\} \right] \right\},$$

where $\tilde{P}_t^{t-1}(i)$ is shorthand notation for $\tilde{P}_t^{t-1}(i|s_t, \tilde{\mathcal{H}}_1^{t-1})$, $i = 0, 1, 2, ...$

Using the definition of $\tilde{h}_t^{t-1}(i|s_t, r_t)$ in equation (10), rewrite $\tilde{P}_t^{t-1}(0)\tilde{U}_{t+1}^{t-1}$ as

$$\tilde{P}_t^{t-1}(0)\tilde{U}_{t+1}^{t-1} = \left(1 - \sum_{i=1}^{\infty} \tilde{P}_t^{t-1}\left(i\right) \right) \tilde{U}_{t+1}^{t-1} = \left(1 - \sum_{i=1}^{\infty} \frac{\tilde{h}_t^{t-1}(i|s_t, r_t)}{1 - F^{[i]}\left(r_t\right)} \right) \tilde{U}_{t+1}^{t-1},$$

and rewrite $\sum_{i=1}^{\infty} \tilde{P}_t^{t-1}(i) E_w^{[i]} \max\left\{ W(w), \tilde{U}_{t+1}^{t-1} \right\}$ as

$$\begin{aligned}
&\sum_{i=1}^{\infty} \tilde{P}_t^{t-1}(i) E_w^{[i]} \max\left\{ W(w), \tilde{U}_{t+1}^{t-1} \right\} = \sum_{i=1}^{\infty} \tilde{P}_t^{t-1}(i) \left[\int_{r_t}^{+\infty} W(w) f^{[i]}\left(w\right) dw + \int_0^{r_t} \tilde{U}_{t+1}^{t-1} f^{[i]}\left(w\right) dw \right] \\
&\quad = \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \left[\int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw + \tilde{U}_{t+1}^{t-1} \frac{F^{[i]}\left(r_t\right)}{1 - F^{[i]}\left(r_t\right)} \right] \\
&\quad = \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{F^{[i]}\left(r_t\right)}{1 - F^{[i]}\left(r_t\right)} \tilde{U}_{t+1}^{t-1}.
\end{aligned}$$

Inserting these both expressions into the above equation for $\tilde{U}_t^{t-1}$,

$$
\begin{aligned}
\tilde{U}_t^{t-1} &= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\tilde{P}_t^{t-1}(0)\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{P}_t^{t-1}(i) E_w^{[i]} \max\left\{ W(w), \tilde{U}_{t+1}^{t-1} \right\} \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\left(1 - \sum_{i=1}^{\infty} \frac{\tilde{h}_t^{t-1}(i|s_t, r_t)}{1 - F^{[i]}\left(r_t\right)} \right) \tilde{U}_{t+1}^{t-1} \right. \right. \\
&\quad \left. \left. + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{F^{[i]}\left(r_t\right)}{1 - F^{[i]}\left(r_t\right)} \tilde{U}_{t+1}^{t-1} \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw \right. \right. \\
&\quad \left. \left. + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{F^{[i]}\left(r_t\right)}{1 - F^{[i]}\left(r_t\right)} \tilde{U}_{t+1}^{t-1} - \sum_{i=1}^{\infty} \frac{\tilde{h}_t^{t-1}(i|s_t, r_t)}{1 - F^{[i]}\left(r_t\right)} \tilde{U}_{t+1}^{t-1} \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw \right. \right. \\
&\quad \left. \left. - \sum_{i=1}^{\infty} \left(1 - F^{[i]}\left[r_t\right] \right) \frac{\tilde{h}_t^{t-1}(i|s_t, r_t)}{1 - F^{[i]}\left(r_t\right)} \tilde{U}_{t+1}^{t-1} \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw \right. \right. \\
&\quad \left. \left. - \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \tilde{U}_{t+1}^{t-1} \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\left(1 - \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \right) \tilde{U}_{t+1}^{t-1} \right. \right. \\
&\quad \left. \left. + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \int_{r_t}^{+\infty} W(w) \frac{f^{[i]}\left(w\right)}{1 - F^{[i]}\left(r_t\right)} dw \right] \right\} \\
&= \max_{\{r_t,\, s_t\}} \left\{ b_t - c\left(s_t\right) + \beta \left[\left(1 - \tilde{h}_t^{t-1}\left(s_t, r_t\right) \right) \tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) E_w^{[i]}\left[W(w) | w \geq r_t \right] \right] \right\},
\end{aligned}
$$

where $\tilde{h}_t^{t-1}\left(s_t, r_t\right)$ is defined in equation (11), and $E_w^{[i]}\left[W(w)|w \geq r_t\right] \equiv \int_{r_t}^{\infty} W(w) \frac{f^{[i]}(w)}{1 - F^{[i]}(r_t)} dw$.

D Derivation of first order conditions

D.1 Reservation wage

The first-order condition for the reservation wage is obtained by differentiating $\tilde{U}_t^{t-1}$ with respect to r_t:

$$\begin{aligned}
\frac{\partial \tilde{U}_t^{t-1}}{\partial r_t} &= \beta \Bigg[-\frac{\partial \tilde{h}_t^{t-1}(s_t, r_t)}{\partial r_t} \tilde{U}_{t+1}^{t-1} \\
&\quad + \sum_{i=1}^{\infty} \left(\frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial r_t} E_w^{[i]}\left[W(w)|w \geq r_t\right] + \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{\partial}{\partial r_t} \left(\int_{r_t}^{\infty} W(w) \frac{f^{[i]}(w)}{1 - F^{[i]}(r_t)} dw \right) \right) \Bigg]
\end{aligned}$$

Using $\tilde{h}_t^{t-1}(i|s_t, r_t) = \tilde{P}_t^{t-1}(i|s_t, \tilde{\mathcal{H}}_1^{t-1}) \left(1 - F^{[i]}(r_t)\right)$, it follows that $\frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial r_t} = -\tilde{P}_t^{t-1}(i|s_t, \tilde{\mathcal{H}}_1^{t-1}) f^{[i]}(r_t)$, so that applying Leibniz' rule to the derivative of the conditional expectation term yields

$$\begin{aligned}
\frac{\partial \tilde{U}_t^{t-1}}{\partial r_t} &= \beta \Bigg[\sum_{i=1}^{\infty} \tilde{P}_t^{t-1}\left(i|s_t, \tilde{\mathcal{H}}_1^{t-1}\right) f^{[i]}(r_t) \tilde{U}_{t+1}^{t-1} - \sum_{i=1}^{\infty} \tilde{P}_t^{t-1}\left(i|s_t, \tilde{\mathcal{H}}_1^{t-1}\right) f^{[i]}(r_t) E_w^{[i]}\left[W(w)|w \geq r_t\right] \\
&\quad + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \left(\int_{r_t}^{\infty} \frac{\partial}{\partial r_t} \left(W(w) \frac{f^{[i]}(w)}{1 - F^{[i]}(r_t)} \right) dw - W(r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \right) \Bigg] \\
&= \beta \Bigg[\sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \tilde{U}_{t+1}^{t-1} - \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} E_w^{[i]}\left[W(w)|w \geq r_t\right] \\
&\quad + \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \left(\int_{r_t}^{\infty} W(w) \frac{f^{[i]}(w) f^{[i]}(r_t)}{\left[1 - F^{[i]}(r_t)\right]^2} dw - W(r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \right) \Bigg] \\
&= \beta \Bigg[\sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \left[\tilde{U}_{t+1}^{t-1} - E_w^{[i]}\left[W(w)|w \geq r_t\right] + \left(E_w^{[i]}\left[W(w)|w \geq r_t\right] - W(r_t) \right) \right] \Bigg] \\
&= \beta \Bigg[\sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \left[\tilde{U}_{t+1}^{t-1} - W(r_t) \right] \Bigg] \\
&= \left[\tilde{U}_{t+1}^{t-1} - W(r_t) \right] \left[\beta \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1 - F^{[i]}(r_t)} \right] = 0
\end{aligned}$$

Under the maintained assumption that interview and wage offers arrive with positive probability, $\beta \sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{f^{[i]}(r_t)}{1-F^{[i]}(r_t)} > 0$, this first order condition further simplifies to

$$\tilde{U}_{t+1}^{t-1} - W(r_t) = 0 \qquad \Leftrightarrow \qquad \tilde{U}_{t+1}^{t-1} = W(r_t) = \frac{r_t}{1-\beta}.$$

D.2 Search effort

The first-order condition for search effort is obtained by differentiating $\tilde{U}_t^{t-1}$ with respect to s_t

$$\begin{aligned}
\frac{\partial \tilde{U}_t^{t-1}}{\partial s_t} &= -c'(s_t) + \beta \left[-\frac{\partial \tilde{h}_t^{t-1}(s_t, r_t)}{\partial s_t} \tilde{U}_{t+1}^{t-1} + \frac{\partial}{\partial s_t} \left(\sum_{i=1}^{\infty} \tilde{h}_t^{t-1}(i|s_t, r_t) E_w^{[i]}[W(w)|w \geq r_t] \right) \right] \\
&= -c'(s_t) + \beta \left[-\sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} \tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} E_w^{[i]}[W(w)|w \geq r_t] \right] \\
&= -c'(s_t) + \beta \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} \left[E_w^{[i]}[W(w)|w \geq r_t] - \tilde{U}_{t+1}^{t-1} \right] = 0
\end{aligned}$$

so that finally

$$c'(s_t) = \beta \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} \left[E_w^{[i]}[W(w)|w \geq r_t] - \tilde{U}_{t+1}^{t-1} \right].$$

D.3 Reservation wage and search effort equations

Reservation wage

Consider value function for unemployment $\tilde{U}_t^{t-1}$ at the optimum (s_t^*, r_t^*). Inserting first order

condition for the reservation wage we get

$$\begin{aligned}
\tilde{U}_t^{t-1} &= b_t - c\left(s_t^*\right) + \beta\left[\left(1-\tilde{h}_t^{t-1}\left(s_t^*, r_t^*\right)\right)\tilde{U}_{t+1}^{t-1} + \sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)E_w^{[i]}\left[W(w)|w \geq r_t^*\right]\right] \\
&= b_t - c\left(s_t^*\right) + \beta\left[\left(1-\sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)\right)W\left(r_t^*\right) + \sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)\int_{r_t^*}^{\infty}W(w)\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_t^*\right)}dw\right] \\
&= b_t - c\left(s_t^*\right) + \beta\left[W\left(r_t^*\right) + \sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)\left(\int_{r_t^*}^{\infty}W(w)\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_t^*\right)}dw - W\left(r_t^*\right)\right)\right] \\
&= b_t - c\left(s_t^*\right) + \beta\left[W\left(r_t^*\right) + \sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)\int_{r_t^*}^{\infty}\left[W(w) - W\left(r_t^*\right)\right]\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_t^*\right)}dw\right] \\
&= b_t - c\left(s_t^*\right) + \beta\left[\frac{r_t^*}{1-\beta} + \sum_{i=1}^{\infty}\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)\int_{r_t^*}^{\infty}\frac{w-r_t^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_t^*\right)}dw\right]
\end{aligned}$$

Evaluating this at $t+1$,

$$\tilde{U}_{t+1}^{t-1} = b_{t+1} - c\left(s_{t+1}^*\right) + \beta\left[\frac{r_{t+1}^*}{1-\beta} + \sum_{i=1}^{\infty}\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)\int_{r_{t+1}^*}^{\infty}\frac{w-r_{t+1}^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_{t+1}^*\right)}dw\right].$$

Since first order condition for the reservation wage requires $\tilde{U}_{t+1}^{t-1} = \frac{r_t^*}{1-\beta}$, inserting this into the left hand side of the above equation and rearranging, we get

$$\begin{aligned}
\frac{r_t^*}{1-\beta} &= b_{t+1} - c\left(s_{t+1}^*\right) + \beta\left[\frac{r_{t+1}^*}{1-\beta} + \sum_{i=1}^{\infty}\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)\int_{r_{t+1}^*}^{\infty}\frac{w-r_{t+1}^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_{t+1}^*\right)}dw\right] \\
\frac{r_t^* - (1-\beta)r_t^*}{1-\beta} + r_t^* &= b_{t+1} - c\left(s_{t+1}^*\right) + \beta\frac{r_{t+1}^*}{1-\beta} + \beta\sum_{i=1}^{\infty}\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)\int_{r_{t+1}^*}^{\infty}\frac{w-r_{t+1}^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_{t+1}^*\right)}dw \\
\frac{\beta r_t^*}{1-\beta} + r_t^* + c\left(s_{t+1}^*\right) &= b_{t+1} + \beta\frac{r_{t+1}^*}{1-\beta} + \beta\sum_{i=1}^{\infty}\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)\int_{r_{t+1}^*}^{\infty}\frac{w-r_{t+1}^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_{t+1}^*\right)}dw \\
r_t^* + c\left(s_{t+1}^*\right) &= b_{t+1} + \beta\left[\frac{r_{t+1}^*}{1-\beta} - \frac{r_t^*}{1-\beta}\right] + \beta\sum_{i=1}^{\infty}\tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*)\int_{r_{t+1}^*}^{\infty}\frac{w-r_{t+1}^*}{1-\beta}\frac{f^{[i]}(w)}{1-F^{[i]}\left(r_{t+1}^*\right)}dw
\end{aligned}$$

and finally

$$r_t^* + c\left(s_{t+1}^*\right) = b_{t+1} + \beta\left\{\sum_{i=1}^{\infty} \tilde{h}_{t+1}^{t-1}(i|s_{t+1}^*, r_{t+1}^*) E_w^{[i]}\left[\frac{w - r_{t+1}^*}{1-\beta} | w \geq r_{t+1}^*\right] + \triangle\, \tilde{U}_{t+1}^{t-1}\right\},$$

where

$$\triangle\, \tilde{U}_{t+1}^{t-1} \equiv \tilde{U}_{t+2}^{t-1} - \tilde{U}_{t+1}^{t-1} = \frac{r_{t+1}^* - r_t^*}{1-\beta},$$

as expressed in equations (13) and (14).

Search effort

Consider first order condition for the search effort. We can see that

$$\begin{aligned}
\frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} &= \frac{\partial}{\partial s_t}\left(\tilde{P}_t^{t-1}\left(i|s_t, \tilde{\mathcal{H}}_1^{t-1}\right)\left[1 - F^{[i]}(r_t)\right]\right) \\
&= \left[1 - F^{[i]}(r_t)\right] \frac{\Gamma\left(i + \tilde{A}_{t-1}\right)}{\Gamma\left(\tilde{A}_{t-1}\right)\Gamma(i+1)} \frac{\partial}{\partial s_t}\left(\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i}\right)
\end{aligned}$$

The derivative of the last term reads

$$\begin{aligned}
&\frac{\partial}{\partial s_t}\left(\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i}\right) \\
&= \left\{\frac{\tilde{A}_{t-1}}{\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}} \frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)\right\}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i} \\
&\quad + \left\{\frac{i}{\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i} \frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)\right\}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}} \\
&= \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right]\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i} \frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) \\
&\quad + \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right]\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i} \frac{i}{\tilde{\mu}_t^{t-1}} \frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) \\
&= \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right]\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i}\left\{\frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) + \frac{i}{\tilde{\mu}_t^{t-1}} \frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)\right.
\end{aligned}$$

Inserting this back into $\partial \tilde{h}_t^{t-1}(i|s_t, r_t)/\partial s_t$ we get

$$\begin{aligned}
\frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} &= \left[1 - F^{[i]}(r_t)\right] \frac{\Gamma\left(i + \tilde{A}_{t-1}\right)}{\Gamma\left(\tilde{A}_{t-1}\right)\Gamma(i+1)} \left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{\tilde{A}_{t-1}} \left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right)^{i} \\
&\quad \times \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right] \left\{ \frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) + \frac{i}{\tilde{\mu}_t^{t-1}} \frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) \right\} \\
&= \tilde{P}_t^{t-1}\left(i|s_t, \tilde{\mathcal{H}}_1^{t-1}\right)\left[1 - F^{[i]}(r_t)\right] \\
&\quad \times \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right] \left\{ \frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) + \frac{i}{\tilde{\mu}_t^{t-1}} \frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) \right\}
\end{aligned}$$

Consider next

$$\begin{aligned}
\frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) &= -\frac{\tilde{A}_{t-1}}{\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right)^2} \frac{\partial \tilde{\mu}_t^{t-1}}{\partial s_t}, \\
\frac{\partial}{\partial s_t}\left(\frac{\tilde{\mu}_t^{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}}\right) &= \frac{\frac{\partial \tilde{\mu}_t^{t-1}}{\partial s_t}\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right) - \frac{\partial \tilde{\mu}_t^{t-1}}{\partial s_t}\tilde{\mu}_t^{t-1}}{\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right)^2} = \frac{\tilde{A}_{t-1}}{\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right)^2} \frac{\partial \tilde{\mu}_t^{t-1}}{\partial s_t}
\end{aligned}$$

and

$$\frac{\partial \tilde{\mu}_t^{t-1}}{\partial s_t} = \frac{\partial}{\partial s_t}\left(\frac{\tilde{A}_{t-1}}{\tilde{B}_{t-1}} s_t\right) = \frac{\tilde{A}_t}{\tilde{B}_t} = \frac{\tilde{\mu}_t^{t-1}}{s_t}.$$

Inserting these back into $\partial \tilde{h}_t^{t-1}(i|s_t, r_t)/\partial s_t$ we get

$$\begin{aligned}
\frac{\partial \tilde{h}_t^{t-1}(i|s_t, r_t)}{\partial s_t} &= \tilde{P}_t^{t-1}\left(i|s_t, \tilde{\mathcal{H}}_1^{t-1}\right)\left[1 - F^{[i]}(r_t)\right] \\
&\quad \times \left[\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right] \left\{ -\frac{\tilde{A}_{t-1}}{\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right)^2} \frac{\tilde{\mu}_t^{t-1}}{s_t} + \frac{i}{\tilde{\mu}_t^{t-1}} \frac{\tilde{A}_{t-1}}{\left(\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}\right)^2} \frac{\tilde{\mu}_t^{t-1}}{s_t} \right\} \\
&= \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}} \frac{\tilde{\mu}_t^{t-1}}{s_t} \left\{ \frac{i}{\tilde{\mu}_t^{t-1}} - 1 \right\} \\
&= \tilde{h}_t^{t-1}(i|s_t, r_t) \frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}} \frac{i - \tilde{\mu}_t^{t-1}}{s_t}.
\end{aligned}$$

Therefore, first order condition for the search effort, evaluated at the optimum (s_t^*, r_t^*) and combined with first order condition for the reservation wage, becomes

$$\begin{aligned} c'(s_t^*) &= \beta \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t} \left[E_w^{[i]} \left[W(w) | w \geq r_t^* \right] - \tilde{U}_{t+1}^{t-1} \right] \\ &= \beta \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t} \left[E_w^{[i]} \left[W(w) - \tilde{U}_{t+1}^{t-1} | w \geq r_t^* \right] \right] \\ &= \frac{\beta}{1-\beta} \sum_{i=1}^{\infty} \frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t} \left[E_w^{[i]} \left[w - r_t^* | w \geq r_t^* \right] \right] \end{aligned}$$

where

$$\frac{\partial \tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{\partial s_t} = \frac{\tilde{A}_{t-1}}{\tilde{\mu}_t^{t-1} + \tilde{A}_{t-1}} \left(i - \tilde{\mu}_t^{t-1} \right) \frac{\tilde{h}_t^{t-1}(i|s_t^*, r_t^*)}{s_t},$$

as expressed in equations (15) and (16).

E The Method of Simulated Moments

E.1 Motivation

In Section 4.3, we argued that the identification arguments naturally lead to a method-of-moments estimator that minimizes the distance between the period-by-period moments of the key outcomes implied by the theoretical model and their observed counterparts. A complication, however, is that information on the key variables is available only for periods 1-4, 9, and 13. The absence of information on realized interviews is particularly problematic because these signals are central to the updating of beliefs at the end of each period, and these beliefs in turn are crucial for determining search choices in subsequent periods.

To address this problem, we employ a Method of Simulated Moments (MSM) estimator. For periods in which interview information is missing, we replace the missing values by simulated realizations that are consistent with both the observed history and the structure of the theoretical model. More specifically, for each period τ with missing interview information, we draw the number of interviews from a Poisson distribution with parameter ιs_τ^*, where s_τ^* denotes the optimal level of search effort implied by the worker's realized search behavior and *perceived* interview history up to period $t-1$, i.e., $\tilde{\mathcal{H}}_1^{t-1} \equiv \{s_\tau^*, \tilde{\Psi}_{t+1-\tau}(\hat{i}_\tau)\}_{\tau=1}^{t-1}$.[29]

[29] We prefer the MSM to Maximum Simulated Likelihood because it remains consistent even when the

Subsection E.2 describes the solution algorithm used within each iteration of the MSM estimator. Subsection E.3 formally presents the estimation procdure, while Subsection E.4 defines the moments used in the estimation.

E.2 Solution Algorithm for the Optimization Problem of the Worker

The worker's optimization problem is defined by (9) with terminal condition (12) at $t = T$, when UI benefits expire. Since welfare benefits remain constant thereafter, the problem becomes stationary beyond T. For a given belief distribution at the start of period t, we obtain the optimal sequence $\{s^*_\tau, r^*_\tau\}_{\tau=t}^{T}$ by backward induction, starting from the stationary solution at T. The belief distribution is held fixed at the posterior formed at the end of period $t-1$ (or at the initial prior when $t = 1$). Because beliefs are updated at the end of each period on the basis of realized job interviews, this procedure must be repeated for every period t. In practice, for each t, we recursively solve the first-order conditions (13) and (15) for $\{s_\tau, r_\tau\}_{\tau=t}^{T}$ while holding fixed the belief distribution inherited from period $t-1$.

The solution algorithm is conditional on the value of the structural parameter vector ξ fixed in the corresponding iteration of the MSM estimator formally defined in the next subsection. Moreover, because interview information is missing in some periods, the algorithm integrates simulated realizations of the number of job interviews that are consistent with both the past optimal choices and the perceived interview history $\tilde{\mathcal{H}}_1^{t-1}$. These simulated interview histories determine the sequence of posterior beliefs and hence the optimal choices along each simulated path.

E.3 Formal Definition of the MSM-Estimator

For any individual k, let $\mathcal{T}_k$ denote the set of periods for which information on the realized number of job interviews is available and let $\mathcal{T}_k^c$ denote the complementary set of periods for which this information is missing. Thus, $\mathcal{T}_k \cup \mathcal{T}_k^c$ corresponds to the complete unemployment spell of individual k. Let $\hat{\mathbf{i}}_{k,\mathcal{T}_k} = \{\hat{i}_{k,\tau}\}_{\tau\in\mathcal{T}_k}$ denote the observed numbers of job interviews and let $\hat{\mathbf{i}}^s_{k,\mathcal{T}_k^c} = \{\hat{i}^s_{k,\tau}\}_{\tau\in\mathcal{T}_k^c}$ denote the simulated numbers of job interviews for the periods with missing information. Given the structural parameter vector ξ and the combined sequence of

number of simulation draws S is small (see e.g. Cameron and Trivedi, 2005, p.402). Solving the individuals' non-stationary optimization problem is computationally demanding. Because this problem must be solved repeatedly for each simulated sequence of interview signals, the number of simulation draws is restricted to $S = 5$.

observed and simulated job interviews, let $\mathbf{m}_k^s\left(\xi; \hat{\mathbf{i}}_{k,\mathcal{T}_k} \cup \hat{\mathbf{i}}^s_{k,\mathcal{T}_k^c}\right)$ denote the vector of theoretical moments implied by the model for individual k. Averaging over S independent simulation draws yields

$$\mathbf{m}_{k,S}(\xi) = \frac{1}{S}\sum_{s=1}^{S} \mathbf{m}_k^s\left(\xi; \hat{\mathbf{i}}_{k,\mathcal{T}_k} \cup \hat{\mathbf{i}}^s_{k,\mathcal{T}_k^c}\right),$$

which is the simulated counterpart of the theoretical moment vector $\mathbf{m}_k(\xi)$. For the sample of n individuals, let $\mathbf{m}_S(\xi) = n^{-1}\sum_{k=1}^{n} \mathbf{m}_{k,S}(\xi)$ denote the vector of simulated theoretical sample moments and let $\hat{\mathbf{m}} = n^{-1}\sum_{k=1}^{n} \mathbf{m}_k$ denote the corresponding empirical sample moments. The MSM estimator is then obtained as the parameter vector that minimizes the weighted distance between the simulated and empirical sample moments:

$$\hat{\xi}_{n,S} = \arg\min_{\xi} \left(\mathbf{m}_S(\xi) - \hat{\mathbf{m}}\right)' \mathbf{W} \left(\mathbf{m}_S(\xi) - \hat{\mathbf{m}}\right), \tag{E-1}$$

where $\mathbf{W}$ is a weighting matrix. The structure and timing of actions and events in the theoretical model (see Section 3.1) provides a natural simulator for $\mathbf{m}_k^s\left(\xi; \hat{\mathbf{i}}_{k,\mathcal{T}_k} \cup \hat{\mathbf{i}}^s_{k,\mathcal{T}_k^c}\right)$, since it implies that the number of job interviews in period τ follows a Poisson distribution with mean $\mu^*_{k,\tau} = \iota s^*_{k,\tau}$.

Denoting by $\boldsymbol{\xi}_0$ the true parameter vector, Gouriéroux and Monfort (1997) show that $\hat{\boldsymbol{\xi}}_{n,S}$ is a consistent and asymptotically normal estimator of $\boldsymbol{\xi}_0$. Specifically,

$$\sqrt{n}\left(\hat{\boldsymbol{\xi}}_{n,S} - \boldsymbol{\xi}_0\right) \overset{a}{\sim} N(\mathbf{0}, \mathbf{Q}_S(\mathbf{W})),$$

where the asymptotic covariance matrix $\mathbf{Q}_S(\mathbf{W})$ is given by

$$\mathbf{Q}_S(\mathbf{W}) = \boldsymbol{\Sigma}_1^{-1}\boldsymbol{\Sigma}_2\boldsymbol{\Sigma}_1^{-1} + \frac{1}{S}\boldsymbol{\Sigma}_1^{-1}\mathbf{D}'\mathbf{W}\tilde{\mathbf{V}}_0\mathbf{W}\mathbf{D}\boldsymbol{\Sigma}_1^{-1}, \tag{E-2}$$

where $\boldsymbol{\Sigma}_1 = \mathbf{D}'\mathbf{W}\mathbf{D}$, $\boldsymbol{\Sigma}_2 = \mathbf{D}'\mathbf{W}\mathbf{V}_0\mathbf{W}\mathbf{D}$, $\mathbf{D} = E[\nabla_{\boldsymbol{\xi}}\mathbf{m}(\boldsymbol{\xi})]$, $\mathbf{V}_0 = Var[\mathbf{m}(\boldsymbol{\xi}) - \hat{\mathbf{m}}]$, and $\tilde{\mathbf{V}}_0 = Var[\mathbf{m}_S(\boldsymbol{\xi}) - \mathbf{m}(\boldsymbol{\xi})]$. Furthermore,

$$\mathbf{m}(\boldsymbol{\xi}) = n^{-1}\sum_{k=1}^{n} \mathbf{m}_k(\boldsymbol{\xi})$$

denotes the vector of theoretical sample moments evaluated using the complete set of true interview-arrival histories, including the interview realizations that are unobserved in the data. The first term, $\boldsymbol{\Sigma}_1^{-1}\boldsymbol{\Sigma}_2\boldsymbol{\Sigma}_1^{-1}$, corresponds to the asymptotic covariance matrix of the standard

method-of-moments estimator.

Gouriéroux and Monfort (1997) further show that

$$\overline{\mathbf{Q}}_S(\mathbf{W}) = \left(1 + S^{-1}\right) \boldsymbol{\Sigma}_1^{-1} \boldsymbol{\Sigma}_2 \boldsymbol{\Sigma}_1^{-1}$$

provides an upper bound on $\mathbf{Q}_S(\mathbf{W})$, thereby avoiding the need to evaluate $\tilde{\mathbf{V}}_0$. In practice, we use this upper bound as our estimator of the asymptotic covariance matrix. We estimate

$$\hat{\mathbf{D}} = n^{-1} \sum_{k=1}^{n} \nabla_{\boldsymbol{\xi}} \mathbf{m}_{k,S}(\hat{\boldsymbol{\xi}}_{n,S}),$$

and

$$\hat{\mathbf{V}}_0 = n^{-1} \sum_{k=1}^{n} \left(\mathbf{m}_{k,S}(\hat{\boldsymbol{\xi}}_{n,S}) - \mathbf{m}_k\right) \left(\mathbf{m}_{k,S}(\hat{\boldsymbol{\xi}}_{n,S}) - \mathbf{m}_k\right)'.$$

Following DellaVigna et al. (2017), the weighting matrix $\mathbf{W}$ is chosen as the diagonal matrix of the inverse variances of the empirical moments.

E.4 Specification of the Moments

The moments matched in the estimation are:
(i) cumulative hazard rates of unemployment duration by 40-day period;
(ii) the average number of job applications;
(iii) the average expected number of job interviews;
(iv) the average realized number of job interviews; and
(v) quantiles of the wage distribution conditional on a transition from unemployment to employment.

(i) *Cumulative hazard function of unemployment duration*
The empirical cumulative hazard function is estimated using the Nelson–Aalen estimator. Since the empirical hazard function is unconditional on the realization of job interviews, its theoretical counterpart is given by

$$\hat{h}_t = \frac{1}{n_t S} \sum_{s=1}^{S} \sum_{k=1}^{n_t} \sum_{j=1}^{\infty} \tilde{P}_{t,k}^{t-1}\left(j; \hat{\mathbf{i}}_{k,t-1} \cup \hat{\mathbf{i}}_{k,t-1}^{s}\right) \left[1 - F^{[j]}\left(r_{t,k}\left(\hat{\mathbf{i}}_{k,t-1} \cup \hat{\mathbf{i}}_{k,t-1}^{s}\right)\right)\right], \tag{E-3}$$

where $\hat{\mathbf{i}}_{k,t-1} \cup \hat{\mathbf{i}}^s_{k,t-1}$ denotes the set of observed and simulated interview realizations up to period $t-1$, n_t is the number of individuals whose unemployment spell lasts at least t periods, and $\{\hat{h}_t\}_{t=1}^{\bar{t}}$ is the set of estimated theoretical hazard rates, where $\bar{t}$ denotes the maximum observed unemployment duration. Summing (E-3) over time yields the theoretical counterpart of the Nelson–Aalen cumulative hazard function.

(ii) *Number of job applications*

The number of job applications serves as a measure of search effort. Its theoretical counterpart is

$$\hat{s}_t = \frac{1}{n_t S} \sum_{s=1}^{S} \sum_{k=1}^{n_t} s_{t,k} \left(\hat{\mathbf{i}}_{k,t-1} \cup \hat{\mathbf{i}}^s_{k,t-1} \right), \tag{E-4}$$

so that $\{\hat{s}_t\}_{t \in \hat{\mathcal{T}}}$ is the set of estimated theoretical mean search efforts in the periods $t \in \hat{\mathcal{T}}$ for which information on job applications is available. In our data, $\hat{\mathcal{T}} = \{1, 2, 3, 4, 9, 13\}$.

(iii) *Number of realized job interviews*

Under the assumption that interviews arrive according to a Poisson process with mean ιs_t, the theoretical counterpart of the observed number of interviews is

$$\hat{\hat{i}}_t = \frac{1}{n_t S} \sum_{s=1}^{S} \sum_{k=1}^{n_t} \iota s_{t,k} \left(\hat{\mathbf{i}}_{k,t-1} \cup \hat{\mathbf{i}}^s_{k,t-1} \right), \tag{E-5}$$

where $\{\hat{\hat{i}}_t\}_{t \in \hat{\mathcal{T}}}$ is the set of estimated theoretical expectations of the realized number of job interviews.

(iv) *Expected number of job interviews*

Following the belief-updating mechanism described in Section 3.2, the theoretical counterpart of the survey measure of expected interviews is

$$\hat{\tilde{\mu}}_t = \frac{1}{n_t S} \sum_{s=1}^{S} \sum_{k=1}^{n_t} \tilde{\mu}^{t-1}_{t,k}, \tag{E-6}$$

where $\{\hat{\tilde{\mu}}_t\}_{t \in \hat{\mathcal{T}}}$ is the set of estimated theoretical expectations of the expected number of job interviews in the periods for which this information is observed.

(v) *Quantiles of the distribution of accepted wages*

The cross-sectional density of observed accepted wages defined in (18) implies the cumulative distribution function

$$F_o(w^o; r_\tau) = \int_0^{w^o} f_o(w; r_\tau)\, dw,$$

which in turn defines the quantile function

$$q_p(r_\tau) = F_o^{-1}(p; r_\tau).$$

Pooling accepted wages across all unemployment durations, the theoretical p-th quantile of the accepted-wage distribution is

$$\hat{q}_p = \frac{1}{n_w S} \sum_{s=1}^{S} \sum_{k=1}^{n_w} q_{p,k} \left(r_{t_k,k} \left(\hat{\mathbf{i}}_{k,t_k-1} \cup \hat{\mathbf{i}}^s_{k,t_k-1} \right) \right), \tag{E-7}$$

where n_w denotes the number of observed accepted wages and t_k denotes the unemployment duration at which individual k exits to employment.

F Simulation of Time Profiles of Reservation Wages During the First Five Periods Depending on the Sequence of Job Interviews

Figure 4 displays the average reservation-wage profile in the no-treatment counterfactual based on 100 simulated trajectories for each of the 327 sampled individuals (both treated and controls). This average profile masks substantial heterogeneity arising from differences in unemployment benefits and previous-job earnings, which affect reservation wages in the first period, as well as from differences in the timing and number of realized job interviews and in the updating rule (Bayesian or quasi-Bayesian), which determine how beliefs about interview-arrival rates and, therefore, reservation wages evolve over time. To illustrate this heterogeneity, we classify simulated trajectories according to their interview sequences during the first four periods and report the reservation-wage profiles associated with the thirty most frequent sequences, separately for Bayesian and quasi-Bayesian updaters.

The wage profiles associated with these most frequent interview sequences are reported in Table A1 and displayed in Figures A4 and A5. For (quasi-)Bayesian updaters these thirty sequences represent 61% (62%) of all simulated trajectories. Since a given interview sequence may correspond to multiple reservation-wage profiles, the table reports average reservation wages

conditional on remaining unemployed. Consequently, the reported profiles are still affected by dynamic sorting, although much less than the average profile displayed in Figure 4 of the main text. Because reservation wages are chosen before interviews are realized and beliefs are updated, a four-period interview sequence gives rise to a sequence of five reservation wages.

Several insights emerge from this analysis. First, sequences consisting predominantly of negative signals, that is, an absence of job interviews, tend to generate declining reservation-wage profiles, whereas sequences containing positive signals tend to generate increasing reservation-wage profiles. Alternating positive and negative signals can in turn generate non-monotonic reservation-wage dynamics. This illustrates that the non-monotonic evolution of the average reservation wage should not be interpreted as the profile of some representative job seeker. Rather, it masks substantial heterogeneity in the evolution of individual reservation wages.

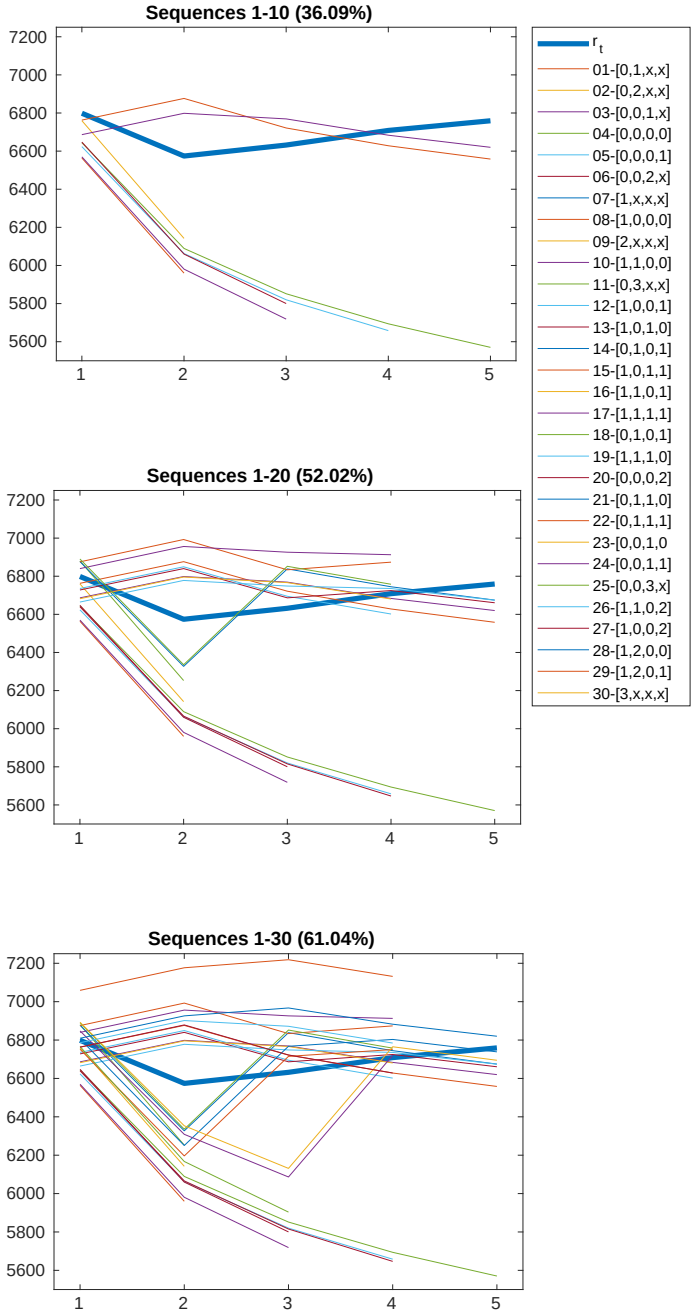
Second, for the first five periods, Bayesian and quasi-Bayesian updaters display qualitatively similar reservation-wage profiles for a given interview sequence. Differences become more apparent at the aggregate level shown in Figure 4, where the interaction of updating behavior with the distribution of interview sequences generates markedly different average dynamics.

Table A1: Thirty Most Frequent Simulated Interview Sequences and Corresponding Reservation-Wage Profiles of Bayesian and Quasi-Bayesian Updaters

	A: Bayesian learner											**B: quasi-Bayesian learner**										
Rank	*Interview invitations*				*Reservation wages*					*Freq.*	*Cumul.*	*Interview invitations*				*Reservation wages*					*Freq.*	*Cumul.*
	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=5	*%*	*freq., %*	t=1	t=2	t=3	t=4	t=1	t=2	t=3	t=4	t=5	*%*	*freq., %*
(1)	0	1	-	-	6564	5960	-	-	-	8.02	8.02	0	1	-	-	6575	5974	-	-	-	8.03	8.03
(2)	0	2	-	-	6760	6142	-	-	-	5.48	13.50	0	2	-	-	6762	6145	-	-	-	5.57	13.61
(3)	0	0	1	-	6570	5981	5719	-	-	4.82	18.32	0	0	1	-	6546	5962	5704	-	-	4.84	18.45
(4)	0	0	0	0	6644	6089	5852	5694	5570	3.52	21.84	0	0	0	0	6580	6028	5790	5632	5508	3.73	22.18
(5)	0	0	0	1	6624	6062	5820	5658	-	2.90	24.75	0	0	0	1	6759	6186	5939	5774	-	3.01	25.20
(6)	0	0	2	-	6647	6060	5800	-	-	2.86	27.60	1	-	-	-	6612	-	-	-	-	2.73	27.93
(7)	1	-	-	-	6609	-	-	-	-	2.57	30.17	0	0	2	-	6614	6026	5766	-	-	2.72	30.65
(8)	1	0	0	0	6763	6876	6721	6628	6568	2.18	32.35	1	0	0	0	6628	6920	6722	6572	6436	2.04	32.69
(9)	2	-	-	-	6656	-	-	-	-	1.90	34.25	0	3	-	-	6825	6201	-	-	-	2.03	34.72
(10)	1	1	0	0	6686	6798	6769	6684	6620	1.84	36.09	2	-	-	-	6484	-	-	-	-	1.87	36.59
(11)	0	3	-	-	6880	6253	-	-	-	1.83	37.92	1	0	0	1	6727	7024	6823	6670	-	1.86	38.45
(12)	1	0	0	1	6736	6850	6695	6602	-	1.82	39.75	1	1	0	0	6684	6978	6927	6787	6661	1.80	40.25
(13)	1	0	1	0	6728	6840	6687	6725	6661	1.72	41.46	1	0	1	0	6801	7100	6897	6946	6821	1.72	41.97
(14)	0	1	0	0	6877	6327	6839	6745	6675	1.63	43.09	1	0	1	1	6767	7068	6864	6914	-	1.64	43.61
(15)	1	0	1	1	6875	6993	6834	6874	-	1.58	44.67	0	1	0	0	6743	6197	6898	6752	6621	1.62	45.23
(16)	1	1	0	1	6682	6796	6766	6680	-	1.54	46.22	1	1	1	1	6769	7072	7020	6983	-	1.60	46.83
(17)	1	1	1	1	6840	6956	6926	6913	-	1.52	47.73	1	1	0	1	6713	7012	6960	6819	-	1.57	48.40
(18)	0	1	0	1	6890	6336	6852	6758	-	1.48	49.22	1	1	1	0	6821	7124	7071	7034	6912	1.56	49.95
(19)	1	1	1	0	6665	6778	6748	6736	6674	1.47	50.69	0	1	0	1	6942	6377	7103	6952	-	1.39	51.34
(20)	0	0	0	2	6640	6066	5815	5647	-	1.34	52.02	0	1	1	0	6652	6114	6806	6812	6693	1.35	52.69
(21)	0	1	1	0	6805	6251	6768	6803	6739	1.25	53.28	0	0	0	2	6557	5987	5738	5570	-	1.34	54.03
(22)	0	1	1	1	6752	6196	6715	6751	-	1.11	54.39	0	1	1	1	6915	6347	7076	7083	-	1.30	55.33
(23)	0	0	1	0	6893	6353	6131	6765	6695	1.09	55.47	0	0	1	0	6850	6318	6100	6924	6797	1.10	56.43
(24)	0	0	1	1	6848	6309	6086	6720	-	0.91	56.39	0	0	1	1	6957	6407	6179	7034	-	0.93	57.36
(25)	0	0	3	-	6766	6167	5903	-	-	0.84	57.23	1	2	1	0	6758	7057	7079	7014	6896	0.92	58.28
(26)	1	1	0	2	6786	6902	6872	6784	-	0.81	58.04	1	0	0	2	6805	7106	6902	6748	-	0.87	59.15
(27)	1	0	0	2	6763	6879	6722	6628	-	0.80	58.84	0	0	3	-	6833	6233	5971	-	-	0.84	59.99
(28)	1	2	0	0	6809	6926	6967	6883	6820	0.75	59.58	1	1	0	2	6771	7074	7022	6879	-	0.82	60.81
(29)	1	2	0	1	7059	7177	7219	7132	-	0.73	60.32	1	2	0	2	6805	7106	7128	6991	6868	0.82	61.63
(30)	3	-	-	-	6789	-	-	-	-	0.72	61.04	1	0	2	0	7160	7472	7259	7401	7276	0.75	62.38

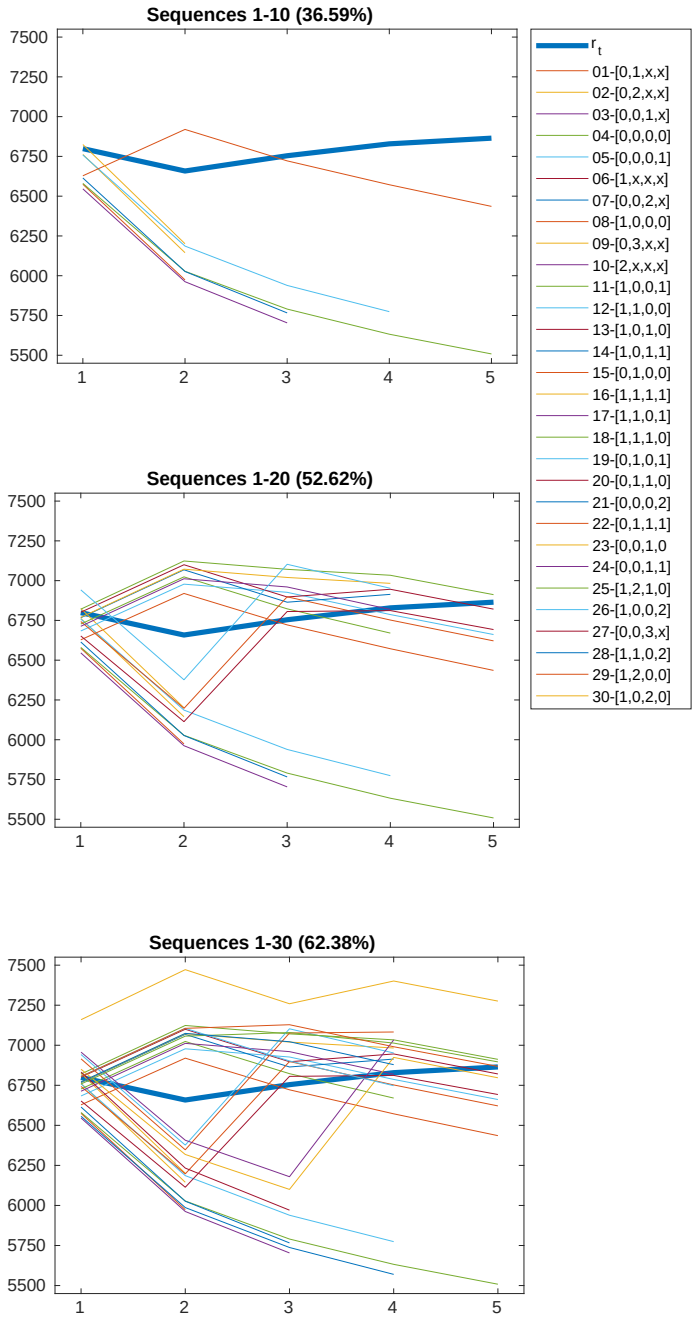
Note: Based on 100 simulated trajectories for each of the 327 sampled individuals, the table reports the 30 most frequent simulated interview sequences in the first four periods and the corresponding reservation-wage profiles for Bayesian (Panel A) and quasi-Bayesian (Panel B) updaters. A missing value in an interview sequence indicates an exit from unemployment. For individuals sharing the same interview sequence, average reservation wages are reported.

Figure A4: Thirty Most Frequent Simulated Interview Sequences and Corresponding Reservation-Wage Profiles of Bayesian Updaters



Note: The figure graphically represents Panel A of Table A1. The three panels successively display the reservation-wage profiles associated with the 10, 20, and 30 most frequent interview sequences for Bayesian updaters. The thick blue line corresponds to the average profile in Figure 4. In the legend x denotes an exit from unemployment.

Figure A5: Thirty Most Frequent Simulated Interview Sequences and Corresponding Reservation-Wage Profiles of Quasi-Bayesian Updaters



Note: The figure graphically represents Panel A of Table A1. The three panels successively display the reservation-wage profiles associated with the 10, 20, and 30 most frequent interview sequences for quasi-Bayesian updaters. The thick blue line corresponds to the average profile in Figure 4. In the legend x denotes an exit from unemployment.

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