

CES ifo

**12420
2026**

January 2026

Working Papers

Wage Expectations and Job Search

Steffen Altmann, Robert Mahlstedt, Malte Rattenborg,
Alexander Sebald, Sonja Settele, Johannes Wohlfart

CES ifo

Imprint:

CESifo Working Papers

ISSN 2364-1428 (digital)

Publisher and distributor: Munich Society for the Promotion
of Economic Research - CESifo GmbH

Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740

Email office@cesifo.de
<https://www.cesifo.org>

Editor: Clemens Fuest

An electronic version of the paper may be downloaded free of charge

- from the CESifo website: www.ifo.de/en/cesifo/publications/cesifo-working-papers
- from the SSRN website: www.ssrn.com/index.cfm/en/cesifo/
- from the RePEc website: <https://ideas.repec.org/s/ces/ceswps.html>

Wage Expectations and Job Search

Steffen Altmann Robert Mahlstedt Malte Jacob Rattenborg
Alexander Sebald Sonja Settele Johannes Wohlfart

January 20, 2026

Abstract

In a field experiment with 9,000 Danish job seekers, we study how unemployed workers' wage expectations affect job search and re-employment. In our survey, we generate exogenous variation in respondents' wage expectations by informing a random half of them about re-employment wages of comparable workers. The intervention increases job-finding as measured in administrative data for both initially optimistic and initially pessimistic respondents, but through different channels: initial optimists lower their reservation wages and intensify search, while pessimists raise reservation wages and redirect applications toward local vacancies. Consistent with spatial search frictions, narrowing the geographic scope accelerates job finding among pessimists.

JEL-Codes: D83, D84, J64.

Contact: Steffen Altmann, University of Würzburg and University of Copenhagen, steffen.altmann@uni-wuerzburg.de. Robert Mahlstedt, University of Copenhagen, robert.mahlstedt@econ.ku.dk. Malte Jacob Rattenborg, University of Copenhagen, malterattenborg@econ.ku.dk. Alexander Sebald, Copenhagen Business School, acs.eco@cbs.dk. Sonja Settele, University of Cologne, ECONtribute, Max Planck Institute for Behavioral Economics and CEBI, settele@wiso.uni-koeln.de. Johannes Wohlfart, University of Cologne, ECONtribute, Max Planck Institute for Behavioral Economics and CEBI, wohlfart@wiso.uni-koeln.de. **Acknowledgements:** We thank conference and seminar participants at the NBER Summer Institute, the EEG Workshop on Behavioral Economics, the IZA Beliefs Workshop, the Workshop on Subjective Expectations, the HiJos Workshop, the WZB Workshop on Innovations in Field and Survey Experiments, the Sixth Joint BoC-ECB-New York Fed Conference on Expectations Surveys, the Berlin Behavioral Econ Seminar, the Bundesbank, the CEBRA Inflation Webinar, the University of Cologne, the University of Copenhagen, Copenhagen Business School, the University of Innsbruck, Lund University, the University of Mannheim, Oxford University and the Vrije University of Amsterdam for helpful comments. Egshiglen Batbayar, Julian Goedel, Giorgos Louvaris and Constanze Zeiss provided excellent research assistance. **Funding:** Financial support through the Rockwool Foundation (project: 3039) is gratefully acknowledged. The activities of CEBI are funded by the Danish National Research Foundation (Grant DNRF134). Settele and Wohlfart: Funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/2-390838866. **Ethics approval:** Ethics approval was received from the IRB of the University of Copenhagen. **Pre-registration:** The experimental design, sampling procedures and main research questions were pre-registered at the AEA RCT Registry (AEARCTR-0012320).

1 Introduction

Expectations play a central role in theories of job search. While traditional models assume full information and rational expectations (McCall, 1970; Mortensen and Pissarides, 1994), a growing body of evidence points to the presence of information frictions and misperceptions among job seekers (He and Kircher, 2023; Krueger and Mueller, 2016; Mueller and Spinnewijn, 2023; Mueller et al., 2021). But how do beliefs and misperceptions shape job search empirically? This paper provides causal evidence on how job seekers' wage expectations—a key variable in job search models—influence their search behavior and labor market outcomes.

Studying the role of beliefs in job search is inherently challenging (Mueller and Spinnewijn, 2023). Measures of job seekers' beliefs are commonly not available or are collected only for small samples, as reaching the relevant population is difficult. Moreover, correlational evidence can be confounded by omitted variables, reverse causality, and measurement error in subjective beliefs. In addition, measures of search behavior are often self-reported and thus prone to noise, reporting biases, and intention–action gaps (Le Barbanchon et al., 2024). Consequently, there is only limited causal evidence on how job seekers' subjective expectations shape search behavior and re-employment outcomes. We overcome these challenges through a field experiment with unemployed workers in Denmark. Our study builds on a unique combination of three essential features.

First, the Danish research infrastructure allows us to sample an exceptionally large and representative group of unemployed job seekers. Drawing on the public employment service's registry of benefit recipients, we invited the full population of current claimants via the official digital public mailing system to participate in a survey on job search. This results in a final sample of more than 9,000 job seekers.

Second, our survey features an information provision experiment designed to generate exogenous variation in job seekers' expected wage offers. Specifically, we first elicit beliefs about the re-employment wages of comparable workers who recently found jobs after a spell of unemployment. We define these comparable workers for each job seeker based on a detailed set of characteristics, including pre-unemployment wages, industry, full- or part-time status, as well as age, gender, and unemployment duration. We then expose a random half of our sample to information on the true average re-employment wage of comparable workers, computed from administrative records covering the universe of Danish workers. The remaining survey participants do not receive any information and form the control group in our experiment. Finally, we elicit individuals' beliefs about their own next wage offer and other aspects related to their job search.

Our design generates exogenous shifts in individuals' expectations by correcting prior misperceptions about the re-employment wages of comparable workers. We rely on the (testable) assumption that job seekers view these wages as informative for their

own prospects. Our wage projections based on comparable workers predict the actual re-employment wages of control group respondents nearly one-to-one, supporting the validity of our approach.

Third, we link the data from our survey to administrative records on search activities and labor market outcomes, which overcome the challenges inherent in self-reported measures. We make use of click-level data on job seekers' browsing of job ads and recorded applications from Denmark's official job search platform, *jobnet.dk*, to construct granular measures of search effort and the targeted types of jobs. Moreover, we obtain precise information on individuals' employment status and realized wages from administrative data. We complement these data with survey measures of variables that are not observable in administrative data, such as reservation wages and willingness to adjust the occupational or geographic scope of search.

To illustrate how job seekers' expected earnings potential should influence their decisions, we start by presenting a job search model with subjective beliefs about future wage offers. According to the model, job seekers respond to wage information by adjusting their search strategies along two dimensions: (i) their selectivity in the job offers they are willing to accept and (ii) their search intensity. Selectivity—captured by reservation wages and acceptable non-wage attributes—shifts in the direction of the information shock about wage offers, provided that job seekers expect high-wage jobs to be associated with weakly better amenities. The prediction for adjustments in search intensity is ambiguous: lower wage expectations may discourage search by diminishing the expected returns to re-employment, but may encourage search if higher effort improves the quality of job offers.

In a first step of the empirical analysis, we study respondents' prior beliefs about the earnings potential of comparable workers. We detect strong heterogeneity in the extent to which these beliefs are aligned with the ground truth observed in the register data. On average, job seekers overestimate the re-employment wages of comparable workers by roughly 2%. However, about a quarter of our respondents overestimate average re-employment wages by more than 15%, while another fifth of our sample underestimate re-employment wages by at least 15%. These misperceptions partially seem to reflect job seekers' tendency to anchor their expectations about re-employment wages too heavily on the pre-unemployment wage: while the average job seeker correctly anticipates the direction of wage changes experienced by comparable workers relative to their previous salary, they underestimate the magnitude of these changes.

Our experiment is designed to generate exogenous variation in job seekers' beliefs about their next wage offer. Job seekers' belief updating in response to our treatment should depend on both the direction and magnitude of their initial misperceptions. For the causal analysis, we therefore group respondents by their perception gap, defined as the logarithmic difference between the actual average re-employment wage of compara-

ble workers and individuals' corresponding prior belief. Individuals with gaps between -2.5% and $+2.5\%$ form a “neutral” reference group that is not expected to update their beliefs in response to the treatment information. The remaining job seekers fall into four categories: moderate positive or negative gaps (between $\pm 2.5\%$ and $\pm 15\%$) and large positive or negative perception gaps (exceeding $\pm 15\%$). The random assignment to treatment and control group then allows us to estimate the causal effect of receiving wage information separately for individuals with different prior misperceptions.

Treated individuals update their expectations about their own next wage offer in response to information on re-employment wages of comparable job seekers. Individuals who were initially overly optimistic and received a negative information shock of 15% or more revise their expectations about the next wage offer downward by 3.8%, relative to control group members with similar prior beliefs. Conversely, initially pessimistic job seekers who receive a positive shock of 15% or more increase their wage expectations by 5.3%. Job seekers with more moderate perception gaps exhibit qualitatively similar but less pronounced updates compared to those with large perception gaps. Individuals whose initial beliefs are confirmed by the treatment do not update their expectations, suggesting that side effects of the treatment, such as priming, are minor (Haaland et al., 2023). The treatment effects on expected wage offers largely persist in a follow-up survey conducted about two weeks after the initial intervention, in which numerical anchoring and experimenter demand effects are likely limited (de Quidt et al., 2018). Overall, the strong first-stage effects of our intervention on expected wage offers show that job seekers regard information about the re-employment wages of comparable workers as relevant for their own wage prospects.

In the next step of our analysis, we examine the impact of our intervention on job search and subsequent labor market outcomes. We mostly focus on respondents who received large positive or large negative information shocks, for which we have the strongest first-stage variation in wage expectations.

We find that the information shocks strongly shift job seekers' reservation wages as measured in the survey. Treated job seekers who are initially highly optimistic—and who revise their wage expectations downward by 3.8%—reduce their reservation wages by approximately 1.6%, relative to similar job seekers in the control group. Initially highly pessimistic job seekers raise their reservation wage by roughly 3.9%.

Beyond reservation-wage adjustments, our design allows us to examine how the treatment affects various dimensions of job search behavior and subsequent labor market outcomes. We find that the margins of adjustment of job search vary with the direction of the information shock. Among initially highly optimistic job seekers, treated individuals not only lower their expected and reservation wages but also increase their search intensity. On average, they click on 0.4 more job ads on the public employment service's job board in the week after the intervention—an increase of about 26%. This pattern is

consistent with the idea that a negative update leads job seekers to recognize the need for more intensive search to secure an attractive offer. Increased effort and lower reservation wages translate into improved job finding: initially over-optimistic job seekers receiving a large negative shock are 4pp more likely to be employed within six months of the intervention than comparable control group participants. The higher re-employment rates are accompanied by increases in accumulated working hours and earnings over the same period. However, conditional on re-employment, treated job seekers earn slightly lower hourly wages than their counterparts in the control group.

Initially highly pessimistic job seekers do not change their overall search effort when updating positively about their earnings potential. Instead, the treatment makes them more selective: besides increasing their reservation wages, treated individuals also shift their search toward larger firms with higher average pay and narrow the geographic scope of their search. They report a lower willingness to relocate or commute and their actual applications on the public employment service's online platform cover a smaller geographic radius. The treatment does not affect other dimensions of search, such as targeted occupations. Surprisingly, the increased selectivity is accompanied by *improved* employment outcomes: among initially overly pessimistic job seekers, the treatment increases employment rates over the next three months by 4pp and increases accumulated working hours and earnings. A potential explanation are mitigated spatial search frictions: job seekers typically face lower chances of generating acceptable offers as the distance to vacancies increases (Caliendo et al., 2023b; Schmutz and Sidibé, 2019). By making job seekers more selective, the intervention redirects their search toward the local market, where re-employment prospects appear to be higher.

Several additional findings support this interpretation. First, the additional matches created by positive shocks occur entirely within job seekers' own municipality. Second, these employment effects are concentrated among job seekers who previously searched broadly across regions and thus had the greatest scope to redirect their search locally. Third, descriptive evidence shows that, for Danish job seekers, applications within their municipality of residence are more than twice as likely to result in job finding as applications outside their broader region. Finally, additional survey evidence suggests that job seekers underestimate the difficulties of non-local search, plausibly leading them to focus too much on distant openings in the absence of our intervention.

Among job seekers receiving moderate updates, the treatment effects on reservation wages, search effort, and labor market outcomes align qualitatively with those among individuals with more extreme priors, but are smaller and less precisely estimated. By contrast, treatment effects are mostly muted and insignificant for the neutral group, whose prior beliefs are confirmed by the treatment.

Related literature and contribution Our study builds on and contributes to several strands of the literature. A growing literature examines the role of subjective beliefs in

the search behavior of unemployed workers (see Mueller and Spinnewijn, 2023, for an overview). These studies show that job seekers are often overly optimistic about their job-finding prospects (Balleer et al., 2026; He and Kircher, 2023; Mueller et al., 2021; Spinnewijn, 2015) and misperceive their earnings potential (Caliendo et al., 2023a; Conlon et al., 2018; Drahs et al., 2018; Krueger and Mueller, 2016). We add to this literature by demonstrating that beliefs have important causal effects on job search behavior and labor market outcomes. Exogenous changes in wage expectations affect not only wage demands—the most direct margin—but also other key dimensions of search, including search intensity and the geographic scope of search. These findings highlight that wage expectations are a central input in the job search process and underscore the relevance of earlier descriptive and structural evidence on beliefs and misperceptions.

Other previous and concurrent work examines subjective wage expectations among employed workers. Jäger et al. (2024) show that currently employed workers anchor their beliefs about outside options too strongly on their current wages, and that correcting these misperceptions alters intentions regarding wage negotiations and job switching. Miano (2025) demonstrates that information on occupation-level wages shifts employed workers' perceived outside options, with more limited effects on search intentions. A key difference to these papers is that we focus on job search while unemployed, which differs fundamentally from on-the-job search, e.g., due to lower application success rates (Faberman et al., 2022). Moreover, unlike these studies, we focus on understanding the causal effects of wage expectations on actual search behavior and re-employment outcomes as measured in detailed administrative data.¹

Related field experiments study the effects of directing job seekers toward specific jobs or occupations (Altmann et al., 2022; Behaghel et al., 2022; Belot et al., 2019, 2025; Le Barbanchon et al., 2023) or of broader interventions alleviating search frictions and misperceptions, such as job fairs and mentoring (Abebe et al., 2025; Alfonsi et al., 2022; Bandiera et al., 2025; Banerjee and Sequeira, 2023). While retaining the external validity of a field experiment, our intervention is closer to a “mechanism experiment”: we isolate the effect of a single key variable in search models—beliefs about available wage offers—on multiple dimensions of job search and labor market outcomes.

Our study also builds on a broad literature using observational data to study job search outcomes, including reservation wages (Banfi and Villena-Roldán, 2019; Fluchtmann et al., 2024; Krueger and Mueller, 2016), wage bargaining (Roussille, 2024), search intensity (DellaVigna et al., 2022; Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021), or the demand for non-wage amenities (Escudero et al., 2024; Le Barbanchon

¹Other related work studies how college graduates' earnings expectations shape initial career choices, with implications for gender differences in entry-level wages (Cortés et al., 2023; Jiang and Zen, 2025). Carranza et al. (2022) and Kiss et al. (2023) show that access to assessment results about absolute and relative skills shapes job search decisions of labor market entrants in developing country contexts. Koşar and van der Klaauw (2025) and Caplin et al. (2023) study workers' beliefs about earnings growth and uncertainty.

et al., 2021; Maestas et al., 2023). Our causal estimates suggest that changes in expected wages pass through to reservation wages with an elasticity of around one-half, while search effort and search radius respond negatively to wage expectations. These estimates could inform future theoretical work.

Finally, we add to a literature that has used information interventions to study the formation and consequences of subjective beliefs in various domains, such as macroeconomics and finance (Coibion and Gorodnichenko, 2025; Fuster and Zafar, 2023; Haaland et al., 2023). Only few of these studies have linked information interventions with non-self-reported outcome data on decisions (Bottan and Perez-Truglia, 2025; Chopra et al., 2025; Coibion et al., 2023, 2021, 2020; Schnorpfeil et al., 2025). Our paper stands out in that it links an information intervention in a high-stakes setting with unusually granular outcome measures from various sources, including click-by-click data from a search platform and detailed register data on labor market outcomes.

2 Empirical setup

2.1 Unemployment and job search in Denmark

Similar to other advanced economies, unemployment in Denmark fluctuates with economic growth, and wage inequality has been rising in recent years (Andersen, 2023). The Danish labor market is relatively flexible and in this sense more comparable to the US than other European labor markets (Kreiner and Svarer, 2022).

Denmark's unemployment benefit system closely resembles those in other European countries. It operates on a two-tier structure. Displaced workers who have paid voluntary contributions for at least 12 months within the past three years are eligible to receive unemployment insurance (UI) benefits for up to two years. These benefits replace 90% of previous income, capped at DKK20,359 gross per month (\approx USD2,850; values for 2024), resulting in an average effective replacement rate of around 60%. When UI benefits expire, or if individuals previously chose not to contribute to the UI system (about 15% of Danish wage earners), they may apply for means-tested social assistance, which provides substantially lower support. For a single person, the maximum social assistance benefit is DKK12,326 per month (\approx USD1,730).

While receiving unemployment benefits, individuals must actively search for new employment. This requirement applies to both UI and social assistance recipients, provided they are deemed capable of working full-time by their caseworker. The official online platform of Denmark's public employment services, *jobnet.dk*, serves as the primary interface between unemployed workers and public employment services. All benefit recipients are required to log in at least once per week. The platform features a comprehensive vacancy database, which is one of Denmark's two most frequently used job boards and in-

cludes approximately 90% of all posted job openings in the country. Vacancy postings on this platform—and other Danish job boards—typically omit earnings information, which potentially contributes to the existence of misperceptions. Benefit recipients are required to document their job search activities—including details of their applications—in a centralized *joblog* system on the online platform, to demonstrate compliance with search requirements (see Fluchtmann et al., 2024, for further details). Typically, benefit recipients must submit at least two applications per week, while there are no restrictions on the types of jobs they can apply for. Although job seekers are officially required to accept suitable job offers, this requirement is only weakly enforced and easy to circumvent.

2.2 Wage projections

Our survey elicits prior beliefs and provides information on the monthly re-employment wages of past job seekers similar to the respondent. The focus on similar workers' re-employment wages allows us to abstract from respondents' idiosyncratic circumstances, which are unobserved by the researcher. This approach facilitates a comparison of subjective beliefs with a clearly defined ground truth from register data and allows us to generate exogenous variation in beliefs by providing job seekers with this information.

Demographic cells We define comparable workers as unemployed job seekers from the past ten years who shared seven characteristics with the respondent at the time of re-employment: age (≤ 35 , 36-50, > 50), gender (male, female), education (lower secondary or less, upper secondary, tertiary), type of previous employment (10-29, ≥ 30 hours per week), current unemployment duration (≤ 3 , 4-6, 7-9, 10-12, 13-18, 19-24, > 24 months), previous monthly salary (ten brackets for full-time, six for part-time), and previous industry (seven categories). This approach yields 14,112 demographic cells.

Our choice of cells was guided by the following considerations. First, all characteristics have to be observable in the register data. Second, survey respondents need to be able to self-classify. Third, the cells need to be sufficiently granular to be considered meaningful by respondents for their own situation. Fourth, the characteristics should strongly predict re-employment wages in Denmark. Finally, for ethical reasons, the wage information derived from registers should meet a minimum precision standard. We therefore require at least 30 observations per cell in the register data and screen out survey participants in smaller cells. This restriction reduces the number of cells from 14,112 to 7,362, which still cover 95.5% of the underlying population of re-employed job seekers.

Construction of wage projections For the information treatment, we calculate average monthly re-employment wages before taxes and excluding pension contributions within each cell. We use Danish labor market registers covering all unemployed job seekers re-employed between 2013 and 2022.

Appendix Table A.1 reports results from a regression of log re-employment wages on the seven demographic dimensions used to construct the cells. Previous wages are a strong predictor of re-employment wages, but the estimated coefficient is substantially below one: conditional on the included demographic variables, a 10% higher pre-unemployment wage is associated with an only 1.5% higher re-employment wage. This magnitude is consistent with a large literature showing that re-employment wages only imperfectly reflect past wages, as unemployment often entails persistent losses driven by industry shifts, occupational downgrading, and other labor market frictions (Jacobson et al., 1993; Jung and Kuhn, 2019; Schmieder et al., 2023). In our setting, average re-employment wages are 9% lower than pre-unemployment wages. Other characteristics also matter: men, those with higher education, middle-aged and older workers, those previously employed in construction or manufacturing, and those earlier in their spell secure higher re-employment wages. Appendix Figure A.5 displays how the patterns translate into wage *changes* relative to pre-unemployment for different subgroups. Most strikingly, previously high-earning job seekers who are late in their spell incur the largest wage penalties, whereas previously low-earning job seekers experience the largest gains.

Validation We validate our wage projection using two different out-of-sample predictions. Figure 1 plots the relationship between our wage projection and actual re-employment wages for control group respondents (Panel A) and for the full population of unemployed job seekers in October 2023 (Panel B). Variation in the benchmark maps nearly one-to-one into realized wages in both cases (both $p < 0.001$), with an R-squared of 0.29 and 0.20, respectively. The strong predictive power suggests that changes in the economy between the period underlying the treatment information and the time of our experiment—such as technological shifts—are unlikely to be a concern.²

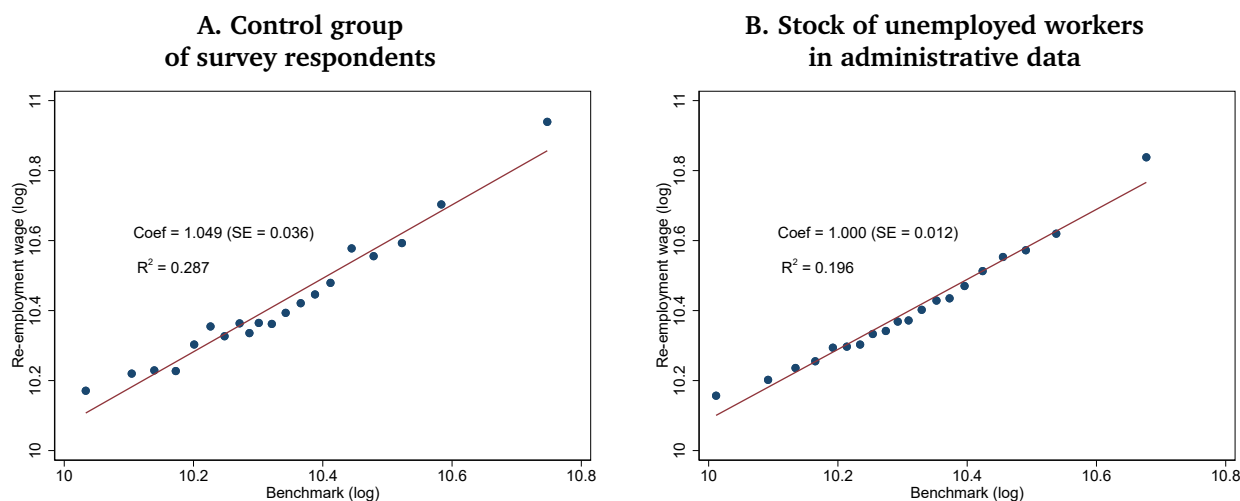
2.3 Survey and experimental design

Our design builds on a main online survey that embeds an information provision experiment and a follow-up survey. We next provide an overview of both surveys. The full instructions can be found in Appendices D.1 and D.2.

Main survey: Background characteristics and prior beliefs The main survey begins by eliciting respondents' background characteristics along seven dimensions: age, gender, education, and current length of unemployment, as well as full-time or part-time status, monthly wages and industry in the previous job. All respondents are then asked

²One potential source of such changes is inflation. Our wage projections do not account for inflation, as we aimed to ensure that the projections are easily understood even by respondents with low economic literacy. Inflation would likely lead to an underprediction of actual re-employment wages. If anything, we observe such underprediction for respondents with very low prior wages; for most respondents, projected and realized wages are well aligned. Two factors may help explain this close alignment: first, inflation and nominal wage growth in Denmark were modest until the post-pandemic shock; second, the post-pandemic inflation surge had only a limited and sluggish pass-through to nominal wages (Huidrom, 2023).

Figure 1 Out-of-sample validation of wage projections



Notes: The figure illustrates the out-of-sample predictive power of the information provided in our experiment for actual re-employment wages. Panel A displays a binned scatter plot (with 20 bins) relating re-employment wages observed in the administrative records to our wage projection for control group respondents who find a full-time job within six months after the survey ($N = 2,775$). Panel B extends this analysis to the full stock of unemployed workers observed in the administrative data at the time of the survey (October 2023), excluding survey respondents ($N = 38,585$).

to estimate the average re-employment wage of unemployed job seekers over the past ten years who were “similar” to them when starting a new full-time job. We restate the seven demographic characteristics and clarify that respondents should estimate the average monthly gross wage before taxes and excluding pension contributions of past job seekers who shared these characteristics with the respondent.

Main survey: Tailored information treatment A random half of the respondents are then informed about the actual average monthly re-employment wage of job seekers in their demographic cell. We display the information in a bar chart comparing the cell-level pre-unemployment wage, the respondent’s prior belief, and the actual average re-employment wage from administrative data. The information on actual re-employment wages is also presented in text format above the chart. Appendix Figure A.3 displays an example treatment screen. Respondents in the control group receive no information and proceed directly to the next survey section.

Main survey: Expected wage offers and intended search behavior After the treatment stage, we first ask all respondents to provide a point estimate of the monthly wage they expect if offered a full-time job within the next four weeks. In addition to the point forecast, respondents report their perceived probabilities that the next offered wage falls into five mutually exclusive and collectively exhaustive bins, which are centered on their previous wage.³ Finally, we elicit outcomes related to job search behavior. Most impor-

³The bins are: below 80%, between 80–95%, 95–105%, 105–120%, and above 120% of the previous wage. We calculate means and standard deviations by assigning midpoints to the three inner bins and 72.5% and 127.5% of the previous wage to the lower and upper bins, respectively.

tantly, respondents report their reservation wage—the lowest wage at which they would accept a full-time job in the next four weeks—and their willingness to make concessions on non-wage characteristics such as location, occupation, or working conditions.

Follow-up survey To address the concern that immediate treatment effects on our main survey-based outcomes reflect experimenter demand effects or numerical anchoring, we re-elicited these outcomes in a follow-up survey one to two weeks after the main survey, when such concerns should be mitigated (de Quidt et al., 2018; Haaland et al., 2023). Specifically, we again elicit respondents’ beliefs regarding the average re-employment wage of comparable workers (not elicited post-treatment in the main survey) and their expected next wage offer. The follow-up survey does not provide any new information, nor does it repeat the initial treatment information.

2.4 Survey administration and sample

Survey administration We invited all individuals registered as unemployment benefit recipients in Denmark as of October 23, 2023, to participate in our main survey.⁴ We distributed the survey invitations through Denmark’s official digital government mailing system, with a reminder sent to non-respondents after one week. The survey remained open for about five weeks. We invited those who completed the main survey to a follow-up survey one to two weeks after completion. Participation in both surveys was voluntary, but incentivized through a raffle of 30 gift cards, each worth DKK1,000 (\approx USD140).

Sample In total, 13,234 individuals completed the main survey, corresponding to a response rate of 15.8%. Those who (i) had already accepted a job, (ii) sought only part-time work, (iii) had never been employed, or (iv) belonged to a population cell with fewer than 30 observations in the register data were directed to a shortened version of the survey and excluded from the experiment. We drop respondents in the top and bottom percentiles of response time in the main survey, as extremely short or long durations likely indicate inattention to the survey. The final sample comprises 9,247 respondents, of whom 3,912 also completed the follow-up survey.⁵

Table 1 reports summary statistics and balance tests for both the main and the follow-up sample, alongside population benchmarks from administrative data. Our sample closely resembles the population of job seekers, though older individuals, women, those with higher education, previously full-time employed, and those with shorter unemployment durations are somewhat over-represented. The sample is well-balanced across treatment and control group in both surveys. We nevertheless control for a comprehensive set of observables in all estimations.

⁴This includes all UI beneficiaries and social assistance recipients deemed fit for full-time work by their caseworker as of October 22, 2023.

⁵We drop those in the top and bottom percentiles of response time to the main survey also from the follow-up sample, but do not restrict the follow-up sample by response time to the follow-up.

Table 1 Summary statistics and balance tests

	Mean values			Balance stat.	Mean values		Balance stat.
	Full	Main survey		<i>P</i> -value	Follow-up survey		<i>P</i> -value
	population	Treated	Control		Treated	Control	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age							
Below 36 years	0.39	0.33	0.33	0.72	0.27	0.27	0.97
36-50 years	0.28	0.27	0.26	0.78	0.25	0.25	0.96
Above 50 years	0.33	0.40	0.41	0.56	0.48	0.48	0.94
Gender							
Female	0.51	0.57	0.55	0.19	0.54	0.50	0.02
Male	0.49	0.43	0.45	0.19	0.46	0.50	0.02
Level of education							
Elementary school	0.16	0.12	0.12	0.92	0.10	0.10	0.97
High school	0.43	0.37	0.39	0.02	0.37	0.38	0.87
University	0.40	0.51	0.49	0.03	0.53	0.53	0.89
Previous employment							
Full-time	0.79	0.87	0.87	0.79	0.88	0.89	0.52
Part-time	0.20	0.13	0.13	0.79	0.12	0.11	0.52
Current unemployment duration (in months)	11.96	6.59	6.69	0.52	6.69	6.88	0.40
Previous industry							
Agriculture	0.01	0.01	0.01	0.27	0.01	0.01	0.51
Manufacturing	0.11	0.12	0.12	0.72	0.12	0.13	0.27
Construction	0.06	0.05	0.05	0.54	0.04	0.05	0.30
Trade	0.25	0.22	0.23	0.23	0.20	0.20	0.97
Business services	0.25	0.21	0.20	0.64	0.24	0.22	0.41
Public sector	0.26	0.32	0.30	0.03	0.33	0.31	0.28
Other services	0.05	0.08	0.09	0.25	0.07	0.08	0.36
Previous monthly wage (in DKK)	32,187	31,222	31,000	0.49	33,290	33,663	0.48
F-test joint sign.				0.90			0.76
Number of observations	83,563	4,628	4,619	9,247	1,974	1,929	3,903

Notes: The table reports summary statistics and balance tests for our study sample. Column (1) presents observable characteristics of all unemployed job seekers at the time of the survey launch. Columns (2)–(3) report characteristics of participants in the main survey by treatment status, with Column (4) showing *p*-values for differences between treatment and control groups. Columns (5)–(6) report characteristics of participants in the follow-up survey, with Column (7) showing the corresponding balance tests. Columns (1), (2), (3), (5), and (6) show percentage shares unless indicated otherwise.

2.5 Administrative outcomes

A key feature of our approach is the integration of rich administrative outcomes. Unlike survey-based measures, these outcomes are immune to demand effects, consistency bias in survey responses, intention–behavior gaps, and imperfect recall of decisions.

We link the survey data with administrative records from two sources. First, we use data on the respondents’ job search behavior from the official online platform of the Danish public employment services (*jobnet.dk*). This includes applications recorded in the centralized system (*joblog*) and click-by-click data from the platform’s job board. The recorded applications allow us to study how job seekers allocate applications across re-

gions and occupations. However, they do not reliably capture search intensity, as many job seekers exactly comply with the requirement of documenting two applications per week, likely omitting additional ones (Fluchtmann et al., 2024). By contrast, the click data provide a good proxy for search intensity through the number of viewed job openings. They also reveal which firms individuals consider, allowing us to calculate the size and average wages paid by the targeted firms. Second, we exploit comprehensive register data from Statistics Denmark on the respondents' labor market outcomes. These data provide monthly information on employment status, working hours, labor earnings, and occupation as reported by employers.

3 Theoretical framework

To guide our empirical analysis, we discuss the effects of wage expectations in a stylized job search model. The model incorporates subjective beliefs (Mueller and Spinnewijn, 2023) and characterizes search strategies along two dimensions: (i) job seekers' selectivity with respect to job offers and (ii) their search intensity.

Model setup During job search, individuals receive a flow utility b and choose their search effort s . Vacancies vary in both wages and non-wage job characteristics (Hall and Mueller, 2018), such as location or working conditions. The overall quality of an offer is defined as: $v = w + \theta a$, where w denotes the wage, a represents amenities, and θ captures the marginal value of amenities. Job offers are drawn independently from a distribution with density $f(v; s)$. The realized value v is revealed only upon receiving an offer, at which point individuals decide whether to accept or reject it. Formally, v is a realization of the random variable $V \sim F(\cdot; s)$, with the average value of an offer denoted by

$$\mu = \mathbb{E}[V] = \mu_w + \theta(\alpha + \beta\mu_w),$$

where μ_w is the expected average wage offer. Job seekers hold beliefs about the systematic relationship between wages and amenities of the form $\mathbb{E}[a | w] = \alpha + \beta w$. Here, α captures the perceived baseline level of amenities, while β governs the direction and strength of the perceived association between wage offers and non-wage characteristics.

The search effort s affects not only the arrival rate of offers but also their quality in the sense of first-order stochastic dominance (FOSD). Specifically, for any $s_2 > s_1$,

$$F(v; s_2) \leq F(v; s_1) \quad \text{for all } v,$$

with strict inequality for some v . Intuitively, exerting more effort shifts the offer distribution toward higher-quality jobs. The job finding rate is given by $\lambda = 1 - F(\bar{v}; s)$, where \bar{v} denotes the reservation value, i.e., the minimum job quality a job seeker is willing to

accept. The cost of search effort is captured by an increasing and convex function $\gamma(s)$.⁶

Given a discount factor ρ , individuals choose their optimal search intensity s^* and the reservation threshold \bar{v} by maximizing the present value of being unemployed:

$$U = \max_{s, \bar{v}} b - \gamma(s) + \rho \left(U + \int_{\bar{v}}^{\infty} (v - U) dF(v; s) \right). \quad (1)$$

Job seekers hold subjective beliefs about the average wage offer $\hat{\mu}_w$ and, consequently, about the average job value $\hat{\mu}$ implied by the distribution F . They then maximize their utility as if these beliefs were the true values.⁷

We expect information about the wage potential of comparable workers to shift job seekers' perceived average wage offer $\hat{\mu}_w$ toward the true value, μ_w . This belief update may, in turn, affect (i) job seekers' selectivity, reflected in the reservation threshold \bar{v} , and (ii) their optimal search intensity s^* . Since individuals with different prior beliefs receive shocks in different directions, the resulting adjustments depend on their initial beliefs. In what follows, we summarize the key mechanisms through which positive shocks to wage expectations, $\hat{\mu}_w$, affect the two dimensions of job seekers' search strategy, with further details provided in Appendix B. By the same reasoning, negative shocks may have opposing effects through reductions in wage expectations.

Selectivity First, adjusting wage expectations changes job seekers' selectivity, as reflected in the reservation value \bar{v} (see Appendix B.1). In the simple case where jobs differ only in wages ($v = w$), the prediction is straightforward: the reservation value coincides with the reservation wage, which shifts in the direction of the shock—being more optimistic about future offers makes it more attractive to wait for a better one.

When jobs also differ in non-wage characteristics ($v = w + \theta a$), the responses become more nuanced and depend on the marginal value of amenities θ and the perceived relationship between wages and amenities β . If job seekers expect a positive wage–amenity relationship ($\beta \geq 0$)—i.e., high-wage jobs are associated with weakly better amenities—higher wage expectations increase reservation wages and, under a mild sufficient condition (see Appendix B.1), also amenity requirements. If job seekers expect compensating differentials—high-wage jobs offer worse conditions—but attach little weight to amenities ($-1/\theta < \beta < 0$), the same shock still raises reservation wages but plausibly lowers amenity requirements (see Appendix B.1). In this case, job seekers are willing to accept worse conditions in return for better pay. Finally, when compensating differentials are

⁶These assumptions imply a generalized version of McCall's (1970) random search framework, consistent with the fact that job postings in Denmark typically omit wage information and other key characteristics. As Nekoei and Weber (2017) note, the generalized random search framework is equivalent to a directed search model, where job seekers observe vacancy attributes and choose which jobs to target, and yields qualitatively similar predictions.

⁷Note that Equation (1) does not include a separate parameter for offer arrivals. In this formulation, search effort s directly determines the distribution of job offers $F(\cdot; s)$, so the probability of receiving an acceptable job in a given period is $1 - F(\bar{v}; s)$, which is already embedded in the integral term.

steep and amenities highly valued ($\beta \leq -1/\theta$), a positive shock to wage expectations can reduce both reservation wages and amenity requirements. Here, higher wage expectations lower the expected job value because they signal poor non-wage amenities, which matter to job seekers. This, in turn, leads to a reduction in overall selectivity.

Search intensity Second, job seekers' wage expectations influence search intensity, but the net effect is ambiguous a priori (see Appendix B.2). On the one hand, raising $\hat{\mu}_w$ increases the perceived returns to search since, *at a fixed reservation value*, it raises the likelihood of receiving an acceptable offer. This incentivizes greater search effort.

However, there is an opposing mechanism because $\hat{\mu}_w$ directly affects the reservation value \bar{v} . When higher expectations *increase the reservation value*, the likelihood that a given offer will be accepted falls, which reduces the returns to search. If search effort only affects the arrival rate of offers but not their quality, the positive effect dominates, so higher wage expectations still encourage greater effort. However, under the more plausible assumption of first-order stochastic dominance (FOSD)—where greater effort improves the distribution of available offers—the negative effect is reinforced. In this case, a positive shock to wage expectations makes it more likely that a given level of effort yields an acceptable offer. This reduces the pressure to search intensively, potentially discouraging effort and rendering the net effect ambiguous.

Summary In a job search model with subjective beliefs, responses to changes in wage expectations hinge on perceptions of the search environment. Selectivity—i.e., reservation wages and acceptable non-wage attributes—moves in the direction of the wage-information shock, provided job seekers do not perceive compensating differentials between wages and amenities. Search intensity is shaped by two opposing forces: higher wage expectations raise the expected returns to re-employment and thus encourage effort, but they may also reduce effort if greater search improves the quality of offers.

4 Results

4.1 Prior beliefs

We start by providing descriptive evidence on respondents' wage expectations absent the treatment. For beliefs about cell-level reemployment wages—elicited pre-treatment—we rely on the full sample. For beliefs about respondents' own next wage offer—elicited post-treatment—we restrict the sample to the control group.

Beliefs about re-employment wages of comparable workers There is substantial heterogeneity in the accuracy of respondents' prior beliefs about the re-employment wages of comparable workers. Panel A of Figure 2 displays a histogram of the difference between prior beliefs and the ground truth calculated from register data. On average, job

seekers appear to be reasonably well calibrated, overestimating re-employment wages of comparable workers by just 2%. Yet, many job seekers hold substantial misperceptions: only about 10% of the sample hold beliefs within 2.5% of the ground truth. 25% of our respondents overestimate actual re-employment wages by more than 15%, while 20% underestimate them by more than 15%. The remaining respondents hold moderate misperceptions between $\pm 2.5\%$ and $\pm 15\%$, with roughly equal shares of overestimators (21%) and underestimators (23%). Overall, there are substantial misperceptions about re-employment wages of comparable workers, giving our information treatment ample room to generate variation in beliefs. Throughout the analysis, we refer to individuals with negative (positive) perception gaps—i.e., those who overestimate (underestimate) re-employment wages of comparable workers—as initial optimists (pessimists).

Comparing oneself to others Job seekers’ beliefs about the wages of comparable workers are closely aligned with their beliefs about their own next wage offer. Panel B of Figure 2 displays the distribution of the difference between beliefs about oneself and about one’s population cell. On average, respondents expect to be offered a wage just slightly higher than their peers’ average re-employment wage. About two-thirds of the respondents expect their next wage offer to be within $\pm 10\%$ of the average re-employment wage of comparable workers. Appendix Figure A.4 displays binned scatter plots of (i) self-beliefs against population cell-level beliefs and, for control group respondents who secure a job, (ii) the difference between beliefs about one’s own next wage offer and actual re-employment wages against misperceptions about one’s group’s average re-employment wage. In both cases, we detect a strong alignment. These patterns corroborate the validity of our approach, which seeks to generate variation in self-beliefs by providing population cell-level information.

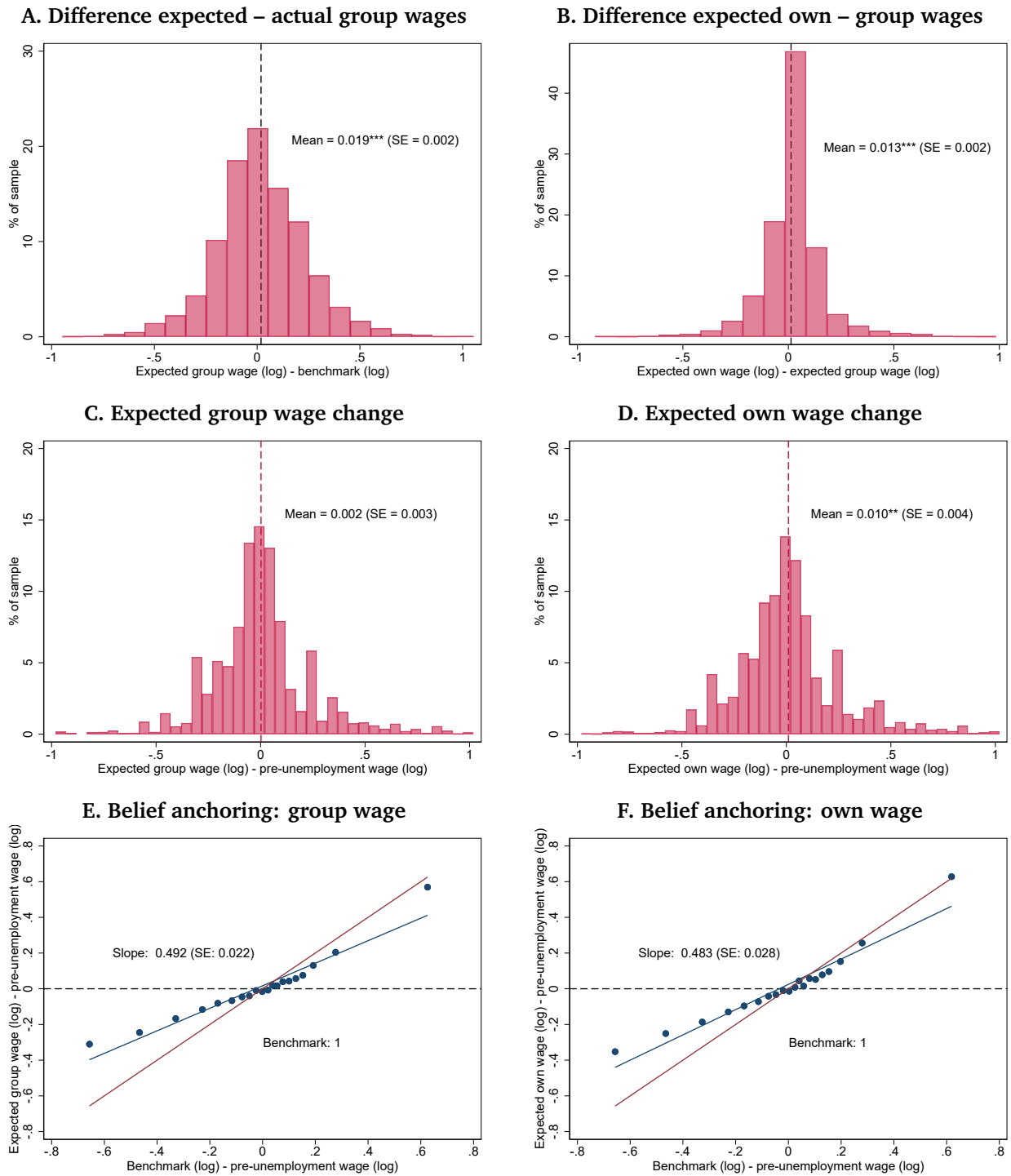
Pre-unemployment wages and wage expectations How are beliefs about re-employment wages linked to pre-unemployment wages? Since respondents are asked to assess full-time re-employment wages, we focus on previously full-time employed workers, ensuring comparability between pre- and post-unemployment wages.

Panel C of Figure 2 presents a histogram of perceived wage changes—beliefs about re-employment wages relative to pre-unemployment wages—for comparable workers. On average, respondents believe that unemployment is not associated with a wage change. We detect a similar pattern for self-beliefs (Panel D).

To quantify the relationship between perceived and actual wage changes, we follow the approach of Jäger et al. (2024) and regress the respondents’ perceived log wage change for comparable workers on the actual wage change implied by our wage projections.⁸ Panel E of Figure 2 displays a binned scatter plot of this relationship. The red 45-degree

⁸We partial out log pre-unemployment wages to account for any mechanical relationship arising from pre-unemployment wages entering the construction of both the dependent and the independent variable. Appendix C.1 shows that our results are robust to excluding this control.

Figure 2 Characteristics of job seekers' wage expectations absent the treatment



Notes: The figure illustrates job seekers' wage expectations absent the intervention. Panels A, C, and E are based on treatment and control groups, while Panels B, D, and F are based on control-group respondents only. Panels A and B show distributions of expected minus actual re-employment wages of comparable workers (Panel A, $N = 9,322$) and of respondents' expected own next wage offer minus expected wages of comparable workers (Panel B, $N = 4,352$). Panels C and D show distributions of expected wages of comparable workers minus pre-unemployment wages (Panel C, $N = 8,039$) and of respondents' expected own next wage offers minus pre-unemployment wages (Panel D, $N = 4,020$) among previously full-time employed respondents. Panels E and F show binned scatter plots (20 bins) relating expected and actual wage changes from pre- to post-unemployment among previously full-time employed workers, using expected wages of comparable workers in Panel E ($N = 8,039$) and expected own next wage offers in Panel F ($N = 4,020$).

line indicates correct beliefs, while the black horizontal line at zero reflects wage expectations that fully align with the previous wage. The estimated slope of 0.5 implies that a 10% actual wage change is associated with a perceived change of only 5%. This pattern suggests that beliefs about re-employment wages are anchored to the pre-unemployment wage: they are too close to the previous wage and too far from the actual re-employment wage. Anchoring appears to be asymmetric. Workers predicted to face wage penalties expect re-employment wages close to the previous wage, while those predicted to incur wage gains align more closely with the benchmark (the slope differs significantly, $p < 0.001$). To illustrate the magnitude of this asymmetry, individuals in the bottom decile of the distribution of predicted wage changes underestimate the wage penalty by roughly 28.3%, while individuals in the top decile underestimate wage gains by only 6.4%. Panel F shows that the anchoring pattern persists when population-level wage beliefs are replaced with respondents' beliefs about their own next offer. Appendix C.1 presents an extensive sensitivity analysis for these results, highlighting robustness to measurement error, potential “mechanical” correlations, and alternative benchmarks.

The finding that job seekers appear to anchor their wage expectations on previous wages is consistent with evidence that job seekers often set reservation wages close to their previous salary (Koenig et al., 2024; Krueger and Mueller, 2016). The degree of anchoring we detect among unemployed job seekers (slope of 0.5) appears somewhat smaller than the extent to which employed workers anchor their beliefs about outside options on their current wage (Jäger et al. (2024) estimate a slope of 0.1). This could reflect a reduced salience of previous wages or the influence of new information among unemployed job seekers.

Appendix Figure A.5 shows how actual cell-level wage changes (Panel A) and respondents' corresponding misperceptions (Panel B) vary across demographic groups. Most groups correctly anticipate the direction of wage changes but underestimate their magnitude. Misperceptions are largest among groups facing severe wage penalties after unemployment—such as those with high previous wages or job seekers who have been unemployed for at least six months. In contrast, misperceptions are smaller for groups that typically experience wage gains relative to their previous salary.

4.2 Updating about own wage potential

We next examine the first-stage effects of our information treatment on the respondents' beliefs about their own next wage offer.

Empirical strategy Treated individuals receive different information shocks depending on the difference between the actual re-employment wage of comparable workers and their prior belief: some learn that wages are higher than expected, others that they are lower. To capture these differences in the direction and size of information shocks, we

divide our sample into five groups depending on their perception gap, defined as the log difference between the actual average re-employment wage of comparable workers and the respondent’s prior belief about it.

We define a “neutral” group as respondents with a perception gap between -2.5% and $+2.5\%$. While the treatment should not shift the level of these respondents’ beliefs, it may reduce the respondents’ uncertainty about their next wage offer. We divide the remaining sample into four roughly equal-sized groups. Those with a moderate (2.5% to 15%) or large positive perception gap (exceeding 15%) are initially pessimistic about re-employment wages and are expected to update positively about their wage potential in response to the information. Those with a moderate (-15% to -2.5%) or large (lower than -15%) negative gap are initially overly optimistic and should update negatively when treated. We demonstrate the robustness of our findings to alternative cutoffs.

The random assignment of respondents into the treatment or the control group ensures that we can identify the causal effect of receiving wage information within each of the five prior-belief groups. As shown in Appendix Table A.2, job seekers with different initial beliefs also differ in other characteristics. In principle, heterogeneity in treatment effects across groups could reflect differences in other group characteristics rather than in prior beliefs. This is a well-known issue in information provision experiments (Haaland et al., 2023), and we address this possibility in robustness checks presented below.

Finally, in our main analysis, we winsorize respondents’ subjective wage expectations—as well as all other wage-related outcome variables—at the 5th and 95th percentiles to mitigate the influence of outliers.

Point forecasts We first examine how information about the re-employment wages of comparable workers affects job seekers’ point expectations about their own next wage offer. Panel A of Figure 3 presents the treatment effects separately for each of the five groups defined according to the extent of prior misperceptions. Job seekers view information on the re-employment wages of comparable workers as relevant for their own future wage offers. Those receiving a large positive shock—for whom the signal exceeds the prior belief by at least 15% —raise their wage offer expectations by about 5.2% ($p < 0.001$) relative to control group members with similar prior beliefs. Conversely, those receiving a large negative shock lower their expectations by 3.8% ($p < 0.001$). Respondents with moderate perception gaps (between $\pm 2.5\%$ and $\pm 15\%$) adjust their expectations in the predicted direction but by smaller, though still statistically significant, amounts. The neutral group shows no significant belief revision.⁹ Relating the treatment effects on own wage expectations to the information shocks about comparable workers’ re-employment wages implies learning rates between 12% and 34% . This is

⁹Appendix Table A.3 shows that treatment effects for moderate and large over- and under-estimators differ significantly from those for the neutral group, supporting the view that changes in wage expectations reflect genuine learning rather than side effects such as priming or salience (Haaland et al., 2023).

within the range of learning rates estimated in other information experiments that shift beliefs about personal outcomes with population group-level information (Bottan and Perez-Truglia, 2025; Haaland et al., 2023; Roth et al., 2022; van Rooij et al., 2024).

Persistence in the follow-up One concern is that the initial changes in respondents' expected next wage offer reflect unconscious numerical anchoring on the information rather than genuine belief updating (Cavallo et al., 2017). By definition, such numerical anchoring is short-lived and should not persist in a follow-up survey (Haaland et al., 2023). Similarly, experimenter demand effects should be mitigated in a follow-up, where respondents are less likely to recall the details of the presentation of the treatment information (de Quidt et al., 2018). We therefore examine the persistence of treatment effects on wage beliefs in the follow-up, conducted one to two weeks after the intervention.

Appendix Figure A.6 shows the persistence of treatment effects in the follow-up survey. Panel A reports effects on beliefs about the past re-employment wages of comparable workers, elicited only in the follow-up. The respondents qualitatively recall the treatment information, although at a somewhat reduced magnitude. Panel B presents effects on expected own next wage offers, alongside the corresponding main-survey estimates for the subsample of respondents who later participated in the follow-up. The downward revision among those receiving a large negative shock persists at nearly its initial magnitude. The effects for those with large positive or moderate gaps somewhat decrease in size and statistical significance, though they remain statistically indistinguishable from the initial estimates. Overall, the extent of persistence is similar to comparable information provision experiments and mitigates concerns related to numerical anchoring or demand effects (Haaland et al., 2023).

Subjective distributions We also analyze respondents' updating about their next wage offer as measured with a subjective probability distribution centered on the respondent's pre-unemployment wage. Appendix Figure A.7 presents treatment effects on the mean and the standard deviation implied by the distribution. The effects on the mean align with the estimates for point forecasts but are somewhat smaller, possibly because the available bins constrain the beliefs respondents can express. In the neutral group, the treatment significantly reduces the standard deviation, indicating reduced uncertainty about wages. We detect no significant effects on uncertainty for those with moderate or large perception gaps.

4.3 Changes in job search behavior and labor market outcomes

Having established strong first-stage effects of the intervention on wage expectations, we next analyze its downstream impacts on job search and labor market outcomes.

4.3.1 Job search behavior

We draw on several data sources: survey-based measures, click data from the public employment service’s job board, and administrative records on registered job applications. Our analysis focuses on different dimensions of respondents’ search strategies, including selectivity in wages and non-wage characteristics as well as search intensity. Figure 3 summarizes the main findings and Appendix Table A.4 presents evidence on complementary outcomes.

Selectivity in wages The information shocks affect job seekers’ reservation wage—the lowest monthly wage they would accept—in line with standard search theory (see Panel B of Figure 3). Treated individuals who were strongly over-optimistic (perception gap below -15%)—and who revise their wage expectations downward by 3.8% —reduce their reservation wage by 1.6% ($p = 0.022$), relative to their non-treated counterparts. Conversely, treated job seekers who were initially moderately or strongly pessimistic increase their reservation wages by 1.4% ($p = 0.008$) and 3.9% ($p < 0.001$), respectively. Moderate negative and neutral shocks have no significant effects on reservation wages.

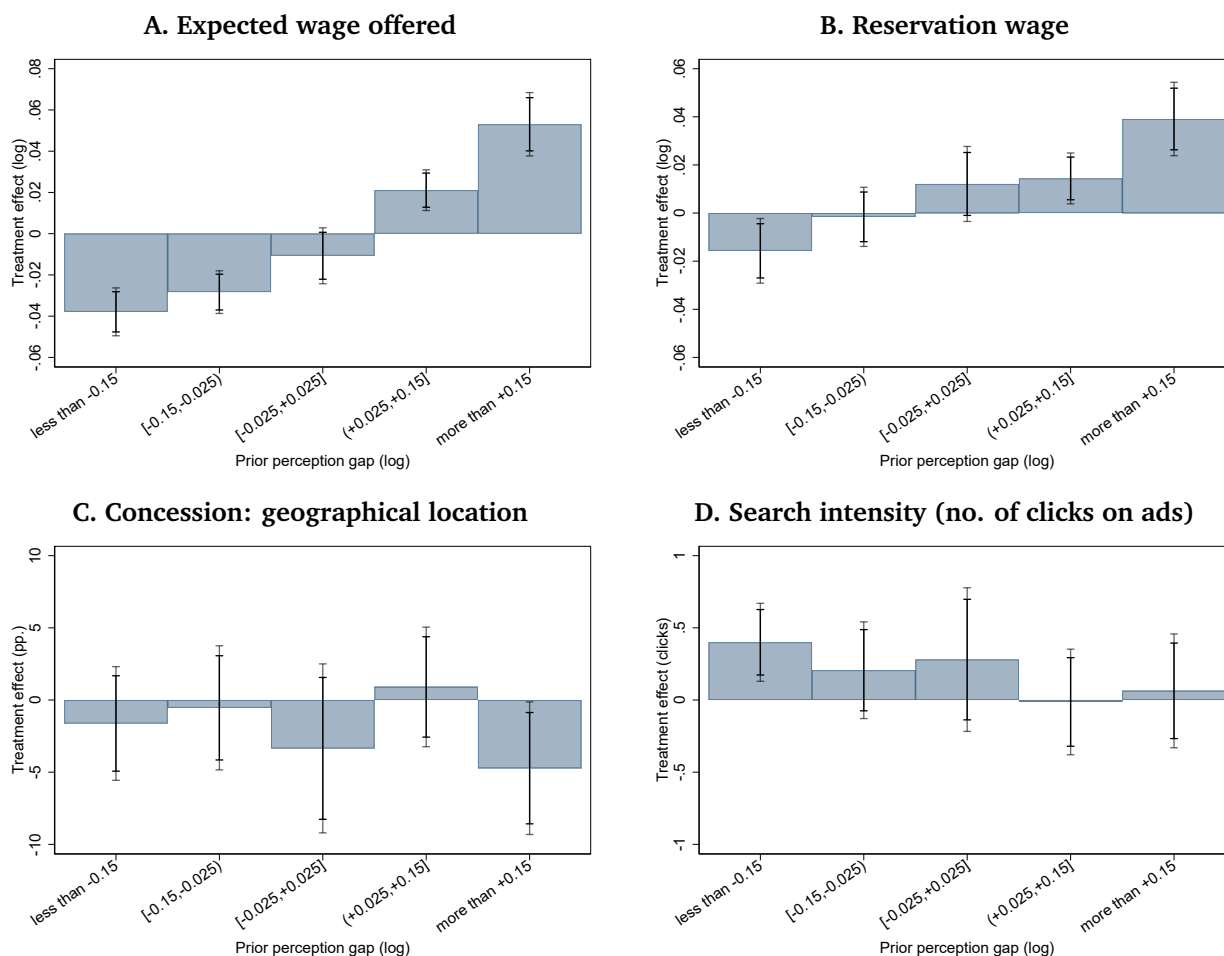
We also scale the treatment effects on reservation wages by the corresponding “first-stage” effects on wage expectations using a 2SLS approach (see Panel A of Appendix Figure A.8): a 1% change in expected offered wages leads to a 0.4% (0.7%) change in reservation wages following large downward (upward) shifts in wage expectations.¹⁰

We complement our reservation-wage estimates with click-by-click data from the on-line platform on the firms targeted by participants. Large positive shocks appear to make job seekers more ambitious in their search: as shown in Appendix Table A.4, individuals receiving large positive updates apply to firms offering higher monthly pay and to larger firms, which are known to pay higher wages (Brown and Medoff, 1989). In the other groups—in which treated job seekers receive negative or smaller positive shocks—we detect no treatment effects on the types of targeted firms.

Selectivity in non-wage characteristics The increased selectivity among job seekers receiving a large positive shock is reflected not only in higher reservation wages but also in the non-wage characteristics of targeted jobs. In the survey, respondents report their willingness to make concessions in three dimensions: geographic location (relocation or long commutes), work conditions (awkward hours, exhausting work, poor conditions, or uninteresting tasks), and skill requirements (switching professions, additional training, or jobs below one’s qualifications). Panel C of Figure 3 shows that large positive shocks reduce job seekers’ willingness to accept jobs requiring relocation or long commutes by 4.7pp (-9% , $p = 0.044$). This suggests that positive wage information makes job

¹⁰We focus on the two groups with large prior misperceptions, as we have strong first-stage variation in wage expectations for these groups. Because the intervention could, in principle, affect beliefs beyond the average next wage offer, this analysis should be viewed purely as a scaling exercise that facilitates the interpretation of the magnitudes.

Figure 3 Treatment effects on expected wages and job search behavior



Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on individuals' job search behavior. The wage respondents expect to be offered in their next job offer (log), reservation wage (log), as well as the willingness to change location and work conditions are measured in the main survey. The search intensity refers to the number of clicks on job ads on the online platform of public employment services, *jobnet.dk*, measured within the first week after the main survey. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers.

$N=2,323$ (less than -0.15); $N=1,980$ (-0.15 to -0.025); $N=1,043$ (-0.025 to +0.025); $N=2,178$ (+0.025 to +0.15); $N=1,723$ (more than +0.15).

seekers more selective—not only by raising their wage demands but also by narrowing the geographic scope of search. Scaling by the first stage implies that a 1% increase in wage expectations is associated with a 0.9pp reduction in the willingness to accept long commutes or relocation (see Panel C of Appendix Figure A.8).

Consistent with the survey results, application data from the online platform show a narrowing of geographic scope in response to positive wage information (Appendix Table A.4, Column 1). In contrast to the effects on geographic scope, positive shocks have no effects on the respondents' occupational focus or desired working conditions. For negative shocks, we find no evidence of changes in selectivity regarding any non-wage characteristic (Appendix Table A.4, Panel E).

Search intensity We also analyze treatment effects on search intensity as proxied with the number of jobs a participant views on the job board embedded in the public employment platform. Panel D of Figure 3 shows treatment effects on clicks during the calendar week following the main survey. Most notably, the intervention encourages initially highly over-optimistic job seekers to increase their search activity: treated individuals in this group click on 0.4 more job ads ($p = 0.004$), a 26% increase relative to the control group. In a 2SLS estimation, a 1% reduction in wage expectations leads to 0.11 additional job-ad clicks—a 7% increase relative to the mean (see Panel B of Appendix Figure A.8). The effect on vacancy clicks persists when extending the time horizon to the four weeks following the survey (Appendix Table A.4). We detect no changes in search intensity following positive or smaller negative information shocks.

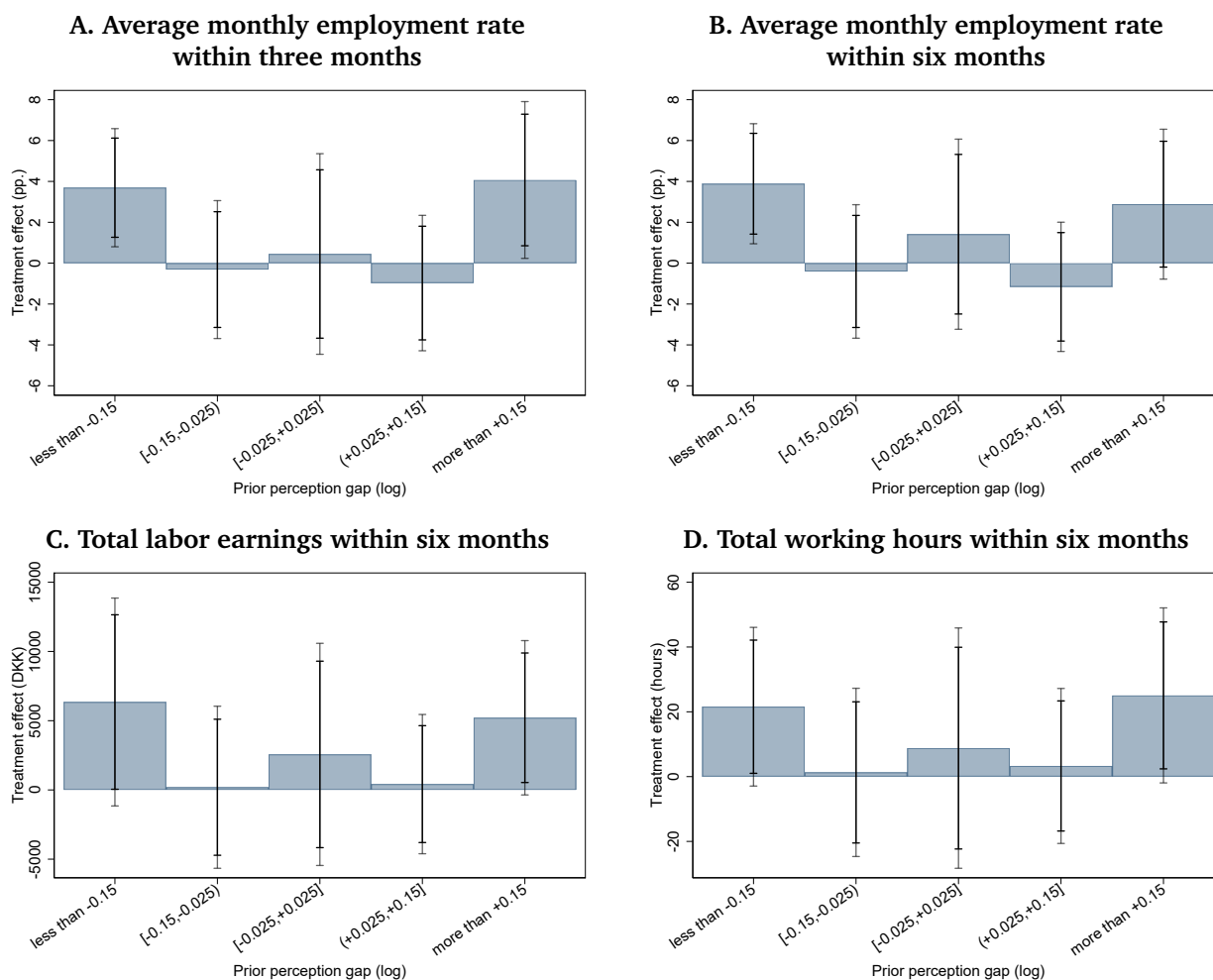
4.3.2 Labor market outcomes

In the final part of our main analysis, we examine the causal effects of shifting job seekers' beliefs on their subsequent labor market outcomes as recorded in administrative data. To capture responses along the extensive margin of employment, we consider average monthly employment rates over three- and six-month horizons. We also study effects on total hours worked, labor earnings and hourly wages, to also capture the intensive margin of employment and changes in job quality. We focus the discussion of labor market effects on initially highly over-optimistic or overly pessimistic job seekers as these groups show significant adjustments in their search strategy.

Large negative information shocks In the previous section, we showed that initially highly optimistic job seekers lower their reservation wage and increase their search intensity in response to the information. Given these adjustments in search behavior, we expect treated individuals within this group to secure employment more quickly than their counterparts in the control group. Panel A and Panel B of Figure 4 confirm that this is the case: the treatment increases average monthly employment rates within three and six months after the intervention by 3.7pp (+15%; $p = 0.012$) and by 3.9pp (+11%; $p = 0.010$), respectively. Similarly, treated job seekers who were initially highly optimistic work on average 21.6 hours more (+8.5%; $p = 0.084$) and earn DKK6,349 more (\approx USD970; +9.1%; $p = 0.098$) over six months than their non-treated counterparts.

Negative information shocks thus cause a larger percentage increase in the extensive margin of employment than in working hours or earnings. This suggests that the increases in overall hours and earnings are driven entirely by higher job-finding rates, with treated job seekers accepting lower-paying jobs. To test this more directly, we examine within-worker changes in hourly wages between the last job before unemployment and the first job thereafter. Focusing on changes mitigates concerns related to differential selection into employment between treated and non-treated job seekers. As shown in

Figure 4 Treatment effects on labor market outcomes



Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on labor market outcomes as observed in the administrative records. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. $N=2,323$ (less than -0.15); $N=1,980$ (-0.15 to -0.025); $N=1,043$ (-0.025 to $+0.025$); $N=2,178$ ($+0.025$ to $+0.15$); $N=1,723$ (more than $+0.15$).

Appendix Figure A.9, receiving a large negative shock is associated with a wage reduction of about 3.1% ($p = 0.064$) relative to the previous job.¹¹ This result is consistent with the reduction in reservation wages measured in our survey (see Figure 3).

Large positive information shocks Initially highly pessimistic job seekers become more selective in response to the treatment, not only by demanding a higher wage but also by reducing their search radius. The implications of these changes in search behavior for the respondents' re-employment prospects are ex-ante ambiguous. On the one hand, higher selectivity reduces the set of potential matches, lowering re-employment prospects. On the other hand, prior literature points to the existence of spatial search frictions, suggesting that job seekers become less effective at attracting offers or less will-

¹¹Since wages are observed only for employed individuals and treatment affects job-finding, we estimate Lee (2009) bounds obtained by trimming the wage distribution of the group with higher employment. The resulting bounds range from -4.8% to -2.4% , close to our baseline estimate.

ing to accept them as the distance from their place of residence increases (Manning and Petrongolo, 2017; Schmutz and Sidibé, 2019). Narrowing the geographic scope could thus improve the effectiveness of job search and thereby increase job finding rates.

Panel A of Figure 4 suggests that the second effect dominates: among initially pessimistic job seekers, the treatment *increases* the average three-month employment rate by 4.1pp (+13%; $p = 0.040$). The effect diminishes over time and is no longer statistically significant at the six-month horizon (Figure 4, Panel B). Nonetheless, the short-run increase in employment results in an 11.1% rise in total working hours ($p = 0.069$) and an 11.4% increase in total labor earnings ($p = 0.067$) over six months. Consistent with these effects operating primarily on the extensive margin, treated individuals earn similar hourly wages as comparable workers in the control group when securing re-employment (Appendix Figure A.9). The absence of a wage effect suggests that positive shocks influence labor market outcomes primarily by narrowing the geographic scope of search rather than by shifting reservation wages. In Section 4.4, we provide additional evidence supporting this interpretation.

Moderate shocks and neutral group The employment effects of moderate shocks or neutral information are close to zero and statistically insignificant (Figure 4, Panels A and B). Similarly, there are no significant changes in total hours worked, total earnings, or wages in the first job. These patterns align with the largely muted treatment effects on job search behavior within these groups.

4.3.3 Additional evidence and robustness

Before examining the mechanisms behind the treatment effects on re-employment, we present some additional analyses and robustness checks for our main results.

Correlational analysis We start by examining how misperceptions about the earnings potential of comparable workers correlate with beliefs, job search behavior, and labor market outcomes in the control group. This analysis helps us link the causal effects of belief shifts documented above—identified from the compliant subpopulation changing their beliefs in response to our treatment—to the broader role of misperceptions among the overall population of job seekers. Specifically, we regress our main outcomes on the actual log re-employment wage of comparable workers, four dummy variables capturing different ranges of perception gaps (from $\pm 2.5\%$ to $\pm 15\%$, as well as gaps exceeding $\pm 15\%$, consistent with our experimental analysis), and a set of controls. The coefficients on the dummy variables thus reflect differences to the neutral group without misperceptions. If the intervention mitigates the impact of initial misperceptions, these coefficients should have a sign opposite to the corresponding treatment effects.

The results are presented in Appendix Table A.5. We focus our discussion on the two groups that exhibit large optimism or pessimism. The correlations predominantly

have the opposite sign of the causal effects detected in our experimental analysis, although they sometimes do not reach statistical significance. In particular, individuals who are highly over-optimistic—with perception gaps lower than -15% —expect and demand higher wages, search less, and experience weaker labor market outcomes than those with accurate beliefs. Those who are highly pessimistic—with perception gaps exceeding 15% —expect and demand lower wages, are more willing to accept distant jobs, but are less likely to find a job (where the last two results miss statistical significance). Unlike our experimental evidence, this correlational analysis is susceptible to omitted variable bias, reverse causality, and measurement error. Nonetheless, the observed patterns align with the idea that our intervention mitigates the impact of job seekers’ initial misperceptions on their search behavior and labor market outcomes.

Heterogeneity in perception gaps vs. information processing As shown in Panel A of Figure 3, the treatment causes a stronger updating of wage expectations among individuals with larger prior misperceptions. This pattern is consistent with the idea that those with more pronounced misperceptions receive larger information shocks when treated. However, because perception gaps are not randomly assigned, differential treatment effects could also reflect differences in information processing along other dimensions that are correlated with the perception gap. To explore this, we regress respondents’ expectations about their next wage offer—measured post-treatment—on dummy variables for the five bins of the perception gap and their interactions with the treatment indicator. We sequentially add interactions between the treatment indicator and background characteristics. Appendix Table A.6 shows that the variation of estimated treatment effects with the perception gap remains almost unchanged. This suggests that differential learning about future wage offers is indeed driven by the varying size of the information shock, rather than by differences in information processing along other dimensions.

Alternative specification In our main analysis, we examine treatment effects separately across five groups defined by their initial misperceptions. As an alternative, we estimate the following specification using the full sample:

$$y_i = \beta_0 + \beta_1 \times \text{Treatment}_i \times \text{Perception gap}_i + \beta_2 \times \text{Treatment}_i + \beta_3 \times \text{Perception gap}_i + \mathbf{X}_i \Pi + \epsilon_i. \quad (2)$$

The coefficient β_1 captures the effect of a one-unit increase in the information shock on the outcome. β_2 captures treatment effects to the extent they do not linearly depend on the perception gap, and β_3 accounts for persistent differences across individuals with varying prior beliefs. \mathbf{X}_i is the vector of baseline control variables.

The results are presented in Appendix Table A.7. Consistent with our main findings, the estimates of β_1 highlight statistically significant adjustments in the respondents’ expected, demanded and realized wages. We also observe changes in the respondents’

search intensity and their willingness to change location, though these effects narrowly miss conventional levels of statistical significance. Moreover, the treatment significantly increases employment rates, earnings and working hours regardless of the initial perception gap. This aligns with our earlier evidence of positive labor market effects among both initially overly optimistic and pessimistic respondents.

Alternative perception-gap thresholds While our main analysis applies a $\pm 15\%$ cut-off, Appendix Figure A.10 reports estimates for the two groups with large perception gaps using alternative thresholds of 10%, 12.5%, 17.5% or 20%. Our estimated treatment effects are robust to different thresholds, though some effects increase with higher cutoffs, which is unsurprising since larger perception gaps imply larger information shocks.

Alternative winsorization In our main analysis, we winsorize expected wage offers and reservation wages at the 5th and 95th percentiles, and search intensity and cumulative earnings and working hours at the 95th percentile. Appendix Table A.8 demonstrates robustness to instead winsorizing at the 1st and 99th percentiles.

Multiple hypotheses testing One concern is that some of our findings are an artifact of multiple hypothesis testing. In Appendix Table A.9, we display estimated treatment effects on our key measures of search effort and selectivity in terms of wages and non-wage characteristics for initially highly optimistic and initially highly pessimistic job seekers. We present both conventional p -values and sharpened q -values (Anderson, 2008), which can be interpreted similarly to regular p -values.¹² All our main findings retain statistical significance when accounting for multiple hypothesis testing.

Excluding previous part-time workers Although our intervention targets individuals currently seeking full-time positions, 13% of them have been part-time employed in their previous job. Transitions from part-time to full-time may be special because (i) they often reflect changing life circumstances, and (ii) prior monthly wages are less likely to serve as an anchor for wage expectations. However, as shown in Appendix Table A.10, the results in the restricted sample of previous full-time workers closely mirror our main findings.

4.4 Mechanisms

Thus far, we have shown that providing job seekers with information about their earnings potential increases job-finding rates among both prior optimists and prior pessimists. At the same time, these groups adjust their search behavior in distinct ways: reducing optimism makes job seekers less selective and increases their search effort; correcting

¹²Specifically, sharpened q -values are the minimum false discovery rates—defined as the expected proportion of Type I errors among all rejections within the family of outcomes—at which the corresponding null hypotheses would be rejected (Anderson, 2008; Benjamini et al., 2006). That is, ordering hypotheses by increasing sharpened q -values, rejecting all null hypotheses with $q \leq q^*$ yields an expected false discovery rate of q^* , i.e., an expected proportion q^* of Type I errors among all rejections.

pessimism makes job seekers more selective and narrows the geographic scope of their search without changing overall search effort. In this subsection, we delve deeper into the mechanisms underlying these patterns and present additional evidence on the most plausible causal pathways. We focus our discussion on those with large initial optimism (perception gaps lower than -15%) or large initial pessimism (gaps exceeding 15%).

4.4.1 Large negative information shocks

The treatment leads initially highly optimistic job seekers to reduce their reservation wage and to increase their search effort, ultimately raising their job-finding rates. These effects are consistent with the predictions of the model in Section 3. In the model, the reservation-wage response aligns with the information shock, while the direction of effort adjustments depends on functional form assumptions. Our findings suggest that job seekers understand that greater effort can improve the quality of job offers, consistent with search models where effort shifts the offer distribution upward (Moen, 1997; Shimer, 2005). Accordingly, job seekers increase their search intensity to offset lower wage expectations. This positive quality effect appears to outweigh the potential discouragement effect from a reduced perceived value of employment.

Reduced reservation wages vs. higher search intensity How much of the increase in re-employment rates reflects lower reservation wages and how much higher search effort? Our data do not allow for a causal decomposition across these margins. Nonetheless, existing estimates provide benchmarks for the plausibility of different channels.

Estimated elasticities of re-employment with respect to reservation or targeted wages in the literature range from -1.9 to -7.7 . (Brown and Taylor, 2013; Fluchtmann et al., 2024; Jones, 1988). This range implies that the decline in reservation wages following large negative information shocks in our data (-1.6%) would translate into an employment increase of between 3% and 12% . Reduced reservation wages may thus account for a substantial share of the 11% increase (3.9pp) in six-month employment that we estimate for this group (Figure 4, Panel B).

Higher search effort may also contribute to increased job finding. Existing evidence suggests elasticities of re-employment with respect to search effort in the range of between 0.01 and 0.30 (Arni and Schiprowski, 2019; Marinescu and Skandalis, 2021). Accordingly, the 26% increase in search intensity following large negative shocks in our data would translate into employment increases of $0.2\text{--}7\%$. Higher search effort thus plausibly accounts for an additional part of the increased re-employment rate.

Selectivity regarding non-wage amenities Adjustments in job seekers' selectivity on non-wage characteristics are unlikely to explain the labor market effects of negative shocks. Negative shocks change neither the characteristics of targeted vacancies (Appendix Table A.4; Panel E) nor of realized jobs (Appendix Table A.12; Panel E).

4.4.2 Large positive information shocks

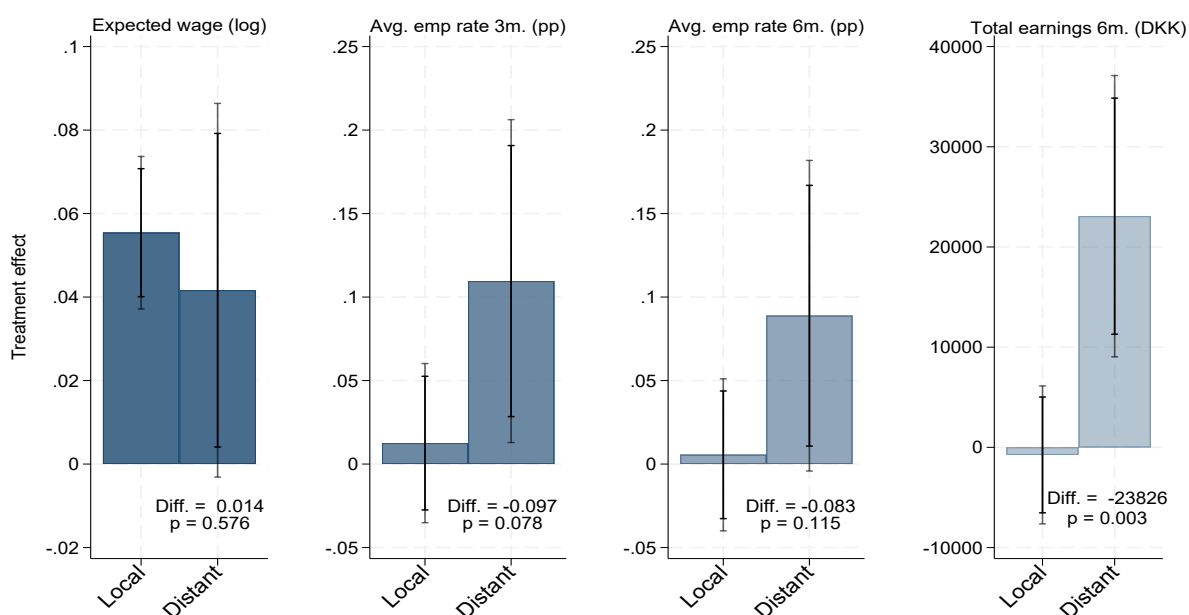
Treated job seekers who are initially overly pessimistic increase their reservation wages and narrow the geographic scope of their search. This aligns with standard search-theoretic reasoning, which predicts that, in the absence of perceived compensating differentials, higher wage expectations make individuals more selective with respect to both wages and non-wage characteristics.

The increased selectivity among initially highly pessimistic job seekers is associated with *higher* re-employment rates. A potential explanation are mitigated spatial search frictions: job seekers become more effective at generating acceptable job offers as the distance between their residence and potential jobs decreases (Manning and Petrongolo, 2017; Schmutz and Sidibé, 2019). If this is the case, the additional matches resulting from large positive information shocks should primarily occur (i) in the local market and (ii) among job seekers who, in the absence of the intervention, would have searched in a broader geographic area. We now test these two predictions.

Location of additional job matches Appendix Table A.12 shows that large positive information shocks increase employment in the initial municipality of residence by 4.5pp within three months ($p = 0.025$; Column 1). Municipalities are the smallest administrative unit in Denmark, and accepting a job within one's municipality should not require relocation or long-distance commuting. Treatment effects on employment outside the municipality of residence are close to zero and statistically insignificant. Moreover, the geographical distance between the first workplace after unemployment and the initial place of residence is 9.4% smaller for treated job seekers ($p = 0.063$; Column 3). Overall, these findings align with the notion that the improved labor market integration of individuals receiving positive shocks are driven by a reduced geographic scope of search.

Heterogeneity by previous geographic scope of search Only individuals who, absent our intervention, would have searched over a broader area can plausibly benefit from narrowing the geographic scope. We calculate individuals' prior search radius as the average commuting distance between openings they applied to in the four weeks before the survey and the place of residence. We then classify individuals as initially distant or local job seekers depending on whether their average search radius is above or below ten kilometers—roughly the average radius of Danish municipalities. Figure 5 shows that the employment effects of large positive shocks are concentrated among individuals who had been searching for distant jobs before the intervention. Within this group, the treatment increases the average three-month employment rate by 11pp ($p = 0.034$) and total earnings over six months by DKK23,072 (\approx USD3,620; $p = 0.001$). By contrast, among those who searched locally before the intervention, employment effects are small and statistically insignificant. The employment ($p = 0.078$) and earnings ($p = 0.003$) effects differ significantly between the two groups. Thus, increased job finding is driven

Figure 5 Heterogeneous treatment effects by previous geographic scope of search



Notes: The figure shows the effects of the information treatment (with 95% confidence intervals) for job seekers with large positive perception gaps (greater than +0.15), i.e., those who were initially highly pessimistic. We report separate treatment effects for individuals who, before the treatment, searched mainly locally versus distantly, measured by the average distance between their residence and the jobs they applied to during the four weeks before the survey. “Local” refers to an average pre-treatment search radius below 10 kilometers, and “distant” to an average radius above 10 kilometers. $N = 1,453$. Heterogeneous treatment effects by pre-treatment search radius for all main outcomes, along with the corresponding effects of negative information shocks, are reported in Appendix Table A.11.

by those who had the largest scope to redirect their search towards local openings.

Plausible magnitude of spatial search frictions Can the increase in effectiveness from searching locally be strong enough to offset the negative effects of higher wage demands on re-employment? Our own calculations based on registered applications show that, in Denmark, applying within the municipality of residence is more than twice as likely to lead to a job than applying outside the broader region (42% vs. 18%). Based on this difference, a 10% reallocation from distant to local search could raise employment by as much as 6% when search is already predominantly local, and by up to 13% if search is initially concentrated in distant jobs. This is broadly consistent with the employment gains of 4pp relative to a control group mean of 30% shown in Figure 4.¹³ In line with this interpretation, structural estimates from Germany (Heise and Porzio, 2022), the UK (Manning and Petrongolo, 2017), and France (Schmutz and Sidibé, 2019) point to

¹³A 10% reallocation seems plausible, as we observe a 5.2pp reduction ($p = 0.040$) in the likelihood of applying outside one’s own region within four weeks after the survey in response to large positive shocks, relative to a control mean of 47%. The calculation further assumes that one unit of local search effort yields one offer, while one unit of distant effort yields only $18/42 \approx 0.43$ offers, consistent with the relative success rates (42% vs. 18%). Shifting $\delta = 0.1$ of effort from distant to local thus raises expected offers by $\Delta = \delta \times (1 - 0.43) = 0.057$, i.e. 5.7% of total effort. Relative employment gains are $\Delta/A(s)$, with $A(s) = s + 0.43(1 - s)$ denoting the baseline success rate and s being the share of local effort. This yields improvements ranging from about 6% ($s = 0.95$) to 13% ($s = 0$).

substantial differences in the effectiveness of local versus distant search.

Beliefs about the effectiveness of local vs distant search If local search is more effective, why do some (initially pessimistic) job seekers search broadly in the absence of our intervention? One explanation is that job seekers underestimate the relative returns of local search. To explore this possibility, we conducted an additional survey in April and May 2025 with a fresh sample of unemployed workers. We provide only a high-level summary and describe the details of the design and the results in Appendix C.2. Respondents report their perceived effectiveness of search within their municipality, within their broader region, and nationwide. Job seekers expect both themselves and others to be more successful when searching more distantly, and they underestimate the relative success of local applications compared to benchmarks from application data. More optimistic beliefs about distant search are associated with a broader geographic scope of applications. These results suggest that job seekers underestimate the difficulties of non-local search, which may lead them to focus too much on distant openings. An intervention that redirects search toward local opportunities—such as our main experiment—may therefore have the positive side effect of improving search effectiveness and job-finding rates.

4.4.3 Asymmetric effects of positive and negative shocks

While negative information shocks increase search intensity, positive shocks narrow the geographic scope of search. While our experiment is not designed to disentangle the drivers of this asymmetry, we briefly discuss two possibilities.

First, positive and negative shocks may have systematically different effects. For example, behavioral biases such as loss aversion (Abeler et al., 2011; DellaVigna et al., 2017, 2022) may motivate job seekers to avoid wages below their expectations. Negative shocks could thus prompt higher effort to counteract the unfavorable signal, whereas positive shocks may elicit a more muted response. Similarly, high mobility costs (see, e.g., Kennan and Walker, 2011; Koşar et al., 2022) may explain why only positive updates affect the geographic scope of search. For many job seekers, family responsibilities or strong social ties may prevent a broadening of geographical scope in response to negative shocks. By contrast, such constraints do not hinder those who initially search broadly from narrowing their scope following positive shocks.

Second, respondents' perception gaps are not randomly assigned, so individuals receiving a positive update differ systematically from those receiving a negative update. Differential adjustments in search behavior could result from differences in preferences, constraints and beliefs that are correlated with the perception gap. For instance, the search effort of initially highly pessimistic individuals could be generally inelastic, e.g., due to the use of search strategies that feature a constant level of effort. This could lead to asymmetric effects of positive and negative shocks on search effort.

Future work building on our approach could attempt to disentangle these potential explanations. For example, designs providing similar job seekers with different signals—which is not feasible in our particular setting—could be used to understand whether job seekers respond systematically differently to positive vs. negative shocks.

5 Conclusion

We present evidence on the causal effects of subjective wage expectations on job search and labor market outcomes of unemployed job seekers. Our design combines three key features: (i) a large-scale survey of unemployed individuals that provides rich data on beliefs and reservation wages; (ii) an information provision experiment that generates exogenous variation in a core belief relevant to job search; and (iii) linkage to detailed administrative data on job search and labor market outcomes, minimizing concerns about experimenter demand effects, consistency bias, intention–behavior gaps, and recall error in survey-based measures. Our paper showcases how one can obtain clear and detailed evidence on the causal role of beliefs in job search.

In our survey, we first elicit beliefs about the re-employment wages of previously unemployed workers with similar characteristics as the respondent and compare these beliefs to benchmarks from administrative records. While average misperceptions are relatively small, substantial shares of job seekers display pronounced optimism or pessimism. When receiving information on actual re-employment wages of comparable workers, treated individuals adjust their own wage expectations and reservation wages toward the information. Treated job seekers who were initially strongly optimistic increase their search effort and find jobs more quickly. Conversely, initial pessimists narrow the geographic scope of their search in response to the treatment, which accelerates re-employment—consistent with mitigated spatial search frictions.

Our findings have direct implications for modeling job search. Most importantly, they suggest that accounting for job seekers’ subjective beliefs is essential when studying search behavior (Conlon et al., 2018; Krueger and Mueller, 2016; Mueller and Spinnewijn, 2023). We also present many concrete results that could inform future theoretical work. For example, we provide causal estimates of the elasticities of job search decisions to upward and downward shifts in wage expectations. Moreover, our findings suggest that job seekers seem to jointly determine multiple dimensions of their search strategy—including their wage demands, search intensity, and geographic scope. Exogenous changes in one domain can spill over into others. Downward revisions of wage expectations increase search intensity, consistent with models in which job seekers anticipate that greater effort improves the quality of offers. Upward revisions make job seekers more selective—not only in terms of wages but also with respect to geographic proximity. By contrast, we find no evidence that job seekers trade off higher expected

wages against a greater willingness to accept unpleasant jobs.

Our findings also have implications for policy. They suggest that low-cost information interventions can have powerful effects on individual search behavior and labor-market prospects. Both initially optimistic and initially pessimistic job seekers find employment more quickly when holding more accurate beliefs. To fully assess the welfare implications of such policies, one would need to account for general-equilibrium effects associated with a large-scale roll-out. In particular, it would be key to understand whether more accurate wage expectations improve the matching process or induce crowding-out. We leave the analysis of such effects to future work. Finally, our findings suggest that—for some job seekers—policymakers may need to weigh the benefits of shorter unemployment spells against the potential cost of lower-quality jobs.

References

- Abebe, Girum, A Stefano Caria, Marcel Fafchamps, Paolo Falco, Simon Franklin, Simon Quinn, and Forhad Shilpi**, “Matching Frictions and Distorted Beliefs: Evidence from a Job Fair Experiment,” *The Economic Journal*, 2025, 135 (671), 2089–2121.
- Abeler, Johannes, Armin Falk, Lorenz Goette, and David Huffman**, “Reference Points and Effort Provision,” *The American Economic Review*, 2011, pp. 470–492.
- Alfonsi, Livia, Mary Namubiru, and Sara Spaziani**, “Meet Your Future: Experimental Evidence on the Labor Market Effects of Mentors,” *G²LM|LIC Working Paper No. 87*, 2022.
- Altmann, Steffen, Anita Marie Glenny, Robert Mahlstedt, and Alexander Sebald**, “The Direct and Indirect Effects of Online Job Search Advice,” *IZA Discussion Paper No. 15830*, 2022.
- Andersen, Torben M**, “The Danish Labor Market, 2000-2022,” *IZA World of Labor*, 2023.
- Anderson, Michael L**, “Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects,” *Journal of the American Statistical Association*, 2008, 103 (484), 1481–1495.
- Arni, Patrick and Amelie Schiprowski**, “Job Search Requirements, Effort Provision and Labor Market Outcomes,” *Journal of Public Economics*, 2019, 169, 65–88.
- Balleer, Almut, Georg Duernecker, Susanne Forstner, and Johannes Goensch**, “The Effects of Biased Labor Market Expectations on Consumption, Wealth Inequality, and Welfare,” *American Economic Journal: Macroeconomics*, 2026, 18 (1), 297–335.
- Bandiera, Oriana, Vittorio Bassi, Robin Burgess, Imran Rasul, Munshi Sulaiman, and Anna Vitali**, “The Search for Good Jobs: Evidence from a Six-year Field Experiment in Uganda,” *Journal of Labor Economics*, 2025, 43 (3), 885–935.
- Banerjee, Abhijit and Sandra Sequeira**, “Learning by Searching: Spatial Mismatches and Imperfect Information in Southern Labor Markets,” *Journal of Development Economics*, 2023, 164, 103111.
- Banfi, Stefano and Benjamín Villena-Roldán**, “Do High-Wage Jobs Attract More Applicants? Directed Search Evidence from the Online Labor Market,” *Journal of Labor Economics*, 2019, 37 (3), 715–746.
- Behaghel, Luc, Sofia Dromundo Mokrani, Marc Gurgand, Yagan Hazard, and Thomas Zuber**, “Encouraging and Directing Job Search: Direct and Spillover Effects in a Large Scale Experiment,” *Banque de France Working Paper No. 900*, 2022.
- Belot, Michèle, Philipp Kircher, and Paul Muller**, “Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice,” *Review of Economic Studies*, 2019, 86 (4), 1411–1447.
- , —, and —, “Do the Long-Term Unemployed Benefit from Automated Occupational Advice during Online Job Search?,” *The Economic Journal*, 2025, 136 (673), 184–206.
- Benjamini, Yoav, Abba M Krieger, and Daniel Yekutieli**, “Adaptive Linear Step-Up Procedures that Control the False Discovery Rate,” *Biometrika*, 2006, 93 (3), 491–507.
- Bottan, Nicolas and Ricardo Perez-Truglia**, “Betting on the House: Subjective Expectations and Market Choices,” *American Economic Journal: Applied Economics*, 2025, 17 (1), 459–500.

- Brown, Charles and James Medoff**, “The Employer Size-Wage Effect,” *Journal of Political Economy*, 1989, 97 (5), 1027–1059.
- Brown, Sarah and Karl Taylor**, “Reservation Wages, Expected Wages and Unemployment,” *Economics Letters*, 2013, 119 (3), 276–279.
- Caliendo, Marco, Robert Mahlstedt, Aiko Schmeißer, and Sophie Wagner**, “The Accuracy of Job Seekers’ Wage Expectations,” *arXiv preprint*, 2023, 2309.14044. Revised September 2024.
- , **Steffen Künn, and Robert Mahlstedt**, “The Intended and Unintended Effects of Promoting Labor Market Mobility,” *Review of Economics and Statistics*, 2023, pp. 1–52.
- Caplin, Andrew, Victoria Gregory, Eungik Lee, Søren Leth-Petersen, and Johan Sæverud**, “Subjective Earnings Risk,” *NBER Working Paper No. 31019*, 2023.
- Carranza, Eliana, Robert Garlick, Kate Orkin, and Neil Rankin**, “Job Search and Hiring with Limited Information about Workseekers’ Skills,” *American Economic Review*, 2022, 112 (11), 3547–3583.
- Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia**, “Inflation Expectations, Learning and Supermarket Prices: Evidence from Field Experiments,” *American Economic Journal: Macroeconomics*, 2017, 9 (3), 1–35.
- Chopra, Felix, Christopher Roth, and Johannes Wohlfart**, “Home Price Expectations and Spending: Evidence from a Field Experiment,” *American Economic Review*, 2025, 115 (7), 2267–2305.
- Coibion, Olivier and Yuriy Gorodnichenko**, “Schumpeter Lecture 2025: The New Causal Macroeconomics of Surveys and Experiments,” *Journal of the European Economic Association*, 2025, jvaf050.
- , **Dimitris Georgarakos, Yuriy Gorodnichenko, and Michael Weber**, “Forward Guidance and Household Expectations,” *Journal of the European Economic Association*, 2023, 21 (5), 2131–2171.
- , **Yuriy Gorodnichenko, and Michael Weber**, “Monetary Policy Communications and Their Effects on Household Inflation Expectations,” *Journal of Political Economy*, 2021.
- , – , **and Tiziano Ropele**, “Inflation Expectations and Firm Decisions: New Causal Evidence,” *The Quarterly Journal of Economics*, 2020, 135 (1), 165–219.
- Conlon, John J, Laura Pilossoph, Matthew Wiswall, and Basit Zafar**, “Labor Market Search With Imperfect Information and Learning,” *NBER Working Paper No. 24988*, 2018.
- Cortés, Patricia, Jessica Pan, Laura Pilossoph, Ernesto Reuben, and Basit Zafar**, “Gender Differences in Job Search and the Earnings Gap: Evidence from the Field and Lab,” *The Quarterly Journal of Economics*, 2023, 138 (4), 2069–2126.
- de Quidt, Jonathan, Johannes Haushofer, and Christopher Roth**, “Measuring and Bounding Experimenter Demand,” *American Economic Review*, 2018, 108 (11), 3266–3302.
- DellaVigna, Stefano, Attila Lindner, Balázs Reizer, and Johannes F Schmieder**, “Reference-Dependent Job Search: Evidence from Hungary,” *The Quarterly Journal of Economics*, 2017, 132 (4), 1969–2018.

- , **Jörg Heining, Johannes F Schmieder, and Simon Trenkle**, “Evidence on Job Search Models from a Survey of Unemployed Workers in Germany,” *The Quarterly Journal of Economics*, 2022, 137 (2), 1181–1232.
- Drahs, Sascha, Luke Haywood, and Amelie Schiprowski**, “Job Search with Subjective Wage Expectations,” *DIW Discussion Papers No. 1725*, 2018.
- Escudero, Verónica, Hannah Liepmann, and Damian Vergara**, “Directed Search, Wages, and Non-wage Amenities: Evidence from an Online Job Board,” IZA Discussion Papers No. 17211 2024.
- Faberman, R Jason and Marianna Kudlyak**, “The Intensity of Job Search and Search Duration,” *American Economic Journal: Macroeconomics*, 2019, 11 (3), 327–57.
- , **Andreas I Mueller, Ayşegül Şahin, and Giorgio Topa**, “Job Search Behavior among the Employed and Non-Employed,” *Econometrica*, 2022, 90 (4), 1743–1779.
- Fluchtmann, Jonas, Anita M Glenney, Nikolaj Harmon, and Jonas Maibom**, “Unemployed Job Search across People and over Time: Evidence from Applied-For Jobs,” *Journal of Labor Economics*, 2024, 42 (4), 1175–1217.
- Fuster, Andreas and Basit Zafar**, “Survey Experiments on Economic Expectations,” in “Handbook of Economic Expectations,” Elsevier, 2023, pp. 107–130.
- Gillen, Ben, Erik Snowberg, and Leeat Yariv**, “Experimenting with Measurement Error: Techniques with Applications to the Caltech Cohort Study,” *Journal of Political Economy*, 2019, 127 (4), 1826–1863.
- Haaland, Ingar, Christopher Roth, and Johannes Wohlfart**, “Designing Information Provision Experiments,” *Journal of Economic Literature*, 2023, 61 (1), 3–40.
- Hall, Robert E and Andreas I Mueller**, “Wage Dispersion and Search Behavior: The Importance of Nonwage Job Values,” *Journal of Political Economy*, 2018, 126 (4), 1594–1637.
- He, Qiwei and Philipp Kircher**, “Updating about Yourself by Learning about the Market: The Dynamics of Beliefs and Expectations in Job Search,” *National Bureau of Economic Research Working Paper 31940*, 2023.
- Heise, Sebastian and Tommaso Porzio**, “Labor Misallocation Across Firms and Regions,” *National Bureau of Economic Research Working Paper 30298*, 2022.
- Huidrom, Raju**, “Wage and Inflation Dynamics in Denmark,” *IMF Selected Issues Papers*, July 2023, (SIP/2023/052). IMF Country Report No. 23/228.
- Jacobson, Louis S, Robert J LaLonde, and Daniel G Sullivan**, “Earnings Losses of Displaced Workers,” *The American Economic Review*, 1993, pp. 685–709.
- Jäger, Simon, Christopher Roth, Nina Roussille, and Benjamin Schoefer**, “Worker Beliefs About Outside Options,” *The Quarterly Journal of Economics*, 2024, 139 (3), 1505–1556.
- Jiang, Michelle and Kai Zen**, “Information Asymmetry in Job Search,” *Unpublished Manuscript*, 2025.
- Jones, Stephen RG**, “The Relationship between Unemployment Spells and Reservation Wages as a Test of Search Theory,” *The Quarterly Journal of Economics*, 1988, 103 (4), 741–765.

- Jung, Philip and Moritz Kuhn**, “Earnings Losses and Labor Mobility over the Life Cycle,” *Journal of the European Economic Association*, 2019, 17 (3), 678–724.
- Kennan, John and James R Walker**, “The Effect of Expected Income on Individual Migration Decisions,” *Econometrica*, 2011, 79 (1), 211–251.
- Kiss, Andrea, Robert Garlick, Kate Orkin, and Lukas Hensel**, “Jobseekers’ Beliefs about Comparative Advantage and (Mis)Directed Search,” *IZA Discussion Paper No. 16522*, 2023.
- Koenig, Felix, Alan Manning, and Barbara Petrongolo**, “Reservation Wages and the Wage Flexibility Puzzle,” *Review of Economics and Statistics*, 2024, pp. 1–32.
- Koşar, Gizem and Wilbert van der Klaauw**, “Workers’ Perceptions of Earnings Growth and Employment Risk,” *Journal of Labor Economics*, 2025, 43 (S1), S83–S121.
- , **Tyler Ransom, and Wilbert van der Klaauw**, “Understanding Migration Aversion Using Elicited Counterfactual Choice Probabilities,” *Journal of Econometrics*, 2022, 231 (1), 123–147.
- Kreiner, Claus Thustrup and Michael Svarer**, “Danish Flexicurity: Rights and Duties,” *Journal of Economic Perspectives*, 2022, 36 (4), 81–102.
- Krueger, Alan B and Andreas I Mueller**, “A Contribution to the Empirics of Reservation Wages,” *American Economic Journal: Economic Policy*, 2016, 8 (1), 142–179.
- Le Barbanchon, Thomas, Johannes Schmieider, and Andrea Weber**, “Job Search, Unemployment Insurance, and Active Labor Market Policies,” in “Handbook of Labor Economics,” Vol. 5, Elsevier, 2024, pp. 435–580.
- , **Lena Hensvik, and Roland Rathelot**, “How Can AI Improve Search and Matching? Evidence From 59 Million Personalized Job Recommendations,” Working Paper 2023.
- , **Roland Rathelot, and Alexandra Roulet**, “Gender Differences in Job Search: Trading off Commute against Wage,” *The Quarterly Journal of Economics*, 2021, 136 (1), 381–426.
- Lee, David S**, “Training, Wages, and Sample Selection: Estimating Sharp Bounds on Treatment Effects,” *The Review of Economic Studies*, 2009, 76 (3), 1071–1102.
- Maestas, Nicole, Kathleen J Mullen, David Powell, Till von Wachter, and Jeffrey B Wenger**, “The Value of Working Conditions in the United States and the Implications for the Structure of Wages,” *American Economic Review*, 2023, 113 (7), 2007–2047.
- Manning, Alan and Barbara Petrongolo**, “How Local Are Labor Markets? Evidence from a Spatial Job Search Model,” *American Economic Review*, 2017, 107 (10), 2877–2907.
- Marinescu, Ioana and Daphné Skandalis**, “Unemployment Insurance and Job Search Behavior,” *The Quarterly Journal of Economics*, 2021, 136 (2), 887–931.
- McCall, John Joseph**, “Economics of Information and Job Search,” *The Quarterly Journal of Economics*, 1970, 84 (1), 113–126.
- Miano, Armando**, “Search Costs, Outside Options, and On-the-Job Search,” Working Paper, 2025.
- Moen, Espen R**, “Competitive Search Equilibrium,” *Journal of Political Economy*, 1997, 105 (2), 385–411.

- Mortensen, Dale T and Christopher A Pissarides**, “Job Creation and Job Destruction in the Theory of Unemployment,” *The Review of Economic Studies*, 1994, 61 (3), 397–415.
- Mueller, Andreas I and Johannes Spinnewijn**, “Expectations Data, Labor Market, and Job Search,” *Handbook of Economic Expectations*, 2023, pp. 677–713.
- , – , and **Giorgio Topa**, “Job Seekers’ Perceptions and Employment Prospects: Heterogeneity, Duration Dependence, and Bias,” *American Economic Review*, 2021, 111 (1), 324–363.
- Nekoei, Arash and Andrea Weber**, “Does Extending Unemployment Benefits Improve Job Quality?,” *American Economic Review*, 2017, 107 (2), 527–561.
- Roth, Christopher, Sonja Settele, and Johannes Wohlfart**, “Risk Exposure and Acquisition of Macroeconomic Information,” *American Economic Review: Insights*, 2022, 4 (1), 34–53.
- Roussille, Nina**, “The Role of the Ask Gap in Gender Pay Inequality,” *The Quarterly Journal of Economics*, 2024, 139 (3), 1557–1610.
- Schmieder, Johannes F, Till Von Wachter, and Jörg Heining**, “The Costs of Job Displacement over the Business Cycle and its Sources: Evidence from Germany,” *American Economic Review*, 2023, 113 (5), 1208–1254.
- Schmutz, Benoît and Modibo Sidibé**, “Frictional Labour Mobility,” *The Review of Economic Studies*, 2019, 86 (4), 1779–1826.
- Schnorpfel, Philip, Michael Weber, and Andreas Hackethal**, “Inflation and Trading,” *Journal of Financial Economics*, 2025, 173, 104166.
- Shimer, Robert**, “The Cyclical Behavior of Equilibrium Unemployment and Vacancies,” *American Economic Review*, 2005, pp. 25–49.
- Spinnewijn, Johannes**, “Unemployed but Optimistic: Optimal Insurance Design with Biased Beliefs,” *Journal of the European Economic Association*, 2015, 13 (1), 130–167.
- van Rooij, Maarten, Olivier Coibion, Dimitris Georgarakos, Bernardo Candia, and Yuriy Gorodnichenko**, “Keeping Up with the Jansens: Causal Peer Effects on Household Spending, beliefs and happiness,” *National Bureau of Economic Research Working Paper*, 2024, (32107).

Supplementary Online Appendix

Wage Expectations and Job Search

Steffen Altmann Robert Mahlstedt Malte Jacob Rattenborg
Alexander Sebald Sonja Settele Johannes Wohlfart

A	Additional figures and tables	2
B	Details on the theoretical framework	22
B.1	Effect of wage expectations on selectivity	22
B.2	Effect of wage expectations on search intensity	26
C	Additional evidence	28
C.1	Robustness: Evidence on anchoring of wage expectations	28
C.2	Additional survey evidence: Beliefs about returns to local and distant job search	31
D	Survey instructions translated to English	35
D.1	Main survey	35
D.2	Follow-up survey	45
D.3	Mechanism survey	50

A Additional figures and tables

Figure A.1 Flowchart of main survey

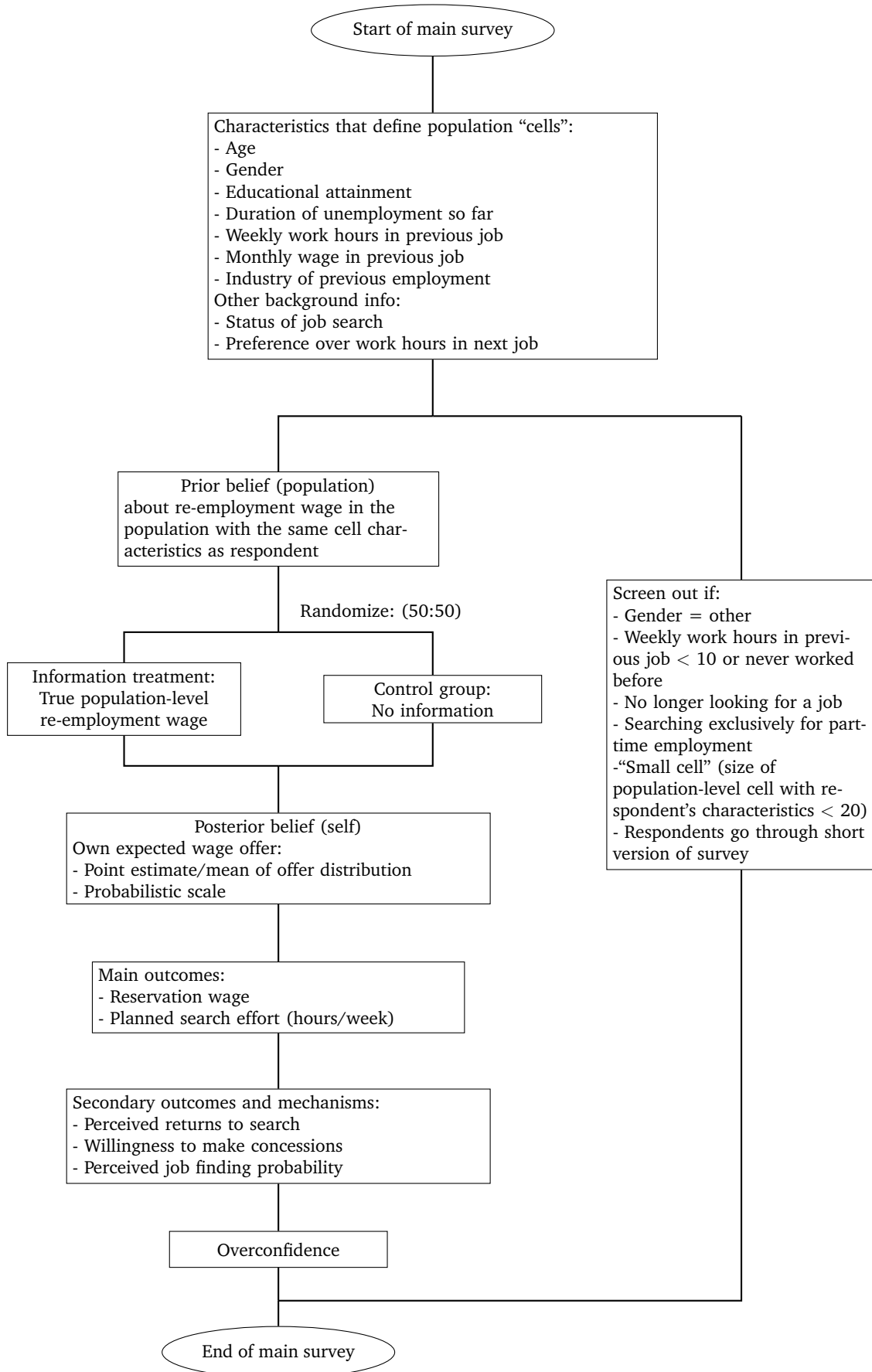


Figure A.2 Flowchart of follow-up survey

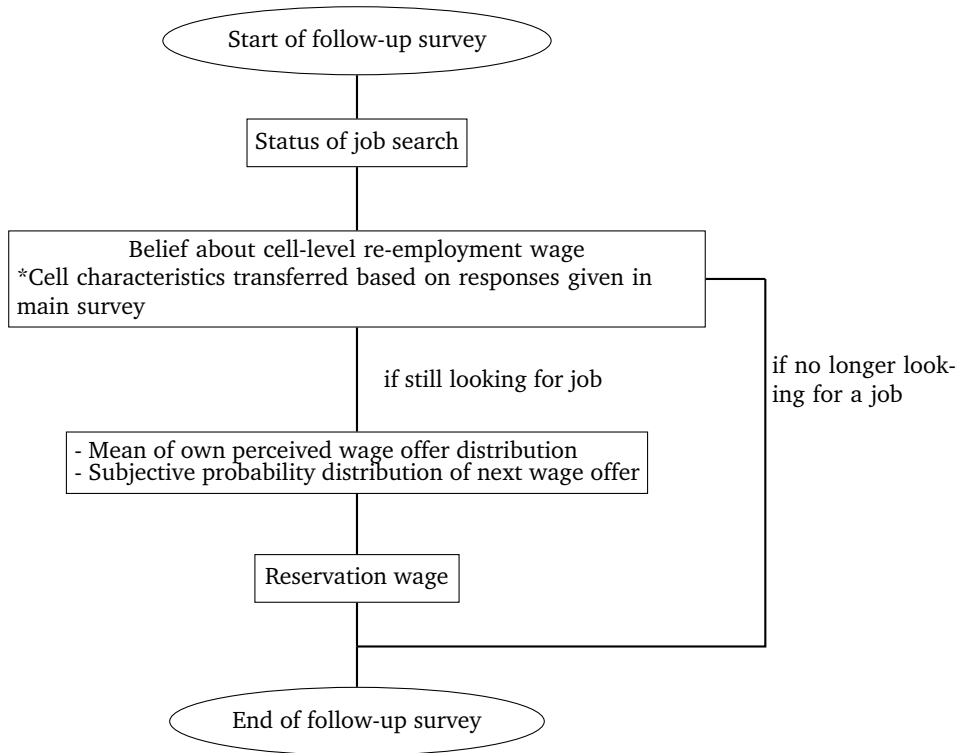
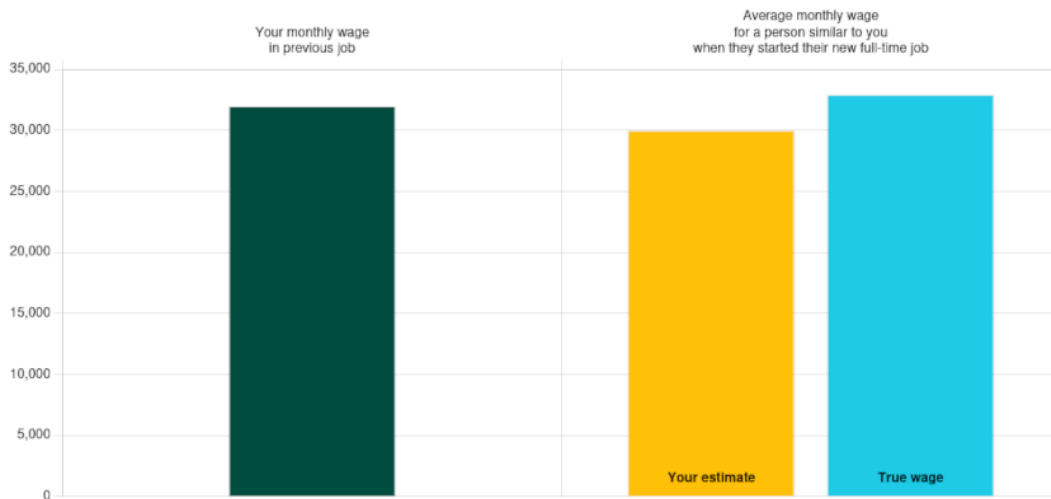


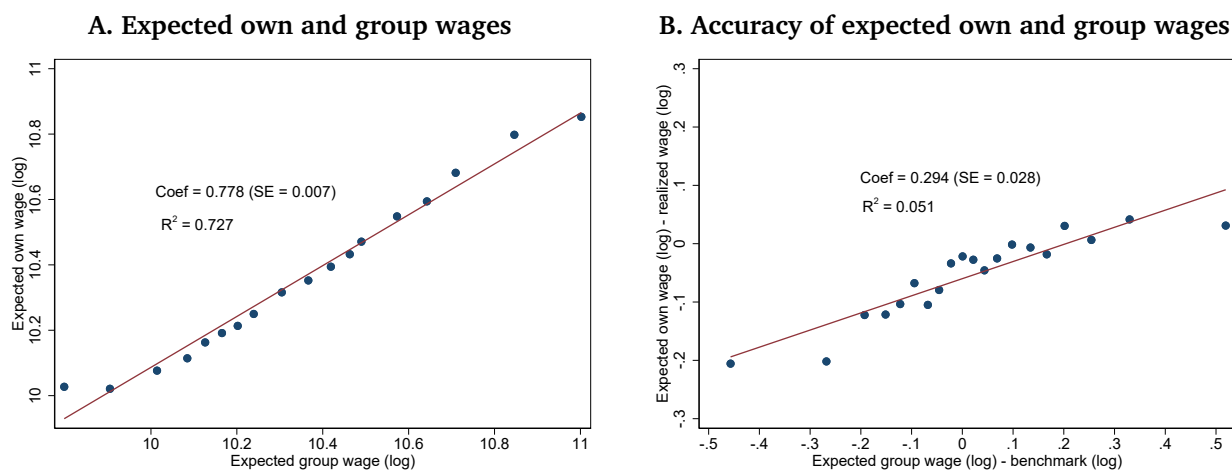
Figure A.3 Example of treatment screen

The average wage is: **DKK32.930**



Notes: The figure shows an English translation of the treatment screen displaying information about the average re-employment wage of comparable workers, as presented to the treatment group in the survey experiment. The left bar (green) represents the respondent’s own previous wage, the middle bar (yellow) shows the respondent’s prior belief about the wage of comparable workers, and the right bar (blue) illustrates the actual re-employment wage of comparable workers. Above the bar chart, the actual re-employment wage of comparable workers is displayed as a numerical value.

Figure A.4 Comparison of expected own wages and expected group wages

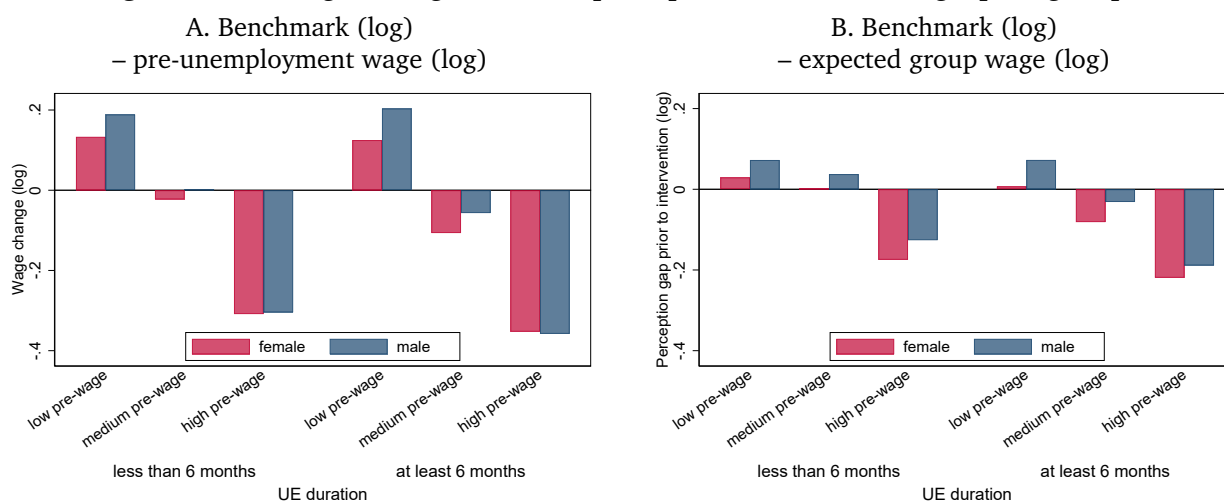


Notes: The figure illustrates job seekers' expectations about their own wages and group wages in the absence of the information intervention.

Panel A shows a binned scatter plot (20 bins) of expected own next wage offer against expected re-employment wages of comparable workers for control-group respondents ($N = 4,352$).

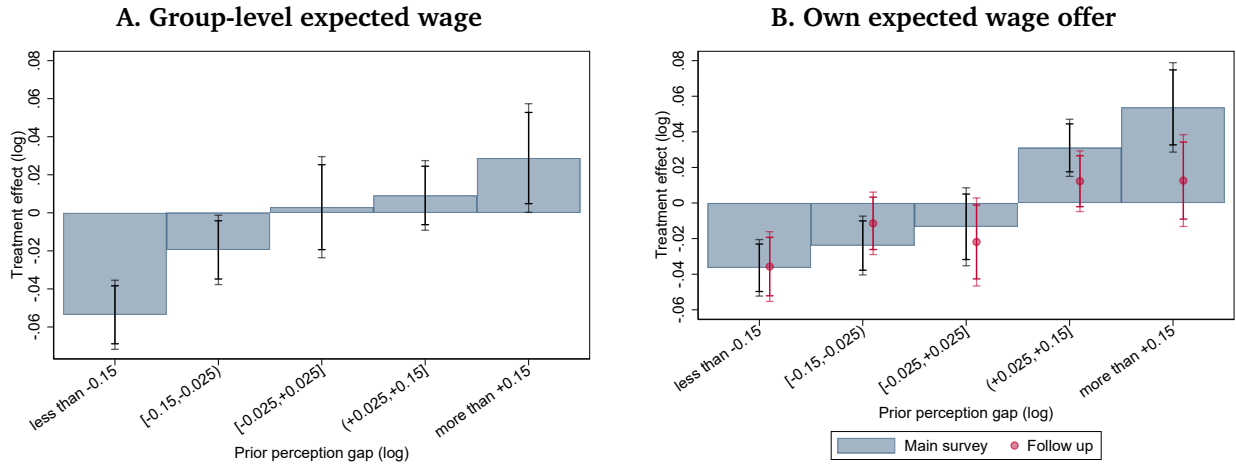
Panel B shows a binned scatter plot (20 bins) of expected own next wage offer minus realized re-employment wages against expected re-employment wages of comparable workers minus actual re-employment wages of comparable workers for control-group respondents who find a job ($N = 2,775$).

Figure A.5 Wage changes and misperceptions across demographic groups



Notes: The figure shows the log difference between benchmarks for re-employment wages and pre-unemployment wages (Panel A), as well as the log difference between benchmarks for re-employment wages and the respondents' expected group wage (Panel B) for various demographic groups. The sample is reduced to previously full-time-employed survey respondents. Income groups represent terciles based on the survey. The medium income group corresponds to monthly pre-tax incomes between DKK28,000 and DKK36,000.

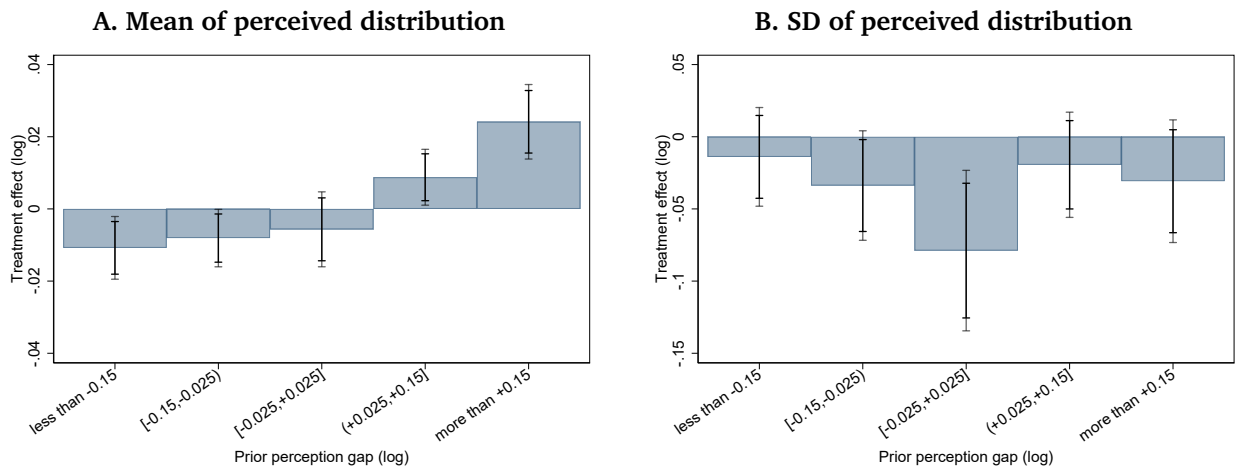
Figure A.6 Treatment effects on expected wages in follow-up survey



Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on respondents' expected group-level re-employment wages (log) measured in the follow-up survey (Panel A) and respondents' own expected wage offer (log) (Panel B). The estimates are provided for respondents who completed the follow-up survey. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers.

$N=1,115$ (less than -0.15); $N=836$ (-0.15 to -0.025); $N=408$ (-0.025 to +0.025); $N=881$ (+0.025 to +0.15); $N=663$ (more than +0.15).

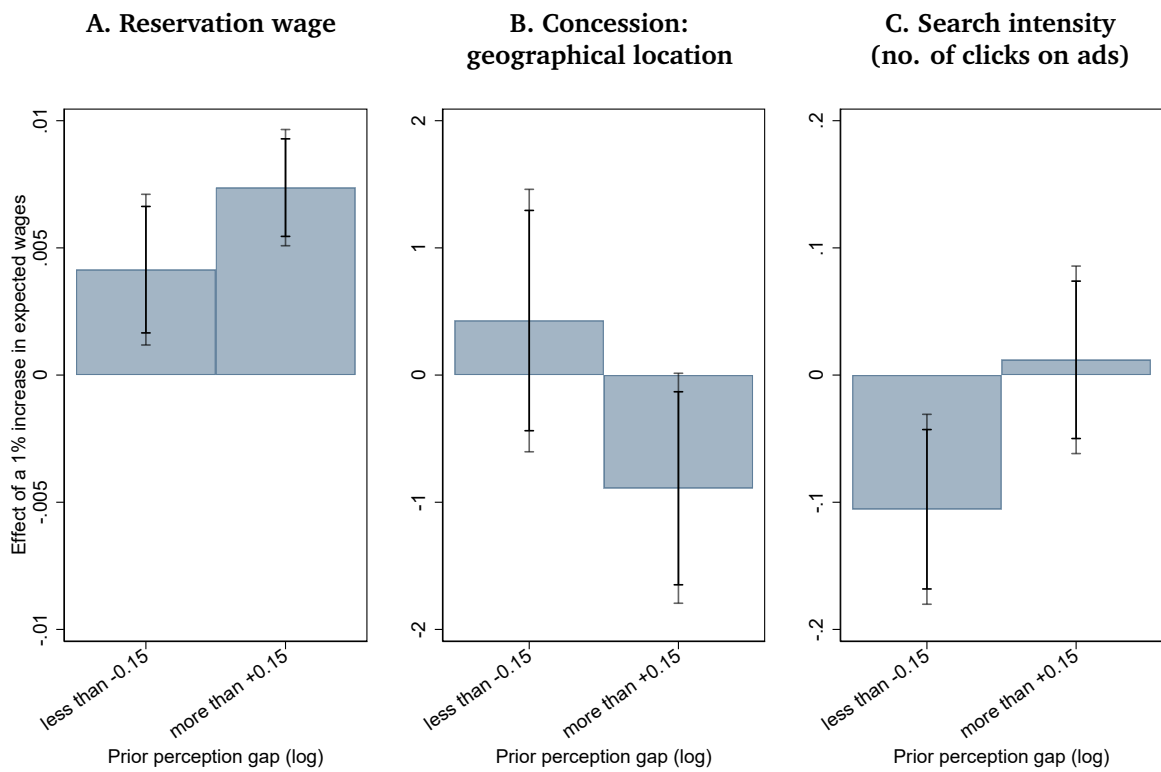
Figure A.7 Treatment effects on perceived wage offer distribution



Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on the mean (log) (Panel A) and the standard deviation (log) (Panel B) of the perceived wage offer distribution reported by the respondent.

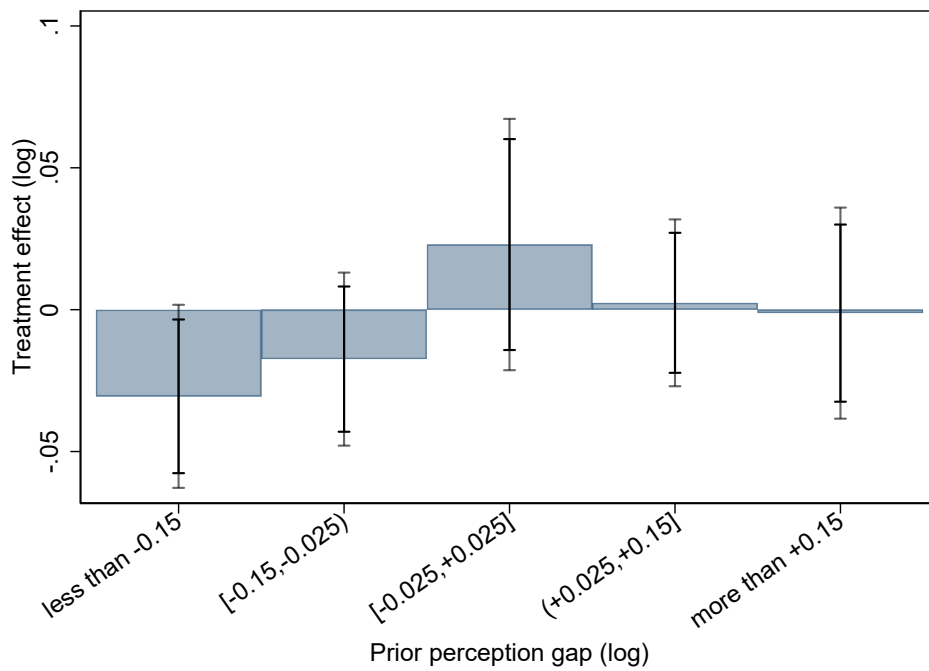
Observations (main survey): $N=2,323$ (less than -0.15); $N=1,980$ (-0.15 to -0.025); $N=1,043$ (-0.025 to +0.025); $N=2,178$ (+0.025 to +0.15); $N=1,723$ (more than +0.15).

Figure A.8 Two-stage least square estimates: wage expectations and job search behavior



Notes: The figure reports the estimated effect of a 1% increase in expected wages, obtained using a two-stage least squares (2SLS) approach that instruments expected offered wages with the treatment indicators. We display point estimates and 90% and 95% confidence intervals for the effects on (A) reservation wages (log), (B) willingness to accept long commutes or relocation, and (C) the number of vacancy clicks in the first week after the main survey. Estimates are shown separately for individuals with (i) large negative perception gaps below -0.15 ($N = 2,323$) and (ii) large positive perception gaps above $+0.15$ ($N = 1,723$).

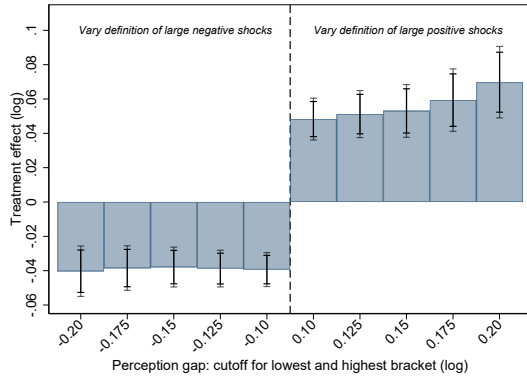
Figure A.9 Treatment effects on first hourly wage difference



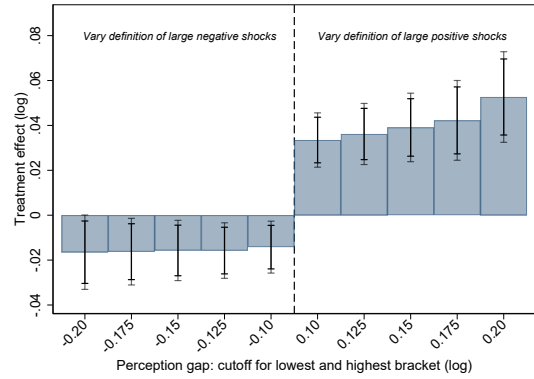
Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on the difference between hourly wage (log) in the first job after the initial survey and the pre-unemployment wage (log). We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. The estimates are based on job seekers who secure employment within five months. $N=1,623$ (less than -0.15); $N=1,447$ (-0.15 to -0.025); $N=798$ (-0.025 to +0.025); $N=1,651$ (+0.025 to +0.15); $N=1,221$ (more than +0.15).

Figure A.10 Robustness: alternative perception-gap thresholds

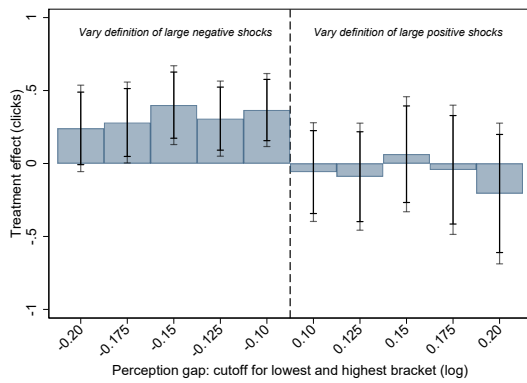
A. Expected wage offered (log)



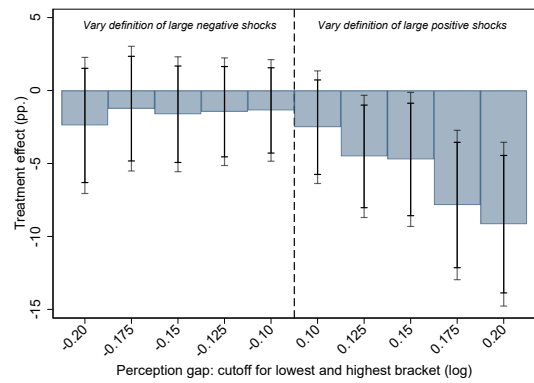
B. Reservation wage (log)



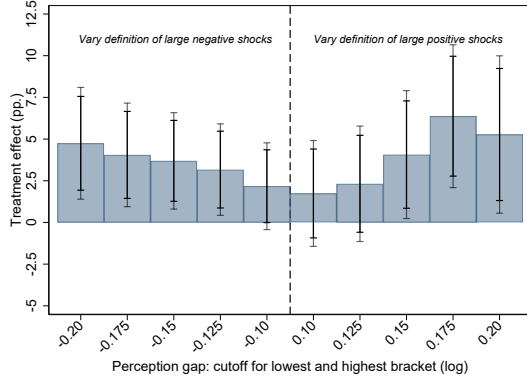
C. No. of ads clicked



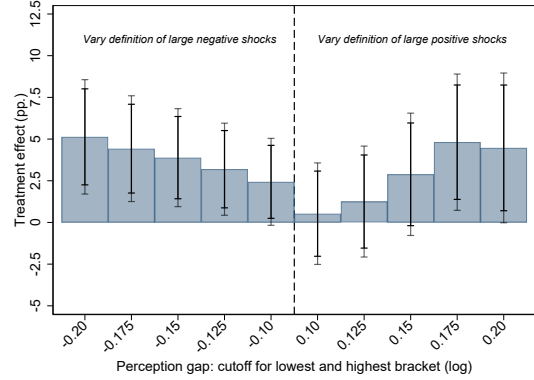
D. Concessions geography.



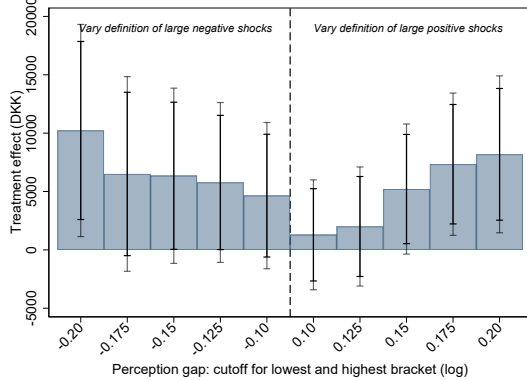
E. Average emp. rate 3m.



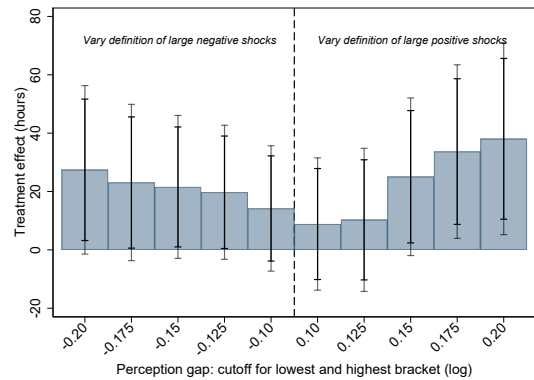
F. Average emp. rate 6m.



G. Total earnings 6m.



H. Total hours 6m.



Notes: The figure reports robustness checks using alternative thresholds to define large positive and negative information shocks. While our main analysis applies a $\pm 15\%$ cutoff for the lowest and highest perception-gap groups, the figure shows estimates for thresholds ranging from $\pm 10\%$ to $\pm 20\%$, along with 90% and 95% confidence intervals for the treatment effects on the main outcomes.

Table A.1 Prediction of re-employment wages

Dependent variable	Monthly re-employment wage (log)
Monthly pre-unemployment wage (log)	0.140*** (0.000)
Male	0.112*** (0.001)
Level of education (ref: University degree)	
High school	-0.145*** (0.001)
Below high school	-0.191*** (0.001)
Age (ref. 35 years or below)	
36–50 years	0.0452*** (0.001)
Above 50 years	0.0436*** (0.001)
Previous industry (ref. Agriculture)	
Manufacturing	-0.007*** (0.002)
Construction	0.046*** (0.002)
Trade	-0.060*** (0.002)
Business services	-0.003 (0.002)
Public sector	-0.086*** (0.002)
Other services	-0.045*** (0.002)
Length of unemployment spell (ref: 3 months or less)	
4-6 months	-0.024*** (0.001)
7-9 months	-0.045*** (0.001)
10-12 months	-0.067*** (0.001)
13-18 months	-0.095*** (0.001)
19-24 months	-0.116*** (0.001)
More than 24 months	-0.127*** (0.001)
Previous job was full-time	-0.089*** (0.001)
Constant	8.991*** (0.005)
Number of observations	1,448,020
R^2	0.232

Notes: The table presents regression results for log monthly re-employment wages of unemployed workers in the ten years preceding our survey experiment. We report regression results for the universe of unemployed workers based on background characteristics observed in administrative records. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level.

Table A.2 Balancing table by perception gap

	Large pessimism			Small pessimism			Neutral			Small optimism			Large optimism		
	Mean val.	Balance		Mean val.	Balance		Mean val.	Balance		Mean val.	Balance		Mean val.	Balance	
	Treat. Control	<i>P</i> -val.	(3)	Treat. Control	<i>P</i> -val.	(6)	Treat. Control	<i>P</i> -val.	(9)	Treat. Control	<i>P</i> -val.	(12)	Treat. Control	<i>P</i> -val.	(15)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	
Age															
Below 36 years	0.40	0.36	0.11	0.34	0.31	0.20	0.38	0.38	0.97	0.34	0.35	0.68	0.24	0.27	0.14
36-50 years	0.25	0.27	0.37	0.27	0.26	0.69	0.28	0.25	0.27	0.26	0.27	0.65	0.28	0.27	0.56
Above 50 years	0.35	0.37	0.42	0.39	0.43	0.12	0.34	0.37	0.30	0.40	0.38	0.42	0.48	0.46	0.44
Gender															
Female	0.52	0.50	0.42	0.57	0.55	0.40	0.61	0.56	0.06	0.62	0.61	0.66	0.53	0.55	0.51
Male	0.48	0.50	0.42	0.43	0.45	0.40	0.39	0.44	0.06	0.38	0.39	0.66	0.47	0.45	0.51
Level of education															
Elementary school	0.19	0.17	0.40	0.15	0.16	0.46	0.11	0.11	0.83	0.09	0.09	0.75	0.06	0.05	0.28
High school	0.36	0.42	0.02	0.42	0.45	0.29	0.39	0.41	0.61	0.38	0.38	0.88	0.31	0.33	0.33
University	0.45	0.41	0.08	0.43	0.39	0.11	0.50	0.48	0.53	0.53	0.53	0.74	0.63	0.62	0.68
Previous employment															
Full-time	0.82	0.81	0.79	0.90	0.91	0.28	0.85	0.87	0.31	0.88	0.86	0.29	0.88	0.88	0.68
Part-time	0.18	0.19	0.79	0.10	0.09	0.28	0.15	0.13	0.31	0.12	0.14	0.29	0.12	0.12	0.68
Current unemployment duration (in months)	6.67	6.64	0.94	5.82	6.64	0.01	6.26	6.12	0.74	6.98	6.79	0.55	7.07	6.94	0.65
Previous industry															
Agriculture	0.01	0.02	0.16	0.01	0.01	0.90	0.01	0.01	0.41	0.00	0.01	0.46	0.00	0.00	0.43
Manufacturing	0.12	0.14	0.18	0.13	0.13	0.85	0.09	0.11	0.34	0.10	0.10	0.84	0.14	0.12	0.29
Construction	0.06	0.05	0.58	0.06	0.05	0.31	0.02	0.05	0.01	0.04	0.06	0.08	0.03	0.03	0.56
Trade	0.24	0.27	0.10	0.23	0.26	0.10	0.24	0.20	0.09	0.21	0.19	0.19	0.18	0.21	0.13
Business services	0.14	0.13	0.31	0.15	0.14	0.55	0.20	0.22	0.66	0.23	0.24	0.59	0.29	0.28	0.81
Public sector	0.34	0.30	0.12	0.34	0.31	0.16	0.33	0.31	0.32	0.32	0.30	0.35	0.29	0.29	1.00
Other services	0.09	0.09	0.63	0.08	0.09	0.22	0.09	0.10	0.70	0.09	0.10	0.22	0.06	0.06	1.00
Previous monthly wage (in DKK)	24649	24732	0.88	27063	27095	0.94	27783	27674	0.88	30766	30413	0.54	41680	41550	0.88
F-test joint sign.			0.261			0.207			0.257			0.803			0.790
Number of observations	841	882	1723	1100	1078	2178	509	534	1043	1001	979	1980	1177	1146	2323

Notes: The table reports summary statistics and balance tests for our study sample, split by prior perception gaps. Columns (1),(2),(4),(5),(7),(8),(10),(11),(13) and (14) report characteristics of participants in the main survey by treatment status split by their prior perception gaps. Columns (3),(6),(9),(12) and (15) show *p*-values for differences between treatment and control groups.

Table A.3 Treatment effects on main outcomes by perception gap

Dependent variable	Expected wage offered ^(a) (log) (1)	Reservation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Concession geograph. location ^(c) (pp.) (4)	Average emp. rate 3m. ^(d) (pp.) (5)	Average emp. rate 6m. ^(d) (pp.) (6)	Total earnings 6m. ^(d) (DKK) (7)	Total hours 6m. ^(d) (8)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$								
Treatment effect	0.053*** (0.008)	0.039*** (0.008)	0.064 (0.201)	-0.047** (0.023)	0.041** (0.020)	0.029 (0.019)	5,211* (2,843)	25.06* (13.78)
<i>P</i> -value (v. neutral group)	0.00	0.01	0.50	0.71	0.25	0.62	0.59	0.48
Mean control group	10.12	10.04	2.81	0.52	0.30	0.38	45,620	226.42
Number of observations	1,723	1,723	1,723	1,723	1,723	1,723	1,723	1,723
B. Moderate pessimism: perception gap (log) $\in (+0.025; +0.150]$								
Treatment effect	0.021*** (0.005)	0.014*** (0.005)	-0.013 (0.187)	0.009 (0.021)	-0.010 (0.017)	-0.012 (0.016)	421 (2,565)	3.29 (12.21)
<i>P</i> -value (v. neutral group)	0.00	0.81	0.34	0.24	0.63	0.36	0.65	0.80
Mean control group	10.22	10.13	3.00	0.46	0.31	0.39	51,160	248.85
Number of observations	2,178	2,178	2,178	2,178	2,178	2,178	2,178	2,178
C. Neutral group: perception gap (log) $\in [-0.025; +0.025]$								
Treatment effect	-0.011 (0.007)	0.012 (0.008)	0.280 (0.254)	-0.034 (0.030)	0.004 (0.025)	0.014 (0.024)	2,565 (4,093)	8.79 (18.92)
Mean control group	10.31	10.19	2.41	0.50	0.32	0.41	56,112	270.14
Number of observations	1,043	1,043	1,043	1,043	1,043	1,043	1,043	1,043
D. Moderate optimism: perception gap (log) $\in [-0.150; -0.025]$								
Treatment effect	-0.028*** (0.005)	-0.002 (0.006)	0.206 (0.171)	-0.005 (0.022)	-0.003 (0.017)	-0.004 (0.017)	193 (2,986)	1.30 (13.25)
<i>P</i> -value (v. neutral group)	0.04	0.17	0.81	0.44	0.80	0.52	0.63	0.74
Mean control group	10.39	10.26	2.17	0.53	0.30	0.39	57,772	262.80
Number of observations	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980
E. Large optimism: perception gap (log) $\in [-\infty; -0.150]$								
Treatment effect	-0.038*** (0.006)	-0.016** (0.007)	0.400*** (0.138)	-0.016 (0.020)	0.037** (0.015)	0.039*** (0.015)	6,349* (3,830)	21.57* (12.50)
<i>P</i> -value (v. neutral group)	0.00	0.01	0.67	0.63	0.26	0.37	0.49	0.57
Mean control group	10.62	10.47	1.51	0.58	0.24	0.34	69,959	254.04
Number of observations	2,323	2,323	2,323	2,323	2,323	2,323	2,323	2,323

Notes: The table reports the effects of the information treatment on individuals' beliefs, job search behavior and labor market outcomes. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Indicates whether the respondent would accept relocation or long-distance commute for new employment.

^(d) Observed in the administrative records.

Table A.4 Treatment effects on various dimensions of job search

Dependent variable	Reg. applications ^(a)		Concession willingness ^(b)			Vacancy clicks ^(c)		
	Search radius (log) (1)	No. of distinct occ. (log) (2)	Geograph. location (pp.) (3)	Working cond. (pp.) (4)	Skills/ occ. (pp.) (5)	No. of job ads clicked 4w. (6)	Target month. earnings (log) (7)	Target firm size (emp.) (8)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$								
Treatment effect	-0.070* (0.038)	0.017 (0.038)	-0.047** (0.023)	-0.025 (0.023)	-0.004 (0.016)	0.140 (1.318)	0.031** (0.016)	1,072*** (358)
<i>P</i> -value (v. neutral group)	0.25	0.51	0.71	0.71	0.70	0.49	0.26	0.14
Mean control group	1.09	0.63	0.52	0.66	0.87	13.07	10.11	5,741
Number of observations	1,425	864	1,723	1,723	1,723	1,723	1,245	1,245
B. Moderate pessimism: perception gap (log) $\in (+0.025; +0.150]$								
Treatment effect	0.000 (0.033)	0.004 (0.034)	0.009 (0.021)	-0.030 (0.020)	0.008 (0.014)	-0.009 (1.042)	0.008 (0.013)	104 (301)
<i>P</i> -value (v. neutral group)	0.98	0.37	0.24	0.79	0.89	0.39	0.85	0.82
Mean control group	1.05	0.61	0.46	0.66	0.88	13.40	10.17	6,137
Number of observations	1,816	1,062	2,178	2,178	2,178	2,178	1,601	1,601
C. Neutral group: perception gap (log) $\in [-0.025; +0.025]$								
Treatment effect	0.002 (0.051)	0.060 (0.054)	-0.034 (0.030)	-0.039 (0.030)	0.005 (0.018)	1.352 (1.210)	0.004 (0.019)	225 (467)
Mean control group	1.08	0.56	0.50	0.68	0.90	10.48	10.20	6,573
Number of observations	851	464	1,043	1,043	1,043	1,043	744	744
D. Moderate optimism: perception gap (log) $\in [-0.150; -0.025]$								
Treatment effect	-0.029 (0.037)	0.076* (0.039)	-0.005 (0.022)	0.032 (0.022)	0.020 (0.013)	0.495 (0.750)	0.000 (0.015)	-42 (378)
<i>P</i> -value (v. neutral group)	0.61	0.80	0.44	0.05	0.49	0.54	0.87	0.65
Mean control group	1.11	0.51	0.53	0.59	0.89	9.32	10.23	6,997
Number of observations	1,642	769	1,980	1,980	1,980	1,980	1,333	1,333
E. Large optimism: perception gap (log) $\in [-\infty; -0.150]$								
Treatment effect	0.044 (0.039)	0.014 (0.044)	-0.016 (0.020)	-0.009 (0.020)	-0.012 (0.013)	1.805*** (0.694)	-0.004 (0.015)	-218 (388)
<i>P</i> -value (v. neutral group)	0.50	0.50	0.63	0.39	0.43	0.74	0.73	0.46
Mean control group	1.12	0.52	0.58	0.57	0.90	6.88	10.31	6,887
Number of observations	1,889	644	2,323	2,323	2,323	2,323	1,350	1,350

Notes: The table reports the effects of the information treatment on various dimensions of job search. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group.

^(a) Measured based on registered job applications (*joblog*). The search radius refers to the average distance between the job seekers' place of residence and the recorded jobs they applied for.

^(b) Measured in the main survey. Column (3): Indicates whether respondent would accept relocation or long-distance commute for new employment. Column (4): Indicates whether respondent would accept unfavorable working conditions (i.e., exhausting work, uninteresting work, awkward conditions or awkward hours) for new employment. Column (5): Indicates whether the respondent would make concessions regarding the skills required for new employment (i.e., take extra training, change profession, or work below their qualifications).

^(c) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first 4 weeks after the survey.

Table A.5 Correlational analysis

Dependent variable	Expected wage offered ^(a) (log) (1)	Reservation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Concession geograph. location ^(c) (pp.) (4)	Average emp. rate 3m. ^(d) (pp.) (5)
Actual group-level wage (log)	0.488*** (0.041)	0.398*** (0.045)	0.026 (1.025)	-0.031 (0.132)	-0.058 (0.097)
Perception gap (ref: neutral group: perception gap (log) \in [-0.025; +0.025])					
Large optimism: perception gap (log) \in $[-\infty; -0.150]$					
	0.172*** (0.008)	0.143*** (0.009)	-0.456** (0.204)	0.051* (0.027)	-0.049** (0.022)
Moderate optimism: perception gap (log) \in [-0.150; -0.025]					
	0.053*** (0.006)	0.042*** (0.007)	-0.105 (0.202)	0.022 (0.026)	-0.007 (0.021)
Moderate pessimism: perception gap (log) \in (+0.025; +0.150]					
	-0.060*** (0.006)	-0.036*** (0.007)	0.353* (0.210)	-0.014 (0.026)	-0.009 (0.021)
Large pessimism: perception gap (log) \in (+0.150; + ∞]					
	-0.160*** (0.008)	-0.114*** (0.008)	0.223 (0.218)	0.027 (0.027)	-0.027 (0.022)
Mean dep. variable	10.35	10.23	2.35	0.52	0.29
Number of observations	4,619	4,619	4,619	4,619	4,619
P-value (large optimism vs. large pessimism)	0.000	0.000	0.000	0.325	0.277

Notes: The table presents correlations between job seekers' initial perception gaps and their beliefs, job search behavior, and labor market outcomes for individuals assigned to the control group. All regressions include the set of covariates listed in Table 1. Robust standard errors are reported in parentheses. */**/** indicates statistical significance at the 10%/5%/1%-level.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Indicates whether respondent would accept relocation or long-distance commute for new employment.

^(d) Observed in the administrative records.

Table A.6 Treatment effects on expected wage offers, controlling for additional interactions

Dependent variable	Expected wage offered (log)				
	(1)	(2)	(3)	(4)	(5)
Treatment × Large positive perception gap	0.070*** (0.010)	0.069*** (0.010)	0.068*** (0.011)	0.069*** (0.012)	0.076*** (0.015)
Treatment × Moderate positive perception gap	0.037*** (0.008)	0.035*** (0.008)	0.035*** (0.009)	0.036*** (0.009)	0.043*** (0.013)
Treatment × Moderate negative perception gap	0.004 (0.009)	0.002 (0.009)	0.002 (0.009)	0.002 (0.010)	0.009 (0.013)
Treatment × Small negative perception gap	-0.016** (0.007)	-0.019** (0.007)	-0.019** (0.008)	-0.019** (0.008)	-0.011 (0.013)
Treatment × Large neg. perc. gap	-0.030*** (0.006)	-0.032*** (0.006)	-0.033*** (0.007)	-0.032*** (0.008)	-0.025** (0.013)
Additional controls					
Treatment ×					
Pre-unemployment wage	Yes	Yes	Yes	Yes	Yes
UE duration ≥ 6m.	No	Yes	Yes	Yes	Yes
Female	No	No	Yes	Yes	Yes
Age	No	No	No	Yes	Yes
Education	No	No	No	No	Yes
Number of observations	9,247	9,247	9,247	9,247	9,247
Mean control group	10.35	10.35	10.35	10.35	10.35

Notes: The table shows the effects of the information treatment on individuals' expected wage (log), measured in the main survey. We provide a fully interacted model with the initial perception gaps, such that all control variables are interacted with the perception groups. Furthermore, the treatment indicator is interacted with the perception groups and five covariates (three income groups, long-term unemployment, gender, three age groups, three education groups). All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level.

Table A.7 Alternative specification

Dependent variable	Expected wage offered ^(a) (log) (1)	Reservation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Concession geograph. location ^(c) (pp.) (4)	Average emp. rate 3m. ^(d) (pp.) (5)	Total earnings 6m. ^(d) (DKK) (6)	Total hours 6m. ^(d) (7)
Treatment × perception gap	0.166*** (0.019)	0.090*** (0.019)	-0.568 (0.347)	-0.035 (0.046)	-0.017 (0.036)	-4,051 (7,448)	4.60 (27.46)
Treatment	0.001 (0.003)	0.009*** (0.003)	0.182** (0.082)	-0.014 (0.010)	0.014* (0.008)	2,863** (1,440)	12.02** (6.07)
Perception gap	-0.505*** (0.016)	-0.385*** (0.016)	1.364*** (0.267)	-0.050 (0.035)	0.033 (0.026)	-13,546*** (5,193)	-28.08 (20.36)
Mean control group	10.35	10.23	2.35	0.52	0.29	56,740	251.27
Number of observations	9,247	9,247	9,247	9,247	9,247	9,247	9,247

Notes: The table reports the effects of the information treatment on individuals' beliefs, job search behavior and labor market outcomes from a fully interacted model including initial perception gaps, a treatment indicator, and their interaction. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Indicates whether the respondent would accept relocation or long-distance commute for new employment.

^(d) Observed in the administrative records.

Table A.8 Robustness of treatment effects to different winsorization cutoffs

Dependent variable	Expected wage offered ^(a) (log) (1)	Reservation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Concession geograph. location ^(c) (pp.) (4)	Average emp. rate 3m. ^(d) (pp.) (5)	Average emp. rate 6m. ^(d) (pp.) (6)	Total earnings 6m. ^(d) (DKK) (7)	Total hours 6m. ^(d) (8)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$								
Treatment effect	0.124*** (0.029)	0.054** (0.021)	0.049 (0.272)	-0.047** (0.023)	0.040** (0.020)	0.029 (0.019)	5,281* (2,831)	25.56* (13.72)
<i>P</i> -value (v. neutral group)	0.00	0.20	0.44	0.72	0.25	0.62	0.58	0.47
Mean control group	9.92	9.93	3.30	0.52	0.30	0.38	45,453	225.57
Number of observations	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732
B. Moderate pessimism: perception gap (log) $\in (+0.025; +0.150]$								
Treatment effect	0.033*** (0.012)	0.009 (0.011)	-0.125 (0.253)	0.009 (0.021)	-0.010 (0.017)	-0.012 (0.016)	317.248 (2,574)	2.745 (12.25)
<i>P</i> -value (v. neutral group)	0.01	0.43	0.22	0.24	0.63	0.35	0.64	0.79
Mean control group	10.20	10.12	3.53	0.46	0.31	0.40	51,318	249.63
Number of observations	2,169	2,169	2,169	2,169	2,169	2,169	2,169	2,169
C. Neutral group: perception gap (log) $\in [-0.025; +0.025]$								
Treatment effect	-0.015 (0.014)	0.022* (0.013)	0.384 (0.341)	-0.034 (0.030)	0.004 (0.025)	0.014 (0.024)	2,565 (4,093)	8.79 (18.92)
Mean control group	10.30	10.18	2.75	0.50	0.32	0.41	56,112	270.14
Number of observations	1,043	1,043	1,043	1,043	1,043	1,043	1,043	1,043
D. Moderate optimism: perception gap (log) $\in [-0.150; -0.025]$								
Treatment effect	-0.032*** (0.011)	-0.002 (0.011)	0.186 (0.220)	-0.005 (0.022)	-0.003 (0.017)	-0.004 (0.017)	193.046 (2,986)	1.300 (13.25)
<i>P</i> -value (v. neutral group)	0.33	0.15	0.62	0.44	0.80	0.52	0.63	0.74
Mean control group	10.39	10.25	2.46	0.53	0.30	0.39	57,772	262.80
Number of observations	1,980	1,980	1,980	1,980	1,980	1,980	1,980	1,980
E. Large optimism: perception gap (log) $\in [-\infty; -0.150]$								
Treatment effect	-0.048*** (0.012)	-0.013 (0.010)	0.571*** (0.185)	-0.016 (0.020)	0.037** (0.015)	0.039*** (0.015)	6,278 (3,823)	21.58* (12.49)
<i>P</i> -value (v. neutral group)	0.07	0.03	0.62	0.63	0.26	0.37	0.50	0.57
Mean control group	10.65	10.49	1.69	0.58	0.24	0.34	69,959	254.04
Number of observations	2,323	2,323	2,323	2,323	2,323	2,323	2,323	2,323

Notes: The table shows the effects of the information treatment on individuals' beliefs, job search behavior and labor market outcomes for different winsorization cutoffs. We winsorize prior beliefs (used to construct the perception gap), expected own wage offers, and reservation wages at the 1st and 99th percentiles, and search intensity, cumulative earnings and working hours in the post-treatment period at the 99th percentile. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level. The reported *p*-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Indicates whether respondent would accept relocation or long-distance commute for new employment.

^(d) Observed in the administrative records.

Table A.9 Robustness: multiple hypothesis adjustment

Dependent variable	Reservation wage ^(a) wage ^(a) (log) (1)	No. of job ads clicked ^(b) (2)	Concession geograph. location ^(c) (pp.) (3)	Concession working cond. ^(c) (pp.) (4)	Concession skills/occ. ^(c) (pp.) (5)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$					
Treatment effect	0.039*** (0.008)	0.064 (0.201)	-0.047** (0.023)	-0.025 (0.023)	-0.004 (0.016)
P-value	$\langle 0.000 \rangle$	$\langle 0.752 \rangle$	$\langle 0.044 \rangle$	$\langle 0.265 \rangle$	$\langle 0.804 \rangle$
FDR adj. q-value	$\langle 0.001 \rangle$	$\langle 0.792 \rangle$	$\langle 0.097 \rangle$	$\langle 0.361 \rangle$	$\langle 0.792 \rangle$
Mean control group	10.04	2.81	0.52	0.66	0.87
Number observations	1,723	1,723	1,723	1,723	1,723
B. Large optimism: perception gap (log) $\in [-\infty; -0.150]$					
Treatment effect	-0.016** (0.007)	0.400*** (0.138)	-0.016 (0.020)	-0.009 (0.020)	-0.012 (0.013)
P-value	$\langle 0.022 \rangle$	$\langle 0.004 \rangle$	$\langle 0.419 \rangle$	$\langle 0.669 \rangle$	$\langle 0.350 \rangle$
FDR adj. q-value	$\langle 0.047 \rangle$	$\langle 0.021 \rangle$	$\langle 0.459 \rangle$	$\langle 0.671 \rangle$	$\langle 0.459 \rangle$
Mean control group	10.47	1.51	0.58	0.57	0.90
Number observations	2,323	2,323	2,323	2,323	2,323

Notes: The table reports results from a robustness check that adjusts for multiple hypothesis testing. We present the effects of the information treatment on several dimensions of job seekers' search behavior, separately by the size of their initial perception gaps. For each coefficient, we show both the unadjusted p -values and the sharpened q -values that control the false discovery rate (FDR; Anderson, 2008). All specifications control for individual background characteristics summarized in Table 1. Robust standard errors are reported in parentheses. */**/** indicates statistical significance at the 10%/5%/1%-level.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Column (3): Indicates whether respondent would accept relocation or long-distance commute for new employment. Column (4): Indicates whether respondent would accept unfavorable working conditions (i.e., exhausting work, uninteresting work, awkward conditions or awkward hours) for new employment. Column (5): Indicates whether the respondent would make concessions regarding the skills required for new employment (i.e., take extra training, change profession, or work below their qualifications).

Table A.10 Robustness of treatment effects to exclusion of previous part-time workers

Dependent variable	Expected wage offered ^(a) (log) (1)	Reservation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Concession geograph. location ^(c) (pp.) (4)	Average emp. rate 3m. ^(d) (pp.) (5)	Average emp. rate 6m. ^(d) (pp.) (6)	Total earnings 6m. ^(d) (DKK) (7)	Total hours 6m. ^(d) (8)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$								
Treatment effect	0.055*** (0.008)	0.042*** (0.008)	0.029 (0.231)	-0.034 (0.026)	0.029 (0.021)	0.020 (0.021)	5,023 (3,232)	23.82 (15.36)
<i>P</i> -value (v. neutral group)	0.00	0.03	0.56	0.89	0.40	0.77	0.56	0.47
Mean control group	10.12	10.05	3.00	0.49	0.29	0.37	46,984	229.62
Number of observations	1,403	1,403	1,403	1,403	1,403	1,403	1,403	1,403
B. Moderate pessimism: perception gap (log) $\in (+0.025; +0.150]$								
Treatment effect	0.020*** (0.005)	0.013** (0.005)	0.059 (0.200)	0.012 (0.022)	-0.013 (0.018)	-0.015 (0.017)	221 (2,713)	2.08 (12.84)
<i>P</i> -value (v. neutral group)	0.01	0.73	0.60	0.30	0.67	0.40	0.75	0.89
Mean control group	10.23	10.14	3.09	0.44	0.30	0.39	51,566	250.31
Number of observations	1,965	1,965	1,965	1,965	1,965	1,965	1,965	1,965
C. Neutral group: perception gap (log) $\in [-0.025; +0.025]$								
Treatment effect	-0.005 (0.007)	0.016* (0.009)	0.235 (0.280)	-0.028 (0.033)	0.000 (0.027)	0.011 (0.026)	1,849 (4,474)	5.42 (20.41)
Mean control group	10.31	10.20	2.54	0.47	0.31	0.40	55,209	263.40
Number of observations	895	895	895	895	895	895	895	895
D. Moderate optimism: perception gap (log) $\in [-0.150; -0.025]$								
Treatment effect	-0.030*** (0.006)	-0.002 (0.007)	0.210 (0.189)	-0.009 (0.024)	-0.011 (0.018)	-0.012 (0.018)	-1,053 (3,226)	-3.48 (14.13)
<i>P</i> -value (v. neutral group)	0.01	0.08	0.94	0.63	0.71	0.47	0.59	0.72
Mean control group	10.40	10.28	2.28	0.50	0.28	0.38	57,568	257.70
Number of observations	1,727	1,727	1,727	1,727	1,727	1,727	1,727	1,727
E. Large optimism: perception gap (log) $\in [-\infty; -0.150]$								
Treatment effect	-0.033*** (0.006)	-0.013* (0.007)	0.534*** (0.148)	-0.028 (0.022)	0.034** (0.015)	0.032** (0.016)	5,938 (4,182)	18.44 (13.27)
<i>P</i> -value (v. neutral group)	0.00	0.01	0.34	1.00	0.27	0.46	0.50	0.59
Mean control group	10.63	10.49	1.49	0.57	0.21	0.33	69,970	246.01
Number of observations	2,049	2,049	2,049	2,049	2,049	2,049	2,049	2,049

Notes: The table shows the effects of the information treatment on individuals' beliefs, job search behavior and labor market outcomes. We restrict the sample to job seekers reporting that they worked full-time in their previous job. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured in the main survey. Indicates whether respondent would accept relocation or long-distance commute for new employment.

^(d) Observed in the administrative records.

Table A.11 Heterogeneous treatment effects by previous geographic scope of search

Dependent variable	Expected wage offered ^(a) (log) (1)	Reser- vation wage ^(a) (log) (2)	No. of job ads clicked ^(b) (3)	Search radius ^(c) (log) (4)	Empl. rate 3m. ^(d) (pp.) (5)	Empl. rate 6m. ^(d) (pp.) (6)	Total earnings 6m. ^(d) (DKK) (7)
A. By search radius: Large pessimism: perception gap (log) $\in (+0.150; +\infty]$							
Treatment x local search	0.055*** (0.009)	0.040*** (0.009)	0.117 (0.258)	0.011 (0.039)	0.013 (0.024)	0.006 (0.023)	-754 (3,513)
Treatment x distant search	0.042* (0.023)	0.032 (0.022)	-0.444 (0.462)	-0.081 (0.094)	0.110** (0.049)	0.089* (0.047)	23,072*** (7,161)
<i>P</i> -value (local v. distant)	0.58	0.77	0.29	0.37	0.08	0.12	0.00
Number of observations	1,453	1,453	1,453	1,287	1,453	1,453	1,453
B. By search radius: Large optimism: perception gap (log) $\in [-\infty; -0.150]$							
Treatment x local search	-0.041*** (0.008)	-0.017* (0.009)	0.511*** (0.184)	0.065* (0.040)	0.033* (0.019)	0.042** (0.019)	6,468 (4,689)
Treatment x distant search	-0.054*** (0.012)	-0.039*** (0.014)	0.334 (0.282)	0.000 (0.089)	0.040 (0.030)	0.027 (0.030)	2,620 (8,635)
<i>P</i> -value (local v. distant)	0.33	0.19	0.60	0.51	0.86	0.68	0.70
Number of observations	1,987	1,987	1,987	1,718	1,987	1,987	1,987

Notes: The table reports heterogeneous effects of the information treatment on individuals' beliefs, job search behavior, and labor market outcomes by pre-treatment search radius, measured by the average distance between a job seeker's residence and the jobs they applied to. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level. The reported *p*-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group.

^(a) Measured in the main survey.

^(b) Clicks on job ads on the online platform of public employment services (*jobnet.dk*) within the first week after the survey.

^(c) Measured based on registered job applications (*joblog*). The search radius refers to the average distance between the job seekers' place of residence and the recorded jobs applied to.

^(d) Observed in the administrative records.

Table A.12 Treatment effects on geographical and occupational scope of employment

Dependent variable	Employed within own municipality 3m. (pp.) (1)	Employed outside own municipality 3m. (pp.) (2)	Distance to first job (log) (3)	Employed within prev. occupation 3m. (pp.) (4)	Employed outside prev. occupation 3m. (pp.) (5)	Employed part-time 3m. (pp.) (6)	Employed full-time 3m. (pp.) (7)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty]$							
Treatment effect	0.045** (0.020)	-0.006 (0.017)	-0.094* (0.051)	0.013 (0.018)	0.024 (0.019)	0.011 (0.020)	0.028 (0.018)
<i>P</i> -value (v. neutral group)	0.25	0.99	0.29	0.81	0.54	0.74	0.39
Mean control group	0.20	0.15	2.88	0.16	0.16	0.20	0.15
Number of observations	1,723	1,723	1,336	1,723	1,723	1,723	1,723
B. Moderate pessimism: perception gap (log) $\in (+0.025; +0.150]$							
Treatment effect	-0.016 (0.017)	-0.014 (0.016)	-0.050 (0.043)	-0.012 (0.016)	0.003 (0.016)	-0.026 (0.017)	-0.004 (0.016)
<i>P</i> -value (v. neutral group)	0.45	0.76	0.58	0.54	0.93	0.35	0.87
Mean control group	0.21	0.16	2.79	0.18	0.17	0.19	0.18
Number of observations	2,178	2,178	1,766	2,178	2,178	2,178	2,178
C. Neutral group: perception gap (log) $\in [-0.025; +0.025]$							
Treatment effect	0.008 (0.026)	-0.005 (0.024)	-0.008 (0.067)	0.005 (0.024)	0.005 (0.025)	0.001 (0.025)	0.002 (0.026)
Mean control group	0.21	0.18	2.80	0.18	0.18	0.18	0.21
Number of observations	1,043	1,043	839	1,043	1,043	1,043	1,043
D. Moderate optimism: perception gap (log) $\in [-0.150; -0.025]$							
Treatment effect	-0.009 (0.018)	-0.017 (0.017)	0.018 (0.048)	-0.013 (0.016)	-0.007 (0.018)	-0.009 (0.017)	-0.017 (0.018)
<i>P</i> -value (v. neutral group)	0.58	0.70	0.75	0.53	0.69	0.74	0.55
Mean control group	0.21	0.19	2.70	0.16	0.20	0.18	0.22
Number of observations	1,980	1,980	1,527	1,980	1,980	1,980	1,980
E. Large optimism: perception gap (log) $\in [-\infty; -0.150]$							
Treatment effect	0.027* (0.014)	0.001 (0.017)	-0.061 (0.048)	-0.009 (0.014)	0.010 (0.016)	0.011 (0.014)	0.016 (0.017)
<i>P</i> -value (v. neutral group)	0.53	0.84	0.51	0.60	0.87	0.71	0.64
Mean control group	0.13	0.21	2.81	0.14	0.19	0.13	0.21
Number of observations	2,323	2,323	1,716	2,323	2,323	2,323	2,323

Notes: The table shows the effects of the information treatment on individuals' labor market outcomes. Columns (1) and (2) examine whether respondents are employed within or outside their municipality of residence—measured at the time of the survey—three months after the intervention. Column (3) examines the geographical distance between respondents' place of residence at the time of the survey and the location of their first subsequent job. Columns (4) and (5) examine whether respondents are employed within or outside their previous three months after the intervention. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. All specifications include the baseline covariates listed in Table 1. Robust standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level.

B Details on the theoretical framework

In this section, we provide additional details on the theoretical framework discussed in Section 3. Specifically, we outline how job seekers wage expectations $\hat{\mu}_w$ influence their selectivity—captured by their reservation wages and amenity requirements—and their search intensity.

B.1 Effect of wage expectations on selectivity

We analyze how a positive shock to wage expectations $\hat{\mu}_w$ affects (i) the reservation wage \bar{w} and (ii) the amenity requirement \bar{a} when the job value is $v = w + \theta a$. Beliefs about the wage–amenity link take the linear form $\mathbb{E}[a \mid w] = \alpha + \beta w$, where $\beta > 0$ (complements) means higher wages predict better amenities and $\beta < 0$ (compensating differentials) means higher wages predict worse amenities. We assume standard search primitives (FOSD improvements of $F(\cdot; s)$ in s , convex $\gamma(\cdot)$), which imply that the reservation value \bar{v} is strictly increasing in the perceived mean job value $\hat{\mu}$.

Note that job seekers determine their reservation wages and amenity requirements simultaneously, and we are interested in identifying both before they have seen a particular offer. To that end, we adopt a modeling approach in which we first assume that job seekers screen potential offers based on wages while forming beliefs about the associated amenities, and then, in a second step, assume that they screen based on amenities while forming beliefs about the associated wages. This sequential structure is not meant to describe actual behavior but serves as a device to separately identify both dimensions.

Step 1: Wage expectations, job values and reservation values

Under $\mathbb{E}[a \mid w] = \alpha + \beta w$, the perceived mean job value is

$$\hat{\mu} = \hat{\mu}_w + \theta \mathbb{E}[a] = (1 + \theta\beta) \hat{\mu}_w + \theta\alpha. \quad (\text{B.1})$$

Let $\phi_\mu \equiv \frac{\partial \bar{v}}{\partial \hat{\mu}} > 0$ denote the sensitivity of \bar{v} to $\hat{\mu}$. By the chain rule,

$$\frac{\partial \bar{v}}{\partial \hat{\mu}_w} = (1 + \theta\beta) \phi_\mu. \quad (\text{B.2})$$

Thus, if $1 + \theta\beta > 0$, a positive shock to $\hat{\mu}_w$ raises \bar{v} ; if $1 + \theta\beta < 0$, it lowers \bar{v} . The latter refers to the case with strong compensating differentials and highly valued amenities.

Step 2: Reservation wage \bar{w} (screening on wages)

Suppose, for identification, we first consider a screening rule based solely on the wage. The expected job value conditional on w is

$$\mathbb{E}[v | w] = w + \theta(\alpha + \beta w) = (1 + \theta\beta)w + \theta\alpha.$$

If $1 + \theta\beta > 0$ (monotonicity), this is increasing in w and the reservation wage is well defined:

$$\bar{w} = \frac{\bar{v} - \theta\alpha}{1 + \theta\beta}$$

with

$$\frac{\partial \bar{w}}{\partial \hat{\mu}_w} = \frac{1}{1 + \theta\beta} \frac{\partial \bar{v}}{\partial \hat{\mu}_w} = \phi_\mu > 0. \quad (\text{B.3})$$

If $1 + \theta\beta \leq 0$, $\mathbb{E}[v | w]$ the mapping from w to v is non-increasing and a simple wage cutoff no longer characterizes behavior since the reservation wage reflects an upper cutoff rule (i.e. accept all offers above \bar{w}). In that case, we locate the relevant threshold along the amenity axis. Suppose $a = 0$, this yields $\bar{w}^{(a=0)} = \bar{v}$ and

$$\frac{\partial \bar{w}^{(a=0)}}{\partial \hat{\mu}_w} = (1 + \theta\beta) \phi_\mu \leq 0. \quad (\text{B.4})$$

Step 3: Amenity requirement (screening on amenities)

Suppose the worker decides on a minimum amenity requirement \bar{a} without knowing the wage of a specific job offer. To determine an amenity cutoff, workers need to know the expected wage given amenities $\mathbb{E}[w | a]$. However, the perceived relationship $\mathbb{E}[a | w] = \alpha + \beta w$ only describes how amenities vary with wages on average. This forward regression does not pin down the reverse mapping from amenities back to wages. In other words, knowing that high wages are associated with better amenities does not by itself tell us how to predict wages from observing amenities. Therefore, we impose a simple signal structure in which amenities are generated as a noisy linear signal of wages.

$$a = \alpha + \beta w + \varepsilon, \quad \mathbb{E}[\varepsilon] = 0, \quad \varepsilon \perp w.$$

This structure delivers a well-defined Bayesian prediction of wages from amenities $\mathbb{E}[w | a]$ and thus allows us to calculate an amenity threshold. We define

$$\delta \equiv \frac{\text{Cov}(w, a)}{\text{Var}(a)} = \frac{\beta \text{Var}(w)}{\beta^2 \text{Var}(w) + \text{Var}(\varepsilon)}, \quad R^2 \equiv \delta\beta \in [0, 1),$$

where δ denotes the slope in the regression of wages on amenities:

$$\mathbb{E}[w | a] = \hat{\mu}_w + \delta(a - \alpha - \beta\hat{\mu}_w),$$

and R^2 is the squared correlation coefficient between wages and amenities, measuring how much of the variation in amenities can be explained by wages. R^2 close to 1 implies that amenities almost perfectly reveal wages and R^2 near 0 means that amenities contain almost no information about wages.

We further impose the monotonicity condition $\theta + \delta > 0$, ensuring that higher amenities always imply a higher expected job value (i.e. $\mathbb{E}[v | a] = \theta a + \mathbb{E}[w | a]$ increases in a). This condition ensures that there is a well-defined cutoff rule, where the job seeker accepts if $a \geq \bar{a}$. Otherwise, higher amenities do not raise (and could even reduce) the expected job value, which breaks the idea of using a one-dimensional amenity threshold. The wage amenity requirement is given by:

$$\bar{a} = \frac{\bar{v} - \hat{\mu}_w(1 - R^2) + \delta \alpha}{\theta + \delta}. \quad (\text{B.5})$$

Differentiating with respect to $\hat{\mu}_w$ and using (B.2) gives

$$\frac{\partial \bar{a}}{\partial \hat{\mu}_w} = \frac{(1 + \theta\beta)\phi_\mu - (1 - R^2)}{\theta + \delta}. \quad (\text{B.6})$$

Step 4: Signs across the three β -regions

(i) Higher wages are perceived to come with better amenities ($\beta \geq 0$). In this case, the wage-amenity regression slope is non-negative, so $1 + \theta\beta > 0$ and the expected job value increases in wages; hence, a wage-based cutoff \bar{w} is well defined. Under the signal structure $a = \alpha + \beta w + \varepsilon$ with $\mathbb{E}[\varepsilon] = 0$ and $\varepsilon \perp w$, we have $\text{Cov}(w, a) = \beta \text{Var}(w)$, so $\delta = \text{Cov}(w, a)/\text{Var}(a) \geq 0$ and $R^2 = \delta\beta \in [0, 1)$. Because both the direct marginal utility of amenities ($\theta > 0$) and the indirect wage signal from amenities ($\delta \geq 0$) are non-negative, it follows that $\theta + \delta > 0$, which implies $\mathbb{E}[v | a]$ increases in a as well. Given these conditions, $(1 + \theta\beta)\phi_\mu > 0$.

A sufficient condition for the amenity requirement to rise with wage expectations is

$$(1 + \theta\beta)\phi_\mu \geq 1 - R^2,$$

i.e., the positive indirect effect through \bar{v} dominates the attenuation from the imperfect wage signal. Intuitively, when wage expectations rise, workers raise their overall reservation value \bar{v} . If amenities are a reliable signal of wages (high R^2), tightening the amenity cutoff is an effective way to implement this higher threshold, so \bar{a} increases. By contrast, if amenities provide little information about wages (low R^2), raising the amenity threshold would reject many offers for the wrong reason; in that case, workers optimally lower their amenity requirement and rely more on the wage once it is revealed. By (B.3), the reservation wage also increases with $\hat{\mu}_w$ in this case.

Remark (why a positive is likely; mildness). The condition $(1 + \theta\beta)\phi_\mu \geq 1 - R^2$ is mild: the left-hand side is strictly positive and typically sizable when workers become more selective as expected job values rise ($\phi_\mu > 0$), while the right-hand side shrinks quickly as amenities contain any meaningful information about wages (i.e., R^2 not close to zero). Hence, unless amenities are almost entirely uninformative about wages and reservation values respond only weakly to expected wages, the inequality will hold and the amenity threshold increases with wage expectations.

(ii) Compensating differentials, amenities lightly weighted ($-1/\theta < \beta < 0$). Here higher wages are perceived to come with worse amenities, but the tradeoff is not too steep. Since $-1/\theta < \beta < 0$, we have $1 + \theta\beta > 0$, so the expected job value increases in wages and a wage-based cutoff \bar{w} is well defined. Under the signal structure, $\delta < 0$ and $R^2 = \delta\beta \in (0, 1)$. Imposing $\theta + \delta > 0$ ensures that $\mathbb{E}[v | a]$ is increasing in a . By (B.3) the reservation wage rises with wage expectations, $\partial\bar{w}/\partial\hat{\mu}_w = \phi_\mu > 0$.

For the amenity threshold, (B.6) yields

$$\frac{\partial\bar{a}}{\partial\hat{\mu}_w} = \frac{(1 + \theta\beta)\phi_\mu - (1 - R^2)}{\theta + \delta},$$

so the sign is *a priori ambiguous*. A sufficient condition for a *negative* effect is

$$(1 + \theta\beta)\phi_\mu < 1 - R^2.$$

Remark (why a negative effect is likely; mildness). The condition for a negative effect, $(1 + \theta\beta)\phi_\mu < 1 - R^2$, is mild in this region for three reasons: (i) since $\beta < 0$, we have $1 + \theta\beta < 1$, which shrinks the left-hand side relative to the complements case; (ii) $\delta < 0$ means amenities tend to signal *lower* wages, making them a less useful screen when wage expectations rise; and (iii) empirically, when $\beta < 0$ the informativeness of amenities about wages is often limited (noise in a), so R^2 is modest and $1 - R^2$ comparatively large. Thus, unless reservation values respond very strongly to wage expectations and/or amenities are highly informative about wages, the amenity requirement will *decrease* as wage expectations increase.

(iii) Strong compensating differentials, highly valued amenities ($\beta \leq -1/\theta$). The perceived wage-amenity tradeoff is so steep that expected job value is non-increasing in wages, i.e. $1 + \theta\beta \leq 0$. A wage-based cutoff is therefore not monotone; tracking the threshold along the amenity axis (set $a = 0$) yields $\bar{w}^{(a=0)} = \bar{v}$. By (B.4),

$$\frac{\partial\bar{w}^{(a=0)}}{\partial\hat{\mu}_w} = (1 + \theta\beta)\phi_\mu \leq 0,$$

so the wage threshold weakly falls when wage expectations rise. For the amenity threshold, (B.6) gives

$$\frac{\partial \bar{a}}{\partial \hat{\mu}_w} = \frac{(1 + \theta\beta)\phi_\mu - (1 - R^2)}{\theta + \delta}.$$

Since $\phi_\mu > 0$, $1 + \theta\beta \leq 0$, and $1 - R^2 > 0$ (with $R^2 \in [0, 1)$), the numerator is strictly negative; under the maintained monotonicity $\theta + \delta > 0$, it follows that

$$\frac{\partial \bar{a}}{\partial \hat{\mu}_w} < 0.$$

Intuition. When amenities are highly valued and strongly negatively related to wages, an upward revision in wage expectations reduces reliance on both dimensions: both the wage threshold and the amenity requirement fall, and overall selectivity declines.

B.2 Effect of wage expectations on search intensity

We consider the effect of a positive shock on wage expectations $\hat{\mu}_w$, which translates into an increase of the expected average job value $\hat{\mu}$. Let $F(v; s, \hat{\mu})$ denote the perceived CDF of offer values v under effort s and belief parameter $\hat{\mu}$. We define the expected surplus from accepted offers

$$G(s, \bar{v}; \hat{\mu}) \equiv \int_{\bar{v}}^{\infty} [1 - F(v; s, \hat{\mu})] dv,$$

and note the identities

$$G_{\bar{v}}(s, \bar{v}; \hat{\mu}) = -[1 - F(\bar{v}; s, \hat{\mu})] \equiv -\lambda(s, \bar{v}; \hat{\mu}), \quad G_{s\bar{v}}(s, \bar{v}; \hat{\mu}) = F_s(\bar{v}; s, \hat{\mu}).$$

Under first-order stochastic dominance (FOSD) of effort, $F_s(v; s, \hat{\mu}) \leq 0$ for all v (strict for some v).

Step 1: Reservation condition and FOC

With $\bar{v} = U$ at the optimum, the Bellman equation (Equation 1 in the main paper) implies

$$(1 - \rho)\bar{v} = b - \gamma(s) + \rho G(s, \bar{v}; \hat{\mu}). \quad (\text{B.7})$$

The first-order condition (holding \bar{v} fixed by envelope logic) is

$$\gamma'(s^*) = \rho G_s(s^*, \bar{v}; \hat{\mu}), \quad (\text{B.8})$$

with the second-order condition

$$\gamma''(s^*) - \rho G_{ss}(s^*, \bar{v}; \hat{\mu}) > 0.$$

Step 2: Comparative statics

Totally differentiating (B.7) at (s^*, \bar{v}) and using (B.8) to cancel the terms in $ds^*/d\hat{\mu}$ gives

$$[(1 - \rho) - \rho G_{\bar{v}}] \frac{d\bar{v}}{d\hat{\mu}} = \rho G_{\hat{\mu}}. \quad (\text{B.9})$$

Since $G_{\bar{v}} = -\lambda$, we obtain

$$\frac{d\bar{v}}{d\hat{\mu}} = \frac{\rho G_{\hat{\mu}}(s^*, \bar{v}; \hat{\mu})}{(1 - \rho) + \rho \lambda(s^*, \bar{v}; \hat{\mu})}, \quad \lambda(s, \bar{v}; \hat{\mu}) \equiv 1 - F(\bar{v}; s, \hat{\mu}). \quad (\text{B.10})$$

Differentiating (B.8) yields

$$[\gamma'' - \rho G_{ss}] \frac{ds^*}{d\hat{\mu}} = \rho \left(G_{s\hat{\mu}} + G_{s\bar{v}} \frac{d\bar{v}}{d\hat{\mu}} \right), \quad (\text{B.11})$$

i.e.

$$\frac{ds^*}{d\hat{\mu}} = \frac{\rho \left(G_{s\hat{\mu}}(s^*, \bar{v}; \hat{\mu}) + G_{s\bar{v}}(s^*, \bar{v}; \hat{\mu}) \frac{d\bar{v}}{d\hat{\mu}} \right)}{\gamma''(s^*) - \rho G_{ss}(s^*, \bar{v}; \hat{\mu})}. \quad (\text{B.12})$$

Step 3: Sign decomposition

The net effect $ds^*/d\hat{\mu}$ is ambiguous since:

- The *direct term* $G_{s\hat{\mu}} \geq 0$ characterizes how the return to search changes with increased expected job values at a fixed reservation value \bar{v} . This is non-negative when s and $\hat{\mu}$ improve offers in the same direction.
- The *indirect term* $G_{s\bar{v}} d\bar{v}/d\hat{\mu} \leq 0$ characterizes how the return to search changes with increased reservation values due to the higher expected job value. Under FOSD, $G_{s\bar{v}} = F_s(\bar{v}; s^*, \hat{\mu}) \leq 0$. If higher wage prospects shift the perceived distribution rightward so that $G_{\hat{\mu}} > 0$, then by (B.10) we have $d\bar{v}/d\hat{\mu} > 0$ and the indirect effect is non-positive.

C Additional evidence

C.1 Robustness: Evidence on anchoring of wage expectations

In Section 4.1, we estimate regressions that relate respondents’ prior beliefs about wage changes associated with unemployment to the corresponding benchmarks implied by the wage projections used in the information treatment (Figure 2, Panels E and F), following Jäger et al. (2024). In particular, we estimate specifications of the following type:

$$\ln(E_i) - \ln(P_i) = \beta_0 + \beta_1 [\ln(B_i) - \ln(P_i)] + \beta_2 \ln(P_i) + \varepsilon_i \quad (3)$$

where E_i denotes the job seekers’ subjective wage expectation and B_i denotes the cell-specific objective benchmark calculated from administrative records. We control for the level of the pre-unemployment wage, P_i , to account for potential “mechanical” correlations arising from the fact that both the dependent and the independent variable are functions of the pre-unemployment wage. Our estimates of β_1 suggest that for a 10% objective wage change, respondents only expect a change of about 5% (Panels E and F of Figure 2). We interpret this as evidence for a moderate degree of anchoring on pre-unemployment wages. Figure C.1 presents a sensitivity analysis for these results. Panel A focuses on beliefs about wage changes for comparable workers, while Panel B considers beliefs about the difference between respondents’ own next wage offer and their pre-unemployment wage. Panel B is restricted to the control group, as beliefs about respondents’ own next wage offer are elicited post-treatment.

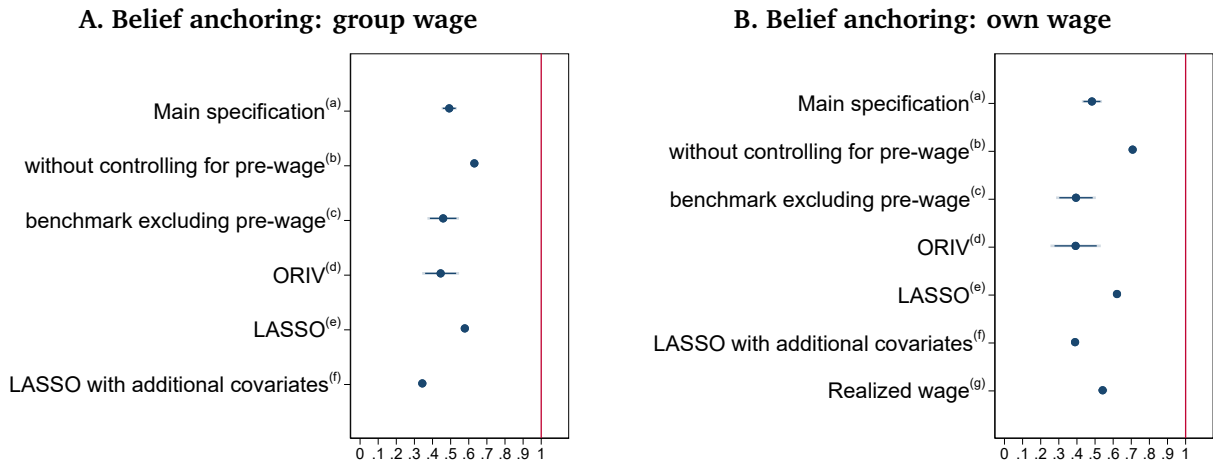
Mechanical correlations Our main regressions control for log pre-unemployment wages to rule out “mechanical” correlations. The estimated coefficient increases somewhat—from 0.49 to 0.63 for cell-level wages—when this control is omitted, suggesting that it is useful to control for pre-unemployment wages. As a robustness check against potential remaining mechanical correlations, we report a specification that instruments the wage projection with an alternative projection that excludes the pre-unemployment wage from the predictor variables. This approach yields similar coefficient estimates as our main specifications, of 0.46 (cell-level wage) and 0.39 (own wage), respectively.

Measurement error Another concern in estimating the degree of “anchoring” in wage expectations is that the researcher typically observes only proxies for the wage change relevant to a given individual. These proxies are noisy and may introduce classical measurement error in the independent variable, potentially attenuating the estimated slope. This concern is mitigated when focusing on beliefs about clearly defined population cells (as we do in Panel A) because population-level statistics abstract from individual-specific circumstances unobserved by the researcher and corresponding benchmarks are precisely measured in administrative data. Remaining sources of noise could arise (i) if respon-

dents misclassify their own characteristics used to construct these benchmarks, or (ii) in the rare case of errors in the administrative data. To address these possibilities, we implement the obviously related instrumental variables (ORIV) approach outlined in Gillen et al. (2019). Specifically, we calculate two alternative versions of the benchmark wage change and the previous wage, taking respondents' characteristics either from their self-reports in the survey or from administrative data. We then use one variable as an instrument for the other in a stacked dataset. We obtain coefficient estimates similar to our baseline results: 0.44 (cell-level wage) and 0.39 (own wage). The fact that these coefficient estimates do not increase relative to the baseline estimates suggests that attenuation bias due to measurement error is unlikely to be a concern.

Alternative benchmarks Although our wage projections predict control-group respondents' actual re-employment wages extremely well (with a coefficient close to one; see Figure 1), we also demonstrate robustness to alternative benchmarks. Specifically, we obtain similar estimates of β_1 as in our main specification when using benchmarks that (i) are constructed using a LASSO procedure that selects the most predictive variables and mitigates potential overfitting from using cell-level averages; or (ii) apply a LASSO procedure with an expanded set of predictors including individuals' municipality of residence and their pre-unemployment occupation and working hours. In addition, two potential concerns with our benchmark are (i) that it is based on past cohorts and (ii) that we do not capture job seekers' idiosyncratic circumstances, which the respondents may have private knowledge about. As a final check, we therefore use actual re-employment wages as a benchmark for control group respondents' beliefs about their own next wage offer (Panel B). This exercise yields an estimate of $\beta_1 = 0.54$ —very close to the estimate of 0.48 from our main specification.

Figure C.1 Robustness of belief anchoring



Notes: The figure reports robustness checks for job seekers' degree of anchoring of wage expectations on their pre-unemployment wages. The sample is restricted to previously full-time employed workers. We report estimates of β_1 in specification (3), relating expected to actual wage changes from pre- to post-unemployment. All specifications, except (b), control for the pre-unemployment wage.

Panel A uses differences between expected average re-employment wages of comparable workers and pre-unemployment wages ($N = 8,039$).

Panel B is based on control group respondents and uses differences between respondents' expected own wage offers and pre-unemployment wages ($N = 4,020$).

(a) Reports the coefficient of interest from the main specification.

(b) Reports the coefficient of interest from the main specification without controlling for the pre-unemployment wage.

(c) Constructs an alternative objective benchmark by excluding the pre-unemployment wage from the set of predictors of the benchmark. We use an instrumental variables approach, instrumenting the difference between the standard benchmark and the pre-unemployment wage with the difference between the alternative benchmark and the pre-unemployment wage.

(d) Constructs alternative measures of the objective benchmark and pre-unemployment wages drawing respondents' characteristics from administrative records. We then employ the obviously related instrumental variables (ORIV) approach (Gillen et al., 2019), using register-based variables as an instrument for survey-based variables and vice versa in a stacked dataset.

(e) Employs a LASSO procedure to select the most predictive variables for realized re-employment wages among the previously considered characteristics and uses these variables to construct an alternative objective benchmark for survey respondents.

(f) Is similar to (e) but in addition includes respondents' municipality of residence, pre-unemployment occupation and working hours when constructing objective benchmarks.

(g) Uses the realized individual re-employment wage as the objective benchmark.

C.2 Additional survey evidence: Beliefs about returns to local and distant job search

The evidence from our field experiment suggests that initially highly pessimistic respondents find employment more quickly when they redirect their job search toward local vacancies. This raises the question of why these job seekers appear to focus “too much” on non-local opportunities in the absence of our intervention. One possible explanation is that they underestimate the extent of spatial search frictions. To explore this possibility, we conduct an additional survey on job seekers’ beliefs about the effectiveness of local versus non-local job search.

Sample and setting In April and May 2025, we invited a fresh random sample of 8,000 UI recipients to participate in an additional survey, employing the same setup as in our main data collection. Again, we raffled a total of 20 gift cards, each worth DKK1,000 (\approx USD140), to incentivize participation. We again drop respondents in the top and bottom percentiles of response time to focus on attentive participants. Our final sample includes 902 complete responses. Table C.1 presents summary statistics. The sample is very similar to the sample from our main experiment.

Design We measure respondents’ beliefs about the effectiveness of search (i) within their municipality of residence, (ii) outside the municipality but within their region of residence, and (iii) outside their region of residence.¹ We consider three dimensions of search effectiveness and, for each dimension, elicit perceived effectiveness across the three geographical areas. First, we measure respondents’ perceived *own application success*—the probability of receiving at least one offer within the next four weeks when applying exclusively for three jobs that are all in a given area. Second, we measure respondents’ perception of *other job seekers’ application success* over the past four years. In particular, the respondents estimate how many out of 100 job seekers from their municipality that applied for at least one job in a given area subsequently started working in that area. This measure enables us to compare respondents’ subjective beliefs with a clearly defined objective benchmark, which we construct using the job application data (*joblog*). Third, we elicit individuals’ perceived *own search productivity* as the probability of identifying at least three interesting job openings within one hour of search in a given area.

Additionally, we collect information on individuals’ background characteristics and their beliefs about the re-employment wages of job seekers similar to themselves, as in our main survey. Finally, we ask the respondents about their job search behavior,

¹Denmark is divided into five administrative regions—Capital Region, Central Denmark, Zealand, North Denmark, and Southern Denmark—each with an approximate radius of 29 to 65 kilometers. Together, these regions include 98 municipalities, most of which have a population of at least 20,000 and an average radius of approximately 11.7 kilometers.

Table C.1 Summary statistics: additional survey

	Mean value
Age	
Below 36 years	0.31
36-50 years	0.24
Above 50 years	0.44
Female	0.55
Level of education	
University	0.56
High school	0.35
Below high school	0.09
Previous job was full-time	0.84
Elapsed unemployment duration in months	7.61
Previous industry	
Agriculture	0.02
Manufacturing	0.13
Construction	0.07
Trade	0.19
Business services	0.24
Public sector	0.25
Other services	0.11
Previous monthly wage in DKK	33,888
Number of observations	902

Notes: The table shows summary statistics for the sample that completed the additional survey.

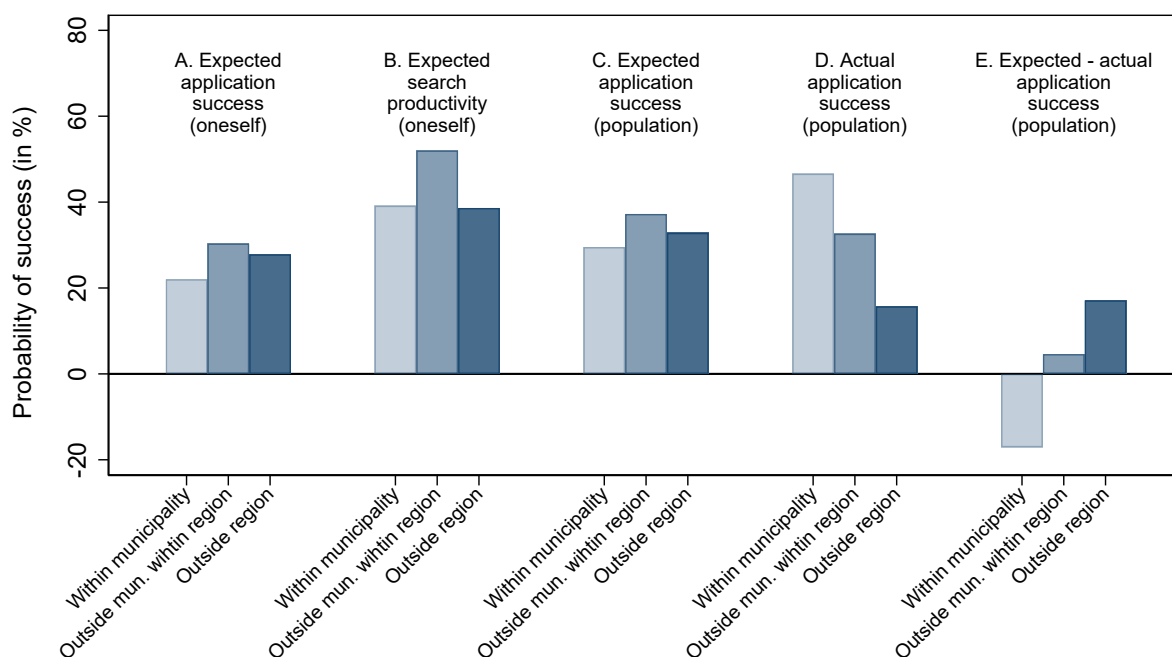
including their search effort and the geographical scope of their search. The full survey instructions can be found in Appendix D.3.

Results We document three additional results on job seekers' beliefs about the effectiveness of local and non-local job search, which facilitate the interpretation of the causal evidence from our field experiment presented in Section 4.

First, on average, job seekers expect to be more effective when searching for jobs outside their municipality of residence than when searching within it. Panels A and B of Figure C.2 show that job seekers perceive themselves to be most effective when searching and applying for jobs located outside their municipality but within their region. Nationwide job search outside one's region is viewed as less promising than searching within one's own region, but still at least as effective as searching within the municipality of residence. These patterns align with the notion that job seekers may not fully account for the challenges of distant job search.

Second, job seekers underestimate the relative success rate of local job search compared to objective benchmarks. Figure C.2 also presents respondents' beliefs about the recent success rates of other job seekers from their municipality when applying in different areas (Panel C), alongside corresponding benchmarks from administrative data (Panel D), and the resulting misperceptions (Panel E). Applications within one's own municipality have the highest actual likelihood of leading to employment (47%). Re-

Figure C.2 Beliefs about local versus distant job search



Notes: The figure shows respondents' average beliefs about the effectiveness of job search across different areas: (i) within one's own municipality, (ii) outside the municipality but within the same region, or (iii) outside the region.

Panel A: Expected probability of receiving at least one job offer after applying to three jobs over a four-week period, with all applications being in the corresponding area.

Panel B: Expected probability of finding three suitable job openings within one hour of search time within the corresponding area.

Panel C: Expected share of other job seekers from own municipality securing a job, conditional on applying in the corresponding area.

Panel D: Actual share of other job seekers from own municipality who found a job, conditional on applying in the corresponding area.

Panel E: Difference between expected and actual shares of other job seekers from own municipality securing a job, conditional on applying in the corresponding area.

spondents underestimate the success rates of local applications by approximately 17pp. At the same time, respondents are slightly over-optimistic about applications within the region but outside the municipality of residence, with expectations exceeding the benchmark by about 5pp. Participants are substantially too optimistic about applications outside their region (+17pp). All three average misperceptions are significantly different from zero ($p < 0.001$).

Third, more optimistic beliefs about the effectiveness of distant job search are associated with a broader geographic scope of search. Table C.2 presents correlations between individuals' perceived efficiency differences across areas and the geographic scope of their own search. For example, a 10pp increase in the perceived efficiency gap between applications outside one's region and local applications within one's municipality is associated with a 3.4% larger search radius ($p < 0.001$; Column 4 of Panel A).

Taken together, the evidence from our additional survey is consistent with job seekers

Table C.2 Correlations between subjective beliefs and geographic scope of search

Dependent variable	Applied to distant job ^(a) (pp.) (1)	Search radius ^(b) (log) (2)	Applied to distant job ^(a) (pp.) (3)	Search radius ^(b) (log) (4)
A. Expected application success				
Perceived success difference (in 10pp)				
Region - municipality ^(c)	0.005 (0.007)	0.059*** (0.015)		
Nationwide - municipality ^(d)			0.005 (0.005)	0.034*** (0.010)
Mean value dep. variable	0.182	3.949	0.182	3.949
Number of observations	902	902	902	902
Control variables	Yes	Yes	Yes	Yes
B. Expected search productivity				
Perceived success difference (in 10pp)				
Region - municipality ^(c)	0.001 (0.005)	0.044*** (0.011)		
Nationwide - municipality ^(d)			0.009*** (0.003)	0.037*** (0.007)
Mean value dep. variable	0.182	3.949	0.182	3.949
Number of observations	902	902	902	902
Control variables	Yes	Yes	Yes	Yes

Notes: The table presents regression results of individuals' search behavior on their perceptions about the success of distant versus local job search. In all specifications, we additionally control for a comprehensive set of respondents' background characteristics (gender, age, education, length of unemployment spell, previous wage, previous industry, previous full-time/part-time employment) and municipality fixed effects (98). Standard errors are reported in parenthesis. */**/** indicates statistical significance at the 10%/5%/1%-level.

^(a)Indicates whether the respondent applied to any job within the past four weeks that would require relocation.

^(b)Distance between the respondent's home and the most distant job applied to within the past four weeks.

^(c)Expected success differences between respondents' own region (excluding their municipality) and their own municipality.

^(d)Expected success differences between the rest of the country (excluding respondent's own region) and their own municipality.

underestimating the difficulties of non-local search, leading them to focus their search too much on distant job openings. An intervention leading job seekers to focus more on local job openings—such as our main experiment—may thus have the positive side effect of making job seekers more effective in their search.

D Survey instructions translated to English

D.1 Main survey

The screen titles, question numbers and text written in “{}”-brackets are not shown to the respondents in the survey. “XXX” in survey questions 4a and 5a are placeholders and are filled with the response options the participant ticked in the corresponding survey questions on screen 1.

Screen 0: Welcome

{Show for all arms}

Thank you very much for participating in this survey about your job search - we greatly appreciate it!

As a token of our gratitude for your time, we are giving away a total of **20 gift cards** to GoGift among those who complete the entire questionnaire (it takes approximately 15 minutes). These gift cards can be used for many things and are very easy to use in both stores and online. Each gift card is worth 1,000 DKK.

If you win one (or more) gift cards, you will receive a direct notification in your e-Boks no later than December 1, 2023.

[pagebreak]

Screen 1: Elicitation of individual characteristics

{Show for all arms}

1a

What is your age?

- 35 years or younger
- Between 36 and 50 years
- 51 years or older

1b

What is your gender?

- Female
- Male
- Other {go to Screen-out arm}

1c

What is the highest educational degree that you have completed?

1. **University degree** (Bachelor, Master, PhD) or **Professional bachelor education**
2. **Upper secondary education** (e.g. Gymnasium, Higher Commercial Examination Programme, Higher Technical Examination Programme, Higher Preparatory Examination Programme) or **vocational education** (e.g. Erhvervsuddannelser, Academy)

Profession degree)

3. **Lower secondary education** (Folkeskole, efterskole) or **preparatory basic education** (e.g. FGU)

1d

What has your last employment type been?

- full-time (at least 30 hours per week)
- part-time (at least 10 and less than 30 hours per week)
- Less than 10 hours per week {go to Screen-out arm}
- I have never been employed before {go to Screen-out arm}

1e

For how many months have you been unemployed?

- Less than 3 months
- At least 3, but less than 6 months
- At least 6, but less than 9 months
- At least 9, but less than 12 months
- At least 12, but less than 18 months
- At least 18, but less than 24 months
- At least 24 months

1fa {if previous job (1d)=full-time}

What was your monthly salary (before taxes, excluding pension contributions) in your last job before becoming unemployed?

- Less than 18,000 DKK
- At least 18,000 DKK, but less than 22,000 DKK
- At least 22,000 DKK, but less than 26,000 DKK
- At least 26,000 DKK, but less than 30,000 DKK
- At least 30,000 DKK, but less than 34,000 DKK
- At least 34,000 DKK, but less than 38,000 DKK
- At least 38,000 DKK, but less than 42,000 DKK
- At least 42,000 DKK, but less than 50,000 DKK
- At least 50,000 DKK, but less than 75,000 DKK
- 75,000 DKK or more

1fb {if previous job (1d)=part-time}

What was your monthly salary (before tax, excluding pension contributions) in your last job before you became unemployed?

- Less than 9,000 DKK
- At least 9,000 DKK, but less than 12,000 DKK
- At least 12,000 DKK, but less than 15,000 DKK

- At least 15,000 DKK, but less than 18,000 DKK
- At least 18,000 DKK, but less than 24,000 DKK
- 24,000 DKK or more

1g

In which industry did you work in your previous job? If you are uncertain, please select the one that appears closest to the industry that you worked in.

- Agriculture, forestry and fishing
- Manufacturing, mining, quarrying
- Construction
- Wholesale, retail trade, transportation, accommodation and food services
- Information, communication, financial and business services
- Public administration, education, health
- Arts, entertainment and other services

[pagebreak]

Screen 2: Type of job searched for

{Show for all arms}

2a

What is the current status of your job search?

- I am still searching for a job
- I have accepted a job offer {go to Screen-out arm}

2b {conditional on still searching}

You are currently looking for a job. Which type of jobs are you (primarily) searching for?

- Full-time (at least 30 working hours per week)
- Part-time (less than 30 working hours per week) {go to Screen-out arm}
- I am open for full-time or part-time jobs

[pagebreak]

Screen 3: Explanation probabilities

{Show for all arms}

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

For example, numbers like:

- 2 and 5 percent may indicate "almost no chance".

- 18 percent or so may mean "not much chance".
- 47 or 52 percent chance may be a "pretty even chance".
- 83 percent or so may mean a "very good chance".
- 95 or 98 percent chance may be "almost certain".

[pagebreak]

Screen 4: Baseline belief

{Show for arms *Control* and *Treatment*, not for arm *Screen-out*}

4a

In order to better understand the earnings potential of workers who take up a new position after a period of unemployment, we analyzed labor market statistics from recent years.

Please think about individuals who started a new **full-time job** in the last ten years and who **had similar characteristics as you have now**.

Specifically, please think about individuals who, **at the time when they took up a new full-time job ...**

- I. had been unemployed for the same time as you have now [XXX months].
- II. had the same level of education as you [XXX].
- III. had the same age as you have now [XXX-XXX].
- IV. had the same gender as you [XXX].
- V. had the same monthly salary before taxes in their last job as you [XXX].
- VI. worked in the same industry in their previous job as you [XXX].
- VII. worked [part-time (at least 10 and less than 30 hours per week)/ full-time (at least 30 hours per week)] in their last job.

When starting their new **full-time job**, what do you think was the **average monthly salary (before taxes, excluding pension contributions)** of a person with these characteristics?

The average monthly salary before taxes was: _____ DKK

[pagebreak]

Screen 5: Information provision

{Show for arm *Treatment*, not for arms *Control* and *Screen-out*}

5a

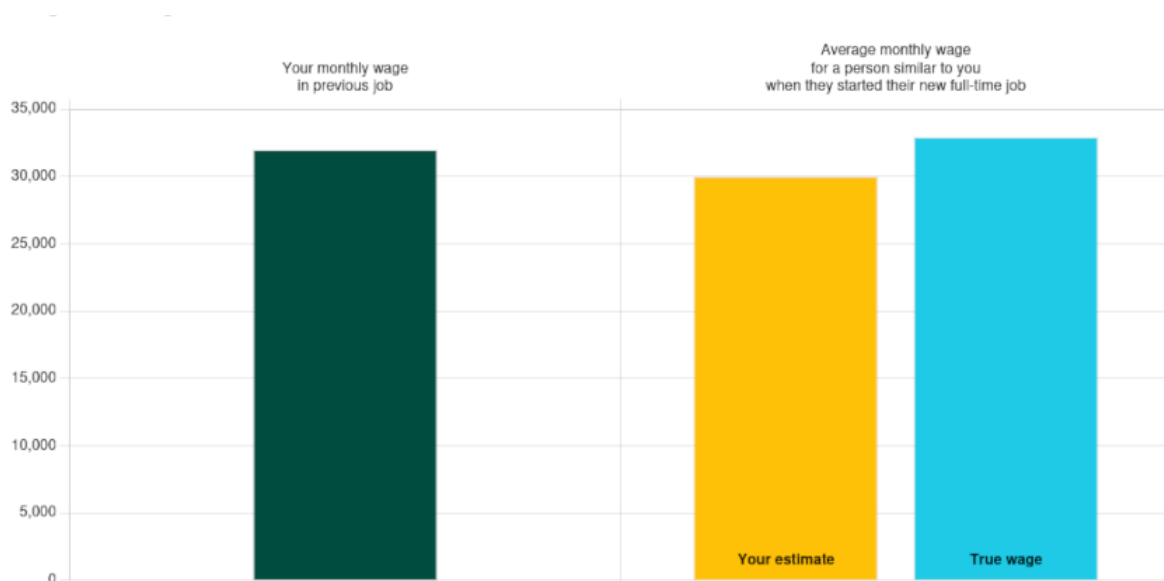
You said you think that the average monthly salary of a person similar to you when starting their new full-time job was [XXX].

We would now like to give you information on the actual average salary of individuals who, **at the time when they took up a new full-time job**,

- I. had been unemployed for the same time as you as you have now [XXX months].
- II. had the same level of education as you [XXX].
- III. had the same age as you have now [XXX-XXX].
- IV. have the same gender as you [XXX].
- V. had the same monthly salary before taxes in their last job as you [XXX].
- VI. worked in the same industry in their previous job as you [XXX].
- VII. worked [part-time (at least 10 and less than 30 hours per week)/ full-time (at least 30 hours per week)] in their last job.

We present you the **average monthly salary** (before taxes, **excluding pension contributions**) of a person with these characteristics when starting their **new full-time job**, according to official Danish labor market statistics.

The average salary is: **XXXX DKK**



[pagebreak]

Screen 6: Perceived mean of the wage offer distribution

{Show for all arms}

6a

Imagine you were offered a **new full-time job within the next 4 weeks**: what do you think would be the **monthly salary** (before taxes, excluding pension contributions) that you would be offered?

I expect that the **offered monthly salary (before taxes, excluding pension contributions)** would be: _____ DKK

[pagebreak]

Screen 7: Subjective probability distribution regarding offered wage

{Show for arms *Control* and *Treatment*, not for arm *Screen-out*}

7a

Please imagine again you were offered a **new full-time job within the next 4 weeks**. We would now like to ask you how likely it is that the salary offered in this job would fall into different intervals. **In your view, what would you say is the percent chance that the offered monthly salary (before taxes, excluding pension contributions) would be ...**

... lower than X1 ___%

... between X1 and X2 ___%

... between X2 and X3 ___%

... between X3 and X4 ___%

... higher than X4 ___%

Total: ___ %

{if previous job (1d)=full-time}

$$\{X1 = 0.8 * 1fa$$

$$X2 = 0.95 * 1fa$$

$$X3 = 1.05 * 1fa$$

$$X4 = 1.20 * 1fa$$

based on midpoint in the brackets for 1fa, assigning DKK 13,000 and DKK 80,000 for the highest and lowest intervals}

{if previous job (1d)=part-time}

$$\{X1 = 0.8 * 1fb * 2$$

$$X2 = 0.95 * 1fb * 2$$

$$X3 = 1.05 * 1fb * 2$$

$$X4 = 1.20 * 1fb * 2$$

based on midpoint in the brackets for 1fb, assigning DKK 6,000 and DKK 27,000 for the highest and lowest intervals}

[pagebreak]

Screen 8: Reservation wage

{Show for all arms}

8a

What is the **lowest** monthly salary (before taxes, excluding pension contributions) for which **you would be willing** to accept a **new full-time job within the next 4 weeks**?

The **minimum monthly salary** (before taxes, excluding pension contributions) for which I would be willing to accept a **full-time job** is: _____ DKK

[pagebreak]

Screen 9: Search effort

{Show for all arms}

9a

How many hours in total do you plan to dedicate to your job search within the **next week**?

Note: By job search we refer to various activities, such as screening job ads, gathering information, writing applications, etc.

[pagebreak]

Screen 10: Perceived returns to search

{Show for all arms}

10a

Think about the type of jobs you applied to over the last weeks, or – in case you did not apply to any jobs – the types of jobs that you have been planning to apply to.

How likely is it that you will receive an offer for a full-time job of this type **within the next 4 weeks** if you spent...?

- **5 hours** per week searching: My percent chance (out of 100) of receiving an **offer for a full-time job** of this type **within the next 4 weeks** is _____ %.
- **15 hours** per week searching: My percent chance (out of 100) of receiving an offer for a **full-time job** of this type **within the next 4 weeks** is _____ %.

[pagebreak]

Screen 11: Willingness to make concession

{Show for all arms}

11a

When searching for a new job, one sometimes has to make certain concessions. What would you accept in order to find a job?

Would you...

(Tick all that apply.)

{Order randomized with “none of the above” at the bottom}

- accept a long commute to work
- accept awkward working hours
- accept a job that is below your specialized abilities
- take additional training
- accept uninteresting work
- accept awkward working conditions (noise, dirt)
- accept exhausting work
- change your residence
- change your profession
- None of the above

[pagebreak]

Screen 12: Question on job finding probability

{Show for all arms}

12a

We would now like you to think about your personal situation in the **next three months**.

How likely do you think it is that you start working in a new job within this period?

My percent chance (out of 100) to start working in a new job within the next three months is XXX.

[pagebreak]

Screen 13: Overconfidence I

{Show for all arms}

You are almost done! We have a few final questions. These are not necessarily related to your job search, but instead ask you to guess a few facts. For some of them, it is not easy to guess them right. Please try and answer the following questions as best you can.

13a

Question 1: Let us assume that you have 10,000 kr. in a savings account, which pays 10% interest each year. How much money will you have in the account after two years if you leave all the money and interest payments in the account?

_____ DKK

13b

Question 2: In a sale, a shop is selling all items at half price. Before the sale, a sofa costs 3,800 kr. How much will it cost in the sale?

_____ DKK

13c

Question 3: A second-hand car dealer sold a used car for 60,000 kr. This is two-thirds of what the car cost when new. How much did the car cost when new?

_____ DKK

13d

Question 4: Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After one year, how much would you be able to buy with the money in this account?

- More than today
- Exactly the same
- Less than today

13e

Question 5: In the BIG BUCKS LOTTERY, the chances of winning a 100 kr. prize are 1%. What is your best guess about how many people would win a 100 kr. prize if 1,000 people each buy a single ticket from BIG BUCKS?

_____ people

[pagebreak]

Screen 14: Overconfidence II

{Show for all arms}

14a

What do you think, how many of the 5 questions on the last screen did you get right?

- 0
- 1
- 2
- 3
- 4
- 5

14b

All respondents to this survey are drawn from the pool of people who are registered as unemployed in Denmark as of October 22nd, 2023. We ask everyone who takes this survey the same five questions you just answered on the last screen.

Out of every 100 individuals who took our survey, how many do you think got **fewer** answers right than you?

For example, if you think you got more answers right than all other respondents, enter 100. If you think you got fewer answers right than all the other respondents, enter 0.

_____ out of 100 got **fewer answers right** than you.

{remainder popping up once respondent enters answer}

You believe that [100 - answer] got at most the same or more answers right than you did.

[pagebreak]

Screen 15: Last Screen

{Show for all arms}

15a

If you have any thoughts or input you would like to share with us, either regarding job search or the survey you have just completed, please write them in the field below:

[Text entry box]

15b

Thank you for your response.

Please remember that we are giving away a total of 20 GoGift gift cards to those who complete the entire survey. These gift cards are good for many things and are very easy to use in stores and online. Each gift card is worth 1000 DKK.

If you win a gift card, you will be notified directly in your e-Boks no later than December 1, 2023.

Please close your browser to complete the survey.

D.2 Follow-up survey

One common arm. Only individuals who completed the main survey and were screened to *Control* or *Treatment* and who completed all questions of the main survey up until question 12 are invited.

The screen titles, question numbers and text written in “{}”-brackets are not shown to the respondents in the survey. “XXX” in survey question 3a are placeholders and are filled with the response options the participant ticked in the corresponding survey questions on screen 1 of the main survey.

Screen 0: Welcome

{Show for all respondents}

Thank you very much for participating in this survey! This is a follow-up survey to one you answered last week. (Again, thank you for sharing your valuable opinions and thoughts with us last week!) Some of the questions you will find in this survey are similar to the ones you answered in the previous survey, while others are different.

Once again, as a token of our appreciation for your time, we are giving away a total of 10 GoGift gift cards among those who complete the entire questionnaire. These 10 cards are in addition to the 20 cards we gave away to those who completed the survey a week ago. The gift cards can be used for many things and are very easy to use both in stores and online. Each gift card is worth 1000 DKK.

If you win a gift card, you will receive a direct notification in your e-Boks no later than December 1, 2023.

[pagebreak]

Screen 1: Type of job searched for

{Show for all respondents}

What is the current status of your job search?

- I am still searching for a job
- I have accepted a job offer

[pagebreak]

Screen 2: Explanation probabilities

{Show for all respondents}

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

For example, numbers like:

- 2 and 5 percent may indicate "almost no chance".
- 18 percent or so may mean "not much chance".
- 47 or 52 percent chance may be a "pretty even chance".
- 83 percent or so may mean a "very good chance".
- 95 or 98 percent chance may be "almost certain".

[pagebreak]

Screen 3: Belief about re-employment wages of similar individuals

{Show for all respondents}

3a

About a week ago, we asked you about your personal characteristics and situation, such as your level of education and how long you had been searching for a job. Based on the information you shared with us, please think about individuals with **similar characteristics as you had at the time of our last survey and who found a new job in the last ten years.**

Specifically, please think about individuals who, **at the time when they took up a new full-time job ...**

- I. had been unemployed for the same time as you [XXX months].
- II. had the same level of education as you [XXX].
- III. had the same age as you [XXX-XXX].
- IV. have the same gender as you [XXX].
- V. had the same monthly salary before taxes in their last job as you [XXX].
- VI. worked in the same industry in their previous job as you [XXX].
- VII. worked [part-time (at least 10 and less than 30 hours per week)/ full-time (at least 30 hours per week)] in their last job.

When starting their **new full-time job**, what do you think was the **average monthly salary (before taxes, excluding pension contributions)** of a person with these characteristics?

The average monthly salary before taxes was:

_____ DKK

[pagebreak]

Screen 4a: Perceived mean of the wage offer distribution

{Show if answer to Question 1a was "I am still searching for a job"}

4a

Imagine you were offered a **new full-time job within the next 4 weeks**: what do you think would be the monthly salary (before taxes, excluding pension contributions) that you would be offered?

I expect that the **offered monthly salary (before taxes, excluding pension contributions)** would be: _____ DKK

[pagebreak]

Screen 4b: Perceived mean of the wage offer distribution

{Show if answer to Question 1 was not “I am still searching for a job”}

4b

Imagine you were still searching for a job and you were offered a **new full-time job within the next 4 weeks**: what do you think would be the monthly salary (before taxes, excluding pension contributions) that you would be offered?

I expect that the **offered monthly salary (before taxes, excluding pension contributions)** would be: _____ DKK

[pagebreak]

Screen 5a: Subjective probability distribution regarding offered wage

{Show if answer to Question 1a was “I am still searching for a job”}

5a

Please imagine again you were offered a **new full-time job within the next 4 weeks**. We would now like to ask you how likely it is that the salary offered in this job would fall into different intervals. **In your view, what would you say is the percent chance that the offered monthly salary (before taxes, excluding pension contributions) would be ...**

... lower than X1 __%

... between X1 and X2 __%

... between X2 and X3 __%

... between X3 and X4 __%

... higher than X4 __%

Total __%

{If previous job (Main survey 1d) = full-time}

$\{X1 = 0.8 * \text{Main survey 1fa}$

$X2 = 0.95 * \text{Main survey 1fa}$

$X3 = 1.05 * \text{Main survey 1fa}$

$X4 = 1.20 * \text{Main survey 1fa}$

Based on midpoint in the brackets for Main survey 1fa, assigning DKK 13,000 and DKK 80,000 for the highest and lowest intervals.}

{If previous job (Main survey 1d) = part-time}

$\{X1 = 0.8 * \text{Main survey 1fb} * 2$

$X2 = 0.95 * \text{Main survey 1fb} * 2$

$X3 = 1.05 * \text{Main survey 1fb} * 2$

$X4 = 1.20 * \text{Main survey 1fb} * 2$

Based on midpoint in the brackets for Main survey 1fb, assigning DKK 6,000 and DKK 27,000 for the highest and lowest intervals.}

[pagebreak]

Screen 5b: Subjective probability distribution regarding offered wage

{Show if answer to Question 1a was not "I am still searching for a job"}

5b

Again, please imagine you were still searching for a job and you were offered a **new full-time job within the next 4 weeks**. We would now like to ask you how likely it is that the salary offered in this job would fall into different intervals. **In your view, what would you say is the percent chance that the offered monthly salary (before taxes, excluding pension contributions) would be ...**

... lower than X1 __%

... between X1 and X2 __%

... between X2 and X3 __%

... between X3 and X4 __%

... higher than X4 __%

Total __%

{If previous job (Main survey 1d) = full-time}

$\{X1 = 0.8 * \text{Main survey 1fa}$

$X2 = 0.95 * \text{Main survey 1fa}$

$X3 = 1.05 * \text{Main survey 1fa}$

$X4 = 1.20 * \text{Main survey 1fa}$

Based on midpoint in the brackets for Main survey 1fa, assigning DKK 13,000 and DKK 80,000 for the highest and lowest intervals.}

{If previous job (Main survey 1d) = part-time}

$\{X1 = 0.8 * \text{Main survey 1fb} * 2$

$X2 = 0.95 * \text{Main survey 1fb} * 2$

$X3 = 1.05 * \text{Main survey 1fb} * 2$

$X4 = 1.20 * \text{Main survey 1fb} * 2$

Based on midpoint in the brackets for Main survey 1fb, assigning DKK 6,000 and DKK 27,000 for the highest and lowest intervals.

[pagebreak]

Screen 6: Reservation wage

{Show if answer to Question 1a was “I am still searching for a job”}

6a

What is the **lowest** monthly salary (before taxes, excluding pension contributions) for which **you would be willing** to accept a new **full-time job within the next 4 weeks**?

The **minimum monthly salary** (before taxes, excluding pension contributions) for which I would be willing to accept a **full-time job** is:

_____ DKK

[pagebreak]

Screen 7: Last Screen

{Show for all respondents}

7a

If you have any thoughts or input you would like to share with us, either regarding job search or the survey you have just completed, please write them in the field below:

[Text entry box]

7b

Thank you for your response.

Remember that we are giving away a total of 10 extra GoGift gift cards to those who complete the entire survey. These 10 cards are in addition to the 20 cards we gave away to those who completed the survey a week ago. Each gift card is worth 1000 DKK.

If you win a gift card, you will receive a notification directly in your e-Boks no later than December 1, 2023.

Please close your browser to complete the survey.

D.3 Mechanism survey

The screen titles, question numbers and text written in “{}”-brackets are not shown to the respondents in the survey. “XXX” in survey questions 4a and 5a are placeholders and are filled with the response options the participant ticked in the corresponding survey questions on screen 1.

Screen 0: Welcome page

{Show for all arms}

Thank you so much for participating in this survey about your subjective views on job search - we really appreciate it!

As a thank you for your time, we’re giving away a total of **20 GoGift gift cards** to those who complete the entire survey (it takes about 10 minutes). These gift cards are valid for many things and are very easy to use both in stores and online. Each gift card has a value of DKK 1,000.

If you win one (or more) gift cards, you will be notified directly in your e-Boks.

[pagebreak]

Screen 1: Elicitation of individual characteristics

{Show for all arms}

1a

What is your age?

- 35 years or younger
- Between 36 and 50 years
- 51 years or older

1b

What is your gender?

- Female
- Male
- Other {go to Screen-out arm}

1c

What is the highest educational degree that you have completed?

- **University degree** (Bachelor, Master, PhD) or **Professional bachelor education**
- **Upper secondary education** (e.g. Gymnasium, Higher Commercial Examination Programme, Higher Technical Examination Programme, Higher Preparatory Examination Programme) or **vocational education** (e.g. Erhvervsuddannelser, Academy Profession degree)
- **Lower secondary education** (Folkeskole, efterskole) or **preparatory basic education** (e.g. FGU)

1d

What has your last employment type been?

- full-time (at least 30 hours per week)
- part-time (at least 10 and less than 30 hours per week)
- Less than 10 hours per week {go to Screen-out arm}
- I have never been employed before {go to Screen-out arm}

1e

For how many months have you been unemployed?

- Less than 3 months
- At least 3, but less than 6 months
- At least 6, but less than 9 months
- At least 9, but less than 12 months
- At least 12, but less than 18 months
- At least 18, but less than 24 months
- At least 24 months

1fa {if previous job (1d)=full-time}

What was your monthly salary (before taxes, excluding pension contributions) in your last job before becoming unemployed?

- Less than 18,000 DKK
- At least 18,000 DKK, but less than 22,000 DKK
- At least 22,000 DKK, but less than 26,000 DKK
- At least 26,000 DKK, but less than 30,000 DKK
- At least 30,000 DKK, but less than 34,000 DKK
- At least 34,000 DKK, but less than 38,000 DKK
- At least 38,000 DKK, but less than 42,000 DKK
- At least 42,000 DKK, but less than 50,000 DKK
- At least 50,000 DKK, but less than 75,000 DKK
- 75,000 DKK or more

1fb {if previous job (1d)=part-time}

What was your monthly salary (before tax, excluding pension contributions) in your last job before you became unemployed?

- Less than 9,000 DKK
- At least 9,000 DKK, but less than 12,000 DKK
- At least 12,000 DKK, but less than 15,000 DKK
- At least 15,000 DKK, but less than 18,000 DKK
- At least 18,000 DKK, but less than 24,000 DKK
- 24,000 DKK or more

1g

In which industry did you work in your previous job? If you are uncertain, please select the one that appears closest to the industry that you worked in.

- Agriculture, forestry and fishing
- Manufacturing, mining, quarrying
- Construction
- Wholesale, retail trade, transportation, accommodation and food services
- Information, communication, financial and business services
- Public administration, education, health
- Arts, entertainment and other services

[pagebreak]

Screen 2: Type of job searched for

{Show for all arms}

2a

What is the current status of your job search?

- I am still searching for a job
- I have accepted a job offer {go to Screen-out arm}

2b {conditional on still searching in 2a}

You are currently looking for a job. Which type of jobs are you (primarily) searching for?

- Full-time (at least 30 working hours per week)
- Part-time (less than 30 working hours per week) {go to Screen-out arm}
- I am open for full-time or part-time jobs

[pagebreak]

Screen 3: Location

{Show for all arms}

3a

In which region do you live?

- Hovedstaden
- Midtjylland
- Nordjylland
- Sjælland
- Syddanmark

→ answer determines {**customized region**}

3b {In which municipality do you live?}

[Dropdown menu that shows all municipalities in {**customized region**}]

→ answer determines {**customized municipality**}

[pagebreak]

Screen 4: Belief about group-level re-employment wages

{Show for all arms}

4a

In order to better understand the earnings potential of workers who take up a new position after a period of unemployment, we analyzed labor market statistics from recent years.

Please think about individuals who started a **new full-time job** in the last ten years and who had **similar characteristics as you have now**.

Specifically, please think about individuals who, at the **time when they took up a new full-time job ...**

- I. had been unemployed for the same time as you have now [XXX months].
- II. had the same level of education as you [XXX].
- III. had the same age as you have now [XXX-XXX].
- IV. had the same gender as you [XXX].
- V. had the same monthly salary before taxes in their last job as you [XXX].
- VI. worked in the same industry in their previous job as you [XXX].
- VII. worked [part-time (at least 10 and less than 30 hours per week)/ full-time (at least 30 hours per week)] in their last job.

When starting their new full-time job, what do you think was the average monthly salary (before taxes, excluding pension contributions) of a person with these characteristics?

The average monthly salary before taxes was: _____ DKK

[pagebreak]

Screen 5: Explanation probabilities

{Show for all arms}

5a

In some of the following questions, we will ask you to think about the percent chance of something happening in the future. Your answers can range from 0 to 100, where 0 means there is absolutely no chance, and 100 means that it is absolutely certain.

For example, numbers like:

- 2 and 5 percent may indicate "almost no chance".
- 18 percent or so may mean "not much chance".

- 47 or 52 percent chance may be a "pretty even chance".
- 83 percent or so may mean a "very good chance".
- 95 or 98 percent chance may be "almost certain".

[pagebreak]

Screen 6: Application efficiency

{Show for all arms}

6a

Think about your job search activities within the next 4 weeks. How likely is it that you will receive at least one job offer **when you apply for 3 jobs** during that period, which are all. . .

... **within {customized municipality}**: My percent chance (out of 100) of receiving an **offer for a job within the next 4 weeks** would be ____ %.

... **outside {customized municipality} but within {customized region}**: My percent chance (out of 100) of receiving an **offer for a job within the next 4 weeks** is ____ %.

... **outside of {customized region} in the rest of Denmark**: My percent chance (out of 100) of receiving an **offer for a job within the next 4 weeks** is ____ %.

[pagebreak]

Screen 7: Application efficiency with benchmark

{Show for all arms}

7a

Please think about **individuals who lived in the same municipality as you and were looking for a job** in the last four years. We have analyzed labor market statistics from recent years in order to understand the success rates of applications.

We are interested in what you think we found. Think of 100 job seekers from your municipality who applied to jobs in the following areas of Denmark in their first three months of unemployment. For every 100 individuals who applied, how many started working in that area in the first 6 months after becoming unemployed?

[emoji]

For each of your answers that is close to the true value based on applications registered on joblog in the years 2021 to 2024, you receive a ticket for an additional lottery of 10 gift cards.

Out of 100 job seekers from your municipality who sent at least one application **within {customized municipality}**, ____ started working in your municipality subse-

quently.

Out of 100 job seekers from your municipality who sent at least one application **outside of {customized municipality} but within {customized region}**, _____ started working outside of customized municipality but within {customized region} subsequently.

Out of 100 job seekers from your municipality who sent at least one application **outside of {customized region} in the rest of Denmark**, _____ started working outside of {customized region} in the rest of Denmark subsequently.

[pagebreak]

Screen 8: Search efficiency

{Show for all arms}

8a

Now we would like to ask you about your chances that you will come across at least 3 interesting job openings you would apply to. Imagine you will spend 1 hour searching for jobs during the next week. How likely is it that you find these 3 job openings during this period when you search...

... **within {customized municipality}**: My percent chance (out of 100) of **finding 3 job openings that are so interesting that I would apply** is _____ %.

... **outside of {customized municipality} but within {customized region}**: My percent chance (out of 100) of **finding 3 job openings that are so interesting that I would apply** is _____ %.

... **outside of {customized region} in the rest of Denmark**: My percent chance (out of 100) of **finding 3 job openings that are so interesting that I would apply** is _____ %.

[pagebreak]

Screen 9: Search effort and search radius

{Show for all arms}

9a

How many hours in total did you dedicate to your **job search** within the **last 7 days**?

Note: By job search we mean various activities, such as screening job ads, gathering information, writing applications, attending job interviews etc.

_____ hours.

9b

How many job applications in total did you send out within the **last 4 weeks**?
_____ applications

9c

In the past four weeks, have you applied for jobs that would **require you to relocate**?
[yes / no]

9d

How **many kilometers from your home** was the farthest job you applied for?
_____ kilometers

[pagebreak]

Screen 10: Willingness to make concession

{Show for all arms}

10a

When searching for a new job, one sometimes has to make certain concessions. What would you accept in order to find a job?

Would you...

(Tick all that apply.)

[Randomize order with “none of the above” at the bottom]

- accept a long commute to work [yes-no]
- accept awkward working hours [yes-no]
- accept a job that is below your specialized abilities [yes-no]
- take additional training or get additional education [yes-no]
- accept uninteresting work [yes-no]
- accept awkward working conditions (noise, dirt) [yes-no]
- accept exhausting work [yes-no]
- change your residence [yes-no]
- change your profession [yes-no]
- none of the above.

[pagebreak]

Screen 11: Feedback

{Show for all arms}

11a

If you have any thoughts or input you would like to share with us, either regarding job search or the survey you have just completed, please write them in the field below:

[Open-text box]

[pagebreak]

Screen 12: Goodbye

{Show for all arms}

12a

Thank you very much for your answer.

If you win a gift card, you will be notified directly in your e-Boks.