Wage Expectations and Job Search

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Abstract

In a field experiment with 9,000 Danish unemployed job seekers, we study how wage expectations causally affect job search and re-employment. We exogenously vary expectations by informing a random half of respondents about re-employment wages of comparable past workers. The induced belief revisions shift behavior asymmetrically. Consistent with downward rigidity, positive updates strongly increase selectivity over wages and location, whereas negative updates only moderately lower reservation wages. Job seekers compensate for negative updates with higher search effort. Both types of updates raise re-employment in administrative data; for positive updates, this seems to reflect the greater effectiveness of local search.

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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 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; correlational evidence can be confounded by omitted variables, reverse causality, and measurement error in subjective beliefs; and 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 combines three essential features.

First, we survey an exceptionally large and representative sample of unemployed job seekers. Using the Danish public employment service's registry, we invited all current benefit claimants via the official digital public mailing system to participate in a survey on job search. This yields a final sample of more than 9,000 job seekers.

Second, our survey includes an information provision experiment designed to generate exogenous variation in job seekers' expected wage offers. 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 seeks to generate exogenous shifts in job seekers' expectations about the wages available to themselves by providing information on the re-employment wages of comparable workers. This approach requires job seekers to view others' re-employment

wages as informative for their own prospects.

Third, we link our survey data to administrative records on search activities and labor market outcomes, which are immune to 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 the official online platform of the Danish public employment service, *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 population registers. We complement these data with survey measures of variables that are not observed in administrative data, such as reservation wages and willingness to adjust the occupational or geographic scope of search.

To organize how wage expectations shape job seekers' decisions, we present a job search model with subjective beliefs and two margins of adjustment: selectivity over acceptable offers—captured by a reservation value that spans both wages and non-wage dimensions, such as location—and search intensity. The framework highlights two forces that shape responses to wage expectations. First, downward rigidity in selectivity—job seekers' reluctance to accept offers below some lower bound—makes responses asymmetric: positive news raises selectivity more strongly than equally sized negative news lowers it. Such a "floor" could be tied to previous earnings or current benefit income, reflecting, for example, consumption commitments, a minimum standard for acceptable pay, or reference dependence. Second, when selectivity responds little to negative news, higher search effort—which increases the probability of getting an acceptable offer—can act as a compensating margin. The asymmetry in selectivity may then carry over to search intensity, with negative news raising effort by more than positive news reduces it.

In a first step of the empirical analysis, we study respondents' prior beliefs about re-employment wages of comparable workers. We detect strong heterogeneity in the extent to which these beliefs align with the corresponding actual re-employment wages observed in the register data. On average, job seekers overestimate the re-employment wages of comparable workers by only about 2%. However, about a quarter of our respondents overestimate average re-employment wages by more than 15%, while another fifth underestimate them by at least 15%. These "misperceptions" about the average re-employment wages of comparable workers partially reflect anchoring on pre-unemployment wages: job seekers tend to underestimate the magnitude of wage changes experienced by comparable workers relative to their previous salary.

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, de-

fined as the logarithmic difference between the actual average re-employment wage of comparable workers and individuals' corresponding prior belief. Individuals with gaps between –2.5% and +2.5% form a "neutral" group that is not expected to update their beliefs in response to the treatment. 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 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 priors.

We find that treated individuals update their expectations about their own next wage offer in response to the information. Individuals who are initially highly optimistic and receive 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 two-week follow-up survey, in which numerical anchoring and experimenter demand effects are likely limited (de Quidt et al., 2018). We detect no systematic spillovers to the perceived dispersion of the wage offer distribution or the perceived mapping from search effort to offer arrival. 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.

We next examine the impact of our intervention on job search and labor market outcomes. We mostly focus on respondents who are initially highly optimistic or highly pessimistic about comparable workers' re-employment wages, as our treatment generates the strongest first-stage variation in wage expectations for these groups.

The information shocks shift job seekers' selectivity in an asymmetric manner: responses are pronounced for positive and only moderate for negative wage news. Treated job seekers who are initially highly pessimistic raise their reservation wage by about 3.9%, whereas initially highly optimistic job seekers lower theirs by only 1.6%. Scaling these responses by the corresponding first-stage changes in expected wages yields an elasticity of reservation wages with respect to wage expectations of about 0.7 for upward revisions but only 0.4 for downward revisions. Initially pessimistic job seekers also increase their selectivity in terms of the geographic scope of search in response to the treatment: they report a reduced willingness to relocate or commute and the ge-

ographic radius of their actual applications falls. We detect no adjustments in terms of geographic selectivity in response to negative updates. Other dimensions of selectivity, such as occupational scope, do not systematically respond to the treatment.

The asymmetric selectivity responses translate into an asymmetric response of search effort. Treated initially highly optimistic job seekers, who reduce their reservation wages only modestly, increase their search intensity: in the week after the intervention, they click on about 0.4 more job ads on the *jobnet.dk* platform, an increase of roughly 26%. By contrast, initially highly pessimistic job seekers, who adjust more strongly through selectivity, do not change their search effort in response to the treatment. Together, these patterns align with the framework's central mechanism: downward rigidity in selectivity makes responses to positive and negative wage news asymmetric and, following negative news, induces margin substitution toward search effort.

How do these behavioral adjustments translate into labor market outcomes? We find that treated initially highly optimistic job seekers, who respond to negative news by increasing search effort and modestly lowering reservation wages, are about 3.7 pp more likely to be employed over the next three months than comparable control group respondents. They also experience gains in total working hours and earnings, although, conditional on re-employment, they earn slightly lower hourly wages. Among initially highly pessimistic job seekers, the treatment also raises re-employment by about 4 pp and increases accumulated hours and earnings, despite greater selectivity in terms of both wages and geographic scope. Unlike for negative news, we detect no significant effect on realized wages in the subsample of re-employed job seekers. As we discuss below, increased re-employment most likely reflects the redirection of applications toward the local labor market, where search is more likely to lead to a match and where higher selectivity can be met through shorter commutes rather than higher pay.

For job seekers with moderate perception gaps, treatment effects on job search and labor market outcomes in most cases align qualitatively with those among individuals with more extreme priors, but are smaller and less precisely estimated. By contrast, treatment effects are largely muted and insignificant for the neutral group, whose prior beliefs are confirmed by the intervention.

We provide evidence on two mechanisms underlying the intervention's effects. First, we directly examine downward rigidity and the margin substitution it induces. If a floor constrains downward adjustment in selectivity, it should be more likely to bind when projected wages are low relative to plausible anchors for that floor, such as previous earnings or current benefit income. In these cases, negative wage news should lead to smaller reductions in reservation wages and larger increases in search effort. The data match this prediction: negative news lowers reservation wages most when projected wages exceed previous earnings or benefit generosity is low, and raises search effort

most when projected wages lie well below previous earnings or benefit generosity is high. Responses to positive wage news show no comparable heterogeneity, consistent with rigidity that binds only downward.

Second, we provide evidence that the employment gains among initially highly pessimistic job seekers—who find work faster despite becoming more selective—reflect an interaction between belief updates and spatial search frictions. Previous evidence highlights that acceptable offers are harder to generate at a distance (Caliendo et al., 2026b; Schmutz and Sidibé, 2019). Indeed, according to Danish register data, applying within one's municipality is more than twice as likely to result in a job as applying outside one's region. An intervention like ours, which induces job seekers to redirect search toward the local market, may then increase re-employment. Four findings support this interpretation: (i) the additional matches created by positive shocks occur almost entirely within job seekers' municipality of residence; (ii) the employment gains are concentrated among those who had previously searched broadly across localities, and thus had the highest scope to redirect search locally, and (iii) among those living in municipalities with relatively high local search effectiveness; and (iv) an additional survey suggests that job seekers underestimate the difficulties of non-local search, plausibly leading them to focus too much on distant jobs in the absence of our intervention.

In the final part of our analysis, we use the experimental treatment effects to discipline a quantitative version of the model. The exercise allows us to quantify how employment effects vary with the size of belief revisions, including revisions beyond those generated by the intervention, and to decompose these effects into the underlying behavioral channels. For negative updates, lower selectivity and greater search effort contribute about equally at the experimental treatment effect, while larger revisions operate increasingly through search effort as downward adjustment in reservation wages becomes more constrained. For positive updates, improved matching from geographic reallocation more than offsets the negative effect of higher reservation wages.

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., 2026a; Conlon et al., 2018; Drahs et al., 2018; Krueger and Mueller, 2016).

We advance this literature by providing causal evidence on how wage expectations shape job search and labor market outcomes. Our central finding is that the effects of wage expectations are asymmetric and spill over across margins of search: selectivity rises strongly after positive news but falls only moderately after negative news

(*downward rigidity*), which job seekers offset through higher search effort (*margin substitution*). Previous earnings and benefit income appear to set a floor on selectivity and thereby shape which margin adjusts in response to belief revisions. Positive wage news redirects job seekers toward a more effective local labor market, suggesting that beliefs can interact with search frictions. Taken together, our findings highlight that wage expectations are a central input into job search decisions 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 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. Our study differs from this work in three important ways. First, this literature examines whether beliefs about an outside option affect the extensive margin decisions of whether to negotiate or switch jobs. We instead study how beliefs shape an ongoing search process—through selectivity, search effort, and geographic scope—and show that these margins are jointly determined: where selectivity is rigid, search effort adjusts instead. Second, we focus on unemployed job seekers, for whom the nature of job search differs fundamentally from on-the-job search (Faberman et al., 2022) and who are of key interest for policymakers deciding about job search assistance or benefit generosity. Third, we move beyond stated intentions by identifying causal effects of wage expectations on actual search behavior and re-employment observed in high-quality administrative data.[1]

Related field experiments study the effects of directing job seekers toward specific jobs or occupations (Altmann et al., 2026; Behaghel et al., 2022; Belot et al., 2019, 2026; 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 setting, our intervention is closer to a "mechanism experiment": we isolate the effects of a single key variable in search models—beliefs about available wage offers—on multiple dimensions of job search and labor market outcomes.

We build on a broad literature using observational data to study job search outcomes, including reservation wages (Banfi and Villena-Roldán, 2019; Fluchtmann et al., 2024; Koenig et al., 2026; Krueger and Mueller, 2016), wage bargaining (Roussille, 2024),

[1] Other related work studies how college graduates' earnings expectations shape initial career choices (Christensen et al., 2026; Jiang and Zen, 2025), with implications for gender differences in entry-level wages (Cortés et al., 2023). 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.

search intensity (DellaVigna et al., 2022; Faberman and Kudlyak, 2019; Marinescu and Skandalis, 2021), or the demand for non-wage amenities (Cordes and Müller, 2026; Escudero et al., 2024; Le Barbanchon et al., 2021; Maestas et al., 2023). A key finding in this literature is that reservation wages are sticky and decline only slowly over the unemployment spell (Koenig et al., 2026; Krueger and Mueller, 2016), consistent with the downward rigidity in selectivity we detect in our experiment. Our estimates indicate that this rigidity also induces responses along the effort margin, linking the persistence of reservation wages found in earlier work to another key margin of job search.

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, 2026b; Fuster and Zafar, 2023; Haaland et al., 2023). Only a few studies in this literature 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, 2022, 2020; Piccolo and Gorodnichenko, 2026; 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

The Danish labor market is relatively flexible and, in this respect, comparable to the US (Kreiner and Svarer, 2022). At the same time, its unemployment benefit system 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 are eligible for unemployment insurance (UI) for up to two years. UI replaces 90% of previous income up to a cap of DKK 19,728 gross per month ($\approx$ USD 2,860; values for November 2023), implying an average effective replacement rate of around 60%. When UI expires, or for the roughly 15% of wage earners who do not contribute to the UI system, means-tested social assistance provides substantially lower support, with a maximum of DKK 11,944 per month ($\approx$ USD 1,732) for a single person. Benefit recipients deemed capable of full-time work must actively search for employment.

Job search is organized through *jobnet.dk*, the online platform of Denmark's public employment services, which all UI recipients must log into at least weekly. The platform's vacancy database covers roughly 90% of posted openings in the country. These postings—like those on other Danish job boards—typically omit wage information. Re-

cipients document their applications in a centralized *joblog* system to demonstrate compliance with search requirements (see Fluchtmann et al., 2024, for details), and face no restrictions on the types of jobs they may apply for. Although they are officially required to accept suitable offers, this requirement is weakly enforced and relatively easy to circumvent.

2.2 Wage projections

Our survey elicits prior beliefs and provides information on the average 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 facilitates a comparison of subjective beliefs with clear benchmarks from register data and allows us to generate exogenous variation in beliefs by providing job seekers with this information. This section describes how these wage projections are constructed.

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 ($\leq$35, 36-50, $>$50), gender (male, female), education (lower secondary or less, upper secondary, tertiary), type of previous employment (10-29, $\geq$30 hours per week), current unemployment duration ($<$3, 3-5, 6-8, 9-11, 12-17, 18-23, $\geq$ 24 months), previous monthly salary (ten brackets for full-time, six for part-time), and previous industry (seven categories). This yields 14,112 demographic cells.

We constructed these cells based on the following considerations. First, all characteristics have to be observable in the registers. Second, 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. 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.[2]

Properties of wage projections We use Danish labor market registers for all unemployed job seekers re-employed between 2013 and 2022 to calculate average monthly re-employment wages before taxes and excluding pension contributions in each cell.

[2]These considerations also led us to exclude certain variables. We do not additionally condition on occupation because, at the level of aggregation required to maintain sufficiently large comparison groups, industry is more informative about realized wages in our data. We also do not use training undertaken while unemployed, as the available data do not consistently identify the type of training, making it difficult to define comparable worker groups.

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 only a 1.4% 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, and those earlier in their spell secure higher re-employment wages. Taken together, the seven characteristics explain 23% of the variation in log re-employment wages in the register data, suggesting that the resulting cells capture meaningful wage differences across job seekers despite substantial variation driven by factors not captured by the cell definitions.

Discussion and validation Our approach requires respondents to treat the wage projection as relevant for themselves—so that our intervention generates exogenous variation in respondents' beliefs about their own future wage offers. We can then use this variation to study the causal effect of wage expectations on job search. In Section 4.1, we present evidence that beliefs about re-employment wages of similar job seekers are indeed strongly correlated with respondents' beliefs about their own earnings potential.

That said, the projection will likely not coincide with the wage a fully rational job seeker should expect to be offered. First, the projection is about average *accepted* rather than *offered* wages—which should differ because low offers tend to be rejected. Second, a respondent may rationally expect a different wage for themselves than for their demographic group, based on their own circumstances. This could be due to predictor variables omitted from the projections, such as occupation, or more idiosyncratic factors that are private knowledge of the respondent, such as additional training undertaken while unemployed. Third, there may have been changes in the economy between the period underlying the projection (2013–2022) and the time of our experiment (2023), e.g., due to the state of the business cycle. This is unlikely to lead to large differences, however, for at least three reasons: (i) business-cycle variation should largely average out over the ten-year reference period underlying the information; (ii) nominal wages tend to respond only sluggishly to the cycle (Hazell and Taska, 2025); and (iii) 2023 was a relatively normal year, with the pandemic recession being over.[3] Lastly, despite

[3]Another potential source is inflation. Our wage projections do not account for inflation, as we aimed to keep the information easily understood even by respondents with low economic literacy. However, inflation and nominal wage growth in Denmark were modest until the post-pandemic shock, and the

our restriction to demographic cells with at least 30 observations in the registers, the projection may be noisy in smaller cells, and it may be a less precise signal of a respondent's own prospects when wages are dispersed within cells. Appendix Figure A.1 shows that cells are substantial in size for the large majority of respondents (average: 332 observations; Panel A), while the within-cell standard deviation of log wages averages 0.26, pointing to some dispersion around the projections (Panel B).

Are the wage projections a good predictor of actual re-employment wages? Low predictive power would not be a concern for our design as long as respondents still *subjectively perceive* the information as sufficiently relevant to themselves. Nevertheless, we validate our wage projection by demonstrating its *objective relevance* in two out-of-sample prediction exercises. Appendix Figure A.2 plots the relationship between our wage projection and actual re-employment wages for control group respondents in our survey (Panel A) and for the full cohort 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 0.19, respectively. Thus, the projection is informative despite idiosyncratic circumstances, changes in the economy between the period underlying the treatment information and the time of our experiment—such as inflation, business cycle movements or technological shifts—and potential noise in the benchmark.

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 E.1 and E.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 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

inflation surge had only a limited and sluggish pass-through to nominal wages (Huidrom, 2023).

respondent's pre-unemployment wage, the respondent's prior belief, and the actual cell-level 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.[4] Finally, we elicit some job search outcomes. Most importantly, 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 survey-based outcomes reflect experimenter demand effects or numerical anchoring, we re-elicit 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 22, 2023, to participate in our main survey.[5] We distributed the 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 one to two weeks after completion. Participation in both surveys was voluntary, but incentivized through a raffle of 30 gift cards, each worth DKK 1,000 (≈USD 145).

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-

[4]The 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.

[5]This includes all UI beneficiaries and social assistance recipients deemed fit for full-time work by their caseworker.

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 3,903 are also part of the follow-up sample.[6]

Appendix Table A.2 reports summary statistics and balance tests for the main and the follow-up sample, alongside population benchmarks from administrative data. Our sample closely resembles the population of unemployed 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 balanced across treatment and control group for most characteristics in both surveys, and we cannot reject the hypothesis that all differences in demographics are jointly zero. We nevertheless control for a comprehensive set of observables in all estimations.

2.5 Administrative outcomes

A key feature of our approach is the use of rich administrative outcomes. Unlike survey-based measures, these outcomes are immune to demand effects, consistency bias in survey responses, intention–action 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 regions 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' monthly employment status, working hours, labor earnings, and occupation as reported by employers.

[6] We 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.

3 Theoretical framework

To guide our empirical analysis, we discuss the effects of wage expectations in a stylized job search model. The framework organizes the mechanisms through which the shifts in wage expectations generated by our information treatment may affect job search behavior, focusing on job seekers' selectivity with respect to job offers and their search intensity. We present the model setup and its key implications below. Detailed derivations, proofs of propositions, and a parameterized illustration can be found in Appendix B. Table 1 summarizes the main implications of the framework.

Model setup While unemployed, workers receive a flow value b reflecting unemployment benefits as well as the value of not working, such as leisure or home production. Workers discount future payoffs by $\beta \in (0, 1)$. Let v denote the value of a job offer, which includes wages as well as non-wage attributes such as commuting distance, occupational fit, and working conditions. Offers are drawn independently from the distribution $F(v; \mu) = G(\ln v - \mu)$, where μ indexes the location of the distribution of log job values. This parameterization implies that changes in μ shift all job values proportionally, allowing us to express belief revisions in log points, as in our empirical analysis. The realized value v is revealed only when an offer arrives, at which point the worker decides whether to accept or reject it. The relevant acceptance threshold is therefore a reservation value $\bar{v}$: the minimum job value the worker is willing to accept. Workers choose search effort s at cost $\gamma(s)$, with $\gamma'(s) > 0$ and $\gamma''(s) > 0$. Effort affects how job opportunities are generated; we describe this process in more detail in the effort analysis below.

Job seekers hold subjective beliefs about the distribution of job values, summarized by $\widehat{\mu}$, which we refer to as perceived job quality, and choose search behavior given these subjective beliefs. Our intervention shifts beliefs about wage offers, which we map into a shift in $\widehat{\mu}$. We interpret higher expected wages as implying a weakly higher expected job value, shifting the perceived distribution $F(\cdot; \widehat{\mu})$ upward.[7]

3.1 Selectivity and reservation values

We first characterize how selectivity depends on job seekers' beliefs about job values, that is, how $\widehat{\mu}$ affects $\bar{v}$. Holding search effort fixed, the reservation value solves

$$\bar{v} = b + \frac{\beta}{1-\beta} \int_{\bar{v}}^{\infty} (v - \bar{v})\, dF(v; \widehat{\mu}), \tag{1}$$

[7]This interpretation requires (i) that the treatment shifts perceived job values primarily through changes in perceived average offers rather than the perceived shape of the offer distribution (consistent with the empirical evidence in Section 4.2), and (ii) that workers do not perceive strong compensating differentials between wages and amenities (consistent with the evidence in Section 4.3).

which captures the standard search trade-off.[8] A worker accepts an offer if its value exceeds $\bar{v}$; otherwise she rejects it and continues searching. A positive shock to $\widehat{\mu}$ raises the value of waiting and therefore increases the reservation value $\bar{v}$, while a negative shock lowers it. The strength of this response is captured by the elasticity of the reservation value with respect to perceived job quality, which we refer to as the pass-through of beliefs to selectivity. As shown in Appendix B.1, it is given by:

$$\varepsilon \equiv \frac{\partial \ln \bar{v}}{\partial \widehat{\mu}} = 1 - \frac{b}{\bar{v}\left(1 + \frac{\beta}{1-\beta}\, q\right)} \in (0, 1), \tag{2}$$

where $q = 1 - F(\bar{v}; \widehat{\mu})$ is the probability that a particular offer is acceptable.

Option value of search Equation (2) has two implications for how selectivity responds to belief revisions. First, the reservation value responds less than one-to-one. This is because it reflects both the flow value of unemployment and the option value of continued search, and only the latter responds to perceived job quality. This pass-through is weaker when the flow value of unemployment is high, so more generous unemployment benefits dampen the selectivity response. Second, the pass-through rises with perceived job quality, making the log reservation value convex in perceived job quality. Positive belief revisions therefore increase selectivity somewhat more strongly than equally sized negative revisions reduce it. The intuition is that perceived job quality affects the option value only through offers the worker would accept, and this share is larger after positive than after negative news.

Downward rigidity Thus far, the reservation value has been allowed to adjust freely in both directions. In practice, job seekers' selectivity may exhibit substantial downward rigidity. For example, reservation wages have been shown to be highly persistent and closely tied to previous earnings (Feldstein and Poterba, 1984; Koenig et al., 2026; Krueger and Mueller, 2016). More generally, workers may be reluctant to accept offers that imply losses relative to their current or past income. Several mechanisms may generate such a floor. Consumption commitments tied to previous income, such as housing or other fixed expenses, can be difficult to adjust in the short run and make earnings reductions particularly costly (Chetty and Szeidl, 2007). Dynamic considerations may also matter: accepting lower pay can be costly if current wages influence future wage setting or bargaining positions (Agan et al., 2025; Barach and Horton, 2021), or affect future earnings-related unemployment benefits. Social norms or fairness considerations may create a minimum standard for acceptable pay (Breza et al., 2026; Falk et al., 2006), while loss aversion may make workers particularly reluctant

[8] Appendix B.4 shows that, when search effort adjusts endogenously, the envelope theorem implies that its response does not enter the first-order effect of $\widehat{\mu}$ on the reservation value, which therefore coincides with the response obtained when holding effort fixed at its optimal level.

to accept wages below reference points anchored in previous income (DellaVigna et al., 2017, 2022). Similar constraints may operate along non-wage dimensions of job quality. Family and housing circumstances can limit geographic mobility, while legal, institutional, or personal constraints can impose lower bounds on acceptable working conditions and schedules.

We capture the resulting downward rigidity in reduced form through a floor below which offers become increasingly unattractive. We parameterize the floor as a minimum premium m over the value of unemployment: the latter anchors the floor in workers' current income while unemployed, while the premium allows acceptable pay to remain above this outside option, consistent with the continued relevance of past earnings. Specifically, we let the effective value of an offer be

$$\widetilde{v}(v) = v - \theta\big[(1+m)b - v\big]_+, \qquad \theta \geq 0; m \geq 0, \tag{3}$$

where θ governs the strength of the penalty. A finite θ yields a soft floor, while $\theta \to \infty$ approaches a hard floor below which offers are never accepted.[9]

The floor affects behavior only when the reservation value would otherwise fall below it. Negative news moves job seekers toward this constraint, whereas positive news moves them away from it. As the floor becomes relevant, it limits further downward adjustment in selectivity and thereby dampens the pass-through of negative belief revisions (see Appendix B.2). With a soft floor, downward adjustment remains possible but becomes weaker as offers below the floor are penalized more strongly. Under a hard floor, the downward response is bounded by the distance to the floor. The upward response remains unconstrained under both versions. Downward rigidity therefore amplifies the asymmetry between positive and negative news by weakening the selectivity response to negative news relative to positive news. If the floor rises with the value of unemployment b, higher benefits make the constraint more likely to bind, so responses to negative news are more strongly dampened at higher benefit levels.

Because the comparative statics operate through the reservation value $\bar{v}$, the selectivity response may manifest in reservation wages or along non-wage dimensions, such as the geographic scope of search. How changes in $\bar{v}$ are allocated across these margins depends on job seekers' beliefs about the joint distribution of wages and amenities, which we remain agnostic about.

Quantitative illustration To gauge magnitudes, we solve a parameterized version of the model for equally sized positive and negative belief revisions of 5 log points (see

[9]The piecewise-linear penalty is similar to standard formulations of reference-dependent preferences (Crawford and Meng, 2011; Kőszegi and Rabin, 2006). We use it more broadly as a reduced-form representation of downward rigidity: the mechanisms discussed above all make offers sufficiently far below a relevant floor disproportionately unattractive.

Panel A of Appendix Figure B.1). Three patterns emerge. First, with low benefits, pass-through is below one-for-one, and the baseline option-value mechanism generates only a very mild asymmetry in selectivity: the reservation value changes by -4.6% after negative news and $+4.8\%$ after positive news. Second, higher benefits somewhat dampen the selectivity response, but without additional downward rigidity the asymmetry remains modest (-3.9% versus $+4.2\%$). Third, introducing a soft floor leaves the positive response unchanged but attenuates the negative response to -2.5%, substantially amplifying the asymmetry.[10]

3.2 Search intensity

We next turn to how wage expectations affect workers' effort choices. We first characterize effort in the baseline model without the additional downward rigidity introduced in Equation (3), and then discuss the effort response in the presence of a floor on acceptable job values (see Appendix B.3 for details). We assume a search technology in which perceived values of future offers shape effort through two channels: (i) the value of additional search and (ii) the extent to which effort can compensate for less favorable opportunities. Formally, the probability $q(\bar{v}, \widehat{\mu}) = 1 - F(\bar{v}; \widehat{\mu})$ that a single generated offer is acceptable depends on the reservation value and the perceived offer distribution, but not directly on search effort. Search effort affects a different margin: it increases the number of opportunities generated. Assume offers arrive according to a Poisson process with arrival rate s. The probability of generating at least one acceptable offer is then

$$P(s, \bar{v}, \widehat{\mu}) = 1 - \exp[-s\, q(\bar{v}, \widehat{\mu})].$$

The corresponding first-order condition for optimal effort, s^*, equates the marginal cost of effort with its marginal return and can be written as

$$\gamma'(s^*) = \frac{\beta}{1-\beta} \underbrace{\exp[-s^* q(\bar{v}, \widehat{\mu})]}_{\substack{\text{compensating-} \\ \text{search channel}}} \underbrace{\int_{\bar{v}}^{\infty} (v - \bar{v}) dF(v; \widehat{\mu})}_{\substack{\text{opportunity-value} \\ \text{channel}}}. \tag{4}$$

This first-order condition highlights two channels through which changes in $\widehat{\mu}$ affect optimal search effort. The integral captures the expected surplus from a generated opportunity, with offers below the reservation value contributing zero surplus. It gives rise to an *opportunity-value channel*: better perceived opportunities raise this surplus

[10] Our baseline illustration considers equally sized positive and negative belief revisions from a common initial value of unemployment relative to perceived job values—the relevant starting point for the selectivity response—and a common distance to the floor. Empirically, respondents receiving positive vs. negative news in our experiment differ in both dimensions. In Appendix B.6, we show that allowing for the empirically observed heterogeneity in these initial conditions yields very similar predicted selectivity responses.

and thus the return to effort, whereas worse perceived opportunities lower it. The exponential term captures the scope for effort to increase the probability of finding an acceptable offer. It gives rise to a *compensating-search channel* that works in the opposite direction: when acceptable offers become harder to generate, additional effort becomes more valuable as a way to offset this decline; when they become easier to generate, this motive weakens. The net effect of changes in $\widehat{\mu}$ on effort is therefore ambiguous and depends on which force dominates.

Margin substitution The strength of the compensating-search channel depends on how strongly the reservation value adjusts to perceived job values. If the reservation value adjusts one-for-one, changes in the probability of finding an acceptable offer are largely absorbed through selectivity, leaving little need to adjust effort. If the reservation value adjusts by less, the acceptance probability changes more strongly, increasing the value of effort as a compensating margin. We refer to this substitution between selectivity and search effort as *margin substitution*.

This mechanism can generate asymmetric effort responses when the downward rigidity introduced in Equation (3) limits selectivity adjustment after negative news. Additional effort then becomes more valuable because it compensates for the lower probability that a generated opportunity is acceptable. Higher benefits strengthen the scope for such margin substitution by dampening the selectivity response and, when the floor becomes relevant, further constraining downward adjustment. Worse perceived opportunities also reduce the expected surplus from search, discouraging effort through the opportunity-value channel. The effort response to negative news is therefore ambiguous in principle and depends on the relative strength of the two channels.

After positive news, the two effort channels again work in opposite directions: the higher expected surplus raises the return to search, while the higher probability of finding an acceptable offer reduces the need for additional effort. However, because selectivity adjusts more strongly, the compensating-search effect is weaker than after negative news, leaving less scope for margin substitution, and generating asymmetry.

Quantitative illustration Panel B of Appendix Figure B.1 illustrates the margin-substitution mechanism under a parameterization in which the compensating-search motive is sufficiently strong.[11] With low benefits, effort responses are small, changing by -1.0% after negative news and $+1.0\%$ after positive news. Higher benefits alone leave these responses modest, but introducing the floor at high benefit levels changes this pattern. By constraining downward selectivity adjustment, the floor raises the effort response to negative news to 7.8%, while leaving the response to positive news essentially unchanged. Thus, higher benefits can strengthen margin substitution when

[11] As we will see below, these conditions on the search technology are consistent with the patterns in our data.

Table 1 Key implications of the theoretical framework

	Selectivity	**Search effort**
Baseline average responses	Response in direction of news.	Opportunity-value effect in direction of news, with opposing compensating-search effect. Ambiguous net response.
Baseline positive vs. negative news	Mildly stronger response to positive news.	Compensating-search effect mildly stronger after negative news.
Baseline role of benefit generosity	Somewhat dampens responses to both positive and negative news.	Somewhat strengthens the compensating-search effect after both positive and negative news.
Downward rigidity	Dampens the negative-news response, particularly when the floor (e.g., benefits or previous wage) is higher.	Increases compensating search after negative news, particularly when the floor (e.g., benefits or previous wage) is higher.

Notes: The table summarizes the main qualitative implications of the theoretical framework for selectivity and search effort. Selectivity refers to the reservation value. Search effort responds through an opportunity-value channel and a compensating-search channel, which work in opposite directions and therefore make the net effort response generally ambiguous.

downward rigidity becomes binding after negative news.

4 Results

4.1 Prior beliefs

We start the empirical analysis by providing descriptive evidence on respondents' prior beliefs about the re-employment wages of comparable workers.

Heterogeneity There is substantial heterogeneity in the extent to which respondents' prior beliefs about the re-employment wages of comparable workers align with the benchmarks from register data. Panel A of Figure 1 displays a histogram of the difference between prior beliefs and benchmarks. On average, job seekers' beliefs about comparable workers' re-employment wages are close to the register benchmark, exceeding it by just 2%. Yet, only about 10% of the sample hold beliefs within 2.5% of the benchmark. 25% of our respondents overestimate actual re-employment wages by more than 15%, while 19% 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 scope 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).

From group beliefs to own wage expectations We next examine how job seekers' beliefs about the re-employment wages of comparable past workers are linked to their beliefs about their own next wage offer. The two are conceptually distinct: the former concerns *accepted*, the latter *offered* wages. We therefore do not expect them to coincide in levels. What matters for our approach is that job seekers view information on comparable workers' re-employment wages as relevant for their own future wage offers. Consistent with this, the binned scatter plot in Panel B of Figure 1 shows a strong positive association between control-group respondents' expected own next wage offer and their beliefs about the average re-employment wage in their population cell.[12]

Pre-unemployment wages and prior beliefs 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 1 presents a histogram of perceived wage changes—beliefs about re-employment wages minus pre-unemployment wages—for comparable workers. On average, respondents believe that unemployment is not associated with a wage change.

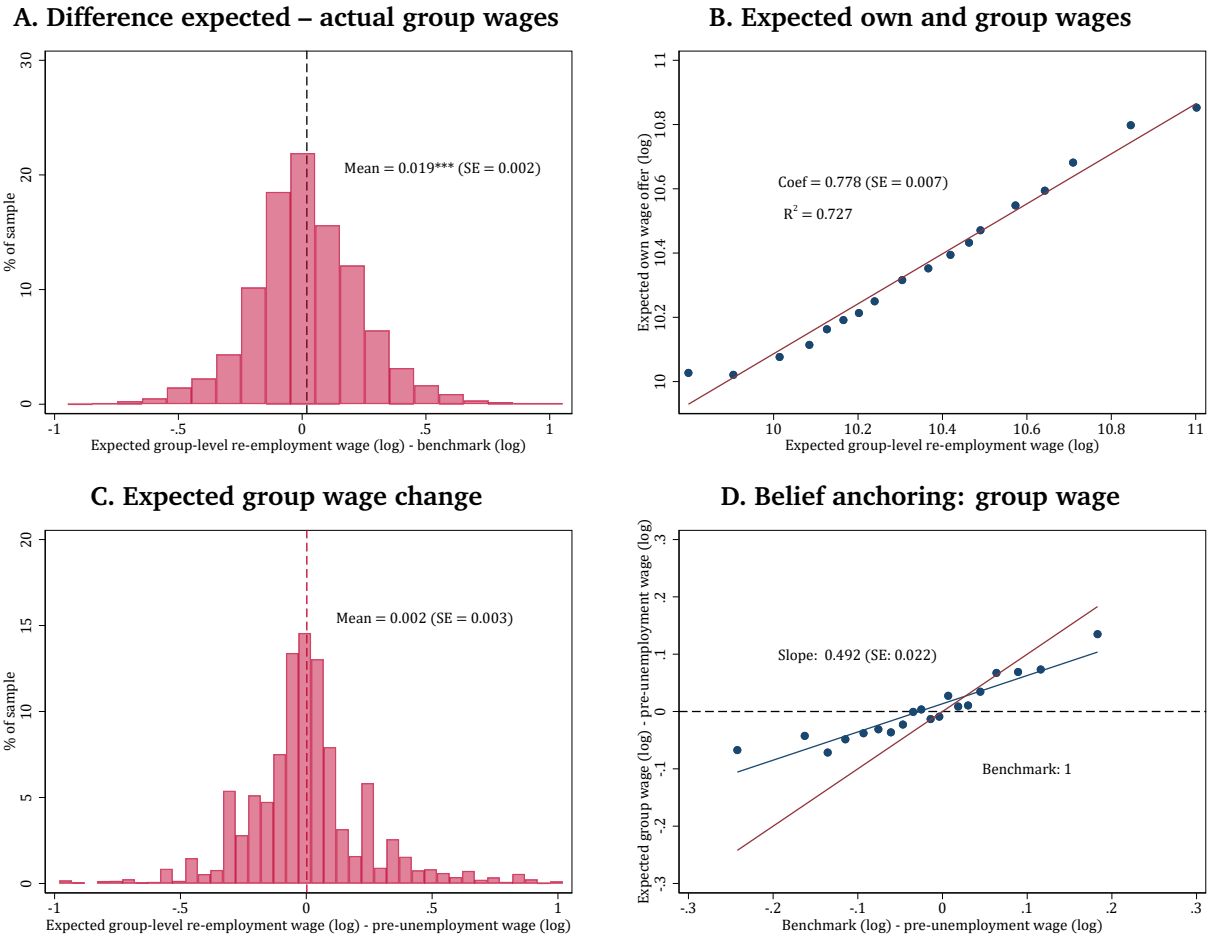
To quantify the relationship between perceived and actual wage changes, we follow the approach of Jäger et al. (2024) and regress the respondents' perceived log wage change for comparable workers on the actual wage change implied by our wage projections.[13] Panel D of Figure 1 displays a binned scatter plot of this relationship. The red 45-degree 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, $p < 0.001$).[14] Appendix C.1 presents an extensive sensitiv-

[12] Appendix Figure A.4 shows that this link persists when beliefs about own offers are taken from the main survey and beliefs about population-cell wages from the follow-up, and vice versa. This mitigates concerns related to unconscious anchoring on earlier survey responses.

[13] We 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.

[14] A reluctance to accept wages below the previous wage could contribute to this asymmetry through motivated reasoning. Our data do not allow us to test this explanation, but it would be an interesting avenue for future research.

Figure 1 Characteristics of wage expectations absent the treatment



Notes: The figure illustrates job seekers' wage expectations absent the intervention. Panels A, C, and D are based on treatment and control groups, while Panel B is based on control-group respondents only. Panel A shows distributions of expected minus actual re-employment wages of comparable workers ($N = 9{,}247$). Panel B shows a binned scatter plot (20 bins) relating expected own and expected group wages ($N = 4{,}619$). Panel C shows the distribution of expected wages of comparable workers minus pre-unemployment wages ($N = 8{,}039$) among previously full-time employed respondents. Panel D shows a binned scatter plot (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 ($N = 8{,}039$).

ity analysis for these results, highlighting robustness to measurement error, potential "mechanical" correlations, and alternative benchmarks.

The finding that job seekers appear to anchor their beliefs about re-employment wages on previous wages is consistent with evidence that job seekers often set reservation wages close to their previous salary (Koenig et al., 2026; Krueger and Mueller, 2016). The degree of anchoring we detect among unemployed job seekers (slope of 0.5) appears somewhat weaker 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 acquired during job search among unemployed workers.

In Appendix C.2, we examine further determinants of how closely job seekers' beliefs about re-employment wages of comparable workers align with register benchmarks. Beliefs are more misaligned in demographic cells in which re-employment wages are more dispersed, possibly because re-employment wages are harder to predict in these cells. By contrast, cell size—a proxy for noise in the benchmark—plays no major role. Beliefs are also linked to the gap between confidence and actual ability, to own experiences, and to the social environment. For example, underconfidence, prior employment at a low-paying firm, and more frequent caseworker contact tilt beliefs toward pessimism, which anchoring on the pre-unemployment wage explains less readily than optimism. Overall, however, the pre-unemployment wage remains one of the strongest predictors of deviations from the benchmark. For policy, this suggests that pre-unemployment wages could be used to target large-scale information campaigns without first eliciting priors, making such interventions more feasible and less costly.

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 corresponding prior.

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 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 treatment assignment ensures that we identify the causal effect of receiving wage information within each of the five prior-belief groups. Appendix Figure A.5 displays the distributions of priors and benchmark wages for each group and highlights the direction in which the treatment shifts respondents in the different groups.

As shown in Appendix Table A.3, job seekers with different initial beliefs also differ in other characteristics. In principle, heterogeneity in treatment effects across groups could reflect differences in such other group characteristics rather than in prior beliefs. This is a well-known feature of information provision experiments (Haaland et al., 2023), and we address it in robustness checks presented below.

Finally, we winsorize survey-elicited wage variables (expected group-level and own wage offers, and reservation wages) at the 5th and 95th percentiles, and search intensity (job-ad clicks), whose distribution has a long right tail, at the 95th percentile, to mitigate the influence of outliers. We demonstrate robustness to alternative cutoffs.

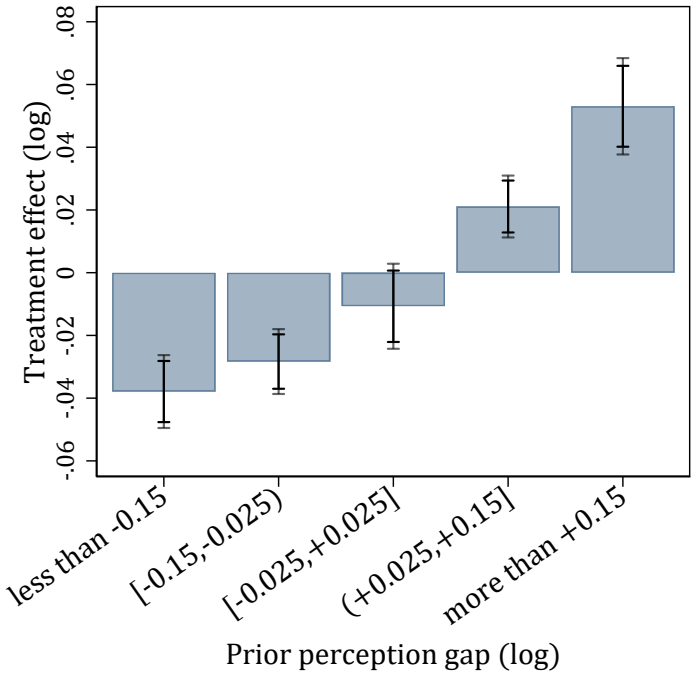
Results We examine how information about the re-employment wages of comparable workers affects job seekers' point expectations about their own next wage offer. Figure 2 presents the treatment effects separately for each of the five perception-gap groups. Job seekers view information on the re-employment 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 5.3% ($p < 0.001$) 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.[15] Relating the treatment effects on own wage offer expectations to the information shocks about comparable workers' re-employment wages implies learning rates between 12% and 34%. These magnitudes are consistent with respondents understanding that the wage projection is an imprecise signal of their own future wage potential, and are in line with learning rates in other information experiments that shift beliefs about personal outcomes using population group-level information (Bottan and Perez-Truglia, 2025; Roth et al., 2022; van Rooij et al., 2026).

Additional evidence and robustness In Appendix C.3, we present additional empirical exercises on our intervention's first-stage effects on wage expectations. We provide a high-level summary here.

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

[15] Appendix Table A.4 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).

Figure 2 Treatment effects on expected wage offers



Note: The figure shows the effects in log points of the information treatment (including 90%- and 95%-confidence intervals) on the wage respondents expect to be offered in their next job offer (log), separately for individuals with varying initial perception gaps regarding the wage potential of comparable workers. Number of observations: 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). The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

likely to recall the details of the presentation of the treatment information (de Quidt et al., 2018). Reassuringly, updating of wage expectations persists in the follow-up survey conducted one to two weeks after the intervention, albeit at a somewhat smaller magnitude in the case of positive shocks.

We also examine treatment effects on moments of respondents' subjective probability distribution over their next wage offer. Treatment effects on the mean of this distribution align with those for point forecasts documented above. The standard deviation of the distribution—a measure of perceived dispersion and uncertainty about wages—does not respond to the treatment, except for a moderate reduction in the neutral group. Finally, we show that differential updating of wage expectations across perception-gap groups persists when accounting for differences in group composition, that the degree of updating is unrelated to cell size and within-cell wage dispersion, and that there are no systematic spillovers to beliefs about the effort-offer arrival mapping.

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 behavior and realized labor market outcomes. We begin with reduced-form treatment effects for all five perception-gap groups, which identify the causal effect of receiving the information without invoking an exclusion restriction or monotonicity. We then report 2SLS estimates that scale these treatment effects by the corresponding first-stage effects on wage expectations, putting the responses to positive and negative wage news on a comparable scale.

4.3.1 Reduced-form treatment effects

Selectivity in wages The information shocks shift job seekers' reservation wages—the lowest monthly wage they would accept (Panel A of Figure 3). Treated job seekers who were initially strongly optimistic reduce their reservation wage by 1.6% ($p = 0.022$) relative to their non-treated counterparts. Initially moderately and strongly pessimistic job seekers increase their reservation wages by 1.4% ($p = 0.008$) and 3.9% ($p < 0.001$) in response to the treatment, while moderate negative and neutral shocks have no significant effects. We complement these survey-based estimates with click-by-click data on the firms targeted by participants. Appendix Table A.5 shows that large positive shocks lead job seekers to target vacancies at firms offering higher pay and at larger firms, which are known to pay higher wages (Brown and Medoff, 1989). We detect no changes in the types of firms targeted for negative, neutral, or smaller positive shocks.

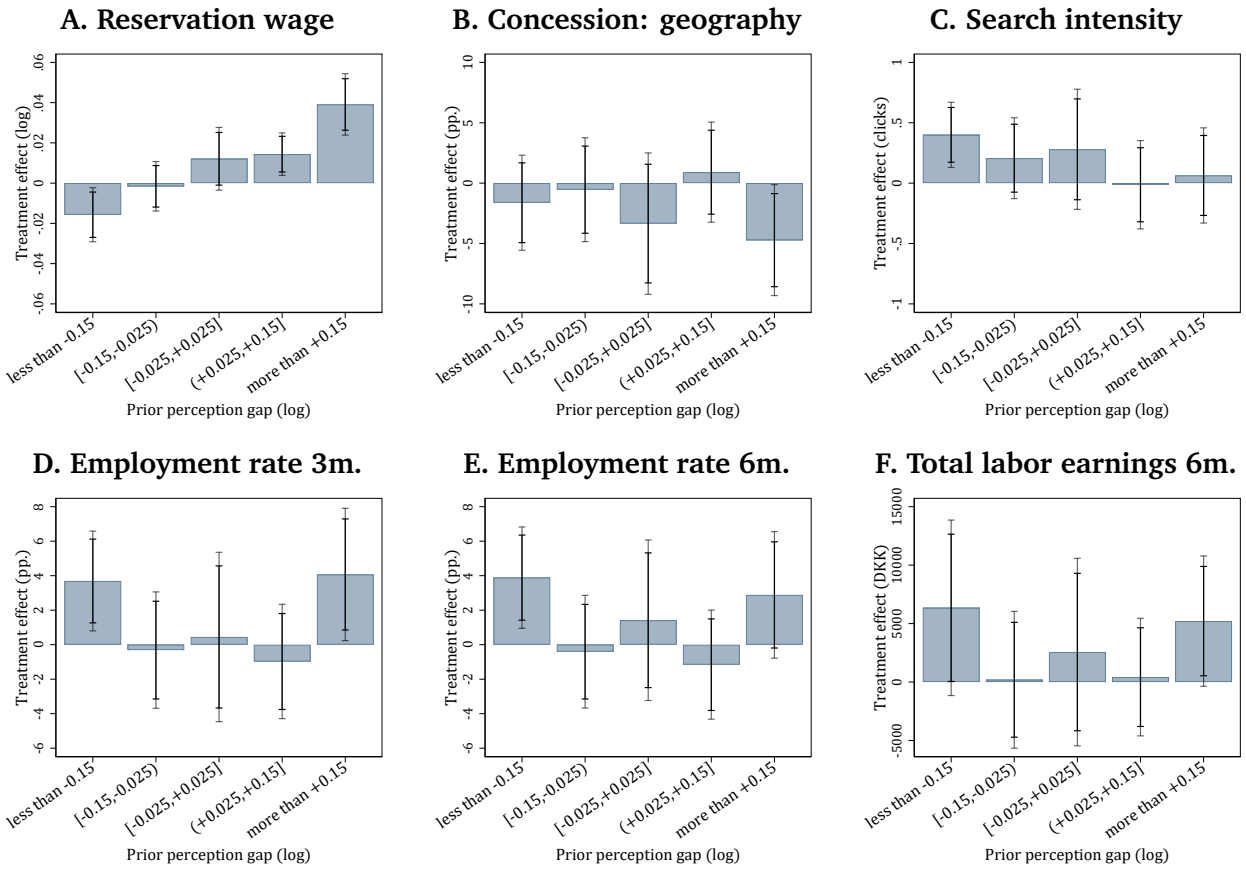
Selectivity in non-wage characteristics The increased selectivity among job seekers receiving large positive shocks extends beyond wages to non-wage job characteristics. Respondents report their willingness to make concessions along three dimensions: geographic location, working conditions, and skill requirements. Panel B of Figure 3 shows that large positive shocks reduce respondents' willingness to accept jobs requiring relocation or long commutes by 4.7 pp (-9%, $p = 0.044$). We find no corresponding effects on the other two dimensions, working conditions and skill requirements, and no effects on any non-wage dimension among the other perception-gap groups.[16] Thus, higher expected wages do not make job seekers more willing to compromise on non-wage attributes; if anything, wage and geographic selectivity move in the same direction.[17]

Search intensity Panel C of Figure 3 shows treatment effects on search intensity, proxied by the number of job ads participants view on the public employment platform

[16] Column 6 of Appendix Table A.5 shows that large positive shocks reduce the share of all elicited concessions job seekers are willing to make by 2.6 pp.

[17] This speaks against strong perceived compensating differentials between wages and amenities and supports interpreting higher expected wages as higher perceived job values (Section 3).

Figure 3 Reduced-form treatment effects on job search and labor market outcomes



Notes: The figure shows reduced-form effects of the information treatment on job search behavior and labor market outcomes, with 90% and 95% confidence intervals. Panel A shows the log reservation wage reported in the survey; Panel B willingness to change location, reported in the survey; Panel C the number of job-ad clicks within one week; Panels D and E average monthly employment rates within three and six months; Panel F total labor earnings within six months. Estimates are shown separately by initial perception-gap group, corresponding to different information shocks about the wage potential of comparable workers. Observations by perception-gap group in the full estimation sample are: $N = 2{,}323$ (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). The figure reports the results of the following regression: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

during the calendar week after the main survey. In contrast to the selectivity effects, which are concentrated among job seekers receiving large positive shocks, search intensity responds primarily to large negative shocks. Initially strongly optimistic job seekers click on 0.4 more job ads ($p = 0.004$), a 26% increase relative to the control group. This effect persists when extending the horizon to the four weeks after the survey (Appendix Table A.5). We detect no changes in search intensity following positive, neutral, or smaller negative information shocks.

Labor market outcomes We next examine whether these changes in search behavior translate into labor market outcomes measured in administrative data. Consistent with lowering reservation wages and increasing search intensity, large negative shocks make

job seekers re-enter employment more quickly: among initially highly optimistic job seekers, the treatment increases average monthly employment by 3.7 pp over three months (+16%; $p = 0.012$; Panel D of Figure 3) and by 3.9 pp over six months (+11%; $p = 0.010$; Panel E). Over six months, it also increases total labor earnings by DKK 6,349 ($\approx$ USD 921; +9.1%; $p = 0.098$; Panel F). These gains appear to operate mainly through the extensive margin: Appendix Figure A.6 shows that the treatment reduces the hourly wage job seekers in this group accept relative to their previous wage by 3.1% ($p = 0.064$), consistent with the reduced reservation wages measured in the survey.

Large positive shocks also improve short-run employment outcomes, despite higher reservation wages and a narrower geographic scope of search. Among initially strongly pessimistic job seekers, the treatment raises average monthly employment over three months by 4.1 pp (+14%; $p = 0.038$; Panel D of Figure 3). The effect decreases at the six-month horizon (Panel E), but the initial employment gain translates into 11.4% higher labor earnings over six months ($p = 0.067$; Panel F). We detect no significant effect on hourly wages in the first job after unemployment, although we cannot rule out increases of up to 3.6% with 95% confidence (Appendix Figure A.6).[18] That greater wage selectivity—higher reservation wages and a shift in search toward higher-paying firms—is not associated with significantly higher realized wages may reflect that higher reservation wages raise accepted wages only to the extent that they increase the fraction of rejected offers. This increase should be small when initial reservation wages are low relative to available wages, as is the case for initially pessimistic job seekers. The link between reservation wages and realized wages may be further weakened because positive news redirects search toward local jobs (Section 4.4.2), which changes the wage offers available and raises the non-wage value of jobs through shorter commutes.

For moderate and neutral shocks, employment, earnings, and wage effects are close to zero and statistically insignificant. These patterns align with the largely muted treatment effects on job search behavior for these groups.

4.3.2 Quantifying the effects of revisions of wage expectations

The reduced-form estimates point to an asymmetric response to wage news: adjustment is concentrated in selectivity regarding wages and location for positive shocks but shifts to search effort for negative shocks. To make the responses to positive and negative shocks comparable, we conduct 2SLS estimations that scale the reduced-form treatment effects by the corresponding first-stage effects on wage expectations. We focus on job seekers who are initially strongly optimistic or strongly pessimistic, as the treat-

[18] Because wages are observed only among the employed and treatment affects job finding, we also estimate Lee (2009) bounds by trimming the wage distribution of the group with higher employment. The resulting bounds are -4.8% to -2.4% for large negative and -3.2% to 2.8% for large positive shocks.

ment generates a strong first-stage effect on wage expectations for these groups.[19] The exclusion restriction is that the treatment affects downstream outcomes only through changes in wage offer expectations. This assumption is supported by the fact that neither perceived uncertainty about wage offers (Appendix Figure C.3) nor beliefs about the mapping from effort to job-offer arrivals (Appendix Table C.3) change in response to the treatment for the relevant groups.

Job search behavior The 2SLS estimates reveal an asymmetry in job search responses to positive and negative changes in expected wage offers consistent with our framework in Section 3. On the selectivity side, a 1% increase in expected wages raises reservation wages by 0.7% after positive updates ($p < 0.001$), but an equally large negative update reduces reservation wages by only 0.4% ($p = 0.006$, Panel A of Figure 4). Both elasticities are significantly smaller than one ($p < 0.001$ for negative and $p = 0.024$ for positive changes). A similar asymmetry emerges for target wages in the click-by-click data, a non-self-reported measure of wage selectivity, with elasticities of 0.4 for positive updates and no significant response for negative updates (see Appendix Figure A.7). Moreover, a 1% increase in the expected offered wage reduces the willingness to accept long commutes or relocation by 0.9 pp ($p = 0.054$), whereas a negative update of the same magnitude leaves it essentially unchanged ($p = 0.416$, Panel B of Figure 4). For search effort, the asymmetry runs the other way: a 1% downward revision raises job-ad clicks by 0.11 ($p = 0.006$)—a 7% increase relative to the mean—whereas search effort does not respond to a comparable increase in wage expectations (Panel C of Figure 4).

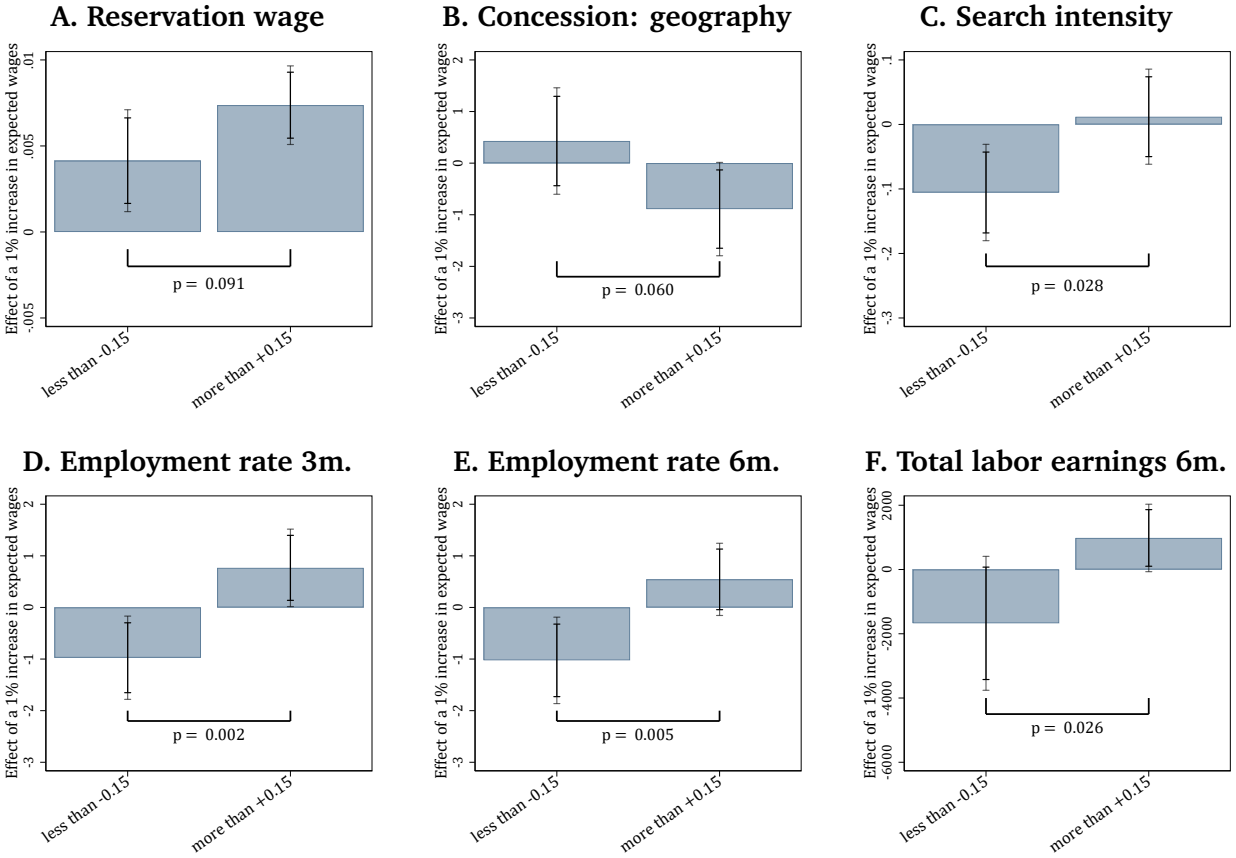
For all three margins, the asymmetry in responses to positive and negative news is statistically significant at least at the 10% level: reservation wages ($p = 0.091$), willingness to make geographic concessions ($p = 0.060$), and search effort ($p = 0.028$). We reject the joint hypothesis of symmetric responses across all three margins ($p = 0.034$).[20] Taken together, these estimates align with the core implications of the framework in Section 3: selectivity responds asymmetrically to wage news, consistent with downward rigidity, and negative wage news induces margin substitution toward higher search effort.

Labor market outcomes The asymmetry in behavioral responses also carries over to labor market outcomes, as reflected in the opposite signs of the 2SLS coefficients for the two groups: a 1% downward revision raises employment by roughly 1 pp at the three-month horizon ($p = 0.018$) and six-month horizon ($p = 0.016$), while a 1% upward revision increases it by about 0.8 pp at the three-month horizon ($p = 0.045$,

[19]The first-stage F-statistic on the excluded instrument is 45.80 for the large-pessimism and 40.91 for the large-optimism group, both well above conventional thresholds for weak-instrument concerns.

[20]We continue to reject joint symmetry when using an index of all elicited concessions rather than willingness to make geographic concessions ($p = 0.032$).

Figure 4 2SLS estimates of the effects of wage expectations on job search and labor market outcomes



Notes: The figure shows 2SLS estimates of the effect of wage expectations on job search behavior and labor market outcomes, with 90% and 95% confidence intervals. We instrument post-treatment expected own wage offers (log) with assignment to the information treatment, estimated separately for job seekers with large negative (perception gap below -0.15; $N = 2{,}323$) and large positive (perception gap above 0.15; $N = 1{,}723$) perception gaps. Panel A shows the log reservation wage reported in the survey; Panel B willingness to change location, reported in the survey; Panel C the number of job-ad clicks within one week; Panels D and E average monthly employment rates within three and six months; Panel F total labor earnings within six months. All coefficients are expressed as the effect of a 1% increase in expected wages; for the negative-shock group, negative coefficients therefore imply that downward revisions *increase* the outcome. The figure reports estimates from the following second-stage equation: $y_i = \delta_0 + \delta_1 \widehat{\text{Expected wage}}_i + \mathbf{X}_i\Phi + \epsilon_i$, with the following first stage: $\text{Expected wage}_i = \gamma_0 + \gamma_1 \text{Treatment}_i + \mathbf{X}_i\Lambda + \nu_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2. The first-stage F-statistic on the excluded instrument is 45.80 for the large-pessimism group and 40.91 for the large-optimism group. Reported p-values test equality of the effect of wage expectations between job seekers with large negative and large positive perception gaps.

Panel D) and by about 0.5 pp at the six-month horizon ($p = 0.127$, Panel E). Cumulative earnings increase by around DKK 1,700 after a 1% downward revision ($p = 0.115$) and by roughly DKK 1,000 after a 1% upward revision ($p = 0.067$, Panel F).

4.3.3 Additional evidence and robustness

Before examining the mechanisms behind the treatment effects, we present additional evidence and robustness checks for our main results. We provide a high-level summary here and relegate details to Appendix C.4.

A well-known feature of information experiments is that differential responses across differently shocked groups may reflect differences in group composition (Haaland et al., 2023). In our setting, individuals with high initial optimism and those with high initial pessimism may differ in their pre-unemployment wages, socio-demographic characteristics, or initial perceived job values relative to their outside option, all of which could directly affect their responsiveness to wage news. Compositional differences might contribute to the observed asymmetry in responses to positive vs. negative wage news. To address this, we adjust for such differences in a reweighting exercise. Reassuringly, the asymmetry persists after reweighting, suggesting that it is not driven by differences in the observable composition of the two groups.

We also present a correlational analysis on the control group. The outcome differences between initial optimists or pessimists and the neutral group mirror the corresponding treatment effects with the opposite sign—consistent with the intervention offsetting the effects of initial perception gaps.

Finally, we demonstrate that the treatment effects on beliefs, job search and labor market outcomes are robust to alternative reduced-form and IV specifications, alternative thresholds for grouping respondents by their priors, alternative winsorization approaches, adjustment for multiple hypothesis testing, and the exclusion of previously part-time employed workers.

4.4 Mechanisms

Thus far, we have shown that providing job seekers with information relevant for 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: a negative shock leads job seekers to somewhat reduce their reservation wages and increase search effort, while a positive shock makes them substantially more selective in terms of both wages and location without changing overall effort. In this subsection, we examine the mechanisms underlying these patterns. First, we examine how downward rigidity constrains selectivity adjustment and induces margin substitution toward higher search effort. Second, we provide evidence that spatial search frictions contribute to the improved re-employment rates following positive wage news. We focus our discussion on those with large initial optimism (perception gaps lower than -15%) or large initial pessimism (gaps exceeding $+15\%$), for whom our intervention generates

a strong first stage in wage expectations.

4.4.1 Downward rigidity and margin substitution

The pronounced asymmetry in responses to positive and negative wage news is consistent with downward rigidity in selectivity. In the framework of Section 3, such rigidity arises from a floor below which job seekers become increasingly reluctant to accept offers. When negative news pushes reservation values toward this floor, further downward adjustment in selectivity becomes constrained, increasing the scope for margin substitution toward search effort. The position of the floor may depend on job seekers' previous earnings, their current benefit income, or both: reservation wages tend to remain close to previous earnings (Krueger and Mueller, 2016) and common microfoundations for downward rigidity, such as consumption commitments, reference points, or norms about acceptable pay, are typically anchored either in workers' income history or in the income available during unemployment.

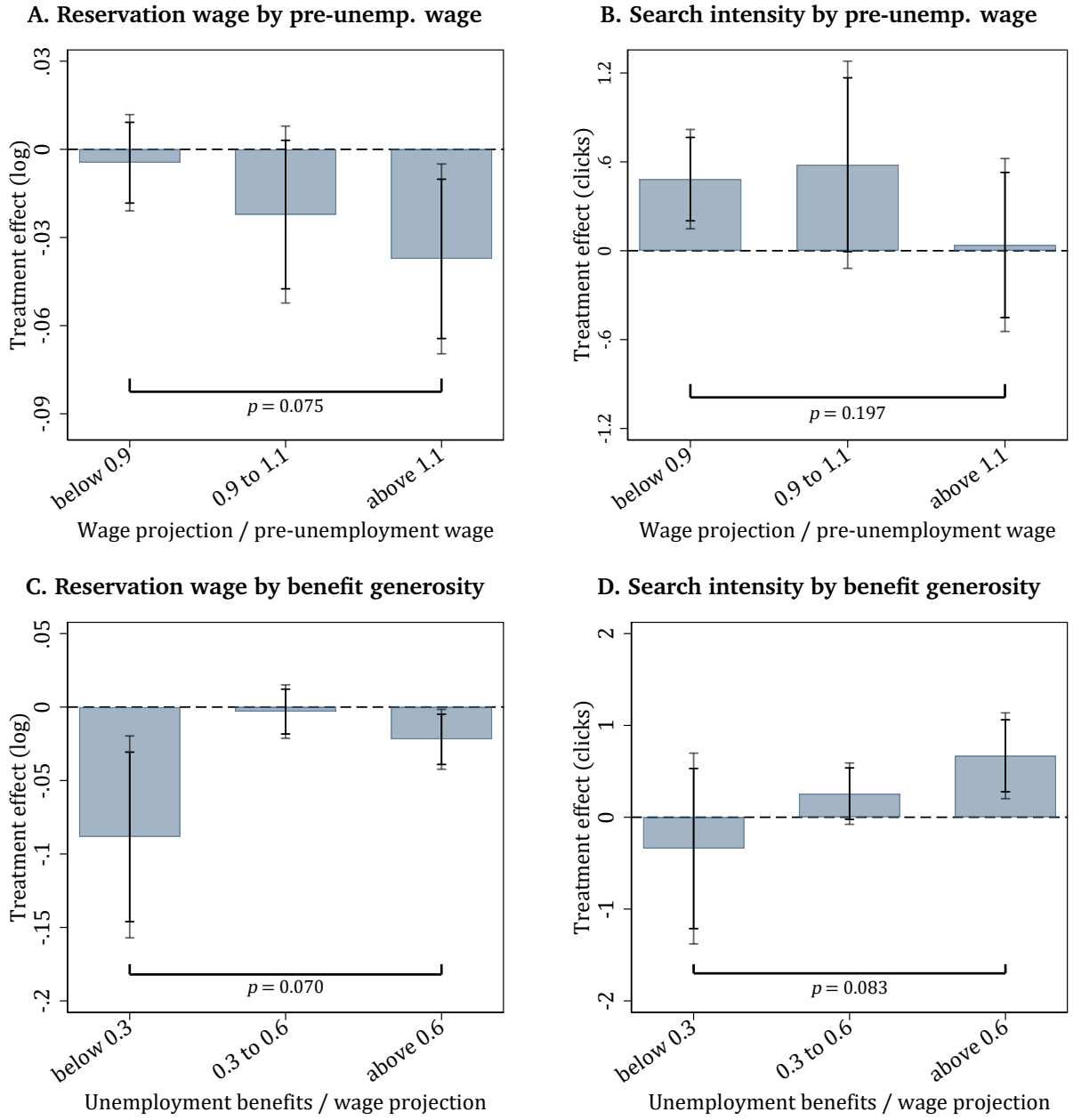
Pre-unemployment wages We first examine whether responses to large negative wage news vary with job seekers' pre-unemployment wages. We divide initially highly optimistic job seekers into three groups depending on whether their projected wage lies more than 10% below their pre-unemployment wage, within 10% of it, or more than 10% above it.

The results, shown in Panels A and B of Figure 5, reveal two patterns.[21] First, reservation wages respond least when the projection lies substantially below the previous wage ($-0.5\%; p = 0.586$) and most when it lies above it ($-3.7\%; p = 0.024$), with the difference between these two groups being statistically significant ($p = 0.075$). Second, search-effort responses exhibit the opposite pattern: negative wage news significantly increases effort only among those whose wage projection lies below the pre-unemployment wage (+0.48 clicks; $p = 0.005$), although differences in effort responses across groups are somewhat less precisely estimated. Taken together, these patterns point to more constrained downward adjustment in selectivity when the wage projection lies below job seekers' pre-unemployment earnings, accompanied by a shift toward higher search effort.

Benefit generosity We next turn to heterogeneity in responses to large negative news by unemployment-benefit generosity, which we capture by the ratio of unemployment benefits to the wage projection for the job seeker's demographic group. This proxies the value of remaining unemployed relative to available wage opportunities. Variation

[21] Throughout this subsection, we focus on reduced-form treatment effects. Appendix Figure A.8 reports corresponding 2SLS estimates that account for heterogeneity in belief updating across groups and, while more demanding in terms of statistical power, yield qualitatively similar patterns.

Figure 5 Heterogeneous effects of negative wage news by proxies for wage floor



Notes: The figure shows heterogeneous treatment effects, with 90% and 95% confidence intervals, among job seekers with large negative perception gaps (below -0.15), i.e., those who were initially highly optimistic. Panels A and B split the sample into three groups based on the ratio of the wage projection to the pre-unemployment wage: projections more than 10% below the pre-unemployment wage ($N = 1{,}354$), within $\pm 10\%$ ($N = 425$), and more than 10% above it ($N = 544$). Panels C and D split the sample into three groups based on the ratio of unemployment benefits to the wage projection: below 0.3 ($N = 128$), 0.3 to 0.6 ($N = 1{,}192$), and above 0.6 ($N = 1{,}003$). Panels A and C report effects on log reservation wages; Panels B and D report effects on search intensity, measured by job-ad clicks in the first week after the survey. The estimates are based on $y_i = \beta_0 + \sum_{g=2}^{G} \gamma_g \text{Group}_{ig} + \delta_1 \text{Treatment}_i + \sum_{g=2}^{G} \delta_g \left(\text{Treatment}_i \times \text{Group}_{ig}\right) + \mathbf{X}_i \Pi + \epsilon_i$, where Group_{ig} denotes indicators for the pre-unemployment-wage or benefit-ratio groups, G denotes the number of groups in the respective specification, and $\mathbf{X}_i$ contains prior log expected wages and the baseline covariates listed in Appendix Table A.2. Reported p-values test equality of the treatment effects between the lowest and highest groups in each panel.

in the ratio reflects (i) the statutory benefit cap, which lowers replacement rates for previously high-wage workers; (ii) systematic differences between previous wages and wage projections; and (iii) lower entitlements for previously part-time workers. Since all individuals in our sample are searching for full-time work, this variation is unlikely to capture differences in current search targets.[22]

Panels C and D of Figure 5 show the effects of negative wage news on reservation wages and search effort across three groups defined by the ratio of benefits to the group-level wage projection. Again, we observe a shift across adjustment margins: reservation-wage adjustment becomes weaker as benefit generosity rises, while the search-effort response becomes stronger. Among job seekers with a benefit ratio below 0.3, negative news reduces reservation wages by 8.8% ($p = 0.012$), whereas the corresponding effect is only around 2% at high benefit ratios ($p = 0.035$). Conversely, the increase in job-ad clicks is concentrated among those with the most generous benefits, reaching 0.67 clicks ($p = 0.005$) for ratios above 0.6. Differences between the lowest- and highest-benefit groups are statistically significant at the 10% level for both reservation wages ($p = 0.070$) and search effort ($p = 0.083$).

Heterogeneity in responses to positive wage news Appendix C.5 analyzes heterogeneity in responses to large positive wage news depending on the position of the wage projection relative to pre-unemployment wages and benefit generosity. Because the positive-news sample is smaller and exhibits less variation in the relevant moderators, these tests have somewhat lower power than the ones for negative news. With this caveat, we find no evidence of systematic heterogeneity in responses to positive wage news. This pattern is consistent with the interpretation that the heterogeneity documented for negative wage news reflects a specific *downward* rigidity in selectivity.

4.4.2 Spatial search frictions and the effects of positive wage news

Initially overly pessimistic job seekers increase their reservation wages and narrow the geographic scope of their search in response to the treatment. Consistent with downward rigidity, the geographic response is one-sided: positive news narrows the search radius as selectivity increases, while the response to negative news is muted.[23]

The narrowing after positive news may have direct employment consequences. In a frictionless world, more selective search would work against re-employment because

[22] By construction, the two heterogeneity measures are not independent. However, their empirical correlation is only moderate ($\rho = -0.45$), and mean ratios of benefits to wage projections are comparable in the groups with wage projections more than 10% below and above pre-unemployment wages (0.56 and 0.50, respectively). The two analyses therefore capture related but distinct variation and provide complementary evidence on the role of downward rigidity.

[23] Convex mobility costs provide one potential foundation for downward rigidity in geographic selectivity: commuting and relocation costs may rise sharply with distance, making it relatively easy to narrow the search radius after positive news but increasingly costly to expand it after negative news.

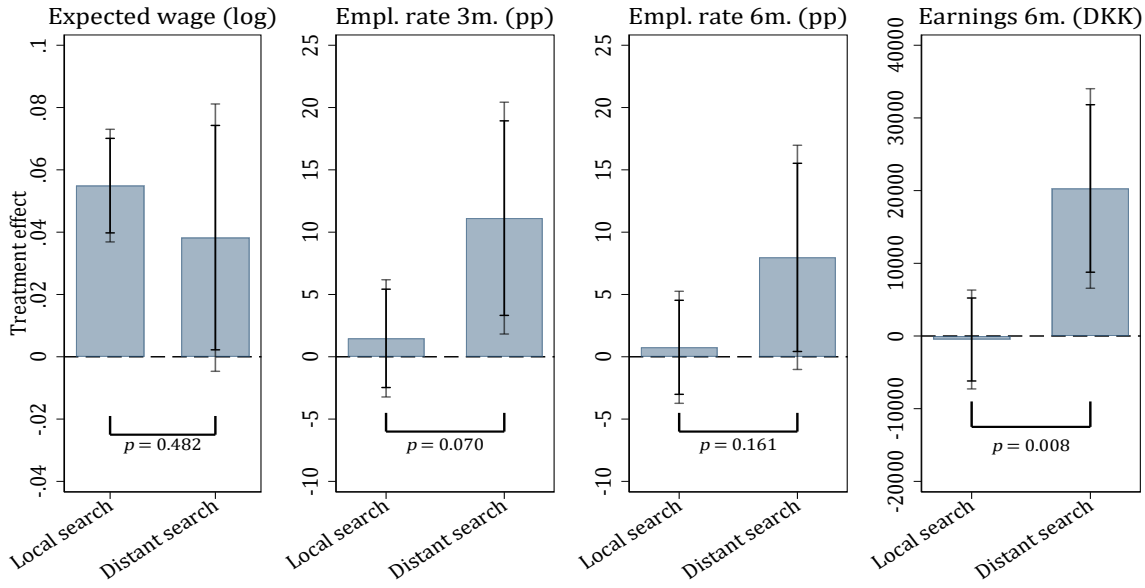
higher wage demands lead workers to reject more offers. The observed increase in employment therefore points to a specific environment—one in which spatial search frictions matter, so that local search is more effective at generating acceptable offers than distant search (Manning and Petrongolo, 2017; Schmutz and Sidibé, 2019). Several factors may reduce the effectiveness of distant search: job seekers may know less about distant labor markets and firms, have weaker referral networks there, and face higher costs of accepting distant jobs, whether through commuting or relocation. When spatial search frictions are sufficiently pronounced, concentrating search on the local market raises the chances of generating an acceptable offer by enough to outweigh the higher wage demands. This reallocation can also help explain why higher reservation wages are not accompanied by significantly higher realized wages (Section 4.3.1). Registered application data suggest a sizable local-search advantage: applying within one's municipality of residence is more than twice as likely to lead to a job as applying outside one's region (47% vs. 18%, see Appendix C.6).

This interpretation raises a natural question: why did job seekers not search more locally absent the intervention? One explanation is that they underestimate the relative effectiveness of local search and therefore search too broadly. This mechanism—the interaction between the upward revision of wage expectations and unanticipated spatial search frictions—yields four implications, which we examine below: the additional matches should be local; they should be concentrated among job seekers who previously searched broadly; they should be more pronounced when local search effectiveness is relatively high; and job seekers should underestimate the relative returns to local search. Appendix B.5 derives these implications formally.

Location of additional job matches Appendix Table A.6 shows that large positive information shocks increase employment in the initial municipality of residence by 4.5 pp three months later ($p = 0.025$; 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 one's municipality are close to zero and statistically insignificant. Moreover, the geographical distance between the first workplace after unemployment and the initial place of residence is 9.5% smaller for treated job seekers ($p = 0.058$; Column 3).

Heterogeneity by prior search radius and local search effectiveness We measure prior search radius as the distance between individuals' residence and the vacancies they applied to in the four weeks before the survey. We then classify them as prior distant job seekers if they have sent at least one application for which this distance exceeds ten kilometers—roughly the average radius of Danish municipalities. Figure 6 shows that, within this group, the treatment increases three-month employment by 11 pp ($p = 0.019$) and six-month earnings by DKK 20,297 ($\approx$ USD 2,943; $p = 0.004$).

Figure 6 Heterogeneous effects of positive wage news by previous search radius



Notes: The figure shows heterogeneous treatment effects, with 90% and 95% confidence intervals, among job seekers with large positive perception gaps (above $+0.15$), i.e., those who were initially highly pessimistic. Effects are shown separately by pre-treatment search radius, measured as the distance to jobs applied to during the four weeks before the survey: *local* (has not applied more than 10 kilometers away; $N = 1{,}160$) and *distant* (applied more than 10 kilometers away; $N = 293$). Job seekers who did not apply to any job in the four weeks before the survey are excluded. The estimates are based on $y_i = \beta_0 + \gamma \text{Local}_i + \delta_1 \text{Treatment}_i + \delta_2 (\text{Treatment}_i \times \text{Local}_i) + \mathbf{X}_i \Pi + \epsilon_i$, where Local_i indicates no pre-treatment application further than 10 kilometers away, and $\mathbf{X}_i$ contains prior log expected wages and the baseline covariates listed in Appendix Table A.2. Reported p-values test equality of the treatment effects between the local and distant groups.

Effects for prior local job seekers are small and insignificant, and the differences between the two groups are statistically significant for both employment ($p = 0.070$) and earnings ($p = 0.008$). Increased job finding is thus concentrated among those for whom spatial search frictions are most relevant. Moreover, Appendix Figure A.9 shows that the improvement in employment outcomes is concentrated in municipalities with high local search effectiveness.[24]

Beliefs about the returns to local search Do job seekers anticipate the higher returns to local search? We explore this question in 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.6. 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

[24]We proxy local search effectiveness by the share of job seekers residing in a municipality who find employment in the same municipality within six months, computed over January 2020 to October 2023, the period preceding our experiment.

of local applications compared to benchmarks from application data. Underestimating the difficulties of non-local search may lead job seekers 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.

Overall, the findings described in this subsection align with the notion that the improved labor market integration of individuals receiving positive shocks is driven by a reduced geographic scope of search.

4.5 Model-based analysis of revisions of wage expectations

In the final part of our analysis, we combine the reduced-form estimates of the effects of our intervention with the theoretical framework from Section 3. Under the additional structure imposed by the calibrated model, we use this framework to address three questions that the reduced-form estimates alone cannot answer: (i) how the model-implied employment effects vary with the size of belief revisions, including revisions beyond those observed in the data; (ii) how these effects decompose into changes in reservation wages, search effort, and the geographic allocation of search; and (iii) how they vary with congestion. We anchor the analysis to the treatment-induced revisions of wage offer expectations among initially highly optimistic and highly pessimistic job seekers—3.8% downward and 5.3% upward, respectively—for whom the intervention produces a strong first stage.

Model calibration We implement separate counterfactual exercises for negative and positive wage news. Appendix D provides implementation details, parameter estimates, model-fit comparisons, and counterfactual results. For each group—initially optimistic and initially pessimistic job seekers—we draw simulated observations from the control-group distributions of pre-unemployment wages and perceived wage offers and choose a parameter governing how search effort translates into employment to reproduce the corresponding control-group re-employment rate. We discipline the remaining parameters using our intervention's effects on reservation wages, employment, and earnings. Holding these parameters fixed, we then simulate smaller and larger belief revisions.

For negative news, we model adjustments in reservation wages and search effort, consistent with the reduced-form experimental effects. We capture the resulting downward rigidity by limiting how far reservation wages can fall relative to their initial level, as detailed in Appendix D. This provides a parsimonious implementation of the downward rigidity mechanism in Equation (3), encompassing different potential sources of the floor. We estimate the corresponding rigidity parameter jointly with the search-cost parameter and the dispersion of the true offer distribution, targeting the treatment

effects on reservation wages, three-month employment, and six-month earnings—the labor market outcomes shifted by our treatment.

For positive news, we carry over the estimated search-cost and offer-dispersion parameters from the negative-news exercise, assuming a common search technology and true offer distribution across initial optimists and pessimists. We model adjustments in reservation wages and the geographic scope of search, incorporating the mechanism developed in Appendix B.5. Given the muted reduced-form response of total search effort, our baseline calibration abstracts from adjustments along that margin. We anchor the geographic response to the experimental effect on application radius and calibrate the resulting matching-productivity gain to reproduce the three-month employment effect. For larger belief revisions, the baseline calibration assumes that these productivity gains scale proportionally with the size of the belief revision.[25] Overall, the model broadly reproduces the targeted moments and correctly predicts the direction of all untargeted responses, despite some differences in magnitudes, supporting the credibility of the counterfactual analysis (see Appendix D).

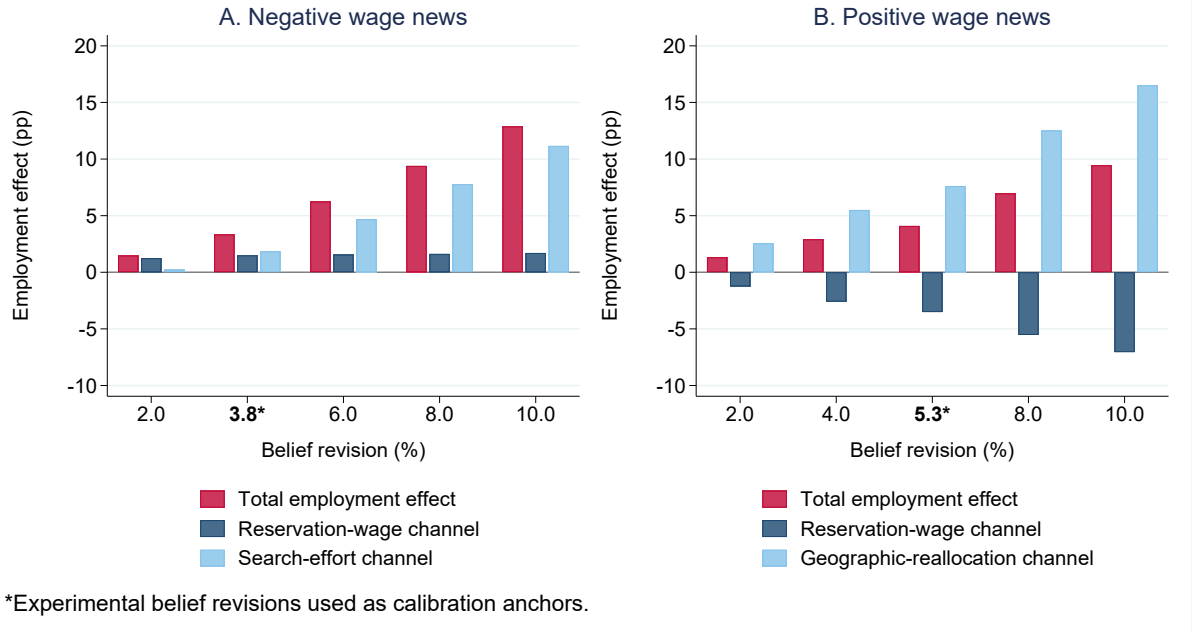
For each belief revision, we use a Shapley decomposition (Shorrocks, 2013) to allocate the predicted employment effect across its underlying behavioral channels. The approach accounts for interactions between the channels and ensures that their contributions sum to the total employment effect. For negative news, we distinguish between the reservation-wage and search-effort channels; for positive news, between the reservation-wage and geographic-reallocation channels.

Counterfactual results and mechanism decomposition For negative news, the predicted three-month employment effect rises from 1.5 pp for a 2% downward revision in wage expectations to 12.9 pp for a 10% revision (see Figure 7, Panel A). At the 3.8% revision induced by our intervention, the two relevant channels contribute almost equally to the 3.3 pp employment effect: 1.5 pp through lower reservation wages and 1.8 pp through higher search effort. For larger revisions, the downward rigidity increasingly constrains further reservation-wage adjustment, so margin substitution becomes more important and a larger share of the model-implied employment gains arise through increased search effort. These employment gains are accompanied by a modest decline in accepted wages, from about 1.1% for a 2% belief revision to 1.6% for a 10% revision (see Appendix Table D.3).

For positive news, the two channels work in opposite directions: higher reservation wages reduce job finding, while geographic reallocation raises it. At the 5.3% revision induced by the experiment, the reservation-wage channel lowers employment by

[25] Appendix D.5 examines the robustness of the positive-news counterfactuals to both assumptions. We allow search effort to adjust endogenously and consider alternative extrapolations in which the productivity gains from further geographic narrowing diminish or eventually reverse.

Figure 7 Counterfactual results and mechanism decomposition



Notes: The figure shows counterfactual three-month employment effects of belief revisions of different sizes and their decomposition into the underlying behavioral channels. Panel A shows the total employment effects of negative news (red bars), decomposed into reservation-wage (dark blue bars) and search-effort (light blue bars) channels, while Panel B shows the total employment effects of positive news (red bars), decomposed into reservation-wage (dark blue bars) and geographic-reallocation (light blue bars) channels. All reported counterfactual results assume the absence of congestion effects. Appendix Table D.4 shows how the predicted employment effects vary with the degree of congestion.

3.5 pp and geographic reallocation raises it by 7.6 pp, yielding a net three-month employment effect of 4.1 pp. Under proportional scaling of the productivity gains from geographic reallocation, this channel remains dominant as the belief revision increases, and the net employment effect rises from 1.3 pp for a 2% revision to 9.5 pp for a 10% revision (Figure 7, Panel B). Appendix D.5 relaxes the proportional-scaling assumption and shows that the positive employment effect remains robust to diminishing returns to geographic narrowing, although sufficiently strong reductions in matching productivity from further narrowing can reverse the effect for very large belief revisions.

Congestion Finally, we examine how congestion affects the counterfactual predictions, for example under widespread belief revisions induced by an information campaign. If many job seekers increase search effort or redirect applications toward the same vacancies, greater competition may crowd out some of the resulting matching gains. We therefore apply congestion to the search-effort and geographic-reallocation channels while leaving the reservation-wage channel, which affects offer acceptance rather than how intensely job seekers compete for vacancies, unchanged.[26]

[26]A full general-equilibrium analysis could allow changes in selectivity to affect matching opportunities through their effects on vacancy filling, in addition to the congestion from changes in search effort and application allocation. Our exercise instead captures only the crowding-out operating through

Congestion changes the employment effects of both negative and positive wage news, but with different implications (Appendix Table D.4). For negative news, the effect remains positive even under complete crowding-out because lower reservation wages continue to raise offer acceptance. At the experimentally induced 3.8% revision, the predicted effect falls from 3.3 pp without congestion to 1.5 pp when the search-effort channel is fully crowded out. Larger revisions are more sensitive because their additional employment gains arise primarily through greater search effort. For positive news, congestion can reverse the sign of the employment effect. At the experimentally induced 5.3% revision, the net effect falls from 4.1 pp without congestion to -3.2 pp under complete crowding-out. Once the productivity gain from geographic reallocation is sufficiently attenuated, the negative effect of higher reservation wages dominates. The same qualitative pattern holds across belief revisions of different magnitudes.

5 Conclusion and implications

We study 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–action gaps, and recall error in survey-based measures. Our study showcases how one can obtain clear and detailed evidence on how beliefs causally shape job search.

Our main insight for understanding and modeling job search is that the effects of wage expectations operate through *downward rigidity* and *margin substitution*: selectivity responds strongly to positive wage news but only moderately to negative wage news, which job seekers instead compensate for through higher search effort. As a result, the effects of wage expectations are profoundly asymmetric. Our evidence suggests that the downward rigidity reflects a floor tied to previous earnings and benefit income, so that these factors shape not only job seekers' search incentives but also how they respond to belief revisions. Belief revisions can also interact with search frictions: in our setting, greater optimism about available wages redirects initially pessimistic job seekers toward a more effective local labor market and improves job finding. Increased selectivity may thus be less detrimental to job finding when initial search is spatially misallocated. Overall, our results highlight that subjective beliefs play a central causal

others' increased search effort and redirected applications and illustrates the sensitivity of employment effects to that margin.

role in shaping job search, and that accounting for them is essential to understand labor market outcomes (Conlon et al., 2018; Krueger and Mueller, 2016; Mueller and Spinnewijn, 2023).

Our findings also have implications for labor market policies, particularly those that inform job seekers about their earnings potential. One is that such policies interact with benefit generosity: when benefits are low, they operate mainly through selectivity, while effort becomes a more important margin at higher benefits. Another is that such policies—despite their low cost—can have sizable effects on re-employment and earnings, although after negative news potentially at the cost of lower accepted wages. Several considerations bear on the design and desirability of such interventions. First, fully assessing their welfare implications requires accounting for the general-equilibrium effects of a large-scale roll-out. Second, policymakers may want to exercise caution when the labor market conditions underlying the information differ from those in which it is delivered (in our case the two are quite similar). Finally, an open question is what form of information is most effective. Should one provide precise wage information or a directional signal? Could caseworkers' assessments be used when administrative data are unavailable, and which is preferable when both are available? We leave these questions to future work.

While we study job search, the core mechanism supported by our evidence could apply to any sequential search problem in which agents can reject a draw and keep searching. Whenever downward adjustment in selectivity is constrained, reductions in the expected quality of a draw could be compensated through additional search. As a result, asymmetry in responses carries over from one margin of adjustment to another. This logic could apply to belief shocks across a broad range of settings, including consumer and housing search, or firms' search for workers.

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Supplementary Online Appendix

Wage Expectations and Job Search

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Alexander Sebald Sonja Settele Johannes Wohlfart

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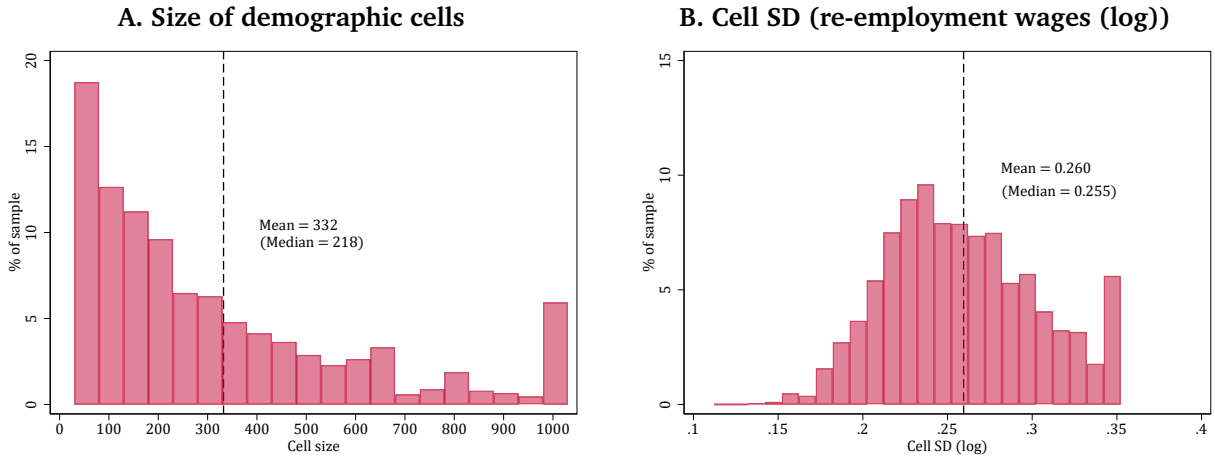
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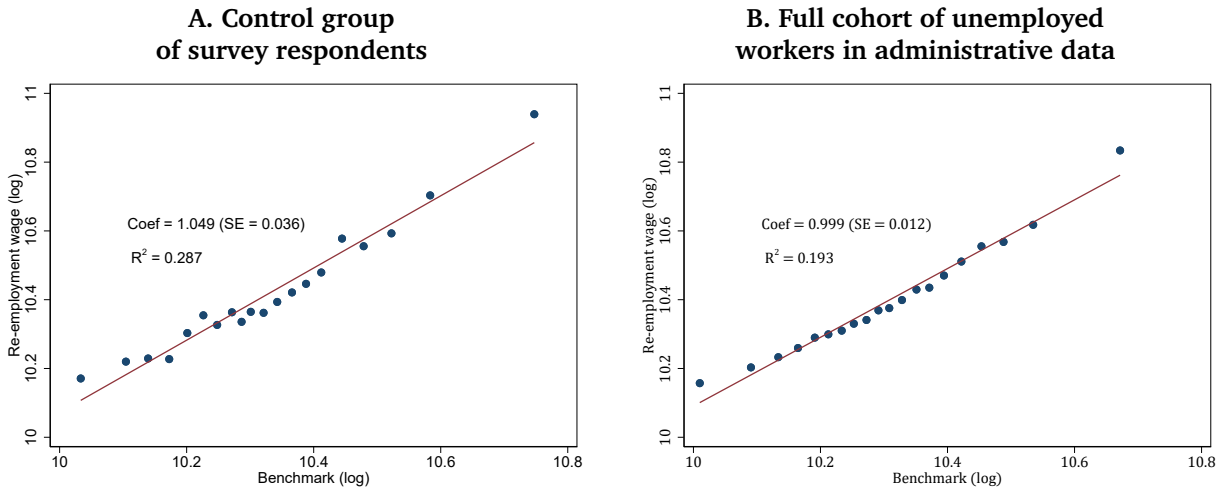
A Additional figures and tables

Figure A.1 Distribution of characteristics of survey respondents' demographic cells in the register data



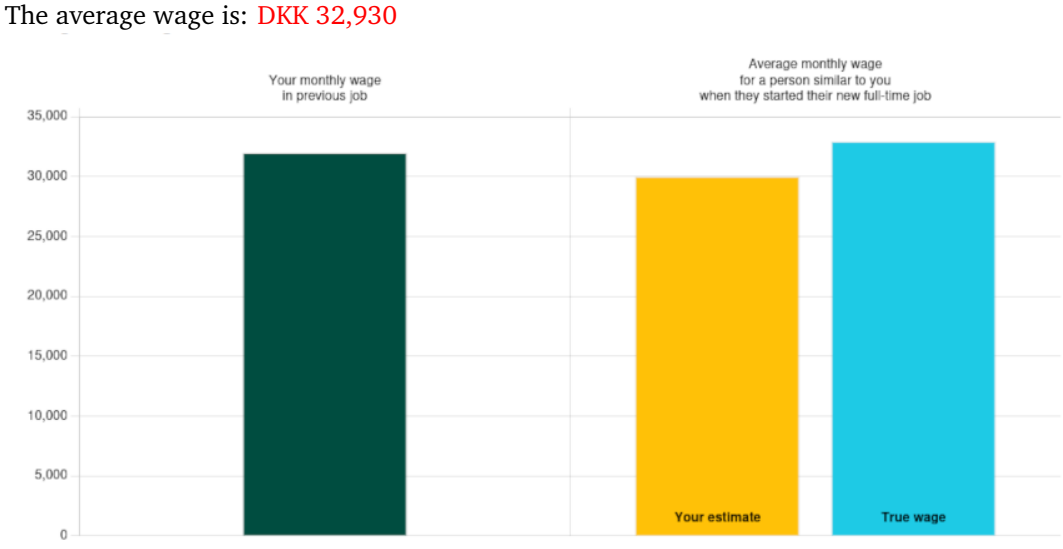
Notes: The figure shows the distribution, across survey respondents, of the characteristics of the demographic cell used to construct each respondent's benchmark. The cell characteristics are computed from the register data, and each respondent is one observation, so a cell with several respondents enters the distribution once per respondent. Only respondents from cells with at least 30 observations in the register data complete the full survey.
Panel A shows the distribution of the number of register observations in the demographic cell assigned to each survey respondent.
Panel B shows the within-cell standard deviation of re-employment wages, computed on log wages.
For readability, both variables are winsorized at the 95th percentile in the figure, and the rightmost bar includes all respondents in cells at or above this threshold. All analyses use the non-winsorized values.
The dashed vertical line in each panel indicates the corresponding mean, the median is also reported. Mean and median are computed on non-winsorized data.

Figure A.2 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 by September 2024 ($N = 2{,}775$). 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 ($N = 38{,}585$).

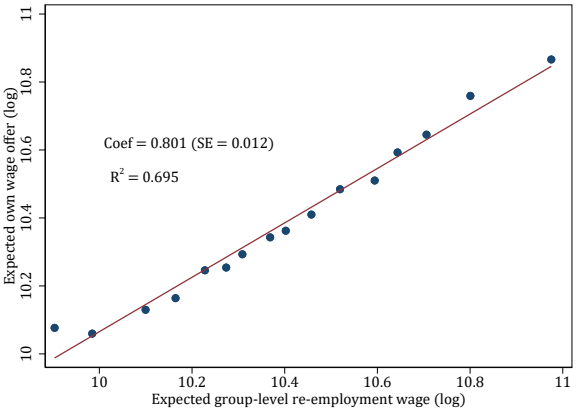
Figure A.3 Example of treatment screen



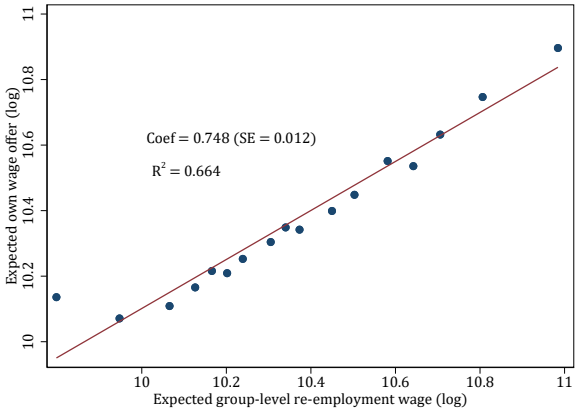
Notes: The figure shows an English translation of the treatment screen displaying information about the average re-employment wage of comparable workers, as presented to the treatment group in the survey experiment. The left bar (green) represents the respondent's own previous wage, the middle bar (yellow) 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 wage offers and expected group-level re-employment wages

A. Expected own and group (follow-up) wages

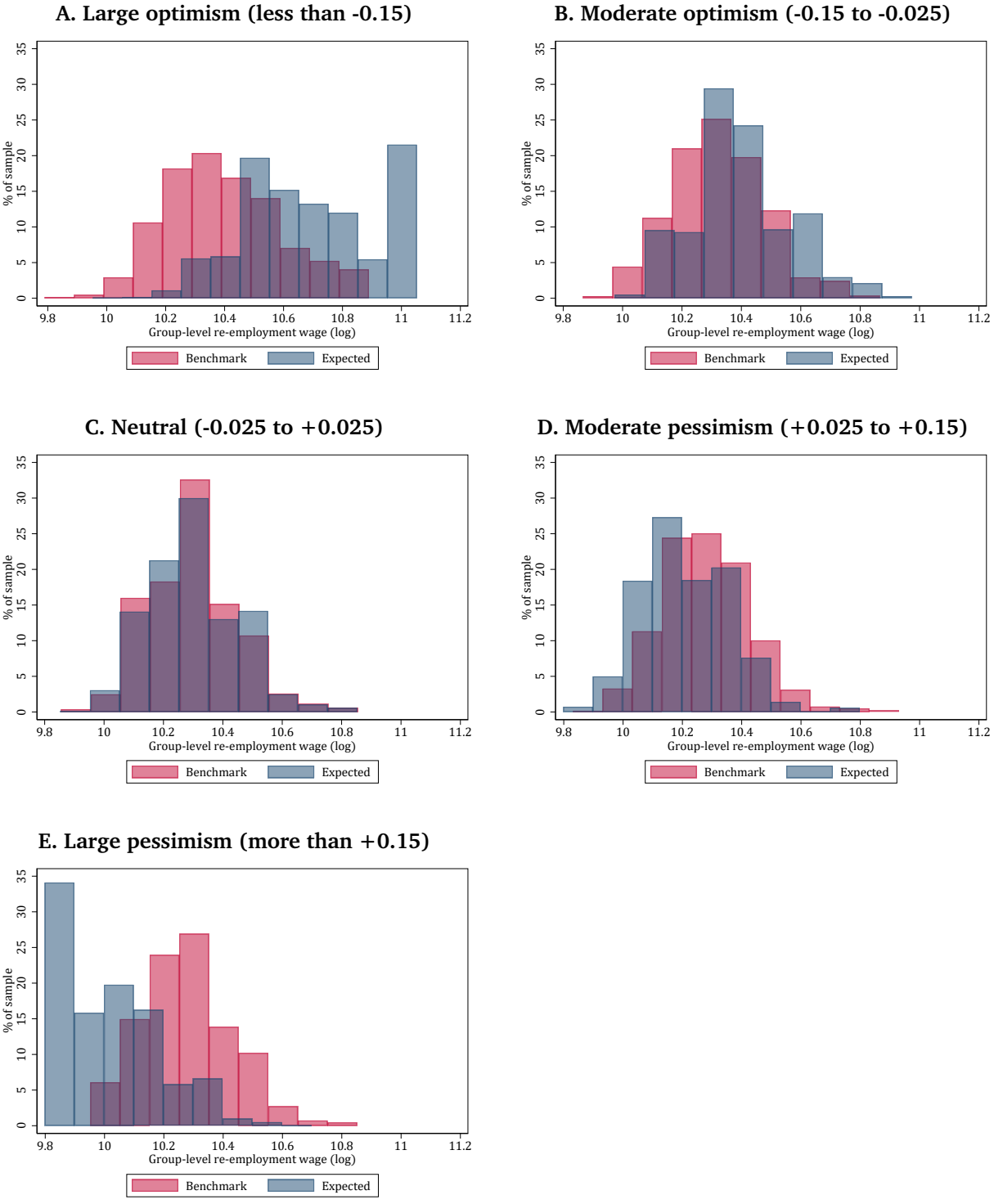


B. Expected own (follow-up) and group wages



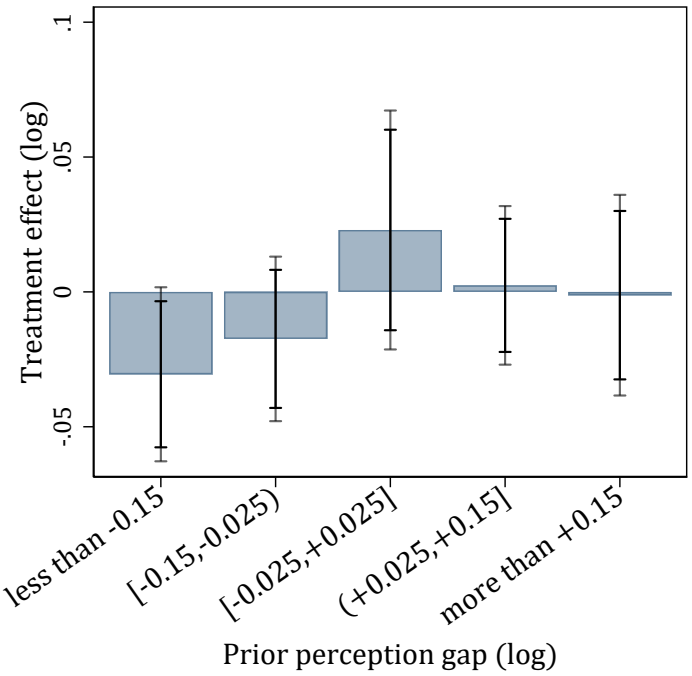
Notes: The figure illustrates job seekers' expectations about their own wages and group wages in the absence of the information intervention.
Panel A shows a binned scatter plot (20 bins) of expected own next wage offer, elicited in the main survey, against expected re-employment wages of comparable workers for control-group respondents, elicited in the follow-up survey ($N = 1{,}929$).
Panel B shows a binned scatter plot (20 bins) of expected own next wage offer, elicited in the follow-up survey, against expected re-employment wages of comparable workers for control-group respondents, elicited in the main survey ($N = 1{,}929$).

Figure A.5 Prior expected group-level re-employment wages relative to the benchmark, by perception gap groups



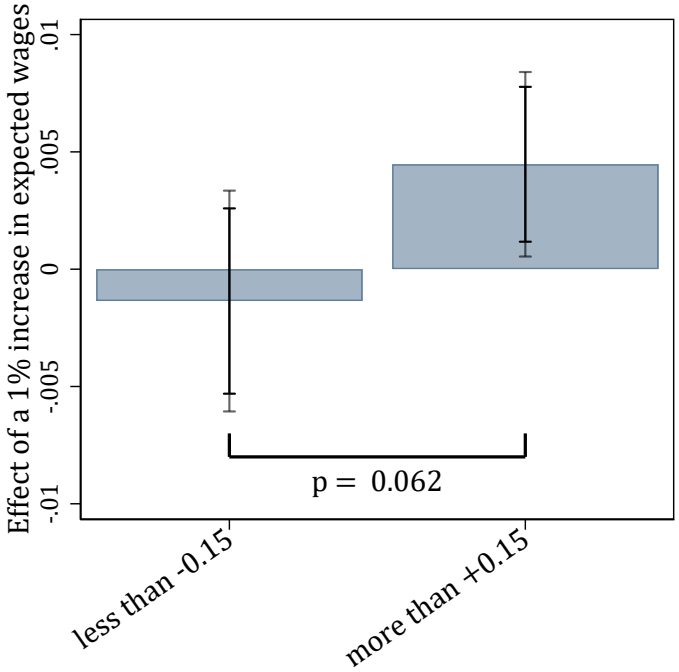
Notes: The figure shows the distribution of respondents' prior expected group wages (log) and the corresponding objective benchmark (log), separately for the five perception-gap groups. Each panel shows the two overlapping histograms as a share (%) of respondents within that group. Number of observations: 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.6 Treatment effects on first hourly wage difference



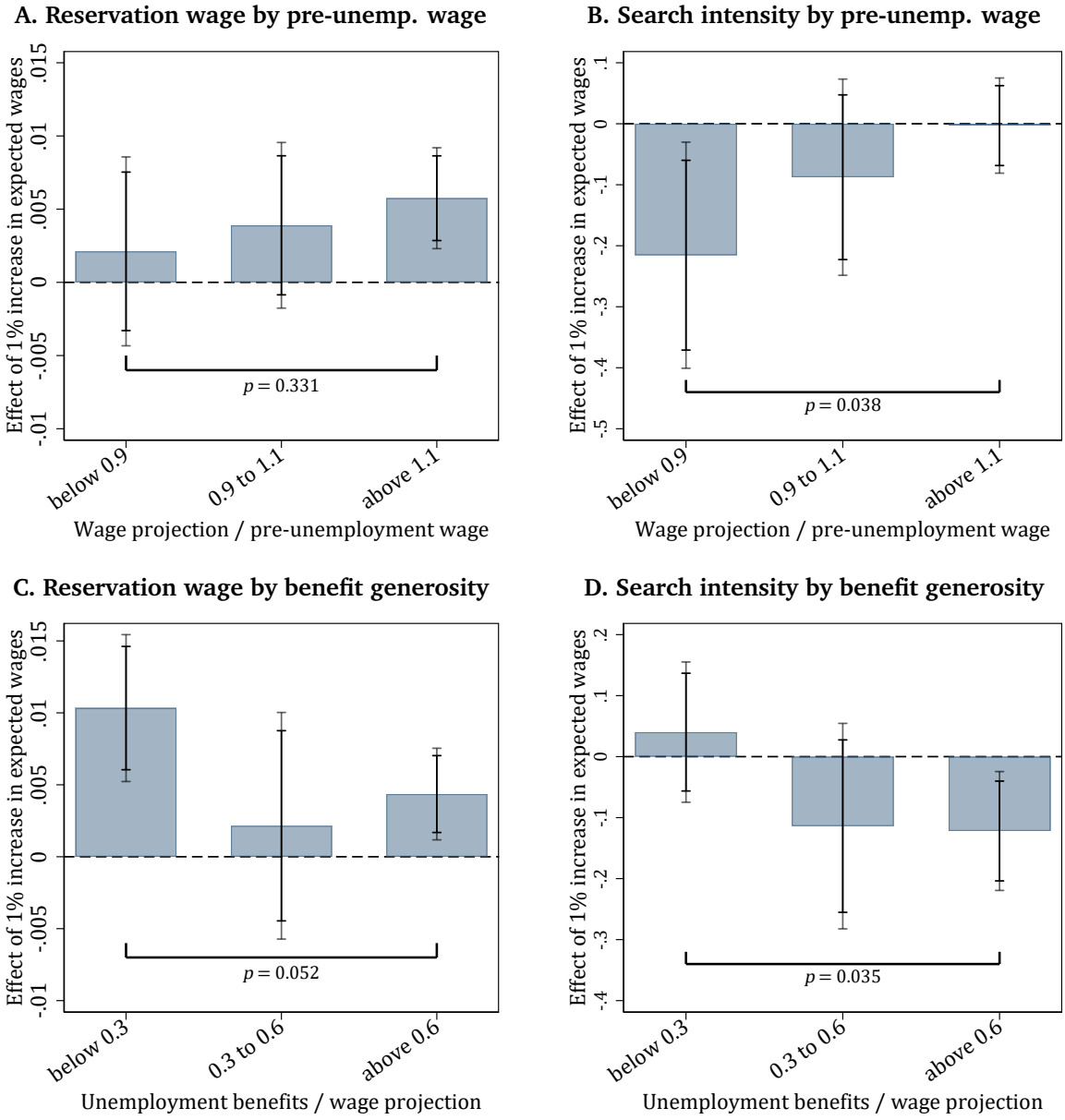
Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on the difference between full-time hourly wage (log) in the first job after the initial survey and the pre-unemployment wage (log). We show separate estimates for individuals with varying initial 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 by September 2024. N=1,346 (less than -0.15); N=1,151 (-0.15 to -0.025); N=606 (-0.025 to +0.025); N=1,278 (+0.025 to +0.15); N=912 (more than +0.15). The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Figure A.7 2SLS estimates: effects of wage expectations on target wages



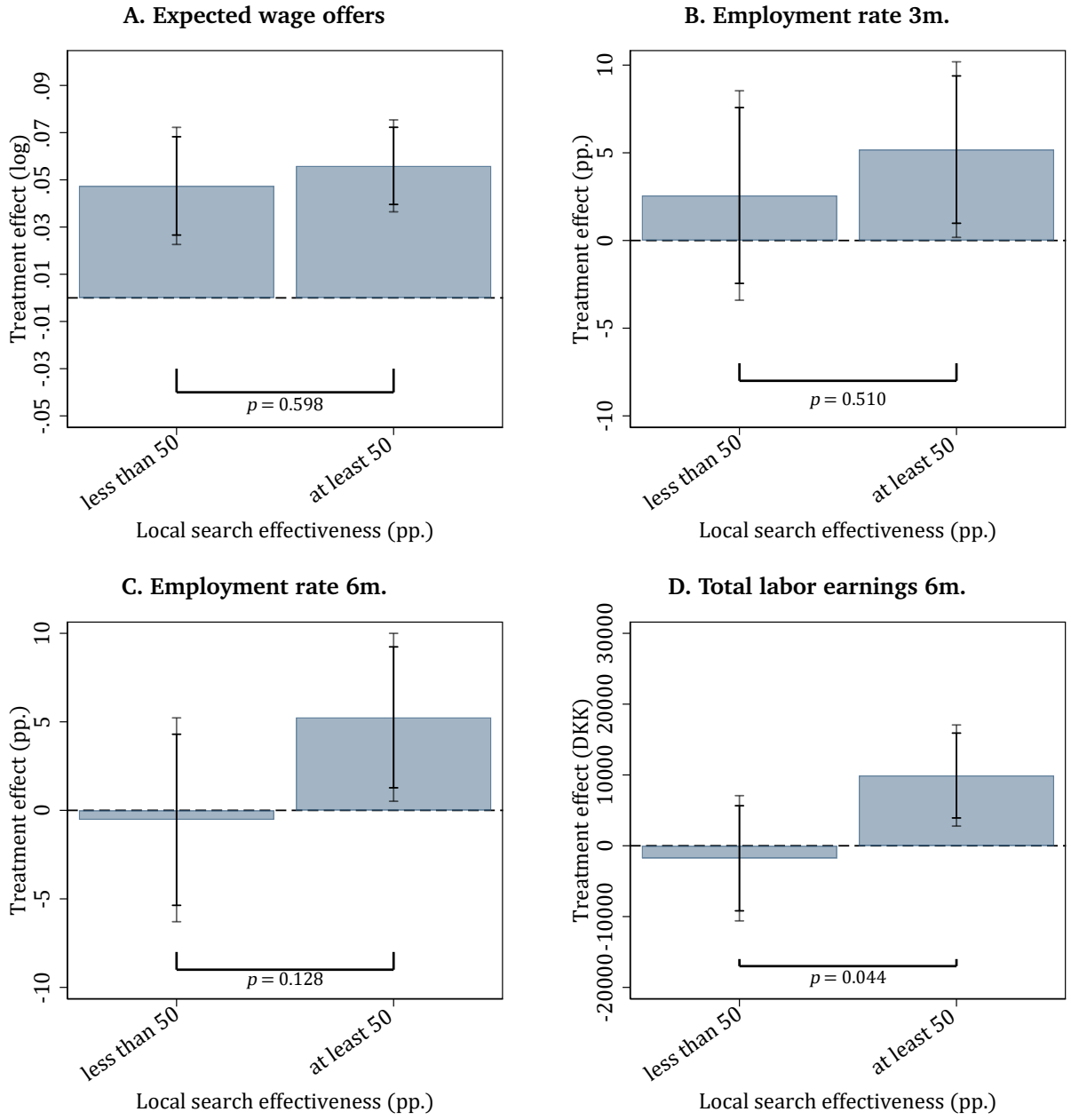
Notes: The figure shows 2SLS estimates of the effect of wage expectations on the log average monthly pay at firms considered within four weeks after the survey as observed in the click-by-click data, with 90% and 95% confidence intervals. We instrument post-treatment expected own wage offers (log) with assignment to the information treatment, estimated separately for job seekers with large negative (perception gap below -0.15; $N = 1{,}350$) and large positive (perception gap above 0.15; $N = 1{,}245$) perception gaps. All coefficients are expressed as the effect of a 1% increase in expected wages; for the negative-shock group, negative coefficients therefore imply that downward revisions *increase* the outcome. The figure reports estimates from the following second-stage equation: $y_i = \delta_0 + \delta_1 \widehat{\text{Expected wage}}_i + \mathbf{X}_i\Phi + \epsilon_i$, with the following first stage: $\text{Expected wage}_i = \gamma_0 + \gamma_1 \text{Treatment}_i + \mathbf{X}_i\Lambda + \nu_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2. The first-stage F-statistic on the excluded instrument is 41.01 for the large-pessimism group and 33.33 for the large-optimism group. The reported p-value tests equality of the effect of wage expectations between job seekers with large negative and large positive perception gaps.

Figure A.8 2SLS estimates of heterogeneous effects of downward revisions in wage expectations by proxies for wage floor



Notes: The figure shows heterogeneous 2SLS estimates of the effect of wage expectations on job search behavior, complementing the reduced-form heterogeneity results in Figure 5. We instrument post-treatment expected own wage offers (log) with assignment to the information treatment. The sample includes job seekers with large negative perception gaps (below -0.15), i.e., those who were initially highly optimistic. Because the treatment lowers expected wages in this sample, the signs of the 2SLS coefficients are reversed relative to the corresponding reduced-form treatment effects: the 2SLS estimates capture the effect of increases in expected wages. Panels A and B split the sample into three groups based on the ratio of the wage projection to the pre-unemployment wage: below 0.9 ($N = 1{,}354$), 0.9 to 1.1 ($N = 425$), and above 1.1 ($N = 544$). The corresponding first-stage F-statistics are 11.13, 7.80, and 27.37. Panels C and D split the sample into three groups based on the ratio of unemployment benefits to the wage projection: below 0.3 ($N = 128$), 0.3 to 0.6 ($N = 1{,}192$), and above 0.6 ($N = 1{,}003$). The corresponding first-stage F-statistics are 17.32, 7.98, and 12.47. Panels A and C report effects on log reservation wages; Panels B and D report effects on search intensity, measured by job-ad clicks in the first week after the survey. The estimates are based on the second-stage equation: $y_i = \delta_0 + \delta_1 \widehat{\text{Expected wage}}_i + \mathbf{X}_i\Phi + \epsilon_i$, with the following first stage: $\text{Expected wage}_i = \gamma_0 + \gamma_1 \text{Treatment}_i + \mathbf{X}_i\Lambda + \nu_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2. Reported p-values test equality of the main 2SLS coefficients between the lowest and highest groups in each panel.

Figure A.9 Heterogeneous effects of positive wage news by local search effectiveness



Notes: The figure shows heterogeneous treatment effects, with 90% and 95% confidence intervals, among job seekers with large positive perception gaps (above $+0.15$), i.e., those who were initially highly pessimistic, by local search effectiveness. We proxy local search effectiveness by the share of job seekers residing in the respondent's municipality who become employed within that same municipality within six months, calculated over the pre-treatment period January 2020 to October 2023. In each panel, the sample is split into respondents in municipalities with a share below 50% ($N = 688$) and those with a share of 50% or above ($N = 1{,}035$). The estimates are based on $y_i = \beta_0 + \gamma \text{Group}_{i2} + \sum_{g=1}^{2} \delta_g \left(\text{Treatment}_i \times \text{Group}_{ig}\right) + \mathbf{X}_i \Pi + \epsilon_i$, where Group_{ig} indicates the two local-search-effectiveness groups and $\mathbf{X}_i$ contains prior log expected wages and the baseline covariates listed in Appendix Table A.2. Reported p-values test equality of the treatment effects between the two groups in each panel.

Table A.1 Correlates 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: Tertiary degree)	
Upper secondary	-0.145***
	(0.001)
Lower secondary	-0.191***
	(0.001)
Age (ref. 35 years or below)	
36–50 years	0.045***
	(0.001)
Above 50 years	0.044***
	(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: less than 3 months)	
3-5 months	-0.024***
	(0.001)
6-8 months	-0.045***
	(0.001)
9-11 months	-0.067***
	(0.001)
12-17 months	-0.095***
	(0.001)
18-23 months	-0.116***
	(0.001)
At least 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 parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table A.2 Summary statistics and balance tests

	Mean values			Balance stat.	Mean values		Balance stat.
	Full	Main survey			Follow-up survey		
	population	Treated	Control	P-value	Treated	Control	P-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age							
Below 36 years	0.42	0.33	0.33	0.72	0.27	0.27	0.97
36-50 years	0.27	0.27	0.26	0.78	0.25	0.25	0.96
Above 50 years	0.32	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 fractions unless indicated otherwise.

Table A.3 Summary statistics and balance tests by perception gap

	Large pessimism			Moderate pessimism			Neutral			Moderate optimism			Large optimism		
	Mean val.		Balance	Mean val.		Balance	Mean val.		Balance	Mean val.		Balance	Mean val.		Balance
	Treat.	Control	P-val.	Treat.	Control	P-val.	Treat.	Control	P-val.	Treat.	Control	P-val.	Treat.	Control	P-val.
	(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)	24,649	24,732	0.88	27,063	27,095	0.94	27,783	27,674	0.88	30,766	30,413	0.54	41,680	41,550	0.88
F-test joint sign.			0.26			0.21			0.26			0.80			0.79
Number of observations	841	882	1,723	1,100	1,078	2,178	509	534	1,043	1,001	979	1,980	1,177	1,146	2,323

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. The F-test reports the p-value of a joint test of significance of all covariates in a regression of treatment status on the covariates listed in the table.

Table A.4 Treatment effects on main outcomes

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***	0.039***	0.064	-4.722**	4.071**	2.886	5,211*	25.06*
	(0.008)	(0.008)	(0.201)	(2.343)	(1.957)	(1.871)	(2,843)	(13.78)
P-value (vs. 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	51.93	29.78	37.74	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***	0.014***	-0.013	0.907	-0.974	-1.159	421	3.29
	(0.005)	(0.005)	(0.187)	(2.113)	(1.691)	(1.613)	(2,565)	(12.21)
P-value (vs. 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	45.73	30.52	39.46	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	0.012	0.280	-3.350	0.448	1.416	2,565	8.79
	(0.007)	(0.008)	(0.254)	(2.986)	(2.504)	(2.374)	(4,093)	(18.92)
Mean control group	10.31	10.19	2.41	50.37	31.71	41.23	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***	-0.002	0.206	-0.542	-0.314	-0.406	193	1.30
	(0.005)	(0.006)	(0.171)	(2.194)	(1.722)	(1.667)	(2,986)	(13.25)
P-value (vs. 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	52.60	29.79	39.14	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***	-0.016**	0.400***	-1.624	3.693**	3.887***	6,349*	21.57*
	(0.006)	(0.007)	(0.138)	(2.009)	(1.475)	(1.499)	(3,830)	(12.50)
P-value (vs. 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	58.29	23.50	34.35	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. The table reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes the prior log expected wages and the baseline covariates listed in Table A.2. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
[(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.5 Treatment effects on various dimensions of job search

Dependent variable	Reg. applications[a]		Concession willingness[b]				Vacancy clicks[c]		
	Search radius (log)	No. of distinct occ. (log)	Geograph. location (pp.)	Working cond. (pp.)	Skills/ occ. (pp.)	Index (3)-(5) (pp.)	No. of job ads clicked 4w.	Target month. earnings (log)	Target firm size (emp.)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
A. Large pessimism: perception gap (log) $\in$ (+0.150;$+\infty$)									
Treatment effect	-0.074**	0.017	-4.722**	-2.543	-0.404	-2.556*	0.057	0.026**	1,072***
	(0.036)	(0.038)	(2.343)	(2.279)	(1.629)	(1.347)	(0.629)	(0.012)	(358)
P-value (vs. neutral group)	0.23	0.49	0.71	0.71	0.70	0.89	0.31	0.19	0.14
Mean control group	1.08	0.63	51.93	66.21	87.07	68.41	10.32	10.13	5,742
Number of observations	1,425	864	1,723	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	-0.001	-0.001	0.907	-2.978	0.828	-0.414	0.321	0.005	104
	(0.031)	(0.034)	(2.113)	(2.040)	(1.374)	(1.228)	(0.594)	(0.010)	(301)
P-value (vs. neutral group)	0.98	0.32	0.24	0.79	0.89	0.39	0.45	0.83	0.82
Mean control group	1.03	0.61	45.73	66.23	87.94	66.64	11.08	10.17	6,137
Number of observations	1,816	1,060	2,178	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	0.060	-3.350	-3.927	0.518	-2.253	1.086	0.002	225
	(0.048)	(0.054)	(2.986)	(2.988)	(1.834)	(1.774)	(0.827)	(0.015)	(467)
Mean control group	1.07	0.56	50.37	67.79	89.89	69.35	9.21	10.21	6,573
Number of observations	851	464	1,043	1,043	1,043	1,043	1,043	744	744
D. Moderate optimism: perception gap (log) $\in$ [-0.150; -0.025)									
Treatment effect	-0.023	0.079**	-0.542	3.192	2.045	1.565	0.396	-0.007	-42
	(0.035)	(0.039)	(2.194)	(2.179)	(1.335)	(1.289)	(0.551)	(0.012)	(378)
P-value (vs. neutral group)	0.72	0.78	0.44	0.05	0.49	0.08	0.48	0.64	0.65
Mean control group	1.09	0.50	52.60	59.35	89.17	67.04	8.30	10.24	6,998
Number of observations	1,642	770	1,980	1,980	1,980	1,980	1,980	1,333	1,333
E. Large optimism: perception gap (log) $\in$ ($-\infty$;-0.150)									
Treatment effect	0.029	0.018	-1.624	-0.872	-1.212	-1.236	1.288***	0.006	-219
	(0.035)	(0.044)	(2.009)	(2.037)	(1.298)	(1.210)	(0.449)	(0.011)	(388)
P-value (vs. neutral group)	0.60	0.53	0.63	0.39	0.43	0.63	0.83	0.79	0.46
Mean control group	1.09	0.52	58.29	56.72	89.70	68.24	6.04	10.30	6,889
Number of observations	1,889	643	2,323	2,323	2,323	2,323	2,323	1,350	1,350

Notes: The table reports treatment effects on various dimensions of job search by initial perception-gap group, based on $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ includes prior log expected wages and the baseline covariates listed in Table A.2. We winsorize the search radius (column 1) and target monthly earnings (column 8) at the 5th and 95th percentiles, and the number of job ads clicked (column 7) at the 95th percentile. Reported p-values refer to post-estimation tests of whether each group's coefficient differs from that of the neutral group. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[a] Based on registered job applications (*joblog*) within four weeks after the survey. The search radius is the average distance between job seekers' residence and the jobs to which they applied. Outcomes are measured for job seekers with at least one recorded application (column 1) and, additionally, non-missing occupational information (column 2).

[b] Measured in the main survey. Indicates willingness to (3) relocate or commute long-distance; (4) accept unfavorable working conditions; (5) make skill-related concessions (training, profession change, or below-qualification work); and (6) the share of these three concessions accepted.

[c] Based on clicks on job ads on the public employment service's online platform (*jobnet.dk*) within four weeks after the survey. Outcomes in columns (8) and (9) are measured for job seekers with at least one recorded click.

Table A.6 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	4.521**	-0.593	-0.095*	1.260	2.386	1.137	2.791
	(2.010)	(1.723)	(0.051)	(1.801)	(1.859)	(1.956)	(1.788)
P-value (vs. neutral group)	0.25	0.99	0.27	0.81	0.54	0.74	0.39
Mean control group	19.50	15.08	2.88	16.44	16.21	19.73	14.85
Number of observations	1,723	1,723	1,333	1,723	1,723	1,723	1,723
B. Moderate pessimism: perception gap (log) $\in$ (+0.025; +0.150]							
Treatment effect	-1.558	-1.415	-0.048	-1.215	0.280	-2.620	-0.353
	(1.745)	(1.577)	(0.043)	(1.624)	(1.621)	(1.680)	(1.644)
P-value (vs. neutral group)	0.45	0.76	0.58	0.54	0.93	0.35	0.87
Mean control group	21.43	16.33	2.80	17.53	16.79	19.48	18.27
Number of observations	2,178	2,178	1,760	2,178	2,178	2,178	2,178
C. Neutral group: perception gap (log) $\in$ [-0.025; +0.025]							
Treatment effect	0.804	-0.538	-0.005	0.545	0.538	0.115	0.152
	(2.617)	(2.424)	(0.067)	(2.442)	(2.460)	(2.454)	(2.576)
Mean control group	20.79	17.98	2.80	17.60	17.98	18.16	20.60
Number of observations	1,043	1,043	837	1,043	1,043	1,043	1,043
D. Moderate optimism: perception gap (log) $\in$ [-0.150; -0.025)							
Treatment effect	-0.928	-1.660	0.018	-1.293	-0.653	-0.873	-1.715
	(1.799)	(1.710)	(0.048)	(1.638)	(1.789)	(1.690)	(1.823)
P-value (vs. neutral group)	0.58	0.70	0.78	0.53	0.69	0.74	0.55
Mean control group	20.74	18.59	2.70	16.45	20.12	17.57	21.76
Number of observations	1,980	1,980	1,526	1,980	1,980	1,980	1,980
E. Large optimism: perception gap (log) $\in$ ($-\infty$;-0.150)							
Treatment effect	2.665*	0.067	-0.055	-0.915	1.031	1.135	1.597
	(1.449)	(1.680)	(0.048)	(1.415)	(1.625)	(1.406)	(1.704)
P-value (vs. neutral group)	0.53	0.84	0.53	0.60	0.87	0.71	0.64
Mean control group	13.09	20.77	2.81	13.70	18.59	13.09	20.77
Number of observations	2,323	2,323	1,712	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 and the location of their first subsequent job. Columns (4) and (5) examine whether respondents are employed within or outside their previous occupation three months after the intervention. Because the previous occupation is unobserved for some respondents, the effects in Columns (4) and (5) do not add up to the employment effect. Columns (6) and (7) examine whether respondents are employed part-time or full-time 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. The table reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes the prior log expected wages and the baseline covariates listed in Table A.2. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

B Derivations for the theoretical framework

This appendix provides the derivations underlying the theoretical framework in Section 3. We proceed in six steps. First, we characterize how the reservation value responds to belief revisions in a model with fixed search effort. Second, we show how a floor on acceptable job values generates downward rigidity, which amplifies the asymmetry between positive and negative belief revisions. Third, we incorporate endogenous search effort and characterize its role as a compensating margin. Fourth, we show that the selectivity results carry over when effort is chosen endogenously. Fifth, we extend the model to the geographic dimension of search. Finally, we present the quantitative illustration referred to in Section 3.

Setup and notation The setup follows Section 3. While unemployed, the worker receives a flow value b that reflects unemployment benefits as well as the value of not working, such as leisure or home production. A job offer has flow value v; once accepted, it lasts forever, so its present value is $v/(1-\beta)$, where $\beta \in (0,1)$ is an effective discount factor governing the weight placed on future payoffs from search and employment. We write $\kappa \equiv \beta/(1-\beta)$.

Job seekers hold subjective beliefs about the distribution of job values. We assume that beliefs shift the perceived distribution of *log* job values:

$$F(v;\widehat{\mu}) = G(\ln v - \widehat{\mu}), \tag{5}$$

where $\widehat{\mu}$ is the perceived level of log job values, which we refer to as perceived job quality, and G has a continuous density $g \equiv G'$ with $\int e^t \, dG(t) < \infty$. A belief revision $d\widehat{\mu}$ thus scales all perceived job values proportionally, so that belief revisions are naturally measured in log points, as in our empirical analysis. Denoting the reservation value by $\bar{v}$, we define the acceptance probability and the expected surplus from an offer as

$$q(\bar{v},\widehat{\mu}) \equiv 1 - F(\bar{v};\widehat{\mu}), \qquad S(\bar{v},\widehat{\mu}) \equiv \int_{\bar{v}}^{\infty} (v-\bar{v}) \, dF(v;\widehat{\mu}),$$

and the expected value of acceptable offers as $M(\bar{v},\widehat{\mu}) \equiv \int_{\bar{v}}^{\infty} v \, dF(v;\widehat{\mu}) = S + \bar{v}q$. Under the log-location assumption (Equation 5), the partial derivatives of S are

$$S_{\bar{v}} = -q, \qquad S_{\widehat{\mu}} = M. \tag{6}$$

The first follows from Leibniz' rule, since the integrand vanishes at the lower limit. For the second, write $v = e^{\widehat{\mu}+t}$ with $t \sim G$, so that $S = \int_{\ln \bar{v} - \widehat{\mu}}^{\infty} (e^{\widehat{\mu}+t} - \bar{v}) \, dG(t)$; the boundary term again vanishes, and differentiating the integrand gives $\int_{\bar{v}}^{\infty} v \, dF = M$.

B.1 Reservation-value response with fixed effort

We first characterize the reservation-value response holding search effort fixed. The worker receives one offer per period and chooses only whether to accept or reject it. The value of unemployment U satisfies

$$U = b + \beta \int \max\left\{\frac{v}{1-\beta}, U\right\} dF(v; \widehat{\mu}),$$

and the worker accepts an offer whenever $v/(1-\beta) \geq U$, so that $U = \bar{v}/(1-\beta)$. Substituting and rearranging gives the reservation-value condition

$$\bar{v} = b + \kappa\, S(\bar{v}, \widehat{\mu}), \tag{7}$$

which corresponds to Equation (1). Since the right-hand side is decreasing in $\bar{v}$, the solution is unique.

The relative value of unemployment The worker's problem depends on $\widehat{\mu}$ and b only through the flow value of unemployment relative to the perceived level of job values, which we call the relative value of unemployment,

$$x \equiv b\, e^{-\widehat{\mu}}.$$

To see this, define $\phi(\omega) \equiv \int_{\ln\omega}^{\infty} (e^t - \omega)\, dG(t)$, so that $S(\bar{v}, \widehat{\mu}) = e^{\widehat{\mu}} \phi(\bar{v} e^{-\widehat{\mu}})$. Dividing Equation (7) by $e^{\widehat{\mu}}$ and writing $\omega \equiv \bar{v} e^{-\widehat{\mu}}$ for the reservation value relative to the perceived level of job values gives

$$\omega = x + \kappa\, \phi(\omega). \tag{8}$$

Hence ω, the acceptance probability $q = 1 - G(\ln \omega)$, and the pass-through derived below are functions of x alone. Two workers with different beliefs and different flow utilities b but the same x therefore respond identically to a given log belief revision.

We denote the elasticity of the reservation value with respect to perceived job quality—the pass-through of belief revisions to selectivity—by

$$\varepsilon \equiv \frac{\partial \ln \bar{v}}{\partial \widehat{\mu}}.$$

Proposition 1 (Selectivity response)**.** *Suppose $q \in (0,1)$. The pass-through of belief revisions to the reservation value is*

$$\varepsilon = 1 - \frac{b}{\bar{v}\,(1+\kappa q)} \in (0,1).$$

It is strictly increasing in perceived job quality $\widehat{\mu}$ and strictly decreasing in the flow value

of unemployment b. Hence, the log reservation value is increasing and strictly convex in perceived job quality, and for any $\Delta > 0$ such that the acceptance probability remains interior over $[\widehat{\mu} - \Delta, \widehat{\mu} + \Delta]$,

$$\ln \bar{v}(\widehat{\mu} + \Delta) - \ln \bar{v}(\widehat{\mu}) > \ln \bar{v}(\widehat{\mu}) - \ln \bar{v}(\widehat{\mu} - \Delta).$$

Proof. Differentiating Equation (7) and using Equation (6) gives $\partial \bar{v}/\partial \widehat{\mu} = \kappa M/(1+\kappa q)$. Since $\kappa M = \kappa S + \kappa \bar{v} q = \bar{v} - b + \kappa \bar{v} q$,

$$\varepsilon = \frac{\kappa M}{\bar{v}(1+\kappa q)} = 1 - \frac{b}{\bar{v}(1+\kappa q)}.$$

Because $q > 0$ implies $S > 0$, Equation (7) implies $\bar{v} > b$, and since $b > 0$, $\varepsilon \in (0, 1)$. Let $Z \equiv \bar{v}(1+\kappa q)$. Since $q = 1 - G(\ln \bar{v} - \widehat{\mu})$, we have $\partial q/\partial \widehat{\mu} = g\,(1-\varepsilon)$, where g is evaluated at $\ln \bar{v} - \widehat{\mu}$, and therefore

$$\frac{\partial Z}{\partial \widehat{\mu}} = \bar{v}\,[\varepsilon(1+\kappa q) + \kappa g\,(1-\varepsilon)] > 0, \qquad \frac{\partial \varepsilon}{\partial \widehat{\mu}} = \frac{b}{Z^2}\frac{\partial Z}{\partial \widehat{\mu}} > 0.$$

By Equation (8), ε depends on $(\widehat{\mu}, b)$ only through $x = be^{-\widehat{\mu}}$. Since $\partial x/\partial \widehat{\mu} = -x$ and $\partial x/\partial b = x/b$, it follows that

$$\frac{\partial \varepsilon}{\partial b} = -\frac{1}{b}\frac{\partial \varepsilon}{\partial \widehat{\mu}} < 0.$$

The asymmetry follows from integrating the strictly increasing derivative ε over $[\widehat{\mu}, \widehat{\mu} + \Delta]$ and $[\widehat{\mu} - \Delta, \widehat{\mu}]$. □

Discussion Proposition 1 has two implications. First, the reservation value responds less than proportionally to belief revisions. The reservation value consists of the flow value of unemployment and the option value of continued search, and only the latter depends on perceived job quality. The pass-through is therefore lower the higher the flow value of unemployment, and hence when unemployment benefits are more generous.

Second, a positive belief revision raises the reservation value by more than an equally sized negative revision lowers it. Better perceived opportunities raise both the reservation value and the acceptance probability, so that the flow value of unemployment accounts for a smaller part of the reservation value and the pass-through increases. This comparison concerns positive and negative revisions around the same starting point. By Equation (8), the relevant starting point is the relative value of unemployment x, and not the level of perceived job values as such.

B.2 Unemployment benefits and downward rigidity

Thus far, the flow value of unemployment b affects the response to belief revisions only through the pass-through in Proposition 1. This effect is the same for positive and negative revisions. We now consider an additional constraint on the downward adjustment of selectivity: a floor on acceptable job values that rises with the value of unemployment. This captures the case in which the floor is tied to income available during unemployment. For workers whose baseline reservation value lies above the floor, such a floor limits downward, but not upward, adjustment, and it becomes more relevant as benefit generosity increases.

As discussed in Section 3.1, several mechanisms may make job seekers increasingly reluctant to accept offers that fall below a minimum premium $m \geq 0$ over the flow value of unemployment. We denote this floor by $\tau(b) \equiv (1+m)b$ and let the effective value of an offer be

$$\widetilde{v}(v) = v - \theta\,[\tau(b) - v]_+, \qquad \theta \geq 0, \tag{9}$$

where θ governs the strength of the penalty.[1] A finite θ yields a soft floor, while $\theta \to \infty$ approaches a hard floor below which offers are never accepted. Let $w \equiv (1-\beta)U$ denote the flow value of continued search, and let v_τ denote the marginal acceptable job value, defined by $\widetilde{v}(v_\tau) = w$. The floor is relevant for the acceptance decision whenever

$$H(\widehat{\mu}, b) \equiv \tau(b) - w(\widehat{\mu}, b) > 0.$$

If $H \leq 0$, all acceptable offers lie above the floor, the unconstrained model from Section B.1 applies, and $v_\tau = w = \bar{v}$. The floor is therefore relevant if and only if the baseline reservation value lies below it, $\bar{v}(\widehat{\mu}, b) < \tau(b)$. We further define $q_\tau \equiv 1 - F(v_\tau; \widehat{\mu})$, $p_\tau \equiv F(\tau; \widehat{\mu}) - F(v_\tau; \widehat{\mu})$, and the expected values of acceptable offers below and above the floor, $M_1 \equiv \int_{v_\tau}^{\tau} v\, dF(v; \widehat{\mu})$ and $M_2 \equiv \int_{\tau}^{\infty} v\, dF(v; \widehat{\mu})$.

Proposition 2 (Downward rigidity)**.** *Suppose $q_\tau > 0$. When the floor is relevant, the pass-through of belief revisions to the marginal acceptable job value is*

$$\varepsilon_\tau \equiv \frac{\partial \ln v_\tau}{\partial \widehat{\mu}} = \frac{\kappa\,[M_1 + M_2/(1+\theta)]}{v_\tau(1+\kappa q_\tau)} \;\leq\; \frac{\kappa\,(M_1 + M_2)}{v_\tau(1+\kappa q_\tau)}, \tag{10}$$

where the right-hand side is the unconstrained pass-through evaluated at the same threshold and acceptance probability. The inequality is strict whenever $\theta > 0$ and $M_2 > 0$, and $\varepsilon_\tau \to 0$ as $\theta \to \infty$. Moreover, $\partial H/\partial \widehat{\mu} < 0$, so negative belief revisions move workers toward the floor, whereas positive revisions move them away from it. Finally, $\partial H/\partial b > 0$, so a

[1] A floor tied instead to previous earnings can be represented by heterogeneity in m. For a given b, workers with higher previous earnings have a larger premium m, and hence a higher floor relative to their current job-value prospects.

higher value of unemployment makes the floor more relevant.

Proof. When the floor is relevant, $w < \tau$. For $v < \tau$, $\widetilde{v} = (1+\theta)v - \theta\tau$, so the marginal acceptable value solves $(1+\theta)v_\tau - \theta\tau = w$, i.e.,

$$v_\tau = \frac{w + \theta\tau}{1+\theta} \in (w, \tau). \tag{11}$$

The value of continued search satisfies

$$w = b + \kappa \left[\int_{v_\tau}^{\tau} \big((1+\theta)v - \theta\tau - w\big) dF(v; \widehat{\mu}) + \int_{\tau}^{\infty} (v - w)\, dF(v; \widehat{\mu}) \right]. \tag{12}$$

As in Equation (6), differentiating an integral $\int h(v)\, dF(v; \widehat{\mu})$ with respect to $\widehat{\mu}$ yields $\int h'(v)\, v\, dF$ plus boundary terms. Here, the boundary terms vanish: the integrand is zero at v_τ, and the two integrands coincide at τ. Hence, the derivative of the bracket with respect to $\widehat{\mu}$, holding w fixed, is $(1+\theta)M_1 + M_2$, and its derivative with respect to w is $-q_\tau$. Therefore

$$\frac{\partial w}{\partial \widehat{\mu}} = \frac{\kappa\left[(1+\theta)M_1 + M_2\right]}{1 + \kappa q_\tau} > 0, \tag{13}$$

and by Equation (11), $\partial v_\tau / \partial \widehat{\mu} = (\partial w / \partial \widehat{\mu})/(1+\theta)$, which gives the expression for ε_τ. The inequality follows because $M_2/(1+\theta) \leq M_2$, with strict inequality if $\theta > 0$ and $M_2 > 0$. As $\theta \to \infty$, Equation (11) implies $v_\tau \to \tau$, so $M_1 \to 0$ and $M_2/(1+\theta) \to 0$, and hence $\varepsilon_\tau \to 0$.

Since τ does not depend on $\widehat{\mu}$, Equation (13) implies $\partial H / \partial \widehat{\mu} = -\partial w / \partial \widehat{\mu} < 0$. When the floor is not yet relevant, $w = \bar{v}$ and $\partial H / \partial \widehat{\mu} = -\varepsilon \bar{v} < 0$ by Proposition 1.

Finally, consider the effect of b. In Equation (12), the derivative of the bracket with respect to τ is $-\theta p_\tau$, since the boundary terms again vanish, and its derivative with respect to w is $-q_\tau$. Differentiating with respect to b therefore gives $\partial w / \partial b = (1 - \kappa\theta\tau' p_\tau)/(1 + \kappa q_\tau)$, so

$$\frac{\partial H}{\partial b} = \frac{(1+m)\,(1 + \kappa q_\tau + \kappa\theta p_\tau) - 1}{1 + \kappa q_\tau} > 0,$$

using $\tau'(b) = 1 + m \geq 1$. When the floor is not yet relevant, $w = \bar{v}$ and differentiating Equation (7) with respect to b gives $\partial w / \partial b = 1/(1+\kappa q)$, so $\partial H / \partial b = (1+m) - 1/(1+\kappa q) > 0$. □

The next result highlights the key implication that distinguishes downward rigidity from the unconstrained model. The floor limits downward, but not upward, adjustment, with stronger effects at higher benefit generosity. For clarity, we state the result for the limiting case of a hard floor and discuss below how it extends to a soft floor.

Corollary 1 (One-sided responses under a hard floor)**.** *Let $\theta \to \infty$, so that $v_\tau = \max\{\bar{v}(\widehat{\mu}, b), \tau(b)\}$, and consider a worker whose baseline reservation value lies weakly above the floor, with log distance*

$$d(\widehat{\mu}, b) \equiv \ln \bar{v}(\widehat{\mu}, b) - \ln \tau(b) \geq 0.$$

For any initial perceived job quality $\widehat{\mu}$ and $\Delta > 0$, consider symmetric belief revisions from $\widehat{\mu}$ to $\widehat{\mu} - \Delta$ and $\widehat{\mu} + \Delta$. Then:

(i) The response to a positive revision coincides with the unconstrained response:

$$\ln v_\tau(\widehat{\mu} + \Delta) - \ln v_\tau(\widehat{\mu}) = \ln \bar{v}(\widehat{\mu} + \Delta) - \ln \bar{v}(\widehat{\mu}).$$

(ii) The response to a negative revision is the unconstrained response capped by the distance to the floor:

$$\ln v_\tau(\widehat{\mu}) - \ln v_\tau(\widehat{\mu} - \Delta) = \min\big\{\ln \bar{v}(\widehat{\mu}) - \ln \bar{v}(\widehat{\mu} - \Delta),\ d(\widehat{\mu}, b)\big\}.$$

(iii) The initial distance to the floor depends on $(\widehat{\mu}, b)$ only through the relative value of unemployment $x = be^{-\widehat{\mu}}$, and is decreasing in x. Hence, holding b fixed, it increases with $\widehat{\mu}$, while holding $\widehat{\mu}$ fixed, it decreases with b:

$$\frac{\partial d}{\partial \widehat{\mu}} = \varepsilon > 0, \qquad \frac{\partial d}{\partial b} = \frac{1}{\bar{v}\,(1 + \kappa q)} - \frac{1}{b} < 0.$$

Hence, whenever a negative revision would push the unconstrained reservation value below the floor, the response equals d and falls with benefit generosity, whereas the response to positive news depends on benefit generosity only through the unconstrained pass-through of Proposition 1.

Proof. By Equation (11), $v_\tau \to \tau$ as $\theta \to \infty$ whenever the floor is relevant, which is the case if and only if $\bar{v} < \tau$; otherwise $v_\tau = \bar{v}$. Hence $v_\tau = \max\{\bar{v}, \tau\}$. Since $\bar{v}$ is increasing in $\widehat{\mu}$ by Proposition 1, $\bar{v}(\widehat{\mu}) \geq \tau$ implies $v_\tau(\widehat{\mu} + \Delta) = \bar{v}(\widehat{\mu} + \Delta)$, which gives (i), and $v_\tau(\widehat{\mu} - \Delta) = \max\{\bar{v}(\widehat{\mu} - \Delta), \tau\}$, which gives (ii). For (iii), $\partial d/\partial \widehat{\mu} = \varepsilon$, and, using $\partial \bar{v}/\partial b = 1/(1 + \kappa q)$ from Equation (7) and $\tau'/\tau = 1/b$, $\partial d/\partial b = 1/[\bar{v}(1 + \kappa q)] - 1/b < 0$ because $\bar{v}(1 + \kappa q) \geq \bar{v} > b$. Finally, $d = \ln \omega - \ln[(1 + m)x]$, where ω solves Equation (8) and thus depends only on x. □

Discussion Downward rigidity amplifies the asymmetry implied by the option value of search and makes the role of benefits one-sided. A worker whose reservation value lies above the floor can raise it freely after positive news, but after negative news, further downward adjustment becomes increasingly costly once the floor is approached.

Because the floor rises with the flow value of unemployment, higher benefit generosity leaves less room for unconstrained downward adjustment, while upward adjustment is the same as in the unconstrained model. Relative to the unconstrained model, downward rigidity therefore strengthens the benefit gradient in the response to negative news but not in the response to positive news. Under a hard floor, the downward response is bounded by the distance to the floor (Corollary 1). Under a soft floor ($\theta < \infty$), which we use in the quantitative illustration, downward adjustment remains possible but weaker: once negative news makes the floor relevant, the pass-through drops from ε to ε_τ (Proposition 2).

The same logic extends to a floor tied to previous earnings through m. Holding b and $\widehat{\mu}$ fixed, a larger m raises the floor and reduces the distance to it, $\partial d/\partial m = -1/(1+m) < 0$. Thus, for workers initially above the floor, higher previous earnings imply more constrained adjustment after negative news, while the response to positive news remains unaffected by the floor.

B.3 Search effort as a compensating margin

We now allow workers to choose search effort. This adds a second margin of adjustment while preserving the selectivity logic above. Search effort s generates job opportunities at a cost $\gamma(s)$, with $\gamma' > 0$ and $\gamma'' > 0$. Offers arrive according to a Poisson process with rate s, so the probability of generating at least one acceptable offer is

$$P(s, \bar{v}, \widehat{\mu}) = 1 - \exp[-s\, q(\bar{v}, \widehat{\mu})]. \tag{14}$$

Since $S = q\, E[v - \bar{v} \mid v > \bar{v}]$, the expected surplus conditional on receiving at least one acceptable offer is S/q. The worker chooses effort to maximize the expected value of search net of effort costs:

$$\max_s \left\{ -\gamma(s) + \kappa \left[1 - \exp(-s\, q)\right] \frac{S}{q} \right\}. \tag{15}$$

The first-order condition corresponds to Equation (4):

$$\gamma'(s^*) = \kappa \, \exp(-s^* q)\, S. \tag{16}$$

The marginal return to effort combines the expected surplus from a generated opportunity, S, and the probability that the worker has not already generated an acceptable offer, $\exp(-s^* q)$.

Proposition 3 (Effort as a compensating margin)**.** *Let ε denote the pass-through of belief revisions to the reservation value, and let $\eta \equiv s^* \gamma''(s^*)/\gamma'(s^*) > 0$ denote the elasticity of*

marginal search costs. The response of optimal effort to a belief revision is

$$\frac{d\ln s^*}{d\widehat{\mu}} = \frac{1}{\eta + s^* q}\Bigg[\underbrace{1 + (1-\varepsilon)\,\frac{\bar{v}\,q}{S}}_{\textit{opportunity-value channel}} \;-\; \underbrace{(1-\varepsilon)\,s^* g}_{\textit{compensating-search channel}}\Bigg], \tag{17}$$

where g is evaluated at $\ln\bar{v} - \widehat{\mu}$. The opportunity-value channel is the proportional change in the expected surplus from a generated opportunity, $d\ln S/d\widehat{\mu} > 0$. The compensating-search channel is the proportional change in the probability that the worker has not already generated an acceptable offer, $-s^*\,dq/d\widehat{\mu} \leq 0$. Two implications follow:

(i) Selectivity governs the strength of the compensating-search channel. *This channel is scaled by $1-\varepsilon$, the part of the belief revision that the reservation value leaves unabsorbed. If the reservation value moved one-for-one with perceived job values ($\varepsilon = 1$), the acceptance probability would be unchanged, the compensating-search channel would be absent, and effort would move in the same direction as beliefs. The lower the pass-through, the stronger the compensating-search channel.*

(ii) The relative strength of the two channels governs the direction. *Effort moves in the opposite direction of the belief revision, rising after negative news and falling after positive news, if and only if the compensating-search channel dominates:*

$$(1-\varepsilon)\,s^* g > 1 + (1-\varepsilon)\,\frac{\bar{v}\,q}{S}.$$

This requires $s^* g > \bar{v}q/S$ and a pass-through sufficiently below one. When $s^* g > \bar{v}q/S$, a lower pass-through makes the effort response to negative news more positive.

Proof. Taking logs of Equation (16), optimal effort solves

$$\Psi(s, \widehat{\mu}) \equiv \ln\gamma'(s) - \ln\kappa + s\,q - \ln S = 0,$$

where q and S are evaluated at $(\bar{v}(\widehat{\mu}), \widehat{\mu})$. We have $\Psi_s = \gamma''/\gamma' + q > 0$. Using Equation (6) and $\partial\bar{v}/\partial\widehat{\mu} = \varepsilon\bar{v}$,

$$\frac{dS}{d\widehat{\mu}} = S_{\widehat{\mu}} + S_{\bar{v}}\,\varepsilon\bar{v} = M - \varepsilon\bar{v}q = S + (1-\varepsilon)\,\bar{v}q, \qquad \frac{dq}{d\widehat{\mu}} = g\,(1-\varepsilon),$$

where the last equality for $dS/d\widehat{\mu}$ uses $M = S + \bar{v}q$. Hence

$$-\Psi_{\widehat{\mu}} = \frac{1}{S}\frac{dS}{d\widehat{\mu}} - s\frac{dq}{d\widehat{\mu}} = 1 + (1-\varepsilon)\left[\frac{\bar{v}\,q}{S} - s\,g\right].$$

Since $ds^*/d\widehat{\mu} = -\Psi_{\widehat{\mu}}/\Psi_s$, dividing by s^* gives Equation (17). Implications (i) and (ii) follow directly from the term in brackets, since $\eta + s^* q > 0$. □

Discussion Proposition 3 is the formal statement of margin substitution. Better perceived opportunities raise the expected surplus from search and thereby the return to effort. This opportunity-value channel has two parts: the surplus from each acceptable offer rises with perceived job values, and, to the extent that the reservation value does not keep up, more offers become acceptable. At the same time, a higher acceptance probability means that fewer search attempts are needed to generate an acceptable offer, which lowers the return to additional effort. This compensating-search channel operates only to the extent that the reservation value leaves the belief revision unabsorbed: if the reservation value moves one-for-one with perceived job values, the acceptance probability does not change and there is nothing to compensate for. An effort increase after negative news requires that the compensating-search channel dominates, which is the case when the pass-through is low, when workers generate many search attempts (high s^*), and when the density of offers around the reservation value is high (high g).

The selectivity responses derived in Sections B.1 and B.2 therefore shape the effort response. The pass-through is lower at higher benefit generosity (Proposition 1) and falls further after negative news once the floor becomes relevant (Proposition 2). This increases the scope for margin substitution toward effort among workers with high benefit generosity, for whom downward adjustment in selectivity is more constrained. Whether their overall effort response is stronger, however, also depends on the opportunity-value channel and the other components of the compensating-search channel. After positive news, by contrast, the floor does not constrain upward adjustment for workers initially above it, so the compensating-search channel is weaker and the effort response is smaller.

Effort when the floor is relevant Equation (17) is derived for the unconstrained model. When the floor is relevant, the acceptance threshold is the marginal acceptable job value v_τ, the acceptance probability is q_τ, and the expected surplus from a generated opportunity is $\widetilde{S} \equiv \int_{v_\tau}^{\infty} \big(\widetilde{v}(v) - w\big)\, dF(v; \widehat{\mu})$. The first-order condition becomes $\gamma'(s^*) = \kappa \exp(-s^* q_\tau)\, \widetilde{S}$, and the same steps as above give

$$\frac{d \ln s^*}{d\widehat{\mu}} = \frac{1}{\eta + s^* q_\tau} \left[\frac{d \ln \widetilde{S}}{d\widehat{\mu}} - (1 - \varepsilon_\tau)\, s^* g_\tau \right], \qquad g_\tau \equiv g(\ln v_\tau - \widehat{\mu}),$$

where ε_τ is the pass-through to the marginal acceptable job value. Because the floor lowers this pass-through (Proposition 2), a larger part of a negative belief revision translates into a change in the acceptance probability, strengthening the pass-through component of the compensating-search channel. Under a hard floor, $\varepsilon_\tau \to 0$, so this component operates at full strength.

B.4 Selectivity with endogenous effort

Proposition 1 characterizes the selectivity response holding the arrival process fixed. We now characterize the conditions under which its main results carry over when effort is chosen optimally. For given effort s, let

$$A(\bar{v}, \widehat{\mu}; s) \equiv \big[1 - \exp(-s\, q)\big] \frac{S}{q}$$

denote the expected surplus from search. With search costs and the search technology in Equation (14), the reservation-value condition becomes

$$\bar{v} = b + \max_{s} \big\{ -\gamma(s) + \kappa\, A(\bar{v}, \widehat{\mu}; s) \big\} = b - \gamma(s^*) + \kappa\, A(\bar{v}, \widehat{\mu}; s^*). \tag{18}$$

The fixed-effort condition in Equation (7) is the special case in which the worker receives one offer per period at no cost, so that $A = S$ and $\gamma = 0$. We assume $A_{\bar{v}} < 0$ at the optimum: for given effort, a higher reservation value lowers the expected surplus from search.

Proposition 4 (Selectivity with endogenous effort)**.** *With optimally chosen effort, the pass-through of belief revisions to the reservation value is*

$$\varepsilon = 1 - \frac{b - \gamma(s^*)}{\bar{v}\left(1 - \kappa A_{\bar{v}}\right)}, \tag{19}$$

where $A_{\bar{v}}$ is evaluated at $s = s^*$. Hence:

(i) By the envelope theorem, the response of optimal effort does not enter the first-order effect of belief revisions on the reservation value: the pass-through is the same as if effort were held fixed at its optimal level.

(ii) The pass-through is strictly positive, and it is below one if and only if the flow value of unemployment net of search costs is positive, $b > \gamma(s^*)$.

(iii) If the term $(b - \gamma(s^*))/[\bar{v}(1 - \kappa A_{\bar{v}})]$ is decreasing in $\widehat{\mu}$, the log reservation value is convex in perceived job quality, and the asymmetry of Proposition 1 carries over to endogenous effort.

Proof. Differentiating Equation (18) with respect to $\widehat{\mu}$ and applying the envelope theorem to the maximization over s gives

$$\frac{\partial \bar{v}}{\partial \widehat{\mu}} = \frac{\kappa A_{\widehat{\mu}}}{1 - \kappa A_{\bar{v}}},$$

with the partial derivatives evaluated at $s = s^*$, which establishes (i). For given s, the acceptance probability depends on $(\bar{v}, \widehat{\mu})$ only through $\bar{v}e^{-\widehat{\mu}}$, and $S = e^{\widehat{\mu}}\phi(\bar{v}e^{-\widehat{\mu}})$. Hence

A is homogeneous of degree one in $(\bar{v}, e^{\widehat{\mu}})$, and Euler's theorem gives $A_{\widehat{\mu}} = A - \bar{v}A_{\bar{v}}$. Using $\kappa A = \bar{v} - b + \gamma(s^*)$ from Equation (18),

$$\varepsilon = \frac{\kappa A - \kappa \bar{v} A_{\bar{v}}}{\bar{v}\,(1 - \kappa A_{\bar{v}})} = \frac{\bar{v}\,(1 - \kappa A_{\bar{v}}) - (b - \gamma(s^*))}{\bar{v}\,(1 - \kappa A_{\bar{v}})},$$

which is Equation (19). Since $A > 0$ and $A_{\bar{v}} < 0$, the numerator of the first expression and the denominator are positive, so $\varepsilon > 0$, and $\varepsilon < 1$ if and only if $b > \gamma(s^*)$, which establishes (ii). Part (iii) follows because ε equals one minus the term in question, so that ε is increasing in $\widehat{\mu}$ whenever this term is decreasing. □

Discussion Proposition 4 generalizes Proposition 1, which it nests as the special case $A = S$ and $\gamma = 0$, since then $-\kappa A_{\bar{v}} = \kappa q$. Because search effort is chosen optimally, its response to beliefs does not enter the first-order response of selectivity. The intuition therefore remains the same. The reservation value is anchored by the flow value of unemployment, now net of search costs, and the pass-through is lower when this anchor is larger relative to the reservation value. The convexity result additionally requires the condition in part (iii), which depends on the endogenous effort response and cannot generally be signed. This condition is satisfied in the parameterizations used for the quantitative illustration in Section B.6. The hard-floor downward-rigidity result in Section B.2 also carries over to endogenous effort. Under a hard floor, the marginal acceptable job value remains $\max\{\bar{v}, \tau(b)\}$ regardless of how $\bar{v}$ is determined. Parts (i) and (ii) of Corollary 1 therefore continue to hold with $\bar{v}$ given by Equation (18).

B.5 Extension: geographic scope and spatial search frictions

Finally, we extend the framework to the geographic scope of search. This extension is motivated by our empirical finding that positive wage news leads initially pessimistic job seekers to narrow the geographic scope of their applications, which in turn increases job finding. We first show how an increase in perceived job quality can narrow the geographic scope of search through the same selectivity logic that governs reservation values. We then show how this narrowing can increase job finding when job seekers overestimate the productivity of distant search.

Setup A job seeker allocates applications across two regions, local (L) and distant (D). Applying to region $r \in \{L, D\}$ costs $k_r > 0$, and generates an offer with perceived probability $\widehat{\lambda}_r$, which is accepted if its value exceeds the reservation value $\bar{v}$. We treat $\widehat{\lambda}_r$ as fixed with respect to perceived job quality $\widehat{\mu}$ and distinguish it below from the actual success probability λ_r. Total search effort is determined as in the preceding search problem, while the geographic extension focuses on the relative returns to directing applications across regions.

Location-specific costs such as commuting or relocation costs reduce the value of jobs in a region proportionally. In region r, perceived job values follow

$$F_r(v;\widehat{\mu}) = G(\ln v - \widehat{\mu} + \ell_r),$$

so that a job in region r is worth a fraction $e^{-\ell_r}$ of an otherwise identical job without location costs. We normalize $\ell_L = 0$ and assume $\ell_D > 0$. Let $q_r \equiv 1 - F_r(\bar{v};\widehat{\mu})$ and $S_r \equiv S(\bar{v}, \widehat{\mu} - \ell_r)$ denote the perceived acceptance probability and expected surplus of an offer from region r. The expected surplus from applying to region r is

$$R_r(\bar{v},\widehat{\mu}) \equiv \widehat{\lambda}_r \, S_r, \tag{20}$$

and the net return to directing an application to region r is $R_r - k_r$. Geographic search therefore depends on the relative returns to local and distant applications.

B.5.1 Geographic narrowing after positive news

Proposition 5 (Geographic narrowing)**.** *Let $\varepsilon \in (0,1)$ denote the pass-through of belief revisions to the reservation value. Then*

$$\frac{d(R_L - R_D)}{d\widehat{\mu}} = (R_L - R_D) + (1-\varepsilon)\,\bar{v}\left(\widehat{\lambda}_L q_L - \widehat{\lambda}_D q_D\right). \tag{21}$$

A positive belief revision raises the return to local relative to distant search, creating an incentive to shift applications toward the local region and thereby narrow the geographic scope of search, whenever

$$R_L - R_D > (1-\varepsilon)\,\bar{v}\left(\widehat{\lambda}_D q_D - \widehat{\lambda}_L q_L\right). \tag{22}$$

Proof. By Equation (6), applied to region r, and $\partial\bar{v}/\partial\widehat{\mu} = \varepsilon\bar{v}$,

$$\frac{dR_r}{d\widehat{\mu}} = \widehat{\lambda}_r\big[M_r - \varepsilon\,\bar{v}\,q_r\big] = \widehat{\lambda}_r\big[S_r + (1-\varepsilon)\,\bar{v}\,q_r\big],$$

where $M_r \equiv \int_{\bar{v}}^{\infty} v\, dF_r(v;\widehat{\mu}) = S_r + \bar{v}q_r$. Taking the difference between local and distant search and using $R_r = \widehat{\lambda}_r S_r$ gives Equation (21). Rearranging the condition

$$\frac{d(R_L - R_D)}{d\widehat{\mu}} > 0$$

gives Equation (22). □

Discussion Proposition 5 shows how the selectivity response to positive news can extend to the geographic scope of search. Positive news changes the return to search in

both regions, but not necessarily by the same amount. The first term in Equation (21) reflects that a proportional increase in job values amplifies any existing difference in expected surplus between local and distant applications. The second term captures differences in the perceived probability that an application generates an acceptable offer and is scaled by $1 - \varepsilon$. Importantly, the two terms need not have the same sign. Even if job seekers perceive distant applications as more likely to generate an acceptable offer, positive news can still increase the relative return to local search if lower location costs make the expected surplus from local applications sufficiently larger. Geographic narrowing can therefore arise even when perceived job-finding rates are higher for distant search.

B.5.2 Job finding under spatial frictions

Narrowing the geographic scope of search reallocates applications toward the local labor market. Whether this improves job finding depends on the true relative productivity of local and distant applications, which need not coincide with workers' perceptions. We define

$$\widehat{\pi}_r \equiv \widehat{\lambda}_r q_r$$

as the perceived probability that an application to region r generates an acceptable offer, and denote its true counterpart by π_r. We allow workers to misperceive these relative productivities. In particular, they may underestimate the productivity advantage of local search,

$$\frac{\widehat{\pi}_L}{\widehat{\pi}_D} < \frac{\pi_L}{\pi_D}. \tag{23}$$

To characterize realized job finding, we denote the share of search directed toward the local region by $a \in [0, 1]$. For a given level of search effort s, the probability of receiving at least one acceptable offer is

$$P(s, a) = 1 - \exp\big\{-s\,[a\pi_L + (1 - a)\pi_D]\big\}. \tag{24}$$

Proposition 6 (Spatial misperceptions and job finding)**.** *Suppose local search is truly more productive than distant search, $\pi_L > \pi_D$. Then a reallocation of applications toward the local region raises job finding:*

$$\frac{\partial P(s, a)}{\partial a} = s\,(\pi_L - \pi_D)\exp\big\{-s\,[a\pi_L + (1 - a)\pi_D]\big\} > 0. \tag{25}$$

Hence, when workers underestimate the relative productivity of local search as in Equation (23)*, the geographic narrowing induced by a positive belief revision can improve job finding by reallocating search toward the more productive local labor market.*

Proof. Differentiating Equation (24) with respect to a gives Equation (25). For $s > 0$, the expression is strictly positive whenever $\pi_L > \pi_D$. □

Discussion Together, Propositions 5 and 6 show how greater geographic selectivity can increase job finding. Positive wage news can make local search relatively more attractive and shift applications toward the local labor market. When local applications are more productive than distant ones, this reallocation raises job finding; if job seekers initially underestimate this productivity advantage, geographic narrowing partly corrects an existing spatial distortion. The framework therefore yields four empirical implications, which we examine in Section 4.4.2:

(i) Geographic narrowing raises the arrival rate of acceptable local opportunities, $sa\pi_L$, while reducing that of acceptable distant opportunities, $s(1-a)\pi_D$:

$$\frac{\partial(sa\pi_L)}{\partial a} = s\pi_L > 0, \qquad \frac{\partial[s(1-a)\pi_D]}{\partial a} = -s\pi_D < 0.$$

Hence, any increase in the overall arrival rate of acceptable opportunities generated by the reallocation is driven by local search, implying that the additional matches should be concentrated in the local labor market.

(ii) The employment gain from reallocating search locally is larger when the initial local search share is lower. Differentiating Equation (25) with respect to a gives

$$\frac{\partial^2 P(s,a)}{\partial a^2} = -s^2(\pi_L - \pi_D)^2 \exp\{-s[a\pi_L + (1-a)\pi_D]\} < 0.$$

Thus, a given shift toward local search has a larger effect on job finding among workers who initially search more broadly.

(iii) The employment gain from geographic reallocation requires a productivity advantage of local over distant search. From Equation (25),

$$\frac{\partial P(s,a)}{\partial a} > 0 \quad \Longleftrightarrow \quad \pi_L > \pi_D,$$

while the effect vanishes when $\pi_L = \pi_D$. Empirically, we proxy this margin using local search effectiveness. Local search effectiveness can be measured based on workers' municipality of residence, whereas constructing a comparable measure of distant search effectiveness is difficult because the relevant distant labor market differs across job seekers and is not directly observable.

(iv) The interpretation that geographic narrowing corrects an existing spatial distor-

tion requires job seekers to underestimate the relative productivity of local search:

$$\frac{\widehat{\pi}_L}{\widehat{\pi}_D} < \frac{\pi_L}{\pi_D}.$$

Our additional survey in Appendix C.6 directly examines this implication by comparing perceived and actual relative search effectiveness across locations.

B.6 Details on the quantitative illustration

This subsection provides details on the quantitative illustration discussed in Section 3. The exercise is intended to illustrate the magnitudes and relative importance of the mechanisms in the theoretical framework rather than to calibrate the model to the experimental treatment effects. We first compute the reservation-value response using the selectivity problem in Sections B.1-B.2 and then compute the associated optimal search-effort response from the first-order condition in Section B.3. We examine these responses for equally sized positive and negative revisions in perceived job values.

Parameterization We normalize earnings potential to one and assume that perceived job values are log-normally distributed,

$$\ln v \sim N(\mu, \sigma^2),$$

with $\sigma = 0.10$ and $\beta = 0.90$. For the baseline illustration, we normalize the initial perceived quality parameter to $\mu = 0$ and consider symmetric revisions of -0.05 and $+0.05$, corresponding to belief revisions of five log points. Using equally sized shocks ensures that any asymmetry in behavioral responses is generated by the model rather than by differences in the magnitude of the belief revisions.

We consider two values of the normalized flow value of unemployment, $b = 0.40$ and $b = 0.80$, which we refer to as low and high benefits. To distinguish the role of benefit generosity from additional downward rigidity, we consider three scenarios: low benefits, high benefits without a floor, and high benefits with a floor. In the first scenario, the floor is present but does not bind, so the comparison between the first two scenarios isolates the effect of a higher value of unemployment.

Downward rigidity is modeled using the effective offer value introduced in Section 3.1,

$$\widetilde{v}(v) = v - \theta\big[(1+m)b - v\big]_+.$$

For the representative worker, we set $m = 0.29$, which is of a similar magnitude to the observed gap between reported reservation wages and individual benefit levels in our data, and $\theta = 0.85$. These values generate a soft floor that is irrelevant at the low

benefit level and around the initial state, but becomes relevant following sufficiently large negative revisions when benefits are high. The comparison between the high-benefit scenarios with and without the floor therefore isolates the additional role of downward rigidity.

Selectivity Panel A of Figure B.1 illustrates the reservation-value responses for the representative worker. With low benefits, pass-through is slightly below one-for-one and the baseline option-value mechanism generates only a very mild asymmetry: the reservation value falls by 4.6% after negative news and rises by 4.8% after positive news. Raising the value of unemployment dampens both responses somewhat. Without the floor, the corresponding responses under high benefits are -3.9% and $+4.2\%$.

Introducing downward rigidity at the high benefit level generates a substantially larger asymmetry. The floor attenuates the response to negative news from -3.9% to -2.5%, while leaving the $+4.2\%$ response to positive news unchanged. This comparison separates the effect of higher benefits from the additional effect of downward rigidity: higher b dampens pass-through in both directions through the standard option-value mechanism, while the floor additionally constrains downward adjustment after negative news.

Search effort We assume quadratic search costs,

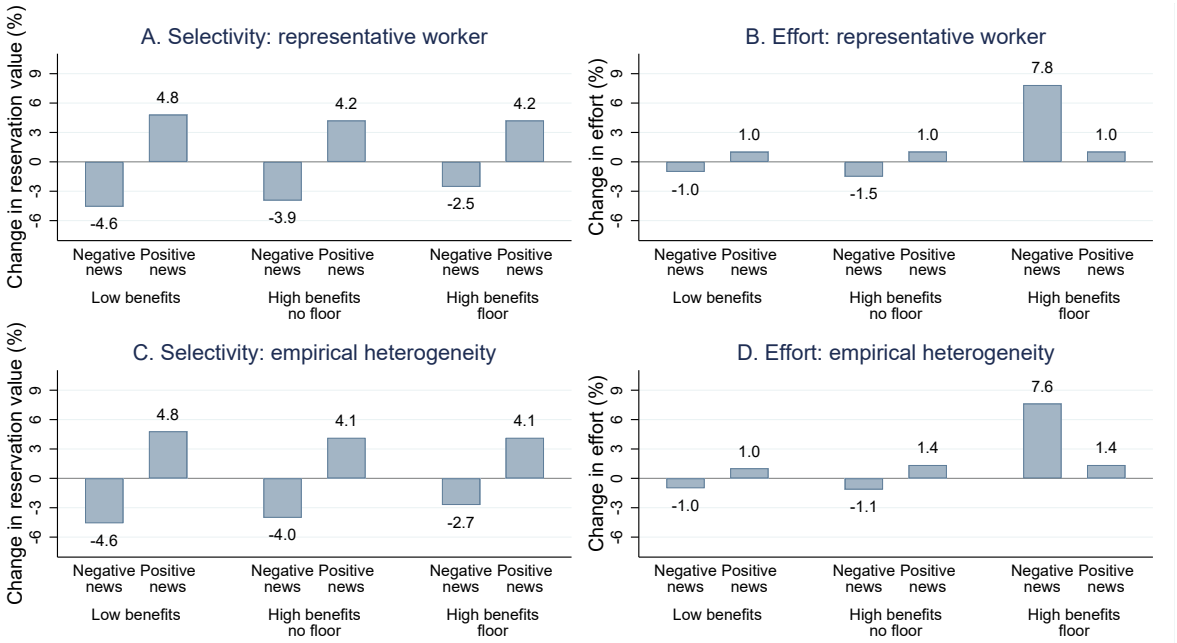
$$\gamma(s) = \frac{c}{2}s^2,$$

and compute optimal effort from the first-order condition in Equation (4). The main illustration uses $c = 0.012$, a low-search-cost parameterization in which the compensating-search channel can become quantitatively important when selectivity adjusts only weakly.

Panel B of Figure B.1 shows the resulting effort responses. With low benefits, effort changes little, falling by 1.0% after negative news and rising by 1.0% after positive news. Higher benefits alone also leave the responses modest: without the floor, effort falls by 1.5% after negative news and rises by 1.0% after positive news. Introducing the floor changes the response to negative news sharply. Because the reservation value can no longer absorb as much of the deterioration in perceived opportunities, the probability that a generated offer is acceptable falls more strongly and effort becomes a more important compensating margin. Effort consequently rises by 7.8%. The positive-news response remains at approximately 1.0%, since the floor does not constrain upward selectivity adjustment.

The exercise thus illustrates the margin-substitution mechanism emphasized in the main text. Higher benefits by themselves weaken the response of selectivity and increase the scope for adjustment through effort. Downward rigidity further strength-

Figure B.1 Illustration of search responses to belief revisions

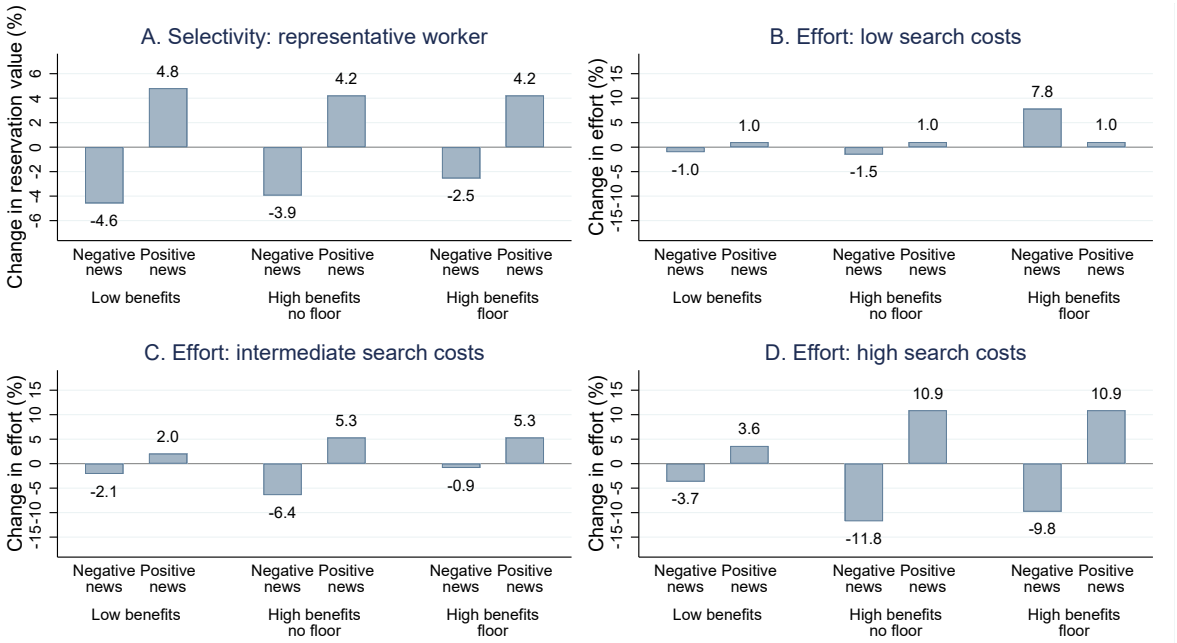


Notes: The figure provides a quantitative illustration of the mechanisms in the theoretical framework. We normalize earnings potential to one and assume $\log v \sim N(\widehat{\mu}, \sigma^2)$, with $\sigma = 0.10$ and $\beta = 0.90$. We consider equally sized negative and positive belief revisions of five log points. The normalized flow value of unemployment is set to $b = 0.40$ under low benefits and $b = 0.80$ under high benefits. For each sign of news, we compare low benefits, high benefits without downward rigidity, and high benefits with the floor introduced in Section 3.1. The floor is parameterized by $m = 0.29$ and $\theta = 0.85$ for the representative worker. Search costs are quadratic, $\gamma(s) = cs^2/2$, with $c = 0.012$, a low-search-cost parameterization in which the compensating-search channel can become important when downward selectivity adjustment is constrained. Panels A and B use a common initial position of perceived job values relative to the value of unemployment, and a common distance to the floor. Panels C and D allow for the empirically observed heterogeneity in initial beliefs and distance to the floor between the negative- and positive-news groups.

ens this mechanism after negative news and thereby amplifies the benefit gradient in the effort response. The sign of the net effort response is nevertheless not a general prediction, because the compensating-search and opportunity-value channels work in opposite directions.

Heterogeneity in initial conditions The representative-worker illustration assumes the same initial perceived job values and the same distance to the floor for positive and negative news. In the data, the initially optimistic and pessimistic groups differ in both respects. We therefore repeat the exercise allowing for these empirical differences while keeping the belief revisions themselves symmetric. First, initial perceived job values differ across the two groups. The negative-news group starts about 7.1 log points above the positive-news group. We retain this difference in the simulation and center the two initial positions around zero, setting $\mu_N = 0.0355$ and $\mu_P = -0.0355$, for the negative- and positive-news groups, respectively. Belief revisions remain fixed at -0.05 and $+0.05$. Second, we allow the location of the floor to differ across the two groups. In the data, the negative-news group has previous wages above its current

Figure B.2 Illustration of search responses to belief revisions with varying search costs



Notes: The figure examines the sensitivity of the quantitative illustration to the search-cost parameter c, assuming quadratic search costs, $\gamma(s) = cs^2/2$. All panels use the representative-worker specification and otherwise maintain the parameterization of Figure B.1. Panel A reports the selectivity responses, which are independent of c. Panels B–D report the corresponding search-effort responses for low ($c = 0.012$), intermediate ($c = 0.05$), and high ($c = 0.20$) search costs, respectively. For each panel, we compare low benefits, high benefits without downward rigidity, and high benefits with the floor. The belief revisions are symmetric at five log points.

earnings benchmark, whereas the reverse holds for the positive-news group. Motivated by the idea that previous earnings can constrain downward adjustment in acceptable wages, we allow the floor premium to increase when previous earnings exceed current earnings potential. We therefore set a higher floor premium for the negative-news group, $m_N = 0.32$, than for the positive-news group, $m_P = 0.26$, while keeping their average equal to the representative-worker value $m = 0.29$.

Panels C and D of Figure B.1 show that incorporating these differences leaves the main conclusions essentially unchanged. The floor continues to attenuate the selectivity response to negative news while leaving the positive-news response largely unaffected, and the corresponding margin substitution toward effort remains of similar magnitude.

Sensitivity to search costs Finally, Appendix Figure B.2 examines how the effort responses depend on search costs. All panels use the representative-worker specification and the same three benefit/floor scenarios as the baseline illustration. Panel A repeats the selectivity responses, which do not depend on the search-cost parameter. Panels B–D vary the search-cost parameter across $c = 0.012$, $c = 0.05$, and $c = 0.20$.

As search costs rise, baseline search effort falls and the compensating-search channel becomes weaker relative to the opportunity-value channel. The floor nevertheless con-

tinues to shift the response to negative news toward greater effort relative to the corresponding high-benefit specification without downward rigidity. At intermediate search costs, for example, the negative-news effort response under high benefits changes from -6.4% without the floor to -0.9% with the floor. At high search costs, the corresponding responses are -11.8% and -9.8%. Thus, downward rigidity consistently strengthens the compensating-search force after negative news, but whether this force is sufficiently strong to make the net effort response positive depends on the search technology. This sensitivity motivates our emphasis on margin substitution as a mechanism rather than on an unconditional sign prediction for search effort.

C Additional empirical evidence and robustness

This appendix provides additional empirical evidence and robustness checks on the following aspects: (i) the anchoring of prior beliefs about comparable workers' re-employment wages on pre-unemployment wages; (ii) correlates of misperceptions about comparable workers' re-employment wages; (iii) the updating of wage expectations in response to the treatment; (iv) the effects of wage expectations on job search and labor market outcomes; (v) heterogeneity in responses to positive wage news; and (vi) the perceived and actual returns to local versus distant search.

C.1 Anchoring of prior beliefs on pre-unemployment wages

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 1, Panel D), following Jäger et al. (2024). In particular, we estimate regressions of the following form:

$$\ln(E_i) - \ln(P_i) = \beta_0 + \beta_1 \left[\ln(B_i) - \ln(P_i)\right] + \beta_2 \ln(P_i) + \varepsilon_i \tag{26}$$

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% (Panel D of Figure 1). We interpret this as evidence for a moderate degree of anchoring on pre-unemployment wages. Figure C.1 presents a sensitivity analysis for this result.

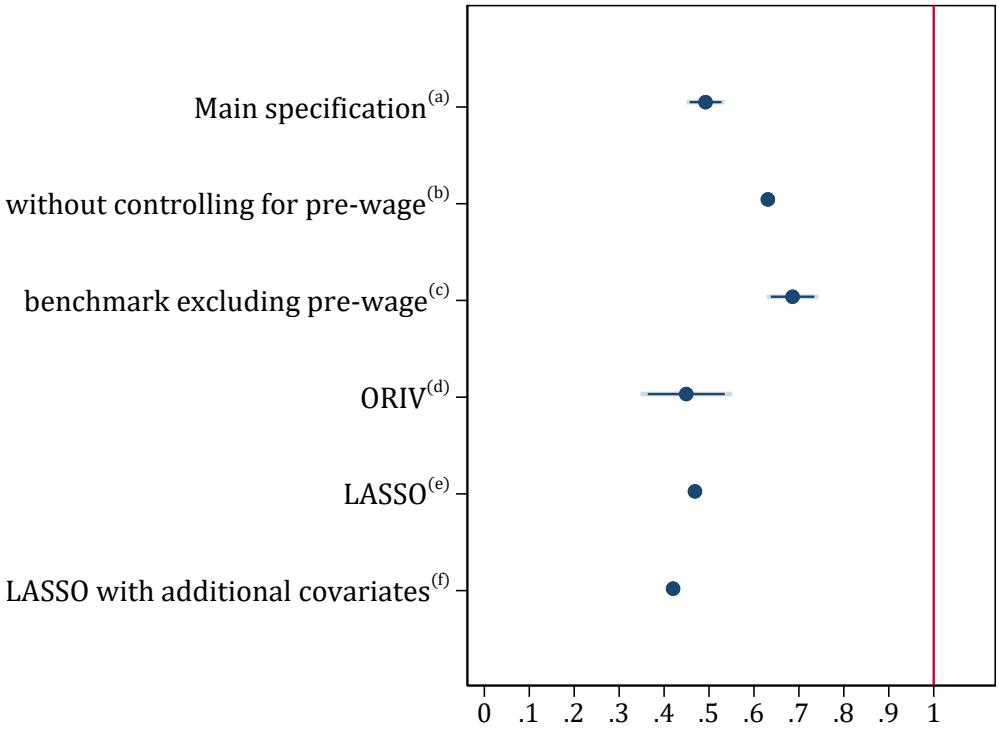
Mechanical correlations Our main regressions control for log pre-unemployment wages to rule out "mechanical" correlations arising because $\ln(P_i)$ enters both sides of Equation (26). Omitting this control raises the estimated coefficient from 0.49 to 0.63, suggesting that it is useful to control for pre-unemployment wages. As a robustness check against remaining mechanical correlations, we instrument the wage projection with an alternative projection that excludes the pre-unemployment wage from the set of predictors. This yields a coefficient of 0.69, a shift toward *weaker* anchoring, which is the opposite of what we would expect if mechanical correlations biased our main specification.

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 in our setting because we elicit beliefs about clearly defined population cells. Population-level statistics abstract from individual-specific circumstances unobserved by the researcher, and the corresponding benchmarks are measured precisely in administrative data. Remaining sources of noise could arise (i) if respondents 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 a coefficient estimate of 0.45—similar to our baseline results. The fact that the coefficient estimate does 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 well (with a coefficient close to one; see Appendix Figure A.2), we also demonstrate robustness to alternative benchmarks. Specifically, anchoring persists 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.

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 (26), relating expected to actual wage changes from pre- to post-unemployment. All specifications, except (b), control for the pre-unemployment wage. The figure reports the results of the regression specification (26).
This figure uses differences between expected average re-employment wages of comparable workers and pre-unemployment wages ($N = 8{,}039$).
$^{(a)}$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.

C.2 Correlates of misperceptions about re-employment wages

What shapes respondents' prior beliefs about re-employment wages of comparable workers, beyond anchoring on the pre-unemployment wage? In Table C.1, we regress the deviation of a respondent's prior belief from the corresponding register benchmark on a broad set of covariates, among others the pre-unemployment wage, cell size and within-cell wage dispersion, proxies for numeracy and overconfidence, previous experiences and aspects of a job seeker's social environment. Alongside the raw deviation, we separately consider its positive part (setting negative deviations to zero), its negative part (setting positive deviations to zero), and its absolute value. This allows us to distinguish shifts in the direction of deviations from changes in overall alignment.

A first set of candidates relates to the benchmark itself. Although we restrict attention to demographic cells with at least 30 observations in the register data, mean re-employment wages are estimated less precisely in smaller cells, so the benchmark itself may be noisy. In this case, deviations from the benchmark could arise even among respondents who are well calibrated about the underlying data-generating process. On top of this, re-employment wages may be inherently harder to predict in cells in which they are highly dispersed. We find evidence for the second channel but not the first. Cell size is not significantly related to absolute deviations from the benchmark, but a one-standard-deviation increase in within-cell dispersion is associated with a 0.02 larger absolute log deviation, about 12% of the average absolute gap ($p < 0.001$, Column 4)[2], reflecting both stronger upward and stronger downward deviations ($p < 0.001$, Columns 2 and 3).

We next turn to cognitive skills and overconfidence. In our survey, respondents complete a short numeracy test and are then asked to self-assess their performance. Higher numeracy is associated with closer alignment of beliefs with benchmarks: each additional correct answer reduces the absolute log deviation by about 0.006 ($p < 0.001$, Column 4), roughly 4% of the average absolute gap. Respondents who overestimate their own performance deviate more strongly upward from the benchmark, but this is offset by weaker downward deviations, leaving absolute deviations unchanged. Overconfidence thus tilts beliefs in an optimistic direction without affecting overall alignment.

We then consider the role of prior experiences. The wage growth respondents experienced over recent years is not significantly related to absolute deviations from the benchmark. Individuals who went through an earlier unemployment spell hold better-calibrated beliefs if the wage change they experienced over that spell was broadly in

[2]The coefficients refer to a one-unit change in the within-cell standard deviation of log wages, which has a mean of 0.26 and a standard deviation of 0.046 across respondents. A one-standard-deviation increase thus corresponds to $0.430 \times 0.046 \approx 0.02$ in Column 4, relative to a mean absolute deviation of 0.165.

line with the population-level benchmark. Experiences at the previous employer also appear to matter. Job seekers whose previous firm paid higher average wages deviate more strongly upward and less strongly downward from the benchmark, resulting in somewhat larger absolute deviations ($p = 0.022$, Column 4). Previous employees of larger firms deviate less strongly upward ($p = 0.003$, Column 2) and slightly less in absolute terms ($p = 0.064$, Column 4), though the magnitudes are small.

Beyond the job seeker's own history, the social environment could matter. Job seekers who have met their caseworker more often deviate more strongly downward from the benchmark, but this is offset by weaker upward deviations; caseworker contact overall does not appear to push job seekers toward better-calibrated beliefs. Finally, we detect no robust link between the alignment of beliefs with benchmarks and unemployment experiences of parents or spouses.

Table C.1 Correlates of misperceptions about group-level re-employment wages

	Expected–actual group wage							
	(1) Difference		(2) Positive part		(3) Negative part		(4) Absolute value	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Cell size and within-cell dispersion								
SD within cell (log)	0.112*	(0.059)	0.271***	(0.038)	-0.159***	(0.034)	0.430***	(0.041)
Observations within cell (per 100 obs.)	-0.002**	(0.001)	-0.001*	(0.001)	-0.001*	(0.000)	-0.000	(0.001)
Cognitive skills and overconfidence								
Number of correct answers	0.022***	(0.002)	0.008***	(0.001)	0.014***	(0.001)	-0.006***	(0.001)
Overestimation (perc.-actual score)	0.010***	(0.002)	0.005***	(0.001)	0.005***	(0.001)	0.001	(0.002)
Prior experiences								
Wage growth, past 3 years	-0.006	(0.009)	-0.002	(0.007)	-0.004	(0.005)	0.002	(0.007)
Wage growth, past 5 years	-0.015*	(0.009)	-0.005	(0.006)	-0.010**	(0.005)	0.005	(0.006)
Unemployment & wage change history (ref. No spells since 2013)								
Wage change close to benchmark	-0.020***	(0.006)	-0.019***	(0.004)	-0.001	(0.004)	-0.018***	(0.004)
Wage change $<$ benchmark (-15%)	-0.014**	(0.006)	-0.010***	(0.004)	-0.004	(0.003)	-0.006	(0.004)
Wage change $>$ benchmark ($+15\%$)	0.023***	(0.006)	0.012***	(0.004)	0.011***	(0.003)	0.001	(0.004)
Prior firm average wage (log)	0.034***	(0.005)	0.021***	(0.003)	0.013***	(0.003)	0.007**	(0.003)
Prior firm size (per 10,000 workers)	-0.006***	(0.002)	-0.004***	(0.001)	-0.001	(0.001)	-0.003*	(0.001)
Social environment								
Caseworker meetings (per 10 meetings)	-0.010***	(0.002)	-0.006***	(0.001)	-0.004***	(0.001)	-0.002	(0.002)
Father experienced unemployment	-0.007	(0.014)	-0.003	(0.009)	-0.004	(0.008)	0.001	(0.009)
Mother experienced unemployment	-0.007	(0.012)	-0.005	(0.007)	-0.002	(0.007)	-0.003	(0.008)
Married	0.018***	(0.005)	0.012***	(0.003)	0.006*	(0.003)	0.007*	(0.004)
Spouse experienced unemployment	-0.007	(0.010)	-0.003	(0.007)	-0.005	(0.006)	0.002	(0.007)
Background characteristics								
Age (ref. 35 years or below)								
36–50 years	-0.018***	(0.006)	-0.011***	(0.004)	-0.007*	(0.004)	-0.004	(0.004)
Above 50	-0.024***	(0.007)	-0.010**	(0.005)	-0.014***	(0.004)	0.003	(0.005)
Female	0.048***	(0.005)	0.023***	(0.003)	0.025***	(0.003)	-0.002	(0.003)
Level of education (ref. lower secondary)								
Upper secondary	0.021***	(0.007)	0.008*	(0.005)	0.013***	(0.004)	-0.005	(0.005)
Tertiary	0.029***	(0.008)	0.015***	(0.005)	0.013***	(0.005)	0.002	(0.006)
Elapsed unemployment duration (ref. less than 3 months)								
3-5 months	0.059***	(0.006)	0.036***	(0.004)	0.023***	(0.004)	0.013***	(0.004)
6-8 months	0.059***	(0.007)	0.036***	(0.005)	0.023***	(0.004)	0.013***	(0.005)
9-11 months	0.065***	(0.008)	0.041***	(0.006)	0.024***	(0.005)	0.017***	(0.006)
12-17 months	0.060***	(0.008)	0.034***	(0.005)	0.025***	(0.005)	0.009	(0.006)
18-23 months	0.069***	(0.013)	0.040***	(0.008)	0.029***	(0.007)	0.011	(0.009)
$\geq$24 months	0.057***	(0.011)	0.026***	(0.007)	0.030***	(0.006)	-0.004	(0.007)
Previous industry (ref. Other services)								
Agriculture	-0.060***	(0.021)	-0.019*	(0.010)	-0.041***	(0.015)	0.021	(0.015)
Manufacturing	0.002	(0.010)	0.008	(0.006)	-0.005	(0.006)	0.013*	(0.007)
Construction	-0.011	(0.012)	0.001	(0.008)	-0.012	(0.008)	0.014	(0.009)
Trade	0.020**	(0.009)	0.016***	(0.006)	0.005	(0.005)	0.011*	(0.006)
Business services	0.008	(0.009)	-0.000	(0.006)	0.008	(0.005)	-0.009	(0.006)
Public sector	-0.005	(0.009)	-0.001	(0.006)	-0.004	(0.005)	0.003	(0.007)
Previous salary (log)	0.136***	(0.008)	0.095***	(0.005)	0.041***	(0.004)	0.055***	(0.005)
Previous job was full-time	-0.079***	(0.011)	-0.082***	(0.007)	0.003	(0.006)	-0.085***	(0.007)
Constant	-1.821***	(0.076)	-1.157***	(0.052)	-0.664***	(0.040)	-0.493***	(0.052)
No. of observations	9,247		9,247		9,247		9,247	
R^2	0.17		0.17		0.09		0.07	

Notes: The table presents regression results for the log difference between expected and actual group-level wages (column 1), restricted to positive differences (column 2), restricted to negative differences (column 3), and in absolute value (column 4), based on respondents' background characteristics. All specifications control for missing-value indicators for the numeracy and overestimation measures, wage growth (3 and 5 years), and prior firm characteristics. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

C.3 Updating of wage expectations

In this appendix, we present additional empirical exercises and robustness checks on our intervention's first-stage effects on wage expectations.

Persistence in the follow-up Appendix Figure C.2 shows the persistence of treatment effects in the follow-up survey conducted one to two weeks after the intervention. 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 C 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.[3] Generally, the smaller sample size, selection into the follow-up, and the unobserved influence of additional signals received after treatment-induced adjustments in search suggest that the follow-up effect sizes should be interpreted with caution. 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 examine updating in the subjective distribution of respondents' next wage offer, centered around their pre-unemployment wage. Figure C.3 presents treatment effects on the mean and standard deviation implied by the distribution. Effects on the mean qualitatively align with the estimates for point forecasts, although they are somewhat smaller, possibly because the available bins constrain the beliefs respondents can express. The treatment significantly reduces perceived wage uncertainty in the neutral group but has no significant effect on the standard deviation among respondents with moderate or large perception gaps. This distinction matters for our causal interpretation because changes in perceived wage uncertainty could affect search behavior over and above changes in the mean of the subjective wage distribution.

Perception gaps and differential updating of wage expectations As shown in Figure 2, the treatment causes a stronger updating of point expectations about the next wage offer among individuals with larger prior perception gaps. This pattern is con-

[3]Follow-up participation differs by gender across treatment arms. Women make up 54% of treated and 50% of control respondents in the follow-up sample ($p = 0.02$), whereas the arms are balanced on gender in the main survey (see Appendix Table A.2). Panels B and D of Figure C.2 therefore reweight, within each treatment arm, the sample of follow-up respondents so that its gender distribution matches that of the full main survey sample, and highlight that our results are robust.

sistent with the idea that those with more pronounced perception gaps receive larger information shocks when treated. However, because perception gaps are not randomly assigned, the profile of treatment effects across perception-gap groups could partly reflect characteristics that are correlated with the perception gap and that shift individuals' responses to being treated independently of the informational content of the signal—for instance, through priming or emotional reactions. 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, sequentially adding interactions between the treatment indicator and background characteristics. Table C.2 shows that the variation of estimated treatment effects with the perception gap remains almost unchanged. This suggests that differential changes in expected future wage offers are indeed driven by the varying size of the information shock, rather than by responses to the treatment that vary with variables correlated with the perception gap.

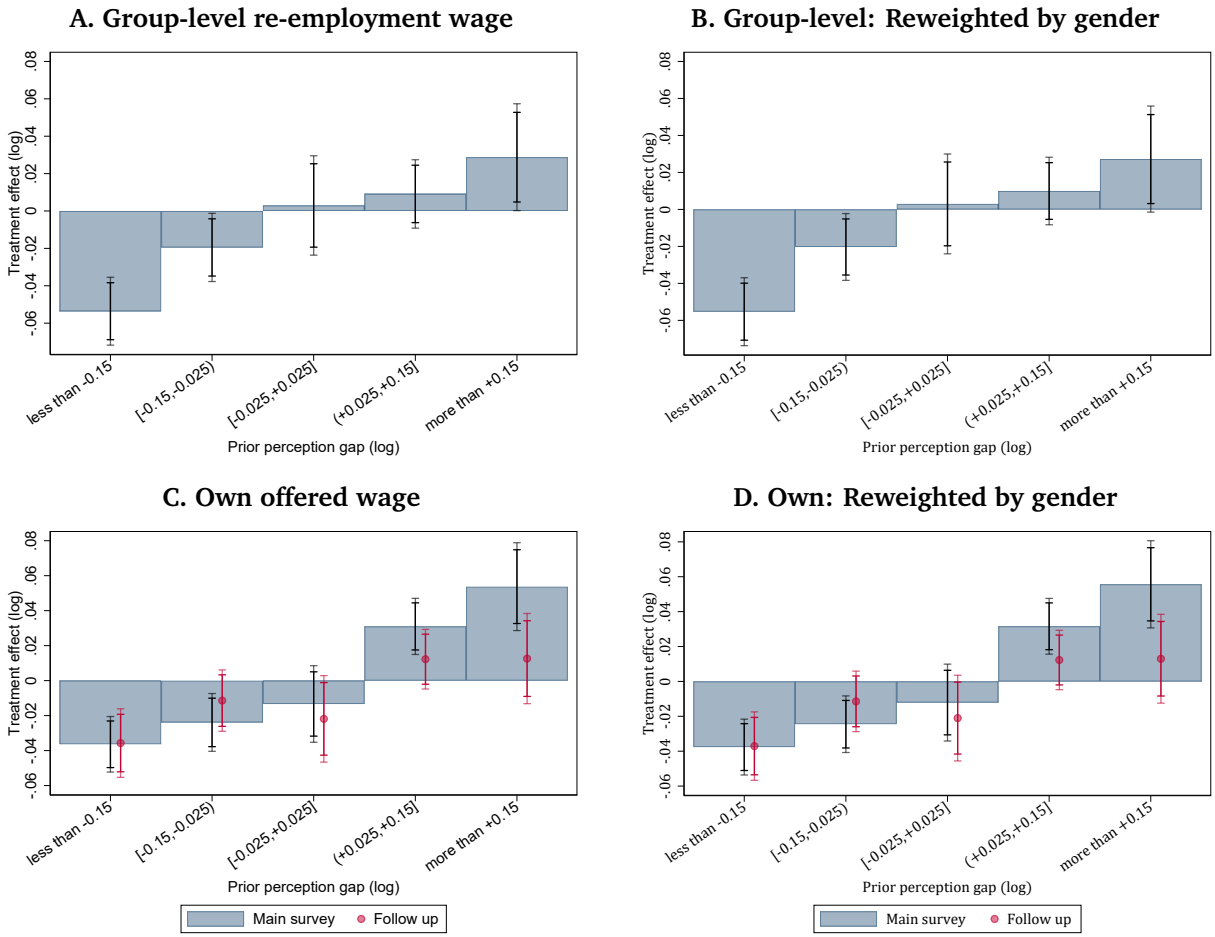
Benchmark noise and wage dispersion We also examine whether noise in the cell-level wage projection or the dispersion of re-employment wages within cells affects the extent of updating. Panels A and B of Figure C.4 show treatment effects separately by the size of respondents' assigned demographic cell and by the within-cell standard deviation of re-employment wages, respectively. We detect no systematic or significant heterogeneity in updating along either dimension. Thus, there is no evidence that job seekers' updating responds to the noisiness of the benchmark or to the dispersion of re-employment wages within their cell.

As a further check on the role of within-cell wage dispersion, we re-examine our main results by estimating precision-adjusted treatment effects. In Figure C.5, we estimate our baseline specification by weighted least squares, using the inverse of the within-cell variance as weights, so that respondents for whom the wage projection provides a more precise signal about their own prospects receive greater weight. This approach yields treatment effects on wage expectations that are close to our main estimates in Figure 2, suggesting that within-cell variation in re-employment wages—and hence differences in how precise a signal the wage projection provides about own prospects—plays only a minor role in job seekers' updating.

Beliefs about the mapping from effort to job-offer arrivals One concern is that the information may shift beliefs not only about the wages available to the respondent but also about how search effort translates into job offers—commonly seen as the other main fundamental in job search (Mueller and Spinnewijn, 2023). Such effects could arise if job seekers update about broader labor market conditions in addition to their own earnings potential and would threaten the exclusion restriction when interpreting the intervention as speaking to the causal effect of wage expectations on job search. We

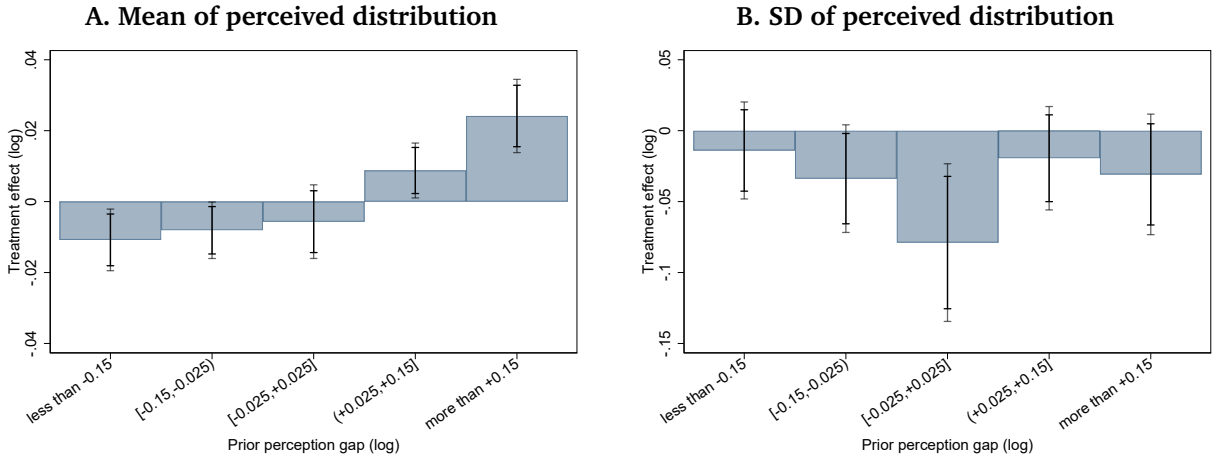
can examine this possibility using additional beliefs elicited in our survey: respondents' perceived probability of receiving at least one job offer within the next four weeks when searching (i) 5 or (ii) 15 hours per week. As shown in Table C.3, the treatment has no significant effect on the perceived probability at five hours in any of the five perception-gap groups. For the increase in this probability when search rises from 5 to 15 hours, we find only a small, marginally significant effect for small positive shocks and no significant effects for the remaining groups. We therefore find no systematic evidence that the treatment changes beliefs about either the baseline likelihood of generating an offer or the returns to additional search effort. Together with the significant effects on job seekers' beliefs about their own wage offers, these patterns support the interpretation that the intervention operates primarily through shifts in wage expectations.

Figure C.2 Treatment effects on expected wages in follow-up survey



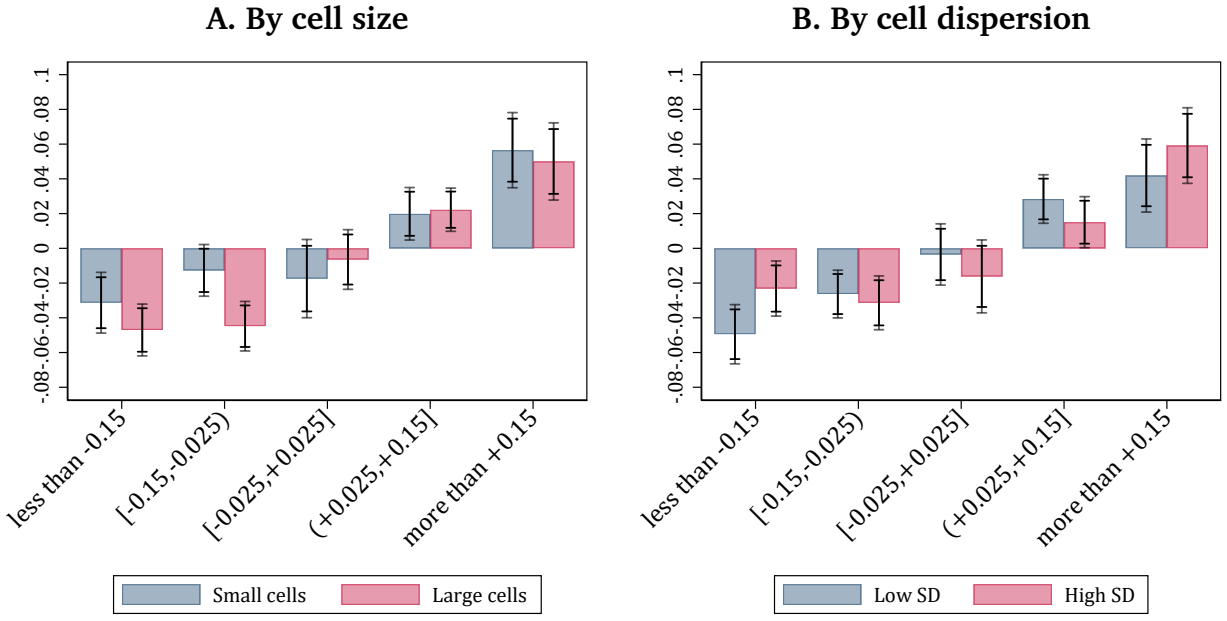
Notes: The figure shows the effects of the information treatment (including 90% and 95% confidence intervals) on respondents' expected group-level re-employment wages (log) measured in the follow-up survey (Panel A), expected group-level re-employment wages (log) measured in the follow-up survey reweighted by gender (Panel B), own expected wage offer measured in the main and follow-up survey (log) (Panel C), and own expected wage offer measured in the main and follow-up survey reweighted by gender (Panel D). The estimates are based on respondents who completed the follow-up survey. Panels B and D reweight these respondents using inverse-probability weights, separately within each treatment arm, so that their gender distribution matches that of the main survey sample. 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). The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Figure C.3 Treatment effects on perceived wage offer distribution



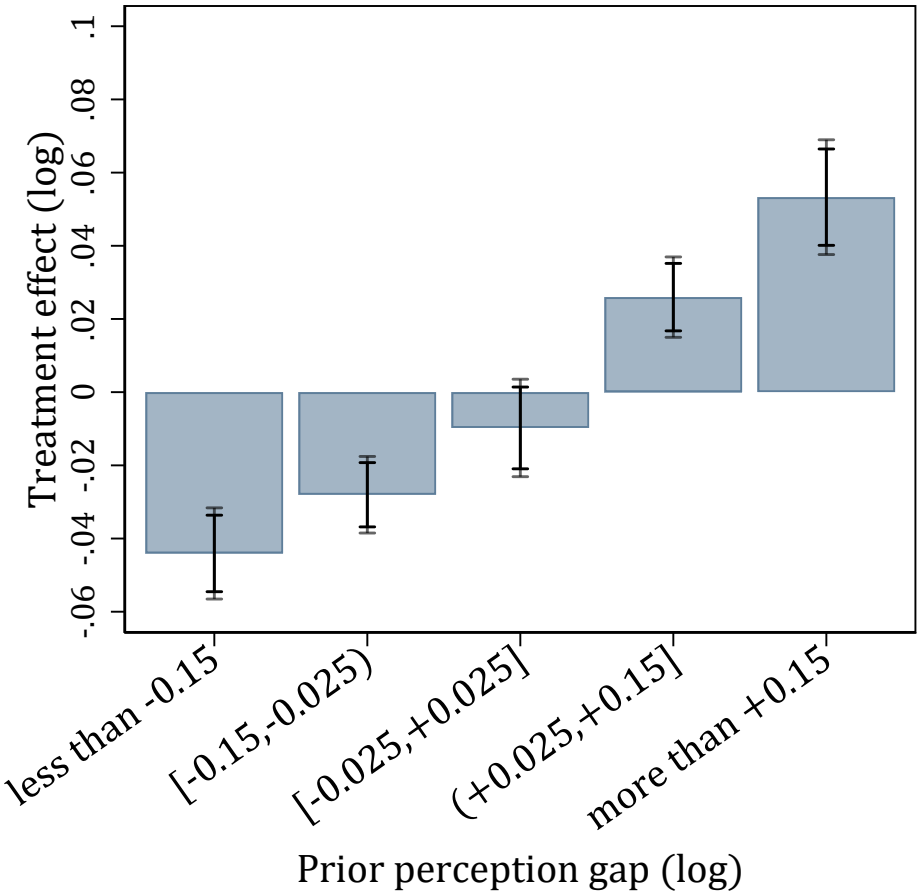
Notes: The figure shows the effects of the information treatment (including 90%- and 95%-confidence intervals) on the mean (log) (Panel A) and the standard deviation (log) (Panel B) of the perceived wage offer distribution reported by the respondent. We show separate estimates for individuals with varying initial perception gaps, that is, who receive varying information shocks regarding the wage potential of comparable workers. 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). The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i \Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Figure C.4 Treatment effects on own expected wage offer by cell characteristics



Notes: The figure shows the effects of the information treatment (including 90% and 95% confidence intervals) on respondents' expected wage offer (log), separately by two measures of cell characteristics. Panel A shows separate estimates by the size of the respondent's assigned demographic cell, split at the median number of register observations underlying the cell. Panel B shows separate estimates by the dispersion of wages within the respondent's assigned cell, split at the median within-cell standard deviation. In all panels, treatment effects are reported separately for individuals with varying initial perception gaps regarding the wage potential of comparable workers. Number of observations: 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). The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Figure C.5 Precision-weighted treatment effects on own expected wage offers



Notes: The figure shows treatment effects on respondents' expected own wage offer (log), including 90% and 95% confidence intervals, adjusted for the precision of the information shock. We use the same grouping of individuals as in the main specification but weight each observation by the inverse of the within-cell variance of comparable workers' re-employment wages, so that respondents from cells with a more precise signal receive greater weight. Number of observations: 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). We estimate the following regression specification throughout: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Table C.2 Treatment effects on own 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***	0.069***	0.068***	0.069***	0.076***
	(0.010)	(0.010)	(0.011)	(0.012)	(0.015)
Treatment ×					
Moderate positive perception gap	0.037***	0.035***	0.035***	0.036***	0.043***
	(0.008)	(0.008)	(0.009)	(0.009)	(0.013)
Treatment ×					
Neutral perception gap	0.004	0.002	0.002	0.002	0.009
	(0.009)	(0.009)	(0.009)	(0.010)	(0.013)
Treatment ×					
Moderate negative perception gap	-0.016**	-0.019**	-0.019**	-0.019**	-0.011
	(0.007)	(0.007)	(0.008)	(0.008)	(0.013)
Treatment ×					
Large negative perception gap	-0.030***	-0.032***	-0.033***	-0.032***	-0.025**
	(0.006)	(0.006)	(0.007)	(0.008)	(0.013)
Additional controls					
Perception-gap group indicator	Yes	Yes	Yes	Yes	Yes
Covariates × group indicators	Yes	Yes	Yes	Yes	Yes
Treatment ×					
Pre-unemployment wage	Yes	Yes	Yes	Yes	Yes
UE duration $\geq$ 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 treatment effects on individuals' expected own wage offer (log), measured in the main survey. The table reports the results of the following regression specification: $y_i = \alpha + \sum_{g=1}^{5} \beta_g \left(\text{Treatment}_i \times \text{PerceptionGap}_{ig}\right) + \sum_{g=2}^{5} \lambda_g \text{PerceptionGap}_{ig} + \mathbf{X}_i'\mathbf{\Pi} + \sum_{g=2}^{5} \left(\text{PerceptionGap}_{ig} \times \mathbf{X}_i\right)' \mathbf{\Theta}_g + \text{Treatment}_i \times \mathbf{Z}_i'\boldsymbol{\gamma} + \epsilon_i$, where $\text{PerceptionGap}_{ig}$ are indicators for the five perception-gap groups (group 1 is the reference group for the group indicators and the covariate interactions), $\mathbf{X}_i$ contains the baseline covariates listed in Table A.2, and $\mathbf{Z}_i$ is the vector of covariates interacted with treatment, added incrementally across Columns (1)–(5): three income groups, long-term unemployment, gender, three age groups, and three education groups. The reported coefficients are the β_g. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C.3 Treatment effects on the perceived mapping from search effort to offer arrival

Dependent variable	Perceived job-arrival (searching 5 hrs/week)$^{(a)}$ (pp.) (1)	Perceived returns to search (diff. 15 vs. 5 weekly hours)$^{(a)}$ (pp.) (2)
A. Large pessimism: perception gap (log) $\in$ (+0.150;$+\infty$)		
Treatment effect	0.988	1.155
	(1.101)	(0.769)
P-value (vs. neutral group)	0.55	0.66
Mean control group	30.61	10.16
Number of observations	1,702	1,702
B. Moderate pessimism: perception gap (log) $\in$ (+0.025; +0.150]		
Treatment effect	1.429	1.232*
	(0.952)	(0.700)
P-value (vs. neutral group)	0.37	0.61
Mean control group	28.81	10.83
Number of observations	2,131	2,131
C. Neutral group: perception gap (log) $\in$ [-0.025; +0.025]		
Treatment effect	-0.046	0.598
	(1.374)	(1.034)
Mean control group	30.48	11.66
Number of observations	1,023	1,023
D. Moderate optimism: perception gap (log) $\in$ [-0.150; -0.025)		
Treatment effect	0.406	0.130
	(0.954)	(0.729)
P-value (vs. neutral group)	0.78	0.71
Mean control group	27.43	12.19
Number of observations	1,951	1,951
E. Large optimism: perception gap (log) $\in$ ($-\infty$;-0.150)		
Treatment effect	0.379	0.563
	(0.849)	(0.684)
P-value (vs. neutral group)	0.79	0.98
Mean control group	25.50	13.19
Number of observations	2,277	2,277

Notes: The table reports the effects of the information treatment on job seekers' perceived job-finding probability and perceived returns to search effort. 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. We estimate the following regression specification throughout: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2. Robust standard errors are reported in parentheses. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.
$^{(a)}$Measured in the main survey.

C.4 Job search and labor market outcomes

In this appendix section, we present additional empirical analyses and robustness checks on treatment effects on job search decisions and labor market outcomes, as well as a correlational analysis of the effects of wage expectations on job search and employment outcomes.

Asymmetric responses: sign of wage news vs. composition of groups One potential issue is that the asymmetric adjustment of selectivity—in terms of wages and geographic scope—and search effort could reflect a differential composition of the groups with high initial optimism vs. high initial pessimism. For example, these groups may differ in pre-unemployment wages, socio-demographic characteristics, or prior beliefs about available jobs, which could all shape job seekers' responsiveness to wage news. While we cannot rule out differences in unobserved characteristics, we examine whether the asymmetric responses survive reweighting on observables. We focus on the two extreme perception-gap groups and use inverse-probability weighting (IPW) to reweight the large-pessimism group to match the covariate distribution of the large-optimism group.

We pursue two complementary strategies. First, we reweight on pre-unemployment wages to account for differences in underlying wage levels, as workers at different points of the wage distribution may differ systematically in their wage opportunities and search behavior. Second, we reweight on respondents' prior beliefs relative to their pre-unemployment wages, measured as the log difference between the two. This makes the groups comparable in the position of their initial beliefs relative to previous earnings, one of the benchmarks to which the floor in Section 3 may be tied. We consider the two approaches separately because conditioning on both simultaneously sharply reduces common support and the effective sample size. For both approaches, we also report specifications that additionally balance gender, age, education, elapsed unemployment duration, and the geographical search radius prior to treatment to account for remaining differences in observable characteristics.

Table C.4 reports the results. As expected, the estimates become somewhat less precise as additional covariates are included in the weights and the effective sample size declines. Nevertheless, the qualitative pattern remains close to the baseline estimates: positive wage news primarily shifts reservation wages and geographic selectivity, whereas negative wage news primarily increases search effort. The joint tests continue to reject symmetric responses across the three search margins in all reweighted specifications. Overall, these results suggest that the asymmetric responses to positive vs. negative wage news are not driven by observable differences in the composition of initially optimistic and initially pessimistic job seekers.

Correlational analysis We examine 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 perception gaps about comparable workers' re-employment wages, these coefficients should have a sign opposite to the corresponding treatment effects.

The results are presented in Table C.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, are less likely to find re-employment, but earn higher re-employment wages conditional on finding a job. 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), with a more muted and insignificant decrease in the re-employment wage. Unlike our experimental evidence, this correlational analysis is susceptible to omitted variable bias, reverse causality, and measurement error. Nonetheless, the observed patterns qualitatively align with the idea that our intervention offsets the effects of job seekers' prior perception gaps on their search behavior and labor market outcomes.

Alternative specifications 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:

$$\begin{aligned} y_i = \beta_0 + \beta_1 \times \text{Treatment}_i \times \text{Perception gap}_i \\ + \beta_2 \times \text{Treatment}_i + \beta_3 \times \text{Perception gap}_i + \mathbf{X}_i \Pi + \epsilon_i. \end{aligned} \tag{27}$$

The coefficient β_1 captures the effect of a one-unit increase in the information shock on the outcome conditional on being treated—i.e., the "intensive margin" of the treatment. β_2 captures treatment effects to the extent they do not linearly depend on the perception gap, and β_3 accounts for common differences across individuals with varying prior

beliefs. $\mathbf{X}_i$ is the vector of baseline control variables.

The results are presented in Table C.6. Consistent with our main findings, the estimates of β_1 highlight statistically significant adjustments in the respondents' expected and demanded wages. We also observe changes in the respondents' search intensity and their willingness to change location, though these effects miss conventional levels of statistical significance. Moreover, the estimates of β_2 highlight that the treatment significantly increases employment rates, earnings and working hours independently of the initial perception gap. This aligns with our earlier evidence of positive labor market effects among both initially overly optimistic and pessimistic respondents.

Table C.6 Panels B and C estimate Equation (27) separately for those with negative and those with positive perception gaps to allow for asymmetric effects of positive and negative information shocks. The corresponding estimates of β_1 broadly confirm our earlier experimental evidence, although the estimates in this demanding sample split sometimes miss statistical significance.

Lastly, we estimate—separately for those with a negative and those with a positive perception gap—the following 2SLS specification, which is commonly used in information-provision experiments (Coibion and Gorodnichenko, 2026a). The specification exploits both the common treatment effect and the extent to which it varies with the perception gap for identification:

$$\begin{aligned}\text{Expected wage}_i = \gamma_0 + \gamma_1 \times \text{Treatment}_i \times \text{Perception gap}_i \\ + \gamma_2 \times \text{Treatment}_i + \gamma_3 \times \text{Perception gap}_i + \mathbf{X}_i\Lambda + \nu_i \quad (28)\end{aligned}$$

$$y_i = \delta_0 + \delta_1 \times \widehat{\text{Expected wage}}_i + \delta_2 \times \text{Perception gap}_i + \mathbf{X}_i\Phi + \epsilon_i, \quad (29)$$

where Equation (28) is the first stage in which we instrument the posterior expected wage offer (log) with both the interaction $\text{Treatment}_i \times \text{Perception gap}_i$ and the non-interacted treatment indicator, and Equation (29) is the second stage. The coefficient of interest, δ_1, captures the effect of a 1% increase in expected offered wages on the outcome. As before, we control for the perception gap and the baseline vector of controls, $\mathbf{X}_i$. The estimates are presented in Figure C.6 and closely align with our main IV estimates in Figure 4. We continue to find significant within-group adjustments consistent with the main IV results. Differences between positive and negative updates are statistically significant for reservation wages ($p = 0.015$) and willingness to make geographic concessions ($p = 0.046$), while the difference in search-effort responses narrowly misses conventional significance ($p = 0.107$). We also reject the joint hypothesis of symmetric responses across all three margins ($p = 0.016$).

Alternative perception-gap thresholds While our main analysis applies a $\pm 15\%$ cutoff, Figure C.7 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.

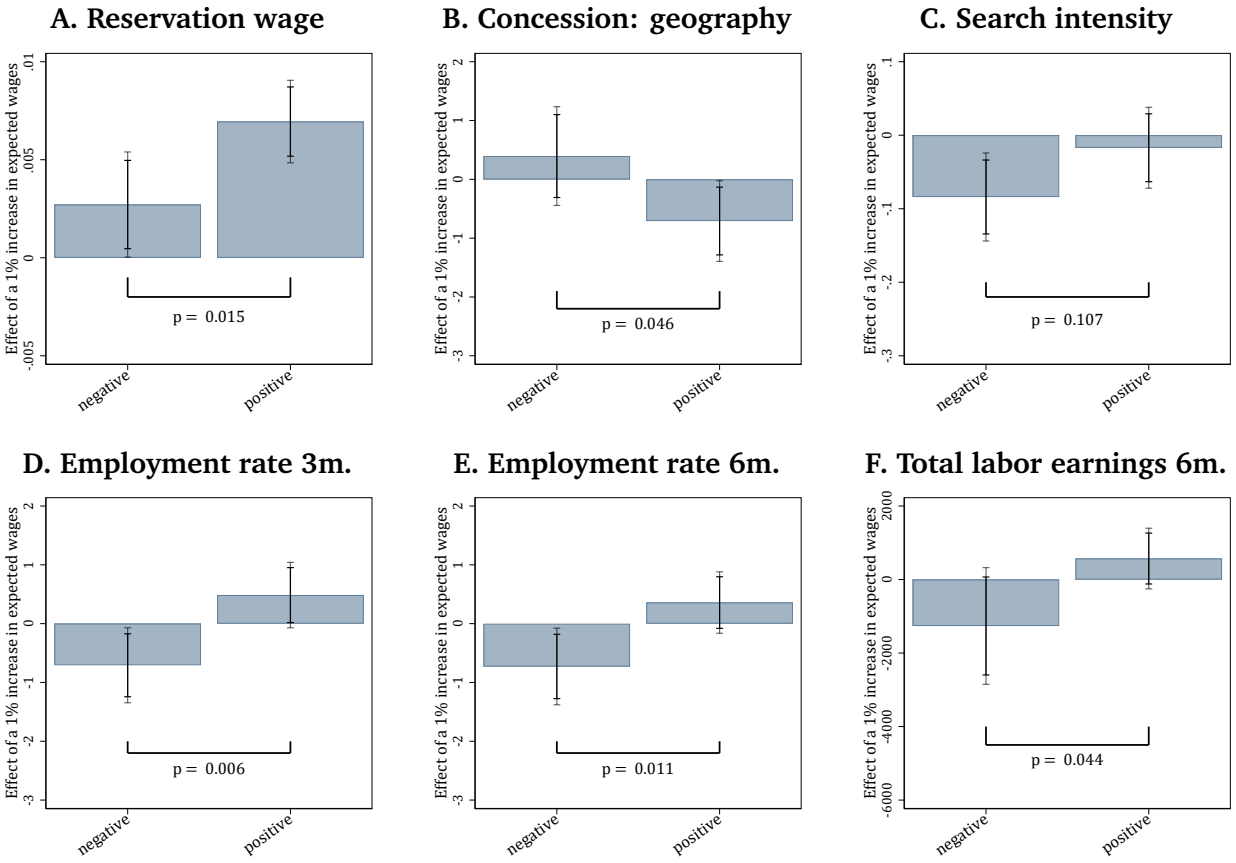
Alternative winsorization In our main analysis, we winsorize expected wage offers and reservation wages at the 5th and 95th percentiles, and search intensity at the 95th percentile. Table C.7 demonstrates robustness to instead winsorizing at the 1st and 99th percentiles for expected wage offers and reservation wages, and at the 99th percentile for search intensity.

Multiple hypothesis testing One concern is that some of our findings are an artifact of multiple hypothesis testing. In Table C.8, 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.[4] 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 Table C.9, the results in the restricted sample of previous full-time workers qualitatively align with our main findings, although they are somewhat less precisely estimated in the restricted sample.

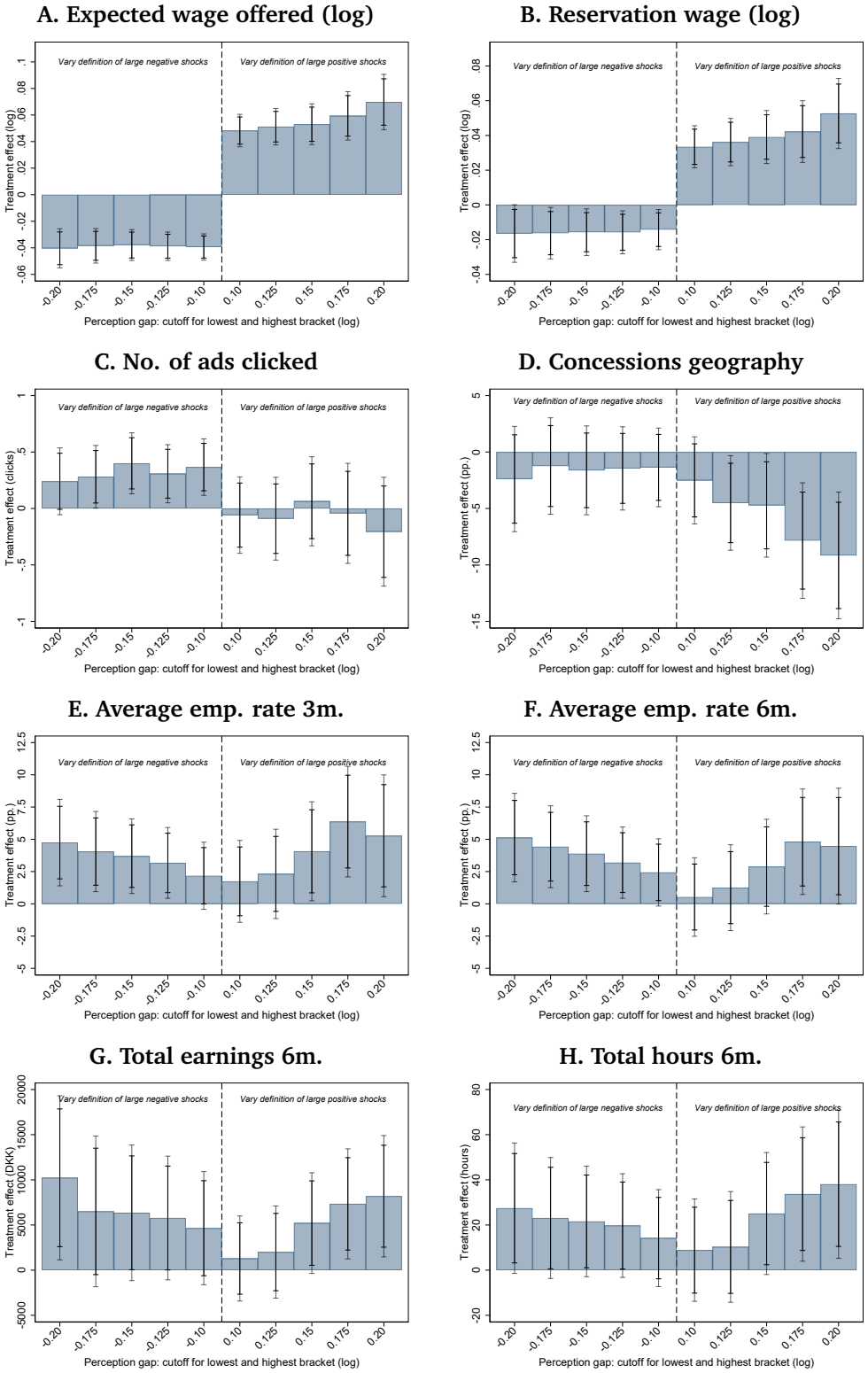
[4]Specifically, sharpened q-values are the minimum false discovery rates—defined as the expected proportion of Type I errors among all rejections within the family of outcomes—at which the corresponding null hypotheses would be rejected (Anderson, 2008; Benjamini et al., 2006). That is, ordering hypotheses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

Figure C.6 2SLS estimates of the effects of wage expectations on job search and labor market outcomes: Alternative specification



Notes: The figure shows 2SLS estimates of the effect of wage expectations on job search behavior and labor market outcomes, with 90% and 95% confidence intervals. We instrument post-treatment expected own wage offers (log) with assignment to the information treatment, and the interaction of treatment assignment and prior perception gaps, estimated separately for job seekers with negative ($N = 4{,}805$) and positive ($N = 4{,}440$) perception gaps. Panel A shows the log reservation wage reported in the survey; Panel B willingness to change location, reported in the survey; Panel C the number of job-ad clicks within one week; Panels D and E average monthly employment rates within three and six months; Panel F total labor earnings within six months. All coefficients are expressed as the effect of a 1% increase in expected wages; for the negative-shock group, negative coefficients therefore imply that downward revisions *increase* the outcome. The figure reports the results of the regression specification (29). The first-stage F-statistic on the excluded instruments is 27.50 for the pessimism group and 30.37 for the optimism group. Reported p-values test equality of the effect of wage expectations between job seekers with negative and positive perception gaps.

Figure C.7 Reduced-form treatment effects on job search and labor market outcomes: Alternative perception-gap thresholds



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. The figure reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i \Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2.

Table C.4 Reduced-form treatment effects on job search and labor market outcomes: Reweighting

	(1)	(2)	(3)	(4)	(5)
Panel A: Treatment effect on reservation wage (log)					
Large pessimism (log. perc. gap > 0.150) (i)	0.039***	0.044***	0.043***	0.032***	0.032***
	(0.008)	(0.011)	(0.015)	(0.009)	(0.011)
Large optimism (log. perc. gap < -0.150) (ii)	-0.016**	-0.016**	-0.016**	-0.016**	-0.016**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
p-value: (i) $= -$(ii)	0.02	0.04	0.10	0.15	0.19
Panel B: Treatment effect on search intensity					
Large pessimism (log. perc. gap > 0.150) (i)	0.064	0.241	0.231	-0.073	0.066
	(0.201)	(0.240)	(0.281)	(0.213)	(0.266)
Large optimism (log. perc. gap < -0.150) (ii)	0.400***	0.400***	0.400***	0.400***	0.400***
	(0.138)	(0.138)	(0.138)	(0.138)	(0.138)
p-value: (i) $= -$(ii)	0.06	0.02	0.04	0.19	0.12
Panel C: Treatment effect on willingness to make geographical concession					
Large pessimism (log. perc. gap > 0.150) (i)	-4.72**	-2.99	-5.57*	-6.99***	-6.68**
	(2.34)	(2.71)	(3.24)	(2.60)	(3.14)
Large optimism (log. perc. gap < -0.150) (ii)	-1.62	-1.62	-1.62	-1.62	-1.62
	(2.01)	(2.01)	(2.01)	(2.01)	(2.01)
p-value: (i) $= -$(ii)	0.04	0.17	0.06	0.01	0.02
p-value: joint symmetry (A)–(C)[(a)]	0.005	0.009	0.023	0.014	0.034
Reweighting variables					
Pre-unemployment wage	No	Yes	Yes	No	No
Prior belief relative to pre-unemp. wage	No	No	No	Yes	Yes
Other characteristics	No	No	Yes	No	Yes
Number of observations					
Large pessimism (eff.)[(b)]	1,723	1,244	742	1,191	762
Large optimism	2,323	2,323	2,323	2,323	2,323

Note: The table examines the robustness of the treatment effects on job search outcomes to reweighting on observable characteristics, separately for the large-pessimism and large-optimism groups. Column (1) reports the baseline estimates. Columns (2)–(5) use inverse-probability weighting (IPW) to reweight the large-pessimism group to match the covariate distribution of the large-optimism group using the variables indicated in the table. Columns (2)–(3) reweight on log pre-unemployment wages. Columns (4)–(5) instead reweight on respondents' prior beliefs relative to their pre-unemployment wages, measured as the log difference between the two. Columns (3) and (5) additionally account for other observed characteristics, including gender, age, education, elapsed unemployment duration, and the geographical search radius prior to treatment. Treatment effects are estimated from $y_i = \beta_0 + \beta_1 \text{Treatment}_i + \mathbf{X}_i \Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Table A.2. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[(a)] The reported joint-symmetry p-values test whether the treatment effects for the large-pessimism and large-optimism groups sum to zero jointly across all three job search outcomes.

[(b)] For the reweighted large-pessimism sample, we report Kish's effective sample size, $N_{\text{eff}} = (\sum_i w_i)^2 / \sum_i w_i^2$.

Table C.5 Correlational analysis using the control group of the effects of wage expectations on job search and labor market outcomes

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)	First hourly wage difference [(e)] (log) (6)
Actual group-level wage (log)	0.488***	0.398***	0.026	-3.128	-5.774	0.037
	(0.041)	(0.045)	(1.025)	(13.173)	(9.749)	(0.112)
Perception gap (ref: neutral group: perception gap (log) ∈ [-0.025; +0.025])						
Large optimism: perception gap (log) ∈ (−∞;-0.150)						
	0.172***	0.143***	-0.456**	5.114*	-4.877**	0.088***
	(0.008)	(0.009)	(0.204)	(2.707)	(2.203)	(0.021)
Moderate optimism: perception gap (log) ∈ [-0.150; -0.025)						
	0.053***	0.042***	-0.105	2.189	-0.745	0.060***
	(0.006)	(0.007)	(0.202)	(2.613)	(2.146)	(0.019)
Moderate pessimism: perception gap (log) ∈ (+0.025; +0.150]						
	-0.060***	-0.036***	0.353*	-1.361	-0.857	0.008
	(0.006)	(0.007)	(0.210)	(2.564)	(2.129)	(0.019)
Large pessimism: perception gap (log) ∈ (+0.150;+∞)						
	-0.160***	-0.114***	0.223	2.701	-2.739	-0.008
	(0.008)	(0.008)	(0.218)	(2.680)	(2.244)	(0.021)
Mean dep. variable	10.35	10.23	2.35	52.02	28.62	-0.08
Number of observations	4,619	4,619	4,619	4,619	4,619	2,624
P-value (large optimism vs. large pessimism)	0.000	0.000	0.000	0.325	0.277	0.000

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. The table reports the results of the following regression specification: $y_i = \alpha + \rho \log(w_i^{\text{group}}) + \sum_{g \neq \text{neutral}} \beta_g \text{PerceptionGap}_{ig} + X_i'\Pi + \epsilon_i$, where $\text{PerceptionGap}_{ig}$ are indicators for the five perception-gap groups and $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Appendix Table A.2. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[(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.

[(e)] Observed in the administrative records. Restricted to respondents who found a job within the observation window.

Table C.6 Reduced-form treatment effects on job search and labor market outcomes: 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)
Panel A: Full sample							
Treatment × perception gap	0.166***	0.090***	-0.568	-3.484	-1.747	-4,051	4.60
	(0.019)	(0.019)	(0.347)	(4.627)	(3.569)	(7,448)	(27.46)
Treatment	0.001	0.009***	0.182**	-1.396	1.368*	2,863**	12.02**
	(0.003)	(0.003)	(0.082)	(1.012)	(0.805)	(1,440)	(6.07)
Perception gap	-0.505***	-0.385***	1.364***	-5.013	3.262	-13,546***	-28.08
	(0.016)	(0.016)	(0.267)	(3.460)	(2.644)	(5,193)	(20.36)
Mean control group	10.35	10.23	2.35	52.02	28.62	56,740	251.27
Number of observations	9,247	9,247	9,247	9,247	9,247	9,247	9,247
Panel B: Negative perception gaps							
Treatment × perception gap	0.083**	0.043	0.367	6.019	-15.558**	-13,707	-22.33
	(0.039)	(0.039)	(0.642)	(9.302)	(6.908)	(16,101)	(55.96)
Treatment	-0.015**	0.001	0.385**	0.047	-1.236	1,174	8.55
	(0.007)	(0.007)	(0.166)	(2.153)	(1.682)	(3,176)	(13.08)
Perception gap	-0.452***	-0.335***	1.271**	-9.487	12.809**	-8,189	10.98
	(0.033)	(0.033)	(0.512)	(7.058)	(5.083)	(11,398)	(42.69)
Mean control group	10.49	10.36	1.89	55.11	26.92	63,313	258.30
Number of observations	4,805	4,805	4,805	4,805	4,805	4,805	4,805
Panel C: Positive perception gaps							
Treatment × perception gap	0.241***	0.142***	-1.081	-19.220*	12.180	7,094	56.46
	(0.047)	(0.048)	(0.893)	(10.664)	(8.804)	(14,012)	(63.57)
Treatment	-0.008	0.002	0.221	1.226	-0.536	1,606	3.55
	(0.007)	(0.007)	(0.187)	(2.190)	(1.786)	(2,829)	(13.09)
Perception gap	-0.461***	-0.343***	0.682	14.782**	-7.278	-20,828**	-95.00**
	(0.034)	(0.035)	(0.635)	(7.498)	(6.203)	(10,221)	(45.05)
Mean control group	10.19	10.10	2.84	48.75	30.46	49,804	244.02
Number of observations	4,440	4,440	4,440	4,440	4,440	4,440	4,440

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. Panel A reports estimates for the full sample. Panel B restricts the sample to respondents with a negative initial perception gap, and Panel C to respondents with a positive initial perception gap, allowing for asymmetric effects of positive and negative shocks. All specifications include the baseline covariates listed in Table A.2. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively. The table reports the results of the regression specification (27).

[(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 C.7 Reduced-form treatment effects on job search and labor market outcomes: Alternative winsorization cutoffs

Dependent variable	Expected wage offered[a] (log)	Reservation wage[a] (log)	No. of job ads clicked[b]	Concession geograph. location[c] (pp.)	Average emp. rate 3m.[d] (pp.)	Average emp. rate 6m.[d] (pp.)	Total earnings 6m.[d] (DKK)	Total hours 6m.[d]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Large pessimism: perception gap (log) $\in$ (+0.150;$+\infty$)								
Treatment effect	0.121***	0.054**	0.041	-4.731**	4.044**	2.863	5,201*	25.01*
	(0.029)	(0.021)	(0.274)	(2.343)	(1.957)	(1.871)	(2,843)	(13.78)
P-value (vs. neutral group)	0.00	0.19	0.43	0.71	0.25	0.63	0.59	0.48
Mean control group	9.93	9.94	3.30	51.93	29.78	37.74	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	0.037***	0.009	-0.130	0.900	-0.968	-1.144	529	3.55
	(0.012)	(0.011)	(0.252)	(2.113)	(1.691)	(1.613)	(2,569)	(12.21)
P-value (vs. neutral group)	0.01	0.45	0.22	0.24	0.63	0.37	0.67	0.81
Mean control group	10.20	10.11	3.53	45.73	30.52	39.46	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	-0.015	0.022*	0.384	-3.350	0.448	1.416	2,565	8.79
	(0.014)	(0.013)	(0.341)	(2.986)	(2.504)	(2.374)	(4,093)	(18.92)
Mean control group	10.30	10.18	2.75	50.37	31.71	41.23	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***	-0.002	0.186	-0.542	-0.314	-0.406	193	1.30
	(0.011)	(0.011)	(0.220)	(2.194)	(1.722)	(1.667)	(2,986)	(13.25)
P-value (vs. 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	52.60	29.79	39.14	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***	-0.013	0.571***	-1.623	3.686**	3.884***	6,278	21.58*
	(0.012)	(0.010)	(0.185)	(2.010)	(1.475)	(1.499)	(3,823)	(12.49)
P-value (vs. 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	58.29	23.50	34.35	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 individuals with varying initial perception gaps. We winsorize prior beliefs, expected own wage offers, and reservation wages at the 1st and 99th percentiles, and search intensity at the 99th percentile. The table reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i\Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Table A.2. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[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 C.8 Reduced-form treatment effects on job search behavior: Multiple hypothesis adjustment

Dependent variable	Reservation wage[a] (log)	No. of job ads clicked[b]	Concession geograph. location[c] (pp.)	Concession working cond.[c] (pp.)	Concession skills/ occ.[c] (pp.)
	(1)	(2)	(3)	(4)	(5)
A. Large pessimism: perception gap (log) $\in (+0.150; +\infty)$					
Treatment effect	0.039***	0.064	-4.722**	-2.543	-0.404
	(0.008)	(0.201)	(2.343)	(2.279)	(1.629)
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	51.93	66.21	87.07
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**	0.400***	-1.624	-0.872	-1.212
	(0.007)	(0.138)	(2.009)	(2.037)	(1.298)
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	58.29	56.72	89.70
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). The table reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i \Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Table A.2. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[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 C.9 Reduced-form treatment effects on job search and labor market outcomes: Excluding previous part-time workers

Dependent variable	Expected wage offered[a] (log)	Reservation wage[a] (log)	No. of job ads clicked[b]	Concession geograph. location[c] (pp.)	Average emp. rate 3m.[d] (pp.)	Average emp. rate 6m.[d] (pp.)	Total earnings 6m.[d] (DKK)	Total hours 6m.[d]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Large pessimism: perception gap (log) $\in$ (+0.150;$+\infty$)								
Treatment effect	0.055***	0.042***	0.029	-3.432	2.895	1.994	5,023	23.82
	(0.008)	(0.008)	(0.231)	(2.640)	(2.135)	(2.051)	(3,232)	(15.36)
P-value (vs. 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	48.88	28.77	37.17	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***	0.013**	0.059	1.233	-1.325	-1.505	221	2.08
	(0.005)	(0.005)	(0.200)	(2.233)	(1.760)	(1.684)	(2,713)	(12.84)
P-value (vs. 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	44.18	30.27	39.44	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	0.016*	0.235	-2.840	0.035	1.051	1,849	5.42
	(0.007)	(0.009)	(0.280)	(3.260)	(2.699)	(2.568)	(4,474)	(20.41)
Mean control group	10.31	10.20	2.54	47.41	30.89	39.87	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***	-0.002	0.210	-0.934	-1.149	-1.169	-1,053	-3.48
	(0.006)	(0.007)	(0.189)	(2.367)	(1.812)	(1.770)	(3,226)	(14.13)
P-value (vs. 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	50.47	28.29	38.14	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***	-0.013*	0.534***	-2.828	3.440**	3.243**	5,938	18.44
	(0.006)	(0.007)	(0.148)	(2.171)	(1.523)	(1.578)	(4,182)	(13.27)
P-value (vs. 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	57.10	21.50	32.64	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. The table reports the results of the following regression specification: $y_i = \beta_0 + \beta_1 \times \text{Treatment}_i + \mathbf{X}_i \Pi + \epsilon_i$, where $\mathbf{X}_i$ denotes prior log expected wages and the baseline covariates listed in Table A.2. The reported p-values refer to post-estimation tests of whether the coefficients for each group differ from that of the neutral group. Robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[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.

C.5 Heterogeneity in responses to positive wage news

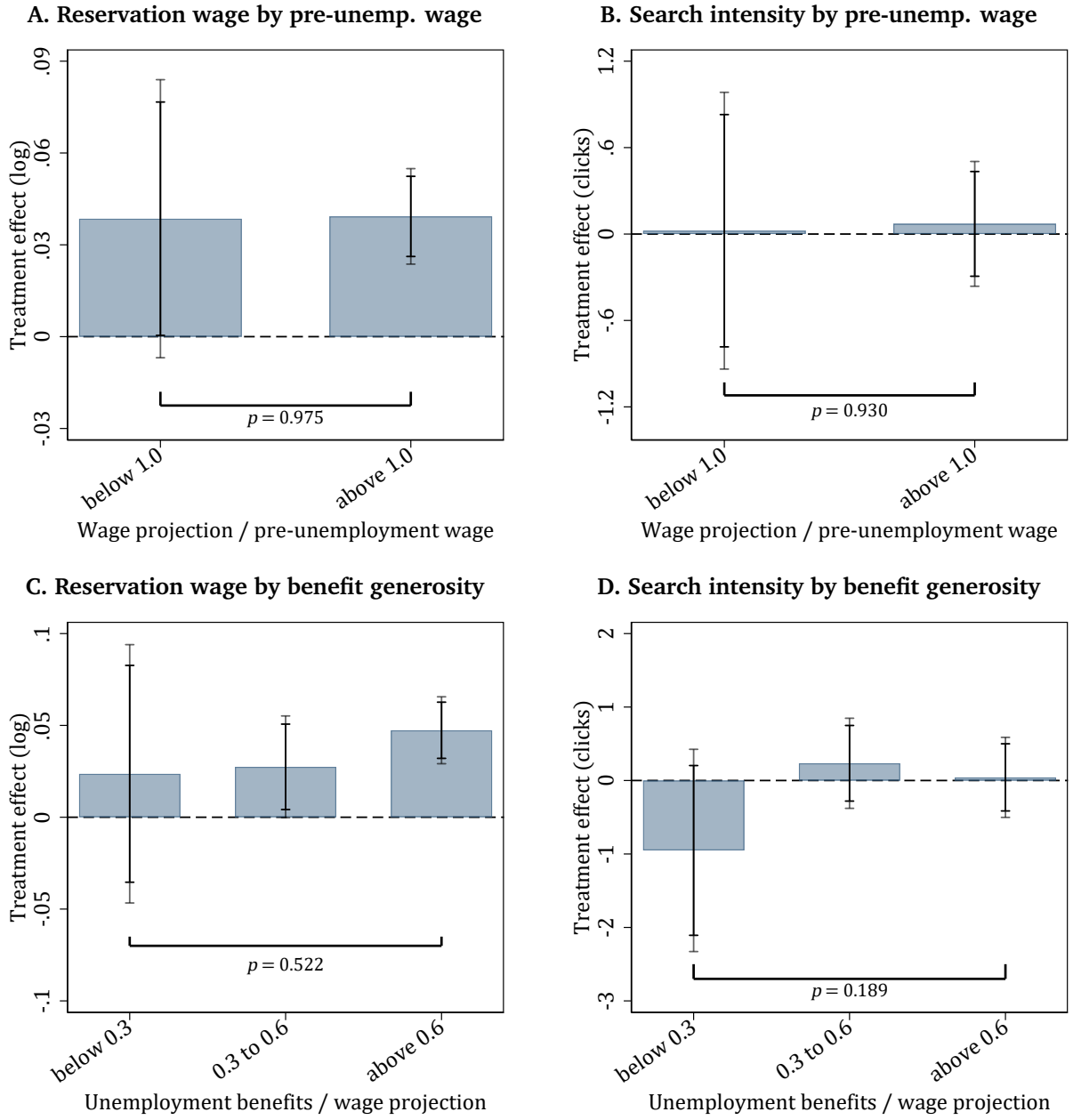
In this appendix section, we examine whether responses to large positive wage news display heterogeneity analogous to the patterns documented for large negative news in Section 4.4.1. Because the positive-news sample is smaller and displays less variation in the relevant moderators, these tests have somewhat lower power than the ones for negative news.

Pre-unemployment wages First, we examine whether responses to large positive wage news vary with the position of the relevant wage projection relative to the pre-unemployment wage. For the negative-news group, the main analysis distinguishes three groups according to the ratio of the projection to the previous wage. Applying the same cutoffs to the positive-news group is less informative because very few job seekers have wage projections substantially below their pre-unemployment wage. We therefore use a simpler split according to whether the projection lies below or above the pre-unemployment wage.[5] Panels A and B of Figure C.8 report the resulting treatment effects on reservation wages and search effort. Reservation wages increase by a similar amount in both groups, and the difference between the estimates is small and statistically insignificant ($p = 0.975$). Search-effort responses are close to zero and likewise show no systematic difference across the two groups ($p = 0.930$). Overall, we find no evidence that responses to positive wage news vary systematically with the position of the projection relative to the previous wage. This contrasts with the heterogeneity we observe for negative news and is consistent with a rigidity that specifically constrains *downward* adjustments in selectivity.

Benefit generosity Second, we examine heterogeneity by unemployment-benefit generosity. Panels C and D of Figure C.8 report treatment effects across groups defined by the ratio of benefits to the respondent's group-level wage projection. In contrast to the clear heterogeneity and margin substitution for negative news, differences across groups are modest and imprecisely estimated for positive news. Reservation-wage effects increase somewhat with the benefit ratio, but the lowest- and highest-benefit groups are statistically indistinguishable ($p = 0.522$). Search-effort estimates are imprecise and do not mirror the negative-news pattern; the lowest-versus-highest difference is also statistically insignificant ($p = 0.189$). Since benefit ratios vary less among respondents receiving positive news, these comparisons have less power than in the negative-news case. Still, the absence of a clear benefit gradient is consistent with rigidity being specific to negative wage news.

[5] Applying that same two-group split to the negative-news group yields qualitatively similar results to the three-group split. We retain the three-group split in the main analysis because it exploits richer variation in the ratio of the wage projection to the previous wage.

Figure C.8 Heterogeneous effects of positive wage news by proxies for wage floor



Notes: The figure shows heterogeneous treatment effects, with 90% and 95% confidence intervals, among job seekers with large positive perception gaps (above $+0.15$), i.e., those who were initially highly pessimistic. Panels A and B split the sample into two groups based on the gap between the benchmark wage and the pre-unemployment wage: benchmark wages below pre-unemployment wages ($N = 313$); and benchmark wages above pre-unemployment wages ($N = 1{,}410$). Panels C and D split the sample into three groups based on the ratio of unemployment benefits to the benchmark wage: below 0.3 ($N = 88$), 0.3 to 0.6 ($N = 632$), and above 0.6 ($N = 1{,}003$). Panels A and C report effects on log reservation wages; Panels B and D report effects on search intensity, measured by job-ad clicks in the first week after the survey. The estimates are based on $y_i = \beta_0 + \sum_{g=2}^{G} \gamma_g \text{Group}_{ig} + \delta_1 \text{Treatment}_i + \sum_{g=2}^{G} \delta_g \left(\text{Treatment}_i \times \text{Group}_{ig}\right) + \mathbf{X}_i \Pi + \epsilon_i$, where Group_{ig} denotes indicators for the pre-unemployment-wage or benefit-ratio groups, G denotes the number of groups in the respective specification, and $\mathbf{X}_i$ contains prior log expected wages and the baseline covariates listed in Appendix Table A.2. Reported p-values test equality of the treatment effects between the lowest and highest groups in each panel.

C.6 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 DKK 1,000 ($\approx$ USD 145), 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.10 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.[6] 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 who 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, including their search effort and the geographical scope of their search. The full survey

[6]Denmark 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.

instructions can be found in Appendix E.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.

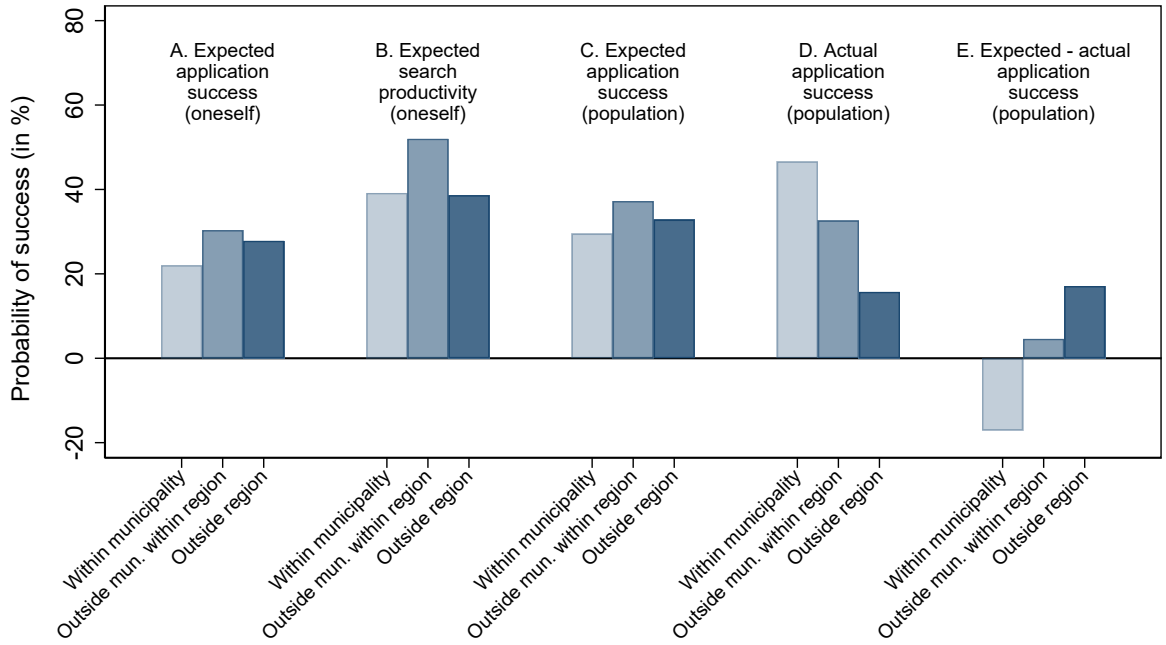
First, on average, job seekers expect to be more effective when searching for jobs outside their municipality of residence than when searching within it. Panels A and B of Figure C.9 show that job seekers perceive themselves to be most effective when searching and applying for jobs located outside their 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.9 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%). Respondents underestimate the success rates of local applications by approximately 17 pp. 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 5 pp. Participants are substantially too optimistic about applications outside their region (+17 pp). 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.11 presents correlations between individuals' perceived efficiency differences across areas and the geographic scope of their own search. For example, a 10 pp 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 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.

Figure C.9 Beliefs about effectiveness of local vs. 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.

Table C.10 Summary statistics for 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.

Table C.11 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)]	0.535	0.059***		
	(0.673)	(0.015)		
Nationwide - municipality[(d)]			0.501	0.034***
			(0.467)	(0.010)
Mean value dep. variable	18.182	3.949	18.182	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)]	0.012	0.044***		
	(0.495)	(0.011)		
Nationwide - municipality[(d)]			0.935***	0.037***
			(0.333)	(0.007)
Mean value dep. variable	18.182	3.949	18.182	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 parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

[(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.

D Model-based analysis of revisions of wage expectations

In this appendix, we provide details on the model-based analysis of revisions of wage expectations presented in Section 4.5, which combines the reduced-form estimates with the theoretical framework from Section 3.

D.1 Model calibration

We implement separate counterfactual exercises for initially highly optimistic and initially highly pessimistic job seekers, the two groups for which our intervention produces strong first-stage effects on wage expectations.

For each group, we simulate 100,000 job seekers. For each simulated worker, we draw a pre-unemployment wage, the point forecast of the expected wage offer, and the perceived dispersion of wage offers constructed from the subjective probability distribution described in Section 2.3, from the corresponding control-group distributions. The perceived distribution determines the job seeker's reservation wage and search effort. We assume that true log wage offers are normally distributed around the worker's pre-unemployment wage with dispersion σ_{true}, which we estimate below, and that labor market outcomes are determined by this true offer distribution. A belief revision shifts the perceived mean while leaving perceived dispersion unchanged. In the counterfactual exercises, we apply the estimated group-average belief revision uniformly to all simulated workers within each group.

Common assumptions Given their beliefs, job seekers choose a reservation wage v_i and search effort s_i.[7] Search effort entails quadratic costs, $\gamma(s) = cs_i^2/2$, where c governs the cost of search and q_i denotes the probability that an individual wage offer exceeds job seeker i's reservation threshold. We map latent search effort into observed job-ad clicks proportionally, choosing the conversion factor λ_{click} to reproduce the control-group mean number of clicks, and map search effort and offer acceptance into employment according to

$$h_i = 1 - \exp\left(-As_iq_i\right),$$

[7] In Section 3, we formulate the acceptance decision in terms of a reservation job value, where job value can depend on both wages and non-wage job attributes, such as location. In the quantitative analysis, however, we separate the geographic search margin—the non-wage dimension relevant for our application—from the acceptance decision: geographic adjustment affects where job seekers search and their matching productivity, while acceptance depends only on the wage offer. The reservation job value in the theoretical model therefore corresponds to a reservation wage in the quantitative implementation. We use the term reservation wage throughout this section.

where A is a matching-scale parameter governing how search effort and offer acceptance translate into employment. For each group, initially optimistic and initially pessimistic job seekers, we choose A such that the model reproduces the corresponding control-group average monthly employment rate over the three months following the intervention.

Negative wage news For initially optimistic job seekers, we compare behavior under the beliefs prevailing in the control group with behavior after a downward revision of X log points. By varying X, we evaluate belief revisions of different sizes. For each value of X, we solve the model under both the control-group and revised belief distributions, allowing the revision to affect reservation wages, search effort, and the probability of accepting an offer.

A downward revision in mean expected wage offers lowers the reservation wage, but the extent of this adjustment is limited by downward rigidity (see Section 3.1). We capture this floor by limiting the decline in the reservation wage. Specifically, we denote the reservation wage implied by control-group beliefs by v_i^0 and the reservation wage after a downward belief revision of X log points by $v_i^1(X)$. We allow reservation wages to adjust subject to

$$v_i^1(X) \geq (1-\delta)v_i^0,$$

where δ governs the maximum decline relative to the reservation wage under control-group beliefs. The constraint is a reduced-form implementation of the downward rigidity observed in the experiment. It parsimoniously captures the different forces discussed in Section 3, including floors linked to previous earnings, current benefit income, or other standards for acceptable pay, and captures the average extent to which downward adjustment in selectivity becomes constrained at the experimental belief revision.

Estimation For the negative-news exercise, we estimate three model parameters: the search-cost parameter c, the maximum decline in reservation wages δ, and the dispersion of the true wage-offer distribution σ_{true}. We collect these parameters in the vector

$$\theta = (c, \delta, \sigma_{\text{true}}),$$

and discipline them using the effects of the 3.8% downward belief revision induced by our treatment on reservation wages, three-month employment, and six-month earnings. The vector $\widehat{\mathbf{m}}$ collects these three reduced-form estimates and $\mathbf{m}(\theta)$ the corresponding model-implied effects. We estimate θ by minimum distance:

$$\widehat{\theta} = \arg\min_{\theta} \left[\widehat{\mathbf{m}} - \mathbf{m}(\theta)\right]' W \left[\widehat{\mathbf{m}} - \mathbf{m}(\theta)\right],$$

where the diagonal weighting matrix

$$W = \text{diag}\left(\frac{1}{0.007^2}, \frac{1}{0.015^2}, \frac{1}{3830^2}\right)$$

weights each moment by the inverse of its estimated variance.[8] The three moments enter the minimum-distance objective as calibration targets, and for each candidate parameter vector we choose the matching-scale parameter A to reproduce the control-group three-month employment rate. We then solve the model under the beliefs prevailing in the control group and after the 3.8% downward revision and calculate the three model-implied treatment effects. Holding the estimated parameters fixed, we subsequently simulate downward belief revisions of different sizes.

The effect on accepted wages is not targeted in the estimation. It is calculated from the estimated true wage-offer distribution conditional on the offer exceeding the reservation threshold and therefore reflects how the belief revision changes the composition of accepted offers.

Positive wage news For initially highly pessimistic job seekers, we compare behavior under the beliefs prevailing in the control group with behavior after an upward revision of X log points. By varying X, we evaluate positive belief revisions of different sizes. We carry over the estimated search-cost parameter c and the dispersion of the true wage-offer distribution σ_{true} from the negative news exercise, assuming a common search technology and true offer distribution across initially optimistic and pessimistic job seekers.

We model adjustments in reservation wages and the geographic scope of search, incorporating the mechanism developed in Appendix B.5, while holding total search effort fixed in line with the reduced-form evidence in our baseline calibration.[9] Upward belief revisions therefore affect employment through reservation wages and the geographic allocation of search. Let z denote the geographic radius within which a job seeker submits applications. We parameterize the response of this application radius to a belief revision of X log points as

$$\Delta \log z(X) = -\kappa X, \qquad \kappa = \frac{0.074}{0.053}.$$

Here, 0.053 is the estimated first-stage increase in mean expected wage offers and 0.074 is the corresponding reduced-form decline in the application radius. Thus, κ maps belief revisions of different sizes into changes in the geographic scope of applications. Con-

[8]The weights follow from the standard errors of the reduced-form estimates for reservation wages, three-month employment, and six-month earnings, respectively.

[9]In Appendix D.5, we examine the robustness of the positive-news exercise to allowing effort to adjust endogenously.

sistent with the reduced-form employment effects, the resulting geographic narrowing raises matching productivity according to

$$M_{\text{geo}}(X) = \exp(\zeta \kappa X),$$

with $M_{\text{geo}}(0) = 1$. Employment after an upward belief revision of X log points is therefore given by

$$h_i(X) = 1 - \exp\left[-A s_i q_i(X) M_{\text{geo}}(X)\right],$$

where $q_i(X)$ is the probability that a wage offer exceeds the reservation threshold under the revised beliefs. Thus, positive wage news affects employment through two countervailing channels: the increase in reservation wages reduces $q_i(X)$, whereas the geographic narrowing raises matching productivity through $M_{\text{geo}}(X)$.

We calibrate ζ such that the reservation-wage and geographic-reallocation channels jointly reproduce the experimental effect on three-month employment at the observed 5.3% belief revision. Because the reservation-wage response is not targeted, it provides an additional assessment of model fit. The spatial extension focuses on differences in matching productivity across local and distant search. We do not model how geographic reallocation changes the distribution of wage offers or non-wage job values across the jobs to which workers apply. We therefore use the positive-news exercise to quantify employment effects and their decomposition, but not the effects on accepted wages.

The positive-news exercise relies on two assumptions, for which we present sensitivity checks in Section D.5. First, when extrapolating beyond the experimentally observed belief revision, the baseline model maintains a constant elasticity of matching productivity with respect to the geographic scope of search. Thus, further reductions in search radius generate productivity gains at the same proportional rate. Our extension relaxes this assumption by allowing additional geographic narrowing beyond the experimental anchor to generate smaller productivity gains and, eventually, to reduce matching productivity. Second, the baseline positive-news exercise holds total search effort s_i fixed, consistent with the absence of a treatment response in the data, while the extension allows search effort to adjust endogenously.

D.2 Parameter estimates and model fit

Parameter estimates Table D.1 summarizes the parameter estimates for the negative- and positive-news exercises. We estimate a search-cost parameter of $c = 0.603$ and a dispersion of true log wage offers of $\sigma_{\text{true}} = 0.271$. The search-cost parameter governs how strongly effort responds to changes in the expected return to search and its absolute magnitude depends on the normalization of search effort. The estimated

Table D.1 Parameters and calibration inputs for counterfactual analysis

A. Common parameters			
c	Search cost	0.603	Estimated: negative news
σ_{true}	True offer dispersion	0.271	Estimated: negative news
β	Effective discount factor	0.9	Assumed
B. Negative news			
δ	Max. downward adjustment	0.0203	Three target moments
A_{-}	Matching-scale parameter	0.0034	Control employment (3m)
λ_{click}	Click conversion	0.097	Control click level
$\sigma^{-}_{perc,i}$	Perceived offer dispersion (med.)	0.106	Large-optimism controls
Pre-unempl. wage (log)	Mean	10.468	Large-optimism controls
Effective replacement rate	Mean	0.548	Large-optimism controls
C. Positive news			
A_{+}	Matching-scale parameter	0.0030	Control employment (3m)
κ_{geo}	Radius response / belief revision	1.396	Experimental responses
ζ_{geo}	Productivity of narrower search	3.942	Employment effect (3m)
M_{+}	Geography multiplier at anchor	1.339	Implied by ζ_{geo}
$\sigma^{+}_{perc,i}$	Perceived offer dispersion (med.)	0.103	Large-pessimism controls
Effort	Search effort after correction	Fixed	No treatment response
Pre-unempl. wage (log)	Mean	10.039	Large-pessimism controls
Effective replacement rate	Mean	0.776	Large-pessimism controls

Notes: The table reports the parameters and calibration inputs for the positive- and negative-news counterfactual exercises. For negative news, we jointly estimate the search-cost parameter c, the dispersion of the true offer distribution σ_{true}, and the parameter δ governing the maximum downward adjustment in reservation wages by matching the treatment effects on reservation wages, three-month employment, and six-month earnings. For positive news, we carry over c and σ_{true}, assuming a common search technology and true offer distribution across groups. We calibrate the response of geographic scope to beliefs using the experimental belief and application-radius effects, and the productivity gain from geographic reallocation using the three-month employment effect. Each exercise uses the corresponding group's distributions of pre-unemployment wages and perceived wage offers, together with a separate matching scale calibrated to control-group employment. The effective replacement rate is the mean ratio of unemployment benefits to pre-unemployment wages in the respective control group.

dispersion of true wage offers is substantially larger than the median perceived dispersion of 0.106 among initially highly optimistic job seekers and of 0.103 among initially highly pessimistic job seekers. Job seekers therefore make search decisions based on a perceived offer distribution that is considerably less dispersed than the distribution of realized wage offers. The latter determines the probability that an actual offer exceeds the reservation wage and the distribution of realized wages.

For the negative-news exercise, we estimate a downward-adjustment parameter of $\delta = 0.0203$. This parameter captures the overall degree of downward rigidity in the group and corresponds to a maximum decline of approximately 2% relative to the level under control-group beliefs. As belief revisions become larger, further reductions in reservation wages are therefore increasingly constrained and adjustment shifts toward search effort. Finally, we choose the matching-scale parameter $A_{-} = 0.0034$ such that the model reproduces the three-month control-group employment rate.

For the positive-news exercise, we retain the estimated search-cost parameter c and true offer dispersion σ_{true}, but choose a separate matching-scale parameter, $A_{+} =$

Table D.2 Calibration targets and model fit

Exercise	Moment	Data	Model	Status
A. Negative wage news				
Negative	Reservation wage (%)	-1.60	-1.64	Calibration target
Negative	Employment after 3 months (pp)	3.70	3.34	Calibration target
Negative	Earnings after 6 months (DKK)	6,349	7,715	Calibration target
Negative	Job-ad clicks (number)	0.40	0.13	Not used in calibration
Negative	Employment after 6 months (pp)	3.90	4.94	Not used in calibration
Negative	Accepted wage (%)	-3.10	-1.32	Not used in calibration
Negative	Hours worked after 6 months	21.57	33.53	Not used in calibration
B. Positive wage news				
Positive	Log application radius	-0.074	-0.074	Calibration target
Positive	Employment after 3 months (pp)	4.10	4.10	Calibration target
Positive	Reservation wage (%)	3.90	3.42	Not used in calibration

Notes: The table reports the calibration moments and compares the reduced-form treatment effects with the corresponding model predictions for both counterfactual exercises.

0.0030, to reproduce the three-month control-group employment rate among initially highly pessimistic job seekers. The geographic-response parameter, $\kappa_{\text{geo}} = 1.396$, reflects the 7.4% reduction in application radius associated with the experimental 5.3% upward belief revision. The productivity parameter, $\zeta_{\text{geo}} = 3.942$, is calibrated to match the corresponding three-month employment effect. Under this geographic-productivity mapping, the calibration implies a 34% increase in effective matching productivity $(M_+ = 1.339)$ at the experimental revision.

Model fit Table D.2 compares the reduced-form treatment effects with the corresponding model predictions. For negative news, the model broadly reproduces the three targeted moments: the decline in reservation wages, the increase in three-month employment rates, and the increase in six-month earnings. The remaining outcomes provide untargeted comparisons. The model correctly predicts an increase in job-ad clicks and six-month employment and a decline in accepted wages, while understating the magnitudes of the click and wage responses and overstating the six-month employment effect. The discrepancy in clicks is likely due to the fact that clicks are only a proxy for the model's latent search effort: clicking on an additional vacancy is relatively inexpensive and need not correspond to a proportionate increase in job applications. The discrepancy in wages could reflect that model-implied accepted wages capture only workers' acceptance decisions, whereas realized wages may also respond through labor demand and selection into employment. The model also overstates the increase in hours worked after six months, predicting 33.53 hours compared with 21.57 in the data. Overall, it captures the direction of the untargeted responses, although it does not fully reproduce their magnitudes.

For positive news, the decline in application radius directly anchors the geographic

response, while the matching-productivity parameter is calibrated so that the model reproduces the three-month employment effect. The reservation-wage response therefore provides the main untargeted comparison. The model predicts an increase of 3.42%, close to the reduced-form estimate of 3.90%. This close fit is notable because the reservation-wage response is generated by the parameters carried over from the negative-news exercise together with the positive-news group's pre-unemployment wage and perceived offer distributions.

D.3 Mechanism decomposition

We decompose each model-implied employment effect into its two channels using a Shapley decomposition (Shorrocks, 2013). For each channel, we compute its contribution twice: once when it is activated first, holding the other channel at its value under control-group beliefs, and once when it is activated second, after the other channel has already been adjusted. Averaging these two marginal contributions assigns any interaction between the channels symmetrically and ensures that the two contributions sum to the total employment effect. For negative news, the two channels are the adjustment in reservation wages and the change in search effort. For positive news, they are the adjustment in reservation wages and the change in matching productivity induced by geographic reallocation.

Let $H(d_1, d_2)$ denote the model-implied employment rate, where $d_j = 0$ evaluates channel j at its value under control-group beliefs and $d_j = 1$ evaluates it at its value after the belief revision. In both exercises, the first channel is the reservation-wage adjustment. The second channel is search effort for negative news and matching productivity for positive news.

The contribution of the first channel is

$$C_1 = \frac{1}{2}\left[H(1,0) - H(0,0) + H(1,1) - H(0,1)\right],$$

and the contribution of the second channel is

$$C_2 = \frac{1}{2}\left[H(0,1) - H(0,0) + H(1,1) - H(1,0)\right].$$

Each contribution is therefore the average marginal effect of activating that channel across the two possible orderings of the channels. This accounts for interactions between the channels and ensures that the two contributions sum to the total model-implied employment effect:

$$C_1 + C_2 = H(1,1) - H(0,0).$$

D.4 Counterfactual results

Table D.3 reports the predicted effects of belief revisions of different sizes in the absence of congestion and decomposes the resulting employment effects into their underlying behavioral channels. The rows marked with a dagger correspond to the experimentally observed belief revisions and therefore serve as the calibration anchors. The remaining rows extrapolate the estimated model to smaller and larger revisions while holding the structural parameters fixed.

Negative wage news For initially highly optimistic job seekers, downward belief revisions raise employment through both lower reservation wages and greater search effort. At the experimental revision of 3.8%, the model predicts a three-month employment effect of 3.3 pp, with the two channels contributing almost equally: 1.5 pp through lower reservation wages and 1.8 pp through greater search effort. For the smaller revision of 2%, the employment gain is 1.5 pp and operates almost entirely through the reservation-wage channel. Search effort contributes only 0.2 pp because the downward adjustment in reservation values is not yet constrained at this revision size. There is therefore little substitution toward the search-effort margin.

As the belief revision increases, the relative importance of the two channels changes substantially. The reservation-wage contribution rises only modestly, from 1.3 pp at a 2% revision to 1.7 pp at a 10% revision. This flattening reflects the estimated limit on downward adjustment in reservation values: as the constraint becomes binding for a growing share of job seekers, further belief revisions produce little additional decline in reservation wages. Adjustment instead shifts increasingly toward search effort, whose contribution rises from 1.8 pp at the experimental revision to 11.2 pp at a 10% revision. Consequently, the total three-month employment effect increases to 6.3 pp for a 6% revision, 9.4 pp for an 8% revision, and 12.9 pp for a 10% revision. The decomposition therefore reveals a clear substitution across adjustment margins: small revisions operate mainly through greater willingness to accept available offers, whereas the additional gains from larger revisions are driven primarily by more intensive search.

The model also predicts modest declines in accepted wages. At the experimental revision, mean accepted wages among workers employed within six months fall by 1.3%. The decline becomes only slightly larger as the revision increases, reaching 1.6% at a 10% revision. This limited variation is consistent with the relatively small additional reductions in reservation wages once the downward-adjustment constraint binds.

Positive wage news For initially highly pessimistic job seekers, the two mechanisms work in opposite directions. An upward revision raises reservation wages and thereby lowers the probability that a given offer is accepted. At the same time, it narrows the geographic scope of applications and, assuming that more locally concentrated search

Table D.3 Counterfactual effects of revising wage expectations

A. Negative wage news

Belief revision (%)	Employment effect (pp)	Mechanism decomposition: contributions to employment		Accepted wage effect (%)
		Reservation wage (pp)	Search effort (pp)	
2.0	1.48	1.25	0.23	-1.12
3.8†	**3.34**	**1.49**	**1.84**	**-1.32**
6.0	6.25	1.56	4.69	-1.38
8.0	9.40	1.63	7.77	-1.48
10.0	12.88	1.71	11.17	-1.61

B. Positive wage news

Belief revision (%)	Employment effect (pp)	Mechanism decomposition: contributions to employment		
		Reservation wage (pp)	Geographic reallocation (pp)	
2.0	1.32	-1.24	2.57	—
4.0	2.91	-2.59	5.51	—
5.3†	**4.10**	**-3.52**	**7.62**	—
8.0	6.97	-5.54	12.51	—
10.0	9.45	-7.07	16.51	—

Notes: The table reports the counterfactual three-month employment effects of belief revisions of different sizes and their decomposition into the underlying behavioral channels. Panel A additionally reports the model-implied percentage change in mean accepted wages. We do not report an analogous effect for positive news because the spatial extension does not model how geographic reallocation affects wage offers or non-wage job values. All counterfactual results assume no congestion ($\phi = 0$). Appendix Table D.4 shows how the predicted employment effects vary with the degree of congestion. The rows marked with † denote the experimental calibration anchors.

is more productive, increases effective matching productivity. At the experimental revision of 5.3%, the increase in reservation wages reduces three-month employment by 3.5 pp, while geographic reallocation raises it by 7.6 pp. The latter effect more than offsets the former, yielding a net employment gain of 4.1 pp.

Both opposing channels become stronger as the size of the belief revision increases. For a 2% revision, the reservation-wage channel lowers employment by 1.2 pp, while geographic reallocation raises it by 2.6 pp, producing a net gain of 1.3 pp. At a 10% revision, the corresponding effects are -7.1 pp and 16.5 pp, respectively, resulting in a net employment increase of 9.5 pp. Thus, throughout the range considered, the matching-productivity gains from geographic reallocation dominate the adverse effect of greater selectivity. Unlike for negative news, however, the positive employment effect

relies entirely on this geographic channel: absent the productivity gain from narrower search, the increase in reservation wages would reduce employment.

Taken together, the decompositions highlight the asymmetry in how negative and positive wage news affect job finding. Negative news accelerates employment through two complementary channels, although larger revisions increasingly operate through search effort. Positive news instead generates offsetting forces, with employment rising only because the productivity gains from geographic reallocation exceed the decline in offer acceptance induced by higher reservation wages.

D.5 Extensions

Congestion We examine how congestion affects the counterfactual predictions. Congestion may arise when many job seekers increase their search effort or redirect applications toward the same vacancies—for example, following widespread belief revisions induced by a large-scale information campaign. Stronger competition may then reduce the resulting matching gains and partly displace other job seekers. The aim of this exercise is to illustrate the sensitivity of our predictions to such crowding-out of additional matching opportunities, rather than to provide a full general-equilibrium analysis, which would allow changes in both search effort and selectivity to affect the matching opportunities available to others. We capture crowding-out with a congestion parameter $\phi \in [0, 1]$, which attenuates the additional matching opportunities generated by greater search effort or geographic reallocation. We do not estimate ϕ, but vary it in a sensitivity analysis. The case $\phi = 0$ corresponds to the benchmark case without crowding-out, in which behavioral responses do not affect other job seekers' matching opportunities. At $\phi = 1$, the additional gains generated by search effort or geographic reallocation are fully crowded out, while the reservation-wage channel remains unchanged.

For negative news, congestion attenuates the increase in offer arrivals generated by greater search effort. If the belief revision changes effort from s_i^0 to s_i^1, the effective effort multiplier is

$$\left(\frac{s_i^1}{s_i^0}\right)^{1-\phi}.$$

Thus, $\phi = 0$ preserves the full increase in offer arrivals implied by the individual effort response, whereas at $\phi = 1$ this increase is fully crowded out.

For positive news, congestion instead attenuates the matching-productivity gain from geographic reallocation:

$$M_{\text{geo}}(X, \phi) = M_{\text{geo}}(X)^{1-\phi}.$$

At $\phi = 0$, geographic narrowing produces the full productivity gain assumed in the

Table D.4 Employment effects under varying degrees of congestion

Belief revision (%)	Congestion parameter ϕ 0.0	0.3	0.5	0.7	1.0
A. Negative wage news					
2.0	1.48	1.40	1.35	1.30	1.22
3.8†	**3.34**	**2.76**	**2.38**	**2.01**	**1.46**
6.0	6.25	4.75	3.80	2.86	1.52
8.0	9.40	6.87	5.28	3.76	1.62
10.0	12.88	9.15	6.86	4.71	1.76
B. Positive wage news					
2.0	1.32	0.55	0.04	-0.46	-1.20
4.0	2.91	1.23	0.15	-0.90	-2.41
5.3†	**4.10**	**1.76**	**0.28**	**-1.16**	**-3.21**
8.0	6.97	3.09	0.66	-1.65	-4.89
10.0	9.45	4.29	1.07	-1.95	-6.14

Notes: The table reports model-implied three-month employment effects, in percentage points, for belief revisions of different sizes and varying degrees of congestion. The congestion parameter ϕ is not estimated but varied as a sensitivity parameter, with $\phi = 0$ denoting the benchmark without congestion. For negative news, higher ϕ attenuates the additional offer arrivals generated by greater search effort; at $\phi = 1$, this channel is fully crowded out and only the reservation-wage channel remains. For positive news, higher ϕ attenuates the matching-productivity gain from geographic reallocation; at $\phi = 1$, only the negative reservation-wage channel remains. The rows marked with † denote the experimental calibration anchors.

benchmark exercise. At $\phi = 1$, this gain is fully crowded out, leaving only the negative employment effect generated by the increase in reservation wages.

Table D.4 shows that congestion changes the employment effects of both negative and positive wage news, but with differences across the two exercises.

For negative news, the predicted employment effects remain positive at all levels of congestion because lower reservation wages continue to raise offer acceptance even when the additional offer arrivals generated by greater search effort are crowded out. At the experimental 3.8% revision, the employment effect declines from 3.3 pp without crowding-out to 2.8 pp at $\phi = 0.3$, 2.4 pp at $\phi = 0.5$, and 1.5 pp under complete crowding-out. Larger belief revisions are more sensitive to congestion because their additional employment gains operate primarily through search effort. For a 10% revision, for example, the predicted effect falls from 12.9 pp without congestion to 6.9 pp at $\phi = 0.5$ and 1.8 pp at $\phi = 1$. By contrast, the effect of a 2% revision changes little because it operates almost entirely through the reservation-wage channel.

For positive news, congestion can reverse the sign of the employment effect because it attenuates the gains from higher matching productivity through geographic reallocation. By contrast, it leaves the negative reservation-wage channel unaffected, so the

accompanying increase in reservation wages continues to reduce offer acceptance. At the experimental 5.3% revision, the net employment effect falls from 4.1 pp without crowding-out to 1.8 pp at $\phi = 0.3$ and is approximately zero at $\phi = 0.5$. It becomes negative at higher levels of congestion, reaching -1.2 pp at $\phi = 0.7$ and -3.2 pp under complete crowding-out. The same pattern holds across revision sizes: geographic reallocation dominates when congestion is limited, but once its productivity gain is sufficiently attenuated, the negative reservation-wage channel dominates. Thus, the positive employment effects of upward belief revisions depend more strongly on the absence of substantial congestion than the effects of downward revisions.

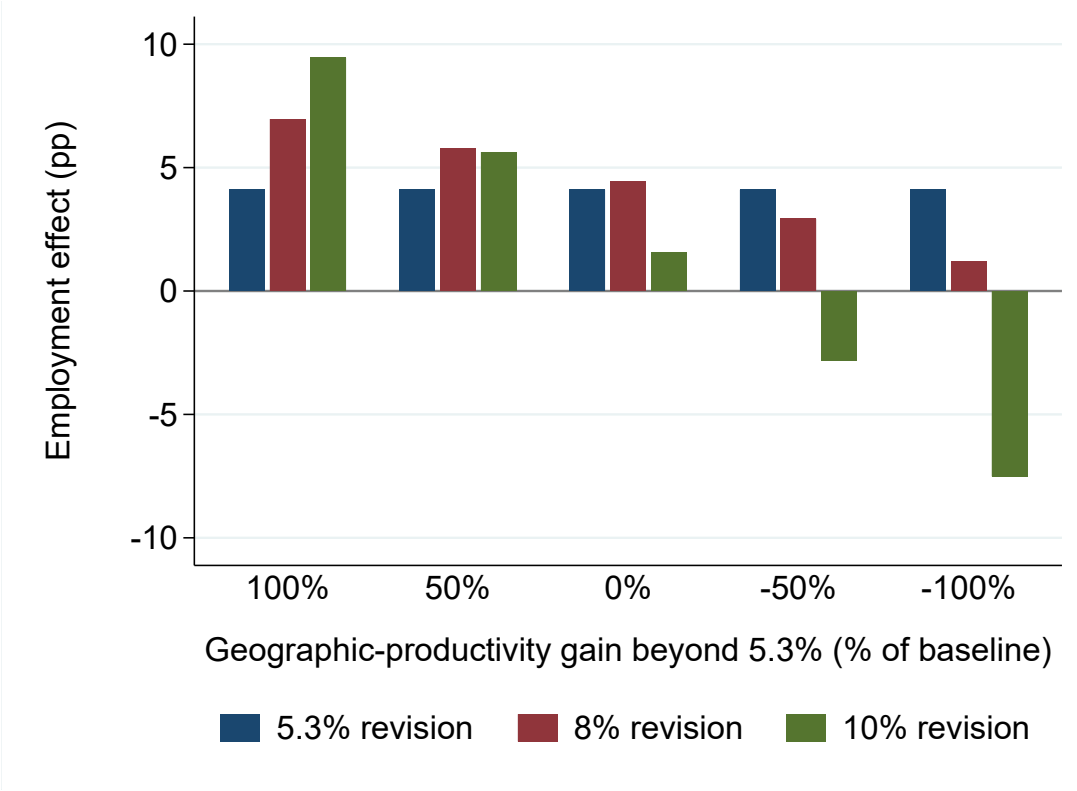
Positive news with alternative geographic-productivity extrapolations We also analyze the sensitivity of the positive-news counterfactuals to the assumption that further geographic narrowing continues to raise matching productivity at the same proportional rate. We keep matching productivity unchanged at the experimentally observed 5.3% belief revision and allow the relationship to flatten or reverse for larger revisions. Specifically, for $X > 0.053$, we use

$$\log M^r_{\text{geo}}(X) = \log M_0 + s_0(X - 0.053) + \frac{1}{2}c_r(X - 0.053)^2,$$

where M_0 and s_0 are the level and slope of the baseline relationship at the experimental anchor. We choose the curvature c_r so that, at a 10% belief revision, a fraction r of the additional matching-productivity gain implied by the constant-elasticity baseline is retained. Thus, $r = 1$ reproduces the baseline, $r = 0$ implies that further narrowing beyond the experimental anchor generates no additional productivity gain, and $r < 0$ implies that further narrowing partly reverses the productivity gain attained at the anchor. The quadratic specification ensures that matching productivity evolves smoothly from the experimental anchor while allowing diminishing or negative returns to further geographic narrowing.

With this specification, positive belief revisions affect employment through three forces. First, a moderate narrowing of the search radius raises matching productivity. Second, for larger belief revisions, search may become excessively concentrated geographically, so that further narrowing generates smaller productivity gains and may eventually reduce matching productivity. Third, higher reservation wages reduce the probability that a given offer is accepted. Figure D.1 shows the resulting model-implied employment effects for the experimental 5.3% belief revision and for larger revisions of 8% and 10%, under alternative assumptions about the geographic-productivity gain beyond the experimental anchor. By construction, the employment effect at the 5.3% revision is identical across all specifications, since the alternative mappings differ only beyond the experimental anchor.

Figure D.1 Sensitivity of positive-news counterfactuals to geographic productivity



Notes: The figure shows predicted employment effects for positive belief revisions under alternative assumptions about the geographic-productivity gain beyond the experimental 5.3% revision. The horizontal axis reports the additional matching-productivity gain relative to the constant-elasticity baseline; negative values imply that further geographic narrowing reverses part of the productivity gain attained at the experimental anchor. The 5.3% effect is unchanged by construction. For a 10% belief revision, the predicted employment effect reaches zero at approximately -18%.

The magnitude of the extrapolated employment effects declines as the geographic-productivity gain is attenuated. However, the employment effect remains positive for an 8% belief revision even when further geographic narrowing substantially reduces matching productivity. The reason is that the initial narrowing of the search radius generates a sufficiently large productivity gain to offset both greater wage selectivity and some degree of overshooting, in the sense that job seekers eventually search too narrowly. For a 10% revision, the employment effect remains positive when further narrowing generates no additional productivity gain and turns negative only when r falls below approximately -18%. At this point, the losses from further geographic narrowing, together with the lower offer-acceptance probability induced by higher reservation wages, outweigh the productivity gain generated by the initial narrowing of search. Thus, while the magnitude of the larger-revision counterfactuals depends on the geographic-productivity extrapolation, diminishing returns alone do not overturn the positive employment effect. Only sufficiently strong geographic overshooting, in the form of an excessively narrow search radius, can make very large positive belief

revisions reduce employment.

Positive news with endogenous effort Finally, we assess the sensitivity of the positive-news counterfactuals to allowing search effort to respond endogenously. Our baseline analysis holds effort fixed, consistent with the near-zero experimental response for this group. As a robustness check, we instead let effort adjust according to the same search-effort condition as used for negative news, carrying over the estimated search-cost parameter, and re-calibrate the geographic-productivity parameter to reproduce the observed three-month employment effect at the 5.3% belief revision. The model then predicts a modest decline in search effort as wage expectations increase. This adds a negative contribution to employment and therefore increases the role of geographic reallocation in generating the overall effect: at the calibration anchor, the geographic contribution rises to 9.5 pp, compared with 7.6 pp in the baseline model, offsetting negative contributions from both higher reservation wages and lower search effort. Despite this change in decomposition, the implied total employment effects remain very similar to the baseline counterfactuals, with differences reaching at most 0.6 pp across revisions of different size. Hence, allowing for endogenous search effort somewhat changes the composition, but not the overall magnitude, of the positive-news counterfactuals.

Table D.5 Positive-news counterfactuals with endogenous search effort

	Employment effect (pp)		Mechanism decomposition with endogenous effort (pp)		
Belief revision (%)	Fixed effort	Endog. effort	Reservation wage	Search effort	Geography
2.0	1.32	1.37	-1.25	-0.58	3.19
4.0	2.91	2.96	-2.60	-1.30	6.85
5.3†	**4.10**	**4.10**	**-3.52**	**-1.85**	**9.48**
8.0	6.97	6.72	-5.52	-3.26	15.50
10.0	9.45	8.83	-7.02	-4.53	20.38

Notes: The table compares the baseline positive-news counterfactual, which holds total search effort fixed, with a robustness specification in which effort is chosen endogenously from the same search-effort condition used for negative news. The robustness specification carries over the search-cost parameter estimated from the negative-news exercise. In each specification, the geographic-productivity parameter is calibrated to reproduce the observed three-month employment effect at the 5.3% belief revision; all other parameters are unchanged. The final three columns report a Shapley decomposition of the endogenous-effort employment effect into reservation-wage, search-effort, and geographic-reallocation channels. † denotes the experimental calibration anchor.

E Survey instructions translated to English

E.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 was your employment type in your last job??

- 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

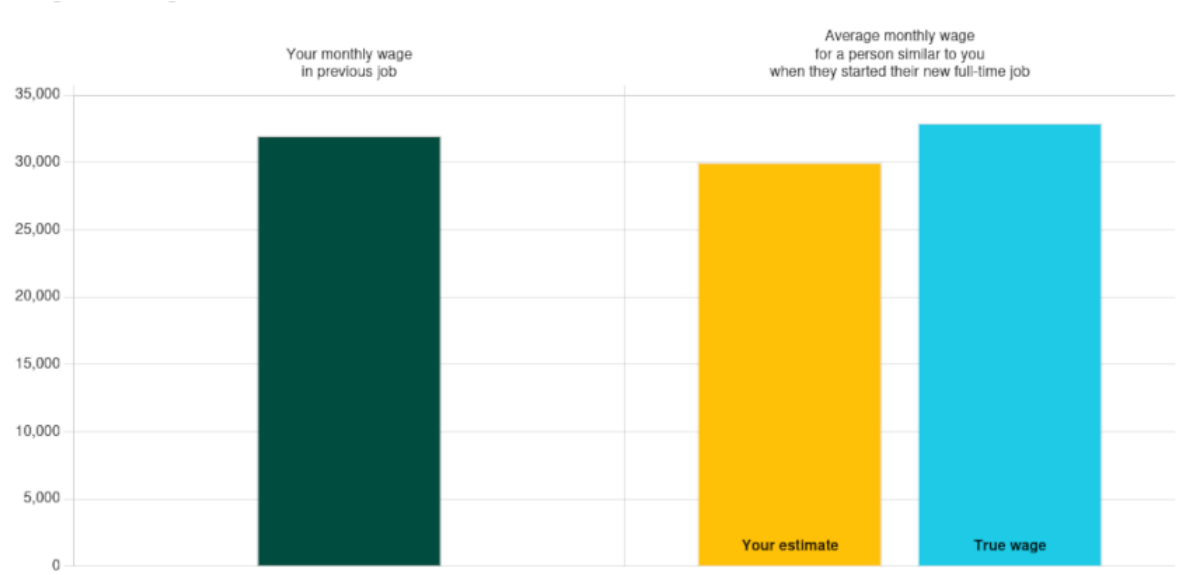
You said you think that the average monthly salary of a person similar to you when starting their new full-time job was [XXX].

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 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.

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 lowest and highest 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 lowest and highest 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.

E.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}

1a
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. 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 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 * Main survey 1fa*
*X2 = 0.95 * Main survey 1fa*
*X3 = 1.05 * Main survey 1fa*
*X4 = 1.20 * Main survey 1fa*
Based on midpoint in the brackets for Main survey 1fa, assigning DKK 13,000 and DKK 80,000 for the lowest and highest intervals.}

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

*{X1 = 0.8 * Main survey 1fb * 2*
*X2 = 0.95 * Main survey 1fb * 2*
*X3 = 1.05 * Main survey 1fb * 2*
*X4 = 1.20 * Main survey 1fb * 2*
Based on midpoint in the brackets for Main survey 1fb, assigning DKK 6,000 and DKK 27,000 for the lowest and highest 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 * Main survey 1fa*
*X2 = 0.95 * Main survey 1fa*
*X3 = 1.05 * Main survey 1fa*
*X4 = 1.20 * Main survey 1fa*
Based on midpoint in the brackets for Main survey 1fa, assigning DKK 13,000 and DKK 80,000 for the lowest and highest intervals.}

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

*{X1 = 0.8 * Main survey 1fb * 2*
*X2 = 0.95 * Main survey 1fb * 2*
*X3 = 1.05 * Main survey 1fb * 2*
*X4 = 1.20 * Main survey 1fb * 2*
Based on midpoint in the brackets for Main survey 1fb, assigning DKK 6,000 and DKK 27,000 for the lowest and highest 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.

E.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 question 4a 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 was your employment type in your last job?

- 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 subsequently.

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.