The Accuracy of Jobseekers' Wage Expectations*

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Abstract

We study the accuracy of wage expectations among unemployed workers by comparing subjective beliefs to objective benchmarks using linked survey-administrative data. A majority of jobseekers overestimate their reemployment wages, with optimism concentrated among those with low earnings potential. Expectations are strongly anchored to past wages and show limited updating over time or in response to increased search incentives. Wage optimism predicts higher reservation wages, search intensity, and delayed reemployment. Finally, our results highlight an asymmetry in belief formation: individuals likely to face wage losses relative to their previous job are particularly rigid in adjusting their expectations.

Keywords: Subjective expectations, objective benchmarks, job search, unemployment, reemployment wages

JEL codes: D83, D84, J64

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1 Introduction

When searching for a job, workers face substantial uncertainty about their job-finding prospects (see, e.g., Spinnewijn, 2015; Balleer *et al.*, 2021, 2023; Mueller *et al.*, 2021; Adams-Prassl *et al.*, 2023) and their potential job matches (see, e.g., Krueger and Mueller, 2016; Sockin and Sojourner, 2023; Davis and Krolikowski, 2024; Jäger *et al.*, 2024). If unemployed workers hold inaccurate beliefs about their labor market potential, this can distort their decision-making and may increase the risk of long-term unemployment. However, despite increasing evidence of systematic biases in jobseekers' beliefs (see Mueller and Spinnewijn, 2023, for an overview), our understanding of the specific groups most inclined to misperceptions, the factors driving belief inaccuracies, and their labor market implications remains limited.

In our study, we examine the accuracy of jobseekers' expectations about their reemployment wages and analyze heterogeneity in the extent to which they exhibit overly optimistic or pessimistic beliefs. We explore a unique combination of survey and administrative data on jobseekers in Germany. The large-scale survey provides insights into the wage expectations of more than 5,000 newly unemployed workers. In addition, we use administrative records to establish objective benchmarks for their true earnings potential based on the realized wages of comparable workers with similar characteristics and employment biographies. To predict the objective wage potential, we account for these factors in flexible LASSO regressions.

This enables us to document four novel results. Our first main result reveals substantial heterogeneity in jobseekers' wage overoptimism. While, on average, jobseekers overestimate their reemployment wages by about 17%, it is those with the lowest objective earnings potential who exhibit particularly high levels of overoptimism. Those positioned in the lowest decile of the objective benchmark distribution overestimate their potential wages by approximately 36%, whereas the level of overoptimism is comparatively modest at around 6% among individuals in the top decile of the distribution. Moreover, by comparing objective benchmarks and subjective expectations to individuals' pre-unemployment wages, we show that jobseekers disproportionately anchor their wage expectations to past earnings – particularly those predicted to face wage penalties upon reemployment. This finding sheds new light on the well-documented tendency of jobseekers to set reservation wages close to their previous salary (Feldstein and Poterba, 1984; Krueger and Mueller, 2016; Le Barbanchon *et al.*, 2019; Koenig *et al.*, 2023; Davis and Krolikowski, 2024). We show, for the first time, that this anchoring exceeds what is objectively justified (Tversky and Kahneman, 1973) and suggest it may reflect a failure to fully account for the scarring effects of unemployment (Arulampalam, 2001; Gregory and Jukes, 2001).

The results suggest that jobseekers misperceive the wages they are likely to be offered, potentially affecting their search behavior and reemployment outcomes. Consistent with this idea, our second main finding is that belief inaccuracies predict jobseekers' search strategy, as well as their perceived and actual job-finding rates. Specifically, we find that greater wage optimism is positively associated with both jobseekers' reservation wages – the minimum wage they are willing to accept – and the number of job applications they submit. At the same time, we document a wedge between the perceived and actual job-finding rates for increasing levels of wage optimism. On the one hand, jobseekers who are most optimistic about their potential wages also report the highest perceived chances of finding a job. On the other hand, actual job-finding rates decline as wage optimism rises. The widening gap between expected and actual job-finding rates suggests that optimistic beliefs about one's earnings potential are tied to overly positive beliefs about individual reemployment prospects.

Our correlational evidence contributes to a growing literature studying the beliefs of unemployed workers (Dubra, 2004; Conlon *et al.*, 2018; Mueller *et al.*, 2021; Cortés *et al.*, 2023). These studies suggest that overoptimistic expectations about labor market chances may increase jobseekers' risk of long-term unemployment. Our findings provide empirical support for this view: while optimistic expectations can boost motivation, they may also cause excessive selectivity, leading jobseekers to reject offers more frequently than warranted.

Jobseekers may be overoptimistic about their wage potential because they have imperfect information about the statistical properties of the wage offer distribution. In this context, it is conceivable that they acquire additional information during job search and revise their subjective beliefs accordingly. If so, incentivizing job search could have the additional benefit of improving the accuracy of beliefs. In the final part of our empirical analysis, we explore this possibility from two perspectives, leading to our third finding: jobseekers are reluctant to revise their optimistic expectations. First, we explore repeatedly elicited wage expectations to examine whether individuals adjust their beliefs as they acquire additional information over the unemployment spell. It turns out that overoptimism even increases among those who are still searching for a job until about one year after becoming unemployed. Second, we investigate the role of financial incentives to search for jobs by leveraging regional differences along the administrative borders of local employment agency (LEA) districts, where jobseekers face varying risks of being subject to punitive benefit sanctions if they provide an insufficient number of job applications.[1] We find that a stricter sanction regime encourages jobseekers to intensify their search and simultaneously fosters even greater optimism about their earnings potential.

[1]We demonstrate that the exploited variation in local sanction risk is independent of jobseekers' characteristics or other aspects of LEAs' policy style, allowing us to estimate the causal effects of jobseekers' perceived incentives for applying to and accepting jobs.

Together, the results suggest that jobseekers who acquire more information about the wage offer distribution during job search do not reduce their overly optimistic beliefs. Instead, they anticipate higher wage offers as they submit more applications, reflecting a perceived sense of control over their reemployment wages. This perception appears to dominate any direct effect of the sanction risk, which might otherwise encourage them to be less selective.

Finally, our fourth finding reveals a fundamental asymmetry in belief formation: individuals predicted to face wage losses compared to the previous job anchor their expectations too rigidly to past earnings, are reluctant to revise their beliefs over time, and do not respond to exogenous search incentives. In contrast, the smaller group of jobseekers who can reasonably anticipate wage gains holds more accurate expectations and adjust them more readily over time and in response to incentives. This indicates that inaccurate beliefs stem not only from limited access to information, but also from how individuals acquire and interpret the information available to them. Therefore, our findings point to the relevance of "behavioral biases" in shaping jobseekers' wage expectation. For instance, a growing literature on motivated reasoning argues that individuals may selectively disregard negative information to preserve overly optimistic beliefs (Bénabou and Tirole, 2002, 2004; Zimmermann, 2020; Huffman *et al.*, 2022). Moreover, loss aversion relative to prior income (DellaVigna *et al.*, 2017, 2022) may further sustain optimistic expectations and hinder adequate updating.

2 Empirical Setting

Our analysis builds on different data sources providing information on unemployed workers in Germany. To begin with, we rely on a large-scale survey involving workers who became unemployed between June 2007 and May 2008 and were eligible for unemployment benefits (see Arni *et al.*, 2014). The first interview was conducted within 7 to 14 weeks after entering unemployment, followed by a second interview wave 12 months later. The survey encompasses detailed data on socio-demographic characteristics, job search behavior, and, notably for our study, subjective beliefs about labor market prospects. Importantly, for about 87% of survey respondents we can link the survey data to administrative records on the actual labor market outcomes and employment histories prior to unemployment (Eberle *et al.*, 2017).

Subjective beliefs: The key variable in our study is the monthly net salary individuals expect to earn upon starting a new job, elicited in the following question:

> "Now, I am interested in the salary you anticipate receiving in your next job. What is your expected monthly net income in €?"

This information is gathered from respondents who were unemployed and actively seeking work at the time of the interview. We also focus on jobseekers who previously held a full-time position to minimize the influence of variation in working hours on monthly wage expectations. This results in an estimation sample of 5,376 individuals in the linked survey-administrative data. As shown in Table 1, column (1), the average jobseeker expects a net income of 1,407€ per month.[2]

Table 1: Summary statistics

Sample	All (1)	Still unemployed in wave 2 (2)
No. of observations	5,376	459
Realized wage in € per month	1,190	1,072
Log realized wage	6.996	6.877
Realized job finding	0.56	0.00
Last wage in € per month	1,413	1,402
Log. last wage	7.137	7.156
Wave 1		
Subjective belief (S_i) in € per month	1,407	1,364
Log subjective belief ($log(S_i)$)	7.184	7.156
Objective benchmark (O_i) in € per month	1,173	1,132
Log objective benchmark ($log(O_i)$)	7.014	6.975
Accuracy of wage belief ($log(S_i) - log(O_i)$)	0.170	0.181
Perceived job finding rate		
Very likely	0.518	0.316
Likely	0.366	0.460
Unlikely	0.082	0.177
Very unlikely	0.034	0.047
Wave 2		
Subjective belief (S_i) in € per month		1,383
Log subjective belief ($log(S_i)$)		7.154
Objective benchmark (O_i) in € per month		1,067
Log objective benchmark ($log(O_i)$)		6.919
Accuracy of wage belief ($log(S_i) - log(O_i)$)		0.235
Perceived job finding rate		
Very likely		0.229
Likely		0.443
Unlikely		0.225
Very unlikely		0.102

Note: The table reports average reemployment wage beliefs, perceived six-months-ahead job finding rates, objective benchmarks, and realizations of all survey respondents in the first interview (column (1)) and those still unemployed and actively searching for employment in the second interview one year after unemployment entry (column (2)). For the latter, we report variables measured both in the first and in the second interview wave. Objective benchmarks in wave 1 (2) are predicted based on the reemployment wages of job seekers who remain unemployed for at least 3 (12) months following their entry into unemployment, as observed in the administrative data (see Section 2 for more information on the prediction). Realized wages are observed for individuals who start a regular job within 24 months after unemployment entry ($N = 4,098$ in column (1) and $N = 227$ in column (2)).

[2]See Appendix Figure A.1 for the full distribution of subjective wage expectations.

Objective benchmarks: A simple way of assessing the accuracy of beliefs is to compare expected and realized wages. However, realized wages may not capture true earnings potential at the time beliefs were formed. They reflect a single draw from the wage offer distribution and can be influenced by prior beliefs, luck, or unexpected labor demand shocks. Moreover, realized wages are only observed for individuals who accept new jobs. To address these concerns, we estimate objective benchmarks for jobseekers' earnings potential based on the realized wages of comparable workers observed in administrative records (see Appendix B for a detailed description of the objective benchmark predictions).

We use administrative data from 84,617 workers who became unemployed between January 2005 and May 2007 (Eberle and Schmucker, 2015). We choose this period to avoid any overlap with the survey sample, ensuring that the predictions are not influenced by the beliefs and behaviors of survey respondents. As a robustness check, we also use entries into unemployment between June 2007 and May 2008, which aligns with the survey period. Detailed summary statistics for both samples can be found in Appendix Table B.1. Average reemployment wages are very similar across cohorts, indicating that macroeconomic trends, such as the financial crisis, do not undermine the validity of our objective benchmarks. Importantly, both the linked survey-administrative and the pure administrative datasets comprise individuals randomly sampled from the same population of entries into unemployment. This ensures that jobseekers across the two samples are directly comparable and that we have access to similar information about their employment biographies. We also impose similar sample restrictions, limiting the administrative sample to individuals who transition into unemployment from full-time employment, who are eligible for unemployment benefits, and who are not reemployed within three months after unemployment entry (the average time until the first survey interview).

We employ flexible LASSO regressions to predict reemployment wages, accounting for a comprehensive set of pre-determined covariates available in both datasets, including socio-demographic information, characteristics of the previous job, employment histories over the past ten years, and local labor market characteristics. The dependent variable is the first monthly salary received in a regular job within 24 months after entry into unemployment. To compare the objective benchmarks with subjective expectations, we convert the realized wages recorded in administrative records from gross to net terms by deducting social security contributions and income taxes (see Appendix B for details).

For the average jobseeker in our sample, the objective benchmarks suggest a monthly net wage of 1,173€. This number is substantially lower than the average expected wage in our sample, but it aligns with the average realized wage of 1,190€ per month that we observe among the survey respondents (see Table 1). To further evaluate the quality of the benchmarks, we estimate the out-of-sample R^2 by regressing realized wages on predicted wages using test samples not used for generating the predictions. As shown in Appendix Table B.3, we find values of R^2 within the range of 0.48 to 0.53, suggesting that we are equipped with meaningful objective benchmarks for individuals' wages.[3] Further supporting this notion, Appendix Table B.4 shows that the objective benchmarks exhibit greater predictive power for survey respondents' realized wages than their own subjective wage expectations. Finally, Appendix Figure B.1 shows the relation between objective benchmarks and jobseekers' realized wages, indicating that prediction errors show minimal systematic variation over the distribution of objective benchmarks.

Robustness: In Appendix C, we discuss several robustness checks to verify that the comparability between subjective beliefs and objective benchmarks is not sensitive to certain choices in our empirical approach. Specifically, we (1) restrict the estimation sample to jobseekers who find reemployment within 24 months and who search for and expect to find a full-time job, (2) vary the observation period (June 2007 to May 2008) and the reemployment time restriction (9 instead of 24 months) of the administrative data that is used to estimate the objective benchmarks, (3) assess the impact of rounding in subjective beliefs, (4) examine potential measurement error arising from the conversion of gross to net wages, and (5) use a two-sample instrumental variable approach to account for measurement error in the objective predictions.

3 Results

In this section, we document four key results. First, jobseekers generally overestimate their reemployment wages and anchor their beliefs too strongly to pre-unemployment wages. Second, we demonstrate that our empirical measure of wage optimism predicts job search behavior and job-finding outcomes consistent with unemployed workers holding misperceptions about their earnings potential. Third, we provide evidence that jobseekers are reluctant to revise their optimistic beliefs both over the course of their unemployment spell and in response to increased incentives to search for jobs. Fourth, anchoring and belief updating are asymmetric: jobseekers facing potential wage losses rely too strongly on their previous earnings and are reluctant to incorporate new information into their wage expectations, while those facing potential wage gains form more accurate beliefs and adapt them more readily.

[3] These figures align with other studies that predict wages of German workers and report out-of-sample R^2 values ranging from 0.4 to 0.5 when accounting for worker characteristics (Card *et al.*, 2013; Jäger *et al.*, 2024).

3.1 Belief accuracy and anchoring

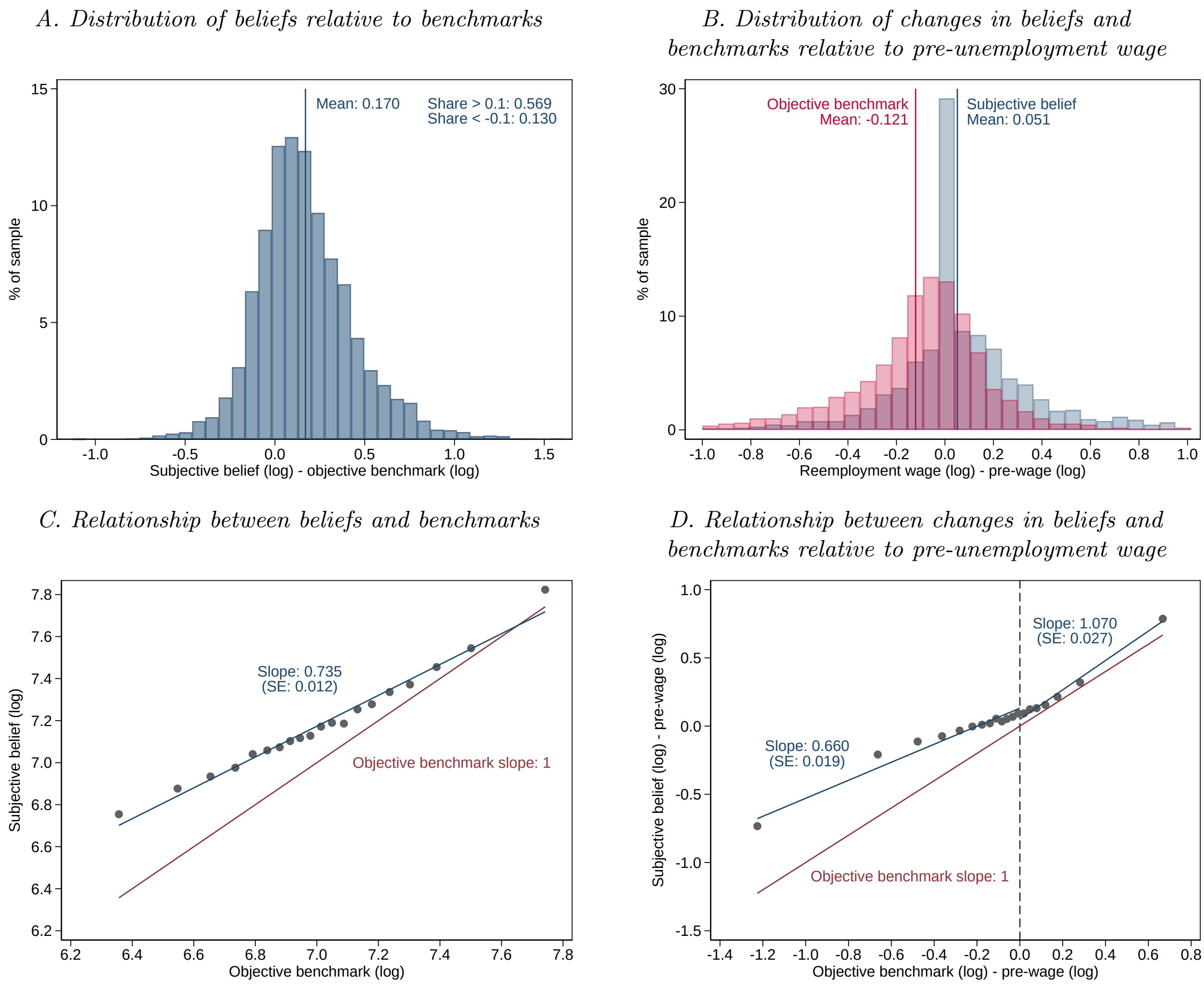
We begin by describing the relationship between individuals' subjective wage beliefs and objective benchmarks, as well as how both compare to their pre-unemployment wage. On average, jobseekers overestimate their reemployment wages by 17% relative to the objective benchmarks (see Panel A of Figure 1). Moreover, they anticipate an average wage increase of 5% compared to their previous job and many respondents anchor their subjective beliefs to their pre-unemployment wage, as evidenced by the pronounced concentration of values at or near zero (see light blue distribution in Panel B). While this is consistent with previous findings that reservation wages tend to align closely with pre-unemployment salaries (Krueger and Mueller, 2016), our approach goes a step further by enabling us to assess the extent to which this anchoring is warranted. Therefore, we consider changes in objective benchmarks relative to the pre-unemployment wage (see light red distribution in Panel B). While the average objective wage potential is about 12% lower than individuals' pre-unemployment wage, the distribution is notably less concentrated around zero compared to changes in subjective beliefs. This indicates that jobseekers have a stronger tendency to anchor their wage expectations to their previous salary than is justified by our objective benchmarks.

We next examine variation in jobseekers' belief accuracy. Panel C of Figure 1 shows a binned scatter plot comparing expected wages with the objective benchmarks. The slope coefficient of 0.74 – significantly below the benchmark value of one – indicates that beliefs do not respond sufficiently to variation in objective benchmarks. As a result, overoptimism is more pronounced among jobseekers with lower objective prospects: individuals in the bottom decile overestimate their reemployment wages by roughly 36%, compared to just 6% in the top decile of the distribution.[4] Panel D of Figure 1 complements this analysis by incorporating jobseekers' prior earnings and plotting changes in subjective wage beliefs against objectively predicted wage changes – both measured relative to the pre-unemploment wage. The pattern reveals an asymmetric pattern of anchoring: jobseekers who are predicted to face wage losses tend to adjust their beliefs insufficiently, with an estimated slope coefficient of 0.66. In contrast, those predicted to earn more than in their previous job hold relatively accurate beliefs, with an estimated slope coefficient of 1.07.

Finally, Appendix Table A.1 explores differences across socio-demographic groups that may explain this pattern. The results show that jobseekers who are predicted to experience larger wage losses – such as those with high pre-unemployment wages, women, younger individuals,non-

[4] In absolute terms, this amounts to wage overestimations of €323 in the bottom decile and €214 in the top decile of the objective benchmark distribution.

Figure 1: Variation in belief accuracy and anchoring



Note: Panel A shows a histogram of individuals' subjectively expected reemployment wage changes and objectively predicted reemployment wage changes (i.e. both in comparison to their pre-unemployment wages). Panel B depicts a binned scatter plot (with 20 bins) for the individual-level relation between the two variables. Slope coefficients are estimated separately for positive and negative variation in objective wage changes. Both coefficients are significantly different from 1 (p-values $<$ 0.001 and $=$ 0.005, respectively). $N = 5,376$.

German citizens, and East Germans (column (1)) – also tend to overestimate their reemployment wages relative to objective benchmarks (column (2)). Overall, the evidence presented in this subsection suggests that overly optimistic wage expectations are tied to jobseekers' failure to fully account for the wage penalties they potentially face upon reemployment.

3.2 Does wage optimism predict job search and reemployment?

The evidence of overly optimistic beliefs raises the possibility that misperceptions about reemployment wages distort the job search behavior of unemployed workers. In the following, we present correlational evidence on the relationship between wage optimism and job search outcomes. We then interpret the empirical patterns through the lens of a job search framework.

3.2.1 Descriptive evidence

Figure 2 shows that jobseekers' wage optimism predicts their job search behavior, and both perceived and actual job-finding rates. The figure depicts binned scatter plots conditioning on socio-demographic characteristics and objective benchmarks (Appendix Table A.2 reports the corresponding regression results).

First, we examine individuals' reservation wages and the number of job applications to assess the relationship between wage optimism and job search behavior. While 73% of respondents would accept a wage offer below their expected wage, more optimistic wage expectations are associated with higher reservation wages: a 10% larger overestimation of wages corresponds to a 9.2% increase in reservation wages (see Panel A of Figure 2). At the same time, wage optimism is positively related to the number of job applications: jobseekers who overestimate their wage by an additional 10% sent out, on average, 1.6% more job applications (see Panel B).

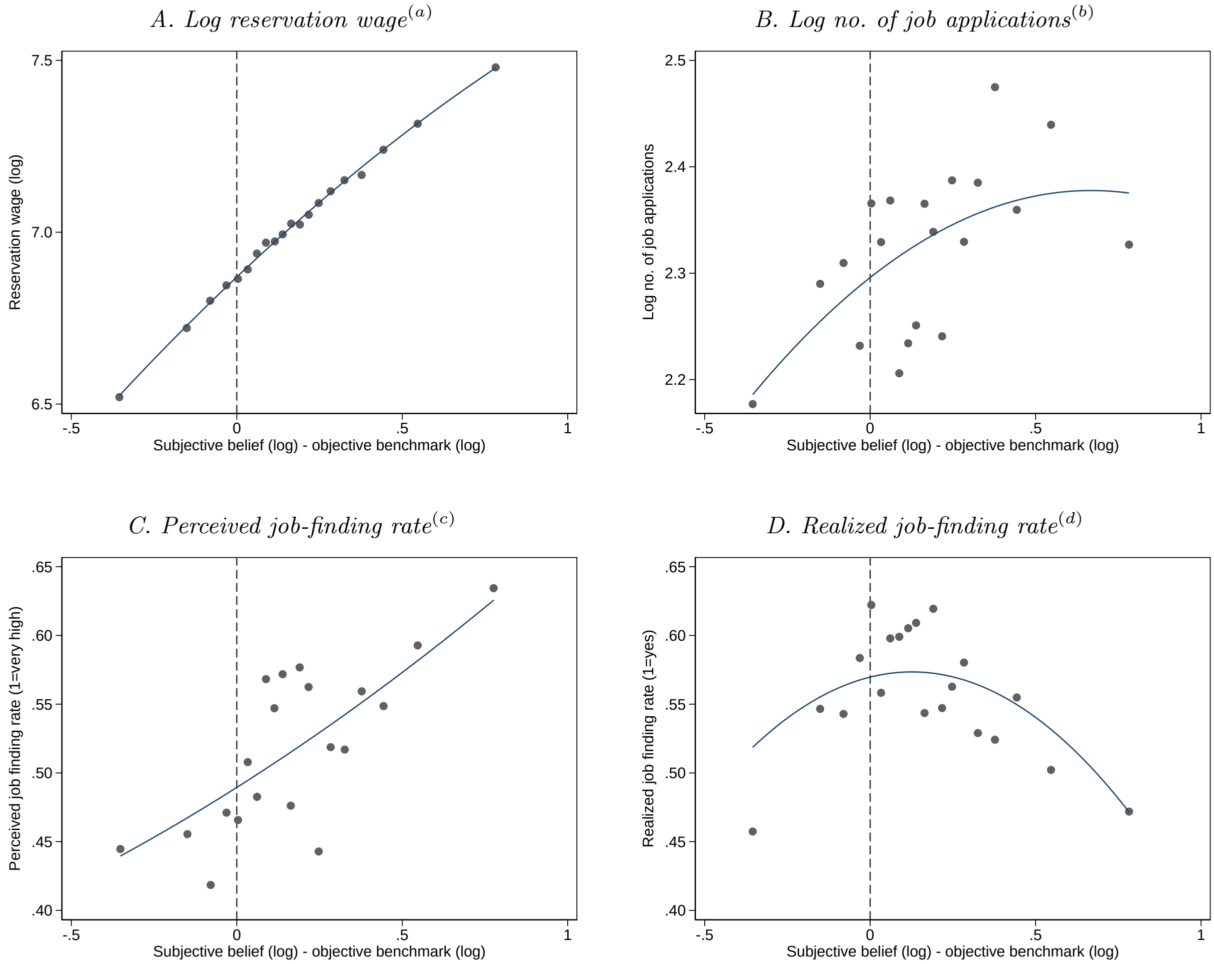
Second, we consider the relationship between wage optimism and the perceived and actual job-finding rates, both measured over a period of six months following the interview. This comparison reveals a remarkable pattern. On the one hand, there is a positive and almost linear relationship between wage optimism and the perceived job-finding probability. Jobseekers who are most optimistic about their reemployment wages also report the highest perceived chances of finding a job (see Panel C). On the other hand, we find a non-linear connection between wage optimism and actual job-finding rates. Jobseekers who hold relatively accurate beliefs about their reemployment wage have the highest likelihood of finding a job within six months, while those who overestimate or underestimate their earnings potential experience lower reemployment rates (see Panel D). Together, these results show that the more optimistic workers are about their reemployment wages, the more they tend to overestimate their job-finding prospects.

3.2.2 Theoretical considerations

To interpret the descriptive results, we relate the observed patterns to the predictions of a simple job search framework. This helps clarifying the extent to which our empirical measure of wage optimism reflects genuine misperceptions about earnings potential, as opposed to confounding factors such as jobseekers' private information about their unobserved abilities or reverse causality.

Setup: While searching for jobs individuals receive a flow utility of b and decide about the number of applications they send out, s, as well their reservation wage, ϕ, the minimal wage offer they would accept. The probability of a successful application, resulting in an offer, is

Figure 2: Correlational evidence: wage optimism, job search and reemployment



Note: The figure shows binned scatter plots (with 20 bins) of individuals' reservation wage, search effort, and perceived and realized six-months-ahead job-finding rates against their wage belief inaccuracy (defined as the log difference between subjective belief S_i and objective benchmark O_i). The blue line shows a quadratic fit for the conditional means after residualizing against socio-demographic characteristics (gender, age categories, German citizen, education categories, married, any children, East Germany) and the objective benchmark. The corresponding regression results are reported in Appendix Table A.2.

$^{(a)}$The dependent variable is the log minimal wage the individual would accept when starting a new job.

$^{(b)}$The dependent variable is the log number of job applications sent since unemployment entry.

$^{(c)}$The dependent variable is an indicator of whether the individual reports the perceived six-month-ahead job-finding rate to be 'very high'.

$^{(d)}$The dependent variable is an indicator of whether the individual actually starts a regular job within the next six months.

denoted by λ, while the effort costs incurred during job search are captured by the increasing and convex function $\gamma(s)$. Each job offer is associated with a wage, denoted by w, which is a random draw from an exogenous wage offer distribution $F(w) \sim N(\mu, \sigma)$. If the wage offer exceeds her reservation wage, the jobseeker accepts the job and receives a wage of w for the rest of time. If not, she rejects the offer and continues searching. Upon receiving multiple job offers, individuals accept the highest wage offer $y = \max\{w_1, w_2, ..., w_n\}$ if it exceeds the reservation wage. The distribution of this maximum offer is given by $F_y(y; \mu, \sigma) = F(y; \mu, \sigma)^n$, where $n = \lambda s$ represents the total number of offers received.

With accurate beliefs, individuals choose their search strategy by maximizing their present value of income:

$$U = \max_{s,\phi} b - \gamma(s) + \rho \left\{ U + [1 - (1 - \lambda)^s] \int_{\phi}^{\infty} (V(y) - U)\, dF_y(y; \mu, \sigma) \right\} \tag{1}$$

where ρ denotes the discount factor and V describes the value of being employed at wage y. In this setting, individuals' optimal decisions have a simple characterization. The reservation wage ϕ, for a given number of applications s, is set such that the jobseeker is indifferent between accepting an offer and remaining unemployed, $V(\phi) = U$. The optimal number of application s^*, trading off the cost of search and its returns, follows from the first-order condition of Equation 1.

Misperceptions about wage offers: One interpretation of our results is that jobseekers hold subjective beliefs about the average wage offer they receive $\widehat{\mu}$ and maximize their utility as if $\widehat{\mu}$ were the true mean of the distribution.[5] Jobseekers with overoptimistic beliefs ($\widehat{\mu} > \mu$) set higher reservation wages than those with accurate expectations ($\widehat{\mu} = \mu$), since anticipating higher future offers makes it more attractive to reject a given offer and continue searching. Moreover, optimistic beliefs may enhance motivation to search, as individuals who expect higher wage offers see greater returns from each application.

The relationship between wage optimism and job-finding is theoretically ambiguous. On the one hand, the increased selectivity of optimistic jobseekers can reduce job-finding prospects. On the other hand, the higher search intensity may enhance job-finding. Our results suggest that the first mechanism dominates for overoptimistic jobseekers: those who overestimate their reemployment wages more strongly tend to have lower reemployment rates. At the same time, we find that larger wage pessimism is also associated with lower job-finding rates, suggesting that for these jobseekers the reduced search intensity plays an important role in lowering job-finding.

[5] In our framework, similar effects may arise if job seekers hold subjective beliefs about the success probability of an application, λ, since the wage offer distribution F and the perceived success probability jointly determine the distribution of wage offers available to a given jobseeker, denoted by F_y.

Our framework also provides a clear prediction about the gap between perceived and actual job-finding rates, $\Delta J(s, \phi, \widehat{\mu})$, that may arise due to misperceptions about potential wage offers (under a given search strategy):

$$\Delta J(\widehat{\mu}; s, \phi) = [1 - (1 - \lambda)^s] \{F(\phi; \widehat{\mu}, \sigma) - F(\phi; \mu, \sigma)\}. \quad (2)$$

Jobseekers who overestimate the mean of the wage offer distribution ($\widehat{\mu} > \mu$) anticipate receiving an acceptable offer more quickly than they actually given their search strategy, creating a gap between perceived and true job-finding rates, $\Delta J(\widehat{\mu}; s, \phi) > 0$. In other words, wage optimism leads jobseekers to underestimate their risk of remaining unemployed. Notably, this aligns with our empirical result, which shows that higher levels of wage optimism are associated with lower actual job-finding rates but higher actual job-finding rates.

Potentially confounding factors: An alternative interpretation of our data is that potential confounders – such as jobseekers' private information about their unobserved abilities – may explain discrepancies between their subjective wage expectations and our objective benchmarks, which are based on realized wages of workers with similar observable characteristics. For instance, jobseekers identified as wage optimistic by our measure may, in fact, receive wage offers from a distribution with a higher mean (μ) compared to their counterparts classified as pessimistic. These interpretation is also consistent with the empirical findings that more optimistic jobseekers search more intensively, set higher reservation wages and anticipate higher job-finding rates. However, in the absence of misperceptions, it is difficult to reconcile these confounding factors with our finding that the gap between expected and actual job-finding rates widens with increasing wage optimism. Absent misperceptions, jobseekers with private information about their abilities should hold accurate beliefs about their job-finding prospects.

In addition, reverse causality may be at play: individuals who submit more applications or set higher reservation wages may be more likely to receive high-paying offers, which in turn may justify higher wage expectations. While such factors may help explain the observed correlation between wage optimism and search behavior, they are also unlikely to account for the gap between expected and actual job-finding rates. This suggests that neither private information nor reverse causality can fully account for the presented correlational evidence, pointing instead to a key role for misperceptions.

3.3 Do jobseekers revise their beliefs during their search?

It is conceivable that jobseekers who gather additional information during their search may adjust their expectations based on the signals they receive (see, e.g., Burdett and Vishwanath, 1988; Gonzalez and Shi, 2010; Conlon *et al.*, 2018), resulting in more accurate beliefs about their reemployment wages. In this section, we explore this possibility from two perspectives, examining how jobseekers revise their expectations (1) over their unemployment spell and (2) in response to exogenous changes in their incentives to search for employment.

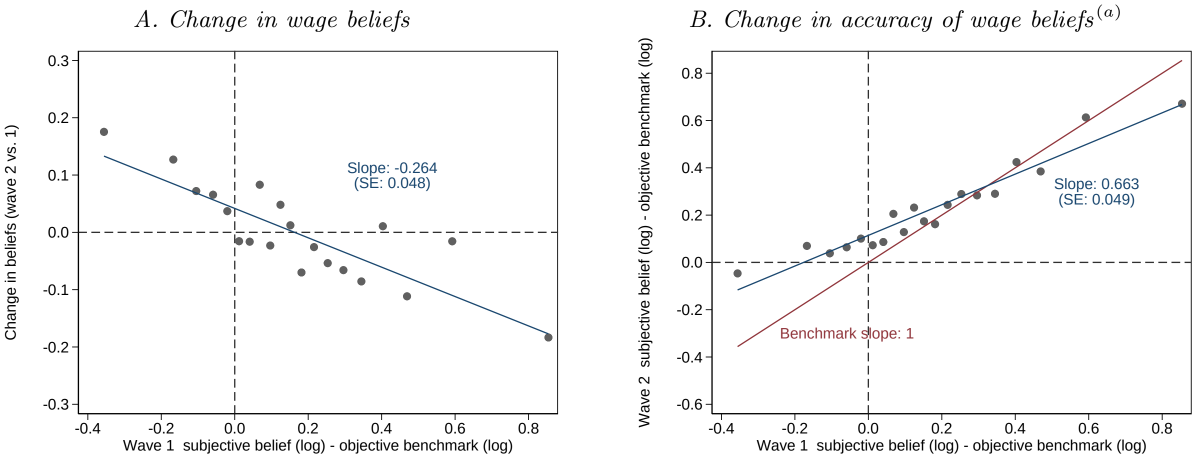
3.3.1 Belief updating over the unemployment spell

To investigate the evolution of beliefs throughout the unemployment spell, we compare wage expectations that were elicited during the first and second survey wave. For that, we focus on the 459 individuals who were still unemployed and actively searching for a job at the time of the follow-up interview, one year after the entry into unemployment. This group consists of workers with poor labor market prospects. As shown in Table 1, the objective earnings potential – measured at the start of the spell – of individuals who remain unemployed for over a year is approximately 4% lower compared to the full initial sample, reflecting dynamic selection during unemployment. These differences are largely reflected in jobseekers' initial beliefs, as those who eventually become long-term unemployed expect their wages to be approximately 3% lower than the average jobseeker.

However, jobseekers who remain unemployed update their beliefs only minimally, with the average expected wage remaining nearly identical between waves 1 and 2 (1,364€ vs. 1,383€). This is further illustrated in Panel A of Figure 3 that plots changes in respondents' expectations from the first to the second interview against their initial wage optimism. The slope coefficient of -0.26 indicates that jobseekers who initially overestimate their reemployment wage by an additional 10% reduce their wage expectations by only 2.6% more. Meanwhile, only jobseekers with substantial optimism during the first interview revise their expectations downward, while those overestimating their wage potential by up to 17% actually increase their expectations over time. Since longer unemployment spells are typically associated with larger wage penalties (Kroft *et al.*, 2013; Eriksson and Rooth, 2014; Schmieder *et al.*, 2016; Zuchtut *et al.*, 2023) – in our sample, there is a 5.6% decline in objective benchmarks over one year – jobseekers become increasingly optimistic relative to benchmarks over time. Panel B of Figure 3 shows that wage optimism rises among those who initially overestimate their potential by up to 34%, declining only among those with even higher initial optimism.

Finally, individuals' willingness to revise their beliefs over time seems to vary depending on whether they are predicted to experience gains or losses relative to their previous salary. As shown in Appendix Figure A.3, jobseekers with a predicted wage gain tend to increase their wage expectations. Conversely, those likely to face wage penalties revise their expectations much less, with substantial downward adjustments occurring only among individuals with predicted losses

Figure 3: Heterogeneity in belief updating over the unemployment spell



Note: The figure depicts binned scatter plots of individuals' change in wage beliefs between waves 1 and 2 (Panel A) and wage optimism in wave 2 (Panel B) against wage optimism in wave 1. Wave 1 was conducted 7 - 14 weeks after unemployment entry and wave 2 was conducted 12 months after entry. The sample only includes individuals who are still in the same unemployment spell in wave 2. The estimated slope in Panel A is significantly different from 0 (p-value < 0.001) and significantly different from -1 (p-value < 0.001). The estimated slope in Panel B is significantly different from 0 (p-value < 0.001) and significantly different from 1 (p-value < 0.001). $N = 459$.
$^{(a)}$Objective benchmarks in wave 2 are predicted based on the reemployment wages of jobseekers who remain unemployed for at least 12 months following their entry into unemployment, as observed in the administrative data.

of 20% or more. This indicates that many individuals who have likely encountered negative feedback during their job search are reluctant to revise their wage expectations accordingly.[6]

3.3.2 How do search incentives shape jobseekers' beliefs?

The final part of our analysis explores exogenous variation in the incentives of unemployed workers to search for jobs and analyzes their impact on jobseekers' initial wage optimism. This expands our analysis along two dimensions. First, it addresses concerns about dynamic selection and explores how job search influences the accuracy of beliefs across a broader segment of the unemployed population. Second, it offers direct causal evidence on how financial incentives to search more intensively influence jobseekers' subjective beliefs.

We exploit variation in the risk that jobseekers will be subject to punitive sanctions along the administrative borders of local employment agency (LEA) districts. These sanctions involve temporary reductions in unemployment benefit payments and are imposed by caseworkers when they detect that jobseekers are not complying with job search requirements.[7] The regional variation arises because LEAs have autonomy in deciding about the local policy style (see, e.g., Fertig *et al.*, 2006; Boockmann *et al.*, 2014; Doerr and Kruppe, 2015), including how strictly they punish jobseekers for inadequate search behavior. As a result, caseworkers in LEA districts with

[6]In contrast to their reluctance to revise wage expectations, individuals become somewhat more pessimistic about their job-finding prospects over time: the share of jobseekers who consider it 'very likely' they will find a job within six months declines from 32% in wave 1 to 23% in wave 2 (see Table 1).

[7]We refer to payments under the German Unemployment Benefit I scheme. Non-compliance by jobseekers may result from submitting too few job applications or rejecting job offers provided by the employment agency.

higher sanction intensities may exert greater pressure on jobseekers, leading them to perceive stronger incentives to search for jobs.

This can have different implications for jobseekers' wage expectations. First, more intensive search activity provides jobseekers with additional signals about their earnings potential, which may help them form more accurate beliefs. Second, the increased sanction risk may make jobseekers less selective, thereby directly reducing their wage expectations. Finally, sending out more applications may increase the expected likelihood of receiving high-wage offers, leading to more optimistic beliefs about reemployment wages.

Econometric strategy: To measure jobseekers' risk of facing benefit sanctions, we leverage data on the annual number of benefit sanctions imposed in the year before each jobseeker entered unemployment, normalized by the stock of unemployed workers, in each of the 178 LEA districts. We incorporate the resulting sanction intensity, SI_j, into a border-pair fixed-effects models of the following form (see also Dube *et al.*, 2010; Caliendo *et al.*, 2023):

$$Y_{ijb} = \alpha + \delta SI_j + \beta X_i + \phi R_j + \kappa_b + \varepsilon_{ijb}, \tag{3}$$

where i denotes the individual jobseeker, j the LEA district in which the individual is located at the beginning of the unemployment spell, and b a pair of bordering LEA districts such that κ_b denotes the border-pair fixed effects for any combination of two neighboring LEA districts. Moreover, we control for individual (X_i) and regional (R_j) characteristics. Standard errors are clustered at the LEA district level. The parameter of interest δ identifies the effect of sanction intensity on the outcome variables Y by comparing individuals living in similar, neighboring LEA districts but facing varying risks of being sanctioned. In Appendix D, we present additional details about our econometric strategy and provide empirical evidence supporting the validity of the identifying assumptions. Specifically, we demonstrate (1) that bordering LEA districts exhibit similar local labor market conditions, (2) that the sanction intensity is independent of regional indicators and jobseekers' individual characteristics and (3) that other dimensions of regional policy styles do not systematically vary with local sanction intensities.

Effect of sanction risk on behavior and beliefs: Table 2 shows the effect of the sanction risk on jobseekers' search effort and wage belief accuracy.[8] As expected, a stricter sanction regime leads jobseekers to exert more effort. A ten percentage point higher sanction risk – equivalent to an increase of approximately one standard deviation – raises the number of weekly applications

[8]Due to data security restrictions, the regional identifiers required for this analysis are available only in the standalone survey data and not in the version linked to administrative records. Consequently, we are unable to examine effects on realized labor market outcomes within the same estimation sample.

by about 9.8% (p = 0.016). Meanwhile, exposure to a stricter sanction regime is associated with slightly higher – but statistically insignificant – reservation wages, and with a significant increase in jobseekers' optimism about their earnings potential. Raising the sanction risk by ten percentage points increases expected wages by 1.8% (p = 0.006) relative to the objective benchmark. When we differentiate between individuals who overestimate and underestimate the potential wages they could earn, we find that the sanction risk enhances optimism while concurrently reducing pessimism.

Table 2: Effect of sanction risk on search behavior and accuracy of wage expectations

	Full sample	Obj. benchmark (O_i) - pre-wage (P_i) Wage penalty $O_i \leq P_i$	Wage gain $O_i > P_i$	P-value
	(1)	(2)	(3)	(3) – (2)
Effect of sanction intensity on:				
No. of job applications (log)$^{(a)}$	0.098**	0.043	0.249***	0.022
	(0.040)	(0.047)	(0.080)	
Reservation wage (log)$^{(b)}$	0.013	0.011	0.020	0.778
	(0.009)	(0.011)	(0.013)	
Subj. wage belief (log) - obj. benchmark (log)$^{(c)}$				
All values	0.018***	0.009	0.039***	0.034
	(0.007)	(0.008)	(0.011)	
Optimism	0.011**	0.003	0.025***	0.043
	(0.005)	(0.005)	(0.009)	
Pessimism	0.007***	0.006*	0.014**	0.279
	(0.003)	(0.003)	(0.0036)	
No. of observations	5,669	3,905	1,764	
Control variables	Yes	Yes	Yes	

Note: The table reports the effect of the local sanction intensity (measured in 10%-points) on job seekers' search effort and their wage belief inaccuracy (defined as the log difference between subjective belief S_i and objective benchmark O_i). In all specification, we account for socio-demographic and regional characteristics, the objective benchmark O_i, as well as border-pair fixed effects. Standard errors clustered at the LEA district level are shown in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.
$^{(a)}$The dependent variable is the log number of job applications sent since unemployment entry.
$^{(b)}$The dependent variable is the log of the minimal wage the individual would accept when starting a new job.
$^{(c)}$The dependent variable is the log difference between subjective wage belief S_i and objective benchmark O_i. In addition to analyzing the overall deviation ("all values"), we distinguish between positive and negative deviations. To isolate variation in positive deviations ("optimism"), we set all negative values to zero. Conversely, to isolate variation in negative deviations ("pessimism"), we set all positive values to zero.

The finding that a higher sanction risk leads to more optimistic wage expectations offers suggestive evidence about the subjective model that unemployed workers consider when deciding about their job search behavior. Specifically, jobseekers appear to perceive control over their reemployment wages, possibly believing that submitting more applications increases their chances of receiving higher wage offers. This perceived control seems to raise their expectations about offered wages and counteract the potential direct effect of sanction risk, which might otherwise lead them to become less selective – potentially explaining the small and insignificant impact on reservation wages.

In addition to estimating the average effect of sanction intensity for the full sample, we also analyze how effects differ across jobseekers who are objectively predicted to earn less and those predicted to earn more than in their previous job. We find that the search behavior and beliefs of those anticipating a wage loss show little responsiveness to exogenous search incentives (see column (2) of Table 2). In contrast, only the smaller group of jobseekers predicted to experience a wage gain significantly increase their search effort in response to higher sanction risk and adopt more optimistic wage expectations (see column (3)). This pattern is notable in two respects. First, the findings support the idea that higher search intensity contributes to more optimistic wage expectations, as both effects are observed within the same group of jobseekers. Second, complementing the descriptive evidence, our causal analysis suggests a fundamental asymmetry in belief formation between individuals with predicted wage losses vs. gains.

4 Conclusion

Our study establishes objective benchmarks for the subjective wage expectations of unemployed workers, allowing us to document four key findings. First, jobseekers tend to overestimate their reemployment wages and anchor their expectations more closely to past wages than objectively justified. Second, individuals' wage optimism predicts their job search and reemployment consistent with the notion that they misperceive their earnings potential. Third, jobseekers are generally reluctant to revise their optimistic beliefs – both over the course of unemployment and in response to stronger search incentives. Fourth, there is an asymmetry in belief formation: individuals predicted to face wage losses anchor their expectations more strongly to past earnings and are especially reluctant to revise them over time and in response to stronger search incentives, whereas those expecting wage gains hold more accurate beliefs and adjust them more readily.

While the combination of survey data and administrative records offers valuable insights into the interrelation of individuals' beliefs, their job search behavior, and their actual labor market outcomes, our setting does not come without limitations. For instance, individuals may possess private information about their earnings potential or search strategy that is not accounted for in our benchmarks. It is noteworthy that our correlational evidence – the widening gap between expected and actual job-finding as wage optimism increases – suggests that our empirical measure of optimism reflects not just private information, but rather misperceptions. Nevertheless, the ideal survey should elicit individuals' beliefs not only about their own earnings potential but also about primitives, such as the perceived returns to search and the distribution of wage offers, to reduce issues of reverse causality.

Despite these limitations, our results suggest that unemployed workers hold inaccurate beliefs that incur decision-making costs, as overly optimistic jobseekers may prolong their unemployment by being too selective in accepting job offers. Hence, information policies that correct misperceptions have the potential to reduce the risk of long-term unemployment. However, this approach is not without risks, as it could discourage unemployed workers by reducing their motivation to search.

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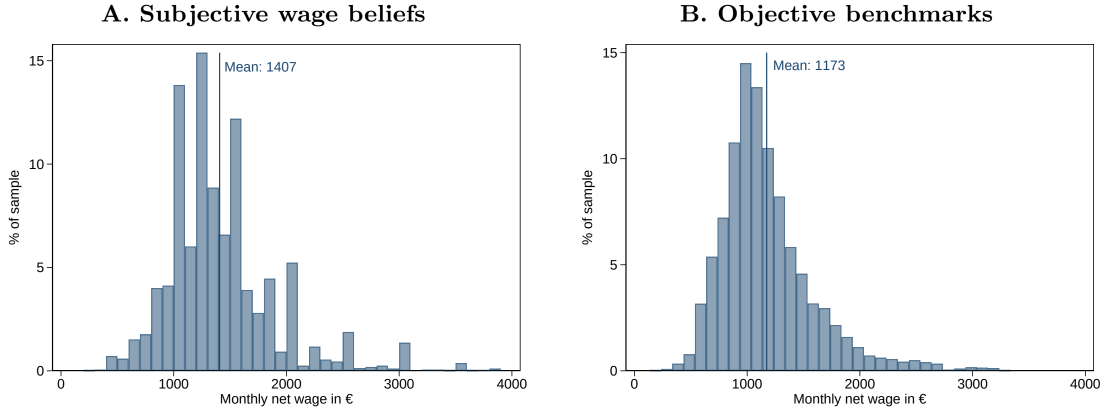
Supplementary Appendix

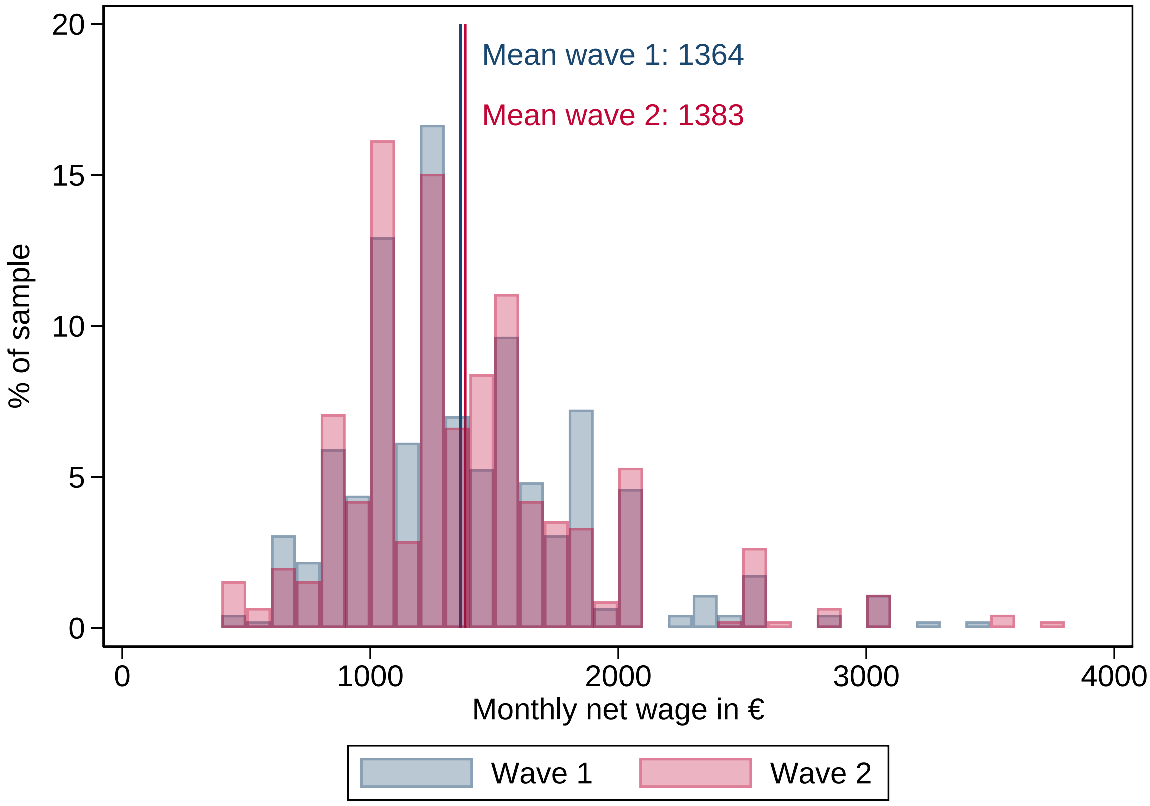
A Additional Figures and Tables

Figure A.1: Distribution of subjective wage beliefs and objective benchmarks



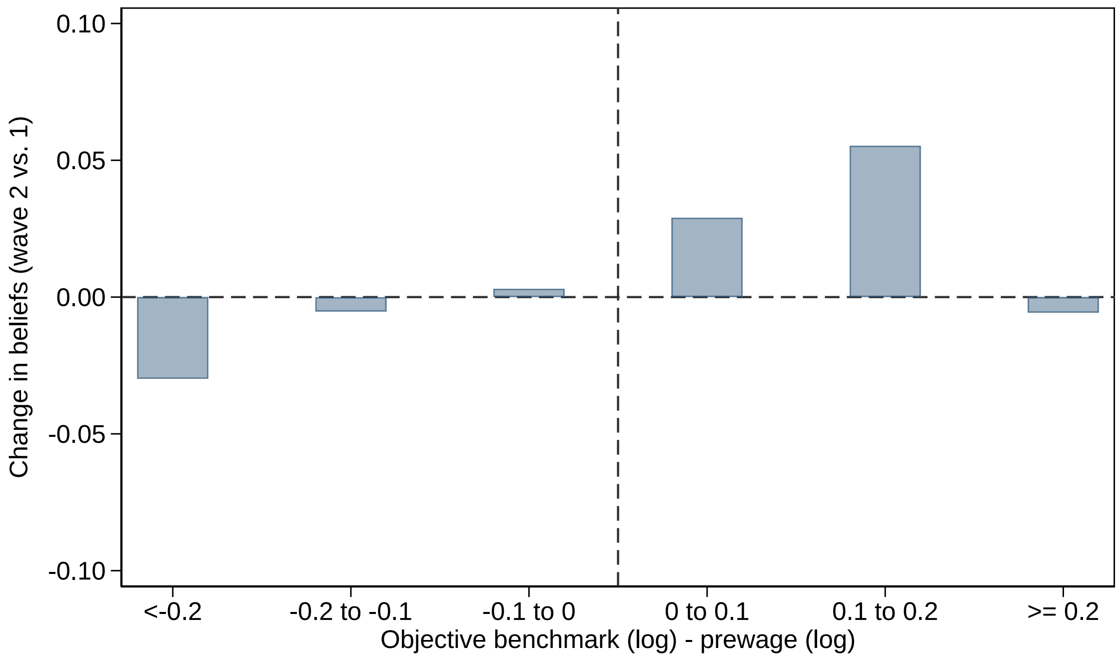
Note: The figure shows the distribution of subjective beliefs (Panel A) and objective benchmarks (Panel B) for individuals' monthly net income upon reemployment among the sample of survey respondents ($N = 5,376$). Objective benchmarks are generated from realized outcomes of similar individuals observed in the administrative records (see Section B for details). Panel A excludes individuals with an expected reemployment wage greater than 4,000€ (< 1% of sample).

Figure A.2: Distribution of wage beliefs in survey waves 1 and 2



Note: The figure shows the distribution of individuals' beliefs about net monthly reemployment wages in survey waves 1 and 2. Wave 1 was conducted 7 - 14 weeks after unemployment entry and wave 2 was collected 12 months later. The sample only includes individuals who are still in the same unemployment spell in wave 2 ($N = 459$). We do not show individuals with an expected reemployment wage in wave 1 or 2 larger than 4,000€ ($<$ 2% of sample).

Figure A.3: Belief updating over time by predicted wage changes



Note: The figure shows the average log change in wage beliefs between survey wave 1 and 2 among jobseekers with varying differences between objective benchmarks and pre-unemployment wages. Wave 1 was conducted 7 - 14 weeks after unemployment entry and wave 2 was collected 12 months later. The sample only includes individuals who are still in the same unemployment spell in wave 2. $N = 459$.

Table A.1: Correlates of wage changes and subjective beliefs

Dependent variable	Obj. benchmark (log) – pre-unemp. wage (log) (1)	Subj. belief (log) – obj. benchmark (log) (2)
Pre-unemployment wage (log)	-0.720***	0.076***
	(0.009)	(0.011)
Female	-0.180***	0.016**
	(0.007)	(0.008)
Age (ref. 16-24 years)		
25 - 34 years	0.029***	0.002
	(0.008)	(0.011)
35 - 44 years	0.086***	-0.039***
	(0.009)	(0.011)
45 - 55 years	0.088***	-0.026**
	(0.009)	(0.012)
German citizen	0.044***	-0.069***
	(0.013)	(0.015)
Educational level (ref. no higher education)		
Vocational certificate	0.074***	-0.027*
	(0.010)	(0.014)
University degree	0.277***	-0.022
	(0.013)	(0.017)
Married	-0.049***	0.030***
	(0.007)	(0.009)
Any children	-0.032***	0.005
	(0.008)	(0.009)
East Germany	-0.142***	0.063***
	(0.007)	(0.008)
Last job was quit	-0.053***	0.023
	(0.014)	(0.017)
Number of unemployment spells in last 2 years (ref. 0 spells)		
1 spell	0.103***	-0.071***
	(0.008)	(0.010)
2 spells	0.078***	-0.069***
	(0.009)	(0.010)
$\geq$ 3 spells	0.078***	-0.066***
	(0.009)	(0.011)
Last unemployment duration	-0.005***	0.004***
	(0.001)	(0.001)
No. of observations	5,376	5,376
R^2	0.669	0.051

Note: The table presents results from OLS regressions. In column (1), the dependent variable is the log difference between individuals' objective benchmark wage, O_i, and their pre-unemployment wage, while column (2) uses the log difference between the subjective belief, S_i, and the objective benchmark, O_i. Robust standard errors are reported in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

Table A.2: Descriptive evidence on labor market implications

Dependent variable	Log reservation wage[(a)]		Log no. of job applications[(b)]	
	(1)	(2)	(3)	(4)
Accuracy of wage expectations: $log(S_i) - log(O_i)$				
linear	0.920***	0.979***	0.163***	0.249***
	(0.014)	(0.019)	(0.057)	(0.075)
squared		-0.118***		-0.171
		(0.034)		(0.107)
No. of observations	5,376	5,376	5,376	5,376
R^2	0.813	0.814	0.023	0.024

Dependent variable	Perceived job finding rate (1=very high)[(c)]		Realized job finding rate (1=yes)[(d)]	
	(5)	(6)	(7)	(8)
Accuracy of wage expectations: $log(S_i) - log(O_i)$				
linear	0.166***	0.158***	-0.046*	0.036
	(0.027)	(0.038)	(0.027)	(0.037)
squared		0.015		-0.163***
		(0.055)		(0.053)
No. of observations	4,953	4,953	5,376	5,376
R^2	0.066	0.066	0.028	0.029

Note: The table reports the results of OLS regressions. The explanatory variable refers to the accuracy of job seekers' wage expectations defined as the log difference between the subjective belief S_i and the objective benchmark O_i. In all specifications, we control for socio-demographic characteristics and objective benchmarks. Robust standard errors are shown in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

[(a)] The dependent variable is the log minimal wage the individual would accept when starting a new job.

[(b)] The dependent variable is the log number of job applications sent since unemployment entry.

[(c)] The dependent variable is an indicator of whether the individual reports the perceived six-month-ahead job finding rate to be 'very high'.

[(d)] The dependent variable is an indicator of whether the individual actually starts a regular job within the next six months.

B Details on Objective Benchmarks

In the following, we present details about the prediction of objective benchmarks for jobseekers' reemployment wages.

Covariates: Monthly wages are modeled as a function of covariates which are pre-determined at the time of unemployment entry. We exploit a rich set of characteristics that are available in both the *IZA/IAB Linked Evaluation Dataset* (LED) and the *IZA/IAB Administrative Evaluation Dataset* (AED). These include socio-demographic information (e.g. gender, age, education, family status), characteristics of the last job before unemployment (wage, part- versus full-time job), detailed information on the labor market biography in the last ten years (e.g. months employed, unemployed, and in labor market programs), and local labor market characteristics (unemployment rate, East versus West German residency). To allow for a flexible functional form, we also use third-order polynomial terms of all continuous variables and first-order interaction terms of all variables with some important characteristics (gender, age, education, East German residency, last wage). See Table B.2 for a complete list of all the 717 included covariates.

LASSO regression: To address the high-dimensional nature of the data and to avoid overfitting, we estimate LASSO regressions, which add a regularization term to the objective function and shrink some coefficients to zero.[9] We optimized the regularization parameter λ using five-fold cross-validation in the training data and considering the following values for λ: 0.001, 0.01, 0.1, 1, 10, 100, 1000. In the estimated models, 66% of all covariates are selected.

Prediction quality: In Table B.3, we evaluate the out-of-sample predictive performance of the LASSO model. Results are presented for the different training samples (AED 01/2005 - 06/2007 or 80% of AED 06/2007 - 06/2008) and test samples (80% of AED 06/2007 - 06/2008 or LED). We calculate the out-of-sample R^2 obtained from a regression of realized gross wages on predicted wages in the test data. The predictions explain between 48% and 53% of the out-of-sample variation. Note that the predictive performance is similar for the two different training samples. The correlation of predictions between both samples is also very high (0.976).

Results in Table B.3 are based on gross wages. For our analyses, we convert the predicted gross wage into net terms (see procedure below). For the converted net wage predictions in the LED sample, we can compare the explanatory power of objective predictions with that of respondents' subjective beliefs. The results in Table B.4 demonstrate that our LASSO model

[9] We use the Stata command `lasso2` from `lassopack` developed by Ahrens *et al.* (2018, 2020).

is better at predicting realized wages than jobseekers themselves are: while jobseekers' beliefs explain 34% of the variation in realized net wages, the objective benchmarks explain 45%.[10] Figure B.1 also examines the fit over the distribution of our predictions. The objective benchmarks predict realized wages in the survey sample with a slope coefficient very close to one, indicating that predictions errors do not vary systematically over the objective benchmark distribution.

In Table B.5, we also investigate whether jobseeker characteristics that are unobserved in the administrative data are likely to affect the validity of our objective benchmarks. For that we regress log realized wages on a set of personality traits, including locus of control, conscientiousness, openness, extraversion, and neuroticism, which are observed in the survey sample. The personality traits show strong correlations with realized wages. However, when we condition on the objective benchmark measure, the correlations vanish almost entirely. An F-test fails to reject joint significance of all personality traits and, individually, only locus of control remains significant. These results indicate the saturation of our prediction model based on the rich set of covariates in the administrative data.

Converting gross to net wages: Wage beliefs in the survey are elicited in net terms, while the administrative data provide realized wages in gross terms. We therefore convert gross into net wages by deducting social security contributions and wage taxes.

Wage taxes are withheld by the employer and deducted from the monthly wage payment. They qualify as a pre-payment of the income tax in case the employee files an annual income tax declaration. We do not perform a complete income tax calculation since we do not have information on individual-specific deductions and other income sources. Moreover, individuals most likely think about their monthly payroll when asked about their net wage. Rather, we calculate withheld wage taxes utilizing contribution and tax schedules of 2008 and taking into account variation in rates according to partnership status, number of children, age, and East versus West German residency.

Exemption thresholds in the wage tax schedule depend on the tax class of the individual. While single individuals without children are always in class I and single parents are always in class II, married couples may choose between a combination of classes IV/IV or III/V. With IV/IV, the standard exemption threshold is applied to both spouses, whereas with III/V the higher-earning spouse obtains twice the standard exemption rate while the second earner is already taxed at lower earnings. Although we do not directly observe the chosen tax classes for married couples, we can infer them from the observed UI benefit payments. UI benefits are generally calculated by the following formula: Monthly benefit = 0.6 × (Average monthly gross

[10] This result is in line with the evidence provided by van den Berg *et al.* (2023) who find that machine learning predictions have higher explanatory power for reemployment probabilities than jobseekers' self assessments.

wage in last 12 months before unemployment - Wage tax - SolZ - Social security payment). Thus, the relation between previous gross wages and UI benefits depends on the chosen tax class. We exploit this relation by calculating the hypothetical benefits under tax classes III, IV, and V and then choose the tax class that minimizes the difference between the actual observed and the hypothetical benefit payments. The derived tax classes match well-known descriptives about taxation of married couples in Germany. For instance, tax class V is chosen more frequently by women than men and this type of splitting is more prevalent in West Germany than in East Germany.

Table B.1: Summary statistics: LED versus AED samples

	LED	AED 01/2005 - 05/2007	AED 06/2007 - 05/2008
No. of observations	5,376	84,617	21,715
Reemployment wage (gross, € per month)[(a)]	1,782	1,704	1,716
Socio-demographic characteristics			
Female	0.41	0.35	0.37
Age	36.16	35.11	34.90
School leaving degree			
lower secondary degree	0.31	0.38	0.35
middle secondary degree	0.44	0.39	0.40
upper secondary degree	0.23	0.18	0.21
Further education			
vocational certificate	0.72	0.68	0.68
university degree	0.20	0.16	0.19
German citizen	0.94	0.91	0.91
Married	0.39	0.45	0.43
Number of children			
one child	0.18	0.16	0.17
two or more children	0.12	0.14	0.13
Last job			
Wage in last job (gross, € per month)	1,726	1,688	1,696
Last job was quit by individual	0.06	0.07	0.09
Labor market history			
# of employers in last 2 years	2.55	1.49	1.61
# of employers in last 10 years	4.64	3.13	3.45
# of UE spells in last 2 years	1.41	0.59	0.44
# of ALMP programs in last 2 years	0.42	0.17	0.21
Duration of last UE spell in months	5.09	5.34	5.80
# of months employed in year t-1	8.64	10.74	10.92
# of months employed in year t-2	7.86	9.27	9.14
# of months employed in year t-3	7.50	8.38	7.73
# of months employed in years t-4 to t-10	46.12	43.18	40.20
# of months unemployed in year t-1	0.79	0.86	0.61
# of months unemployed in year t-2	1.07	1.57	1.49
# of months unemployed in year t-3	1.29	1.75	2.19
# of months unemployed in years t-4 to t-10	8.81	8.37	10.42
# of months in ALMP in year t-1	0.60	0.22	0.25
# of months in ALMP in year t-2	0.68	0.53	0.57
# of months in ALMP in year t-3	0.63	0.61	0.61
# of months in ALMP in years t-4 to t-10	1.35	1.20	1.42
Average wage in year t-1 (quintiles)	3.17	3.25	3.19
Average wage in year t-2 (quintiles)	2.97	3.00	2.89
Average wage in year t-3 (quintiles)	2.78	2.81	2.59
Average wage in years t-4 to t-10 (quintiles)	17.88	17.01	16.41
Local labor market			
West, UE rate <3%	0.02	0.00	0.01
West, UE rate 3-6%	0.29	0.07	0.26
West, UE rate 6-9%	0.25	0.24	0.26
West, UE rate >9%	0.11	0.39	0.18
East, UE rate <12%	0.07	0.00	0.04
East, UE rate 12-14%	0.10	0.01	0.08
East, UE rate 14-16%	0.10	0.05	0.12
East, UE rate >16%	0.04	0.23	0.05

Note: The table compares the mean characteristics of the linked survey-administrative sample (LED) with those of the two adminstrative samples used for the prediction of objective benchmarks (AED).
[(a)] Realized wages are observed for individuals who start a regular job within 24 months after unemployment entry.

Table B.2: List of covariates used to generate objective benchmarks

Type	Covariate
Socio-demographic characteristics	
Continuous	Age
Categorical	Female
	School degree (4 categories: none, lower sec. degree, middle sec. degree, upper sec. degree)
	Further education (3 categories: none, vocational certificate, university degree)
	German citizen
	Married
	# of children (3 categories: 0, 1, ≥ 2)
Last job	
Continuous	Wage in last job (gross, € per month)
Categorical	Last job was quit by individual
Labor market history	
Continuous	Duration of last UE spell in months
	# of months employed in year t-1
	# of months employed in year t-2
	# of months employed in year t-3
	# of months employed in years t-4 to t-10
	# of months unemployed in year t-1
	# of months unemployed in year t-2
	# of months unemployed in year t-3
	# of months unemployed in years t-4 to t-10
	# of months in ALMP in year t-1
	# of months in ALMP in year t-2
	# of months in ALMP in year t-3
	# of months in ALMP in years t-4 to t-10
Categorical	# of employers in last 2 years (5 categories)
	# of employers in last 10 years (5 categories)
	# of UE spells in last 2 years (5 categories)
	# of ALMP programs in last 2 years (5 categories)
	Average wage in year t-1 (5 categories)
	Average wage in year t-2 (5 categories)
	Average wage in year t-3 (5 categories)
	Average wage in years t-4 to t-10 (5 categories)
	All months regularly employed in year t-1
	Zero months regularly employed in year t-2
	All months regularly employed in year t-2
	Zero months regularly employed in year t-3
	All months regularly employed in year t-3
	Zero months regularly employed in years t-4 to t-10
	All months regularly employed in years t-4 to t-10
	Zero months unemployed in year t-1
	Zero months unemployed in year t-2
	Zero months unemployed in year t-3
	Zero months unemployed in years t-4 to t-10
	Zero months in ALMP in year t-1
	Zero months in ALMP in year t-2
	Zero months in ALMP in year t-3
	Zero months in ALMP in years t-4 to t-10
Local labor market	
Categorical	Unemployment rate in employment agency district at time of UE entry (8 categories: West <3%, 3-6%, 6-9%, >9%; East <12%, 12-14%, 14-16%, >16%)
Timing of unemployment spell	
Categorical	Calendar month of entry into unemployment (12 categories)

Note: The table reports the list of covariates used in the lasso regression to predict reemployment wages. We also include second- and third-order polynomials of all continuous variables, as well as interaction terms of all variables with *female*, *age*, *upper secondary degree*, *East German residency*, and the *monthly gross wage in the last job*, yielding a total of 717 covariates included.

Table B.3: Prediction performance based on out-of-sample R^2

	Test dataset[a]			
	Administrative data		Survey data	
Training dataset[b]	Baseline	Robustness	Baseline	Robustness
Out-of-sample R^2	0.525	0.516	0.511	0.481

Note: The table reports the out-of-sample R^2, which is obtained based on a regression of realized reemployment wages as observed in the respective test dataset on predictions of objective benchmarks generated in the training dataset.
[a] The administrative test dataset includes a 20% sample of all entries into unemployment between June 2007 and May 2008, while the survey test dataset includes all individuals observed in the matched survey-administrative data.
[b] The baseline training dataset includes all entries into unemployment between January 2005 and May 2007 as observed in the administrative records. As a robustness check, we use an 80% sample of all entries into unemployment between June 2007 and May 2008 (i.e. the same period during which the survey was conducted) excluding observations from the respective test dataset.

Table B.4: Predictive power of objective benchmarks and subjective beliefs

Dependent variable	Log realized net monthly wage	
	(1)	(2)
Objective benchmark (log)	0.951^{***}	
	(0.017)	
Subjective belief (log)		0.758^{***}
		(0.018)
No. of observations	4,098	4,098
R^2	0.454	0.335

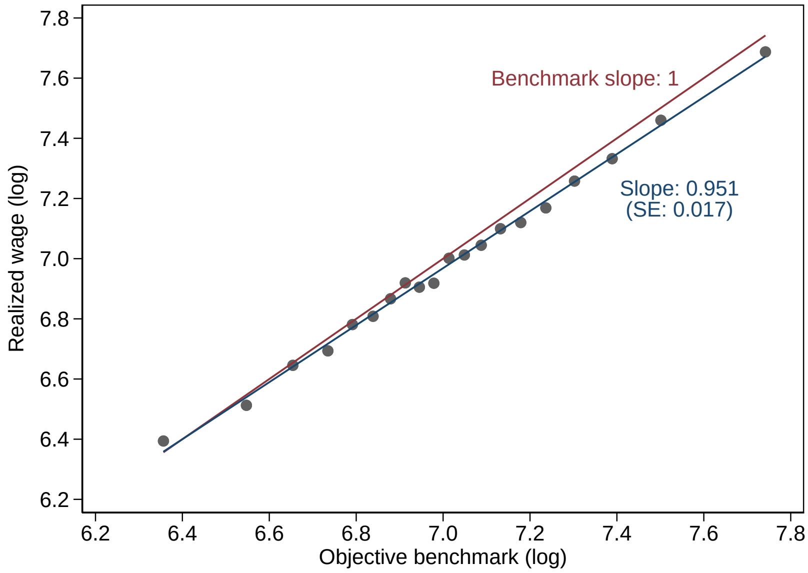
Note: The table reports the results of an OLS regressions of log realized reemployment wages on objective benchmarks and subjective wage expectations, respectively. The sample includes survey respondents as observed in the matched survey-administrative data who found a new job within 24 months after the beginning of the unemployment spell. Standard errors reported in parenthesis. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

Table B.5: Personality traits and realized wages

	Log realized net monthly wage	
	(1)	(2)
Internal locus of control	0.039***	0.014**
	(0.007)	(0.006)
Conscientiousness	-0.001	0.002
	(0.007)	(0.005)
Openness	0.029***	0.004
	(0.007)	(0.005)
Extraversion	-0.029***	-0.004
	(0.008)	(0.006)
Neuroticism	-0.041***	0.002
	(0.007)	(0.005)
Objective benchmark O_i		0.941***
		(0.017)
No. of observations	3,959	3,959
R^2	0.024	0.453
p-value joint significance	<0.001	0.247

Note: The table reports the results of OLS regressions of log realized net monthly reemployment wages on personality traits and objective benchmarks for reemployment wages. It also reports p-values for the joint significance of all personality traits. Robust standard errors are shown in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

Figure B.1: Relation between realized wages and objective benchmarks



Note: The figure depicts a binned scatter plot (with 20 bins) for the relation between individuals' realized reemployment wages and objective benchmarks for reemployment wages. $N = 4,098$.

C Robustness Checks

A series of robustness checks confirms our result that the slope coefficient in Model **??** is smaller than one, showing that jobseekers with lower objective earnings potential exhibit the highest levels of optimism. The results across the various specifications are shown in Figure C.1 and Table C.1 and indicate similar slope coefficients between 0.64 and 0.75.

First, we restrict our survey sample to jobseekers who find reemployment within 24 months, since we have also estimated the objective benchmarks from wages of individuals who become reemployed after 24 months.

Second, we vary the time period of the administrative sample used to estimate the objective benchmark. In particular, we rely on alternative training data including individuals who became unemployed in 2007 and 2008 (i.e. the same time during which the survey was conducted).

Third, we address concerns that the estimated slope coefficients may suffer from attenuation bias due to measurement error in the objective predictions. Therefore, we conduct an instrumental variable (IV) regression, where we use objective predictions from the alternative training data as an instrument for objective predictions from our baseline training data.

Fourth, we restrict the administrative sample to jobseekers who find employment within nine months of becoming unemployed, rather than 24 months, when calculating objective benchmarks. This nine-month horizon corresponds to, on average, six months after the initial interview. This choice is motivated by the fact that jobseekers answered the question about their wage expectations shortly after discussing their anticipated likelihood of finding a job during the next six months, suggesting a consistent time frame for wage expectations.

Fifth, we assess the role of rounding in subjective beliefs by also rounding the objective benchmarks to the nearest 50, 100, or 250€ values.

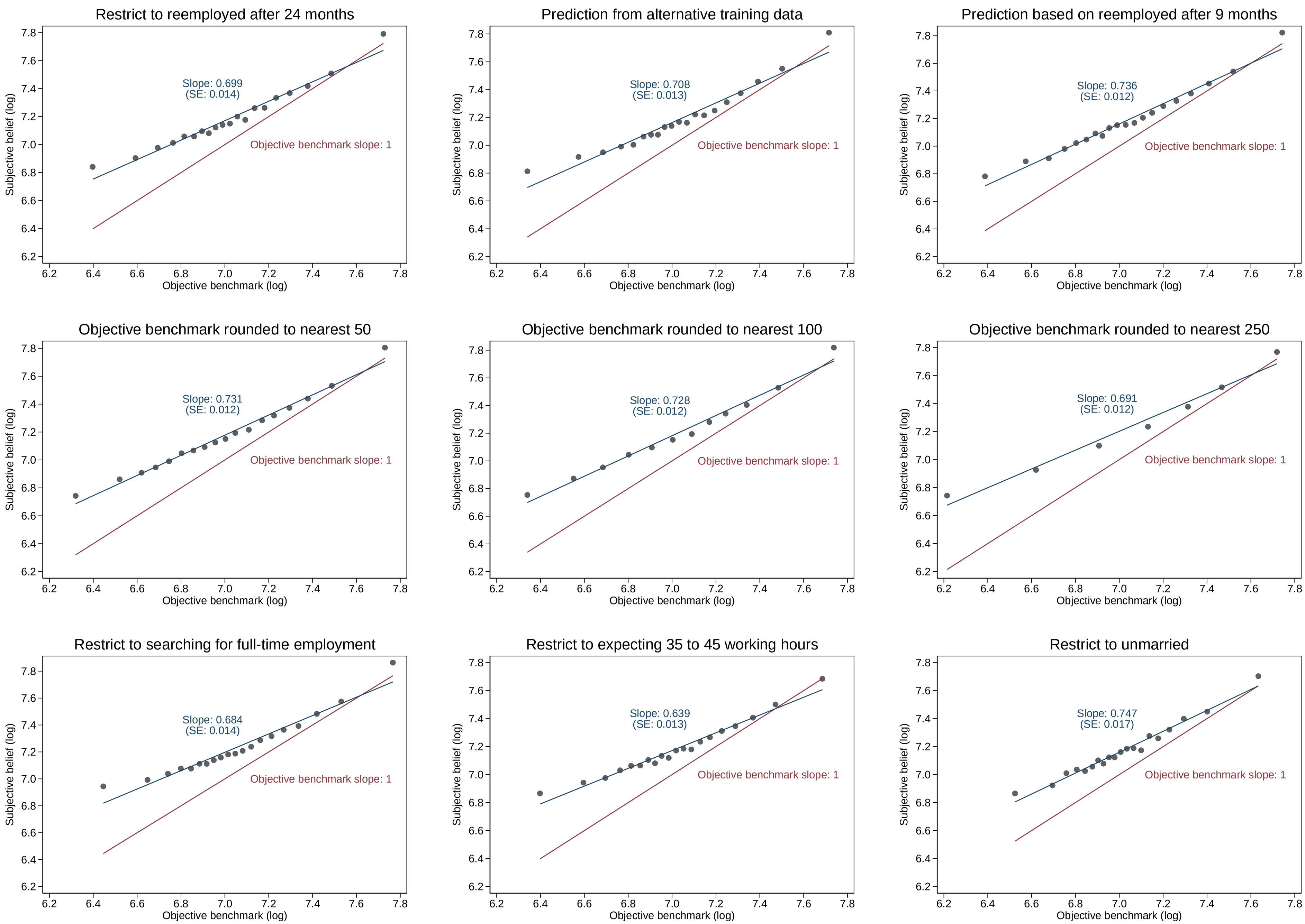
Lastly, we impose two additional restrictions on the survey sample, considering only (i) individuals who search for and expect to find a full-time job and (ii) unmarried individuals. This enables us to examine whether differences in expected working hours (full-time) and measurement error arising from the conversion of gross to net wages (unmarried individuals) affect our estimates. Note that calculating social security contributions and income taxes is straightforward for unmarried individuals. Therefore, any measurement error arising from the conversion of gross to net wages is unlikely to impact the objective benchmarks for this group of individuals.

Table C.1: Robustness: relationship between subjective beliefs and objective benchmarks

	Mean difference	Share with diff. > 0.1	Share with diff. < -0.1	$\widehat{\beta}_1$	N
Baseline	0.170	0.569	0.130	0.735*** (0.012)	5,376
Restrict to individuals who are employed after 24 months	0.162	0.127	0.559	0.699*** (0.014)	4,180
Prediction from alternative training data (survey period)	0.154	0.536	0.152	0.708*** (0.013)	5,376
Instrument prediction from baseline training data with prediction from alternative training data	-	-	-	0.740*** (0.013)	5,376
Prediction based on all individuals reentering employment within 9 months after unemployment entry	0.153	0.540	0.147	0.736*** (0.012)	5,376
Objective benchmark rounded to nearest 50	0.170	0.572	0.127	0.731*** (0.012)	5,376
Objective benchmark rounded to nearest 100	0.170	0.565	0.127	0.728*** (0.012)	5,376
Objective benchmark rounded to nearest 250	0.173	0.564	0.143	0.691*** (0.012)	5,376
Restrict to individuals searching for full-time employment	0.179	0.579	0.110	0.684*** (0.014)	4,284
Restrict to individuals expecting between 35 and 45 working hours	0.165	0.560	0.118	0.639*** (0.013)	4,396
Restrict to unmarried	0.155	0.566	0.117	0.747*** (0.017)	3,229

Note: Robustness tests for comparisons between subjective beliefs S_i and objective predictions O_i for net monthly reemployment wages (both in log). The table reports the mean difference between S_i and O_i, the shares of individuals who overestimate and underestimate wages by more than 10% (difference > 0.1 / < 0.1), the slope coefficient $\widehat{\beta}_1$ (with its robust standard error in parenthesis) from a regression of S_i on O_i, and the number of individuals in the sample. ***/**/* indicate statistical significance at the 1%/5%/10%-level for a test of the null hypothesis that $\beta_1 = 1$.

Figure C.1: Robustness: relationship between subjective beliefs and objective benchmark



Note: The figure depicts binned scatter plots (with 20 bins) of the robustness tests for comparisons between subjective beliefs S_i and objective predictions O_i for net monthly reemployment wages (both in log). The slope coefficients (with its robust standard error in parenthesis) from a regression of S_i on O_i, correspond to the results in Table C.1.

D Details on Sanction Analysis

D.1 Econometric strategy

To capture variations in the local sanction regime, we utilize regional data on the annual number of benefit sanctions imposed in each of the 178 LEA districts (indexed by j) and normalize this information by the average annual stock of unemployed workers in each LEA district. The resulting sanction intensity, SI_j, can be linked to the administrative and survey data, as explained in Section 2, both of which include identifiers for jobseekers' place of residence.[11] To ensure that our estimation sample does not contribute to the sanction intensity measure, we rely on the corresponding numbers as observed in the year before a jobseeker entered unemployment. In the Appendix, we illustrate the distribution of the sanction intensity across survey respondents (see Figure D.1), as well as LEA districts in Germany (see Figure D.2).

While the local sanction intensity serves as a proxy for the personal risk of being exposed to a benefit sanction, LEA districts imposing more sanctions might face a different composition of the unemployed workforce. This makes it unlikely that a simple regression of jobseekers' outcomes on the local sanction intensity will identify the causal effect of jobseekers' personal sanction risk. Therefore, we exploit discontinuities with respect to the sanction intensity along the administrative borders of the LEA districts (similar to Dube *et al.*, 2010; Caliendo *et al.*, 2023). Specifically, we estimate border-pair fixed-effects models of the following form:

$$Y_{ijb} = \alpha + \delta SI_j + \beta X_i + \phi R_j + \kappa_b + \varepsilon_{ijb}, \tag{4}$$

where i denotes the individual jobseeker, j the LEA district in which the individual is located at the beginning of the unemployment spell, and b a pair of bordering LEA districts such that κ_b denotes the border-pair fixed effects for any combination of two neighboring LEA districts. Since one LEA district usually has several neighboring districts, an individual living in region j can belong to different sets of boarder pairs b and therefore enters the estimation multiple times (depending on the number of neighboring regions). Therefore, we use sampling weights referring to the inverse of the number of neighboring LEA districts. The parameter of interest δ identifies the effect of sanction intensity on the outcome variables Y by comparing individuals living in similar, neighboring LEA districts but facing varying risks of being sanctioned. More-

[11]Due to data security restrictions, we are unable to utilize regional identifiers for the linked survey-administrative data in our analysis. Consequently, in this section, we rely on the survey and administrative data without linking them at the individual level. This requires us to re-estimate the objective benchmarks using a reduced set of covariates available in both the survey and administrative records. This includes socio-demographic characteristics, previous wage, regional information, and month of entry into unemployment. Despite this adjustment, our model demonstrates strong out-of-sample predictive power (with an R^2 of 0.39), and the re-estimated objective predictions closely align with the measure employed in the previous sections ($\rho = 0.75$).

over, R_j captures regional characteristics including the local unemployment rate, vacancy rate, gross domestic product, industry structure, and federal state fixed effects, and X_i accounts for individual-level characteristics. Standard errors are clustered at the LEA district level.

D.2 Validity of the empirical approach

The underlying assumption of this approach is that two LEA districts with a common border are similar in all relevant characteristics except the sanction intensity. LEA districts represent relatively small geographical entities and delineations of functional local labor markets in Germany typically result in larger geographical entities (see, e.g., Kropp and Schwengler, 2016, who identify 50 local labor market regions, compared to 178 LEA districts). For example, the two largest metropolitan areas in Germany – the Rhine-Ruhr region and the Berlin-Brandenburg area – are home to approximately 10.9 million and 6.2 million residents, respectively. At the same time, they encompass 13 and eight distinct LEA districts each. Multiple LEA districts being part of larger local labor markets makes it likely that bordering LEA districts will exhibit similar characteristics. To empirically support this premise, Table D.1 contrasts disparities in regional labor market indicators – such as unemployment rates, vacancy rates, GDP, etc. – within 487 pairs of neighboring LEAs with differences in randomly selected LEA district pairs (see also Caliendo *et al.*, 2023). For instance, the average disparity in unemployment rates between two randomly chosen LEA districts is approximately 4.0 percentage points. In contrast, when examining pairs of LEAs that share a common border, this disparity is markedly reduced by about 70%, resulting in a mere 1.2 percentage point difference.

Moreover, we conduct balancing tests regressing the local sanction intensity on a rich set of individual-level characteristics to further examine the validity of our approach. As in our main analysis, we condition on border-pair fixed effects, as well as the set of regional characteristics, and we explore the predictive power of socio-demographic characteristics, labor market histories and personality traits, all variables that have been proven to be important for individuals' labor market success. As shown in Appendix Table D.2, we find very little evidence that individual characteristics as observed in our data are correlated with the conditional sanction intensity (i.e. see p-values at the bottom of Table D.2).

Another concern relates to the possibility that LEAs with more restrictive sanction regimes also adjust other dimensions of their policy style. In that case, any effect of the sanction intensity could possibly reflect changes in the usage of other policy instruments rather than sanctions. To test this, we exploit survey data on various dimensions of caseworkers' counseling activities including notifications about labor market programs (i.e. training, workfare programs, job creation schemes, and start-up subsidies), the number of caseworker meetings, and the provision

Table D.1: Similarity of bordering regions

	Absolute difference within pair of LEA districts		%-change
	Simulated border pairs (1)	Actual border pairs (2)	Simulated - actual (3)
Unemployment rate	0.040	0.012	-70.4%
GDP per capita in € 1,000	7.576	4.948	-34.7%
Vacancy rate	0.066	0.028	-58.6%
Share of working population			
in agriculture sector	0.017	0.008	-49.6%
in manufacturing sector	0.079	0.043	-45.1%
in service sector	0.084	0.047	-43.9%
Migration rate	0.009	0.005	-36.4%
No. of LEA districts	178	178	
No. of border pairs	1,068	487	

Note: The table compares absolute differences in regional indicators within the 487 actual border pairs to a set of simulated regional pairs. Simulated regional pairs are generated by matching each LEA district to three other randomly selected LEA districts, which yields 1,068 simulated pairs. Columns (1) and (2) report absolute average differences in regional indicators across all actual and simulated pairs, respectively. Column (3) reports the %-difference between average differences reported in columns (2) and (1).

of vacancy referrals. These variables are the most direct measures of the LEA's policy style, since they reflect the caseworkers' information strategy. The findings presented in Appendix Table D.3 provide no evidence that the local sanction risk is related to caseworkers' counseling activities.

Table D.2: Balancing test of sanction intensity (survey data)

Dependent variable	Sanction intensity TI_j	
	Coef.	SE
Education		
School leaving degree (Ref.: None)	ref.	
Lower sec. degree	-0.239	(0.197)
Middle sec. degree	-0.091	(0.170)
Upper sec. degree	-0.069	(0.172)
Higher education (Ref.: None)	ref.	
Vocational training	0.243	(0.156)
University degree	0.264	(0.178)
Socio-demographic characteristics		
Female	0.010	(0.050)
Migration background	-0.031	(0.092)
Age (Ref.: 16-24 years)	ref.	
25-34 years	0.065	(0.074)
35-44 years	0.035	(0.086)
45-55 years	-0.023	(0.088)
Married	-0.071*	(0.042)
Children (Ref.: None)	ref.	
One child	0.029	(0.065)
Two or more children	0.087	(0.096)
Homeowner	0.103	(0.064)
Unemployment and labor market history		
UI Benefit recipient	-0.001	(0.071)
Level of UI benefits in €100	-0.005	(0.006)
Lifetime months in unemployment (div. by age-18)	-0.228	(0.210)
Lifetime months in employment (div. by age-18)	-0.100	(0.091)
Last hourly wage in €	0.012*	(0.006)
Employment status before UE (Ref.: Other)	ref.	
Regular employed	-0.020	(0.103)
Subsidized employed	-0.064	(0.111)
School, apprentice, military, etc.	-0.023	(0.126)
Parental leave	-0.269*	(0.143)
Time between entry into UE and interview (Ref.: 7 weeks)		
8 weeks	-0.052	(0.248)
9 weeks	-0.076	(0.278)
10 weeks	0.046	(0.274)
11 weeks	-0.005	(0.313)
12 weeks	-0.104	(0.316)
13 weeks	-0.023	(0.344)
14 weeks	-0.066	(0.344)
Personality traits$^{(a)}$		
Openness	-0.019	(0.021)
Conscientiousness	-0.023	(0.025)
Extraversion	0.044	(0.040)
Neuroticism	0.023	(0.029)
Locus of control	-0.040	(0.036)
Constant	-0.058	(0.472)
No. of observations	5,669	
Additional control variables		
Federal state fixed effects	Yes	
Basic regional characteristics	Yes	
P-value joint significance		
Education	0.454	
Socio-demographic characteristics	0.238	
Unemployment and labor market history	0.286	
Personality traits	0.526	

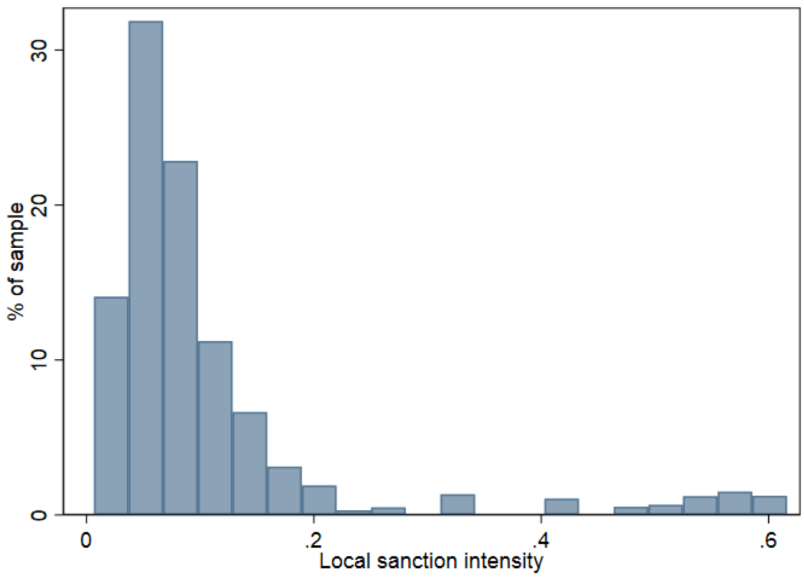
Note: The table reports the results of balancing tests regressing the local treatment intensity on individual-level characteristics. Standard errors in parenthesis are clustered at the LEA district level. ***/**/* indicate statistical significance at the 1%/5%/10%-level.
$^{(a)}$Personality traits are measured with different items on a 7-point Likert-scale and standardized to have a mean of zero and a variance of one.

Table D.3: Sanction intensity and counseling activities of caseworkers

Dependent variable	Notification about labor market programs: Workfare program	Job creation schemes	Training program	Start-up subsidies	Any vacancy referral	Caseworker meetings: three or more
	(1)	(2)	(3)	(4)	(5)	(6)
Sanction intensity	0.004	-0.054	0.125	-0.109	-0.083	0.244
	(0.402)	(0.021)	(0.114)	(0.078)	(0.105)	(0.164)
No. of observations	5,669	5,669	5,669	5,669	5,669	5,669
Mean dep. variable	0.014	0.020	0.164	0.048	0.239	0.634

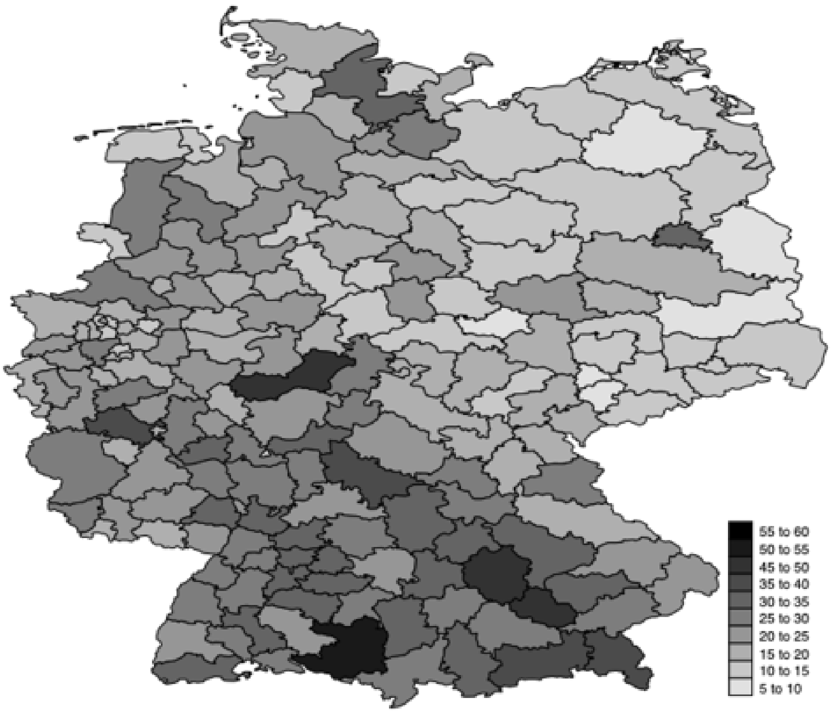
Note: The table reports the effect of the local sanction intensity on caseworkers' counseling activities. In all specifications, we account for socio-demographic and regional characteristics, as well as border-pair fixed effects. Standard errors clustered at the LEA district level are shown in parentheses. ***/**/* indicate statistical significance at the 1%/5%/10%-level.

Figure D.1: Distribution of local sanction intensity across survey respondents



Note: The figure shows the distribution of local sanction intensity across all survey respondents ($N = 5,669$).

Figure D.2: Distribution of local sanction intensity across LEA districts



Note: The figure shows the geographical distribution of local sanction intensity across LEA districts in Germany.