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Almut Balleer, Georg Duernecker, Susanne Forstner, Johannes Goensch

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Abstract

We measure individual bias in labor market expectations in German survey data and find that workers on average significantly overestimate their individual probabilities to separate from their job when employed as well to find a job when unemployed. These biases vary significantly between population groups. Most notably, East Germans are significantly more pessimistic than West Germans. We find a significantly negative relationship between the pessimistic bias in job separation expectations and wages, and a significantly positive relationship between optimistic bias in job finding expectations and reservation incomes. We interpret and quantify the effects of (such) expectation biases on the labor market equilibrium in a search and matching model of the labor market. Removing the biases could substantially increase wages and expected lifetime income in East Germany. The bias difference in labor market expectations explains part of the East-West German wage gap.

JEL-Codes: E240, J310, D840.

Keywords: labor market risk, biased beliefs, wages, reservation wages.

Almut Balleer
RWTH Aachen University / Germany
balleer@ewifo.rwth-aachen.de

Georg Duernecker
Goethe-University Frankfurt / Germany
duernecker@em.uni-frankfurt.de

*Susanne Forstner**
Institute for Advanced Studies (IHS)
Vienna / Austria
forstner@ihs.ac.at

Johannes Goensch
Goethe-University Frankfurt / Germany
Goensch@econ.uni-frankfurt.de

*corresponding author

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1 Introduction

Economic agents form expectations about various outcomes in the labor market, such as the risk to leave an existing job when employed or the probability to find a new job when unemployed. These expectations affect individual economic decision making. A common approach is to assume that all agents correctly assess the probability of various labor market transitions. However, if workers are more optimistic or pessimistic about their risk of finding or separating from a job, this might affect their wage through a change in both the reservation wage and the wage bargaining outcome. As a consequence, if optimism or pessimism differ between groups in the population, this might explain wage differentials. In this paper, we measure biased labor market expectations and provide evidence on whether this bias is important to understand individual outcomes as well as differences in outcomes across groups in the population. We specifically address the role of biased labor market expectations for the East-West German wage differential.

We document labor market expectations in survey data from the German Socio-Economic Panel (GSOEP). The GSOEP questionnaires regularly include an assessment of the individual probability to separate from a job when employed or to find a job when unemployed. Based on subsequently realized labor market transitions, we then statistically predict transition probabilities in narrowly defined groups, that is, conditional on a large number of demographic and industry characteristics. A bias in individual labor market expectations is then defined as the difference between a person's expected probability of a given labor market event and the respective predicted probability of that event.

We find that, on average, workers in Germany are pessimistic with respect to separating from their job, i.e., they significantly overestimate the risk of separating from their job within two years by about 7 percentage points (48 percent). We also find that, on average, unemployed persons in Germany are optimistic, that is, they significantly overestimate their probability to find a job within two years by about 8 percentage points (16 percent). Biases in job separation and job finding expectations are significant across a large number of subgroups of employed and unemployed persons in Germany. The pessimistic bias in job separation expectations decreases with job security. We generally do not find strong evidence in favor of learning, as biases do not strongly decrease (or even increase) between two surveys at the individual level. A striking finding is that East Germans are substantially more pessimistic than their West German counterparts, both with respect to their job separation risk and their job finding chance.

We then relate workers' biases in expectations about job separation and job finding to wages and reservation income. We document a negative relation between the degree of pessimistic bias in job separation expectations and individual net hourly wage rates, which is statistically significant both overall and net of controls. The overall effect states that an increase in pessimism by one standard deviation is associated, on average, with 2.1% lower wages. Similarly, we document a significant and positive relation between the degree of optimistic bias in job finding expectations and reservation income: An increase in optimism by one standard deviation is associated, on average, with about 2% higher reservation income.

We present a search-and-matching model of the labor market with biased expectations that is in line with the empirical relationship between workers' expectation bias, wages and reservation wages. We use the model to quantify how biased expectations affect the labor market equilibrium, i.e., wages and unemployment jointly. This allows us to compare changes in expected lifetime income in a counterfactual exercise in which we remove the bias in labor market expectations. While the effects are not strikingly large on average, they mask substantial effects across subgroups of the population. Removing all biases for persons in East Germany, for example, leads to an increase in wages by about 1.5 percent and an increase in expected lifetime income by about 1 percent. We then also quantify the contribution of workers' biased expectations to the East-West German wage differential. Our results predict that if East German biases were at Western levels, the unconditional East-West German wage gap would be about 3 percentage points lower. The wage gap reduces by over 5 percentage points when we calibrate the model to alternative measures of bias in expectations, or if we assign a low bargaining power to East German workers.

Our study relates to a growing literature on the effect of biased labor market beliefs on macroeconomic labor market outcomes. One part of the literature explores bias in households' expectations about aggregate outcomes such the unemployment rate (compare Bovi (2009) or Souleles (2004)) and relates these expectations to individual choices such as savings decisions (see e.g. Den Haan et al. (2017) or Broer et al. (2021)). In contrast, our measure of biased beliefs reflects households' expectations about individual outcomes which captures both aggregate and idiosyncratic risk and may provide a better estimate of the risk that actually affects households' decisions.

Mueller and Spinnewijn (2022) contains a great overview of the literature on individual bias in labor market expectations. Previous empirical studies document individual perceived labor market risk (see for example Dominitz and Manski (1997) or Dixon et al. (2013)) or pessimistic bias in job separation beliefs (Stephens (2004) and Hendren (2017)). Based on earlier waves in the GSOEP, Dickerson and Green (2012) document qualitative bias in beliefs of labor market risk. Emmler and Fitzenberger (2022) also use early waves of the GSOEP to assess overpessimism in job loss expectations, document differences between East and West Germany and document convergence in pessimism between these two regions in the decade following the German reunification. A recent larger literature documents optimistic bias of job seekers (e.g., Mueller et al. (2021) or Conlon et al. (2018)). In a complementary study (Balleer et al. (2021)) we document differences in bias in labor market expectations across educational groups in the US. In the present study, we provide evidence about bias in job separation expectations in Germany. Our findings are consistent with the specific results in existing contributions. Our study is more comprehensive in that it addresses bias in beliefs in job finding and job separation jointly and that we can follow individuals over time.

A few studies relate perceived risk about job separation to wages or earnings and generally find a negative relationship. Campbell et al. (2007) use the British Household Panel in the years 1996 and 1997. Hübler and Hübler (2006) use the GSOEP which is also used here. Both studies do not define or measure bias in job separation risk and can hence not distinguish whether wage changes are due to changes in actual conditions or biased expectations. A recent contribution by Jäger et al. (2022) investigates bias in beliefs about outside wage options. The literature on bias in job finding mostly investigates the relationship to job search behavior (see Mueller and Spinnewijn (2022)). Mueller et al. (2021) explore how this bias affects employment and unemployment outcomes. Conlon et al. (2018) show that a model with the corresponding informational frictions fits observed reservations wages better than without. Drahs et al. (2018) show that job seekers overestimate their future re-employment wage. Menzio (2022) investigates the role of stubborn beliefs about productivity and addresses the consequences about wage outcomes over the business cycle.

We directly link the bias in job separation expectations to wage outcomes and the bias in job finding expectations to reservation incomes. Our direct evidence on biased beliefs in job finding risk and reservation wages is in line with the previously mentioned findings. Moreover, we relate differences in bias across groups to wage and reservation income differentials. Only Cortés et al. (2021) address a similar question and discuss the relationship between optimism about post-graduation earnings and the gender earnings gap. Our study jointly assesses biases in job separation and job finding risk in a search-and-matching framework and links the bias to wages. In a complementary study (Balleer et al. (2023)) we consider the role of wage bargaining and the underlying foundations of the theoretical link in more detail. Here, we use the model to interpret the empirical findings and quantify the effect on wages, lifetime income and wage differentials.

The paper is organized as follows. Section 2 presents the data and measurement. Section 3 documents facts about biased labor market expectations. Section 4 relates the bias to wages and reservation income in the data, Section 5 relates the bias to wages and reservation income in the model. Section 6 concludes.

2 Data

For our empirical analysis, we use individual and household data from the German Socio-Economic Panel (GSOEP), an annual representative longitudinal survey of private households in Germany.[1] The core survey started in 1984 in West Germany and was enlarged in 1990 to include a representative sample from East Germany. It covers a large number of topics, ranging from work, employment and income to health and family and to time use, attitudes, and personality. In each year (or wave), around 15,000 households and 30,000 persons participate in the GSOEP survey. Within Europe, the GSOEP is unique in regularly including questions on individual labor market expectations since more than 20 years. We use data based on the core individual and household questionnaires covering the period 1999 to 2017. We further restrict our sample to individuals of working age (e.g. between 25 and 65 years of age).

[1] The GSOEP is available to researchers upon application (`https://www.diw.de/en/diw_01.c.601584.en/data_access.html`)

2.1 Expectations about labor market transitions

The individual questionnaires of the GSOEP bi-annually include several questions about individual labor market expectations. Since the 1999 wave, respondents who are employed at the time of the interview are asked ”How likely is it that you will experience the following career changes within the next two years?” upon which they should assess the probability of seeking a job at their own initiative, losing their job or receiving a promotion at the current employer on a scale from 0% to 100% (in steps of 10%). Using the corresponding variable for the answer on job loss provides us with a direct measure of an individual's expected job separation probability.[2]

Similarly, since 1999 respondents who are not working at the time of the interview are asked ”How likely is it that one or more of the following occupational changes will take place in your life within the next two years?” upon which they should assess the probability of taking up a paid job, become self-employed or attend additional qualifications or training on a scale from 0% to 100% (in steps of 10%). Using the corresponding variable for the answer on taking on a paid job provides us with a direct measure of an individual's expected job finding probability.[3]

Both questions were also asked before 1999, but with verbal instead of numeric answer options. The questions were excluded in 2011. After 2015, the last available survey information is 2018. We exclude this last data point, since we need to follow respondents two years after the interview to measure actual transitions, and this period includes the onset of the Covid-pandemic, which may severely affect our results. Our expected job separation and job finding variables are therefore measured in the years 1999, 2001, 2003, 2005, 2007, 2009, 2013, and 2015.

Employed workers, on average, state a 20% probability to separate from their job within two-years. Job separation expectations are very dispersed, include the full range of 0% to 100% probability and bunch at 0% and 50% (see Section 3, Table 1 for summary statistics and Figure A.3 in the Appendix for the respective histogram). Unemployed workers, on average, state a 54% probability to find a job within two-years. Also job finding expectations are very dispersed, including the full range of 0% to 100% probability. They are, however, more uniformly distributed than job separation expectations and bunch at 50% and 100% (see Section 3, Table 1 for summary statistics and Figure A.3 in the Appendix for the respective histogram).

We interpret the answers to these question as taking into account all information that is available to the respondents at the time of the interview and that is relevant to the corresponding labor market transitions. This means, for example, that the probability with which a person expects to separate from their job takes into account their own current or future actions such as exerting more effort on the job or searching for an alternative job. Likewise, the probability with which a person expects to find a job takes into account their own current or future decisions such as searching harder for a job or accepting a job offer at a lower wage.

[2] Figure A.1 in the Appendix depicts the original question on expected job loss.

[3] Figure A.2 in the Appendix depicts the original question on expected job finding.

2.2 Predicted labor market transitions

Due to the panel structure of the data, we can identify actual job separation and job finding events of individuals within a period of two years following their interview. Thus, we can construct indicators whether respondents separated from or found a job within 24 months following the interview at which the expectations questions were asked.

Regarding job separation, survey respondents in each wave are asked the retrospective question "Did you leave your job since the beginning of the last calendar year?". If the answer is positive, they state the month in which the job ended and what the reason for leaving the job was. Table A.1 in the Appendix lists all possible answers regarding the reasons for a job end. The reasons "Place of work closed" or "Dismissed by employer" are probably most closely related to the measured expectations about job separation, if this question is taken literally and refers to involuntary job loss only. These two reasons form our most narrow measure of actual job separation (referred to as dismissal). The reasons "Mutual agreement" or "Temporary employment ended" could, however, also be included in the expectation to separate from a job, in particular if employees expecting job separation preemptively search for a new job or are uncertain about the possibility to renew the contract. Although not literally job loss, this may very well be included in the assessment of subjective job separation expectations. Adding these two reasons to dismissal and closure is a broader measure of actual job separation (we refer to this measure as selected reasons). The existing macroeconomic literature on labor market flows, however, typically addresses job separation as a whole, and only sometimes distinguishes between quits and layoffs. In order to be close to the familiar broad measures in the literature, we will therefore include all reasons for leaving a job in a general measure of job separation as our baseline and explore robustness with respect to the more narrow definitions.

We can also measure job spells from respondents' activity calendars.[4] The data set contains monthly information on the beginning and ending of individuals' activities such as being employed full-time or part-time, being registered as unemployed, in retirement or on parental leave, but also taking care of the household or attending school or college (see Table A.2 in the Appendix for the complete list). We assign each of the possible spell types to one of three labor market states: employment (E), unemployment (U) and out-of-the-labor force (O). The status of employment comprises full-time, part-time and marginal employment, short-time work, second job and mini-job, as well as vocational training, first job training and apprenticeship. The status of unemployment is restricted to registered unemployment. All other spell types are categorized as out-of-the-labor force. We then rank the three states according to the prioritization $E > U > O$ and assign to each month the highest ranking labor market state across all of an individual's spells that cover this month.

Based on these monthly spell variables, we can identify individual transitions between the three labor market states. This provides us with an additional measure of job separation,

[4] The "ARTKALEN" data set contains spells (monthly) for events starting in January 1983. The information on activity status is collected on a monthly basis in the yearly individual questionnaire and stored in the file "ARTKALEN".

namely at least one transition from employment to unemployment within 24 months after the interview (referred to as spell measure). More importantly, the spell data also provide the source for measuring job finding.[5] Our indicator of job finding captures all individuals who are unemployed or out-of-the-labor-force at the time of the interview and experience at least one transition to employment within 24 months after the interview. As our baseline measure, we report job finding of unemployed respondents only (referred to as job finding out of U). We explore robustness to measuring job finding of out-of-the-labor-force respondents only (job finding out of O), or of unemployed and out-of-the-labor-force respondents grouped together (job finding out of U and O).

Table A.3 in the Appendix documents average job separation and job finding rates within two years after the interview, based on the different indicator variables. The probability to separate from a job for general reasons over the period of two years is about 13 percent on average, and decreases to about 6 and 4 percent for more restricted reasons (selected and dismissal respectively), or to about 5 percent when measuring flows from employment to unemployment using spell data. The average probability to find a job out of unemployment within two years is about 44 percent, and decreases to about 30 percent if job finding from out-of-the-labor-force is considered as well.

We can convert the biannual to quarterly rates by means of a geometric series. This delivers a quarterly job separation rate of 1.7 percent (general measure) and a quarterly job finding rate of 7.8 percent (out of unemployment).[6] We can also directly compute average job separation and job finding rates within one quarter after the interview from our data, which are documented in Table A.4 in the Appendix. On average, 1.5 percent of employed workers separate from their job due to general reasons and 18 percent of unemployed workers find a job within one quarter. Hence, while the job separation rate is evenly distributed over time, job finding probabilities decrease over time. The latter fact might be due to productive workers leaving unemployment quickly and, hence, the pool of unemployed workers becoming more unproductive with the length of the unemployment spell. Our job separation and job finding measures are at the lower end of comparable measures from other datasets that are also used to calibrate monthly and quarterly models of the labor market to German data. Based on German administrative data from the Institute for Employment Research, quarterly job separation rates range from 1.4% (0.5% monthly) to 4.7% (1.6% monthly) and quarterly job finding rates range from 16.9% (6% monthly) to 40.7% (16% monthly).[7]

3 Bias in labor market expectations

3.1 Measuring bias in labor market expectations

Using our indicators for actual job separation and job finding described in Section 2.2, we estimate probit models of individuals' job separation and job finding probabilities.

[5] Since the GSOEP does not contain a retrospective question about job finding comparable to the one about job separation, we use only measures of job finding obtained from spell data.

[6] $p^{biannual} = 1 - (1 - p^{quarterly})^8$.

[7] Compare Klinger and Rothe (2012) and Hochmuth et al. (2021), or Hartung et al. (2018).

Different to estimating actual job separation and job finding rates by sample means of realized labor market transitions, the probit models allow to predict individual probabilities within a narrowly defined group and based on individual outcomes on a number of characteristics. We therefore choose specifications that maximize the predictive power of the model according to a range of information criteria (McFadden's pseudo-R^2, McKelvey and Zavoina's R^2, AIC) across our different measures of job separation and job finding.

We predict job separation probabilities for individuals employed at the time of the interview and job finding probabilities for those unemployed at the time of the interview. Doing so, we include a large number of individual and job characteristics as well as survey year indicators. For predicting job separation, we also add employer characteristics. Tables A.5 to A.8 in the Appendix provide summary statistics for the covariates. Regression outputs of the job separation probit estimations are reported in Table B.1 in the Appendix. Regression outputs of the job finding probit estimations are reported in Table B.2 in the Appendix.

Based on the probit estimation, we obtain individual predicted probabilities of losing a job or finding a job. In order to compare them to our measured expectations, we round the predicted probabilities to the next decile on the probability scale (0%, 10%, 20%, ...). We describe robustness to not rounding, and to rounding up to the next decile (conservative measure) below. Bias in labor market expectations is then defined as the difference between individual expected job separation and job finding probabilities and their statistical (predicted) counterpart.

3.2 Documenting bias in labor market expectations

Table 1 documents summary statistics for expected and predicted job separation and job finding probabilities as well as the resulting bias. For the general job separation measure, employed workers are predicted to separate from their job within the next two years with an average probability of 13%. Predicted job separation ranges between 0% and 70%, while expected job separation probabilities range between 0% and 100%. The resulting bias shows that optimists and pessimists coexist in the sample. On average, however, employed workers are pessimistic regarding (general) job separation, as they overestimate the risk of losing their job within two years by about 6 percentage points, which is significantly different from zero. The average bias is positive and significantly different from zero for all our job separation measures (see Table B.3 in the Appendix). For the narrowest measure of job separation (dismissal), the bias increases to as much as 17 percentage points. Figures B.1 to B.4 in the Appendix plot histograms of expected and predicted job separation probabilities and the resulting bias for all measures.

Regarding job finding out of unemployment, (unemployed) workers are predicted to find a job within two years with an average probability of 48%, while they expect to do so with 57% probability.[8] Hence, unemployed workers, on average, are optimistic regarding job finding, as they overestimate the chance of finding a job in this time interval by

[8] Note that here, the predicted job finding probability of 48% differs slightly from the sample mean of actual transitions which is 44% as reported in Table A.3.

Table 1: Job Separation and Job Finding: Summary statistics

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
				Job separation				
All								
Expected	19.767	24.529	0	100	0	10	50	67772
Predicted	13.329	10.385	0	70	0	10	30	67772
Bias	6.4376***	24.199	-70	100	-20	0	40	67772
East								
Expected	27.208	26.171	0	100	0	20	60	15653
Predicted	15.140	10.976	0	70	0	10	30	15653
Bias	12.067***	25.471	-70	100	-20	10	40	15653
West								
Expected	17.532	23.560	0	100	0	10	50	52119
Predicted	12.785	10.138	0	70	0	10	30	52119
Bias	4.7468***	23.542	-70	100	-20	0	40	52119
				Job finding				
All								
Expected	57.022	32.334	0	100	10	50	100	6423
Predicted	48.800	19.551	0	90	20	50	70	6423
Bias	8.2220***	28.711	-80	100	-30	10	40	6423
East								
Expected	51.855	31.998	0	100	10	50	100	2717
Predicted	49.971	18.700	0	90	20	50	70	2717
Bias	1.8844***	27.649	-80	90	-30	0	40	2717
West								
Expected	60.809	32.058	0	100	10	60	100	3706
Predicted	47.941	20.112	0	90	20	50	70	3706
Bias	12.868***	28.590	-80	100	-20	20	50	3706

Notes: Predicted job separation refers to the general measure, predicted job finding refers to out of unemployed (out of U). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero.

about 8 percentage points, which is significantly different from zero. Predicted job finding ranges between 0% and 90%, similar to the range of expected job separation probabilities. Again, the resulting bias shows that there are both optimistic and pessimistic unemployed workers in the sample. The average bias is positive and significantly different from zero for all our job finding measures (see Table B.4 in the Appendix). When measuring job finding from out-of-the-labor-force, the optimistic bias increases to about 11 percentage points (see Table B.4 in the Appendix). Figures B.5 to B.7 in the Appendix document the corresponding histograms for all job finding measures.

3.3 Bias in labor market expectations across subgroups

The significant pessimistic bias in job separation expectations and significant optimistic bias in job finding expectations among German workers also holds within different subgroups in our sample. Moreover, we find substantial heterogeneity in the degrees of pessimism and optimism across subgroups.

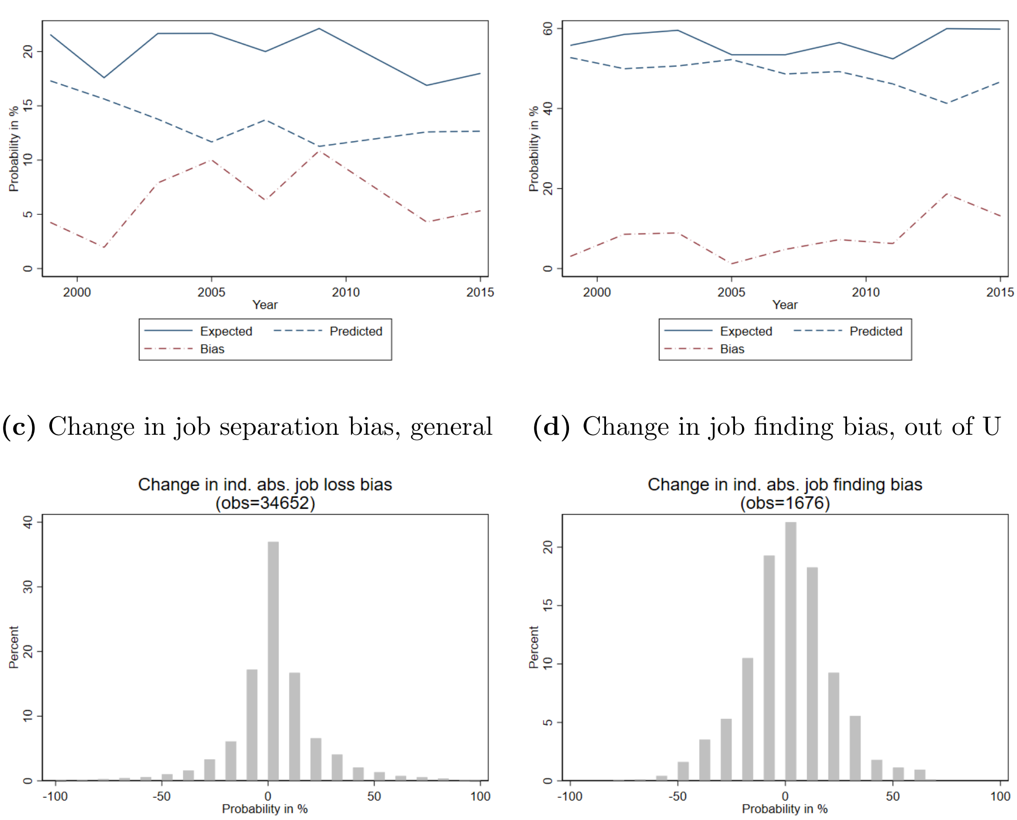
Table 1 documents summary statistics for East and West Germany separately, two subsamples that exhibit particularly striking differences in expectations biases. On average, East Germans are about 7 percentage points more pessimistic than West Germans with respect to job separation. Since East Germans already have a higher predicted job separation risk, differences in expected job separation rates between East and West Germany are therefore substantial. Another notable difference is that East Germans exhibit an optimistic job finding bias that is about 11 percentage points lower than their West German counterparts. Together with the results regarding job separation, East Germans are therefore generally more pessimistic, respectively less optimistic, than West Germans. These results continue to hold if we take into account differences in composition between East and West Germany. Tables B.5 and B.6 in the Appendix document the output from regressing the estimated biases in job separation and job finding probabilities on their predicted levels, demographic characteristics, labor market experience, and industry and occupational information in the sample, respectively. Controlling for composition, the East-West difference in job separation bias remains at 8 percentage points and reduces to 7 percentage points for job finding, both bias differences being highly significant.[9]

Tables B.7 and B.8 show summary statistics for all subgroups. For both job separation and job finding, we consider demographic aspects such as gender, age, and migration background, a broad measure of educational attainment, and labor market experience with respect employment and unemployment. For job separation, we can additionally address tenure, occupation and industry groups. Tables B.5 and B.6 in the Appendix document differences in biases between subgroups holding the composition with respect

[9] Different to our result, Emmler and Fitzenberger (2022) document overpessimism with respect to job loss in East relative to West Germany in 1991 that substantially declines a decade later. They use the verbal earlier version of the expectation question and define an indicator of expected job loss (indicated as "definite" or "probable", and above 60% in the later sample) which they compare to actual job loss events. Their measure is therefore much more coarse than ours and may not uncover the differences in expectations and outcomes documented here. Their measure does not directly relate to the expected or predicted transition probabilities as well as the resulting bias measured here and cannot directly be mapped into the corresponding transition probabilities in the model.

to other subgroups and characteristics constant.
Subgroup comparisons provide plausibility checks to our measures of biased expectations. To assess credibility about expected job separation probabilities and the corresponding pessimistic bias, we expect the bias in job separation expectations to be smaller in occupations with high job security and expect the bias to be small for persons which generally worry about their job insecurity. This is indeed the case. The pessimistic bias is low for persons that state that they are not concerned about their job insecurity. It is also low for persons that have high job security such as persons with high tenure, long employment experience, or persons in secure jobs such as civil servants or working in the public administration generally. The pessimistic bias is high for persons that state that they are very concerned about their job insecurity, that have low tenure or work experience or previous long unemployment experience. Persons with higher predicted job separation risk have a smaller job separation bias on average (are less pessimistic). This indicates that even though the bias exists, individuals are aware of (relative) job security and take this into account when assessing their job separation probabilities. Similar patterns emerge with respect to the optimistic bias in job finding. Persons with higher predicted job finding chance have smaller optimistic bias on average. Persons with previous employment experience exhibit a lower optimistic bias in job finding probability.
Subgroup comparisons also inform us about learning, i.e., whether individuals reduce their bias over time. The pessimistic job separation bias decreases with age, which suggests that individuals correct their bias over time. Again, this holds for a given predicted level of job separation probability. Note that the predicted job separation risk decreases with age (compare Table B.7). Hence, expected job separation risk decreases by more reducing the pessimistic bias. The differential effect on age is small and not significant for our baseline, however. The optimistic bias in job finding decreases with age, which indicates that persons correct their bias over time. The age effect is significant, but relatively small, i.e., bias correction is slow. The optimistic bias in job finding decreases with unemployment experience, hence persons with more information about unemployment have more precise expectations. The pessimistic bias in job separation increases with unemployment experience, hence persons with previous adverse labor market experience are more pessimistic with respect to their employment prospects. Section 3.4 addresses bias in labor market expectations across time further.
With respect to other subgroup comparisons, there are no systematic or large differences between men and women or native Germans versus non-native Germans persons with respect to job separation bias in our sample. For job finding, females are significantly less optimistic with respect to finding a job than males. Interestingly, pessimistic bias in job separation expectations increases with educational degree. In this case, both expected and predicted job separation decrease with education, but expected job separation decreases less with increasing education. Persons with higher education exhibit a lower job finding bias. Since predicted job finding rates increase with education, expected job finding rates increase by less. Persons with a higher educational degree are therefore generally less optimistic, similar to the results for job separation probabilities. The pessimistic bias in

Figure 1: Bias in job separation and job finding expectations over time



(a) Job separation bias, general

(b) Job finding bias, out of U

(c) Change in job separation bias, general

(d) Change in job finding bias, out of U

job separation expectations is substantially larger in industry and manufacturing relative to other sectors, while predicted job separation rates are relatively small.

3.4 Bias in labor market expectations across time

Figures 1a and 1b plot the average expected and predicted job separation and job finding rates together with the corresponding biases for the two baseline measures across time.[10] Regarding predicted probabilities, the graphs exhibit a clear downward trend in both job separation and job finding rates over the sample period. Since job separation rates fall more strongly, this reflects an overall downward trend in unemployment in Germany over the sample period, which is well documented in the literature.[11] Expected job separation and job finding probabilities are not only larger than the corresponding predictions, but also fairly stable over time. This leads the pessimistic job separation bias and the optimistic job finding bias to mildly increase in our sample.

The aggregate development of the bias in job separation and job finding expectations over time suggests that, on average, learning does not play a substantial role in our data. Due to the panel structure of the data, we can follow a subset of individuals across two consecutive surveys in which they answered the same expectations question and compute

[10] Figures B.8 and B.9 in the Appendix document the corresponding graphs for all job separation and job finding measures.

[11] See e.g. Hochmuth et al. (2021) or Hartung et al. (2018).

the difference in the absolute values of their job separation or job finding bias between two surveys, i.e., two years apart. The subset therefore only includes persons who did not change their employment status between two surveys. Figures 1c and 1d plot the histograms of this difference for the two baseline measures.[12] Positive values indicate that the bias has increased since the last survey, negative values indicate that the bias has decreased. The histograms exhibit substantial dispersion. The average difference in the job separation bias between two surveys equals 0.9 percentage points, i.e., employed persons do not reduce their bias between two surveys on average. The average difference in job finding bias between to surveys is equal to -0.9 percentage points, i.e. unemployed persons do correct their bias between two surveys on average. Overall, average revisions are small, and the respective median measures are zero (see Table B.9 in the Appendix for details on summary statistics). Hence, on average, individuals do not revise their expectations much.

Tables B.10 and B.11 in the Appendix regress the change in job separation and job finding bias on various subgroups in our sample. For the baseline measure of job separation (general), the positive change in job separation bias is larger, i.e., persons become more pessimistic (or more optimistic) over time, when predicted job separation high. For the baseline measure of job finding (out of unemployment), we observe a similar pattern when predicted job finding rates are high. Generally, there are no substantial and significant differences in the change in the bias in both job separation and job finding across subgroups. An exception is that the job separation bias increases with tenure and the job finding bias decreases with part time work experience. Again, these results do not deliver very strong evidence in favor of learning as substantially affecting expectations in our data.

4 Relating bias to wages

4.1 Hourly wages and reservation income in the GSOEP

We want to analyse the relationship between bias in labor market expectations and wages and reservation income. The GSOEP contains information about individual labor income and hours worked. To obtain individual hourly wages, we use the net labor income in Euro that employed respondents are asked to provide for the respective last month in the main job. Respondents also provide the actual work time per week in hours which we use in order to compute the net hourly wage rate. Table A.9 in the Appendix reports summary statistics for these variables. Employed persons in our sample work about 37 hours per week on average and earn a net amount of 1684 Euro per month. This results in 11 Euro net per hour. The GSOEP also asks unemployed persons to state their monthly net salary at which they would take a job. The reservation income of unemployed persons in our sample amounts to about 1212 Euro on average (see Table A.9 in the Appendix).

[12] Figures B.10 and B.11 in the Appendix plot the corresponding histograms for all job separation and job finding measures.

4.2 Baseline results

We use the current net wage rate and the reservation income as described in Section 2 in order to explore their relationship with the biases in job separation and job finding expectations. Table 2 documents the output from regressing the log wage rate on our baseline measure of job separation bias and predicted job separation, also adding education and labor market experience (a basic Mincer regression) and further controls. Standard errors are bootstrapped.[13] All specifications show that a higher predicted job separation is associated with a lower current wage, and that, in addition to the predicted job separation risk, employed persons with a higher pessimistic bias in job separation expectations have significantly lower hourly wages on average. Net of controls, a pessimistic bias that is one standard deviation higher is associated with a wage rate that is about 2.1 percent lower on average. When controlling for education and experience only, wages are about 4.8 percent lower. Tables C.1 to C.3 in the Appendix show very similar results for the other measures of job separation bias.

Table 2: Wages and bias in job separation expectations

	log hourly wage rate		
job separation bias	-0.00245***	-0.00197***	-0.000850***
	(0.000111)	(0.000105)	(0.0000797)
predicted job separation	-0.0164***	-0.0146***	-0.00487***
	(0.000462)	(0.000436)	(0.000324)
N	212114	212114	212114
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Mincer specification: educational attainment, full time work experience

Additional controls: East/West dummy, German citizenship, gender, actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year fixed effects

We confirm the negative relationship between job separation bias and hourly wages using data for the U.S. Here, we use the Current Population Survey (CPS) to predict quarterly transition rates out of employment and compare these to the corresponding expectations measured in the Survey of Consumer Expectations (SCE) based on observable characteristics. As documented in Balleer et al. (2021), employed persons in the US are over-optimistic about leaving their current job, on average (see Table C.7). The composition of the sample, the reference transition rates and the measure of hourly wages are substantially different between the US and the German data (see Table C.6 and Balleer et al. (2021) for details). However, when we perform a regression comparable to the Table 2, we find a similarly negative and significant link between the job separation bias and wages

[13] The bootstrap includes both the predicted labor market probability from the probit regression as described in section 3, the computation of the bias and the wage regression.

(see Table C.8).
Table 3 documents the output from regressing the log reservation income on our baseline measure of job finding bias and predicted job finding, again also adding education and labor market experience (a basic Mincer regression) and further controls. Standard errors are again bootstrapped. All specifications show that unemployed persons with a higher predicted job finding rate have significantly higher reservation income. In addition, higher optimistic bias in job finding expectations is also significantly and positively related to higher reservation income on average. Net of controls, an optimistic bias that is one standard deviation higher is associated with reservation income that is about 2.0 percent higher on average. When controlling for education and experience only, reservation income is about 4.7 percent higher. Tables C.4 and C.5 in the Appendix show very similar results for the respective other measures of job finding bias.

Table 3: Reservation income and bias in job finding expectation

	log reservation income		
job finding bias	0.00145***	0.00165***	0.000692***
	(0.000286)	(0.000317)	(0.000255)
predicted job finding	0.00362***	0.00413***	0.00292***
	(0.000405)	(0.000537)	(0.000523)
N	18789	18789	18789
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Mincer specification: educational attainment, full time work experience
Additional controls: East/West dummy, German citizenship, gender, relationship status, kids less 16 years, unemployment experience, survey year fixed effects

4.3 The East-West wage differential

We use our results to investigate how bias in job separation and job finding affects wage differences between East and West Germany. Our sample exhibits an East-West German wage gap of about 30% overall and 23% net of controls (see Table C.9 in the Appendix). Here, the wage gap is measured as the difference between West and East German log hourly wage rates as computed and described in Section 2. Section 3 documents that East Germans are substantially more pessimistic with respect to their job separation and less optimistic with respect to their job finding expectations. We extend our baseline wage regressions by adding an interaction term between job separation bias and the East Germany indicator. This allows wages to react differently to the job separation bias in East and West Germany. East German wages are significantly lower than their Western counterparts when the pessimistic job separation bias increases equally. While already being more pessimistic, East German wages also relate close to twice as much to a bias in job separation expectations. More precisely, when the pessimistic bias in job separation increases by 10 percentage points, East German wages are about 1.3% lower, while West German wages are only about 0.7% lower on average (see first column in Table C.10 in the Appendix).

Our estimation results predict that if Eastern Germans' pessimistic bias in job separation expectations was at West German levels, hourly wages would be 0.7% higher in the linear case, and about 1% higher when job separation bias is allowed to affect wages differently in East and West. This amounts to a reduction in the unconditional wage gap by about 1.3 percentage points in the linear and about 2 percentage points in the non-linear case.[14]

We can also consider the gap in reservation incomes between East and West Germany which is about 13% overall and 10% net of controls (as documented in Table C.11 in the Appendix). Again, the gap measures the log difference in reservation incomes as described in Section 2. In this case, East German reservation wages are not linked significantly differently to reservation incomes than their West German counterparts (see Table C.12 in the Appendix). With respect to job finding expectations, East Germans are less optimistic than West Germans. If we assign the more optimistic Western job finding bias level to the East, the East German reservation income would be about 0.57% higher (0.62% in the non-linear case). This corresponds to a reduction in the unconditional East-West German reservation income gap by about 3.1 percentage points.[15]

5 A search-and-matching model with biased expectations

In this section, we present a model that is in line with the negative relation between pessimistic job separation expectations and wages as well as the positive relation between optimistic job finding expectations and reservation wages documented above. In addition to providing an interpretation of our estimated relationships, the model serves four purposes. First, we can quantify how expectation biases and wages are related in cases that we do not observe in the data, namely, the relationships between job separation bias and reservation wages and between job finding bias and realized wages. Second, we can investigate the effect of the biases on the labor market equilibrium, and, in particular, on unemployment. Third, we can quantify the effects of removing the bias in job separation or job finding or both expectations on the labor market equilibrium and on the expected lifetime income of economic agents. Finally, we can use the model to quantify to what extent biased expectations play a role in explaining the East-West German wage differential.

[14] For the counterfactual East German wages, we assign the difference in bias from Table B.5 (column 1), and use the estimated linear effect of job separation bias from Table 2 (column 3), and the estimated non-linear effect of job separation bias from Table C.10 (column 1). The counterfactual wage gap is computed as the log difference between West and the counterfactual East German wages.

[15] For the counterfactual East German reservation incomes, we assign the difference in bias from Table B.6 (column 1), and use the estimated linear effect of job finding bias from Table 3 (column 3), and the estimated non-linear effect of job finding bias from Table C.12 (column 1). The counterfactual reservation income gap is computed as the log difference between West and the counterfactual East German reservation incomes.

Our model builds on the canonical Diamond-Mortensen-Pissarides (DMP) framework of random search-and-matching in the labor market in which wages are determined by (generalized) Nash bargaining between workers and firms.[16] In the standard DMP model, agents have rational expectations. In particular, the actual (objective) probabilities of match formation and separation are known to all agents and form the basis for their decision-making. We depart from this by allowing individual beliefs about these probabilities to deviate from actual probabilities. The following subsection presents core features of our model and its equilibrium properties in concise form. A detailed analysis and discussion of the model can be found in Balleer et al. (2023).

Generally, both firms and workers in our framework may have biased beliefs. However, since we cannot measure firm expectations about labor market outcomes in our data, we abstract from firm bias in the present setting.[17] We also abstract from learning since the empirical evidence in Section 2 provides no conclusive evidence in support of bias reduction over time.

5.1 Model

Time is discrete. There is a measure one of risk-neutral workers who receive wage ω when employed and income $b \geq 0$ when unemployed, and a continuum of small, competitive firms with one potential job each. Firms post vacancies at period cost $\kappa > 0$ and produce output $z > b$ per period if matched with a worker. Unemployed workers and job vacancies are randomly matched according to an aggregate matching function, $M(u, v)$, where u is the measure of unemployed workers, v is the measure of vacant jobs, and $M(\cdot, \cdot)$ satisfies standard properties.[18] An unemployed worker meets a vacancy with probability $M(u, v)/u = M(1, \theta) \equiv p(\theta)$, and a vacancy meets an unemployed worker with probability $q(\theta) \equiv p(\theta)/\theta$, where $\theta \equiv v/u$ denotes labor market tightness. Existing worker-firm matches separate each period with exogenous probability σ.

We allow workers' job finding and job separation expectations to deviate from actual probabilities as follows: Workers expect to find a job with probability $\lambda_w \equiv (1 + \Delta_{\lambda w})p(\theta)$ when unemployed, and to separate from their job with probability $\sigma_w \equiv (1 + \Delta_{\sigma w})\sigma$ when employed. $\Delta_{\lambda w}$ and $\Delta_{\sigma w}$ thus denote the workers' biases in job finding and job separation expectations. When $\Delta_{\lambda w} = \Delta_{\sigma w} = 0$, workers have rational expectations. When $\Delta_{\lambda w} > 0$, workers have an optimistic job finding bias, expecting to find a job with a higher than the actual probability. When $\Delta_{\sigma w} > 0$, workers have a pessimistic job separation bias, expecting to separate from a match with a higher than the actual probability. Workers base their valuations of labor market states and job matches, and therefore their decisions, on their subjective rather than on objective probabilities.

[16] See Diamond (1981) and Mortensen and Pissarides (1994) or Pissarides (2000), Chapter 1. The negative relation between pessimistic job separation bias and wages as well as the positive relation between optimistic job finding bias and reservation wages may potentially be explained by different economic models of wage setting and labor market outcomes. Here, we investigate this within the workhorse DMP framework of frictional labor markets widely used in the literature.

[17] Note that our qualitative results hold as long as firm bias is smaller than worker bias. See Balleer et al. (2023) for further discussion on the role of worker and firm bias.

[18] That is, $M(\cdot, \cdot)$ is homogeneous of degree 1, increasing and concave in both arguments, continuously differentiable, and satisfies $M(0, u) = M(v, 0) = 0$ and $M(u, v) \leq \min[u, v]$.

Let $E(\omega)$ and U denote a worker's perceived values of being employed in a match paying current wage ω, and of being unemployed, respectively. These values satisfy the Bellman equations

$$E(\omega) = \omega + \beta\Big\{(1-\sigma_w)E(\omega') + \sigma_w U\Big\} \tag{1}$$

and

$$U = b + \beta\Big\{\lambda_w E(\omega') + (1-\lambda_w)U\Big\}\ , \tag{2}$$

where $0 < \beta < 1$ denotes the worker's discount factor and ω' is the wage next period. Equations (1) and (2) differ from the standard DMP setting only by the potentially biased job separation and job finding probabilities, σ_w and λ_w.

A firm's values of a match paying current wage ω, $J(\omega)$, and of a vacancy, V, satisfy the standard Bellman equations,

$$J(\omega) = z - \omega + \beta\Big\{\sigma V + (1-\sigma)J(\omega')\Big\} \tag{3}$$

and

$$V = -\kappa + \beta\Big\{\lambda_f J(\omega') + (1-\lambda_f)V\Big\}\ , \tag{4}$$

where σ and $\lambda_f \equiv q(\theta)$ are the actual probabilities of match separation and of vacancy filling, respectively.

The period wage ω a worker receives from a specific match with a firm is determined by (generalized) Nash bargaining and solves

$$\omega = \arg\max\,[E(\omega) - U]^{\gamma}\,[J(\omega) - V]^{1-\gamma} \tag{5}$$

where $\gamma \in (0,1)$ denotes the worker's bargaining power. If the worker's beliefs are biased (i.e. $\Delta_{\lambda w} \neq 0$ or $\Delta_{\sigma w} \neq 0$), firm and worker disagree about transition probabilities, and, in consequence, about the values of a job, of a vacancy, or of being unemployed. Regarding the bargaining procedure, we make two central assumptions: First, we assume that the bargaining parties truthfully report their own valuations and accept the reported valuations of the other party. They neither try to convince the other nor take advantage of discrepancies in expectations, but instead agree to disagree. This assumption allows tractability of the Nash bargaining solution.[19] Second, we assume that, when a firm and a worker meet for the first time, they negotiate a contract that specifies the wage for each period of the employment spell. This implies that, in stationary equilibrium, $\omega' = \omega$ in equations (1) to (4). In Balleer et al. (2023), we analyze different bargaining protocols in the presence of expectation bias, ranging from firms and workers negotiating the wage every period to setting a fixed wage for the duration of the match. We show that with period-by-period bargaining, the model is not consistent with the negative relation between pessimistic job separation bias and wages found in our data.

[19] Hence, while workers and firms do not form rational expectations, there is full information. The underlying bargaining game can then be described by the alternating offer protocol as in Binmore et al. (1986).

The bargaining results in sharing the surplus of the match according to the following sharing rule:

$$\frac{J(\omega)-V}{E(\omega)-U}=\frac{(1-\gamma)}{\gamma}\frac{1-\beta(1-\sigma_w)}{1-\beta(1-\sigma)} \tag{6}$$

Equation (6) differs from the surplus-sharing rule in the standard DMP model without expectation bias, as it takes differences in separation expectations between the two parties into account.[20] Separation expectations determine the agents' effective discounting of the future values of the match. Whenever workers have biased separation expectations, their effective discount rate, $\beta(1-\sigma_w)$, differs from that of firms, $\beta(1-\sigma)$. Because the bargained wage affects the current as well as the future values of the match, this implies that the wage level not only determines how the match surplus is split between the two parties, but also the size of the total surplus. Consider the case in which the worker has a pessimistic separation bias ($\Delta_{\sigma w}>0$), and thus discounts the future value of the match more heavily than the firm. A marginal increase in the wage leads to a lower gain for the worker compared to the loss it generates for the firm. Reallocating resources from the worker to the firm thus increases total match surplus, and the worker optimally receives a lower share of the surplus than his bargaining weight γ.

Substituting the agents' value functions into the sharing rule and imposing free entry ($V=0$) leads to the equilibrium wage equation,

$$\omega=(1-\gamma)b+\gamma\left[z+\frac{1-\beta(1-\sigma)}{1-\beta(1-\sigma_w)}(1+\Delta_{\lambda w})\theta\kappa\right] \tag{7}$$

The structure of (7) is similar to the equilibrium wage equation in the standard DMP model without expectation bias: Workers receive a linear combination of unemployment benefits and match output plus saved hiring costs to the firm (equal to average hiring costs per unemployed worker, $\theta\kappa$), with weights equal to the respective parties' bargaining power.[21] However, the term capturing saved hiring costs deviates from the standard DMP model. First, since hiring costs are saved in all future periods for which the match continues to hold, the wage equation again takes the difference in effective discounting of worker and firm into account. Second, average hiring costs are evaluated on the basis of the worker's subjective job finding probability.

Both workers' job separation and job finding biases thus affect the equilibrium wage by interacting with saved hiring costs in equation (7). If workers are pessimistic with respect to job separation ($\Delta_{\sigma w}>0$), wages are lower. Due to higher effective discounting of the future job match, saved hiring costs also have a lower present value and, hence, wages compensate less for these costs. If workers are optimistic with respect to job finding ($\Delta_{\lambda w}>0$), wages are higher. In this case, workers overestimate the hiring costs that are saved by forming a match. Being employed, they perceive the outside option of unemployment as higher relative to the firm's assessment and need to be compensated accordingly through

[20] In the absence of separation bias ($\Delta_{\sigma w}=0$), equation (6) reduces to the standard DMP surplus-sharing rule, $\gamma\left[J(\omega)-V\right]=(1-\gamma)\left[E(\omega)-U\right]$.

[21] In the absence of expectation bias ($\Delta_{\sigma w}=\Delta_{\lambda w}=0$), equation (7) reduces to the standard DMP wage equation, $\omega=(1-\gamma)b+\gamma\left[z+\theta\kappa\right]$.

higher wages. Appendix D shows the corresponding comparative statics. A higher bargaining power of workers γ and higher vacancy costs κ increase the wage, all other things constant. As a consequence, they intensify the gain of the worker from the marginal wage increase and the respective loss of the firm and, as the comparative statics show, they therefore intensify the wage response to a change in the job separation bias of workers. A higher time-preference parameter β leads to a larger effective discounting of the worker relative to the firm, due to the larger bias in job separation of workers. This also intensifies the effect of job separation bias on wages.

The reservation wage of workers (i.e. the wage level that makes them indifferent between accepting a job and remaining unemployed) is given by

$$\underline{\omega} = \frac{b\big[1-\beta(1-\sigma_w)\big] + \beta\lambda_w\omega}{1-\beta(1-\lambda_w-\sigma_w)} \ . \tag{8}$$

The effect of job finding bias on the reservation wage is unambiguously positive (see Appendix D for the derivation), which is in line with the empirical estimates presented in Section 4. Hence, if workers are optimistic with respect to finding a job ($\Delta_{\lambda w} > 0$), their reservation wage is higher.[22]

Imposing free entry leads to the job creation condition,

$$\omega = z - \frac{\kappa\big[1-\beta(1-\sigma)\big]}{\beta q(\theta)} \ , \tag{9}$$

which is equivalent to the standard DMP model, as is the Beveridge curve,

$$u = \frac{\sigma}{\sigma + p(\theta)} \ . \tag{10}$$

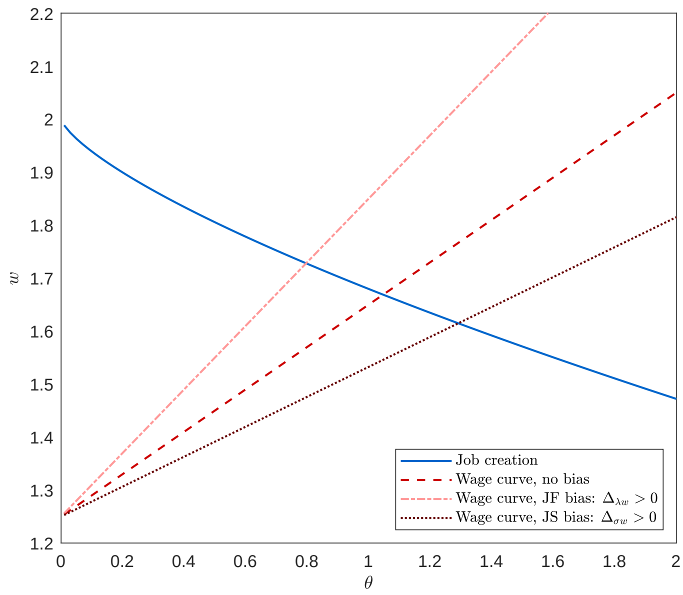
Equations (7), (9) and (10) define the stationary equilibrium of the model economy, where only the wage equation is directly affected by biases in worker expectations.

Figure 2 illustrates how workers' expectation biases rotate the wage curve, thereby affecting the labor market equilibrium.[23] A pessimistic bias in job separation expectations ($\Delta_{\sigma w} > 0$) induces a flatter slope of the wage curve (outward rotation) and results in lower wages and higher labor market tightness (lower unemployment). An optimistic bias in job finding expectations ($\Delta_{\lambda w} > 0$) leads to a steeper slope of the wage curve (inwards rotation) and results in higher wages and lower labor market tightness (higher unemployment).

[22] An alternative way to model reservation wages is to extend the model following Hornstein et al. (2011) in accounting for heterogeneous match productivity z. This allows to model job acceptance decisions, an explicit reservation productivity and corresponding reservation wage. Appendix D.2 lists the key components of this model. Here, the reservation wage unambiguously increases if workers become more optimistic with respect to their job finding probability. The resulting wage equation in this model extension is equivalent to equation 7 in the baseline model.

[23] The parametrization of the model behind this figure is close to the one described below, with some parameters changed to create more informative graphs.

Figure 2: Labor market equilibrium with biased expectations of workers



5.2 Calibration

We calibrate the baseline model to match, first, the German economy as a whole, and, second, East Germany only. The first calibration allows comparison to existing applications of the model without bias to Germany and, moreover, can be used to make statements about the average effects of counterfactual exercises. The second calibration addresses the role of biased expectations for the subgroup of East German workers and the East-West German wage differential. The length of a model period is one quarter. Table 4 documents the resulting parametrization for both cases. The discount factor β is set to match the usually targeted annual interest rate of 4%. Unemployment income b is set to match the German replacement rate of 65%. We use $M(u, v) = \chi u^{\eta} v^{1-\eta}$ to describe the matching technology in the labor market. Vacancy costs κ are set to normalize labor market tightness to $\theta = 1$ in steady state, such that the matching function efficiency (scale parameter) χ can be set to match the quarterly job finding rate that corresponds to the quarterly value in the GSOEP for the respective sample (see Table A.4 in the Appendix). We follow the literature in setting the elasticity of the matching function with respect to labor market tightness η to 0.65 (see e.g. Balleer et al. (2016) or Kohlbrecher et al. (2016)). The bargaining power of workers is set to 0.5 (see e.g. Balleer et al. (2016)). We will explore robustness with respect to this parameter in Section 5.5.

The separation rate σ is set to match the quarterly separation rate in the GSOEP in the respective sample. The implied steady state unemployment rate then equals about 7.7% for Germany as a whole and 8.6% for East Germany.[24] The implied unemployment

[24] The average annual unemployment rate between 1999 and 2015 equals 8.8%. Source is the federal employment agency. Destatis provides time series here: www-genesis.destatis.de, Table 13211-0001. The corresponding average unemployment rate in East Germany equals 14.5%. The implied unemployment rate in the GSOEP is, hence, substantially lower than the officially reported figures. We explore robust-

Table 4: Model calibration

Parameter	Description	Value All	Value East	Source/Target
β	discount factor	0.9900		annual interest rate (4%)
b	unemployment income	0.6185	0.6083	replacement rate (65%)
κ	vacancy costs	0.3510	0.4313	normalization ($\theta = 1$)
χ	matching fnct efficiency	0.1860	0.1850	JF rate (GSOEP)
η	matching fnct elasticity	0.6500		literature
γ	workers' bargaining power	0.5000		literature
σ	separation rate	0.0156	0.0174	JS rate (GSOEP)
$D_{\sigma w}$	job separation bias	0.0094	0.0186	own estimate
$D_{\lambda w}$	job finding bias	0.0199	0.0044	own estimate

Notes: JF rate refers to out of unemployment only, JS rate refers to general measure.

duration equals 5.4 quarters for both entire Germany and East Germany. We further set the bias in workers' job finding and job separation expectations equal to the values measured in the GSOEP in the respective sample. Our bias estimates refer to the biannual frequency of job finding and separation rates. Section 5.5 shows the respective calibration and simulation output for the biannual frequency. In the quarterly calibration, we convert both the expected and the predicted transition rates into quarterly rates (see footnote 6) and compute the resulting quarterly bias as the difference of the two.

5.3 Quantitative effects of bias on wages and unemployment

Table 5 shows results from the calibrated and simulated baseline model. We perform three counterfactual exercises: removing the job separation bias, removing the job finding bias, and removing both biases at the same time. In the counterfactual exercises we only change the respective bias parameters and do not recalibrate the model. Note that, while the job separation rate is a fixed parameter, labor market tightness and, hence, the job finding rate is endogenous and changes across counterfactual exercises.

The first panel in Table 5 shows results from these simulations for the entire German economy.[25] The first three columns report changes in the unemployment rate, log wages and log reservation wages. When removing job separation bias, both wages and unemployment increase. When removing job finding bias, both wages and unemployment decrease. This reflects the upward-shift in the wage curve as depicted in Figure 2 above. Removing job separation bias implies about 0.8 percent higher wages and an about 0.7 percentage points higher unemployment rate. Removing job finding bias implies about 0.3 percent lower wages, 0.6 percent lower reservation wages and a 0.2 percentage points lower unemployment rate.

Regarding wage elasticities, our model implies a wage elasticity with respect to job separation bias of -0.0086 (column 4), and an elasticity of the reservation wage with respect to

ness to setting the job separation rate in the East to a higher value in line with the officially reported unemployment rate, see Section 5.5.

[25] More detailed simulation output can be viewed in Table D.1 in the Appendix.

Table 5: Counterfactual experiments in the baseline model

	$\Delta[u]$	$\Delta[ln(\omega)]$	$\Delta[ln(\underline{\omega})]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\underline{\omega})]}{\Delta[D_{\lambda w}]}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
			All Germany			
no JS bias	0.0070	0.0081	0.0170	-0.0086		0.0052
no JF bias	-0.0020	-0.0028	-0.0059		0.0030	-0.0019
no bias	0.0045	0.0054	0.0114	-0.0058	-0.0057	0.0035
			East Germany			
no JS bias	0.0120	0.0160	0.0340	-0.0086		0.0106
no JF bias	-0.0005	-0.0008	-0.0017		0.0039	-0.0006
no bias	0.0113	0.0152	0.0324	-0.0082	-0.0736	0.0101
JS bias west	0.0065	0.0094	0.0202	-0.0081		0.0065
JF bias west	0.0031	0.0047	0.0100		0.0036	0.0033
all bias west	0.0102	0.0140	0.0297	-0.0119	0.0107	0.0094

Notes: All Germany and East Germany calibrated to respective sample, see Table 4. Values in steady state. Counterfactual experiments not recalibrated.

job finding bias of 0.003 (column 5). The simulated elasticities are very similar when being computed with respect to a 1 percentage point change in the respective bias which corresponds directly to the estimation (see Table D.2). Hence, the effect of biases in our model are close to linear. There are at last two reasons why wage elasticities in the model are not directly comparable to the estimated wage elasticities from our data. First, the empirical estimates ignore that job finding bias may affect the behavior of employed workers and job separation bias may affect the behavior of unemployed workers. Second, the model reflects changes in the labor market equilibrium in response to changes in expectation biases, while the empirical estimates may refer to partial effects only, or to effects outside of equilibrium. Nevertheless, the wage elasticities generated in the model are generally within the ballpark of our empirical estimates (compare Tables 2 and 3).

Removing all biases implies about 0.54 percent higher wages and a 0.45 percentage points higher unemployment rate. The effects of the two types of biases are hence close to additive. The overall effects of removing all bias are, on average, small. First, optimism with respect to job finding and pessimism with respect to job separation are offsetting each other. Second, the effect of bias on wages depends on the wage response to labor market tightness in our model, which is generally small and strongly depends on the model calibration. We explore robustness to different values of the bargaining power γ, and different targeted separation rates and biases in Section 5.5.

In order to assess the importance of workers' expectation bias, taking into account both the effect on wages and on unemployment, we compute the unbiased expected lifetime income of a person entering the economy,

$$\mathbb{E}(\mathcal{I}_{W,U}) = (1-u)\mathcal{I}_W + u\mathcal{I}_U \tag{11}$$

where

$$\mathcal{I}_W = \omega + \beta(1-\sigma)\mathcal{I}_W + \beta\sigma\mathcal{I}_U \tag{12}$$

$$\mathcal{I}_U = b + \beta\big[1-\theta q(\theta)\big]\mathcal{I}_U + \beta\theta q(\theta)\mathcal{I}_W. \tag{13}$$

The computation uses actual job separation and finding rates and, hence, the unbiased average risk of unemployment. The last column in Table 5 reports the results.[26] Again, the effects are not strikingly large. Removing the job separation bias implies 0.52 percent higher expected lifetime income, while removing the job finding bias implies about 0.19 percent lower expected lifetime income. Removing all biases implies about 0.35 percent higher expected lifetime income on average.

5.4 Bias and the East-West German wage differential

Small average effects potentially mask substantial heterogeneity, as removing job separation and job finding biases may have much larger effects for subgroups in our sample. Let us consider the example of East Germans for whom the job separation bias is substantially larger, and the job finding bias is substantially lower, than for West Germans, as documented in Section 3. Hence, removing both biases in this case should have much smaller offsetting effects. We perform the same counterfactual exercise in the model calibrated to East Germany and find that removing all biases implies about 1.5 percent higher wages, a 1.13 percentage points higher unemployment rate and about 1 percent higher unbiased expected lifetime income (see second panel in Table 5).[27] Hence, the effect of removing expectation bias is about three times as large for Eastern German as for average German workers.

We can also use our model to investigate the quantitative relationship between workers' expectation biases and the East-West German wage differential. Section 4 has documented this differential to be about 30% overall, and 23% net of controls. The empirical estimates imply that if Eastern pessimism about job separation was at Western levels, wages would be 0.6% higher, which amounts to about 1.3 percentage points of the wage differential. We perform the corresponding counterfactual experiment in our model and show the results in the bottom panel of Table 5. This exercise delivers a wage increase of about 0.9%. Using our model, we can also counterfactually set East Germans' bias in job finding expectations to Western levels. This leads to an additional 0.47% higher wages. Finally, setting both job separation and job finding bias simultaneously to Western levels leads to about 1.4% higher wages. The difference in job separation pessimism and job finding optimism between East and West Germany thus accounts for about 2.8 percentage points of the East-West German wage gap.[28]

A decrease in the wage gap is accompanied by an increase in the unemployment gap. Unemployment in the East now increases by about 1 percentage point. Unbiased expected

[26] Table D.3 in the Appendix shows the components of lifetime income.

[27] More detailed output is reported in Tables D.4 and D.5 in the Appendix.

[28] To compute the effect on the wage gap, we compare the log difference between West and East German wages to the log difference between West and counterfactual East German wages.

lifetime income takes the beneficial wage gain and adverse unemployment increase into account and reports an increase in lifetime income of about 0.94 percent. Hence, East Germans would be better off, if they experienced job separation and job finding biases at Western levels.

5.5 Robustness

We investigate the sensitivity of the quantitative results. First, we impose bias in job separation based on dismissal only. Second, we consider the bargaining power of workers as a critical parameter regarding the elasticity of wages with respect to the expectation bias. Third, we calibrate the model to the biannual frequency in which we originally measure the bias in expectations. Fourth, we increase the East German job separation rate to match the East German unemployment rate in official statistics. Our findings are robust to all robustness exercises. In fact, the increase in wages and expected lifetime income as well as the reduction in the East-West German wage gap are substantially larger in some cases.

We calibrate the quarterly model to the alternative measure of job separation based on dismissals only. Dismissals cover only part of all job separations and, hence, predicted rates are much lower. Job separation bias is much larger, however, as already discussed in Section 3. Table D.10 shows the resulting calibration and Table D.11 shows the simulation output. The effects are substantially larger compared to the general measure of job separation. Lifetime income now increases by 1.7% in the baseline economy. Wages in the East increase by 2.7% when Western biases are assigned which reduces the East-West German wage gap by about 5.6 percentage points.

Table D.6 in the Appendix documents the simulation results when recalibrating the model with high and low bargaining power of workers relative to the baseline value of $\gamma = 0.5$. A lower bargaining power leads to a larger increase in wages when job separation bias is removed, to a larger decrease in wages when job finding bias is removed, and to a larger total wage change when both biases are removed. The reverse happens if the bargaining power of workers is higher. A lower bargaining power directly reduces wages, and also reduces the size of the response of wages to changes in the bias (see e.g. the comparative statics in equations (D.1) and (D.2) in the Appendix). However, since lower wages spur job creation, observable job finding rates can then only be replicated with substantially higher costs of posting a vacancy, which both increases the slope of the job creation condition and increases the response of wages to changes in the bias (degree of rotation of the wage curve). This last effect dominates when recalibrating the model economy to a lower bargaining power. Our results therefore suggest that removing biases in an economy where workers have lower bargaining power generates larger effects than in our baseline. A lower bargaining power may be realistic in East Germany which experiences lower collective worker representation (see e.g. Bachmann et al. (2022)). If we recalibrate the East German economy to a lower bargaining power ($\gamma = 0.3$) and repeat our counterfactual exercise, East Germans would gain 2.86% higher wages if all biases were changed to Western levels. In this economy, the difference in optimism and pessimism between East and West Germany

accounts for over 5 percentage points of the East-West wage differential.
Table D.8 documents the simulation results when recalibrating the model to the biannual frequency. Due to the higher job separation rate, the slope of the job creation curve is steeper, and the rotation of the wage curve is larger for a given bias change than in the model calibrated to the quarterly frequency. However, the relative change in the bias is not identical due to the interpolation to the different frequency. As a result, the wage effects from removing the bias in the overall economy are slightly smaller. The wage increases from assigning the Western bias to Eastern Germans are larger than in the quarterly calibration.
Our baseline calibration implies an East German unemployment rate that is too low compared to official statistics. Table D.9 reports the results when recalibrating the model to East Germany while changing the job separation rate in to $\sigma = 0.027$ such that the implied unemployment rate in steady state equals about 13%. The change in wages and lifetime income is similar, but a bit smaller both when removing the bias or assigning the Western bias to the East German economy relative to the baseline.

6 Conclusion

Our study addresses how biased expectations about individual labor market outcomes affect labor market aggregates, in particular wages and wage differences in the economy. We use survey data from the German Socio-Economic Panel (GSOEP) and document substantial pessimistic bias in job separation expectations and optimistic bias in job finding expectations. We find remarkable differences in the bias across subgroups. Most importantly, East Germans are substantially more pessimistic regarding job separation, and less optimistic regarding job finding, than their Western counterparts. We document that the pessimistic bias in job separation expectations negatively relates to individual net hourly wage rates and that the optimistic bias in job finding expectations positively relates to reservation wages on average.
We present a macroeconomic model of the labor market that is consistent with our empirical results and provides a corresponding interpretation. If workers are more pessimistic with respect to job separation than firms, higher effective discounting of the future job match and saved hiring costs yield a lower share of the match surplus to workers and, hence, lower wages. If workers are more optimistic with respect to job finding than firms, workers overestimate the hiring costs that are saved, i.e., they perceive the outside option as higher relative to the firm's assessment. In consequence, their reservation wages increase and they need to be compensated accordingly through higher wages. Low bargaining power on side of the workers intensifies these effects.
While not explicitly addressed in this paper, our model also allows firms' expectations about job filling and job separation to be biased in general. In fact, bias in job separation expectations of workers only affects wages if firms and workers disagree about the job separation probability. Here, we assume that the bias in job separation expectations of firms is lower than that of workers. Our data does not allow the empirical assessment of

the sign and degree of firm bias in expectations and we are not aware of other studies that have estimated these. It will be useful to shed more light on this in future research.
We can use our model to investigate the role of the larger pessimistic (less optimistic) bias in labor market expectations in East Germany for the East-West German wage differential. We show that the unconditional East-West German wage gap of 30% would reduce by close to 3 percentage points if East Germans experienced West German bias levels. This reduction could be even larger if workers in East Germany experience low bargaining power or if the difference in pessimism between workers and firms is larger in East than in West Germany. Our results therefore suggest that it might be desirable to reduce bias in expectations, e.g., through information treatment. Our results also suggest that policy makers should take existing biases in expectations about labor market outcomes into account when assessing the effectiveness of labor market policy.

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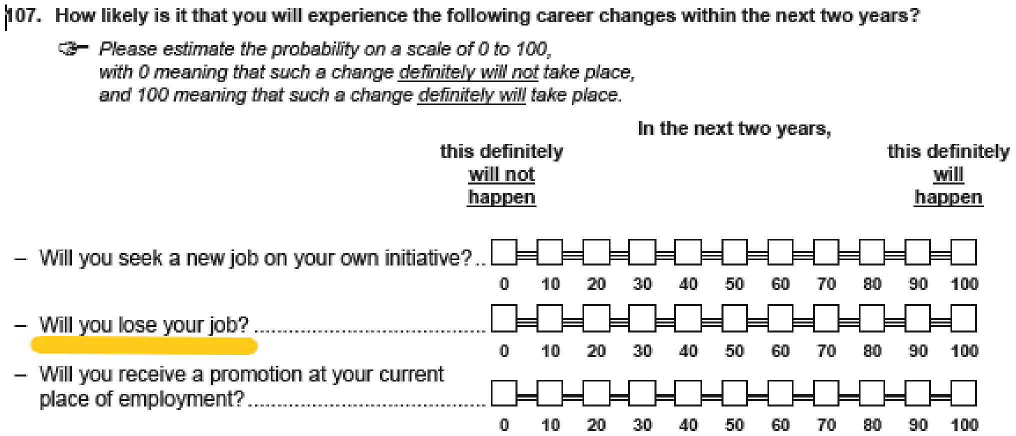
A Data Appendix

Figure A.1: Job loss expectations in the GSOEP



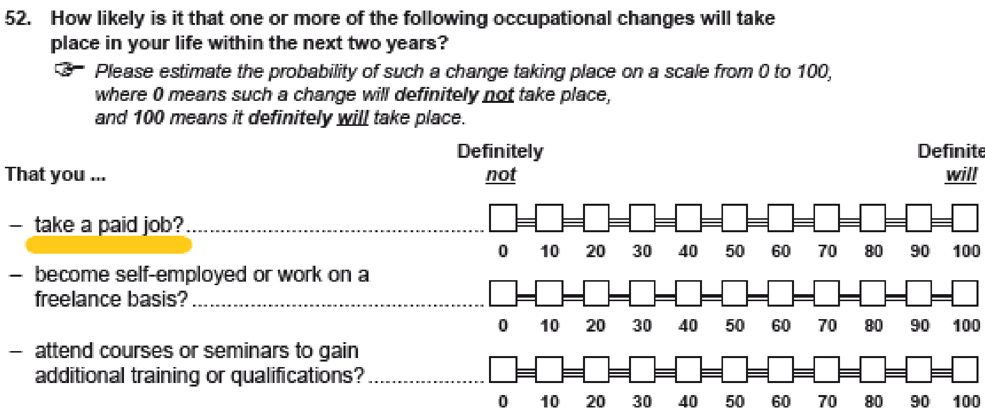
107. **How likely is it that you will experience the following career changes within the next two years?**

Please estimate the probability on a scale of 0 to 100,
with 0 meaning that such a change definitely will not take place,
and 100 meaning that such a change definitely will take place.

In the next two years,

	this definitely will not happen										this definitely will happen
– Will you seek a new job on your own initiative?	0	10	20	30	40	50	60	70	80	90	100
– Will you lose your job?	0	10	20	30	40	50	60	70	80	90	100
– Will you receive a promotion at your current place of employment?	0	10	20	30	40	50	60	70	80	90	100

Figure A.2: Job finding expectations in the GSOEP



52. **How likely is it that one or more of the following occupational changes will take place in your life within the next two years?**

Please estimate the probability of such a change taking place on a scale from 0 to 100,
*where **0** means such a change will **definitely not** take place,*
*and **100** means it **definitely will** take place.*

That you ...	Definitely not										Definitely will
– take a paid job?	0	10	20	30	40	50	60	70	80	90	100
– become self-employed or work on a freelance basis?	0	10	20	30	40	50	60	70	80	90	100
– attend courses or seminars to gain additional training or qualifications?	0	10	20	30	40	50	60	70	80	90	100

Figure A.3: Job separation and job finding expectations histograms

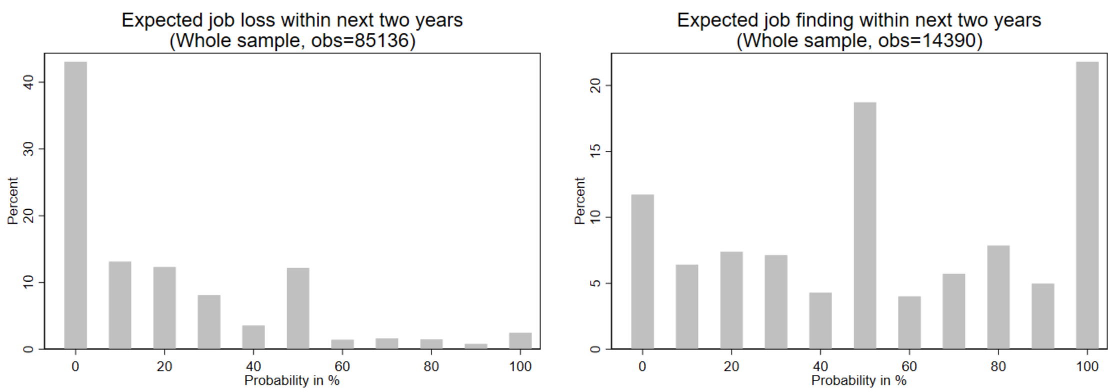


Table A.1: Reasons to have left the job in the GSOEP

"Reason Left Job [harmonized]"	
1	Place of Work Closed
2	I Resigned
3	Dismissed by Employer
4	Mutual Agreement
5	Temporary Employment Ended
6	Reached Retirement Age
7	Leave of Absence, Maternity/Parental Leave
8	Gave Up Self-Employment

Table A.2: Employment, unemployment and out of the labor force spells in the GSOEP

`spelltyp` ("Type of Event")	
1	Full-Time Employment
2	Short Work Hrs
3	Part-Time/ Marginal Employment
4	Vocational Training
5	Registered Unemployment
6	Retired
7	Maternity Leave
8	School, College
9	Military, Community Service
10	Housewife, Husband
11	Second Job
12	Other
13	First Job Training, Apprenticeship
14	Continuing Education, Retraining
15	Minijob (up to 400 Euro)
99	Gap

Table A.3: Biannual job separation and job finding indicators

	Job separation		
	Mean	std.dev.	Obs.
general	13.454	34.123	212114
dismissal	3.6325	18.710	212114
selected	6.2575	24.220	212114
spell	5.4881	22.775	108836

	Job finding		
	Mean	std.dev.	Obs.
out of U	44.416	49.690	9616
out of U or O	29.967	45.812	36147
out of O	24.730	43.145	26531

Notes: Measure of actual job separation from retrospective question two years after interview including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Measure of actual job finding from spells two years after interview out of unemployed (out of U), out of unemployment and out of the labor force (out of U or O) and out of the labor force only (out of O).

Table A.4: Quarterly job separation and job finding indicators

	Job separation		
	Mean	std.dev.	Obs.
general	1.5618	12.399	163148
dismissal	0.5185	7.1824	163148
selected	0.7876	8.8399	163148
spell	0.9188	9.5413	84241
	Job finding		
	Mean	std.dev.	Obs.
out of U	18.625	38.933	9616
out of U or O	12.128	32.646	36147
out of O	9.7735	29.696	26531

Notes: Measure of actual job separation from retrospective question one quarter after interview including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Measure of actual job finding from spells one quarter after interview out of unemployed (ouf of U), out of unemployment and out of the labor force (out of U or O) and out of the labor force only (out of O).

Table A.5: Continuous variables in job separation probit estimation

	Mean	std.dev.	min	max	P50	Obs.
Age	43.744	9.9330	25	65	44	212114
Tenure in Firm	10.903	9.8850	0	51.600	8.1000	210317
Unemployment experience	0.6241	1.7042	0	34.300	0	208300

Notes: All variables in years

Table A.6: Discrete variables in job separation probit estimation

	freq	pct	cumpct
Male	110194	51.95	51.95
Female	101920	48.05	100.00
West	166330	78.42	78.42
East	45784	21.58	100.00
No German citizen	29358	13.84	13.84
German citizen	182756	86.16	100.00
No kids less 16	95487	45.02	45.02
Kids less 16	116627	54.98	100.00
Married, Partnered	146859	69.64	69.64
Single, Divorced, Widowed	64009	30.36	100.00
Low (School)	14586	6.91	6.91
Middle (Vocational Training)	138519	65.59	72.50
High (University)	58073	27.50	100.00
No new job since last year	171287	82.88	82.88
New job since last year	35387	17.12	100.00
Not trained for occupation	71961	37.18	37.18
Trained for occupation	121605	62.82	100.00
0 Satisfied: On Scale 0-Low to 10-High	1211	0.60	0.60
1 Satisfied: On Scale 0-Low to 10-High	1402	0.69	1.28
2 Satisfied: On Scale 0-Low to 10-High	3602	1.77	3.05
3 Satisfied: On Scale 0-Low to 10-High	6658	3.27	6.33
4 Satisfied: On Scale 0-Low to 10-High	8059	3.96	10.29
5 Satisfied: On Scale 0-Low to 10-High	20745	10.20	20.48
6 Satisfied: On Scale 0-Low to 10-High	20635	10.14	30.63
7 Satisfied: On Scale 0-Low to 10-High	38117	18.74	49.36
8 Satisfied: On Scale 0-Low to 10-High	56000	27.52	76.89
9 Satisfied: On Scale 0-Low to 10-High	29716	14.61	91.49
10 Satisfied: On Scale 0-Low to 10-High	17307	8.51	100.00
Agriculture, Forestry, Fishery and Mining	3839	1.95	1.95
Industry and Manufacturing	45168	22.98	24.93
Energy and Construction	14206	7.23	32.16
Services, Tourism, Trade, Business and Transport	66226	33.69	65.85
Public Administration, Health, Social Work and Education	58239	29.63	95.48
Private Households and Membership Organizations	8876	4.52	100.00
firm size < 20	55006	28.09	28.09
firm size $\geq 20 < 200$	54949	28.07	56.16
firm size $\geq 200 < 2000$	40524	20.70	76.86
firm size ≥ 2000	45308	23.14	100.00
Total	212114	100.00	

Table A.7: Continuous variables in job finding probit estimation

	Mean	std.dev.	min	max	P50	Obs.
Age	44.702	11.068	25	65	45	18789
Unemployment experience in years	4.7444	4.5714	0	39	3.3000	18450
Work experience (full time)	14.618	12.009	0	50.100	12.300	18450
Work experience (part time)	1.9215	4.2388	0	40	0	18450

Notes: All variables in years

Table A.8: Discrete variables in job finding probit estimation

	freq	pct	cumpct
Male	9039	48.11	48.11
Female	9750	51.89	100.00
West	11555	61.50	61.50
East	7234	38.50	100.00
No German citizen	4626	24.62	24.62
German citizen	14163	75.38	100.00
Married, Partnered	10516	56.49	56.49
Single, Divorced, Widowed	8101	43.51	100.00
Low (School)	3939	21.19	21.19
Middle (Vocational Training)	12565	67.58	88.76
High (University)	2089	11.24	100.00
Very Good Health	1286	6.85	6.85
Good Health	5956	31.74	38.60
Satisfactory Health	6152	32.79	71.38
Poor Health	3880	20.68	92.06
Bad Health	1490	7.94	100.00
Total	18789	100.00	

Table A.9: Hourly wages and reservation income

	Mean	std.dev.	P01	P50	P99	Obs.
Hourly wage rate	11.025	8.0486	1.2625	9.5625	35	205184
Net labor income	1684.0	1349.7	100	1472	6000	212112
Actual work hours	37.943	13.478	5	40	70	205184
Reservation income	1212.5	532.27	400	1200	3000	10728

Notes: Hourly wage rates refer to actual hours worked, labor income is net, in Euro and refers to main job last month, work time is actual work time per week in hours. Wage, income and hours refer to sample of employed persons used in wage regressions. Reservation income refers monthly net salary at which person would take a job and refers to unemployed persons used in reservation income regressions.

B Bias Appendix

Table B.1: Job separation probit estimation

	general	dismissal	selected	spell
Age	-0.185***	-0.00448	-0.0375***	-0.0334***
Age, squared	0.00213***	0.000143*	0.000475***	0.000477***
Female	0.124***	-0.0169	-0.0305*	-0.0194
Married, Partnered	0	0	0	0
Single, Divorced, Widowed	-0.0444***	0.0752***	0.0542***	0.128***
Children under 16 in household	-0.0724***	-0.0436**	-0.0291*	-0.00897
East-Germany	0.0142	0.163***	0.143***	0.195***
Born in Germany	0.0432**	-0.0534**	0.0119	-0.0899***
Tenure in Firm	-0.0637***	-0.0410***	-0.0546***	-0.0613***
Tenure in Firm, squared	0.00144***	0.000813***	0.00112***	0.00129***
Unemployment experience	0.0501***	0.0762***	0.0945***	0.146***
Unemployment experience, squared	-0.00298***	-0.00498***	-0.00568***	-0.00683***
Working in occupation trained for	-0.0130	-0.0393**	-0.0367**	-0.0466*
New Job Since Previous Year	0.183***	0.152***	0.264***	0.314***
Satisfaction With Work	-0.0799***	-0.0708***	-0.0747***	-0.0937***
Low (School)	0	0	0	0
Middle (Vocational Training)	0.0718**	-0.0361	-0.0345	-0.0760*
High (University)	0.160***	-0.153***	0.00326	-0.149***
Agriculture, etc.	0	0	0	0
Industry and Manufacturing	-0.205***	-0.0903*	-0.208***	-0.337***
Energy and Construction	-0.0344	0.109*	-0.0231	-0.0431
Services, etc.	-0.128***	-0.0944*	-0.192***	-0.309***
Public Administration, etc.	-0.204***	-0.444***	-0.275***	-0.436***
Private Households, etc.	-0.208***	-0.255***	-0.206***	-0.340***
Apprentice/Trainee	0	0	0	0
Manual Worker	-0.0588	0.153	-0.275**	-0.466***
Self-Employed, Family Business	-0.433***	-0.597***	-0.960***	-1.068***
Free-Lance Professional	-0.527***	-0.675***	-0.986***	-1.031***
Employees with Simple Tasks	-0.0812	0.158	-0.285**	-0.494***
Qualified Professional/Managerial	-0.0502	0.101	-0.326***	-0.533***
Civil Service	-0.137	-0.192	-0.584***	-1.336***
LT 20	0	0	0	0
GE 20 LT 200	-0.0730***	-0.179***	-0.111***	-0.0845***
GE 200 LT 2000	-0.118***	-0.326***	-0.159***	-0.178***
GE 2000	-0.133***	-0.411***	-0.145***	-0.241***
Constant	3.853***	-0.786***	0.635***	0.928***
Observations	163148	163148	163148	84241
McFadden R2	0.0947	0.120	0.108	0.182
McKelvey Zavoina R2	0.164	0.198	0.169	0.285
AIC	0.709	0.279	0.414	0.323

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Years 1999, 2001, 2003, 2005, 2007, 2009, 2013, 2015, employed persons between 25 and 65 years. Measure of actual job separation from retrospective question including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Agriculture, etc. includes Forestry, Fishery and Mining, Services, etc. includes Tourism, Trade, Business and Transport, Public Administration, etc. includes Health, Social Work and Education, Private Households, etc. includes Membership Organizations. GE: greater or equal. LT: lower than.

Table B.2: Job finding probit estimation

	out of U	out of U or O	out of O
Female	-0.183***	-0.257***	-0.201***
Age	0.0938***	0.0702***	0.0378***
Age, squared	-0.00154***	-0.00148***	-0.00111***
Married, Partnered	0	0	0
Single, Divorced, Widowed	0.0448	0.137***	0.119***
Health Very Good	0	0	0
Health Good	-0.00793	0.0415	0.0648
Health Satisfactory	-0.0864	-0.0687*	-0.0619
Health Poor	-0.370***	-0.302***	-0.268***
Health Bad	-0.745***	-0.688***	-0.619***
East-Germany	0.0299	0.0414*	-0.0383
Born in Germany	0.100*	0.0440	0.0942**
Germany	0	0	0
Europe and Russia (without Germany)	-0.0953	-0.0880*	-0.0803
America	0.201	-0.263	-0.394*
Asia	-0.320***	-0.303***	-0.321***
Africa	-0.438*	-0.0855	0.105
Oceania	0	0	
No nationality	0.108	0.432	1.033**
Low (School)	0	0	0
Middle (Vocational Training)	0.265***	0.141***	0.0715*
High (University)	0.479***	0.403***	0.345***
Work experience (full time)	0.0471***	0.0438***	0.0330***
Work experience (full time), squared	-0.000924***	-0.000474***	-0.000257***
Work experience (part time)	0.0495***	0.0875***	0.0963***
Work experience (part time), squared	-0.00144**	-0.00178***	-0.00209***
Unemployment experience	-0.0752***	0.0160**	0.00766
Unemployment experience, squared	0.00218***	-0.000947**	0.0000233
Constant	-1.309***	-0.981***	-0.414*
Observations	9362	35332	25970
McFadden R2	0.137	0.184	0.190
McKelvey Zavoina R2	0.270	0.360	0.354
AIC	1.195	1.001	0.910

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Years 1999, 2001, 2003, 2005, 2007, 2009, 2013, 2015, unemployed persons between 25 and 65 years. Measure of actual job finding out of unemployed (out of U), unemployment and out of the labor force (out of U or O) and out of the labor force only (out of O).

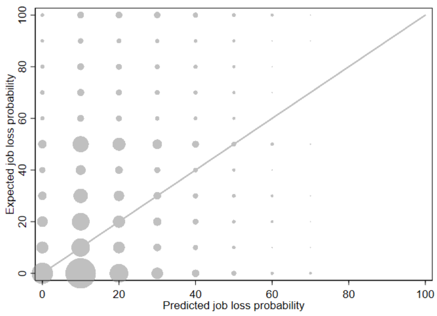
Table B.3: Expected, predicted and bias in job separation: Summary statistics comparison

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
Expected job separation	19.767	24.529	0	100	0	10	50	67772
Predicted, general	13.329	10.385	0	70	0	10	30	67772
Bias, general	6.4376***	24.199	-70	100	-20	0	40	67772
Predicted, dismissal	2.7845	5.2868	0	50	0	0	10	67772
Bias, dismissal	16.982***	23.675	-40	100	0	10	50	67772
Predicted, selected	5.3814	7.3096	0	70	0	0	10	67772
Bias, selected	14.385***	23.268	-50	100	-10	10	50	67772
Predicted, spell	4.2491	7.9522	0	90	0	0	10	67772
Bias, spell	15.518***	23.452	-70	100	0	10	50	67772

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero.

Figure B.1: Expected, predicted and bias in job separation, general: Histograms

(a) Expected vs. predicted job separation



(b) Bias in job separation

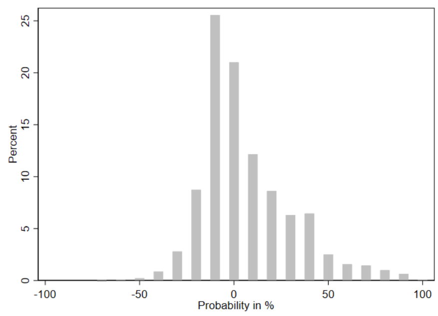
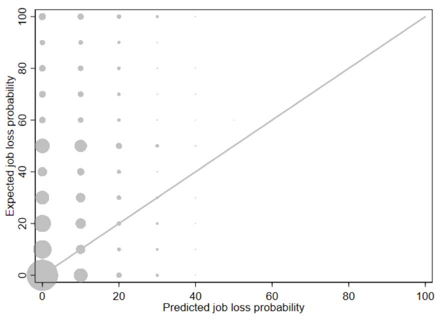


Figure B.2: Expected, predicted and bias in job separation, dismissal: Histograms

(a) Expected vs. predicted



(b) Bias

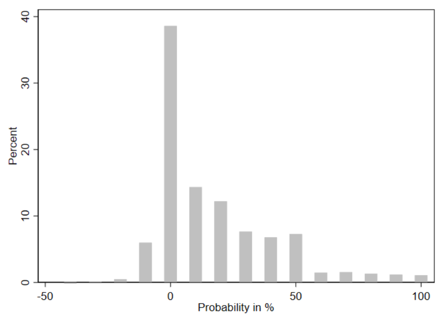
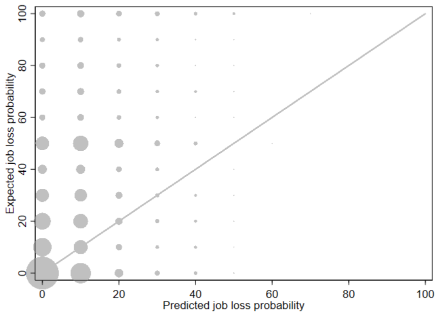


Figure B.3: Expected, predicted and bias in job separation, selected: Histograms

(a) Expected vs. predicted



(b) Bias

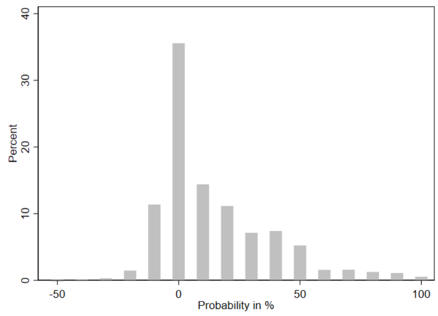
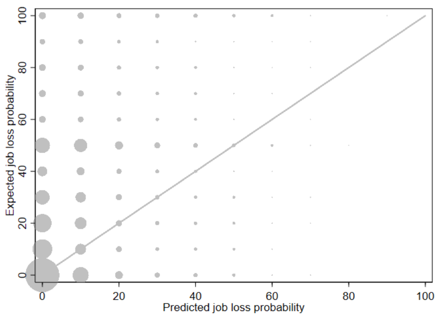


Figure B.4: Expected, predicted and bias in job separation, spell: Histograms

(a) Expected vs. predicted



(b) Bias

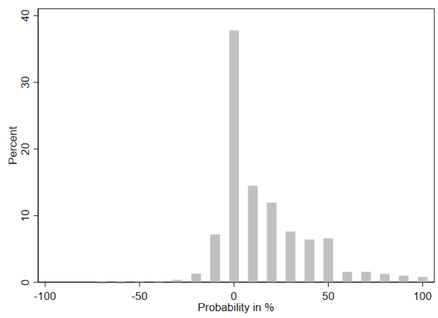
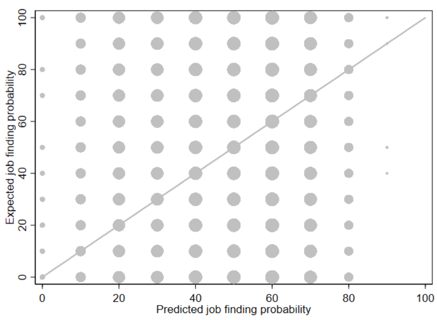


Figure B.5: Expected, predicted and bias in job finding, out of U: Histograms

(a) Expected vs. predicted



(b) Bias

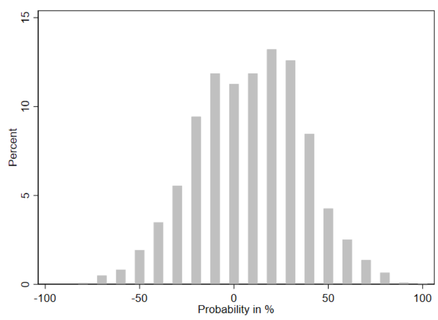
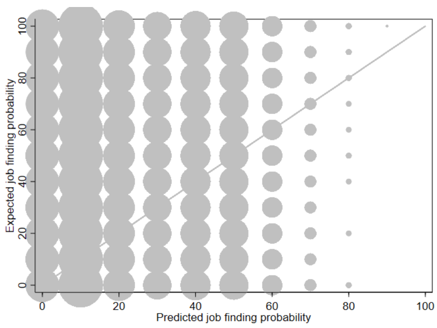


Figure B.6: Expected, predicted and bias in job finding, out of O: Histograms

(a) Expected vs. predicted



(b) Bias

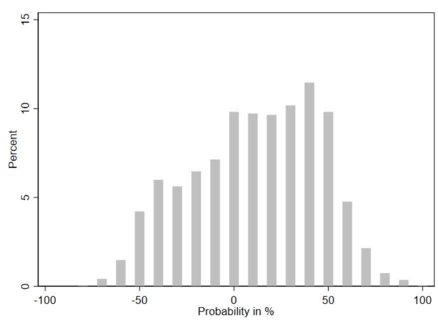


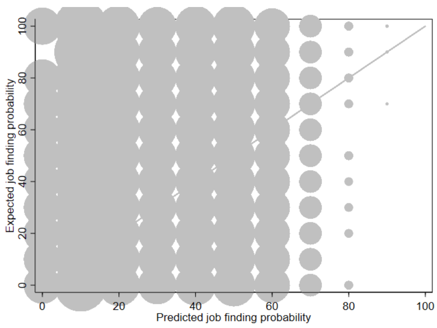
Table B.4: Expected, predicted and bias in job finding: Summary statistics comparison

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
Expected job finding	57.022	32.334	0	100	10	50	100	6423
Predicted, out of U	48.800	19.551	0	90	20	50	70	6423
Bias, out of U	8.2220***	28.711	-80	100	-30	10	40	6423
Expected	54.295	34.609	0	100	0	50	100	14049
Predicted, out of U or O	43.295	17.380	0	90	20	50	60	14049
Bias job, oug of U or O	11.000***	31.936	-80	100	-30	10	50	14049
Expected	52.005	36.261	0	100	0	50	100	7627
Predicted, out of O	40.674	16.496	0	90	20	40	60	7627
Bias, out of O	11.331***	34.021	-80	100	-40	10	50	7627

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero.

Figure B.7: Expected, predicted and bias in job finding, out of U or O: Histograms

(a) Expected vs. predicted



(b) Bias

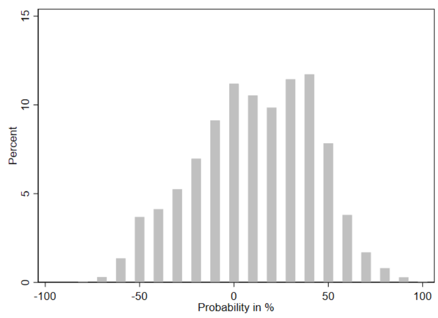


Table B.5: Bias in job separation across groups

	general	dismissal	selected	spell
predicted job separation	-0.628***	-0.236***	-0.228***	-0.313***
East-Germany	7.751***	6.552***	6.203***	6.309***
Born in Germany	0.243	0.636**	-0.0472	0.632**
Female	-0.0281	0.866***	1.043***	0.947***
Tenure in Firm	-0.172***	-0.171***	-0.0676***	-0.132***
Age	-0.0320	-0.101***	-0.0662***	-0.0875***
Unemployment experience in years	0.857***	0.725***	0.329***	-0.189***
Work experience (full time)	0.0206	0.0406*	0.0324	0.0319
Work experience (part time)	0.0344	0.0432	0.0582**	0.0600**
Low (School)	0	0	0	0
Middle (Vocational Training)	2.090***	2.595***	2.871***	3.120***
High (University)	1.907***	3.884***	3.143***	4.140***
Agriculture, etc.	0	0	0	0
Industry and Manufacturing	4.234***	3.724***	5.388***	5.766***
Energy and Construction	2.777***	0.937	2.668***	2.664***
Services, etc.	1.765**	1.600**	3.076***	3.504***
Public Administration, etc.	-1.541**	-0.442	0.239	0.507
Private Households, etc.s	-0.0772	0.0462	0.773	1.181
Apprentice/Trainee	0	0	0	0
Manual Worker	-11.57***	-16.85***	-6.576***	-4.088*
Self-Employed, Family Business	-20.53***	-24.77***	-12.88***	-11.91***
Free-Lance Professionals	-19.32***	-25.66***	-12.88***	-12.39***
Employees With Simple Tasks	-12.67***	-17.35***	-7.165***	-4.351*
Qualified Professional/Managerial	-13.56***	-17.79***	-7.371***	-4.958**
Civil Service	-23.09***	-28.81***	-16.72***	-15.24***
Constant	26.21***	35.05***	19.39***	18.95***
Observations	67772	67772	67772	67772

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Measure of actual job separation from retrospective question including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Agriculture, etc. includes Forestry, Fishery and Mining, Services, etc. includes Tourism, Trade, Business and Transport, Public Administration, etc. includes Health, Social Work and Education, Private Households, etc. includes Membership Organizations.

Table B.6: Bias in job finding across groups

	out of U	out of U or O	out of O
predicted job finding	-0.377***	-0.312***	-0.257***
East-Germany	-8.262***	-2.564***	4.306***
Born in Germany	-0.208	-0.224	-0.411
Female	-4.405***	-4.988***	-3.600***
Age	-0.348***	-0.224***	-0.129
Low (School)	0	0	0
Middle (Vocational Training)	-1.208	-0.0718	1.550
High (University)	-2.066	0.583	2.061
Log monthly net household income	2.111***	-1.819***	-3.424***
Work experience (full time)	-0.0995	0.0959*	0.209***
Work experience (part time)	-0.131	-0.0807	-0.0799
Unemployment experience in years	-0.342***	-0.621***	-1.004***
Constant	36.56***	52.67***	54.37***
Observations	6182	13418	7237

Note: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Measure of actual job finding out of unemployed (out of U), unemployment and out of the labor force (out of U or O) and out of the labor force only (out of O).

Table B.7: Expected, predicted and bias in job separation (general) by group

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
	Born German							
Expected	19.698	24.478	0	100	0	10	50	60621
Predicted	13.315	10.420	0	70	0	10	30	60621
Bias	6.3831	24.120	-70	100	-20	0	40	60621
	Born foreign							
Expected	20.351	24.955	0	100	0	10	50	7151
Predicted	13.451	10.081	0	70	0	10	30	7151
Bias	6.8997	24.849	-50	100	-20	0	40	7151
	Female							
Expected	20.160	25.140	0	100	0	10	50	31924
Predicted	15.039	10.500	0	70	0	10	30	31924
Bias	5.1209	24.707	-70	100	-20	0	40	31924
	Male							
Expected	19.416	23.967	0	100	0	10	50	35848
Predicted	11.806	10.040	0	70	0	10	20	35848
Bias	7.6102	23.676	-70	100	-20	0	40	35848
	18 to 25 year old							
Expected	23.520	25.684	0	100	0	20	50	929
Predicted	32.691	11.450	10	70	20	30	50	929
Bias	-9.1712	25.160	-70	80	-40	-10	20	929
	26 to 35 year old							
Expected	22.342	25.090	0	100	0	20	50	14307
Predicted	19.768	10.850	0	70	10	20	30	14307
Bias	2.5743	24.736	-70	100	-20	0	40	14307
	36 to 45 years old							
Expected	20.322	23.816	0	100	0	10	50	21895
Predicted	9.9607	8.0669	0	50	0	10	20	21895
Bias	10.361	22.939	-50	100	-10	0	40	21895
	46 to 55 years old							
Expected	19.421	24.261	0	100	0	10	50	20697
Predicted	9.5724	8.0114	0	60	0	10	20	20697
Bias	9.8483	23.087	-50	100	-10	0	40	20697
	56 to 65 years old							
Expected	15.209	25.041	0	100	0	0	50	9944
Predicted	17.493	10.499	0	70	10	10	30	9944
Bias	-2.2838	24.601	-70	100	-20	-10	30	9944
	Low education (School)							
Expected	19.940	25.479	0	100	0	10	50	2651
Predicted	14.319	11.160	0	70	0	10	30	2651
Bias	5.6205	25.453	-60	100	-20	0	40	2651
	Middle education (vocational training)							
Expected	20.725	24.816	0	100	0	10	50	46230
Predicted	13.257	10.454	0	70	0	10	30	46230
Bias	7.4685	24.627	-70	100	-20	0	40	46230

	High education (university)							
Expected	17.398	23.506	0	100	0	10	50	18891
Predicted	13.368	10.092	0	70	0	10	30	18891
Bias	4.0294	22.743	-70	100	-20	0	40	18891
	Not concerned at all about job insecurity							
Expected	8.8754	17.413	0	100	0	0	30	32715
Predicted	12.247	9.8478	0	70	0	10	20	32715
Bias	-3.3718	18.336	-70	100	-20	-10	10	32715
	Somewhat concerned about job insecurity							
Expected	25.667	22.356	0	100	0	20	50	25584
Predicted	13.605	10.286	0	70	0	10	30	25584
Bias	12.063	22.594	-70	100	-10	10	40	25584
	Very concerned about job insecurity							
Expected	44.601	29.848	0	100	0	50	90	8190
Predicted	16.722	11.682	0	70	0	10	30	8190
Bias	27.879	29.368	-60	100	-10	30	70	8190
	Tenure >15 year							
Expected	32.231	30.022	0	100	0	30	80	6446
Predicted	28.548	10.913	10	70	20	30	40	6446
Bias	3.6829	29.793	-70	90	-30	0	50	6446
	Tenure 1-15 years							
Expected	20.646	24.097	0	100	0	10	50	39778
Predicted	13.933	8.8046	0	70	10	10	30	39778
Bias	6.7133	23.986	-70	100	-20	0	40	39778
	Tenure <1 year							
Expected	14.353	21.767	0	100	0	0	50	21314
Predicted	7.5875	7.6108	0	70	0	10	20	21314
Bias	6.7655	22.640	-70	100	-10	0	40	21314
	Employment experience (part time) <1 year							
Expected	19.501	24.152	0	100	0	10	50	40802
Predicted	12.397	10.386	0	70	0	10	30	40802
Bias	7.1038	23.897	-70	100	-20	0	40	40802
	Employment experience (part time) 1-15 years							
Expected	20.742	25.230	0	100	0	10	50	23103
Predicted	15.097	10.412	0	70	0	10	30	23103
Bias	5.6452	24.744	-70	100	-20	0	40	23103
	Employment experience (part time) >15 year							
Expected	16.747	23.917	0	100	0	0	50	3867
Predicted	12.604	8.7217	0	60	0	10	20	3867
Bias	4.1427	23.793	-60	90	-20	0	40	3867
	Employment experience (full time) <1 year							
Expected	24.352	28.685	0	100	0	10	70	2128
Predicted	22.101	13.116	0	70	10	20	40	2128
Bias	2.2509	28.125	-70	90	-30	-10	40	2128
	Employment experience (full time) 1-15 years							
Expected	20.764	24.567	0	100	0	10	50	29524
Predicted	16.013	10.332	0	70	10	10	30	29524

Bias	4.7510	24.170	-70	100	-20	0	40	29524
	Employment experience (full time) >15 years							
Expected	18.672	24.148	0	100	0	10	50	35431
Predicted	10.532	9.2952	0	70	0	10	20	35431
Bias	8.1403	23.842	-70	100	-10	0	40	35431
	No unemployment experience							
Expected	16.663	22.751	0	100	0	10	50	44792
Predicted	11.243	9.2044	0	70	0	10	20	44792
Bias	5.4199	23.101	-70	100	-20	0	40	44792
	Unemployment experience <12 months							
Expected	23.699	25.171	0	100	0	20	50	13675
Predicted	15.411	10.583	0	70	0	10	30	13675
Bias	8.2881	25.119	-70	100	-20	0	40	13675
	Unemployment experience >12 months							
Expected	28.930	28.402	0	100	0	20	70	9305
Predicted	20.313	11.705	0	70	10	20	40	9305
Bias	8.6169	27.461	-70	100	-20	0	40	9305
	Agriculture, Forestry, Fishery and Mining							
Expected	20.812	26.677	0	100	0	10	50	1195
Predicted	16.167	11.807	0	60	0	10	30	1195
Bias	4.6444	26.009	-60	90	-20	0	40	1195
	Industry and Manufacturing							
Expected	22.690	24.009	0	100	0	20	50	15962
Predicted	11.260	9.4976	0	70	0	10	20	15962
Bias	11.430	24.135	-70	100	-10	10	40	15962
	Energy and Construction							
Expected	24.049	25.288	0	100	0	20	50	4967
Predicted	16.062	11.146	0	70	0	10	30	4967
Bias	7.9867	24.719	-70	100	-20	0	40	4967
	Services, Tourism, Trade, Business and Transport							
Expected	21.487	24.456	0	100	0	10	50	22321
Predicted	15.041	10.985	0	70	0	10	30	22321
Bias	6.4455	24.564	-70	100	-20	0	40	22321
	Public Administration, Health, Social Work and Education							
Expected	14.637	23.678	0	100	0	0	50	20715
Predicted	12.174	9.5315	0	60	0	10	20	20715
Bias	2.4625	22.749	-60	100	-20	0	30	20715
	Private Households and Membership Organizations							
Expected	19.273	25.873	0	100	0	10	50	2612
Predicted	14.008	10.743	0	70	0	10	30	2612
Bias	5.2642	24.862	-70	100	-20	0	40	2612
	Apprentice / Trainee							
Expected	42.381	38.990	0	100	0	30	100	105
Predicted	31.238	11.154	10	60	20	30	40	105
Bias	11.143	40.462	-50	90	-40	0	70	105
	Manual Worker							

Expected	24.980	26.148	0	100	0	20	50	17590
Predicted	14.743	11.300	0	70	0	10	30	17590
Bias	10.237	26.107	-70	100	-20	0	40	17590
	Self-Employed, Family Business							
Expected	11.625	20.122	0	100	0	0	50	3373
Predicted	7.4563	8.0105	0	60	0	10	20	3373
Bias	4.1684	20.507	-60	100	-10	0	30	3373
	Free-Lance Professionals							
Expected	10.153	19.410	0	100	0	0	30	1309
Predicted	5.6073	6.4159	0	30	0	0	10	1309
Bias	4.5455	18.722	-30	90	-10	0	30	1309
	Employees With Simple Tasks							
Expected	22.849	25.591	0	100	0	20	50	9106
Predicted	16.173	10.925	0	70	10	10	30	9106
Bias	6.6758	25.629	-70	100	-20	0	40	9106
	Qualified Professional/Managerial							
Expected	19.966	23.714	0	100	0	10	50	30642
Predicted	13.377	9.6759	0	70	0	10	30	30642
Bias	6.5890	23.740	-70	100	-20	0	40	30642
	Civil Service							
Expected	4.1509	14.576	0	100	0	0	10	5647
Predicted	9.0473	8.2478	0	60	0	10	20	5647
Bias	-4.8964	15.723	-60	100	-20	-10	0	5647

Notes: All means significantly different from zero at 1% significance, except for foreign born (too few observations).

Table B.8: Expected, predicted and bias in job finding (out of U) by group

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
	Born German							
Expected	56.973	32.407	0	100	10	50	100	4995
Predicted	50.428	19.060	0	90	20	50	70	4995
Bias	6.5445	28.281	-80	90	-30	10	40	4995
	Born foreign							
Expected	57.192	32.090	0	100	10	50	100	1428
Predicted	43.102	20.177	0	90	10	40	70	1428
Bias	14.090	29.434	-80	100	-20	10	50	1428
	Female							
Expected	53.211	31.734	0	100	10	50	100	3198
Predicted	45.854	18.817	0	90	20	50	70	3198
Bias	7.3577	29.439	-80	90	-30	10	40	3198
	Male							
Expected	60.800	32.485	0	100	10	60	100	3225
Predicted	51.721	19.828	0	90	20	50	80	3225
Bias	9.0791	27.949	-80	100	-30	10	40	3225
	18 to 25 years old							

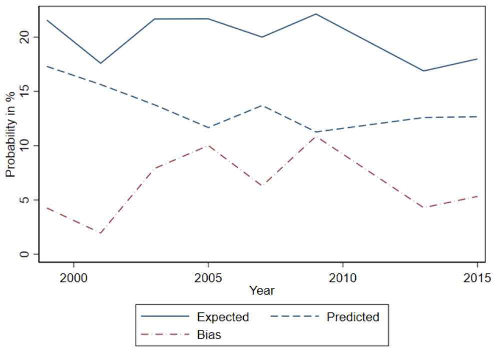
Expected	74.494	26.531	0	100	50	80	100	158
Predicted	56.392	12.630	20	80	40	60	70	158
Bias	18.101	27.256	-70	70	-20	30	40	158
	26 to 35 years old							
Expected	69.520	29.836	0	100	30	80	100	1583
Predicted	58.749	14.585	10	90	40	60	80	1583
Bias	10.771	28.157	-70	80	-30	20	40	1583
	36 to 45 years old							
Expected	62.745	30.222	0	100	20	60	100	1880
Predicted	57.202	16.631	10	90	30	60	80	1880
Bias	5.5426	28.302	-80	80	-30	10	40	1880
	46 to 55 years old							
Expected	51.323	30.570	0	100	10	50	100	1799
Predicted	43.947	16.789	0	80	20	40	70	1799
Bias	7.3763	29.106	-70	80	-30	10	40	1799
	56 to 65 years old							
Expected	34.038	29.186	0	100	0	30	80	1003
Predicted	24.855	12.270	0	60	10	20	40	1003
Bias	9.1825	29.183	-50	100	-20	0	50	1003
	Low education (School)							
Expected	53.993	31.675	0	100	10	50	100	1217
Predicted	37.683	17.431	0	80	10	40	60	1217
Bias	16.311	28.913	-70	100	-20	20	50	1217
	Middle education (Vocational Training)							
Expected	56.968	32.232	0	100	10	50	100	4407
Predicted	50.263	18.783	0	80	20	50	70	4407
Bias	6.7052	28.633	-80	90	-30	10	40	4407
	High education (University)							
Expected	61.927	33.329	0	100	10	60	100	799
Predicted	57.660	19.656	10	90	30	60	80	799
Bias	4.2678	26.560	-80	80	-30	10	30	799
	Employment experience (part time) <1 year							
Expected	57.716	32.373	0	100	10	50	100	4159
Predicted	49.082	19.576	0	90	20	50	70	4159
Bias	8.6343	28.308	-80	100	-30	10	40	4159
	Employment experience (part time) 1-15 years							
Expected	56.399	32.206	0	100	10	50	100	2119
Predicted	48.896	19.418	0	90	20	50	70	2119
Bias	7.5035	29.401	-80	80	-30	10	40	2119
	Employment experience (part time) >15 years							
Expected	46.207	31.160	0	100	10	50	100	145
Predicted	39.310	18.509	0	80	20	40	60	145
Bias	6.8966	29.919	-50	80	-30	0	50	145
	Employment experience (full time) <1 year							
Expected	58.713	31.163	0	100	10	50	100	769
Predicted	46.450	17.381	0	90	20	50	70	769
Bias	12.263	28.715	-70	80	-30	10	50	769

	Employment experience (full time) 1-15 years							
Expected	63.017	30.769	0	100	20	60	100	2980
Predicted	53.591	18.321	0	90	30	60	70	2980
Bias	9.4262	28.577	-80	90	-30	10	40	2980
	Employment experience (full time) >15 years							
Expected	50.004	32.938	0	100	10	50	100	2593
Predicted	44.069	20.295	0	90	20	40	70	2593
Bias	5.9352	28.627	-80	100	-30	10	40	2593
	No unemployment experience							
Expected	64.341	33.139	0	100	10	70	100	205
Predicted	59.854	16.962	10	80	40	60	80	205
Bias	4.4878	29.495	-70	80	-40	10	40	205
	Unemployment experience <12 months							
Expected	71.555	31.139	0	100	20	80	100	1132
Predicted	62.032	17.342	10	90	40	70	80	1132
Bias	9.5230	27.985	-80	80	-30	20	40	1132
	Unemployment experience >12 months							
Expected	53.492	31.607	0	100	10	50	100	5086
Predicted	45.409	18.680	0	90	20	50	70	5086
Bias	8.0830	28.828	-80	100	-30	10	40	5086

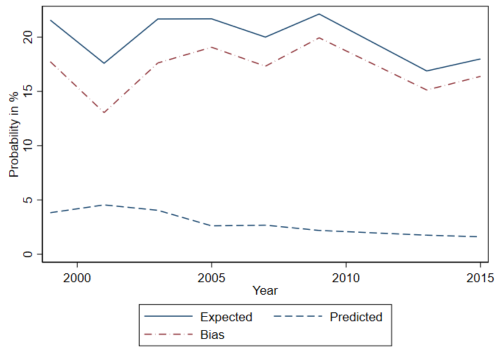
Notes: All means significantly different from zero at 1% significance, except for foreign born (too few observations).

Figure B.8: Bias in job separation expectations over time, different measures

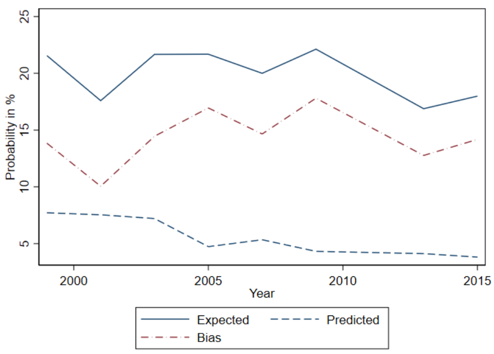
(a) general



(b) dismissal



(c) selected



(d) spell

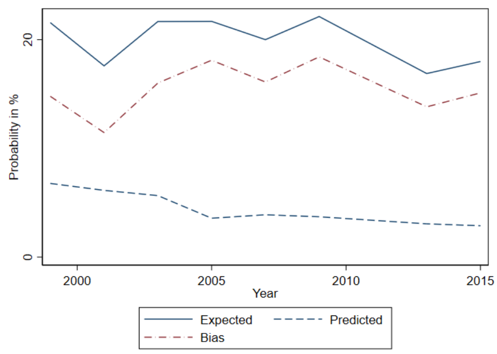
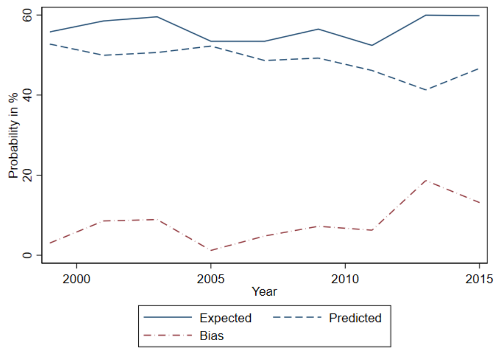
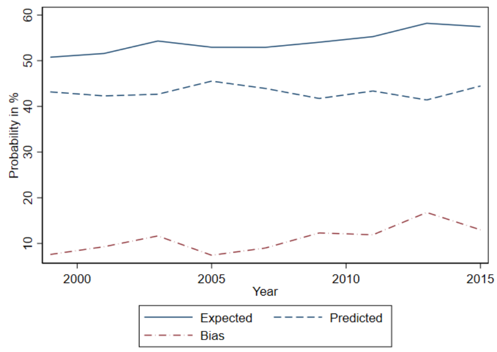


Figure B.9: Bias in job finding expectations over time, different measures

(a) out of U



(b) out of U or O



(c) out of O

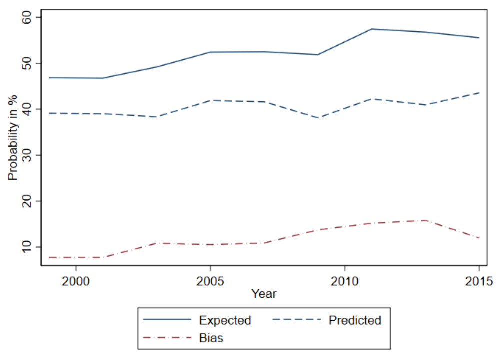
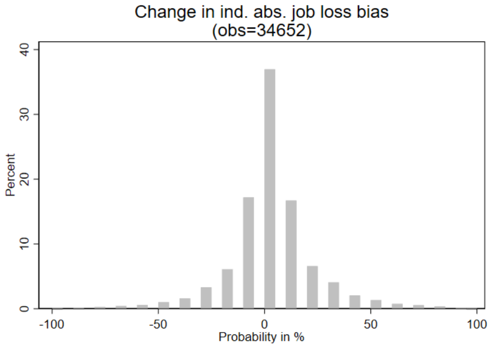


Table B.9: Change in job separation and finding bias between surveys: Summary statistics

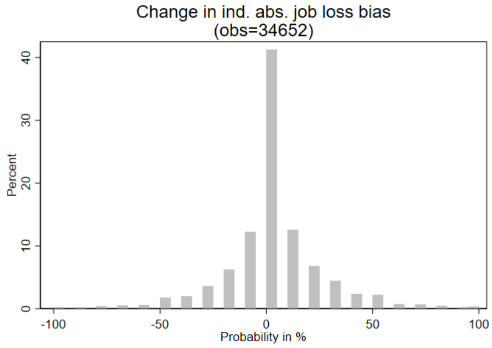
	Mean	std.dev.	min	max	P50	Obs.
			Job loss bias			
general	0.9339	20.461	-100	100	0	34652
dismissal	1.0825	24.057	-100	100	0	34652
selected	1.2069	23.018	-100	100	0	34652
spell	1.2527	23.611	-100	100	0	34652
			Job finding bias			
U only	-0.9368	20.788	-80	70	0	1676
U and O	-1.1212	22.542	-90	90	0	4299
O only	-0.4290	23.056	-90	80	0	1818

Figure B.10: Change in job separation bias between surveys, different measures

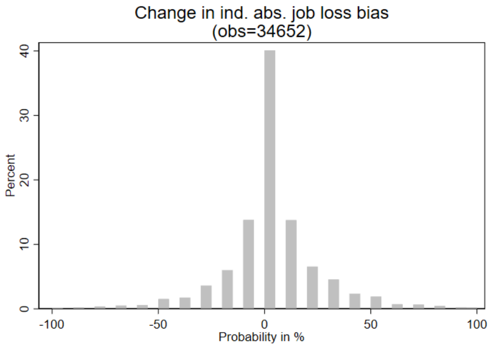
(a) general



(b) dismissal



(c) selected



(d) spell

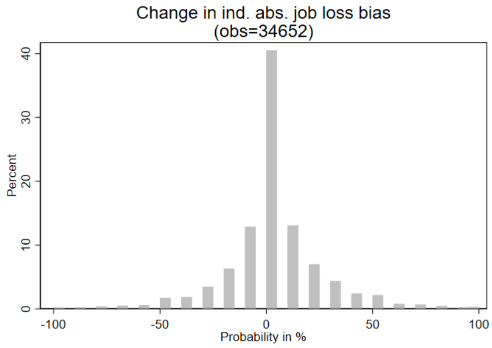
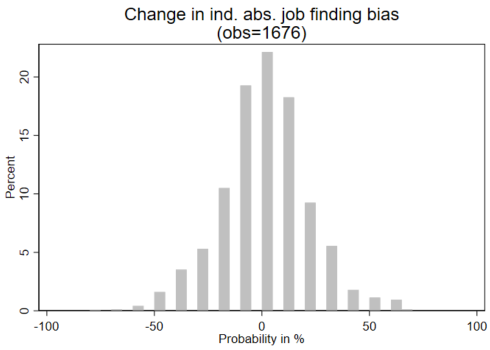
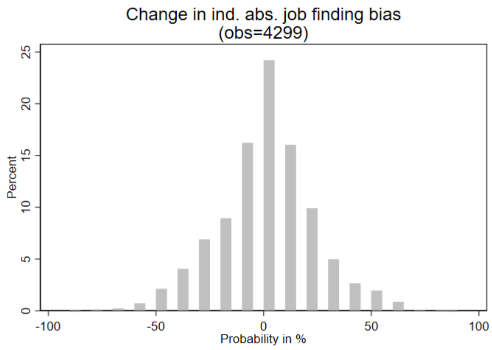


Figure B.11: Change in job finding bias between survey, different measures

(a) out of U



(b) out of U or O



(c) out of O

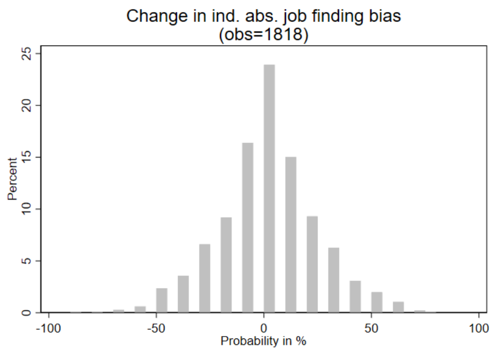


Table B.10: Change in job separation bias across groups

	general	dismissal	selected	spell
predicted job separation	0.0237*	-0.00702	-0.0734***	-0.0652**
East-Germany	0.361	-0.332	0.0897	-0.0401
Born in Germany	-0.448	-0.0710	-0.158	-0.105
Female	-0.0701	-0.0803	-0.0584	-0.0484
Tenure in Firm	0.123***	0.0895***	0.0787***	0.0757***
Age	0.0378	0.0201	0.00962	0.0117
Unemployment experience in years	-0.109	-0.148	-0.00114	-0.00299
Work experience (full time)	-0.00455	-0.0340	-0.0303	-0.0342
Work experience (part time)	0.0225	0.00913	0.00488	-0.00176
Low (School)	0	0	0	0
Middle (Vocational Training)	0.306	1.182	1.051	0.860
High (University)	-0.0872	0.408	0.522	0.141
Agriculture, etc.	0	0	0	0
Industry and Manufacturing	1.657*	1.421	1.129	1.429
Energy and Construction	0.588	0.0508	0.0663	0.422
Services, etc.	0.857	1.054	0.746	1.139
Public Administration, etc.	-0.482	-0.974	-1.271	-0.845
Private Households, etc.	0.286	-0.0506	-0.501	0.0838
Apprentice/Trainee	0	0	0	0
Manual Worker	-0.775	2.772	1.303	3.180
Self-Employed, Family Business	-1.598	2.097	0.266	2.223
Free-Lance Professionals	-1.503	1.395	-0.168	1.545
Employees With Simple Tasks	-0.797	2.931	1.445	3.235
Qualified Professional/Managerial	-1.014	2.175	0.678	2.489
Civil Service	-1.632	1.604	-0.192	1.734
Constant	-2.027	-3.822	-1.056	-3.084
Observations	34652	34652	34652	34652

Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Measure of actual job separation from retrospective question including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Agriculture, etc. includes Forestry, Fishery and Mining, Services, etc. includes Tourism, Trade, Business and Transport, Public Administration, etc. includes Health, Social Work and Education, Private Households, etc. includes Membership Organizations.

Table B.11: Change in job finding bias across groups

	out of U	out of U or O	out of O
predicted job finding	0.0849*	-0.0951**	-0.256***
East-Germany	0.409	0.0864	0.627
Born in Germany	-0.940	2.081**	2.929*
Female	-0.316	-0.849	0.500
Age	0.0263	-0.179*	-0.311*
Low (School)	0	0	0
Middle (Vocational Training)	-1.214	0.624	1.597
High (University)	-4.004	1.542	4.275*
Log monthly net household income	0.00896	0.402	-1.594
Work experience (full time)	0.0119	0.0595	0.152
Work experience (part time)	-0.393*	-0.0546	0.0954
Unemployment experience in years	0.0943	0.105	-0.210
Constant	-4.118	4.593	28.27**
Observations	1613	4121	1727

Note: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Measure of actual job finding out of unemployed (out of U), unemployment and out of the labor force (out of U or O) and out of the labor force only (out of O).

C Wage results Appendix

Table C.1: Wages and bias in job separation expectations, dismissal

	log hourly wage rate		
job separation bias	-0.00207***	-0.00183***	-0.000886***
	(0.000122)	(0.000109)	(0.0000804)
predicted job separation	-0.0337***	-0.0272***	-0.00735***
	(0.000920)	(0.000763)	(0.000651)
N	212114	212114	212114
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Mincer specification: educational attainment, full time work experience
Additional controls: East/West dummy, German citizenship, gender, actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year fixed effects

Table C.2: Wages and bias in job separation expectations, selected

	log hourly wage rate		
job separation bias	-0.00156***	-0.00138***	-0.000775***
	(0.000117)	(0.000109)	(0.0000850)
predicted job separation	-0.0262***	-0.0218***	-0.00754***
	(0.000620)	(0.000656)	(0.000526)
N	212114	212114	212114
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Mincer specification: educational attainment, full time work experience
Additional controls: East/West dummy, German citizenship, gender, actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year fixed effects

Table C.3: Wages and bias in job separation expectations, spell

	log hourly wage rate		
job separation bias	-0.00178***	-0.00157***	-0.000757***
	(0.000106)	(0.0000985)	(0.0000811)
predicted job separation	-0.0238***	-0.0196***	-0.00718***
	(0.000533)	(0.000491)	(0.000396)
N	212114	212114	212114
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Mincer specification: educational attainment, full time work experience
Additional controls: East/West dummy, German citizenship, gender, actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year fixed effects

Table C.4: Reservation income and bias in job finding expectation, UandO

	log reservation income		
job finding bias	0.00145***	0.00165***	0.000692**
	(0.000247)	(0.000272)	(0.000311)
predicted job finding	0.00362***	0.00413***	0.00292***
	(0.000373)	(0.000431)	(0.000598)
N	71584	71584	71584
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Mincer specification: educational attainment, full time work experience
Additional controls: East/West dummy, German citizenship, gender, relationship status, kids less 16 years, unemployment experience, survey year fixed effects

Table C.5: Reservation income and bias in job finding expectation, Only

	log reservation income		
job finding bias	0.00108***	0.000914***	0.000481**
	(0.000326)	(0.000334)	(0.000223)
predicted job finding	0.00824***	0.00934***	0.00510***
	(0.000757)	(0.000796)	(0.000963)
N	52795	52795	52795
mincer spec.	No	Yes	Yes
add. controls	No	No	Yes

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Mincer specification: educational attainment, full time work experience

Additional controls: East/West dummy, German citizenship, gender, relationship status, kids less 16 years, unemployment experience, survey year fixed effects

Table C.6: Sample comparison, Germany versus US

Germany	**US**
Sample	
Age: 25 – 65 Years: 1999, 2001, 2003, 2005, 2007, 2009, 2013, 2015	Age: 25 – 65 Time: 2014/07 – 2021/03 not in school, only full-time employed, not self-employed (sample restriction due to unobserved hours worked)
Job-separation expectations	
Definition: General job-separation probability about **next 2 years**	Definition: Being in a certain labor market state **in 4 months**
Predicted job-separation	
Probit regression with control variables: age, age squared, female, married, children, East/West, born German, tenure, Tenure squared, unemployment experience, unemployment experience squared, training, new job since previous year, work satisfaction, education, industry, occupation, firmsize; for outcome in **next 2 years**	Probit regression **based in information in CPS** with control variables: education, year, age, age squared, sex, race, family income, part-time, state, children; **for outcome in next 3 and 9 months, 4 months linearly interpolated**
Wage regression	
Definition: net earnings last month divided by 4 times the actual working hours per week Regression of log hourly wage on job-separation bias, predicted job-separation, education, employment experience, East, German born, gender, actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year	Definition: gross annual earnings last month divided by 12x4x40 (no information on hours worked) Regression of log hourly wage on job-separation bias, predicted job-separation, education, age, U.S. state, race, gender, tenure, tenure squared, industry, type of employer, year

Table C.7: Expected, predicted and bias in job separation, US

	Mean	std.dev.	min	max	P10	P50	P90	Obs.
Expected	3.0692	9.6884	0	100	0	0	10	11274
Predicted	3.3483	1.9861	0.7521	18.708	1.4998	2.8240	5.8594	11274
Bias	-0.2791	9.7471	-18.708	98.721	-5.2715	-2.3141	6.2439	11274

Table C.8: Wages and bias in job separation expectations, US

	log hourly wage rate		
job separation bias	-0.00490***	-0.00494***	-0.00498***
	(0.000912)	(0.000941)	(0.000903)
predicted job separation	-0.186***	-0.139***	-0.282***
	(0.00811)	(0.00558)	(0.0106)
N	11117	11130	11117
Mincer spec.	No	Yes	Yes
Add. controls	No	No	Yes

Standard errors in parentheses (not bootstrapped).

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Mincer specification: educational attainment, age

Additional controls: US federal states (dummy), gender, race tenure, tenure squared, industry, job type, year fixed effects

Table C.9: East-West wage differentials

	log hourly wage rate		
East dummy	-0.295***	-0.231***	-0.226***
	(0.00293)	(0.00375)	(0.00378)
N	204285	65736	65736
add. controls	No	Yes	Yes
add job separation bias	No	No	Yes

Standard errors in parentheses (not bootstrapped)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls: educational degree, full time work experience, German citizenship, gender, actual hours worked, tenure industry, occupation, firm size, survey year fixed effects

Table C.10: Wages, job separation bias and East-West interaction

	log hourly wage rate general	dismissal	selected	spell
job separation bias	-0.000693***	-0.000766***	-0.000669***	-0.000686***
	(0.0000907)	(0.0000780)	(0.0000959)	(0.000108)
East dummy	-0.214***	-0.202***	-0.199***	-0.200***
	(0.00609)	(0.00716)	(0.00804)	(0.00903)
East dummy × job separation bias	-0.000585***	-0.000445**	-0.000395**	-0.000265
	(0.000178)	(0.000199)	(0.000197)	(0.000222)
N	212114	212114	212114	212114

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Controls: predicted job separation, educational attainment, full time work experience, East/West dummy, German citizenship, gender,actual hours worked, tenure, tenure squared, industry, occupation, firm size, survey year fixed effects

Table C.11: East-West reservation income differentials

	log reservation income		
East dummy	-0.126***	-0.105***	-0.100***
	(0.00837)	(0.0142)	(0.0143)
N	10728	4083	4083
add. controls	No	Yes	Yes
add find. bias	No	No	Yes

Standard errors in parentheses (not bootstrapped)

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Controls: educational degree, full time work experience, German citizenship, gender, relationship status, kids less 16 unemployment experience, survey year fixed effects

Table C.12: Wages, job finding bias and East-West interaction

	(log reservation income)		
	U only	U and O	O only
job finding bias	0.000639*	0.000790***	0.000421
	(0.000338)	(0.000227)	(0.000372)
East dummy	-0.110***	-0.0442***	0.0378
	(0.0176)	(0.0160)	(0.0249)
East dummy × job finding bias	0.000117	0.000224	0.000324
	(0.000587)	(0.000439)	(0.000691)
N	18789	71584	52795

Bootstrapped standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Controls: predicted job finding, educational attainment, full time work experience
East/West dummy, German citizenship, gender, relationship status,
kids less 16 years, unemployment experience, survey year fixed effects

D Details on the quantitative analysis

D.1 Comparative statics

Comparative statics of the equilibrium wage with respect to bias in job separation and job finding probabilities of workers

$$\frac{\partial \omega}{\partial \Delta_{\lambda w}} = \gamma \frac{[1-\beta(1-\sigma)]}{\big[1-\beta\big(1-(1+\Delta_{\sigma w})\sigma\big)\big]}\theta\kappa \ > 0 \tag{D.1}$$

$$\frac{\partial \omega}{\partial \Delta_{\sigma w}} = \gamma \frac{[1-\beta(1-\sigma)]\,(1+\Delta_{\lambda w})}{\big[1-\beta\big(1-(1+\Delta_{\sigma w})\sigma\big)\big]}\theta\kappa \cdot \frac{(-1)}{\big[1-\beta\big(1-(1+\Delta_{\sigma w})\sigma\big)\big]^2} \cdot \beta\sigma \ < 0 \tag{D.2}$$

Comparative statics of the reservation wage with respect to subjective job finding probabilities of workers:

$$\frac{\partial \underline{\omega}}{\partial \lambda_w} = \frac{-\beta\,[b\,[1-\beta(1-\sigma_w)] + \beta\lambda_w \omega]}{1-\beta(1-\lambda_w-\sigma_w)} + \frac{\beta\omega + \beta\lambda_w \frac{\partial \omega}{\partial \lambda_w}}{1-\beta(1-\lambda_w-\sigma_w)} \tag{D.3}$$

The previous expression is > 0 if

$$(\omega - \underline{\omega}) + \lambda_w \frac{\partial \omega}{\partial \lambda_w} > 0 \tag{D.4}$$

which generally holds in this model.

D.2 Model extension: Heterogeneous matches and reservation wages

We can extend the model to account for heterogeneous match productivity, which allows to model job acceptance decisions and analyzing workers' reservation wages. Doing so, we closely follow Hornstein et al. (2011). In this extension, z is now match-specific. Its value is randomly drawn from a distribution with cumulative density $H(z) : [0, \bar{z}] \rightarrow [0, 1]$ at the time when a firm and an unemployed worker first meet and remains constant throughout the duration of the match.

The values to a worker of being employed in a match with productivity z, denoted by $E(z)$, and of being unemployed, denoted by U, satisfy

$$E(z) = \omega(z) + \beta\Big\{\sigma_w U' + (1-\sigma_w)W'(z)\Big\} \tag{D.5}$$

$$U = b + \beta\left\{\lambda_w \int_0^{\bar{z}} \max\big[E'(z) - U', 0\big]dF(z) + (1-\lambda_w)U'\right\} \tag{D.6}$$

The Bellmann equations for the firm's values of a filled job $J(z)$ and of a posted vacancy V are given by

$$J(z) = z - \omega(z) + \beta\Big\{\sigma V' + (1-\sigma)J'(z)\Big\} \tag{D.7}$$

$$V = -\kappa + \beta\left\{\lambda_f \int_0^{\bar{z}} \max\Big[J'(z) - V, 0\Big]dF(z) + (1-\lambda_f)V'\right\}. \tag{D.8}$$

Generalized Nash bargaining in line with the baseline model then delivers the following reservation wage (or reservation productivity, since $\omega(z^*) = z^*$)

$$\omega(z^*) = b + \frac{\gamma}{(1-\gamma)} \frac{[1-\beta(1-\sigma)]}{[1-\beta(1-\sigma_w)]}(1+\Delta_{\lambda w})\theta\kappa. \tag{D.9}$$

The reservation wage covers the worker's loss of income in unemployment b and the firms average hiring cost weighted with the bargaining weights. The workers' bias in expectations about job separation and job finding probabilities now enters as a new term in this weight. Reservation wages unambiguously increase if workers are optimistic with respect to their job finding probability ($\Delta_{\lambda w} > 0$), and decrease if workers are pessimistic with respect to their job separation probability ($\Delta_{\sigma w} > 0$).

The resulting wage equation in this model extension is equivalent to equation 7 in the baseline model. Job creation is unaffected by bias in workers expectations. With respect to the wage, the implications of the extended model are identical to the ones from the baseline model.

D.3 Additional tables and graphs

Table D.1: Counterfactual experiments - All Germany

Model	σ	σ_w	$\Delta_{\sigma w}$	$D_{\sigma w}$	$p(\theta)$	λ_w	$\Delta_{\lambda w}$	$D_{\lambda w}$
base	0.0156	0.0250	0.6026	0.0094	0.1860	0.2059	0.1070	0.0199
no JS bias	0.0156	0.0156	0.6026	0.0000	0.1693	0.1892	0.1175	0.0199
no JF bias	0.0156	0.0250	0.6026	0.0094	0.1915	0.1915	0.0000	0.0000
no bias	0.0156	0.0156	0.6026	0.0000	0.1750	0.1750	0.0000	0.0000
	θ	u	v	ω	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\underline{\omega})]}{\Delta[D_{\lambda w}]}$
base	1.0000	0.0774	0.0774	0.9515				
no JS bias	0.7649	0.0844	0.0645	0.9593	0.0070	0.0081	-0.0086	
no JF bias	1.0862	0.0753	0.0818	0.9488	-0.0020	-0.0028		0.0030
no bias	0.8401	0.0818	0.0688	0.9567	0.0045	0.0054	-0.0058	-0.0057

Notes: Values in steady state. Counterfactual experiments not recalibrated. $D_{\sigma w} = \sigma_w - \sigma$ and $D_{\lambda w} = \lambda_w - p(\theta)$.

Table D.2: Counterfactual experiments - small change in bias

	$\Delta[u]$	$\Delta[ln(\omega)]$	$\Delta[ln(\underline{\omega})]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\underline{\omega})]}{\Delta[D_{\lambda w}]}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
	All Germany					
+1pp JS bias	-0.0050	-0.0074	-0.0156	-0.0074		-0.0052
+1pp JF bias	0.0010	0.0013	0.0028		0.0028	0.0009
+1 pp all bias	-0.0042	-0.0060	-0.0127	-0.0060	-0.0127	-0.0042
	East Germany					
+1pp JS bias	-0.0040	-0.0069	-0.0149	-0.0069		-0.0051
+1pp JF bias	0.0011	0.0018	0.0038		0.0038	0.0013
+1 pp all bias	-0.0030	-0.0051	-0.0110	-0.0051	-0.0110	-0.0038

Notes: All Germany and East Germany calibrated to respective sample, see Table 4. Values in steady state. Counterfactual experiments not recalibrated.

Table D.3: Expected lifetime income - All Germany

Model	$\mathcal{I}_W$	$\Delta[ln(\mathcal{I}_W)]$	$\mathcal{I}_U$	$\Delta[ln(\mathcal{I}_U)]$	$\mathbb{E}\mathcal{I}_{W,U}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	88.71	0.0000	91.11	0.0000	92.57	0.0000
no JS bias	88.93	0.0025	91.43	0.0036	93.05	0.0052
no JF bias	88.61	-0.0011	90.97	-0.0015	92.39	-0.0019
no bias	88.87	0.0018	91.34	0.0025	92.90	0.0035

Table D.4: Counterfactual experiments - East Germany

Model	σ	σ_w	$\Delta_{\sigma w}$	$D_{\sigma w}$	$p(\theta)$	λ_w	$\Delta_{\lambda w}$	$D_{\lambda w}$
base	0.0174	0.0360	1.0690	0.0186	0.1850	0.1894	0.0238	0.0044
no JS bias	0.0174	0.0174	0.0000	0.0000	0.1602	0.1646	0.0275	0.0044
no JF bias	0.0174	0.0360	1.0690	0.0186	0.1862	0.1862	0.0000	0.0000
no bias	0.0174	0.0174	0.0000	0.0000	0.1614	0.1614	0.0000	0.0000
	θ	u	v	ω	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\underline{\omega})]}{\Delta[D_{\lambda w}]}$
base	1.0000	0.0860	0.0860	0.9359				
no JS bias	0.6624	0.0980	0.0649	0.9509	0.0120	0.0160	-0.0086	
no JF bias	1.0180	0.0855	0.0870	0.9351	-0.0005	-0.0008		0.0039
no bias	0.6773	0.0973	0.0659	0.9502	0.0113	0.0152	-0.0082	-0.0736

Model	σ	σ_w	$\Delta_{\sigma w}$	$D_{\sigma w}$	$p(\theta)$	λ_w	$\Delta_{\lambda w}$	$D_{\lambda w}$
base	0.0174	0.0360	1.0690	0.0186	0.1850	0.1894	0.0238	0.0044
JS bias west	0.0174	0.0243	0.3966	0.0069	0.1707	0.1751	0.0258	0.0044
JF bias west	0.0174	0.0360	1.0690	0.0186	0.1781	0.2102	0.1803	0.0321
all bias west	0.0174	0.0243	0.3966	0.0069	0.1635	0.1956	0.1963	0.0321
	θ	u	v	ω	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\underline{\omega})]}{\Delta[D_{\lambda w}]}$
base	1.0000	0.0860	0.0860	0.9359				
JS bias west	0.7950	0.0925	0.0735	0.9448	0.0065	0.0094	-0.0081	
JF bias west	0.8964	0.0890	0.0798	0.9403	0.0031	0.0047		0.0036
all bias west	0.7024	0.0962	0.0676	0.9490	0.0102	0.0140	-0.0119	0.0107

Notes: Values in steady state. Counterfactual experiments not recalibrated. $D_{\sigma w} = \sigma_w - \sigma$ and $D_{\lambda w} = \lambda_w - p(\theta)$.

Table D.5: Expected lifetime income - East Germany

Model	$\mathcal{I}_W$	$\Delta[ln(\mathcal{I}_W)]$	$\mathcal{I}_U$	$\Delta[ln(\mathcal{I}_U)]$	$\mathbb{E}\mathcal{I}_{W,U}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	86.63	0.0000	89.35	0.0000	90.77	0.0000
no JS bias	87.19	0.0064	90.07	0.0081	91.74	0.0106
no JF bias	86.59	-0.0004	89.31	-0.0005	90.72	-0.0006
no bias	87.17	0.0062	90.05	0.0078	91.70	0.0101
Model	$\mathcal{I}_W$	$\Delta[ln(\mathcal{I}_W)]$	$\mathcal{I}_U$	$\Delta[ln(\mathcal{I}_U)]$	$\mathbb{E}\mathcal{I}_{W,U}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	86.63	0.0000	89.35	0.0000	90.77	0.0000
JS bias west	87.00	0.0042	89.81	0.0051	91.36	0.0065
JF bias west	86.82	0.0022	89.59	0.0027	91.07	0.0033
all bias west	87.13	0.0058	90.00	0.0072	91.63	0.0094

Table D.6: Counterfactual experiments - varying γ

$\gamma = 0.300$	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0774	0.0774	0.8937	0.0000	0.0000
no JS bias	0.7858	0.0836	0.0657	0.9091	0.0171	0.0139
no JF bias	1.0762	0.0756	0.0813	0.8885	-0.0058	-0.0049
no bias	0.8551	0.0814	0.0696	0.9040	0.0114	0.0094
$\gamma = 0.500$	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0774	0.0774	0.9515	0.0000	0.0000
no JS bias	0.7649	0.0844	0.0645	0.9593	0.0081	0.0052
no JF bias	1.0862	0.0753	0.0818	0.9488	-0.0028	-0.0019
no bias	0.8401	0.0818	0.0688	0.9567	0.0054	0.0035
$\gamma = 0.770$	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0774	0.0774	0.9850	0.0000	0.0000
no JS bias	0.7520	0.0848	0.0638	0.9875	0.0026	-0.0003
no JF bias	1.0925	0.0752	0.0822	0.9841	-0.0009	-0.0001
no bias	0.8309	0.0821	0.0682	0.9867	0.0017	-0.0001
$\gamma = 0.500$	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0860	0.0860	0.9359	0.0000	0.0000
JS bias west	0.7950	0.0925	0.0735	0.9448	0.0094	0.0065
JF bias west	0.8964	0.0890	0.0798	0.9403	0.0047	0.0033
all bias west	0.7024	0.0962	0.0676	0.9490	0.0140	0.0094
$\gamma = 0.300$	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0860	0.0860	0.8622	0.0000	0.0000
JS bias west	0.8187	0.0916	0.0750	0.8790	0.0193	0.0161
JF bias west	0.9100	0.0886	0.0806	0.8704	0.0095	0.0080
all bias west	0.7346	0.0948	0.0697	0.8872	0.0286	0.0236

Table D.7: Model calibration - biannual frequency

Parameter	Description	Value		Source/Target
		All	East	
β	discount factor	0.9200		annual interest rate (4%)
b	unemployment income	0.5822	0.5686	replacement rate (65%)
κ	vacancy costs	0.2313	0.2626	normalization ($\theta = 1$)
χ	matching fnct efficiency	0.4880	0.4997	JF rate (GSOEP)
η	matching fnct elasticity	0.6500		literature
γ	workers' bargaining power	0.5000		literature
σ	separation rate	0.1333	0.1514	JS rate (GSOEP)
$D_{\sigma w}$	job separation bias	0.0644	0.1207	own estimate
$D_{\lambda w}$	job finding bias	0.0822	0.0188	own estimate

Notes: JF rate refers to out of unemployment only, JS rate refers to general measure.

Table D.8: Counterfactual experiments - biannual frequency

All	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.2146	0.2146	0.8956		
no JS bias	0.8460	0.2246	0.1900	0.9064	0.0119	0.0063
no JF bias	1.0965	0.2092	0.2293	0.8892	-0.0072	-0.0041
no bias	0.9398	0.2182	0.2051	0.8997	0.0046	0.0025
East	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.2325	0.2325	0.8747		
JS bias west	0.8815	0.2405	0.2120	0.8846	0.0112	0.0063
JF bias west	0.8964	0.2394	0.2146	0.8833	0.0098	0.0055
all bias west	0.7788	0.2485	0.1935	0.8935	0.0213	0.0114

Table D.9: Counterfactual experiments - higher East German separation rate

East	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.1274	0.1274	0.9263		
no JS bias	0.7351	0.1398	0.1028	0.9397	0.0143	0.0084
no JF bias	1.0171	0.1267	0.1289	0.9255	-0.0009	-0.0006
no bias	0.7503	0.1390	0.1043	0.9389	0.0135	0.0079
East	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.1274	0.1274	0.9263		
JS bias west	0.8389	0.1344	0.1127	0.9343	0.0085	0.0052
JF bias west	0.9011	0.1315	0.1185	0.9311	0.0052	0.0032
all bias west	0.7472	0.1391	0.1040	0.9390	0.0136	0.0080

Table D.10: Model calibration - job separation dismissal

Parameter	Description	Value All	East	Source/Target
β	discount factor	0.9900		annual interest rate (4%)
b	unemployment income	0.6158	0.6060	replacement rate (65%)
κ	vacancy costs	0.6405	0.7546	normalization ($\theta = 1$)
χ	matching fnct efficiency	0.1860	0.1850	JF rate (GSOEP)
η	matching fnct elasticity	0.6500		literature
γ	workers' bargaining power	0.5000		literature
σ	separation rate	0.0052	0.0065	JS rate (GSOEP)
$D_{\sigma w}$	job separation bias	0.0236	0.0330	own estimate
$D_{\lambda w}$	job finding bias	0.0199	0.0044	own estimate

Notes: JF rate refers to out of unemployment only, JS rate refers to dismissals.

Table D.11: Counterfactual experiments - job separation dismissal

All	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0272	0.0272	0.9473		
no JS bias	0.4406	0.0359	0.0158	0.9691	0.0227	0.0191
no JF bias	1.0844	0.0265	0.0287	0.9445	-0.0030	-0.0027
no bias	0.4957	0.0345	0.0171	0.9666	0.0202	0.0171
East	θ	u	v	ω	$\Delta[ln(\omega)]$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
base	1.0000	0.0339	0.0339	0.9323		
JS bias west	0.8097	0.0365	0.0295	0.9410	0.0093	0.0082
JF bias west	0.8981	0.0352	0.0316	0.9368	0.0049	0.0043
all bias west	0.7175	0.0380	0.0272	0.9454	0.0140	0.0122