Biased expectations and labor market outcomes: Evidence from German survey data and implications for the East-West wage gap

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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 difference in biases in labor market expectations explains part of the East-West German wage gap.

Keywords: Labor market risk, biased beliefs, wages, reservation wages
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1 Introduction

Economic agents form expectations about various outcomes in the labor market, such as the risk to lose their 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 finding or separating from a job, this will likely affect their wage through a change in the reservation wage or the evaluation of the outside option in wage bargaining. As a consequence, if optimism or pessimism differ between groups in the population, biases in expectations presumably affect wage differentials.

In this paper, we measure bias with respect to the chance of finding a job and the risk of separating from a job in long panel data for Germany. We show that biases matter for economic outcomes, providing empirical evidence that these biases are important to understand wages and reservation wages. We combine the evidence with a quantitative model to assess the role of the biases for wages and unemployment in labor market equilibrium. As biases remarkably differ between East and West Germany, we show that they substantially contribute to 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 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 job separation, 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). 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. Biases remain significantly different if we take into account compositional differences between East and West Germany. While we observe some updating of biases (learning), biases do not vanish over time.

We then link workers' expectation biases 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 and individual fixed effects. 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 subsequently 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. In this framework, workers' expectations affect the future valuation of the job match and saved hiring costs. If workers are pessimistic with respect to job separation, 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 optimistic with respect to job finding, they overestimate saved hiring costs, and their reservation wages and realized wages increase. Low bargaining power on the side of the workers intensifies these effects.

We use the model to quantify how biased expectations affect the labor market equilibrium, i.e., the trade-off between wages and unemployment. Our model allows us to compare changes in expected lifetime income in counterfactual experiments where expectation biases are removed. While the effects are not strikingly large on average, they mask substantial heterogeneity across subgroups of the population. 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. Taking both the beneficial wage gain and the adverse unemployment increase into account, (unbiased) expected lifetime income in the East would increase by about 0.94 percent. 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 lower 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 (e.g. Bovi, 2009, or Souleles, 2004) and relates these expectations to individual choices such as savings decisions (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 (2023) contains a great overview of the literature on individual bias in labor market expectations. Early empirical studies document individual perceived labor market risk, but not biased beliefs (e.g. Dominitz and Manski, 1997, or Dixon et al., 2013). Dickerson and Green (2012) document qualitative bias in beliefs of labor market risk based on earlier waves in the GSOEP. Stephens (2004) and Hendren (2017) document pessimistic bias in job separation beliefs. 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). Our findings are consistent with the specific separate 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. The literature on bias in job finding mostly investigates the relationship to job search behavior (see Mueller and Spinnewijn, 2023). Mueller et al. (2021) explore how this bias affects employment and unemployment outcomes. We add to this literature by directly linking the bias in job separation expectations to actual wages and the bias in job finding expectations to reservation income. Our direct evidence on biased beliefs in job finding risk and reservation wages is in line with the previously mentioned findings. A recent related contribution by Jäger et al. (2022) investigates bias in beliefs about outside wage options. Similarly, Drahs et al. (2018) show that job seekers overestimate their future re-employment wage. These studies hence address bias in beliefs about wages, not about the underlying risk in beliefs and the link to realized wages.

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. By examining differences between East and West Germany, our study therefore also links to the literature addressing other reasons behind the East-German wage gap, e.g., Fuchs-Schündeln and Izem (2012), and the literature on recent gaps in East-German convergence more generally (see, e.g., Bachmann et al., 2022).

Conlon et al. (2018) show that a model with the corresponding informational frictions fits observed reservations wages better than without. Menzio (2022) investigates the role of stubborn beliefs about productivity and addresses the consequences about wage outcomes over the business cycle. Our model relates to Menzio (2022) but addresses different beliefs, closely links to the empirical evidence, and quantifies the effect of the biases in counterfactual exercises, in particular with respect to wage differentials.

Two own complementary studies address related questions. In Balleer et al. (2021) we document differences in bias in labor market expectations across educational groups in the US and relate these to savings decisions and wealth differentials. In Balleer et al. (2023) we consider the theoretical foundations of bias in wage bargaining in more detail. In the present paper, we use the model to interpret the empirical findings and quantify the effect on wages, lifetime income and wage differentials, in particular, regarding differences between East and West Germany.

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 biases to wages and reservation income in the data, and Section 5 relates the biases 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. In each year (or wave), around 15,000 households and 30,000 persons participate in the GSOEP survey. The GSOEP is unique in regularly including questions on individual labor market expectations, both referring to job separation and job finding, since more than 30 years. Moreover, in 1999, the answer options to the expectations questions were changed from verbal to numeric format. At the same time, the SOEP provides rich demographic information as well as information about income, hours worked and employment status. 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 (i.e. between 25 and 65 years of age).

2.1 Expectations about labor market transitions

The individual questionnaires of the GSOEP bi-annually include several questions about individual labor market expectations. Since 1999, 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 new job at their own initiative, losing their job, or receiving a promotion at the current employer. Answers are given on a scale from 0 to 100 percent (in steps of 10 percentage points). 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] Even though the question is clearly stated about job loss, i.e., an involuntary end to a job, it might be interpreted by respondents as referring to flows from employment to unemployment (or non-employment) more generally, i.e., for different reasons. This is likely, as the alternative answers to the question describe flows from employment to employment or remaining with the same employer. We therefore refer to answers as expectations in job separations and address this issue in our measure of actual job separation below.

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

[2] Figure A.1 in the appendix shows the original question on expected career changes, including job separation.

Similarly, since 1999, respondents who are not working (i.e. unemployed or out of the labor force) 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, where, again, answers are given on a scale from 0 to 100 percent (in steps of 10 percentage points). 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.[4] The questions were excluded in 2011. After 2015, the questions were included again in 2018 and 2021. Since we need to follow respondents for two years after the interview to measure actual labor market transitions, we cannot include the 2021 wave, as the respective follow-up data are not available yet. We also exclude the 2018 wave, since the follow-up period includes the onset of the Covid-pandemic in 2020, which we consider a very particular type of worldwide disruption over and above an economic downturn (such as the 2009 financial crisis, which is included in our sample period). 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.

[3] Figure A.2 in the appendix shows the original question on expected occupational changes, including job finding.

[4] The verbal answer options applied between 1985 and 1998 were "Definitely", "Probable", "Improbable", and "Definitely Not".

2.2 Actual 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 "Have you left a job since December 31, xx?", where xx refers to the calendar year two years before the survey year (SOEP Group, 2017). If the answer is positive, they are asked "When did you leave your last job?" and state the month in which the job ended and, moreover, the reason for the job end. Table A.1 in the appendix lists all possible answers regarding the reasons for a job end.[5] We use different combinations of reasons to identify actual job separations.

For our most narrow definition of actual job separation, we combine the reasons "Place of work closed" and "Dismissed by employer". These two reasons are probably most closely related to the measure of job separation expectations, if the underlying question is taken literally and refers to involuntary job loss only. For brevity of notation, we will refer to job separations due to closure or dismissal jointly under the label of *dismissals*.

For a slightly broader definition of actual job separation, we add the two reasons 'Mutual agreement" and "Temporary employment ended" to the two reasons from before. Although neither involuntary nor unexpected job loss, they may very well be included in individuals' assessment of subjective job separation expectations as discussed above. Also, employees expecting job loss might preemptively search for a new job or are uncertain about the possibility to renew the contract. We will refer to job separations due to any of these four reasons under the label of *selected* reasons.

Finally, we include all eight possible reasons in our most general definition of actual job separations and refer to them under the label of *general* separations. The existing macroeconomic literature on labor market flows 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 use this general definition of job separation as our baseline and explore robustness with respect to the more narrow definitions.

We can also identify labor market spells from respondents' activity calendars, that is, data on persons' activities in spell format based on individual questionnaires and released in an additional GSOEP data file.[6] The data contains monthly information on the beginning and ending of individuals' activities such as being employed full-time or part-time, being

[5] The eight answer options listed in Table A.1 in the appendix were continuously included throughout our sample period. We exclude additional answer options that were added in single waves.

[6] The "ARTKALEN" data file 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". See Schmelzer et al. (2020)

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 of spell types recorded). 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.[7] 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, for each individual, assign to each month the highest ranking labor market state across all of the individual's spells that cover this month. Based on these monthly spell data, we can identify individual transitions between the three labor market states across months. This provides us with an additional definition of actual job separation, namely, at least one transition from employment to unemployment within 24 months after the interview. We will refer to the corresponding measure under the label of *spell* measure of job separations.

The spell data also provide the source for identifying and measuring actual job finding.[8] Our definition of actual job finding comprises 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 will use job finding of unemployed respondents only (referred to as *job finding out of* U), and explore robustness to measuring job finding of respondents out of the labor force only (*job finding out of* O), or of respondents who are unemployed or out of the labor force grouped together (*job finding out of* U *or* O).

For each of the definitions of job separation and of job finding events, we construct indicator variables for each individual which are equal to one if the respective event took place within two years after the interview, and equal to zero otherwise. Table A.3 in the appendix documents average job separation and job finding rates within two years after the interview, based on the different definitions and indicators. The average probability to separate from a job for general reasons over the period of two years is about 13 percent, and decreases to about 6 and 4 percent for narrower sets of 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 rates to a quarterly frequency 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).[9] We can also

[7] Only registered unemployed receive benefits. When receiving benefits, persons need to actively search for new employment.

[8] 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.

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

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 might be due to productive workers leaving unemployment quickly and the pool of unemployed workers thus 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 data sets 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).[10]

3 Bias in labor market expectations

3.1 Measuring bias

In order to measure expectation bias, we need to compare an individual's expected probability of experiencing a certain labor market transition with a statistical counterpart. The simplest estimators for statistical transition probabilities are the sample means of the actual job separation and job finding indicators described in Section 2.2. These, however, do not take into account the well documented and substantive heterogeneity in transition probabilities across population groups (see, e.g., Hall and Schulhofer-Wohl, 2018, among many others). To control for this heterogeneity, we estimate probit models of individuals' job separation and job finding probabilities, using the indicators for actual labor market transitions from 2.2. The probit models allow to predict individual probabilities within narrowly defined groups based on various individual characteristics and labor market outcomes.

We estimate probit models of job separation probabilities for individuals employed at the time of the interview, and of job finding probabilities for those unemployed or out of the labor force at the time of the interview. In the models, we include a large number of individual and job characteristics as well as survey year indicators. In the case of job separation, we also add employer characteristics. Our choice of model specification for each of the measures of job separation and job finding aims at maximizing the predictive power of the models according to a range of information criteria (McFadden's pseudo-R^2, McKelvey and Zavoina's R^2, AIC). Tables A.5 to A.8 in the appendix provide summary statistics for the covariates that remain in the probit models due to predictive power.[11,12]

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

[11] Covariates in job separation probit models: age, gender, relationship status, children under 16 in household, East Germany, born in Germany, education group, unemployment experience, tenure in firm, working in occupation trained for, new job since last year, work satisfaction, industry, firm size.

[12] Covariates in job finding probit models: age, gender, relationship status, East Germany, born in Germany,

Regression results of the job separation probit estimations are reported in Table B.1, and those of the job finding probit estimations in Table B.2 in the appendix.[13]

Based on the probit estimation, we obtain individual predicted probabilities of job separation or job finding. Since expected probabilities in the data are measured on a discrete scale, we also round the predicted probabilities to the nearest decile on the probability scale (0%, 10%, 20%, ...).[14] 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

Table 1 presents summary statistics for expected and predicted job separation and job finding probabilities and the resulting expectation bias. The results here refer to the general measure of job separation and to job finding out of unemployment. Results for the other job separation and job finding measures are documented in the appendix.

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%.[15] Between the first and the ninth decile, the resulting bias ranges between −20 and +40 percentage points, showing that optimists and pessimists coexist in the sample. On average, however, employed workers are pessimistic regarding job separation, as they overestimate the risk of separation from their job within two years by about 6 percentage points (i.e., 46 percent; the difference is significantly different from zero). The average bias is positive and significantly different from zero also for all our other job separation measures (see Table B.3 in the appendix). For the narrowest measure (dismissal), the bias increases to as much as 17 percentage points. Histograms of expected and predicted job separation probabilities and the resulting biases for all measures are shown in Figures B.1 to B.4 in the appendix.

Regarding job finding out of unemployment, 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.[16] Hence, unemployed workers are, on average, optimistic regarding job finding, as they overestimate the chance of finding a job in this time interval by about 8 percentage points (i.e., 16 percent, the difference is significantly different from zero). Similar to job separation, predicted job finding probabilities range between 0% and 90%, while expected probabilities range between 0% and 100%. Again, the range of the resulting bias

German citizenship, education group, health status, unemployment experience, work experience (full/part time).

[13] Note that while covariates affect the probability of job separation and finding similarly for different measures in general, there are some differences with respect to significance. The sign differs for some covariates determining different reasons for job separation. Females, e.g., more often take a leave of absence and, hence, separate from jobs more often for general reasons, but not in dismissals.

[14] We discuss the robustness of results to rounding up to the next decile (conservative measure) below.

[15] Note that the predicted job separation probability is near identical to the sample mean of actual transitions which is reported in Table A.3.

[16] 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 unemployment. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero.

shows that there are both optimistic and pessimistic unemployed workers in the sample. The average bias is positive and significantly different from zero also for our two other job finding measures (see Table B.7 in the appendix). When measuring job finding from out of the labor force alone, or from unemployment and out of the labor force together, the optimistic bias increases to about 11 percentage points. Histograms of expected and predicted job finding probabilities and the resulting biases for all measures are shown in Figures B.5 to B.7 in the appendix.

The bias in job separation is robust to and very close in size when considering full time employed persons on permanent contracts only (see Table B.4 in the appendix). The separation bias persists, but becomes smaller when extreme expectations are taken out, i.e., if we take out expectations below the 5th and above the 95th percentile (see Table B.5). The bias is also smaller, but significantly different from zero when predicted job separation is rounded up to the next 10th percentile of the probability in all cases (see Table B.6). For job finding, the bias increases when extreme expectations are taken out (see Table B.8). The bias falls, but remains significantly positive when predicted job finding is rounded up in all cases (see Table B.9).

3.3 Bias 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.[17] 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. Tables B.12 and B.15 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. While predicted levels already take into account these covariates, this regression visualizes significant differences in bias across various subgroups holding composition constant. 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.[18]

[17] Tables B.10 and B.11 show summary statistics for all subgroups.

[18] Different to our result, Emmler and Fitzenberger (2022) document overpessimism with respect to job

Tables B.13 and B.14 as well as Tables B.16 and B.17 explore these differences in bias between East and West Germany further by interacting the East Germany indicator with age and birth cohorts, respectively. The East Germans do not exhibit a larger bias in job separation risk when older. The bias in job finding risk decreases somewhat with age. However, there are substantial differences across cohorts. Relative to the oldest cohorts born before 1950, pessimistic bias first increases and then decreases for later born cohorts. The bias is substantially larger for cohorts born in the 1950's and 1960's which have actively experienced life in the communist German Democratic Republic as well as the reunification with West Germany. The optimistic bias in job finding risk which is lower in East Germany does not change for the cohorts born in the 1950's and 1960's relative to the oldest ones, but significantly increases for later born cohorts.

Tables B.12 and B.15 in the appendix also document differences in biases between other subgroups and characteristics, holding composition 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 to be small for persons who do not 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 (see Table B.10). It is also low for persons that have high job security such as persons with high tenure, or persons in secure jobs such as civil servants or employees in the public administration generally. The pessimistic bias is high for persons that state that they are very concerned about their job insecurity. Persons with higher predicted job separation risk have a smaller job separation bias (are less pessimistic) on average. 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.

Subgroup comparisons also inform us about learning, i.e., whether individual biases reduces 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.10). Hence, expected job separation risk decreases by more, thus 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

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.

small, i.e., bias correction is slow (compare Table B.15).

We know whether employed persons have been previously unemployed, and whether unemployed persons have been previously employed and for how long. The pessimistic bias in job separation increases with unemployment experience, hence persons who have experienced transitions from unemployment to employment and who have longer previous unemployment experience are more pessimistic with respect to their employment prospects (see Table B.10). The pessimistic bias decreases with tenure in the firm, but not with work experience. The optimistic bias in job finding decreases with unemployment experience, hence persons with more information about unemployment have more precise expectations (see Table B.11). Previous work experience does not significantly affect the optimistic bias. Hence, persons who have transitioned from employment to unemployment and who have worked longer are no more or less optimistic on average. Overall, our findings suggest that labor market experience with respect to unemployment matters, but not with respect to employment. This suggests bias correction over time with respect to job finding, which, again, is slow as coefficients are relatively small compared to the level of the bias. Section 3.4 further addresses bias in labor market expectations over time.

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. 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. This is in line with the evidence for the U.S. documented in Balleer et al. (2021).

3.4 Bias over time

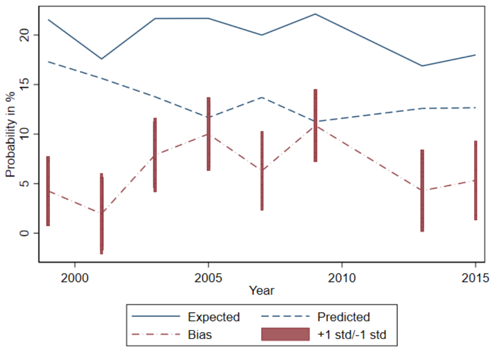
Figures 1a and 1b plot the average expected and predicted job separation and job finding rates together with the corresponding biases for the two baseline measures across time. The vertical bars show standard errors around the bias measures.[19] Regarding predicted probabilities, the graphs exhibit a 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.[20] 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.

Figure B.10 in the appendix plots Figure 1 separately for East and West Germany. West Germany clearly reflects the overall pattern described above. In East Germany, expected

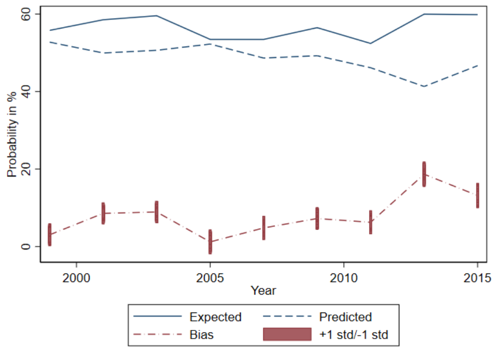
[19] Figures B.8 and B.9 in the appendix document the corresponding graphs for all job separation and job finding measures.
[20] See e.g. Hochmuth et al. (2021) or Hartung et al. (2018).

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

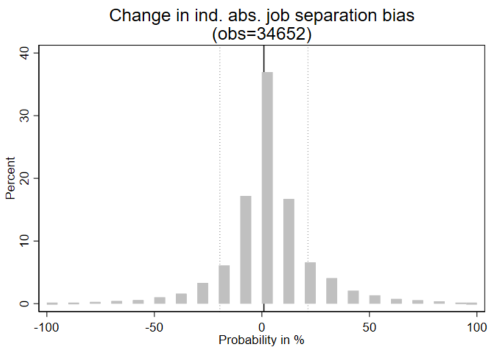
(a) Job separation bias, general



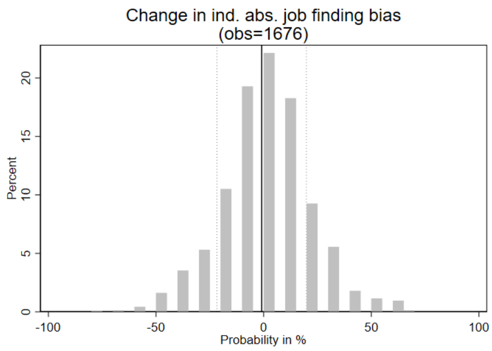
(b) Job finding bias, out of U



(c) Change in job separation bias, general



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



job separation risk falls over time. Since predicted job separation also falls, the bias decreases mildly in our sample. While this is consistent with the findings in Emmler and Fitzenberger (2022), however, in our measure a significant bias remains even towards the end of the sample period. As the Western bias increases, the gap in separation bias between East and West does not close substantially. The bias in job finding risk moves around zero in the East for most of our sample and increases only above zero towards the end.

Bias in expectations might be affected by business cycle conditions. Our sample covers a short, relatively mild recession in 2001 and the Great Recession in 2008 and 2009. We regress bias in job separation and job finding on dummies for these recession dates net of covariates and find negative effects (which are significant for some of our measures of job finding and separation, see Table B.18). Bias in job separation and finding risk is, hence, countercyclical and decreases in recessions. This is in line with the discussion and evidence in Mueller and Spinnewijn (2023).

As the biases in job separation and job finding expectations do not fall over time, learning does not seem to play a substantial role in our data on average. 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 the difference in the absolute values of their job separation or job finding bias between two surveys, i.e., two years apart.

Figures 1c and 1d plot the histograms of this difference for the two baseline measures.[21] Positive values indicate that the bias has increased since the last survey, negative values indicate that the bias has decreased. Means are depicted by vertical solid lines, dotted lines show the standard deviation. The histograms exhibit substantial dispersion, i.e. the bias decreases for some persons and increases for others. The average change 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, the respective median measures are zero and standard errors are large (see Table B.19 in the appendix for details on summary statistics). Hence, on average, individuals do not revise their bias much. There is no substantial difference in revisions to bias at the individual level between East and West Germany (see Figure B.13 in the appendix).

4 Relating bias to wages

4.1 Hourly wages and reservation income in the GSOEP

If workers have biased expectations about job finding, this might affect at which conditions they accept a new job when unemployed. In particular, an optimistic bias in job finding expectations could increase the reservation wage at which an unemployed accepts a job. If workers have biased expectations about job separation, this might affect their position in the wage bargain. Pessimistic workers expect their job separation risk to be too large, which should affect the value of their current job which, in turn, is a key input in many models of wage determination. Section 5 provides a theoretical interpretation of the relationship between bias in job separation and job finding risk and (reservation) wages.

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).

[21] Figures B.11 and B.12 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 relation with 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, successively adding education and labor market experience in levels and squared (a basic Mincer regression) as well as further controls and individual fixed effects in the different specifications. Standard errors are bootstrapped.[22] All specifications show that a higher predicted job separation probability 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. The effect of bias on the wage remains significant when individual fixed effects are included. 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***	-0.000379***
	(0.000119)	(0.0000933)	(0.0000775)	(0.0000699)
predicted job separation	-0.0164***	-0.0146***	-0.00487***	-0.00359***
	(0.000400)	(0.000410)	(0.000345)	(0.000314)
N	212114	212114	212114	212114
mincer spec.	No	Yes	Yes	Yes
add. controls	No	No	Yes	Yes
indiv. FE	No	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 3 documents the output from regressing the log reservation income on our baseline measure of job finding bias and predicted job finding, again adding education and labor market experience (a basic Mincer regression), further controls and individual fixed effects in the different specifications. 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

[22] 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.

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.

We confirm the significantly negative relationship between job separation bias and hourly wages in a subsample of fulltime employed with permanent contracts only as well as in a subsample that excludes the most extreme job separation expectations. We also confirm the significantly positive relationship between job finding bias and reservation income in the subsample excluding the most extreme job finding expectations (Section 3 also uses these subsamples, Tables C.8 to Table C.10 in the appendix show the results). Moreover, 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 U.S. 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 U.S. 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 (see Table C.11).

Table 3: Reservation income and bias in job finding expectation

	log reservation income			
job finding bias	0.00145***	0.00165***	0.000692**	0.0000625
	(0.000312)	(0.000316)	(0.000304)	(0.000306)
predicted job finding	0.00362***	0.00413***	0.00292***	0.000506
	(0.000460)	(0.000509)	(0.000593)	(0.00141)
N	18789	18789	18789	18789
mincer spec.	No	Yes	Yes	Yes
add. controls	No	No	Yes	Yes
indiv. FE	No	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

Next, we investigate how bias in job separation and job finding relates to 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.12 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. Table 4 shows the results. 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.

Table 4: Wage and job separation bias: East versus West

	log hourly wage rate			
	general	dismissal	selected	spell
Bias	-0.000693***	-0.000766***	-0.000669***	-0.000686***
	(0.0000907)	(0.0000780)	(0.0000959)	(0.000108)
East	-0.214***	-0.202***	-0.199***	-0.200***
	(0.00609)	(0.00716)	(0.00804)	(0.00903)
East × 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

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.[23]

We can also consider the gap in reservation incomes between East and West Germany

[23] For the counterfactual East German wages, we assign the difference in bias from Table B.12 (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 4 (column 1). The counterfactual wage gap is computed as the log difference between West and the counterfactual East German wages.

which is about 13% overall and 10% net of controls (as documented in Table C.13 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 5). 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.[24]

Table 5: Reservation income and job finding bias: East versus West

	log reservation income		
	out of U	out of U or O	out of O
Bias	0.000639*	0.000790***	0.000421
	(0.000338)	(0.000227)	(0.000372)
East	-0.110***	-0.0442***	0.0378
	(0.0176)	(0.0160)	(0.0249)
East × 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

5 A search-and-matching model with biased expectations

In this section, we present a model that is in line with both the negative relation between pessimistic job separation expectations and wages and 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 and its quantitative analysis 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, how job separation bias affects reservation wages, and how job finding bias affects 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 expectations, or both, on the labor market equilibrium and on the

[24] For the counterfactual East German reservation incomes, we assign the difference in bias from Table B.15 (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 5 (column 1). The counterfactual reservation income gap is computed as the log difference between West and the counterfactual East German reservation incomes.

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.

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.[25] 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 the central 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).

In general, both firms and workers in our framework may have biased beliefs. In the present setting, however, we abstract from firm bias, since we cannot measure firm expectations about labor market outcomes in our data.[26] We also abstract from learning, since the empirical evidence in Section 2 provides no clear evidence in support of a substantial reduction in bias over time. We further do not address aggregate fluctuations in this paper.

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.[27] 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

[25] 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. Details about the bargaining protocol and the assumptions we make are discussed in Section 5.1.

[26] 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.

[27] 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 $M(u, v) \leq \min[u, v]$.

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 actual probability. When $\Delta_{\sigma w} > 0$, workers have a pessimistic job separation bias, expecting to separate from a match with a higher than 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.

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' 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 each party's expected values are common knowledge, and that the parties agree to disagree (i.e. they neither try to convince the other, nor take advantage of discrepancies in expectations).[28] 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 examine the model's properties under different bargaining frequencies, ranging from firms and workers negotiating the wage every period to them 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.

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.[29] 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.[30] However, the term capturing saved hiring costs deviates from the standard

[28] Although workers do not form rational expectations, there is no private information in our model. Under these conditions, the alternating-offer bargaining protocol of Binmore et al. (1986) yields the same solution as Nash bargaining, thus offering a micro foundation of the bargaining procedure also in our setting (see Balleer et al., 2023, for details).

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

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

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 curve (7) by interacting with saved hiring costs. Starting from a situation without expectation bias and keeping everything else constant, the partial equilibrium effects of the biases on wages are the following:[31] If workers are pessimistic regarding job separation ($\Delta_{\sigma w} > 0$), wages decrease. In this case, workers discount the future value of the match, including future saved hiring costs, more strongly, thus wages need to compensate less for these costs. If workers are optimistic with respect to job finding ($\Delta_{\lambda w} > 0$), wages increase. In this case, workers perceive the outside option of the match as higher than the firm, thereby overestimating the hiring costs that are saved by forming a match, and need to be compensated accordingly through higher wages.

Everything else constant, a higher bargaining power of workers γ or higher vacancy costs κ increase the wage, thereby intensifying the partial equilibrium response of wages to a change in either type of expectation bias.[32] 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 partial equilibrium 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

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

Keeping everything else constant, the effect of workers' job finding bias on the reservation wage is unambiguously positive (see Appendix D.1 for the comparative statics), 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.[33]

Imposing free entry leads to the job creation condition,

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

[31] See Appendix D.1 for the corresponding comparative statics.
[32] See comparative statics in Appendix D.1.
[33] 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.

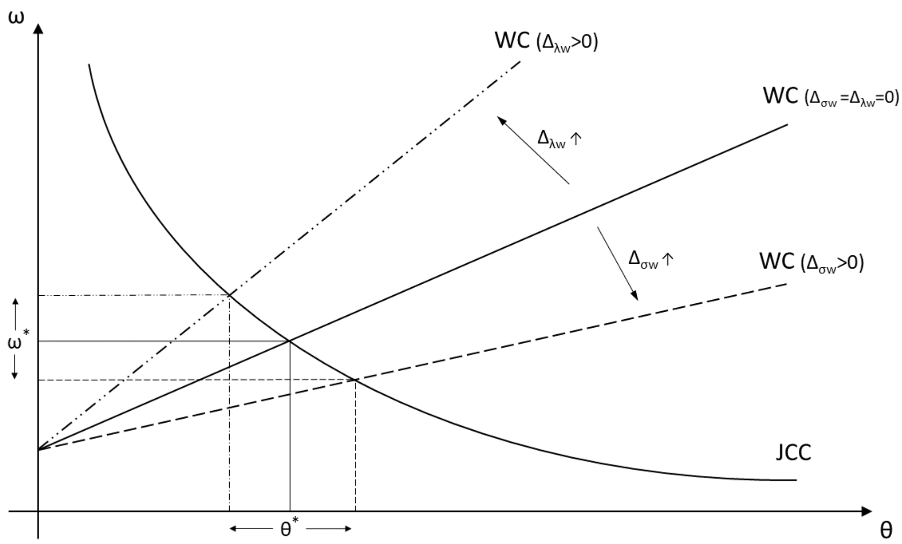
which is equivalent to the standard DMP model, as is the Beveridge curve,

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

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 affect the labor market equilibrium by rotating the wage curve. A pessimistic bias in job separation expectations ($\Delta_{\sigma w} > 0$) leads to a flatter wage curve (downward rotation), resulting in lower wages and higher labor market tightness, and therefore lower unemployment, in equilibrium. An optimistic bias in job finding expectations ($\Delta_{\lambda w} > 0$) leads to a steeper wage curve (upwards rotation) and results in higher equilibrium wages, lower labor market tightness, and higher unemployment.

Figure 2: Effects of workers' expectation biases on labor market equilibrium



Notes: Labor market tightness (θ) on the x-axis, wage (ω) on the y-axis. JCC denotes the job creation condition, equation (9). WC($\Delta_{\sigma w} = \Delta_{\lambda w} = 0$) denotes the wage curve, equation (7), in a setting without worker expectation bias, and (θ^*, ω^*) the corresponding equilibrium labor market tightness and wage. WC($\Delta_{\sigma w} > 0$) and WC($\Delta_{\lambda w} > 0$) denote the wage curve in settings with pessimistic job separation bias, or optimistic job finding bias, respectively.

5.2 Calibration

We calibrate two versions of the baseline model, the first matching statistics for the German economy as a whole, and the second for East Germany only. The first calibration allows us to compare our framework to existing applications of the standard DMP model and to analyze average effects of counterfactual exercises for Germany. With the second calibration, we can address the role of biased expectations for the subgroup of East German workers and for the East-West German wage differential. Table 6 summarizes the resulting parametrization for both calibrations (labeled *All* and *East* Germany, respectively).

We set the length of a model period to one quarter to jointly match labor market flows and the level of unemployment.[34] The discount factor β is set to match the usually targeted annual interest rate of 4%. Unemployment income b is set to match the average 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, so 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), and the bargaining power of workers γ to 0.5 (see e.g. Balleer et al., 2016). Given the quantitative importance of γ for the effects of biases in our model (see discussion in Section 5.1), we explore robustness with respect to this parameter in Section 5.5.

The probability of separation σ is set to match the quarterly separation rate in the GSOEP in the respective samples, which imply a steady state unemployment rate of about 7.7% for Germany as a whole, and about 8.6% for East Germany.[35] The implied unemployment duration equals 5.4 quarters for both. We also set workers' expectation biases regarding job finding and job separation equal to the average values measured in the GSOEP in the respective samples. Our bias estimates refer to the biannual frequency of job finding and separation rates. Given the model calibration at the quarterly frequency, we convert both the expected and the predicted transition rates into quarterly rates (see Footnote 9) and compute the resulting quarterly bias as the difference of the two. We explore robustness with respect to the calibration frequency in Section 5.6.

5.3 Quantitative effects of bias on wages and unemployment

In this section, we use the model calibrated to Germany as a whole to analyze the qualitative and quantitative average effects of expectation biases on wages, unemployment and lifetime income. To this end, we perform three counterfactual experiments: removing the job separation bias, removing the job finding bias, and removing both biases at the same time. In each of 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 counterfactuals.

The first panel in Table 7 shows results of the counterfactual experiments for the German

[34] The quarterly frequency is comparable to the literature and applies often-used calibration targets.

[35] According to the German Federal Employment Agency, the average annual unemployment rate between 1999 and 2015 equals 8.8% for Germany as a whole, while the corresponding average unemployment rate in East Germany equals 14.5%. The time series are publicly available on the homepage of the Federal Statistical Office of Germany (www-genesis.destatis.de), Table 13211-0001. Hence, particularly for East Germany, the unemployment rate implied by transition rates in the GSOEP is substantially lower than the officially reported figures. We explore robustness to setting the job separation rate in the East to a higher value in line with the officially reported unemployment rate in Section 5.6.

Table 6: Model calibration

Parameter	Description	Value *All*	*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: *All* and *East* denote the baseline model for Germany as a whole, and for East Germany, respectively. Job separation and job finding biases are defined as $D_{\sigma w} \equiv \sigma_w - \sigma$ and $D_{\lambda w} \equiv \lambda_w - p(\theta)$. JF refers to job finding out of unemployment only, JS to the general measure of job separation.

economy as a whole.[36] The first three columns report changes in the unemployment rate, log wages and log reservation wages. When removing the pessimistic job separation bias, the wage curve shifts up (see Figure 2 above), and both wages and unemployment increase. When removing the optimistic job finding bias, the wage curve shifts down, and both wages and unemployment decrease. Removing the average job separation bias of German workers implies about 0.8 percent higher wages and increase in the unemployment rate by about 0.7 percentage points. Removing the average job finding bias implies about 0.3 percent lower wages, 0.6 percent lower reservation wages, and a decrease in unemployment by about 0.2 percentage points.

Columns four and five in Table 7 report wage elasticities with respect to expectation biases from the counterfactuals. Removing each bias separately, the experiments imply a wage elasticity with respect to the job separation bias of -0.0086 (column 4), and an elasticity of the reservation wage with respect to the job finding bias of 0.003 (column 5). The values are very similar when being computed from counterfactuals with a 1 percentage point change in the respective bias, which correspond more closely to the empirical estimation.[37] Hence, the effects of biases on wages 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 (see Tables 2 and 3).

Removing both biases jointly implies about 0.54 percent higher wages and an increase

[36] More detailed simulation outputs are shown in Table D.1 in the appendix.
[37] See Table D.2 in the appendix for the simulation output.

Table 7: Counterfactual experiments in the baseline model

	$\Delta[u]$	$\Delta[ln(\omega)]$	$\Delta[ln(\underline{\omega})]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\lambda w}]}$	$\Delta[ln(\mathbb{E}\mathcal{I}_{W,U})]$
			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: Baseline models for *All Germany* and *East Germany* calibrated to respective samples (c.f. Table 6). Reported are changes in steady state values relative to the baseline. Counterfactual experiments not recalibrated. Variables: unemployment rate (u), wage (ω), reservation wage ($\underline{\omega}$), job separation bias ($D_{\sigma w}$), job finding bias ($D_{\lambda w}$), ex-ante unbiased expected lifetime income ($\mathbb{E}\mathcal{I}_{W,U}$).

in the unemployment rate by about 0.45 percentage points. Thus, the effects of the two types of biases on the labor market equilibrium are close to additive. Moreover, when considering the German economy as a whole, the overall effects of removing expectation biases are, on average, small. This is hardly surprising, given that optimism with respect to job finding and pessimism with respect to job separation are offsetting each other. In addition, the quantitative effects of biases on wages depend on the wage response to labor market tightness, which is generally small in a DMP type framework and depends on the model calibration.[38] We explore robustness to different values of the bargaining power γ in Section 5.5, and to different targets for separation rates and biases in Section 5.6.

Since expectation biases move wages and unemployment in parallel, their net impact on workers' income is ambiguous. In order to assess their net effect, 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, reflects the objective average risk of unemployment. The results are reported in the last column

[38] The ability of the DMP model to generate low volatility of labor market tightness has been extensively debated in the literature (see e.g. Shimer, 2005, among many others).

of Table 7.[39] In all counterfactuals, the bias effects on wages dominate the effects on unemployment. 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. Again, the effects are not strikingly large. However, considering the German economy as a whole, removing all expectation biases implies an increase in expected lifetime income by about 0.35 percent on average.

5.4 Bias and the East-West German wage differential

In this section, we turn to examining the importance of expectation biases for East Germany. As documented in Section 3, the job separation bias of East German workers is substantially larger, and the job finding bias is substantially lower than that of West German workers in our sample. Hence, when removing both biases in this subgroup, the offsetting effects on wages and unemployment should be considerably smaller, and the overall effect considerably larger.

Using the model calibrated to East Germany and performing the same counterfactual experiments as before, we find that removing all biases implies about 1.5 percent higher wages, an increase in the unemployment rate by 1.13 percentage points, and an increase in expected lifetime income by 1 percent (see the second panel in Table 7).[40] The effects of removing expectation biases for Eastern German workers are thus about three times as large as for average German workers.

Based on our model, we can also examine the quantitative relationship between workers' expectation biases and the East-West German wage differential. As documented in Section 4, the wage differential between East and West Germany in our data is about 30% overall, and 23% net of controls. Our empirical estimates imply that if the pessimism of East Germans regarding job separation were at the level of West Germans, wages would be 0.7% higher, amounting to a around 1.3 percentage points of the wage differential (see Section 4.3). Performing the corresponding counterfactual experiment in our model delivers a wage increase of about 0.9% (see the bottom panel in Table 7). In the model, we can go further than with our empirical estimates, and counterfactually set also the job finding bias of East Germans to the Western level. This leads to an additional increase in wages by 0.47% and about 1.4% higher wages in total. The differences in expectation biases between East and West German workers thus account for about 2.8 percentage points of the East-West wage gap.[41]

The decrease in the wage gap is accompanied by an increase in the unemployment gap. When setting both expectation biases to Western levels, unemployment in the East increases by about 1 percentage point. Taking both the beneficial wage gain and the ad-

[39] Table D.3 in the appendix shows results for the different components of lifetime income.
[40] More detailed simulation outputs are shown in Tables D.4 and D.5 in the appendix.
[41] 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.

verse unemployment increase into account, (unbiased) expected lifetime income increases by 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 Additional results on the role of bargaining power

As discussed in the previous sections, the bargaining power of workers is a critical parameter regarding the elasticity of wages with respect to expectation biases. Therefore, we recalibrate the model for the German economy as a whole with higher and lower bargaining power of workers relative to the baseline value of $\gamma = 0.5$ and repeat the counterfactual experiments of Section 5.3. The results are shown in the upper panels of Table D.6 in the appendix. A lower bargaining power ($\gamma = 0.3$) 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 ($\gamma = 0.77$).

As shown in Section 5.1, keeping everything else equal, a lower bargaining power reduces wages, and also reduces the size of the partial equilibrium response of wages to changes in the bias.[42] 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 for East Germany, where the degree of collective worker representation is significantly lower than in West Germany (see e.g. Bachmann et al., 2022). Moreover, according to our estimates from Table 4, East German wages react about twice as strongly to changes in job separation bias as West German wages, which could be interpreted as indirect evidence for lower bargaining power. If we recalibrate our model for 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.[43] 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.

5.6 Robustness

In addition to examining the role of bargaining power, we investigate the sensitivity of our quantitative results in several dimensions. First, we impose bias in job separation based on dismissal only. Second, we calibrate the model to the biannual frequency in which

[42] See comparative statics in equations (D.1) and (D.2) in the Appendix).
[43] The results are shown in the lower panels of Table D.6 in the appendix.

we originally measure the bias in expectations. Third, we increase the East German job separation rate to match the East German unemployment rate in official statistics. Our findings are robust to all these sensitivity analyses. 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.

As first exercise, we calibrate the quarterly model to the alternative measure of job separation based on dismissals only. Dismissals cover only part of all job separations, therefore predicted separation rates are much lower. Job separation bias, however, is now much larger, as already discussed in Section 3. Tables D.7 and D.8 in the appendix show the resulting calibration and simulation outputs, respectively. The effects are substantially larger compared to the general measure of job separation. For the German economy as a whole, removing all bias now increases expected lifetime income by 1.7%. 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.10 documents the simulation results when recalibrating the model to the biannual frequency.[44] 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 German economy as a whole 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. We therefore recalibrate the model for East Germany, setting the job separation rate to $\sigma = 0.027$, such that the implied unemployment rate in steady state equals about 13%. Table D.11 in the appendix reports the corresponding simulation results. The changes in wages and lifetime income are slightly smaller than in the baseline, both when removing biases and when assigning Western biases to the East German economy.

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. 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

[44] The calibration is shown in Table D.9 in the appendix.

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.

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 increase up to 5 percentage points if workers in East Germany experience low bargaining power. 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.

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 this case, expectation biases matter for wage determination only if firms and workers disagree. 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.

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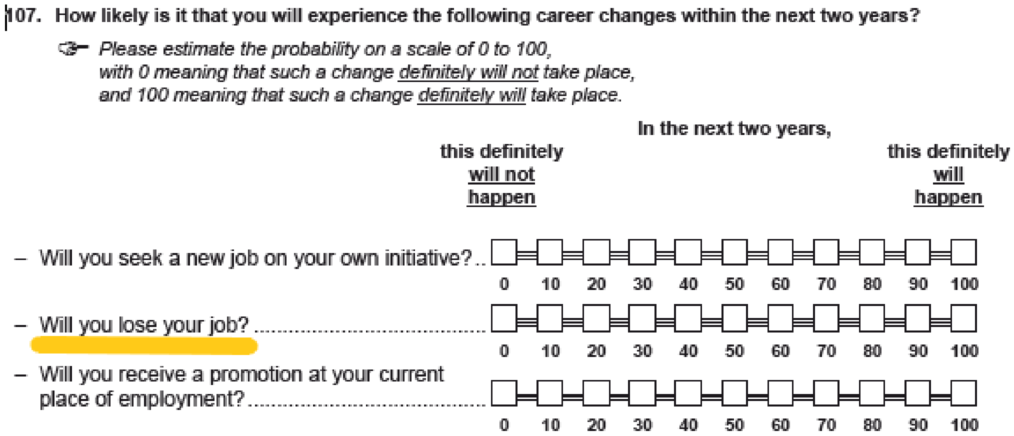
A Data Appendix

Figure A.1: Question on job separation expectations in the GSOEP



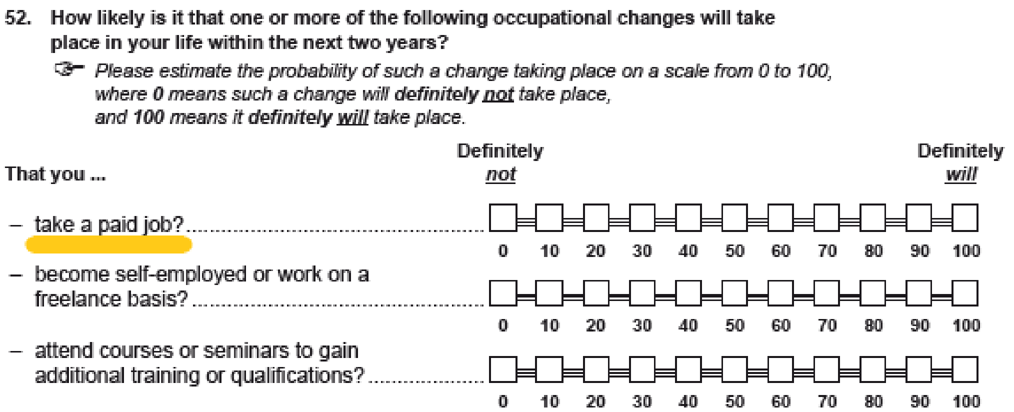
107. **How likely is it that you will experience the following career changes within the next two years?**

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: Question on 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

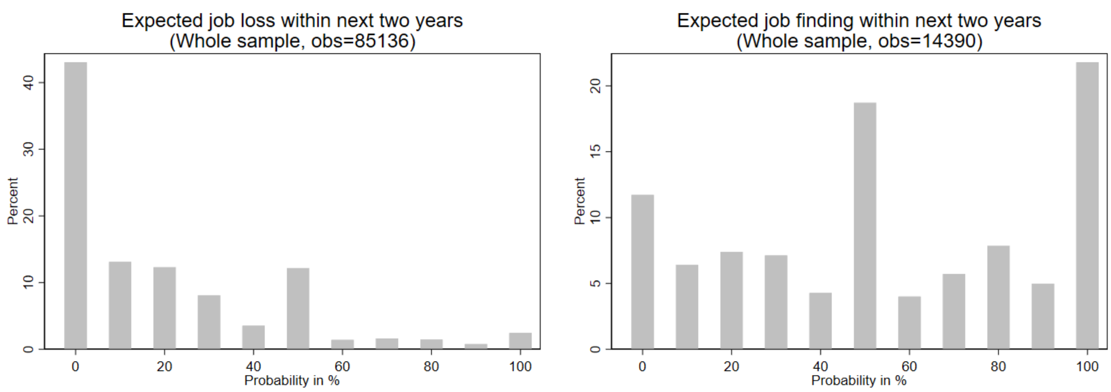


Table A.1: Reasons for having left a job in the GSOEP

"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: Summary statistics

	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*), dismissal or closure or 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: Summary statistics

	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*), dismissal or closure or 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 models: Summary statistics

	Mean	Std.Dev.	Min	Max	P50	Obs.
Age	43.744	9.9330	25	65	44	212114
Unemployment experience	0.6241	1.7042	0	34.300	0	208300
Tenure in firm	10.903	9.8850	0	51.600	8.1000	210317

Note: All variables in years

Table A.6: Discrete variables in job separation probit models: Summary statistics

	freq	pct	cumpct
Male	110194	51.95	51.95
Female	101920	48.05	100.00
Married, Partnered	146859	69.64	69.64
Single, Divorced, Widowed	64009	30.36	100.00
No children under 16 in household	95487	45.02	45.02
Children under 16 in household	116627	54.98	100.00
West Germany	166330	78.42	78.42
East Germany	45784	21.58	100.00
Not born in Germany	29358	13.84	13.84
Born in Germany	182756	86.16	100.00
No German citizen	29358	13.84	13.84
German citizen	182756	86.16	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 previous year	171287	82.88	82.88
New job since previous year	35387	17.12	100.00
Not working in occupation trained for	71961	37.18	37.18
Working in occupation trained for	121605	62.82	100.00
Satisfaction with work: 0 (low)	1211	0.60	0.60
Satisfaction with work: 1	1402	0.69	1.28
Satisfaction with work: 2	3602	1.77	3.05
Satisfaction with work: 3	6658	3.27	6.33
Satisfaction with work: 4	8059	3.96	10.29
Satisfaction with work: 5	20745	10.20	20.48
Satisfaction with work: 6	20635	10.14	30.63
Satisfaction with work: 7	38117	18.74	49.36
Satisfaction with work: 8	56000	27.52	76.89
Satisfaction with work: 9	29716	14.61	91.49
Satisfaction with work: 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 models: Summary statistics

	Mean	Std.Dev.	Min	Max	P50	Obs.
Age	44.702	11.068	25	65	45	18789
Unemployment experience	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

Note: All variables in years

Table A.8: Discrete variables in job finding probit models: Summary statistics

	freq	pct	cumpct
Male	9039	48.11	48.11
Female	9750	51.89	100.00
Married, Partnered	10516	56.49	56.49
Single, Divorced, Widowed	8101	43.51	100.00
West Germany	11555	61.50	61.50
East Germany	7234	38.50	100.00
Not born in Germany	4626	24.62	24.62
Born in Germany	14163	75.38	100.00
No German citizen	4626	24.62	24.62
German citizen	14163	75.38	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***
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***
Unemployment experience	0.0501***	0.0762***	0.0945***	0.146***
Unemployment experience, squared	-0.00298***	-0.00498***	-0.00568***	-0.00683***
Tenure in firm	-0.0637***	-0.0410***	-0.0546***	-0.0613***
Tenure in firm, squared	0.00144***	0.000813***	0.00112***	0.00129***
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***
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***
Firm size < 20	0	0	0	0
Firm size $\geq 20 > 200$	-0.0730***	-0.179***	-0.111***	-0.0845***
Firm size $\geq 200 < 2000$	-0.118***	-0.326***	-0.159***	-0.178***
Firm size ≥ 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

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Employed persons, age 25 to 65 years, survey years 1999, 2001, 2003, 2005, 2007, 2009, 2013, 2015 (dummies included). Measure of actual job separation from retrospective question two years after interview including all reasons (*general*), dismissal or closure (*dismissal*), dismissal or closure or 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. Age, tenure in firm, and unemployment experience measured in years, firm size in number of employees, satisfaction with work on a discrete scale from 0 (low) to 10 (high).

Table B.2: Job finding probit estimation

	out of U	out of U or O	out of O
Age	0.0938***	0.0702***	0.0378***
Age, squared	-0.00154***	-0.00148***	-0.00111***
Female	-0.183***	-0.257***	-0.201***
Married, Partnered	0	0	0
Single, Divorced, Widowed	0.0448	0.137***	0.119***
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***
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***
Unemployment experience	-0.0752***	0.0160**	0.00766
Unemployment experience, squared	0.00218***	-0.000947**	0.0000233
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***
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

Notes: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Persons unemployed or out of the labor force, age 25 to 65 years, survey years 1999, 2001, 2003, 2005, 2007, 2009, 2013, 2015 (dummies included). 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*). Age, unemployment experience and work experience measured in years.

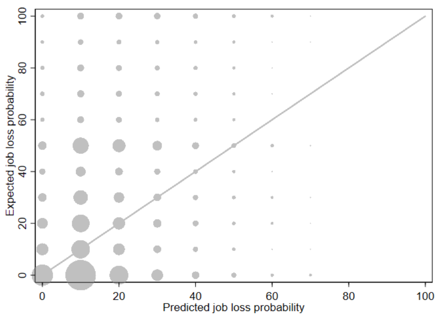
Table B.3: Job separation, all measures: Summary statistics

	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

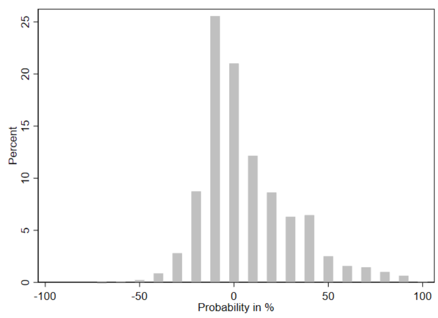
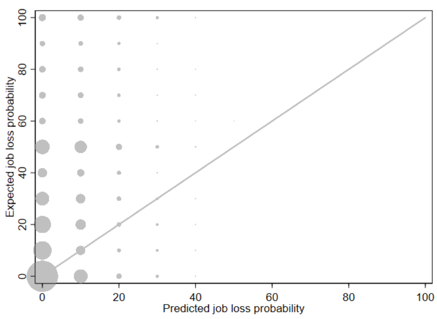


Figure B.2: Expected, predicted and bias in job separation, dismissal: Histograms

(a) Expected vs. predicted



(b) Bias

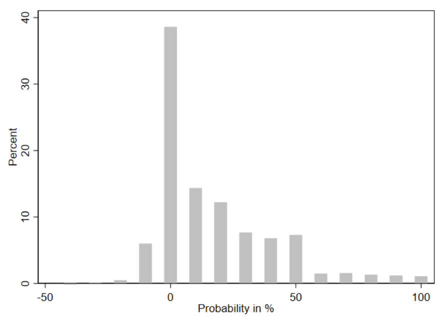


Table B.4: Job Separation, full time employed and permanent contract: Summary statistics

	Mean	Std.Dev.	Min	Max	P10	P50	P90	Obs.
Expected job loss	18.903	22.863	0	100	0	10	50	42273
Predicted job loss, general	12.251	9.6030	0	70	0	10	20	42273
Bias in job loss, general	6.6520	23.285	-70	100	-20	0	40	42273
Predicted job loss, dismissal	2.5939	5.0431	0	50	0	0	10	42273
Bias in job loss, dismissal	16.309	22.170	-40	100	0	10	50	42273
Predicted job loss, selected	4.9126	6.7221	0	50	0	0	10	42273
Bias in job loss, selected	13.991	22.102	-50	100	-10	10	50	42273
Predicted job loss, spell	3.6390	6.9719	0	70	0	0	10	42273
Bias in job loss, spell	15.264	22.263	-70	100	0	10	50	42273

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

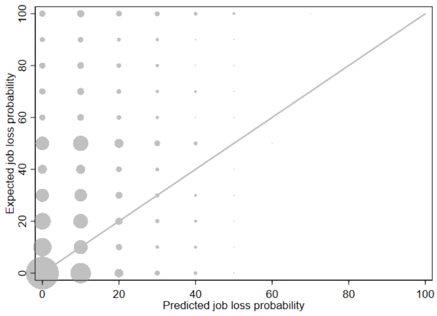
Table B.5: Job Separation, capped: Summary statistics

	Mean	Std.Dev.	Min	Max	P10	P50	P90	Obs.
Expected job loss	16.512	19.523	0	70	0	10	50	64831
Predicted job loss, general	12.997	10.142	0	70	0	10	30	64831
Bias in job loss, general	3.5145	20.159	-70	70	-20	0	30	64831
Predicted job loss, dismissal	2.6447	5.1243	0	50	0	0	10	64831
Bias in job loss, dismissal	13.867	18.884	-40	70	0	10	40	64831
Predicted job loss, selected	5.1176	7.0299	0	60	0	0	10	64831
Bias in job loss, selected	11.394	18.781	-50	70	-10	0	40	64831
Predicted job loss, spell	3.9625	7.5063	0	80	0	0	10	64831
Bias in job loss, spell	12.549	19.034	-70	70	0	10	40	64831

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero. Values are rounded. Sample excludes expected job loss above the 95th and below the 5th percentile.

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

(a) Expected vs. predicted



(b) Bias

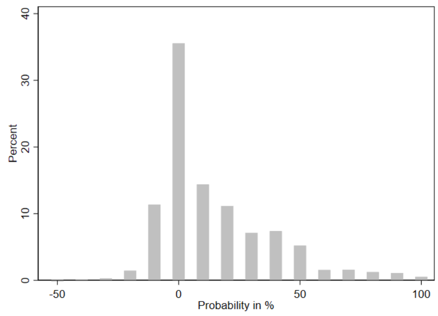
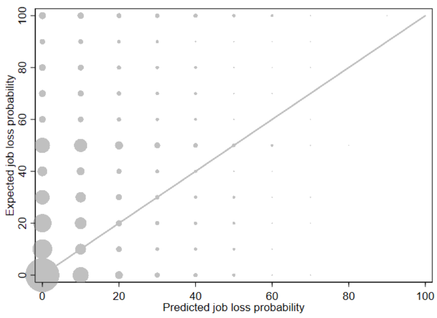


Figure B.4: Expected, predicted and bias in job separation, spell: Histograms

(a) Expected vs. predicted



(b) Bias

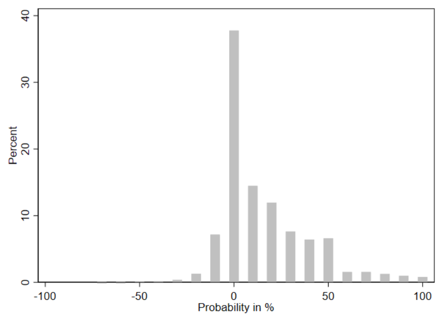
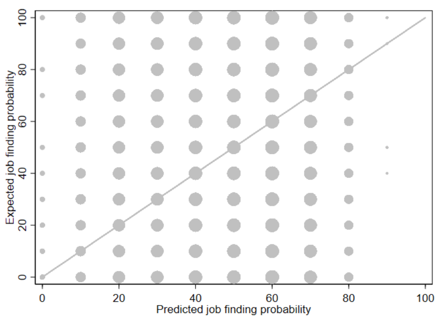


Figure B.5: Expected, predicted and bias in job finding, out of U: Histograms

(a) Expected vs. predicted



(b) Bias

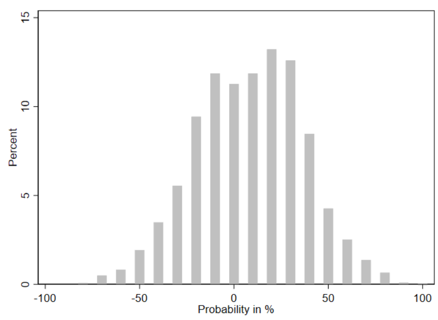
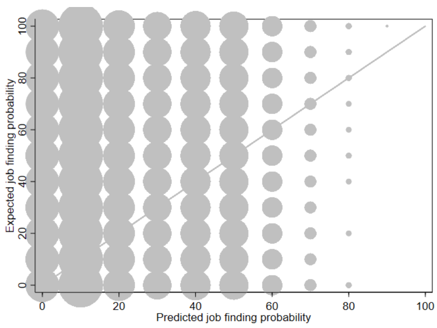


Figure B.6: Expected, predicted and bias in job finding, out of O: Histograms

(a) Expected vs. predicted



(b) Bias

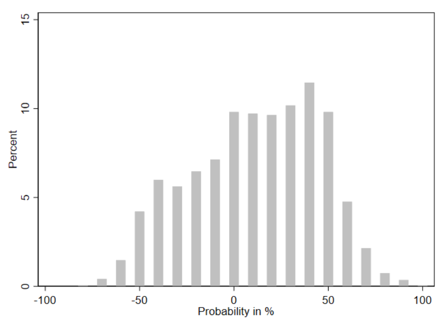


Table B.6: Job Separation, rounded up: Summary statistics

	Mean	Std.Dev.	Min	Max	P10	P50	P90	Obs.
Expected job loss	19.767	24.529	0	100	0	10	50	67772
Predicted job loss, general	18.340	10.147	10	80	10	20	30	67772
Bias in job loss, general	1.4271***	24.211	-80	90	-20	-10	40	67772
Predicted job loss, dismissal	10.939	3.3803	10	60	10	10	10	67772
Bias in job loss, dismissal	8.8275***	24.051	-40	90	-10	0	40	67772
Predicted job loss, selected	12.348	5.6270	10	70	10	10	20	67772
Bias in job loss, selected	7.4188***	23.616	-60	90	-10	0	40	67772
Predicted job loss, spell	12.175	6.3558	10	90	10	10	20	67772
Bias in job loss, spell	7.5916***	23.715	-80	90	-10	0	40	67772

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

Table B.7: Job finding, all measures: Summary statistics

	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 job finding	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, out of U or O	11.000***	31.936	-80	100	-30	10	50	14049
Expected job finding	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. Means of expected job finding are different across measures due to differences in sample.

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

(a) Expected vs. predicted **(b)** Bias

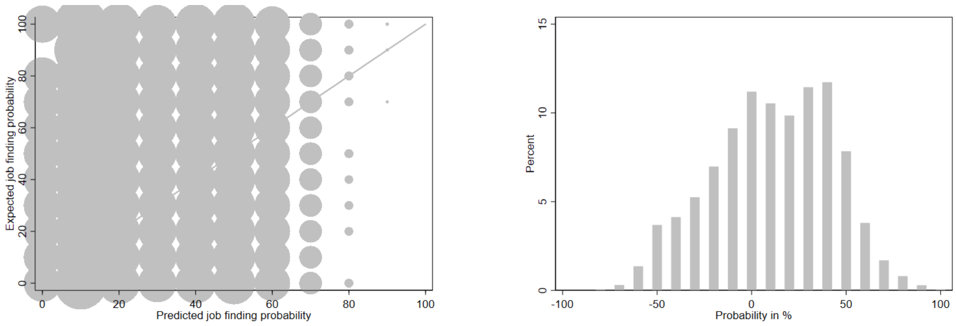


Table B.8: Job finding, capped: Summary statistics

	Mean	Std.Dev.	Min	Max	P10	P50	P90	Obs.
Expected job finding	60.859	29.703	10	100	20	50	100	6018
Predicted, out of U	49.679	19.291	0	90	20	50	70	6018
Bias, out of U	11.180	26.786	-70	100	-20	10	40	6018
Expected job finding	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, out of U or O	11.000	31.936	-80	100	-30	10	50	14049
Expected job finding	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. Means of expected job finding are different across measures due to differences in sample. Values are rounded. Sample excludes expected job loss above the 90th and below the 10th percentile.

Table B.9: Job finding, rounded up: Summary statistics

	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	53.804	19.470	10	90	30	60	80	6423
Bias, out of U	3.2181***	28.776	-80	90	-30	0	40	6423
Expected job finding	54.295	34.609	0	100	0	50	100	14049
Predicted, out of U or O	48.359	17.419	10	100	20	50	70	14049
Bias, out of U or O	5.9364***	31.969	-90	90	-40	10	40	14049
Expected job finding	52.005	36.261	0	100	0	50	100	7627
Predicted, out of O	45.702	16.454	10	100	20	50	70	7627
Bias, out of O	6.3026***	34.008	-90	90	-40	10	50	7627

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ refer to t-test of mean bias equal to zero. Means of expected job finding are different across measures due to differences in sample.

Table B.10: 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.11: 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).

Table B.12: 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.13: Bias in job separation in East by age

	general	dismissal	selected	spell
East-Germany	8.843***	7.323***	6.412***	6.669***
	(9.17)	(7.56)	(6.67)	(6.93)
Age	-0.0279	-0.0977***	-0.0654***	-0.0862***
	(-1.26)	(-4.42)	(-2.99)	(-3.92)
East × Age	-0.0249	-0.0176	-0.00476	-0.00820
	(-1.16)	(-0.82)	(-0.22)	(-0.38)
Observations	67772	67772	67772	67772

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. Regression equation is identical to output shown in Table B.12 adding interaction between East Germany indicator and age. Table shows only coefficients for East Germany, age and interaction.

Table B.14: Bias in job separation in East by cohort

	general	dismissal	selected	spell
East-Germany	6.234***	6.630***	4.994***	5.210***
	(10.07)	(10.69)	(8.09)	(8.42)
East × cohort1950	3.185***	1.197*	2.584***	2.418***
	(4.73)	(1.79)	(3.88)	(3.62)
East × cohort1960	2.978***	0.205	2.000***	1.843***
	(4.28)	(0.30)	(2.92)	(2.68)
East × cohort1970	0.136	-0.964	0.206	0.134
	(0.18)	(-1.28)	(0.28)	(0.18)
East × cohort1980	-5.210***	-3.700***	-3.196***	-3.095***
	(-5.38)	(-3.81)	(-3.31)	(-3.20)
East × cohort1990	-12.23***	-6.840	-6.778	-6.632
	(-2.79)	(-1.56)	(-1.56)	(-1.52)
Observations	67772	67772	67772	67772

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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. Regression equation is identical to output shown in Table B.12 adding interaction between East Germany indicator and cohorts born in different decades. Table shows only coefficients for East Germany and interaction terms. Coefficient for East Germany shows bias for cohorts born before 1950.

Table B.15: 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.16: Bias in job finding in East by age

	out of U	out of U or O	out of O
East-Germany	-5.674*	15.91***	33.12***
	(-1.83)	(6.41)	(8.34)
Age	-0.328***	-0.159**	-0.0780
	(-3.58)	(-2.18)	(-0.71)
East × Age	-0.0597	-0.446***	-0.746***
	(-0.86)	(-7.73)	(-7.56)
Observations	6182	13418	7237

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: 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). Regression equation is identical to output shown in Table B.15 adding interaction between East Germany indicator and age. Table shows only coefficients for East Germany, age and interaction.

Table B.17: Bias in job finding in East by cohort

	out of U	out of U or O	out of O
East-Germany	-11.84***	-11.26***	-11.52***
	(-6.55)	(-6.54)	(-3.22)
East × cohort1950	2.195	4.268**	5.409
	(1.17)	(2.33)	(1.38)
East × cohort1960	2.507	5.900***	9.119**
	(1.21)	(3.03)	(2.32)
East × cohort1970	7.193***	15.37***	24.08***
	(3.12)	(7.45)	(6.11)
East × cohort1980	6.658**	15.66***	24.66***
	(2.45)	(6.58)	(5.65)
East × cohort1990	21.30**	25.16***	24.19
	(2.13)	(2.83)	(1.57)
Observations	6182	13418	7237

t statistics in parentheses

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

Notes: 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). Regression equation is identical to output shown in Table B.15 adding interaction between East Germany indicator and cohorts born in different decades. Table shows only coefficients for East Germany and interaction terms. Coefficient for East Germany shows bias for cohorts born before 1950.

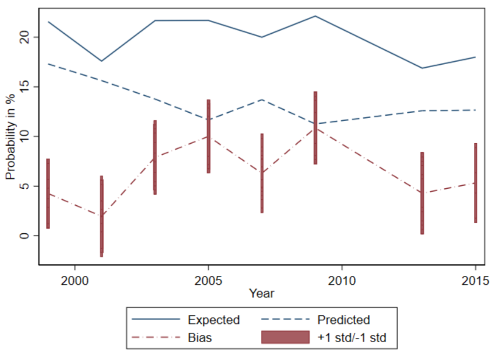
Table B.18: Bias in job separation and job finding in recessions

	general	dismissal	selected	spell	out of U	out of U or O	out of O
recession	0.0511	-0.467**	-0.426**	-0.541***	0.395	-1.501**	-2.919***
	(0.25)	(-2.30)	(-2.11)	(-2.68)	(0.46)	(-2.29)	(-3.09)
obs	67772	67772	67772	67772	6182	13418	7237

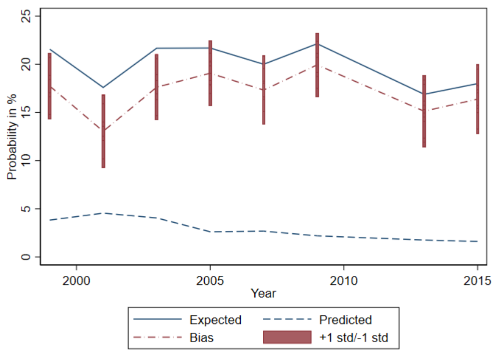
Notes: t statistics in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Measure of actual job separation from retrospective question including all reasons (general), dismissal or closure (dismissal), mutual agreement or end of contract (selected), or from spell measure. Measure of actual job 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). Regression equations are identical to output shown in Tables B.12 and B.15 plus recession dummies. Recessions occurred in 2001, 2008 and 2009.

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

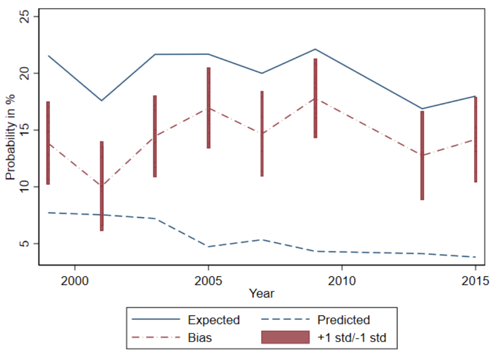
(a) general



(b) dismissal



(c) selected



(d) spell

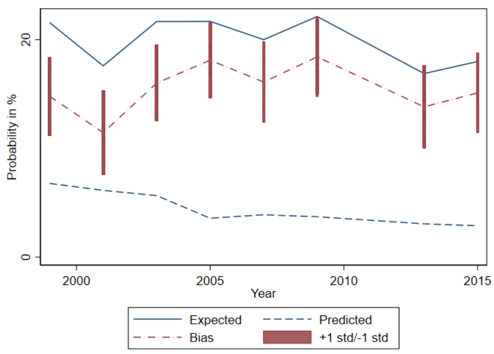
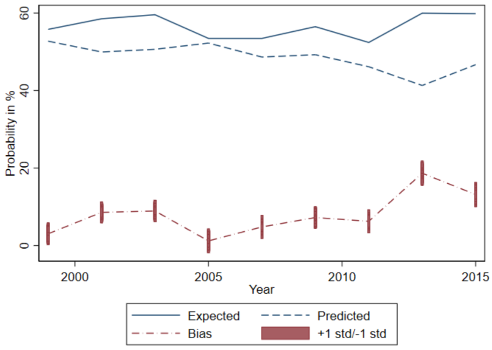
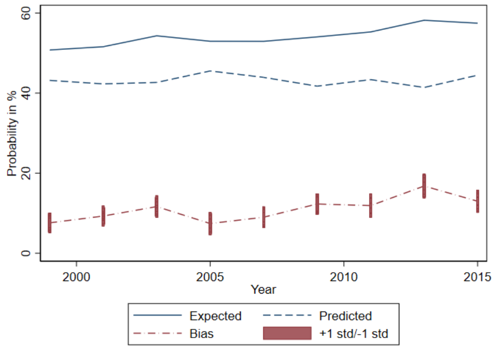


Figure B.9: Bias in job finding expectations over time, different measures

(a) out of U



(b) out of U or O



(c) out of O

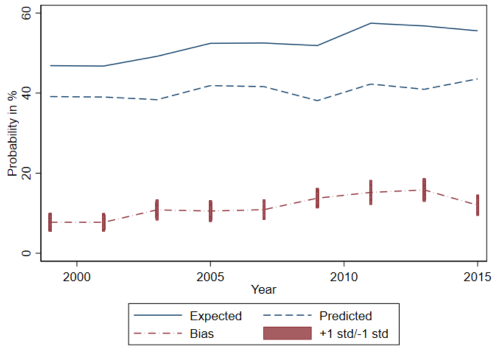
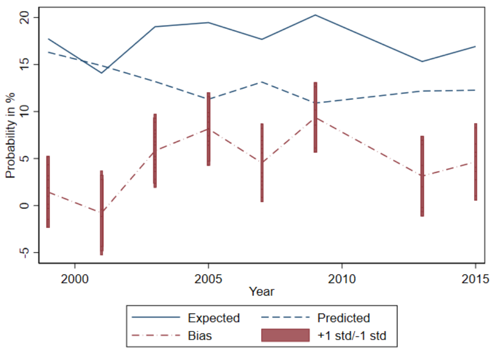
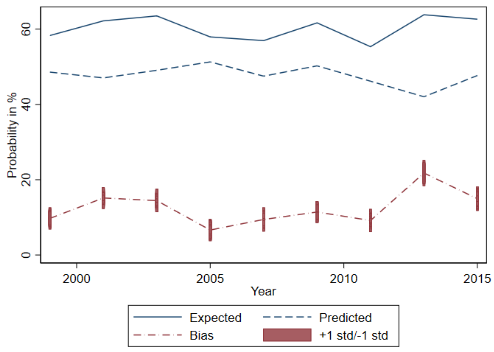


Figure B.10: Bias in job separation and job finding expectations over time: East versus West

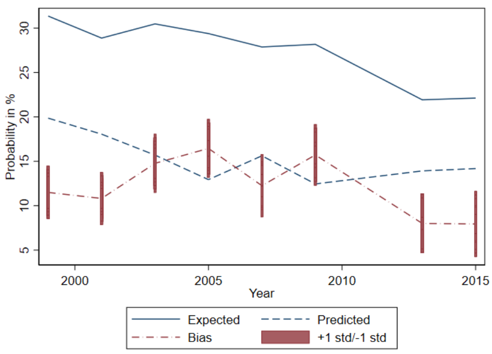
(a) West: general JS



(b) West: JF out of U



(c) East: general JS



(d) East: JF out of U

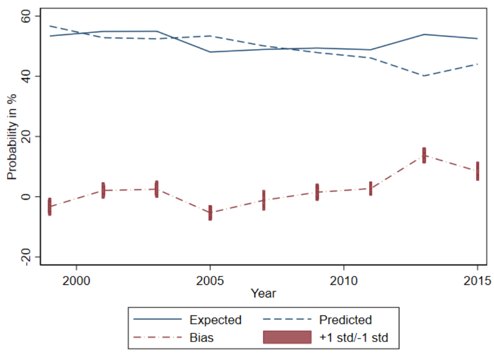
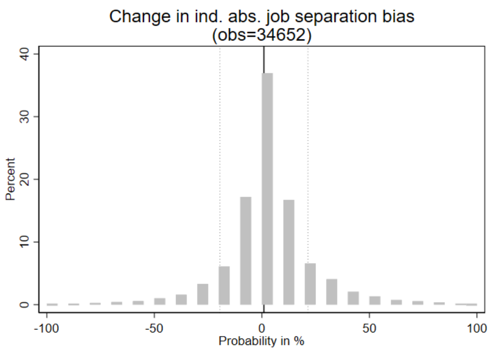


Table B.19: Change in job separation and finding bias between surveys: Summary statistics

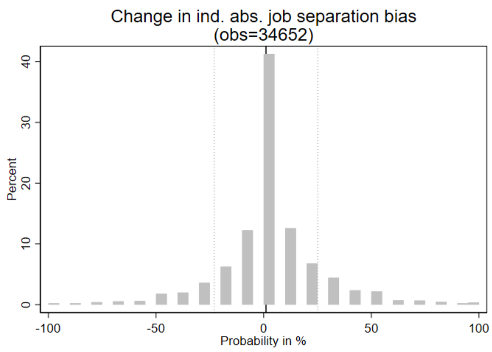
	Mean	std.dev.	min	max	P50	Obs.
			Job loss bias			
general	0.9339	20.461	-100	100	0	34652
dismissal	1.0825	24.057	-100	100	0	34652
selected	1.2069	23.018	-100	100	0	34652
spell	1.2527	23.611	-100	100	0	34652
			Job finding bias			
U only	-0.9368	20.788	-80	70	0	1676
U and O	-1.1212	22.542	-90	90	0	4299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

Figure B.11: Change in job separation bias between surveys, different measures

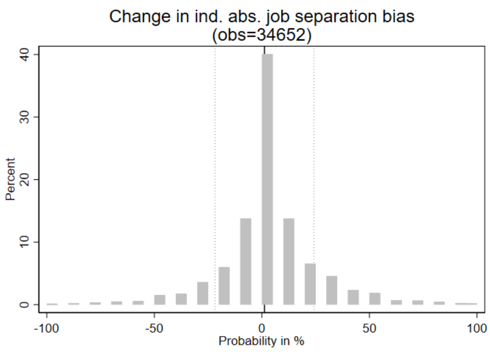
(a) general



(b) dismissal



(c) selected



(d) spell

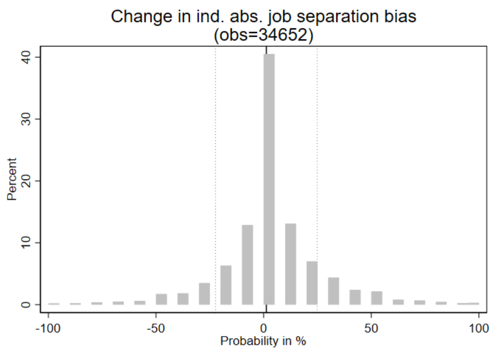
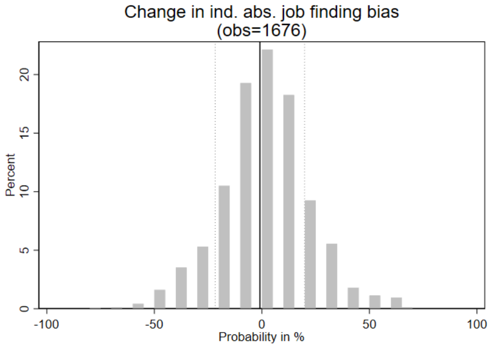
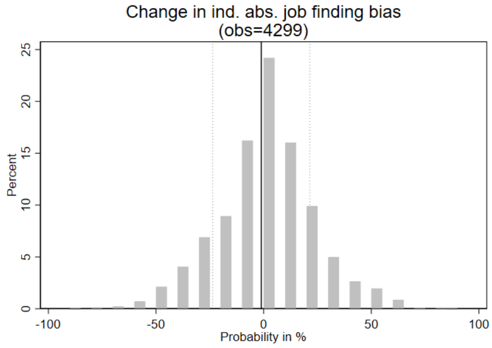


Figure B.12: Change in job finding bias between survey, different measures

(a) out of U



(b) out of U or O



(c) out of O

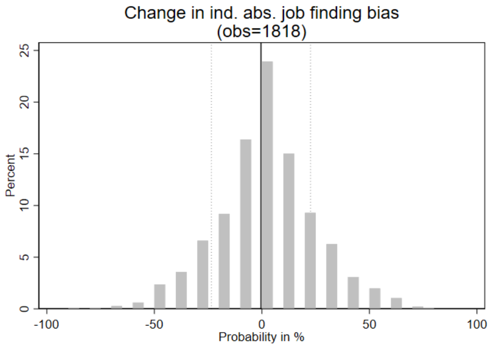
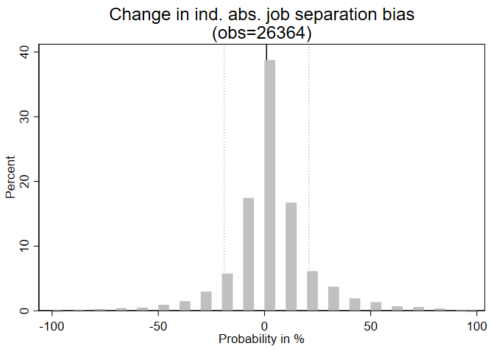
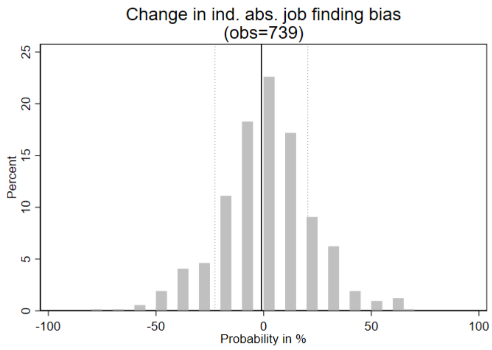


Figure B.13: Change in job separation and job finding bias: East versus West

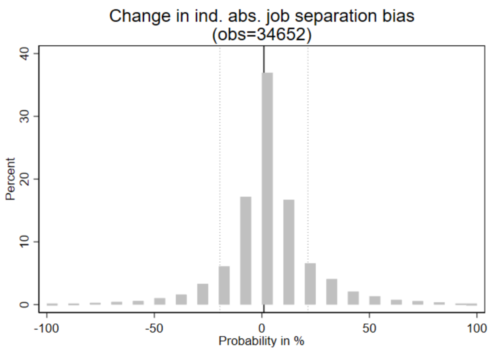
(a) West: general JS



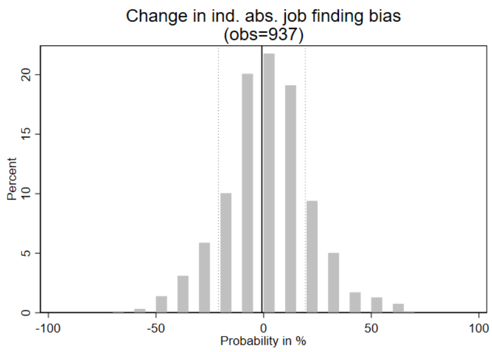
(b) West: JF out of U



(c) East: general JS



(d) East: JF out of U



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, out of U or O

	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, out of O

	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: fulltime employed and permanent employment

	log hourly wage rate			
	general	dismissal	selected	spell
Bias	-0.000601***	-0.000726***	-0.000642***	-0.000637***
	(0.0000842)	(0.0000853)	(0.0000850)	(0.0000906)
N	118681	118681	118681	118681

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.9: Wages and bias in job separation expectations: capped sample

	log hourly wage rate			
	general	dismissal	selected	spell
Bias	-0.000654***	-0.000865***	-0.000757***	-0.000607***
	(0.0000737)	(0.0000965)	(0.0000831)	(0.0000894)
N	85136	85136	85136	85136

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.10: Reservation income and bias in job finding expectations: capped sample

	log reservation income		
	out of U	out of U or O	out of O
Bias	0.000769***	0.000935***	0.000580**
	(0.000276)	(0.000224)	(0.000237)
N	6576	14390	7814

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.11: 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.12: 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.13: 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

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 $H(z) : [0, \bar{z}] \to [0, 1]$ 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: Detailed results

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	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\lambda w}]}$
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: Baseline model for *All Germany* calibrated to whole sample (c.f. Table 6). Values in steady state. Counterfactual experiments not recalibrated.

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: Baseline models for *All Germany* and *East Germany* calibrated to respective samples (c.f. Table 6). Values in steady state. Counterfactual experiments not recalibrated.

Table D.3: Counterfactual experiments, All Germany: Expected lifetime income

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

Notes: Baseline model for *All Germany* calibrated to whole sample (c.f. Table 6). Values in steady state. Counterfactual experiments not recalibrated.

Table D.4: Counterfactual experiments, East Germany: Detailed results

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	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\lambda w}]}$
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	$\Delta[u]$	$\Delta[ln(\omega)]$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\sigma w}]}$	$\frac{\Delta[ln(\omega)]}{\Delta[D_{\lambda w}]}$
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: Baseline model for *East Germany* calibrated to subsample (c.f. Table 6). Values in steady state. Counterfactual experiments not recalibrated.

Table D.5: Counterfactual experiments, East Germany: Expected lifetime income

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

Notes: Baseline model for *East Germany* calibrated to subsample (c.f. Table 6). Values in steady state. Counterfactual experiments not recalibrated.

Table D.6: Counterfactual experiments: Varation of bargaining power (γ)

All Germany						
$\gamma = 0.300$	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
East Germany						
$\gamma = 0.500$	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

Notes: Models for *All Germany* and *East Germany* fully recalibrated to subsamples (c.f. Table 6). Reported are steady state values (columns 2 to 5) or changes relative to the baseline (columns 6 and 7). Counterfactual experiments not recalibrated.

Table D.7: Model calibration, 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 refers to job finding out of unemployment only, JS to the dismissal measure of job separation.

Table D.8: Counterfactual experiments, 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

Notes: Models for *All* and *East* Germany fully recalibrated to subsamples (c.f. Table D.7). Reported are steady state values (columns 2 to 5) or changes relative to the baseline (columns 6 and 7). Counterfactual experiments not recalibrated.

Table D.9: Model calibration, biannual frequency

Parameter	Description	Value *All*	*East*	Source/Target
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 refers to job finding out of unemployment only, JS to the general measure of job separation.

Table D.10: 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

Notes: Models for *All* and *East* Germany fully recalibrated to subsamples (c.f. Table D.9). Reported are steady state values (columns 2 to 5) or changes relative to the baseline (columns 6 and 7). Counterfactual experiments not recalibrated.

Table D.11: Counterfactual experiments, East Germany: Higher separation rate

	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
	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

Notes: Model for *East Germany* fully recalibrated to subsamples (calibration table not shown). Reported are steady state values (columns 2 to 5) or changes relative to the baseline (columns 6 and 7). Counterfactual experiments not recalibrated.