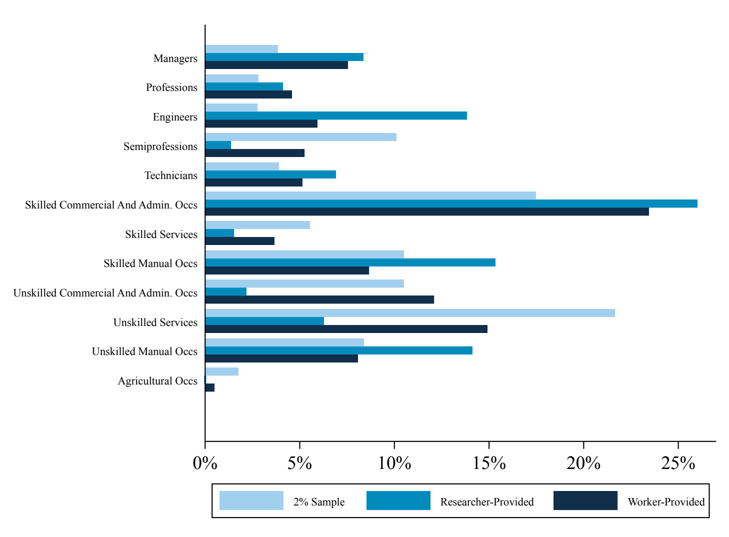
Online Appendix for "Why Workers Stay: Pay, Beliefs, and Attachment"
(Caldwell, Haegele & Heining)

A Appendix Figures and Tables

Figure A1: Occupational Distribution of Researcher-Provided Firms

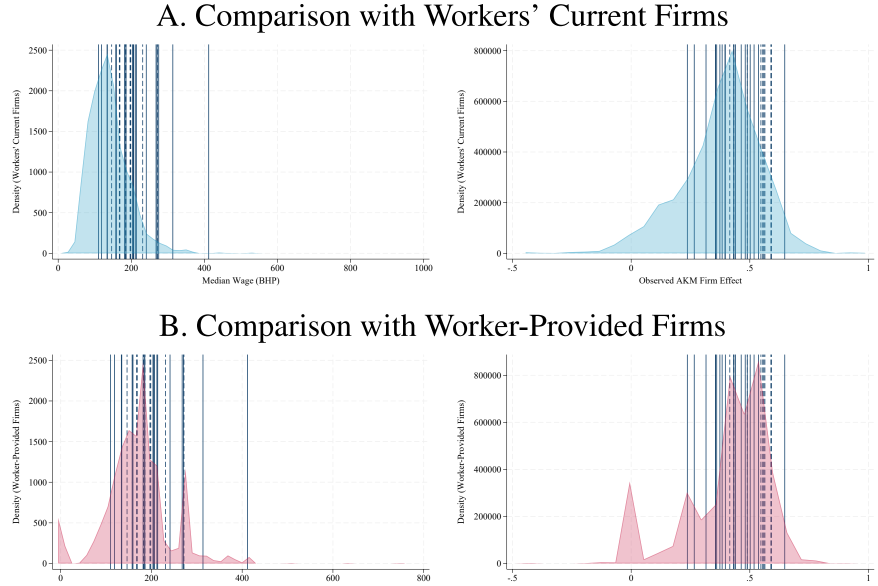


Note: This figure compares the span of major occupational groups in the overall German workforce using a 2% random sample to workers at our researcher-provided and worker-provided firms.

Figure A2: Comparison of Researcher-Provided Firms and Workers' Firms

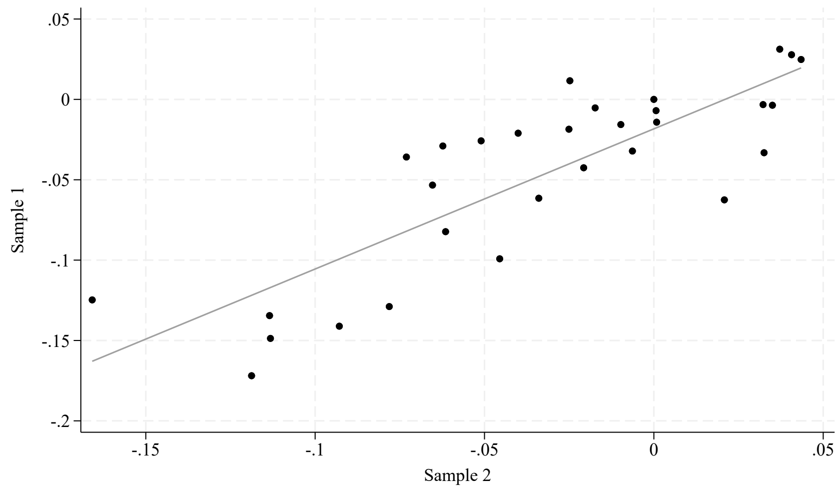
A. Comparison with Workers' Current Firms

B. Comparison with Worker-Provided Firms



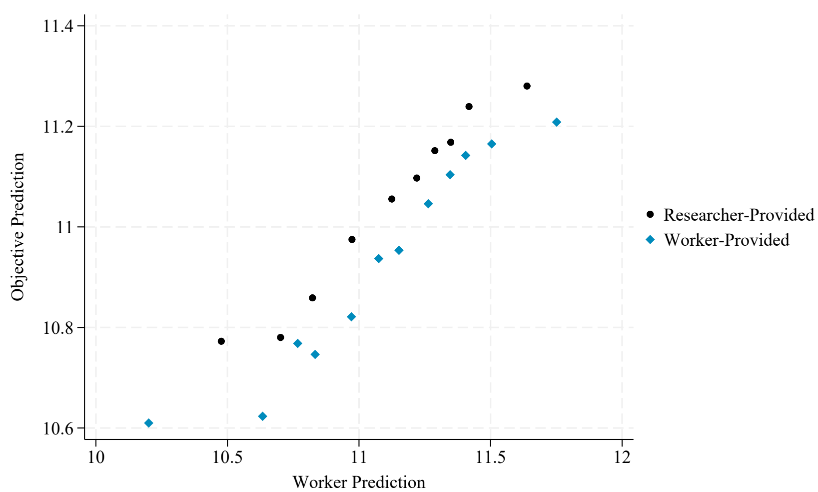
Note: This figure compares the 30 researcher-provided firms to the workers' current firms (Panel A) and to the worker-provided firms (Panel B). The left (right) figures plot the kernel density of workers' current or provided firms' median pay (firm wage premium from Bellmann et al. (2020)). The vertical lines indicate the values for researcher-provided firms. Solid lines indicate firms included in the initial survey. Dashed lines indicate firms only included in the follow-up survey. Results are weighted using sampling weights.

Figure A3: Expected Firm Pay Premia: Split-Sample Evidence



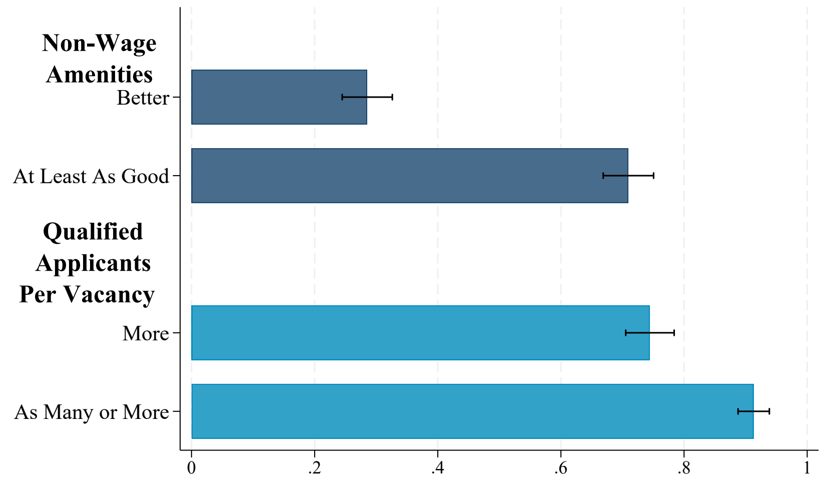
Note: This figure examines the relationship between workers' expected pay premia estimated by fitting equation 8 in two subsamples of workers in the researcher-provided firm module. We created the subsamples by randomly dividing our sample in half. Each dot represents the expected pay premium associated with one researcher-provided firm. There are 30 dots, one of which is constrained to be 0 in each sample (ψ_1). Table 4 presents tests of equality for estimates of ψ_j in different groups of workers, as well as correlations in the estimates for each sample.

Figure A4: Correlation Between Worker Expectations and Objective Pay Predictions



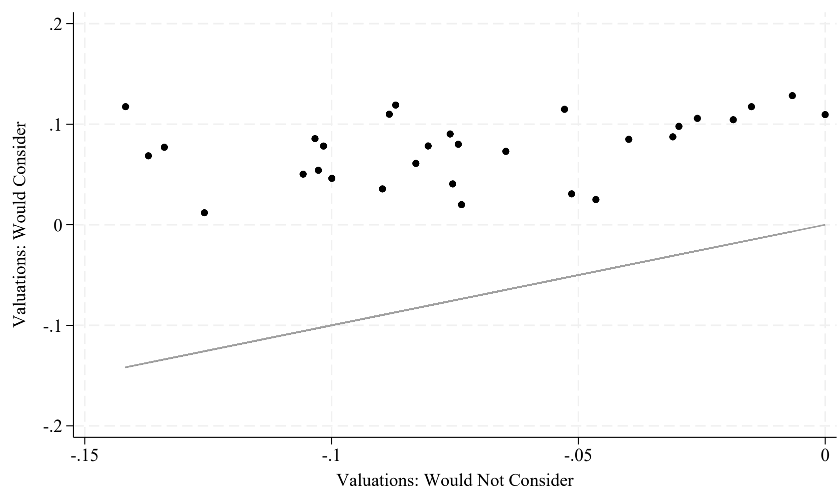
Note: This figure compares workers' expectations to the objective pay predictions. We estimate workers' expected pay premia by fitting equation 8. We construct the objective prediction by taking the logarithm of a worker's current pay, subtracting the firm pay effect of their current firm, and adding the firm pay effect of the specified firm. The black dots are based on data from the researcher-provided firm modules in both the initial and follow-up surveys. The blue diamonds are based on data from the worker-provided firm module in the initial survey. The plot is created using the package created by Cattaneo et al. (2024). Results are weighted using sampling weights.

Figure A5: Workers' Perceptions about Amenities and Application Rates



Note: In the follow-up survey, respondents compared two firms in the same labor market—one paying 10% above and one 30% above market average. They indicated which firm had better non-wage amenities and attracted more qualified applicants. The figure shows the fraction selecting the higher-paying firm as strictly better (top bar) or similar or better (bottom bar). Results use sampling weights; whiskers show 95% confidence intervals.

Figure A6: Valuations by Consideration



Note: This figure shows the valuations for each of the 30 researcher-provided firms for those who say they would (y-axis) and would not (x-axis) consider applying to the firm if they wanted to switch firms. Each dot presents the estimate from a separate firm; the estimate of a_1 for those who would not consider applying to the firm is constrained to be zero. We estimate valuations using a rank-ordered logit model applied to the discrete choice experiments in the researcher-provided firm module. The model includes a control for the (randomized) wage offer, the order in which the firm was listed, and a full set of firm dummies, interacted with worker-firm specific consideration. We convert valuations to monetary equivalents by dividing by the coefficient on the randomized wage offer.

Table A1: Firm Effects Have Explanatory Power Beyond Sector and Location

	Sector Fixed Effects		Sector and State Fixed Effects		Sector-State Fixed Effects	
	(1)	(2)	(3)	(4)	(5)	(6)
	A. Researcher-Provided Firms					
Adjusted R-Squared	0.858	0.866	0.862	0.866	---	---
Observations	19734	19734	19734	19734	---	---
Parameters Tested	24		17		---	---
F-Statistic	7		5			
p-value	<.01		<.01		---	---
	B. Worker-Provided Firms					
Adjusted R-Squared	0.888	0.907	0.868	0.885	0.871	0.881
Observations	10733	10733	8527	8527	8138	8138
Parameters Tested	535		387		334	
F-Statistic	17370894		392000000000		18485608	
p-value	<.01		<.01		<.01	

Note: This table reports the adjusted R-squared from regressions of log expected earnings at researcher-provided (Panel A) or worker-provided (Panel B) firms. Columns 1, 3, and 5 include worker fixed effects, and the fixed effects indicated in the column. Columns 2, 4, and 6 add firm fixed effects. The F-statistic tests whether firm dummies are jointly zero. Standard errors are clustered at the worker level. Regressions use sampling weights. We exclude results with limited within-sector/state firm pairs.

Table A2: Decomposition of Workers' Firm-Specific Pay Expectations

	Worker Expectations					
		Informed at Application		Recent Search Activity		
	All Workers	Yes	No	Yes	No	Objective Predictions
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Parameters						
Person Effects	5305	2643	2662	3971	1334	1103
Firm Effects	30	30	30	30	30	29
Summary of Parameter Estimates						
Std. Dev. Person Effects	0.365	0.386	0.344	0.358	0.386	0.516
Std. Dev. Firm Effects	0.051	0.055	0.049	0.051	0.053	0.091
RMSE	0.105	0.108	0.102	0.105	0.106	0.315
Addendum						
Std. Dev. Log(Salary)	0.378	0.401	0.357	0.371	0.401	0.254
Variance Log(Salary)	0.143	0.160	0.127	0.138	0.160	0.064
Observations	19431	9692	9739	14580	4851	3879

Note: This table describes the results of estimating equation 8 using data from the researcher-provided firm module and controlling for survey wave. Column 1 presents the baseline results. Columns 2 and 3 present results for workers who did and did not know pay at time of application to their current firm. Columns 4 and 5 present results for workers who did and did not engage in job search in the previous six months. Column 6 presents analogous statistics for our objective predictions, which use firm effects from Bellmann et al. (2020). Regressions use sampling weights.

Table A3: Relationship Between Pay Expectations and Consideration: Additional Specifications

	Alternative Specifications of Distance			Alternative Samples		Alternative Weighting Schemes	
	Quadratic in Distance	Direct Distance	Closest Establishment	Initial Survey Only	Follow-Up Only	Unweighted	Population Weights
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Own-Pay Expectation	0.312***	0.309***	0.331***	0.427***	0.249	0.225***	0.255***
	(0.050)	(0.050)	(0.050)	(0.122)	(0.174)	(0.026)	(0.085)
Observations	21272	21272	21272	15095	5980	21272	21236
Number of Workers (Clusters)	6440	6440	6440	0.396	0.309	0.330	0.335
Mean of Outcome	0.31	0.31	0.31	0.35	0.24	0.33	0.32
Implied Elasticity	1.004***	0.996***	1.067***	1.214***	1.052	0.677***	0.788***
	(0.162)	(0.161)	(0.161)	(0.347)	(0.736)	(0.079)	(0.261)

Note: Each regression uses data from the researcher-provided firm module and controls for worker and firm fixed effects, for whether the firm and worker are in the same sector, for the log driving distance between the worker and indicated firm, for the survey wave, and for indicators for whether the respective controls are missing. Columns 1–3 replace log driving distance with quadratic driving distance (1), log point-to-point distance (2), or log distance to the firm's closest establishment (3). Columns 4–5 restrict the sample to initial and follow-up survey waves, respectively. Columns 1–5 use sampling weights; Column 6 is unweighted; Column 7 is reweighted to match the German full-time population. Standard errors are clustered at the worker level. Elasticities of consideration with respect to pay expectation (evaluated at the mean) are provided at the bottom. Levels of significance: * 10%, ** 5%, and *** 1%.

Table A4: Robustness of Switching Costs

	Alternative Specifications of Distance				Alternative Samples		Alternative Weighting	
	Log Distance	Quadratic in Distance	Direct Distance	Closest Establishment	Initial Survey Only	Follow-Up Only	Unweighted	Population Weights
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Researcher-Provided Firms							
Implied Switching Cost	0.112***	0.123***	0.113***	0.167***	0.142***	0.083***	0.127***	0.094***
	(0.019)	(0.011)	(0.019)	(0.011)	(0.025)	(0.023)	(0.007)	(0.022)
Observations	29961	29961	29961	29961	16594	13367	29961	29961
Number of Workers	7735	7735	7735	7735	4322	2351	7735	7735
	B. Worker-Provided Firms							
Implied Switching Cost	0.079***	0.078***	0.066***	0.072***	---	---	0.099***	0.059***
	(0.010)	(0.008)	(0.009)	(0.008)			(0.005)	(0.010)
Observations	15259	15259	17539	17539			15259	15259
Number of Workers	4784	4784	4796	4796			4784	4784

Note: This table describes the results of estimating a rank-ordered logit model model fit to workers' preferences over outside firms specified in the researcher-provided firm module (Panel A) or the worker-provided firm module (Panel B). The model includes controls for the randomized raise of the outside firm, an indicator for whether the worker currently works at that firm, and the log driving distance between that firm and the worker's current place of work. Columns 2 to 4 use alternative distance metrics: quadratic driving distance (2), log point-to-point distance (3), and log distance to the closest firm establishment (4). Columns 5 and 6 restrict the sample to initial and follow-up survey waves, respectively. Columns 1 to 6 use sampling weights; Column 7 is unweighted; Column 8 re-weights to match the German full-time population. Levels of significance: * 10%, ** 5%, and *** 1%.

B Additional Results and Robustness Checks

B.1 Robustness to Alternative Weighting Schemes

Our main analysis uses survey weights to account for the fact that we over-sampled workers from firms that participated in a firm survey studied in Caldwell, Haegele and Heining (2024). However, our results are robust re-weighting the sample to match the overall population of regular full-time workers in Germany. We use the following variables to match our sample: female, labor market experience, federal state, German citizenship, occupational group (i.e., labor market entrant, experienced non-manager, manager), industry (i.e., manufacturing, retail, professional), and pay.

Results in Section 3. Appendix Table B1 shows how reweighting changes sample composition.

Table B1: Characteristics of Surveyed Workers: Reweighted

	Unweighted			Sampling Weights		Population Weights	
	Mean	Std. Dev.	N	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demographics							
Female	0.31	(0.46)	9756	0.40	(0.49)	0.38	(0.49)
Age	33.35	(6.23)	9756	31.13	(5.18)	34.98	(7.31)
German Citizen	0.92	(0.27)	9756	0.89	(0.32)	0.97	(0.16)
College Degree	0.60	(0.49)	9756	0.53	(0.50)	0.37	(0.48)
Apprenticeship	0.33	(0.47)	9756	0.37	(0.48)	0.55	(0.50)
Employment							
Daily Pay (Allocated)	170.80	(57.50)	9756	136.06	(47.81)	126.27	(63.66)
Censored Pay	0.22	(0.41)	9756	0.06	(0.24)	0.11	(0.31)
Hours (Survey)	40.27	(5.99)	9756	40.36	(6.47)	39.54	(7.44)
CBA Covered (Survey)	0.59	(0.49)	9547	0.48	(0.50)	0.49	(0.50)
Manufacturing Sector	0.47	(0.50)	9756	0.22	(0.41)	0.29	(0.45)
Retail Sector	0.09	(0.28)	9756	0.09	(0.29)	0.11	(0.31)
Professional Sector	0.13	(0.34)	9756	0.15	(0.36)	0.04	(0.20)
Observations				9756			

Note: This table describes the individuals in our sample under different weighting schemes, indicated in each column.

Results in Section 4. Appendix Table B2 shows that our finding that many workers were informed about pay at the time they applied to their current firm is robust to re-weighting: our main specification says 45% said firm-specific information, we obtain 44% using population weights. Appendix Table B3 shows that, after re-weighting, we still find that workers perceive a heterogeneous (in pay) outside option.

Table B3: Variation in Expected Pay at Other Firms: Robustness to Reweighting

	Fraction Identical			
	Baseline	Unweighted	Population Weights	N
	(1)	(2)	(3)	(4)
A. Researcher-Provided Firms				
Initial Survey	0.26	0.23	0.25	3518
Follow-Up Survey	0.30	0.26	0.37	3057
B. Worker-Provided Firms				
All Workers	0.25	0.26	0.28	4305
All in Same State	0.22	0.27	0.34	507
All in Same District	0.26	0.33	0.43	172
All in Same Municipality	0.22	0.34	0.43	158

Note: This table presents re-weighted results analogous to those in Table 3. Column 1 presents our baseline specification. Columns 2 and 3 present unweighted and population-weighted results, respectively.

Table B2: Stated Knowledge at Time of Application: Robustness to Reweighting

	Knew Pay in Position at This Company		Rough Idea of Pay in Industry or	Little or No	
	Exactly	Rough Idea	Region	Idea	Obs
	(1)	(2)	(3)	(4)	(5)
Baseline	18%	27%	29%	26%	9756
Unweighted	14%	36%	29%	22%	9756
Population Weights	13%	31%	26%	30%	9756

Note: The first row is the baseline specification (Figure 2). Rows 2 and 3 present unweighted and population-weighted results, respectively.

Results in Section 5. Appendix Table A3 documents that our results on search in Section 5.1 of the main text are robust to re-weighting. Appendix Table B4 below confirms that the results from the two alternative designs (Section 5.2) are also robust.

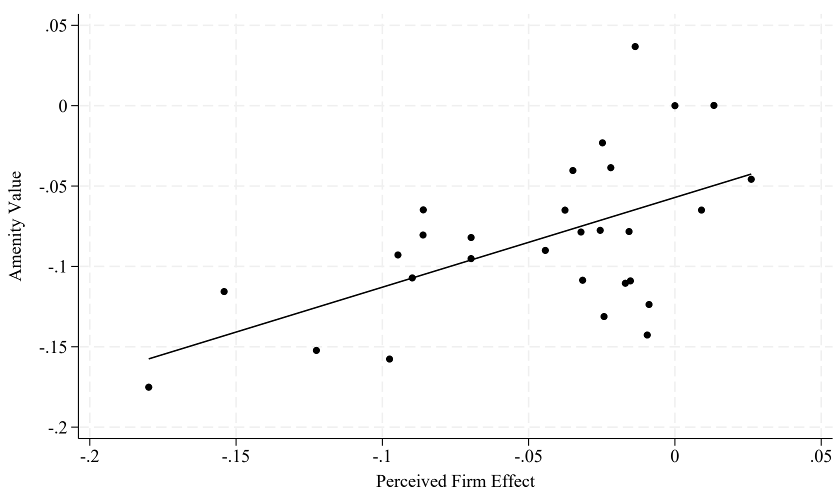
Results in Section 6. Appendix Table A4 shows that our main estimates of switching costs are robust reweighting. Appendix Figure B1 and Appendix Table B5 show other core results are robust to population weighting.

Table B4: Alternative Designs Linking Pay Expectations and Consideration: Robustness

	Stated Consideration			Free-Text Responses		
	Sample Weights	Unweighted	Population Weights	Sample Weights	Unweighted	Population Weights
	(1)	(2)	(3)	(4)	(5)	(6)
Mean of Dependent Variable						
	A. Perceived Firm Effect (Split-Sample)					
Firm Premium (Split-Sample)	0.986***	1.309***	0.457***	0.101***	0.161***	0.034***
	(0.127)	(0.127)	(0.127)	(0.013)	(0.013)	(0.013)
Observations	89742	89742	89742	224388	224388	224388
Number of Workers	9756	9756	9756	9756	9756	9756
	B. Observed Firm Effect					
Firm Premium (Observed)	0.173***	0.245***	0.087	0.014***	0.012***	0.011**
	(0.035)	(0.021)	(0.061)	(0.005)	(0.004)	(0.005)
Observations	89258	89258	89258	214632	214632	214632
Number of Workers	9756	9756	9756	9756	9756	9756
	C. Observed Log(Mean Daily Pay)					
Firm Mean Daily Pay	0.093***	0.149***	0.088***	0.008***	0.010***	0.006***
	(0.011)	(0.007)	(0.020)	(0.002)	(0.001)	(0.002)
Observations	89258	89258	89258	214632	214632	214632
Number of Workers	9756	9756	9756	9756	9756	9756

Note: This table probes the robustness of results in Table 6, which uses sampling weights, to no weighting (Columns 2 and 5) and population weights (Columns 3 and 6). Estimation details are in Section 5.2. Standard errors are clustered at the worker level. Levels of significance: * 10%, ** 5%, and *** 1%.

Figure B1: Perceived Pay Premia and Amenity Valuations: Robustness to Population Weighting



Note: This figure compares estimates of the perceived value of firm-specific amenities ($\frac{a_j}{\beta}$) and the perceived pay premia (ψ_j) for each of the researcher-provided firms. The methodology is described in Figure 6, but we replace sample weights with population weights. The line is a simple line of best fit. After accounting for their estimates' reliability, the slope of the regression is 0.602 with a standard error of 0.191.

Table B5: Firm-Specific Preferences: Robustness to Population Weighting

	Outside Firms Only		All Firms		Consider or Incumbent Only
	(1)	(2)	(3)	(4)	(5)
Log Raise (β)	9.723***	15.561***	7.008***	9.594***	16.260***
	(3.131)	(3.235)	(2.461)	(2.247)	(4.157)
Observations	4217	4217	5671	5671	3001
Number of Workers (Clusters)	1177	1177	1200	1200	1192
Test: Ex Ante Firm Effects are Zero					
p-value	<.001	<.001	<.001	<.001	<.001
Chi-Squared Statistic	207.258	187.988	188.388	131.007	70.891
Degrees of Freedom	29	29	29	29	29
Test: Ex Ante Effects For Those Who Would and Would Not Apply Are Equal					
p-value		<.001		<.001	
Chi-Squared Statistic		164.417		209.519	
Degrees of Freedom		30		30	
Test: Ex Post Effects = Ex Ante Effects					
p-value			<.001	<.001	<.001
Chi-Squared Statistic			7244.552	5500.808	6557.928
Degrees of Freedom			17	17	16
Test: Ex Post Effects = Ex Ante Effects For Those Who Would Apply					
p-value				<.001	
Chi-Squared Statistic				51603.366	
Degrees of Freedom				80	

Note: This table presents results analogous to Table 9, in which the regressions are weighted to match the overall population of full-time German workers. We provide more details on estimation in Section 6. Standard errors are clustered at the worker level.

B.2 Robustness to Alternative Winsorization Schemes

Our preferred specifications winsorize workers' pay expectations at the 90% level. For most of our analysis this represents a conservative assumption. Our decision to winsorize expectations, for instance, leads us to underestimate the amount of within-worker variation in pay; this biases us against our finding that workers believe in a heterogeneous outside option.

The main piece of analysis which could be influenced by this decision is our analysis of the agreement in the firm pay premia between different demographic groups (Table 4). Intuitively, by reducing the variation in workers' expectations, winsorization could lead us to over-state the amount of agreement. Appendix Table B6 shows that we continue to find agreement in the perceived pay premia across demographic groups when using the raw elicitations (Column 1), winsorizing at the 98% level (Column 2), or trimming at the 98% level (Column 4).[40]

[40] In unreported results we have probed the robustness of other findings to these decisions.

Table B6: Correlation in Perceived Pay Premia: Robustness to Data Cleaning

	Raw	98% Winsor	90% Winsor	98% Trim	90% Trim
	(1)	(2)	(3)	(4)	(5)
Split-Sample	0.67	0.67	0.98	0.92	0.99
Sex	0.43	0.44	0.93	0.91	0.96
CBA	0.48	0.51	0.96	0.94	0.98
College Education	0.52	0.53	0.97	0.96	0.98
Current Firm AKM Effect (Split at Median)	0.65	0.63	0.95	0.91	0.98
Searched in Past 6 Mo.	0.49	0.49	0.96	0.95	0.99
Knew Wages at Application	0.61	0.64	0.97	0.96	0.99
Easy to Get a Better Job	0.60	0.59	0.98	0.95	0.98
Tenure (Split at 2 Years)	0.31	0.34	0.96	0.96	0.99

Note: This table looks at the correlation in the estimates of ψ_j as estimated by fitting equation 8 for different samples of workers (indicated in each row) under different data cleaning procedures (indicated in each column). Column 1 uses workers' raw pay expectations. Columns 2 and 3 (our baseline) use winsorized pay expectations. Columns 4 and 5 use trimmed pay expectations.

B.3 Provision of Worker-Provided Firms and Pay Responsiveness

Most of our analysis relies on the researcher-provided firm module. However, we also present several specifications which rely on data from the worker-provided firm module of the initial survey. Appendix Table B7 shows that, if anything, workers who do not provide firm names are less responsive to changes in outside pay, suggesting that, if anything, analysis based on this module may understate the extent to which workers are infra-marginal to their firm. Column 1 presents search elasticities; Columns 2 and 3 show separation elasticities based on the researcher-provided firm module.

Table B7: Stated Mobility Preferences and Provision of Firms

			Researcher-Provided Firm Module			
	Search		Baseline		Same Commute	
	(1)		(2)		(3)	
Provided Specific Firm Names	0.08	***	1.61	**	1.94	***
	0.01		0.68		0.72	
	1986		11898		5715	
Did Not Provide Specific Firm Names	0.08		0.83		1.69	**
	0.01		0.66		0.75	
	1571		9974		4202	

Note: This table presents search (Column 1) and separation (Columns 2 and 3) elasticities for workers who did (Row 1) and did not (Row 2) provide names of specific firms in the worker-provided firm module. Column 1 uses data from the search question in the follow-up survey. Columns 2 and 3 use data from the discrete choice experiments including researcher-provided firms. Standard errors are computed using the delta method. Levels of significance: * 10%, ** 5%, and *** 1%.

B.4 Workers Believe Firms Vary in Amenities: Robustness

Section 6.3 documents that workers believe firms vary in pay and non-pay characteristics. In the follow-up survey, we embedded additional discrete choice experiments, which allow us to confirm that this workers' believe this is true even when the training and learning opportunities would be the same at each of the outside firms.[41] We fit our baseline rank-ordered logit model to workers' preferences—as elicited in these experiments—using only the rankings on outside firms (i.e. excluding the incumbent). Appendix Table B8 shows that, across all models, we can reject the null that there are no unobserved firm-specific factors such as amenities which drive workers' preferences (beyond those we specified would remain the same).

Table B8: Workers Have Firm-Specific Preferences: Robustness

	Follow-Up Survey		
	Baseline	Same Growth	Same Training and Learning Opportunities
	(1)	(2)	(3)
Log Raise (β)	8.395***	8.941***	8.290***
	(0.800)	(0.815)	(0.763)
Observations	10012	9971	10001
Number of Workers (Clusters)	3375	3352	3363
Test: Ex Ante Firm Effects are Zero			
p-value	<.001	<.001	<.001
Chi-Squared Statistic	279.112	324.183	300.252
Degrees of Freedom	27	27	27

Note: This table presents logit coefficients (first row) and p-values and test statistics (remaining rows) from fitting a rank-ordered logit model to workers' stated preferences in the discrete choice experiments in the follow-up survey that include researcher-provided firms. The data include workers' choices over outside firms in the baseline scenario (Column 1), if the firms provided equal the training and learning opportunities (Column 2) or if their work would stay constant (Column 3). Regressions use sampling weights.

B.5 Robustness to Allowing for Preference Heterogeneity

To allow for preference heterogeneity, we estimated a random coefficient model allowing variation in workers' wage and commute preferences. Table B9 shows there is substantial variation in preferences. However, the valuations are similar to those of our baseline model ($\rho = 0.91$) and we continue to see a positive correlation between perceived premia and amenity valuations.

[41] We included similar discrete choice experiments in the initial survey, but only for the worker-provided firms.

Table B9: Random Coefficient Model Estimates

	Estimate (1)	Standard Error (2)
Model Estimates		
Mean		
Log(Wages)	15.71	0.81
Log(Distance)	-0.32	0.03
Variance		
Log(Wages)	353.99	1.54
Log(Distance)	0.05	0.04
Correlations		
With Baseline Amenity Values	0.91	
With Baseline Perceived Premia	0.73	
Comparison Values		
Correlation Between Baseline Amenities and Premia	0.58	

Note: This table presents the estimates and standard errors from fitting a random coefficient rank-ordered model to workers' stated preferences over outside researcher-provided firms. The model includes the randomized raise, for the log distance between the worker and the firm, for the order in which the firm was presented, and for firm fixed effects. We allow preferences on distance and wages to be heterogeneous.

B.6 Expected Impacts of Information Treatments

We calculate the potential impacts of information treatments under alternative definitions of whether a worker is informed. We fit OLS regression models to workers' stated search and stated mobility choices, as elicited in the worker-provided firm module (preferred firm) or researcher-provided firm module (random firm). We assume that informed workers do not change their behavior; uninformed workers increase their search or mobility by the amount predicted by the regression model (i.e. the slope, multiplied by the information treatment).[42]

Appendix Table B10 shows that, if no workers are informed, telling workers they could increase their pay by an amount equal to the gap between the median pay premium firm and their current firm $\left(\psi^{\text{med}} - \psi_{j(i)}\right)$ would increase search by 19 percentage points. This shrinks to 5 to 6 percentage points if workers who knew pay when they applied to their current firm (Column 2) or who believe it would be easy to find a better job (Column 3) are informed. This further shrinks to less than 2 percentage points if workers who believe in a heterogeneous outside option are informed (Column 4). Search may not translate into mobility: under realistic assumptions on information, the increase in mobility is closer to 1 to 3 percentage points for workers' preferred firms.[43]

[42] Our predicted impacts on search and mobility likely overstate the impact of information treatments for two reasons. First, we implicitly assume that all workers can obtain jobs with the pay raises that we assign. Second, we ignore the role that firm-specific beliefs play; as outlined in Section 2, workers may search if they have optimistic beliefs about a single firm.

[43] For the worker-provided firm module, we can only estimate this model for workers who provided the names of specific firms. Because—as we document in a separate section—workers who did not provide the names of specific firms are more attached to their firm—this means that we will overstate the impacts of providing information to all workers when we extrapolate from this sample.

Table B10: Changes in Search or Mobility and Information Provision

	All Workers Are Uninformed	Did Not Know Pay at Application	Difficult to Get a Better Job	Provide Uniform Pay
	(1)	(2)	(3)	(4)
Percent Informed	0	49.826***	44.107***	77.288***
	---	(0.854)	(0.897)	(1.131)
P(Search)	17.606***	4.867***	4.356***	2.048***
	(2.504)	(0.761)	(0.758)	(0.472)
P(Move to a Preferred Firm)	11.837***	2.784***	2.579***	1.486***
	(2.904)	(0.789)	(0.675)	(0.453)
P(Move to a Random Firm)	1.127	0.837*	0.963**	0.741**
	(1.761)	(0.475)	(0.454)	(0.294)

Note: The first row shows the percent of informed workers across different definitions. The remaining rows present the predicted impact on search or mobility. The sample includes workers who work at firms with below-median pay premia. Coefficients and standard errors are estimated via 200 bootstrap replications. Levels of significance: * 10%, ** 5%, and *** 1%.

C Relationship with Findings in Jäger et al. (2024)

A natural question arises as to why our results—demonstrating that workers possess detailed, firm-specific information about outside wages—differ from Jäger et al. (2024) (JRRS), who report that workers often have limited or inaccurate information about outside options. Our findings align with Guo (2025), who also documents accurate worker perceptions of external wage offers.

In this section, we explain the differences in the studies. We focus on two key elements. First, JRRS elicited a measure which combines beliefs about pay with beliefs about offer rates and preferences. By contrast, we elicited a measure of beliefs about pay. We provide a speculative reconciliation of the findings by noting that workers at low-wage firms receive offers at lower rates than similar workers at high-wage firms; this is true both among searchers and non-searchers. Our findings echo those from the literature (Faberman et al., 2022; Faberman, Mueller and Şahin, 2025) which has shown that heterogeneity in the intensity and productivity of search can resolve several puzzles in the literature. Second, we note it is difficult to separate survey anchoring (due to priming or question order effects) from true anchoring in beliefs.

C.1 Similarity of Empirical Settings

JRRS use two samples for their analysis: (1) a sample of 1,068 German job-seekers surveyed in the German Socio-Economic Panel (GSEOP) and (2) a sample of German workers recruited via internet panels. JRRS use the first dataset to describe workers' beliefs about outside options; they use the second to present experimental evidence on the relationship between biased beliefs and search and to replicate their findings on anchoring. Our sample (13,680 workers surveyed by the Institute for Employment Research) is similar to the first dataset.

C.2 Differences in What and How Beliefs are Elicited

A key result in JRRS is that "workers wrongly anchor their beliefs about outside options on their current wage" (abstract). Specifically, they report that a large share of workers (41%) believe they would earn the "same pay" at their outside option. In the GSOEP module, they first asked workers whether workers who switch jobs (to or from their employer) receive the "same pay" or "higher pay" or "lower pay" (with follow-up questions if they did not indicate the worker would receive the same pay); they then asked a similar question about whether the worker themself would earn the "same pay" at another employer if forced to switch firms. In the internet panel, they first asked what a worker currently made and then (immediately afterwards) asked what they thought they would make if forced to switch firms (Appendix Section C.5).

Differences in Approach. We differ both in what we elicit and in methodology. First, because we were interested in beliefs about pay (and how these varied across outside firms), we directly asked workers how much they believed they would earn if employed at each of three specific outside firms. These questions did not require assumptions about offer probabilities or other workers' preferences. By contrast, to form a belief about the expected wage following a forced job-to-job transition, workers must consider both the wages at outside firms and the probability they receive an offer from those firms. To form a belief about the wage changes of movers, workers must consider both these factors, as well as what factors lead workers to switch jobs and what factors workers consider when weighing outside offers.[44]

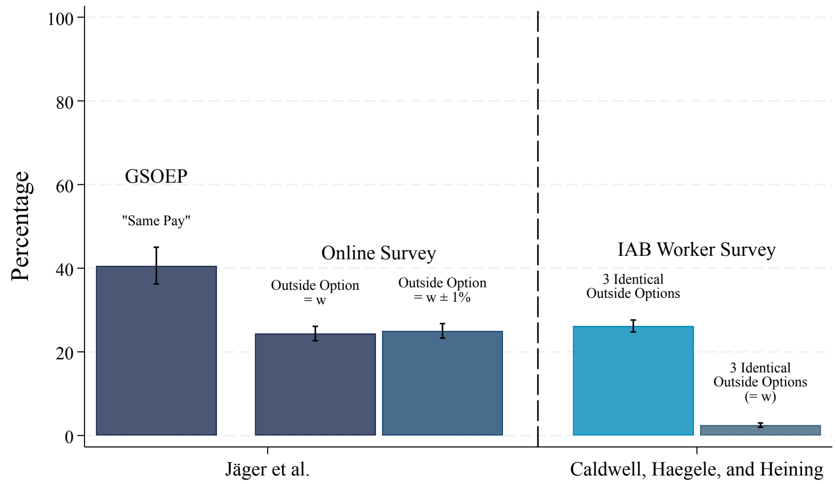
Second, because we could link all responses to administrative records, we did not ask respondents for their current salary. Research demonstrates that survey respondents anchor responses to previously provided or elicited numbers, even if those numbers are arbitrary or irrelevant (Tversky and Kahneman, 1974). Standard textbooks on survey methodology caution that priming effects can significantly affect responses (Schwarz, 1999; Dillman, Smyth and Christian, 2014). This suggests that eliciting a worker's current wage before eliciting their expectation about outside wages—as was done in the Internet panel used to provide a causal link between beliefs and search—would lead respondents to anchor to this number.

Comparison of Results. Appendix Figure C1 compares the extent of anchoring across the two studies. The first bar shows that 41% of workers in the GSOEP panel selected the "same pay" option. Their internet panel exhibits much lower anchoring, with fewer respondents exactly matching their outside wage expectations to their current pay (second and third bars). Differences observed between the GSOEP and internet panel samples may arise from several factors, including population differences or the precise interpretation respondents gave to the phrase "same pay"—whether respondents understood this literally or interpreted it more loosely, as within a monetary range. In our data, the share of respondents reporting identical wage expectations across different outside firms (fourth bar) is similar to the internet panel from JRRS.

Survey-induced anchoring occurs when respondents provide answers which are more similar (or, the same) to responses they have previously provided. Because JRRS asked internet respondents (the sample used for their experiment) for their current wage immediately before asking for

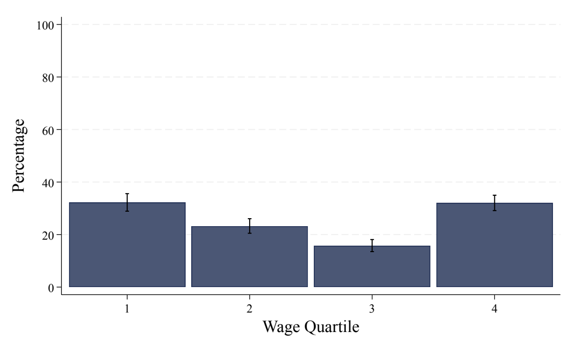
[44] We did collect a summary measure—the perceived ease with which workers could find a more preferred job elsewhere—which aligns somewhat more closely with that in JRRS, which we discuss below.

Figure C1: Comparison of Anchoring Behavior



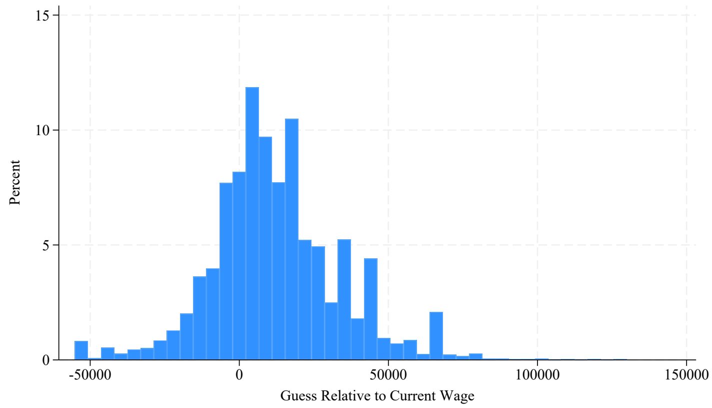
Note: This figure compares our estimates (right of the dashed line) of the prevalence of anchoring (measured as indicated above each bar) to those in Jäger et al. (2024) (left of the dashed line).

Figure C2: Share of Workers Reporting Identical Salaries: Heterogeneity by Wage



Note: This figure presents our estimates of the prevalence of anchoring (measured as the share of respondents indicating the same expected wage at all three outside options) by wage quartile.

Figure C3: Anchoring in Beliefs at Workers' Current Salary



Note: This figure plots the difference between workers' expected pay at outside firms, relative to their pay at their current firm.

their outside option pay, it is natural to think that any survey-induced anchoring will lead respondents to provide beliefs which are anchored to this number. Because we asked respondents for the wage they expect at each of three outside firms, it is natural to expect respondents may anchor beliefs to the first number they provide.[45] A comparison of the third and fourth bar indicates that workers who provide the same three numbers do not typically provide their wage (not elicited in this survey). Appendix Figure C2 reveals minimal heterogeneity in the proportion of respondents reporting identical salaries across different wage groups. Appendix Figure C3 illustrates the distribution of the difference between workers' firm-specific wage expectations and their current salaries; this figure shows we do not see a spike in pay expectations precisely at respondents' current wage. Although the distribution is centered around zero, it is smoothly bell-shaped, displaying no substantial clustering at zero.

C.3 Economic Explanation for Differences in Findings

Setting aside potential issues with survey anchoring, there is a coherent economic story—the combination of Bayesian updating about wages with heterogeneity in offer probabilities—which can plausibly reconcile the descriptive results in both studies.

JRRS (Section IV.C) suggest Bayesian updating as a potential explanation: workers rationally incorporate their own wage experience and skill into their beliefs about outside pay. This would explain why workers provide more accurate estimates about their own potential wages (as elicited directly in our study) compared to the realized pay changes of other workers or their own pay given a forced transition (as elicited in their study). As discussed in JRRS, aside from the finding that workers in low-wage jobs disproportionately underestimate outside pay, Bayesian updating accounts for the empirical patterns.

Rational pessimism about offer probabilities—heterogeneous by firm wage premium—could

[45] Any survey-induced anchoring in our survey would reduce the variance in perceived wage premia and thus bias our analysis against detecting that workers perceive systematic firm wage premia and actively direct their search based on expected pay differences—central results we robustly document.

Table C1: Search Productivity by Firm Wage Premium

	All			Recent Search	
				No	Yes
	(1)	(2)	(3)	(4)	(5)
	A. Received Job Information				
Current Firm Wage Effect	0.377***	0.182***	0.179**	0.212*	0.231***
	(0.055)	(0.057)	(0.069)	(0.118)	(0.081)
Person Wage Effect			0.048*	0.155**	0.030
			(0.028)	(0.064)	(0.030)
Observations	9319	9319	7506	2065	5441
	B. Received Information or Offer				
Current Firm Wage Effect	0.295***	0.133**	0.104	0.062	0.196**
	(0.052)	(0.055)	(0.071)	(0.145)	(0.079)
Person Wage Effect			0.015	0.179***	-0.014
			(0.026)	(0.065)	(0.027)
Observations	9319	9319	7506	2065	5441

Note: This table examines the relationship between the wage premium of a worker's firm and whether they received information on outside jobs in the previous six months (Panel A) or whether they either received such information or a job offer (Panel B). Column 1 presents results from a bivariate regression; Columns 2-5 include controls for experience and for education and occupation dummies. Columns 3-5 control for the person effect from an AKM wage regression. Columns 4–5 split by whether a worker has searched for employment in the previous six months. Regressions use sampling weights. Levels of significance: * 10%, ** 5%, and *** 1%.

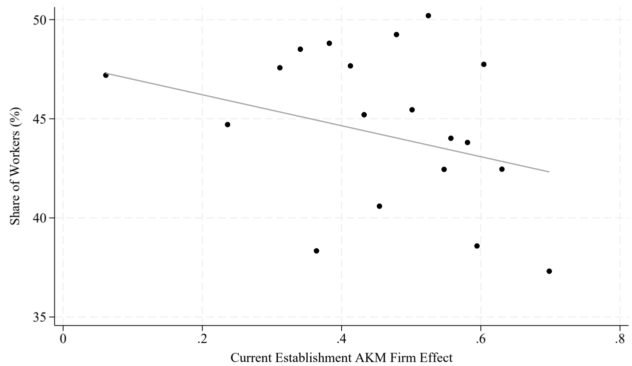
reconcile the results of the two studies. Appendix Table C1 shows that, conditional on education, occupation, and experience, workers at low-wage firms receive significantly fewer job offers and less job-related information than similar workers at higher-wage firms (Column 2). This pattern is robust to controlling for unobserved differences in worker skill by controlling for the AKM worker effects (Column 3) and to focusing on workers who are not actively searching (Column 4).[46] This explanation is also consistent with the finding by Miano (2023) that information treatments on search difficulty affect behavior, while information treatments on wages do not.

C.4 Additional Result: Summary Measure of Outside Options

We also elicited a summary measure: how easy a worker believed it would be to get a better job. Caldwell, Haegele and Heining (2024) show this correlates with objective measures of outside options (Online Appendix Table A8) and predicts pay renegotiation (Table 5). Appendix Figure C4 shows that workers at lower-wage firms are generically more optimistic about the ease with which they could find a preferred job than workers at higher-wage firms.

[46]This pattern echoes findings in a large literature which has documented differences in the productivity of search (typically higher among employed than unemployed workers) and showed that these differences explain several other puzzles in the literature (Faberman et al., 2022; Faberman, Mueller and Şahin, 2025; Cederlöf et al., 2025).

Figure C4: Share of Workers Who Believe it Would be “Easy” To Get a Better Job



Note: This is a binned scatterplot of whether a worker said it would be “easy” to find a job they would prefer to their current position against their current AKM firm effect.

C.5 Jäger et al. (2024) Belief Elicitations

In the GSOEP JRRS elicited beliefs as follows:

3. **Beliefs About Firm Pay** Think of the typical employee with work experience that switches from another employer to your employer. Would this employee receive a lower, higher or the same pay compared to his previous employer?

   - Higher pay
   - Same pay
   - Lower pay

   [Asked only if previous answer is not “Same pay”] How much lower/higher would the monthly pay before taxes of this employee be (in percent) after the switch compared to his/her prior employer?

   - Between 0% and 2%
   - Between 2% and 5%

   ⋮

   - Between 50% and 75%
   - More than 75% (in data normalized to 87.5%)

   Think of the typical employee with work experience that switches from your current employer to another employer. Would this employee receive a lower, higher or the same pay compared to his previous employer?

   - Higher pay
   - Same pay
   - Lower pay

   [Asked only if previous answer is not “Same pay”] How much lower/higher would the monthly pay before taxes of this employee be (in percent) after the switch compared to his/her prior employer?

   - Between 0% and 2%
   - Between 2% and 5%

   ⋮

   - Between 50% and 75%
   - More than 75% (in data normalized to 87.5%)

11. **Posterior About Outside Option: Point Belief** Imagine that you were forced to leave your current job and that you had 3 months to find a job at another employer in the same occupation. Do you think that you would find a job that would offer you a higher overall pay, the same pay or a lower pay?
    - Higher pay
    - Same pay
    - Lower pay

    [Asked only if previous answer is not "Same pay"] What do you think: how much more/less would you earn in that new job?
    - Between 0 and 50 EUR
    - Between 50 and 100 EUR

      ⋮
    - Between 2000 and 3000 EUR
    - More than 3000 EUR (in data normalized to 3500 EUR)

In the online survey, they elicited beliefs in a single step, immediately after eliciting current wages:

4. **Wage Income** How high is your current monthly gross income from work in EUR before taxes?

    __EUR
5. **Beliefs About Personal Outside Option** Imagine that you were forced to leave your current job and that you had 3 months to find a job at another employer. In the job with another employer, how much would you receive per month as gross employment income in EUR?

    __EUR

D Theoretical Appendix

Define

$$\begin{aligned}\widetilde{V}_{ik} &= \widetilde{u}_{ik} &(12)\\ &+ \max_{A\subseteq\mathcal{J}\setminus\{k\}}\Big\{-\kappa|A| + \delta\,\mathbb{E}_{B(A)}\big[(1-\lambda)\max\{\widetilde{V}_{ik}, \max_{m\in B(A)}(\widetilde{V}_{im}-s_i)\} &(13)\\ &\qquad + \lambda\max\{V_{i0,t+1}, \max_{m\in B(A)}(\widetilde{V}_{im}-s_i)\}\big]\Big\}. &(14)\end{aligned}$$

Lemma. *Contraction Mapping*

The operator $\mathcal{T}$ that maps a bounded function V to the right-hand side of the above Bellman equation is a contraction on $(\mathcal{X}, \|\cdot\|_\infty)$ with modulus δ. Hence a unique bounded fixed point $\widetilde{V}$ exists.

Proof. Let $V, V' \in \mathcal{X}$. For any state s, the difference $|(\mathcal{T}V)(s) - (\mathcal{T}V')(s)| \le \delta\,\mathbb{E}\big[\|(V - V')(s')\|_\infty\big] \le \delta\|V - V'\|_\infty$. Taking sup over s yields $\|\mathcal{T}V - \mathcal{T}V'\|_\infty \le \delta\|V - V'\|_\infty$. Because $\delta < 1$, Banach's fixed-point theorem applies. □

Prediction 1: Probability of Searching Increases with Increased Perceived Outside Options and Decreased Switching Costs *If any $\tilde{V}_{ik}$ increases, the probability that worker i chooses a non-empty application set $A \neq \emptyset$ weakly increases. Equivalently, a worker's incentive to search is (weakly) increasing in her perceived outside options.*

Proof Sketch.

1. *Define search vs. no-search.* Let $\Phi(\{\tilde{V}_{ij}\})$ be the *maximum* expected payoff over all $A \subseteq \mathcal{J} \setminus \{j\}$, net of application costs. That is,

$$\Phi(\{V_{ij}\}) = \max_{A \subseteq \mathcal{J} \setminus \{j\}} \Bigg\{ -\kappa\,|A| \;+\; \delta\,\mathbb{E}_{B(A)}\Big[(1-\lambda)\,\max\Big\{\overbrace{\tilde{V}_{ik}}^{\text{stay}},\; \overbrace{\max_{m \in B(A)}\big(\tilde{V}_{im} - s_i\big)}^{\text{switch employers}}\Big\} + \lambda\,\max\Big\{\underbrace{V_{i0}}_{\text{unemployed}},\; \underbrace{\max_{m \in B(A)}\big(\tilde{V}_{im} - s_i\big)}_{\text{switch employers}}\Big\}\Big]\Bigg\}.$$

If the worker ends up choosing $A = \emptyset$, it means:

$$\emptyset \in \operatorname*{argmax}_{A \subseteq \mathcal{J} \setminus \{j\}} \Bigg\{ -\kappa\,|A| \;+\; \delta\,\mathbb{E}_{B(A)}\Big[(1-\lambda)\,\max\Big\{\overbrace{\tilde{V}_{ik}}^{\text{stay}},\; \overbrace{\max_{m \in B(A)}\big(\tilde{V}_{im} - s_i\big)}^{\text{switch employers}}\Big\} + \lambda\,\max\Big\{\underbrace{V_{i0}}_{\text{unemployed}},\; \underbrace{\max_{m \in B(A)}\big(\tilde{V}_{im} - s_i\big)}_{\text{switch employers}}\Big\}\Big]\Bigg\}.$$

2. *Increase some $\tilde{V}_{ik}$.* Suppose $\tilde{V}_{ik}$ rises. The payoff from any set A that includes k increases, since with probability $p_k > 0$ the worker may receive the offer. The payoff from any set that does not include k is unchanged. Thus the *optimal* objective, Φ weakly increases.r
3. *Hence, search is at least as likely.* If the worker did not find any profitable $A \neq \emptyset$ before, a rise in $\tilde{V}_{ik}$ may make some A' profitable.
4. Notice that the same argument works when s_i is reduced.

Prediction 2: Fewer Mistaken Non-Search Outcomes Under Directed Search *When workers have firm-specific beliefs $\{\tilde{V}_{ik}\}$, they are less likely to fail to search when at least one firm is potentially profitable. By contrast, if they cannot match beliefs to firm identities, they may not search even when a single high-value firm would justify searching.*

Proof Sketch.

1. Consider two otherwise identical workers who differ in whether or not they can match beliefs to firm identities. The worker who cannot assign beliefs to firms searches when the expected payoff exceeds the cost, κ:

$$\delta \frac{1}{J} \sum_k p_k[(1-\lambda)\max(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{ik} - s_i - V_{i0}, 0)] > \kappa. \tag{15}$$

The worker who can assign beliefs to firm identities searches when

$$\max_k \Big\{ \delta p_k [(1-\lambda)\text{max}(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \text{max}(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \Big\} > \kappa \tag{16}$$

2. Define mistaken non-search as a case where the worker fails to search (the corresponding inequality above fails), but the search is worthwhile under full information. Suppose the directed searcher (the second worker) fails to search. Then

$$l \in \underset{k}{\text{argmax}} \Big\{ \delta p_k [(1-\lambda)\text{max}(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \text{max}(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \Big\} \tag{17}$$

$$\delta p_l [(1-\lambda) \max(\tilde{V}_{il} - s_i - V_{ij,t+1}, 0) + \lambda \max(\tilde{V}_{il} - s_i - V_{i0}, 0)] \leq \kappa \tag{18}$$

This implies the non-directed searcher also fails to search because:

$$\begin{aligned} &\delta \frac{1}{J} \sum_k p_k [(1-\lambda) \max(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \\ &\leq \delta \frac{1}{J} \sum_k p_l [(1-\lambda) \max(\tilde{V}_{il} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{il} - s_i - V_{i0}, 0)] \\ &= \delta p_l [(1-\lambda) \max(\tilde{V}_{il} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{il} - s_i - V_{i0}, 0)] \end{aligned} \tag{19}$$

3. Now consider the case where the non-directed searcher fails to search:

$$\delta \frac{1}{J} \sum_k p_k [(1-\lambda) \max(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \leq \kappa. \tag{20}$$

Suppose

$$l \in \underset{k}{\text{argmax}} \Big\{ \delta p_k [(1-\lambda)\text{max}(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \text{max}(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \Big\} \tag{21}$$

and that l is not a member of the set containing the corresponding $\arg\min$. Then, the expected value of applying to firm l is strictly greater than a random application. There is some level of κ such that the directed searcher searches:

$$\begin{aligned} &\delta \frac{1}{J} \sum_k p_k [(1-\lambda) \max(\tilde{V}_{ik} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{ik} - s_i - V_{i0}, 0)] \\ &\leq \kappa < \delta p_l [(1-\lambda) \max(\tilde{V}_{il} - s_i - V_{ij}, 0) + \lambda \max(\tilde{V}_{il} - s_i - V_{i0}, 0)]. \end{aligned} \tag{22}$$

Prediction 3: Directed Search Implies Higher Application Rates for Higher-Wage Firms, All Else Equal *If the worker engages in directed search*, then—holding amenities a_k and offer probabilities p_k constant—the probability of applying to firm k increases with $\tilde{w}_{ik}$. Conversely, if the worker believes all firms pay the same wage, then the probability of applying to a specific firm is uncorrelated with w_{ik}.

Proof Sketch.

1. *Worker's objective over sets A.* For each set $A \subseteq \mathcal{J} \setminus \{j\}$, define

$$U_j(A) \;=\; -\,\kappa\,|A| + \delta\mathbb{E}_{B(A)}\big[(1-\lambda)\max\{\max_{m\in B(A)}(\tilde{V}_{im}-s_i), V_{ij}) + \lambda\max\{\max_{m\in B(A)}\{(\tilde{V}_{im}-s_i)\}, V_{i0}\}\}\big].$$

   The worker picks A^* to maximize $U_j(A)$ given the probability distribution of offer sets B from each application set A.
2. *Incremental value of adding k.* Let $\Delta_{k;j,A} = U_j(A \cup \{k\}) - U_j(A)$. As $\tilde{w}_{ik}$ (and thus $\tilde{V}_{ik}$) increases, any state in which firm k extends an offer becomes more valuable. Hence $\Delta_{k;j,A}$ *weakly* increases.
3. *Probability of including k in A^*.* The event "$\text{Apply}_{ik} = 1$" means $k \in A^*$. Since A^* is chosen to maximize $U_j(\cdot)$, if $\Delta_{k;j,A^*}$ becomes positive after an increase in $\tilde{w}_{ik}$, the worker is more likely to include k. Hence Apply_{ikt} is weakly increasing in $\tilde{w}_{ik}$.
4. *No perceived variation.* If $\tilde{w}_{ik} = \bar{w}_i$ for all k, then workers do not base application decisions on the wages of individual firms at all, so the choice of A is uncorrelated with w_{ik}.

E Survey and Administrative Data

This appendix describes the survey modules designed for this paper, as well as the additional data sources. An additional survey appendix, available here, describes the logistics of inviting workers to the survey and response rates. Much of that material is included in the main text and appendix of Caldwell, Haegele and Heining (2024). The full text of the initial and follow-up surveys are available on the authors' websites.

E.1 Researcher-Provided and Worker-Provided Firm Modules

Two separate survey modules elicit firm-specific information from respondents. Appendix Figure E1 provides an overview of the survey flow. We randomized the provision of many of the follow-up questions to keep the length of the survey manageable. After workers provided the names of firms they would consider, we randomized them into three groups (with probability 50%, 25%, and 25%) and presented them with additional questions accordingly.

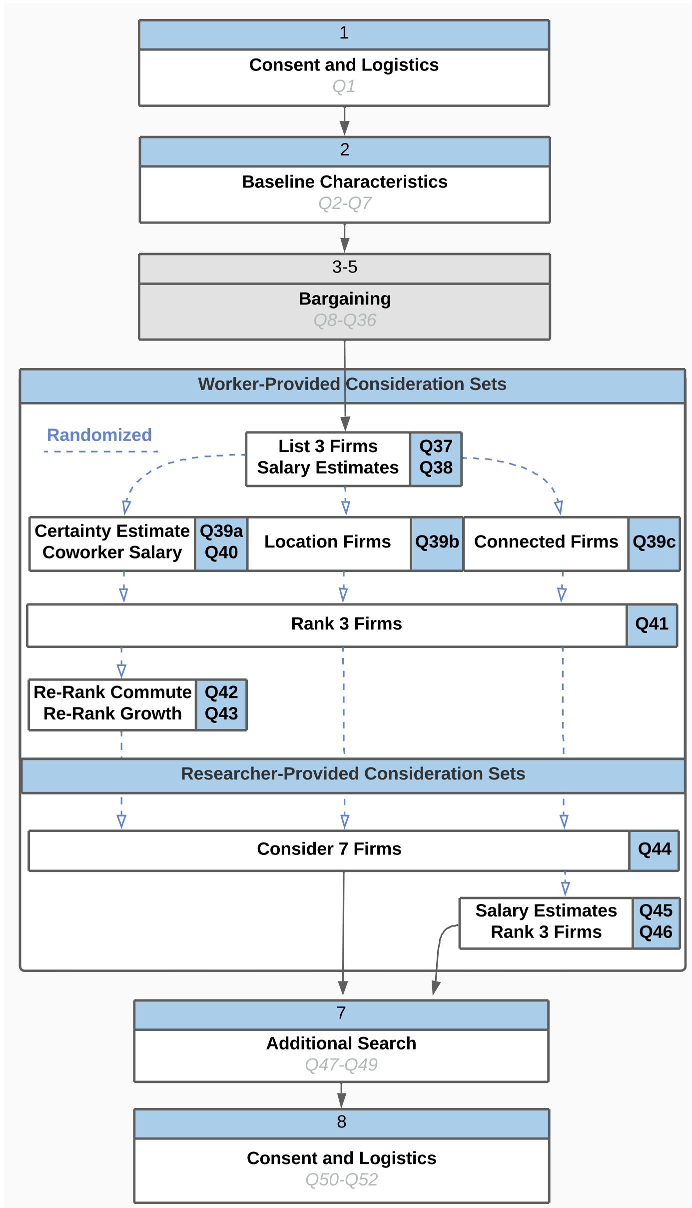
In the researcher-provided firm module we asked a random 50% of workers to provide their expected pay at and rankings over three researcher-provided firms. We selected these firms at random from the seven researcher-provided firms we provided in the question on consideration; whether a firm was selected was unrelated to whether a worker said they would consider applying.

The follow-up survey proceeded similarly. However, we only posed the worker-provided firm module to workers who declined to complete it in the initial wave. We posed researcher-provided firm questions on pay expectations and preferences to all workers in this wave.

E.1.1 Selecting Researcher-Provided Firms

We had to select a subset of German firms to ask workers about in the researcher-provided firm module. Due to IAB's strong confidentiality requirements, we could not select firms on the basis

Figure E1: Flow of the Initial Survey



Note: This figure provides an overview over the modules in the worker survey. The main questions used for our analysis are posed in the worker-provided and researcher-provided modules.

of firm-to-firm flows or networks.[47] Further, these requirements do not allow us to export the list of firms included in our final list from the IAB. We instead describe the systematic process through which we selected firms for inclusion in the survey.

Selection Process. To balance the criteria described in Section 3.3, we focused on 30 well-known German firms. We included 20 of these in the initial survey, and 30 in the follow-up survey. For the initial survey, we used two publicly-available lists of German firms to select our 20 firms: the top 40 publicly listed firms and the top 100 family-owned firms in Germany. While the first list contains large, well-known firms, the second list also includes somewhat smaller firms.

To select firms from these lists, we first grouped them by their industry. We prioritized firms that were in the six major industries covered by our worker sample.[48] Because manufacturing is by far the most important industry in our sample (69%), we included multiple manufacturing firms in our list. Second, we excluded firms with poor name recognition (e.g., those not known under their official name) or with ambiguous names. Third, within each industry, we prioritized firms that participated in our firm-survey on wage-setting (Caldwell, Haegele and Heining, 2024).[49] All of the 20 firms included in the initial wave of the survey can be linked to the Social Security records.

Initial Set of Firms. We verified that the final set of 20 firms included in the initial survey met the criteria listed above in two ways. First, we compared the firms to those provided by the 518 respondents to an IAB pilot conducted in February 2022. In that pilot, we asked respondents to name five firms that they would consider applying to if they were interested in switching firms. Ten of the 20 firms we selected were listed at least once. This test allows us to verify both that the firms we identified as well-known (from the publicly listed set) were likely to be self-reported by respondents and that the firms we believed to be lesser-known (from the family-owned set) were less likely to be listed. Second, to ensure familiarity with the chosen firms, we surveyed 50 German Prolific users in June 2022. This pilot confirmed that the firms on our final list are generally well-known to respondents (though there was substantial variation), and that the firms that are less well-known are those drawn from the second list.

Expanded Set of Firms. For the follow-up survey, we selected 10 additional firms. We again focused on firms that are reasonably well-known in Germany. In selecting these firms, we made sure that we have firms in the same industry across different regions. We also made sure to have variation in how large and popular the new firms were to avoid only including the most desirable German employers. All 10 additional firms were named by respondents in the initial survey.

E.1.2 Researcher-Provided Firm Module: Randomization Assessment

In the researcher-provided firm module, we performed several randomizations within the survey code. We posed the initial question in researcher-provided firm module—which asked respondents

[47] While we link survey respondents' answers about specific firms to the administrative data, we were not allowed to *export* firm names from the administrative data for inclusion in the survey.

[48] The gap in frequency between the sixth and seventh most frequent industry was large.

[49] For privacy reasons, we are not allowed to release the list of firms that participated in that survey; 9 of the 20 firms included in the initial wave of the survey participated in this survey.

Table E1: Randomization Assessment: Assignment of Workers to Provided Firms

	Initial Survey			Follow-Up		
	Firm Group	Firm	Firm Quality	Firm Group	Firm	Firm Quality
	(1)	(2)	(3)	(4)	(5)	(6)
Demographics						
Female	0.375	0.576	0.570	0.094	0.064	0.570
Age	0.094	0.332	0.817	0.886	0.783	0.817
German Citizen	0.334	0.374	0.195	0.591	0.697	0.195
Education						
College	0.526	0.643	0.947	0.005	0.014	0.947
Apprenticeship	0.496	0.714	0.607	0.069	0.146	0.607
Employment and Earnings						
Daily Earnings	0.227	0.189	0.552	0.941	0.971	0.552
Earnings are Censored	0.391	0.764	0.893	0.682	0.822	0.893
Weekly Hours (Survey)	0.085	0.128	0.106	0.451	0.639	0.106
Covered by a CBA (Survey)	0.351	0.785	0.736	0.882	0.965	0.736
Sector						
Manufacturing	0.998	0.999	0.941	0.481	0.704	0.941
Retail	0.628	0.945	0.297	0.813	0.818	0.297
Professional	0.730	0.980	0.785	0.399	0.360	0.785

Note: Firm group is an indicator for the set of firms a worker is assigned to, firm is an indicator for the firm a worker is assigned to, and firm quality is the objective pay premium (Bellmann et al., 2020). We perform separate regressions of each covariate (indicated in the row) on the characteristics indicated in the column. Each entry provides the p-value from an F-test that all of the included regressor(s) (other than the constant) are equal to zero. P-values are calculated using standard errors clustered at the worker level. We assigned each worker to one of 18 groups, which defined the set of firms they would see.

whether they would consider applying to each of these firms—to all survey respondents. In the initial survey we randomized each respondent into one of three lists of seven firms, each of which contained one of two randomly chosen focal firms: there were six randomization groups. We asked respondents whether they considered each of seven (rather than 20) firms to reduce the burden of the survey. We performed a similar randomization for the follow-up Appendix Table E1 shows that the randomization of workers to firms in the initial survey (Columns 1 to 3) and follow-up survey (Columns 4 to 6) was successful. Appendix Table E2 shows analogous results for the randomization of pay raises; as before, there is no evidence that the randomization failed.

E.1.3 Cleaning Worker-Provided Firms

To use data from the worker-provided firm module, we had to clean the firm names that workers provided. In the initial survey, respondents (overall, including those dropped from our main analysis sample) provided 5,828 unique strings. Of these, we could assign 5,016 (86%) to uniquely identifiable firms. We performed this assignment manually through online searches to ensure that the strings matched a unique firm.

Of the 812 strings that could not be uniquely identified, the majority are unspecific firm types (e.g., "City government", "police"); a small share (10%) represent non-response (e.g., "I do not want to answer") or unidentifiable content (e.g., "XXX"). Our manual assignment procedure,

Table E2: Randomization Assessment: Assignment of Pay Offers to Firms

	Initial Survey	Follow-Up
	(1)	(1)
Number of Employees	0.39	0.31
Sector		
Manufacturing	0.64	0.64
Retail	0.44	0.09
Professional Services	0.71	0.15
Information Services	0.33	0.92
Transportation	0.21	0.34
Finance	0.74	0.27
Other Firm Characteristics		
HQ in Eastern Germany	0.78	0.59
Year of Incorporation	0.79	0.20
Financial Characteristics		
Total Assets per Employee	0.94	0.36
Fixed Assets per Employee	0.85	0.30

Note: We regress each covariate (indicated in the row) on the randomly assigned pay offer, controlling for the position of the firm (whether listed first, second, or third), and clustering standard errors at the worker level. Each entry is the p-value from a test that the coefficient on the pay offer is zero.

which corrects for differences in spelling and pools subdivisions of the same firm, assigns the 5,016 identifiable strings to 3,018 unique firms. Of these 3,018 firms, 2,013 can be matched to establishments in the IAB records. Among the firms that we cannot link to the IAB, 29% are foreign entities and 37% are in the public sector; these firms may not have any workers in Social Security-covered employment in Germany. We link 79% of the firms that were at least named twice—for which we also collect additional firm characteristics (Appendix Section E.1.4)—to the IAB records. We obtained the municipality of firms' headquarters for 99% of linked firms.

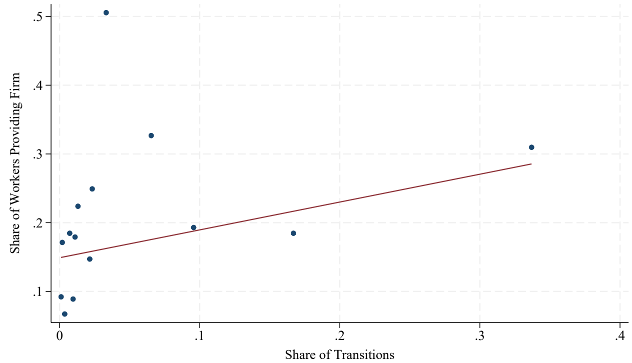
E.1.4 Measuring Firm Characteristics Using the IAB Social Security Records

We follow standard linkage approaches at the IAB to match the firms to the IAB data. We assign each firm the employment-weighted average for all matched establishments. For each establishment, we collect the following information: number of full-time employees, average pay, share of women, share of college educated workers, and the AKM establishment effect. We use the AKM establishment effects as estimated by Bellmann et al. (2020).

To examine the geographic coverage of our firms, we use information on the location of all firm establishments. Based on the headquarter addresses of the researcher-provided and worker-provided firms, we assigned each firm a 7-digit municipality code ("Gemeindeschlüssel") that represents the finest geographical distinction in the IAB records. We have this code for over 99% of linked firms. Based on the municipality code, we can aggregate to the district ("Kreis") and state ("Bundesland").

We measure distance as the driving distance between a worker's workplace and the headquarters of the indicated firm. In some specifications, we use an alternative measure of distance, based on the driving distance between a worker's current place of work and the closest establishment of the provided firm (rather than the largest). We have verified our results are robust to using this

Figure E2: Relationship Between Stated and Revealed Destinations



Note: For each origin-destination pair we calculate the share of workers at the origin firm who move to a given destination firm between 2019-2019. We then calculate the share of workers at this firm who name each destination firm as a place they would apply if they wanted to switch firms. This is a binned scatterplot of the former share (x-axis) against the latter (y-axis).

alternative measure; many of these specifications are in the appendix.

E.1.5 Additional Characteristics of Researcher-Provided and Worker-Provided Firms

Appendix Table 2 shows that both the researcher-provided firms and the worker-provided firms span a broad range of the German labor market.[50] While the most common industry is manufacturing—covering 75% of researcher-provided firms and 31% of worker-provided firms—our sample also captures other major sectors, such as retail, professional services, information services, and finance. Appendix Table E3 shows that, when including non-headquarters establishments, the firms operate in all German states. The researcher-provided firms capture a large span of the major occupational groups in the labor market, with the exception of agriculture (Appendix Figure A1).

These firms represent important employers in the German labor market. The researcher-provided firms employ over 1.8 million German workers (4% of the workforce). 63% are on lists of the largest German employers (Deutsche Wirtschaft, 2022) and 53% are rated among the most popular employers in Germany (Statista 2023). In total, the 30 researcher-provided firms received over 70,000 reviews on Kununu, almost 3% of total reviews. Nine are in the top 20 by number of reviews. The firms also received more than 39.1 million page views, almost 3% of total page views. Seven are in the top 20 by page views. In the past 10 years, 23% of respondents have worked at least at one of the 30 researcher-provided firms, highlighting the relevance of these firms for the German workforce.

The worker-provided firms listed at least twice collectively employ over 6.2 million German workers. They have received over 295,000 reviews and over 190 million page views. Figure E2 shows workers' provided firms are firms which workers from their firm have historically moved to.

[50] Our current dataset captures worker-provided firms that were named at least twice as well as a randomly drawn set of 200 worker-provided firms that were named only once.

Table E3: Coverage of the Worker- and Researcher-Provided Firms

	German Labor Market	Researcher-Provided Firms	Worker-Provided Firms	
			Unweighted	Weighted
	(1)	(2)	(3)	(4)
Region				
Baden-Württemberg	0.14	0.13	0.13	0.35
Bavaria	0.19	0.33	0.25	0.45
Berlin	0.05	0.07	0.05	0.24
Brandenburg	0.03	0.00	0.00	0.00
Bremen	0.01	0.00	0.00	0.00
Hamburg	0.03	0.07	0.08	0.32
Hesse	0.08	0.10	0.11	0.28
Lower Saxony	0.09	0.07	0.05	0.35
Mecklenburg Western Pomerenia	0.02	0.00	0.00	0.00
Northrhine-Westphalia	0.20	0.17	0.05	0.29
Rhineland Palatinate	0.05	0.07	0.02	0.07
Saarland	0.01	0.00	0.00	0.00
Saxony	0.04	0.00	0.00	0.00
Saxony-Anhalt	0.02	0.00	0.00	0.00
Schleswig Holstein	0.04	0.00	0.00	0.00
Thuringia	0.02	0.00	0.00	0.00
Sector				
Information and Communication	0.05	0.10	0.07	0.27
Manufacturing	0.08	0.57	0.31	0.49
Professional Services	0.19	0.10	0.13	0.35
Retail	0.22	0.07	0.12	0.30
Number of Employees				
1-49	0.97	0.00	0.01	0.08
50-249	0.03	0.00	0.04	0.07
250+	0.01	1.00	0.95	0.11

Note: This table compares firm characteristics for the universe of all German firms (Column 1) to our sample of researcher-provided (Column 2) and worker-provided firms (Columns 3 and 4). Column 4 re-weights the worker-provided firms by the number of times they were listed by survey respondents. Information on all German firms stems from Hiersemenzel, Sauer and Wohlrabe (2022). The sample of worker-provided firms contains only those that were named at least twice and for which we collected this data.

E.1.6 Cleaning Workers’ Expected Pay

In both firm-specific modules, we elicited what workers believe they would earn at specific outside firms. The questionnaire included free-form text entries. The survey tool required responses to be numeric or missing to proceed to the subsequent question. Workers responses are high quality. Less than 3% of workers who provide at least one pay estimate, do not provide all three requested estimates. The vast majority of pay estimates are within a reasonable range. Only 5% of workers report numbers that are below the annual pay that a full-time worker would receive if they earned the minimum wage. Less than 0.1% of provided pay estimates are above 1,000,000 Euros. There are no numbers reported that can be classified as gibberish (e.g., “999999”).

We clean these free-form text responses in several ways. First, we scale up pay which was input in thousands. Second, to deal with outlier observations we winsorize workers’ expected pay at the 90% level. As we document in Appendix B.2, we have implemented alternative winsorization schemes (e.g., at the 98% level) or trimming schemes and obtained similar results. To generate Figure A4, we scale the researcher predictions (from 2022) by the CPI when comparing our predictions to the workers’ predictions in the follow-up survey (conducted in 2024).

E.2 Additional Data Sources

IEB Social Security Records We used the German Social Security records, which are assembled by the Institute for Employment Research (IAB) into the Integrated Employment Biographies (IEB) database, to select the sample of workers to whom we fielded the survey. These data capture all private-sector and public-sector employees with Social Security contributions. They contain information on employee demographics (e.g., gender, age, and education), employer information (e.g., sector and location), and job-spell-based information (e.g., full-time status, daily pay, and occupation). We impute daily pay for individuals whose pay is top-coded.

Orbis We collected information on firms’ assets, year of incorporation, sector based on the 4-digit NACE industry code, the headquarters zip-code, and the number of employees from Orbis.[51] For each variable from Orbis, we select the last year that the data is available; we CPI-adjust monetary values. We match firms based on firm name and address. We match 100% of the researcher-provided and 79% of worker-provided firms named at least twice in the initial survey.

Kununu We collected firm-level information from Kununu, the leading employer review platform in Germany. Kununu is similar to the review platform Glassdoor but has a stronger presence in Germany. We linked firms in the Kununu data to our data based on firm name. Among the researcher-provided firms, 100% of firms appear on Kununu. Among the worker-provided firms that were named at least twice in the initial survey, this is true for 88% of firms. As of February 2023 (when we collected the Kununu data), Kununu contained reviews for almost 200,000 German firms. In total, these firms received over 2.5 million ratings and had around 1.5 billion page views.

[51] Since Orbis draws on firms’ balance sheet information, the number of employees may include employees outside of Germany. We hand-collected the number of employees firms have in Germany from the firms’ websites.

Employer Ratings We hand-collected information on firms' reputations from three established employer rankings; we use data from 2022. First, we identify whether a firm is listed as one of the largest German employers (Deutsche Wirtschaft, 2022). Second, we identify whether a firm is listed as one of the most popular employers in Germany based on a rating of worker reviews (Statista, 2023). Third, we obtain information about the importance of the firm's brand, which may affect workers' familiarity with the firm (Kantar, 2023).

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