Online Appendix

A Data Description

A.1 Data Sources and Variables

The data that we use originate from the following three sources: The Integrated Employment Biographies (IEB), the IAB Job Vacancy Survey (JVS), and the Panel Study Labour Market and Social Security (PASS).

The IEB originate from social security notifications of employers and process-generated data of the Federal Employment Agency. They include individuals' labor market biographies in Germany from 1975 onward (East Germany since 1993). The IEB covers employer-employee-level information on the majority of employment relationships, only excluding civil servants and the self-employed. The data contain day-to-day information on each employment period in all jobs that are covered by social security. Unique worker and firm identifiers allow to follow individuals over time and across different employers. In addition, these data contain important individual characteristics such as gender, birth date, nationality, place of residence and work, educational attainment, as well as the individual job characteristics such as occupation and industry codes, and the average daily wage.

The JVS is a representative establishment survey conducted in each fourth quarter of the year. As in the main text, we refer to "firms" instead of "establishments" in this Appendix. The JVS has two parts. The first part contains general information about the firm, including employment size, location, industry, whether the firm was facing financial, demand and/or workforce restrictions as well as its current vacancy stock. The second part provides information about the recruitment behavior among the surveyed firm. These firms can be categories into three separate groups: (i) those that reported not engaging in any recruitment activity during the last 12 months (32% of firms); (ii) those that reported recruitment activity but were unsuccessful in filling all of their available job openings in the last 12 months (2% of firms); and (iii) those that reported recruitment activity and filled all or some of their openings in the last 12 months (66% of firms). All firms complete the first part of the survey, but only the last two groups complete the second part. Among the latter, the JVS collects detailed information about the recruitment process pertaining to the last case of a successful hire. This information includes the search channels used in the hiring process, the number of applications and suitable applications received, the duration of the vacancy, recruitment costs incurred as well as information about the educational requirement and occupation of the vacancy, and the age, education and previous employment status of the individual who ultimately filled the job.

The PASS is an annual representative household panel survey that can be linked to administrative IEB data. This survey contains about 10,000 households including about 15,000 persons aged 15 or older. Information from these persons is collected in several module questionnaires. We use information elicited from the person questionnaire. The latter covers a large set of demographic characteristics and information about the individual's employment and unemployment histories. Household members (employed or non-employed) report whether they are currently looking for work. Conditional on active search during the last four weeks, they report use of search channels, applications sent, job interviews and some further job search information like their reservation wages and hours. Those employed workers that found a new job during the past year also report through which search channel they got notice about the job. See Trappmann et al. (2019) for a further description of these data.

A.2 Sample Construction and Descriptive Statistics

The samples used for the data analysis are constructed in the following steps. On the one hand, we take the JVS for the years 2010-2016. The unique firm identifiers, available from 2010 onwards, allow us to link the JVS to administrative data. On the other hand, we estimate a two-way fixed effects wage regression (AKM) using the IEB, that is the universe of German full-time employees (see Bellmann et al., 2020). From this estimation, we obtain firm fixed effects and worker fixed effects. The first can be directly merged to the JVS via firm identifiers. In order to merge the latter to the information about the firms' most recent case of hiring, we need two additional steps. First, the method described in Lochner (2019) identifies individuals whose hiring is reported in the JVS (using a deterministic algorithm). The outcome is a one-to-one mapping between JVS and IEB hirings as well as the possibility to link the individual's employment history. This allows us to assign the estimated worker fixed effect to a JVS hired worker.

One limitation of our AKM model is that it is only estimated for full-time workers (due to missing information on hours). Hence, in a second step, we estimate the AKM model for earlier time windows and recover the worker fixed effect from previous periods, where workers worked full-time, and link those to the JVS data. For our analysis on the stability of matches, we additionally merge the employment history from the IEB to the JVS hirings. Furthermore, in a robustness check (see Section S.3), we show results from regressions, where we used AKM firm and worker effects from a time period previous to our sample period.

Table A.1 reports descriptive statistics of the IEB data. In the first column we report

Table A.1: Summary statistics I: IEB data

	Full sample	JVS sample
Number workers	30,787,610	3,913,826
Number firms	2,103,301	68,591
Worker/year observations	161,468,712	5,953,189
Workers		
Age (years, mean)	41.10	42.17
Male (%)	66.9	69.3
High school or below (%)	19.52	17.84
Vocational education (%)	58.43	58.16
University (%)	19.34	22.42
Missing education (%)	2.72	1.59
Daily log wage (mean)	4.51	4.64
Daily log wage (st.dev.)	0.54	0.50
Firms		
Mean employment size	14.83	59.84
Age (years, mean)	15.82	19.97
Industry 1 (%)	1.28	3.18
Industry 2 (%)	27.01	35.44
Industry 3 (%)	1.86	6.38
Industry 4 (%)	6.81	2.88
Industry 5 (%)	12.72	3.33
Industry 6 (%)	5.92	5.84
Industry 7 (%)	25.43	21.24
Industry 8 (%)	4.77	7.89
Industry 9 (%)	14.20	13.80

Notes: The full sample refers to the largest connected set in IEB data used for estimation of the AKM regression in 2010–2016. The JVS sample is the subset of the full sample containing only JVS firms and their workers. For industry classification see the main text.

statistics of the full IEB. The second column shows statistics for firms and their workers in the IEB when firms are surveyed in the JVS. Descriptive statistics are similar in this subsample except of firm size because larger firms are oversampled in the JVS. We test whether firm size differences matter for our main conclusions. Section S.1 in the Supplementary Appendix shows that our main empirical results do not meaningfully change when we condition on firm size. Section S.4 further shows that using hiring weights does not meaningfully change our results.

Table A.2 reports descriptive statistics for various JVS samples used in our analysis with merged AKM fixed effects. The first column (JVS) includes all surveyed firms which reported a hire in the last 12 months. Note that this sample is slightly different from the JVS sample in Table A.1 because of the AKM restriction (e.g., largest connected set). The second column includes the reported last hires for which we can identify worker fixed effects using the AKM regressions. The third column includes all the JVS firms for which we can identify AKM firm fixed effects. The fourth column includes JVS firm and their last hires for which we find both worker and firm fixed effects. Descriptive statistics are similar across all these samples. The second and fourth columns show that we can identify worker effects more frequently in larger firms.

Table A.2: Summary statistics II: JVS data

	JVS	JVS & worker identified	JVS & firm AKM	JVS & firm AKM & worker AKM
Firm/year observations	72,362	36,062	68,168	25,176
Firms				
Mean employment size	129.49	143.78	133.53	148.46
Age (years, mean)	19.90	20.00	20.12	20.16
Financial constraints (%)	4.72	4.68	4.63	4.51
Demand constraints (%)	10.83	11.62	10.91	12.23
Workforce constraints (%)	14.19	12.23	14.54	12.65
Industry 1 (%)	4.93	4.69	4.98	4.83
Industry 2 (%)	21.22	21.29	21.96	22.81
Industry 3 (%)	6.60	6.79	6.78	7.57
Industry 4 (%)	4.30	4.01	4.49	4.32
Industry 5 (%)	4.02	3.97	4.00	3.79
Industry 6 (%)	4.55	4.33	4.68	4.74
Industry 7 (%)	26.03	25.43	26.00	25.56
Industry 8 (%)	6.36	6.90	6.27	6.44
Industry 9 (%)	22.01	22.58	20.83	19.94
Last hires				
Age (years, mean)	36.14	35.97	36.07	37.33
Male (%)	54.56	54.15	55.90	58.06
Weekly working hours (mean)	36.50	36.54	36.95	37.29
Previously employed (%)	51.30	52.13	52.05	53.89
Job requirements:				
Unskilled (%)	13.35	11.40	13.15	10.97
Vocational education (%)	66.72	68.26	66.94	68.44
University (%)	17.07	18.17	17.20	18.86
Missing education (%)	2.86	2.17	2.72	1.73

Notes: The JVS are all pooled observations during 2010–2016 with last hires reported in the survey; "worker identified" means that the hired worker can be identified with the algorithm of Lochner (2019); "firm AKM" ("worker AKM") means that fixed effects for the firm (for the hired worker) can be recovered from AKM regressions. For industry classification see the main text.

In both Tables A.1 and A.2 we use the Classification of Economic Activities (Issue 2008) to classify industries into: 1) Agriculture, forestry and fishing; mining and quarrying; 2) Manufacturing; 3) Electricity, gas, steam and air conditioning supply; Water supply, sewerage, waste management and remediation activities; 4) Construction; 5) Wholesale and retail trade; repair motors; 6) Transportation and storage; 7) Accommodation and food service activities; Information and communication services; Financial and insurance activities; Real estate activities; Professional, scientific and technical activities; Administrative and support service activities; 8) Public administrative and defence, compulsory social security; 9) Education; Human health and social work activities; Arts, entertainment and recreation; Other service activities.

Finally, Table A.3 reports descriptive statistics for the PASS and for the subsample for which we can identify worker fixed effects from our AKM model. The sample with AKM worker effects includes younger individuals with higher educational attainment, who are less often self-employed and non-participants. These differences point to the fact that we can only identify a worker effect if workers have had a full-time job before.

Table A.3: Summary statistics III: PASS

	PASS	PASS & worker AKM
Number of workers	43,408	11,006
Number of observations	154,454	51,602
Age	48.45	40.10
Schooling		
Missings	3.97	0.22
No degree	4.10	2.66
Secondary	36.49	28.39
O-level	28.42	36.30
High school	27.01	32.44
Education		
Missings	3.97	0.22
No degree	3.82	2.53
Vocational training	36.49	28.39
Technical college	33.56	43.45
Masters	21.90	25.30
University	0.26	0.11
Labor market status		
Dependent employed	64.34	83.92
Self-employed	7.30	1.79
Unemployed	7.21	6.55
Non-participation	21.15	7.74
Search behavior		
Active search	11.88	12.33
Number of channels used	2.34	2.33
Number of applications	0.56	0.85
Number of interviews	0.60	0.67
Callback rate	0.14	0.15
Search hours	5.21	4.98

Notes: "Worker AKM" means that worker fixed effects can be recovered from AKM regressions.

A.3 Additional Data Explanations

A.3.1 Multiple Hires

From the matching procedure linking the JVS and the IEB data sets we are able to identify any additional hires that could have arisen from the same job opening. We do this by using the firm identifier, the job occupational code and the date in which these hires were recorded in the administrative data. This procedure reveals that during the period 2010-2016 one can find additional hires in the IEB data that share the same firm identifier, 5-digit occupational code and calendar starting date (day/month/year) with hires recorded in the JVS in only 3% of the cases. If one uses instead a 30-day time interval around the recorded date of the JVS hire to allow for different starting dates, this proportion increases to 13%. Further, nearly all of these multiple hires occur at large firms (over 500 employees). This evidence then suggests that a large proportion the observed hires in the JVS data correspond to a single job opening.

A.3.2 Transition Rates

In Section 3.2, we explain how we calibrate the model. To this end, we use workers' transition rates obtained from the IEB data. First, we select all firms that have been surveyed in the JVS in the years 2010-2016. For these firms, we collect all the worker spells. Then, on each tenth day of every month in our sample years, we cut through the spell data and convert the spell data into a monthly worker panel. If we observe longer (than two months) gaps in workers' (un)employment records, we treat those as unemployment. From this monthly panel, we define the following rates: i) EE rate as the number of workers who experience an employment to employment transition (from one month to another) divided by the stock of employed workers in a given month. ii) UE rate as the number of workers who experience an unemployment to employment transition (from one month to another) divided by the stock of unemployed workers in a given month. iii) EU rate as the number of workers who experience an employment to unemployment transition (from one month to another) divided by the stock of employed workers in a given month.

A.3.3 Recruitment Costs

In Section 3.2 we use information on recruitment costs as part of our calibration strategy. For the identification of the parameters that determine the flow recruitment costs separate for each search channel, we build on the JVS waves of the years 2013 and 2014 where firms reported the number of hours spent recruiting the last hire as well as all other monetary costs incurred in this hiring process. To obtain the total recruitment cost in each JVS firm, we first compute the hours cost by multiplying the average daily wage of full-time workers in that firm times the reported recruitment hours. We then add this measure to the reported monetary costs and divide it by the number of days the firm reported searching. In this way we obtain an estimate of the flow recruitment cost at the firm level. Since the JVS does not collect cost information for each separate recruitment channel used, we approximate the cost per channel by using the derived daily recruitment costs for the subset of firms that only used one search channel: either job postings, networks or the public employment agency.

These restrictions imply that the cost statistics are based on an overall subsample of 1,234 observations drawn from the 2013 and 2014 JVS, where 40% come from firms that only use postings, 45% from firms that only use employment networks and 15% from firms that only use the public employment agency. A potential limitation of this approach is that the firms that only used one search channel are not representative of the full JVS sample. Although the firms that only used postings have on average very similar characteristics as those that use two or more channels, firms that use only networks or the public employment agency are (on average) somewhat smaller, slightly younger, their JVS positions require less skilled workers and are positioned lower in the AKM or poaching ranks.

A.4 Further Descriptive Statistics

A.4.1 Search Channels

In the main text we show that firms use on average just below two search channels, where the most common and successful ones are "postings", "networks" and "public employment agency". These results where derived using firm weights. Table A.4 show that a very similar conclusion holds if instead we use hiring weights.

Table A.4: Search channels in the JVS using hiring weights

Search channel	Use (%)	Successful (%)
Postings	72.6	37.6
Networks	47.7	28.3
Public Emp. Agency	47.7	13.0
Unsolicited	30.9	10.7
Internal	26.5	5.4
Private Recruiting Agency	10.1	3.7
Others	2.7	1.3
Total	**238.3**	**100.0**

Further, we also show in the main text that workers use on average 2.3 search channels, where the most common and successful ones are "postings", "networks" and "public employment agency". Table A.5 shows that the same conclusion arises when separating the sample into employed and non-employed workers where the latter use on average more channels.

Table A.5: Use and success of search channels by employment status (PASS)

	Employed		**Non-employed**	
Search channel	Use (%)	Successful (%)	Use (%)	Successful (%)
Postings	85.4	19.2	90.7	18.3
Networks	52.8	26.2	67.1	29.7
Public Emp Agency	43.1	7.4	69.9	12.7
Private Recruiting Agency	7.8	2.1	15.9	2.9
Others	17.0	45.1	16.7	36.5
Total	**206.0**	**100.0**	**260.4**	**100.0**

In the JVS, our channel categories are: (i) Postings of job advertisements; (ii) Networks of personal contacts; (iii) Public employment agency; (iv) Unsolicited contacts; (v) Internal recruiting; (vi) Private Recruiting Agency; (vii) Others. (i) is composed of job advertisements in newspapers or magazines, online job boards, on the firm's website or in social media, and (ii) is composed of personal contacts of the firm's managers and/or employees. The number of survey options decreased from 13 in 2010 to 12 in 2016 due to the aggregation of the categories "hiring from own trainees" and "temporary workers" into one category. Otherwise the remaining choices retained the same meaning and all but one the same wording. In addition, Davis and Samaniego de la Parra (2021) find that online job boards, which are part of (i) in our categorization, play an important role in matching workers and firms in the U.S. This suggests that one may want to separately analyze online job boards from the rest of the categories that make up postings in our analysis. Although not shown here we find that doing so reveals very similar patterns as described below for these two types of postings channels.

In the PASS, an (employed or non-employed) individual actively looking for a job is asked "From where have you gathered information on jobs during the past four weeks?", followed by a multiple choice answer where more than one channel can be selected. An individual who found a new job since last year's interview is then asked "How did you get notice of this job?", where *this job* refers to the current job and the same choices of possible channels are offered. In this case we group all the possible channels into five categories: (i) Postings of job advertisements; (ii) Networks of personal contacts; (iii) Public employment agency; (iv) Private Recruiting Agency; (v) Others.

In the PASS, (i) is composed of job advertisements in newspapers and online sources, (ii) is composed of relatives and acquaintances (which may include former colleagues or employers) and (iii) is composed of the employment agencies' online job market as well as information from the placement officers at the employment agency. As in the PASS there are no separate questions about the JVS fourth or fifth search channels, unsolicited and internal applications are included in the "Others" category for workers. During the period of study, the PASS did not present any changes in the wording of these questions or number of options given to respondents.

For the exercise presented in Section 3.6 we investigate the categories that compose the public employment agency channel. These are distinguished in both surveys into "online services" and "services of placement officers". While the PASS features these two categories in all survey years, the JVS 2014 includes three categories: (i) online services of the agency, (ii) international placement services, (iii) other contacts to the agency. For this year we pool (ii) and (iii) into a joint "placement officer" category. Table A.6 shows the use and success proportions in both the JVS and PASS surveys. As before, the two subcategories sum to the total "Agency (all)" for success, while firms and workers that use the public agency make often use of both services. Among workers succeeding to find a job through the public agency, about 48% do so through the placement officers and the rest through online services.

Table A.6: Use and success of services of the public employment agency

	Firms (JVS 2014)		Workers (PASS)	
Search channel	Use (%)	Successful (%)	Use (%)	Successful (%)
Agency (all)	37.3	14.5	57.3	8.4
Internet services	20.6	6.2	50.0	4.4
Placement officers	30.3	8.3	29.1	4.0

Notes: Firm weights (JVS) and population weights (PASS) are applied.

A.4.2 AKM Fixed Effects

In the main text we use AKM fixed effects to consistently rank firms and workers. Here we provide further details of the estimated coefficients. Table A.7 shows the correlation matrix (top panel) and the variance decomposition of wages (bottom panel) into worker and firm fixed effects, further controls and the residuals. This is done for two samples: (i) all firms and workers in the largest connected set in IEB data during 2010–2016 and (ii) the sample restricted to JVS firms and their workers which is used for the match-level outcomes shown in the main text.[41] The correlation coefficients between α_i and γ_j are very similar in both

[41]Descriptive statistics about firms and workers in these two samples are shown in Table A.1 above.

data sets. Note that its value is higher than the one documented by Card et al. (2013) for the 1998–2004 and 2003–2010 periods and Lochner et al. (2020). Further, the reported correlation between worker and firm fixed effects is also higher than those obtained using the same methodology for other countries; see, for example, Lopes de Melo (2018) who reports zero or negative correlations for the U.S., France, Brazil and Italy. We highlight that a large literature has emerged in recent years warning about using the correlation coefficient of AKM fixed effects to draw conclusions about labor market sorting. In this paper we do not take this route. Instead, one of our aims is to use the AKM fixed effects to rank workers and firms based on a common, comparable measure, and use our structural model to draw conclusions about the sorting of workers and firms and how different search channels affect labor market sorting, among other dimensions.

Table A.7: Correlation and variance decomposition from AKM regressions (2010-2016)

	Correlation Matrix							
	Full sample				**JVS sample**			
	α_i	γ_j	βX	u	α_i	γ_j	βX	u
α_i	1.000				1.000			
γ_j	0.326	1.000			0.327	1.000		
βX	-0.130	0.006	1.000		-0.153	0.022	1.000	
u	0.000	0.000	-0.023	1.000	0.003	0.004	-0.017	1.000

	Variance Decomposition							
	var(y)	var(α_i)	var(γ_j)	var(βX)	var(u)	2cov($\alpha_i, \beta X$)	2cov($\gamma_j, \beta X$)	2cov(α_i, γ_j)
Full sample								
level	0.290	0.165	0.049	0.012	0.018	-0.012	0.000	0.058
%		56.93	16.74	4.25	6.14	-4.03	0.10	20.12
JVS sample								
level	0.252	0.152	0.036	0.012	0.016	-0.013	0.001	0.048
%		60.11	14.30	4.75	6.47	-5.16	0.37	19.16

Notes: The full sample refers to the largest connected set in IEB data used for estimation of the AKM regression in 2010–2016. The JVS sample is the subset containing only JVS firms and their workers.

The variance decomposition of log wages in the bottom panel of Table A.7 shows that in both samples permanent worker (firm) heterogeneity accounts for around 60% (15% resp.), while the sorting component accounts for around 20% of the total wage variation. These results are in line with the aforementioned literature estimating AKM regressions.

B Further Results

In this appendix section, we present additional results that complement the analysis presented in the main text. We start by documenting how firm and worker AKM fixed effects correlate with their broader search behavior. We then present the regression results that complement the plots presented in Sections 2.2, 2.3 and 2.4.

B.1 Firms' Search Strategies

To investigate whether the general search behavior of firms correlates with their position in the wage distribution, measured through their AKM rank, we use various survey questions about recruitment strategies from the JVS, which we relate to the firm fixed effects and further controls. As an alternative to ranking firms by their AKM fixed effects we use the "poaching index" proposed by Bagger and Lentz (2019). This index ranks firm types by the revealed preferences of workers who move between employers, and is calculated as the fraction of a firm's hires that come directly from other firms in relation to all hires, including those from non-employment, where we include all hires observed in IEB data during the 2010–2016 period. While the poaching index and AKM fixed effects rank firms in different ways, they are positively correlated. Specifically, we obtain a correlation coefficient of 0.35 (0.40) between these two measures when using the full IEB sample (the sample restricted to JVS firms, respectively). In our firm-level analysis, we control for the educational requirements of the job (high school or less, vocational education, university degree) as well as several firm characteristics (age, size, industry and whether financial, workforce and/or demand constraints were faced). The impact of age is measured by a quadratic function, while we divided size into six categories: 1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees. For industries we use one-digit industry codes based on the classification described earlier in the appendix. Financial, workforce and demand constraints are measured through three indicators variables each taking the value of one when the firm reports it faces the respective constraint. For worker-level results, we control for a quadratic in worker age, gender, previous employment status, and one-digit occupation.

Table B.1 shows OLS regressions of various recruitment variables where firms are either ranked by their AKM fixed effects (top panel) or by the poaching index (bottom panel). High-ranked firms attract more applicants and more suitable applicants than lower-ranked firms. However, high-ranked firms are more selective, reporting a smaller proportion of all their applicants to be suitable for the vacant job. These firms also exert more effort in the recruitment process, spending more hours and money in the recruitment process.[42] We highlight the importance of controlling for educational requirements of the job, as this dimension naturally segments the labor market with considerable effects on recruitment policies. Using the lowest category (high school or below) as our reference category, Table B.1 shows that firms are more selective and exert more search effort when recruiting for

[42] All years of the survey include the respondents' answers regarding the number of applications and suitable applications and the duration of the vacancy (the number of days between the start of search and the date the hiring decision was made). Monetary costs and hours of search were only asked in 2013 and 2014. We use cost information to construct target moments as part of our calibration strategy in Section 3.2 and described these further in Section A.3.3.

Table B.1: Relationship between recruitment, firm types and job requirements

	(1) Sel. rate	(2) Suit. App.	(3) All App.	(4) Ad. costs	(5) Rec. Hours	(6) No. channels	(7) Vac. dur.
AKM firm effect	-0.085***	1.552***	9.509***	1260.073***	5.364***	-0.001	3.710**
	(0.008)	(0.114)	(0.466)	(140.277)	(0.780)	(0.004)	(1.616)
Vocational training	-0.066***	0.233***	2.669***	318.120***	4.121***	0.020***	15.140***
	(0.005)	(0.063)	(0.258)	(73.538)	(0.387)	(0.002)	(0.888)
University degree	-0.106***	0.750***	6.111***	1378.387***	11.238***	0.042***	32.401***
	(0.006)	(0.078)	(0.319)	(92.962)	(0.504)	(0.003)	(1.093)
st.d. AKM firm effect	0.206	0.206	0.206	0.201	0.203	0.212	0.205
Observations	51,071	52,437	54,752	6,673	21,498	43,555	51,580
Adj. R^2	0.039	0.094	0.090	0.105	0.051	0.147	0.048
Poaching index	-0.062***	0.307***	2.967***	790.908***	3.083***	0.022***	6.679***
	(0.008)	(0.102)	(0.425)	(124.792)	(0.692)	(0.003)	(1.485)
Vocational training	-0.069***	0.346***	3.171***	343.291***	4.528***	0.020***	15.326***
	(0.005)	(0.061)	(0.252)	(71.677)	(0.382)	(0.002)	(0.875)
University degree	-0.112***	0.956***	7.249***	1469.758***	12.031***	0.040***	32.467***
	(0.006)	(0.074)	(0.308)	(89.540)	(0.489)	(0.002)	(1.062)
st.d. poaching index	0.205	0.206	0.206	0.208	0.205	0.202	0.214
No. Obs.	52,596	54,014	56,417	6,905	21,810	45,650	53,012
Adj. R^2	0.040	0.092	0.084	0.099	0.052	0.152	0.049

Notes: All columns are OLS regressions with different dependent variables. Further controls: quadratic polynomial of firm age, six firm size categories, one-digit industry codes, and financial, demand and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

higher skilled positions. We also highlight the importance of controlling for firm size. We obtain that larger firms are also more selective and exert more search effort relative to firms of 1-10 employees (our reference category). The number of search channels does not vary with the AKM fixed effects, although there is a low positive correlation with the poaching index. The last column of the table complements these results and shows that higher-ranked firms and firms filling positions with higher skilled requirements take longer to fill their vacancies.

B.2 Workers' Search Strategies

We now investigate to what extent the search behavior of workers correlates with their position in the wage distribution, measured by their AKM rank. Here we use various survey questions about job search behavior from the PASS which we relate to the AKM fixed effects and further controls.

Table B.2 shows how job search behavior relates to the worker's wage rank and employment status. While the first column shows that high-wage workers are less likely to search actively, the second and fourth columns show that these workers, conditional on ac-

Table B.2: Relationship between job search and worker types

	Active search	No. applications	Callback rate	Log search hours	No. channels
AKM worker effect	-0.0347***	1.2020***	0.0192	0.2079***	-0.0168
	(0.0056)	(0.4205)	(0.0160)	(0.0713)	(0.0312)
dep.empl.=reference					
self-employed	0.0981***	2.5383**	0.0139	0.4820***	0.2912***
	(0.0139)	(1.0857)	(0.0419)	(0.1742)	(0.0805)
unemployed	0.5147***	4.7281***	0.0524	1.0125***	0.4743***
	(0.0178)	(1.5656)	(0.0593)	(0.2609)	(0.1161)
non-participant	0.0354***	0.6619	0.1396**	0.7155**	0.0665
	(0.0190)	(1.6740)	(0.0636)	(0.2793)	(0.1241)
Observations	36,007	9,000	7,491	1,598	9,000
Adj. R^2	0.3024	0.0501	0.0045	0.1164	0.0709

Notes: All columns are OLS regressions with different dependent variables. Columns 2-5 are conditional on active search. Further controls are a quadratic polynomial of worker age, gender, one-digit occupation, and year dummies. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

tive search, send more applications and spend more time searching. However, the callback rate (i.e., interviews per application) does not correlate with the worker's wage rank. Unsurprisingly, registered unemployed workers are much more likely to search actively than dependent employed workers. Moreover, conditional on search, they send more applications, spend more time searching and use more search channels (cf. Table A.5). This evidence is consistent with the results of Faberman et al. (2022) who study workers' search patterns (although not with AKM fixed effects) using the U.S. Survey of Consumer Expectations.

Tables B.1 and B.2 show that the average number of search channels used by either firms or workers does not appear to differ across the relative rank of firms or workers when using the AKM fixed effects. As in the main text, we show in the next subsection that instead there is a clear relationship between the type of search channel used and whether this channel was successful and the relative rank of firms and workers.

B.3 Use and Success of Search Channels

Table B.3: Search channels and firm types

	Use of search channel			Successful channel		
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM firm effect	0.101***	-0.102***	-0.273***	0.140***	-0.101***	-0.125***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.008)
Vocational training	0.082***	-0.085***	0.034***	0.085***	-0.080***	0.010**
(ref: high school or less)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
College degree	0.178***	-0.112***	-0.034***	0.177***	-0.108***	-0.031***
(ref: high school or less)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
size (11-25)	0.059***	-0.036***	0.035***	0.032***	-0.061***	-0.010**
(ref: size (1-10))	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
size (26-50)	0.106***	-0.062***	0.068***	0.057***	-0.112***	-0.010**
(ref: size (1-10))	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
size (51-100)	0.152***	-0.104***	0.097***	0.092***	-0.171***	-0.012**
(ref: size (1-10))	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
size (101-1000)	0.221***	-0.145***	0.154***	0.138***	-0.225***	-0.022***
(ref: size (1-10))	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
size (>1000)	0.272***	-0.173***	0.158***	0.204***	-0.256***	-0.041***
(ref: size (1-10))	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.010)
firm age	-0.008***	-0.003***	-0.002**	-0.004***	-0.000	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
firm age^2	0.000***	0.000**	0.000	0.000***	0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. Obs.	64,884	64,884	64,884	60,837	60,837	60,837
Adj. R^2	0.105	0.056	0.060	0.074	0.071	0.019
Poaching index	0.152***	-0.041***	-0.058***	0.098***	-0.042***	-0.049***
	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.007)
Vocational training	0.084***	-0.091***	0.026***	0.089***	-0.087***	0.006
(ref: high school or less)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
College degree	0.186***	-0.123***	-0.064***	0.190***	-0.123***	-0.044***
(ref: high school or less)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
size (11-25)	0.074***	-0.050***	0.029***	0.042***	-0.077***	-0.010**
(ref: size (1-10))	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
size (26-50)	0.123***	-0.077***	0.057***	0.071***	-0.129***	-0.012***
(ref: size (1-10))	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
size (51-100)	0.172***	-0.124***	0.082***	0.109***	-0.192***	-0.016***
(ref: size (1-10))	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
size (101-1000)	0.245***	-0.171***	0.125***	0.161***	-0.252***	-0.033***
(ref: size (1-10))	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)
size (>1000)	0.302***	-0.202***	0.111***	0.235***	-0.286***	-0.060***
(ref: size (1-10))	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.010)
firm age	-0.005***	-0.003***	-0.001	-0.003***	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
firm age^2	0.000***	0.000	-0.000***	0.000***	-0.000	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
No. Obs.	66,881	66,881	66,881	62,659	62,659	62,659
Adj. R^2	0.109	0.056	0.050	0.074	0.072	0.015

Notes: The standard deviation of the AKM firm effect is 0.206 (0.205), while the standard deviation of the poaching index is 0.207. All regressions are linear probability models where the outcome is one if the particular channel is used (left panel) or successful (right panel) and zero otherwise. Further controls: one-digit industry codes and financial, demand and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3 mirrors the findings depicted in Figure 1, indicating that firms ranked higher in AKM exhibit a greater likelihood of utilizing and recruiting via job postings, whereas lower-ranked firms demonstrate a higher likelihood of utilizing and recruiting through networks or the public employment agency. The top panel of Table B.3 shows these outcomes employing a linear probability model, controlling for the educational prerequisites of the job (high school or less, vocational education, university degree), as well as the firm's age, size, industry, and whether it faces financial, workforce, and/or demand constraints. The role of age is gauged by a quadratic function, while size is divided into six categories: 1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees. One-digit industry codes are used to represent industries. Financial, workforce, and demand constraints are measured through three indicator variables, each taking the value of one when the firm reports facing the respective constraint. The bottom panel of Table B.3 presents similar results from estimating the same regression but utilizing the poaching index instead of the AKM fixed effect.

Table B.4: Search channels and worker types

	Use of search channel			**Successful channel**		
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM person effect	0.008	-0.039**	-0.037***	0.067***	-0.038**	-0.072***
	(0.010)	(0.016)	(0.014)	(0.014)	(0.015)	(0.012)
dep.empl.=reference						
self-empl.	0.051**	0.117***	0.016	-0.077***	0.009	-0.048**
	(0.025)	(0.041)	(0.037)	(0.027)	(0.030)	(0.024)
unempl.	-0.031	0.227***	0.201***	0.131***	-0.048	0.028
	(0.035)	(0.059)	(0.053)	(0.045)	(0.049)	(0.039)
non-part.	-0.105***	0.182***	-0.042	0.096**	-0.075	-0.085**
	(0.038)	(0.063)	(0.057)	(0.047)	(0.052)	(0.041)
age	0.000	-0.001	-0.000	0.011***	0.004	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
age^2	0.000	-0.000	0.000	-0.000***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
male.=reference						
female	0.034***	0.001	0.007	0.027***	-0.030***	-0.006
	(0.007)	(0.011)	(0.010)	(0.009)	(0.010)	(0.008)
Observations	9000	9000	9000	9463	9463	9463
Adjusted R^2	0.015	0.014	0.092	0.016	0.005	0.022

Notes: All regressions are linear probability models where the outcome is one if the particular channel is used (left panel) or successful (right panel) and zero otherwise. The standard deviation of the AKM person effect is 0.359 (0.362) in the left (right) part of the table. Further controls are one-digit occupations. Source is PASS-ADIAB. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4 mirrors the results depicted in Figure 2, illustrating that workers ranked higher in AKM have a greater likelihood of securing employment via job postings, whereas lower-ranked workers exhibit a higher likelihood of utilizing and securing a job through networks or the public employment agency. It is noteworthy that here we also find no differential effect across the AKM rank of a worker on the use of job postings.

B.4 Poaching and Employment Stability

We complement the analysis of Sections 2.3 and 2.4 in the main text by investigating which search channel is more conducive to poach a worker from another employer, how the AKM fixed effects of firms and their hired workers are related across the three channels, and how search channels matter for employment stability.

We conduct a linear probability model where the dependent variable indicates whether the hired worker was previously employed (coded as one) or not (coded as zero). We estimate regressions for each successful search channel separately, comparing the effects of each channel relative to the others, similar to the approach used in the previous tables. In addition to Figure 3, Table B.5 illustrates that hiring through job postings or personal networks increases the likelihood that the new hire originates from another firm rather than from non-employment. Moreover, higher-wage firms are more inclined to engage in poaching, reflecting the positive correlation between the AKM firm effect and the poaching index observed in our data, as discussed earlier. The interaction term indicates that the likelihood of hiring an employed worker increases more rapidly with the AKM firm effect when the hiring occurs through job postings compared to personal networks and the public employment agency, where a lower probability of the worker being previously employed is observed.

Table B.5: Search channels and poaching

	Prob. hiring employed worker		
	Posting	Networks	Public agency
AKM firm effect	0.141***	0.222***	0.165***
	(0.012)	(0.013)	(0.011)
Successful search channel	0.119***	0.113***	-0.234***
	(0.004)	(0.004)	(0.004)
Search channel × AKM firm effect	0.084***	-0.105***	-0.104***
	(0.021)	(0.020)	(0.030)
Observations	66,755	66,755	66,755
Adj. R^2	0.047	0.046	0.056

Notes: Linear probability regressions where the outcome is one if the hired worker was previously employed and zero otherwise. Further controls: quadratic polynomial of firm age, six firm size categories, one-digit industry codes, and financial, demand and workforce constraints.. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.6 complements Figure 4 in the main text. This table reports the results from regressing the AKM fixed effect of the hired worker on the AKM fixed effect of the new employer, the search channel used to contact the worker and the interaction between them. The estimates show a positive relationship between the hired worker and the firm fixed effects: higher ranked firms tend to hire also higher ranked workers, complementing the results about the positive correlation between worker and firm fixed effects documented in Table A.7 in this appendix. Further, when hiring through job postings or employment networks, firms tend to hire higher ranked workers. The interaction term, however, implies that when hiring through postings the positive relationship between the AKM of the hired worker and his/her employer is about 25% higher and about 40% lower when firms hire through employment networks. The results also show that when hiring through the public employment agency, firms tend to hire lower ranked workers which in turn reduces this correlation by about 30%. These estimates reflect the steepness of the relationship between firm and worker fixed effects depicted in Figure 4 in the main text.

Table B.6: Relationship between AKM worker and firm fixed effects and the successful channel

	Hired worker AKM fixed effect (full sample)			**Hired worker AKM fixed effect (full-employed workers)**		
	Posting	Networks	Public agency	Posting	Networks	Public agency
AKM firm effect	0.146***	0.189***	0.162***	0.106***	0.144***	0.110***
	(0.012)	(0.013)	(0.011)	(0.014)	(0.015)	(0.013)
Successful search channel	0.019***	0.013***	-0.048***	0.029***	0.009*	-0.058***
	(0.009)	(0.004)	(0.006)	(0.005)	(0.005)	(0.007)
Search channel × AKM firm effect	0.039*	-0.071***	-0.062**	0.003	-0.079***	-0.041**
	(0.021)	(0.019)	(0.029)	(0.025)	(0.023)	(0.033)
Observations	25,084	25,084	25,084	14,708	14,708	14,708
Adj. R^2	0.215	0.215	0.217	0.304	0.303	0.306

Notes: The standard deviation of the AKM firm effect is 0.215. Both panels are OLS regressions. The right panel is restricted to workers with fixed effects from 2010–2016 (i.e., full-time workers in this period). Further controls: quadratic polynomial of firm age, six firm size categories, one-digit industry codes, and financial, demand and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To investigate whether match stability is influenced by the search channel used to hire the worker, we estimate a linear probability model where the dependent variable takes the value of one if the hired worked remained employed at least 12 or 24 months since the start of the job. We control for worker and firm AKM fixed effects and run these regressions separately for each search channel which is further interacted with the worker and firm AKM fixed effects. The first two rows of Table B.7 show that matches involving high-wage firms and high-wage workers are generally more stable. Networks have a direct positive relationship between match stability, while hiring through the public employment agency has a negative relationship. Additionally, there are differences by firm and worker ranks: match stability beyond 24 months and involving high-wage firms or high-wage workers is higher when the match is formed via job postings. The public employment agency, in contrast, delivers greater match stability for low-ranked workers.

Table B.7: Search channels and match stability

Probability of staying at the firm		>12 **months**			>24 **months**	
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM firm effect	0.120***	0.155***	0.130***	0.171***	0.205***	0.190***
	(0.020)	(0.022)	(0.019)	(0.024)	(0.025)	(0.022)
AKM worker effect	0.066***	0.072***	0.072***	0.061***	0.069***	0.079***
	(0.013)	(0.012)	(0.011)	(0.015)	(0.014)	(0.013)
Successful search channel	0.009	0.019**	-0.062***	0.002	0.030***	-0.080***
	(0.007)	(0.007)	(0.010)	(0.009)	(0.009)	(0.012)
Search channel × AKM firm effect	0.055	-0.042	-0.003	0.077*	-0.028	-0.057
	(0.036)	(0.033)	(0.048)	(0.042)	(0.038)	(0.055)
Search channel × AKM worker effect	0.023	0.008	-0.003	0.042**	0.020	-0.064*
	(0.020)	(0.021)	(0.032)	(0.024)	(0.024)	(0.037)
Observations	19,152	19,152	19,152	16,097	16,097	16,097
Adj. R^2	0.035	0.035	0.037	0.040	0.040	0.042

Notes: Linear probability regressions where the outcome is one if the hired worker stays with the same firm more than 12 (24) months. Further controls: quadratic polynomial of firm age, six firm size categories, one-digit industry codes, and financial, demand and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Search channels and employment stability

Probability of an EU transition		<12 **months**			<24 **months**	
	Posting	Networks	Public agency	Posting	Networks	Public agency
AKM firm effect	-0.030***	-0.047***	-0.029***	-0.055***	-0.057***	-0.052***
	(0.010)	(0.011)	(0.009)	(0.012)	(0.012)	(0.011)
AKM worker effect	-0.048***	-0.045***	-0.037***	-0.052***	-0.050***	-0.039***
	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)	(0.006)
Successful search channel	-0.002	-0.020***	0.035***	-0.003	-0.017***	0.035***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)
Search channel × AKM firm effect	-0.006	0.031*	0.001	0.007	0.006	0.023
	(0.018)	(0.016)	(0.024)	(0.020)	(0.019)	(0.027)
Search channel × AKM worker effect	0.010	0.004	-0.056***	0.011	0.007	-0.068***
	(0.010)	(0.010)	(0.016)	(0.012)	(0.012)	(0.018)
Observations	19,152	19,152	19,152	16,097	16,097	16,097
Adj. R^2	0.025	0.027	0.029	0.030	0.031	0.033

Notes: Linear probability regressions where the outcome is one if the hired worker separates into non-employment within the next 12 (24) months. Further controls: quadratic polynomial of firm age, six firm size categories, one-digit industry codes, and financial, demand, and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we explore the probability that a worker separates into non-employment within the next 12 or 24 months after a new employment relationship is formed. Consistent with the results in Table B.7, high-wage workers and workers employed in high-wage firms are less likely to separate into non-employment (first rows). When hired through networks (the public agency), the probability of job loss is higher (lower), while being hired through job postings does not relate to the job loss probability.

C Sensitivity Analyses

In this section, we provide details of several robustness exercises for the analysis presented in Section 2 of the main text. Specifically, we address potential measurement error in the estimated firm fixed effects and show that our main results remain unchanged. In the Online Supplementary Appendix, we present additional robustness tests and further results.

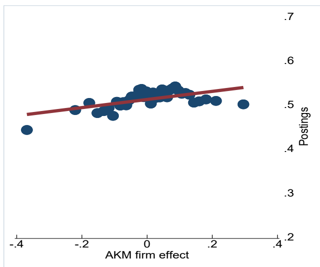
C.1 Sample Split IV

Adopting the methodology of Schmieder et al. (2023), we employ an instrumental variable approach to gauge the extent of limited mobility bias in the AKM estimates. We tackle potential measurement errors in establishment effects by implementing a split-sample instrumental variable (IV) estimator. This method entails randomly dividing the worker sample, producing two sets of AKM estimates, and utilizing one set of establishment effects as an instrumental variable for the other. This technique yields unbiased estimates under the assumption that the errors in the instrument are uncorrelated with the errors in the linear probability models that examine the utilization and effectiveness of search channels.

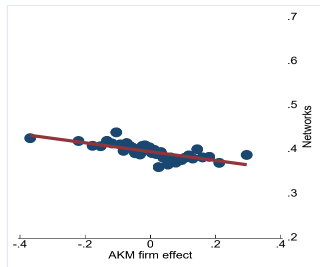
Figure C.1 illustrates the correlation between the probability of using and achieving success through a channel and the AKM rank of the firms when employing the sample split IV approach. The observations remain consistent with those presented in the main text: i) Higher-wage firms tend to utilize job postings more frequently to seek applicants, whereas lower-wage firms are inclined to use networks and the public employment agency. ii) High-wage firms demonstrate a higher success rate in hiring via job postings and a lower success rate via networks or the public agency compared to low-wage firms.

Figure C.2 plots the probability of poaching against the rank of the AKM firm. Again, the results from the sample split IV approach deliver similar results as in the main text: The probability of poaching is larger and has a stronger increase with firms' wage rank when using job postings relative to networks. The public employment agency offers the lowest probability of poaching and the lowest increase in this probability with the AKM firm effect.

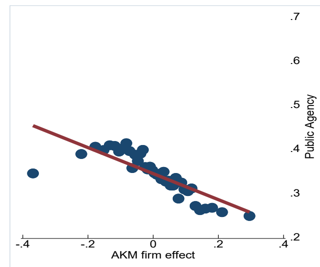
Figure C.3 depicts the correlation between worker and firm AKM fixed effects across different hiring channels. Employing the sample split IV approach yields results similar to those obtained using the standard AKM method. The figure illustrates that firms tend to recruit workers with higher fixed effects through job postings compared to other channels, with the public agency resulting in hires with the lowest fixed effects.



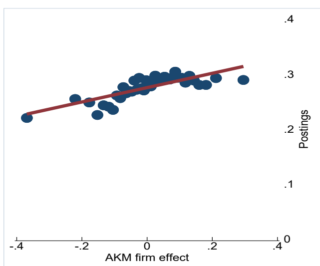
(a) Postings (Use)



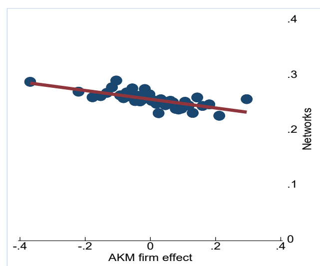
(b) Networks (Use)



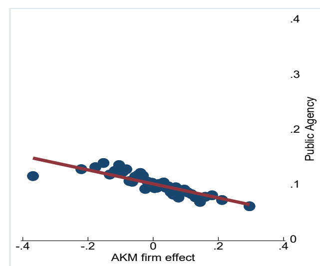
(c) Public Agency (Use)



(d) Postings (Success)



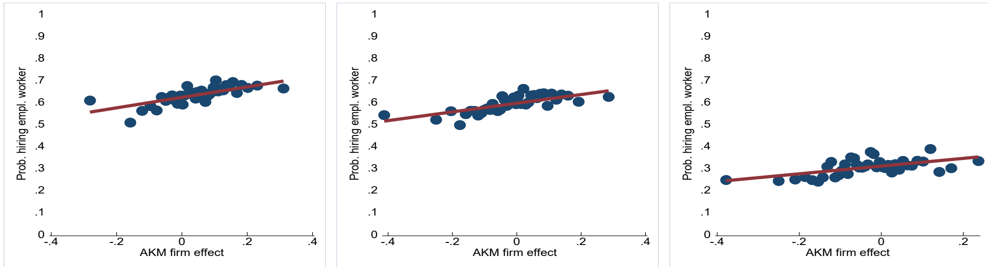
(e) Networks (Success)



(f) Public Agency (Success)

Figure C.1: Use and success of search channels by AKM firm fixed effect (IV)

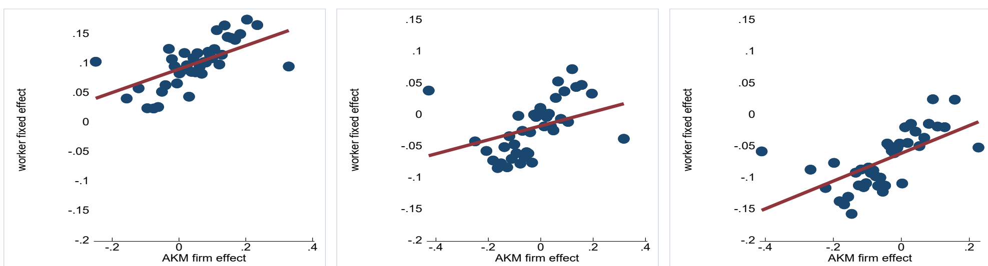
Notes: The figures show binscatter plots that relate the firm's AKM fixed effect (IV) to the probability of using the channel (top panels) or hiring through the channel (bottom panels) for one of the three channels "Postings" (left), "Networks" (middle), or "Public Agency" (right). Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.



(a) Postings (b) Networks (c) Public Agency

Figure C.2: Probability of hiring an employed worker by AKM firm fixed effect (IV)

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect (IV) to the probability of hiring an employed worker separately for each of the three channels “Postings”, “Networks”, or “Public Agency”. Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.



(a) Postings (b) Networks (c) Public Agency

Figure C.3: Relationship between worker and firm AKM fixed effect by hiring channel (IV)

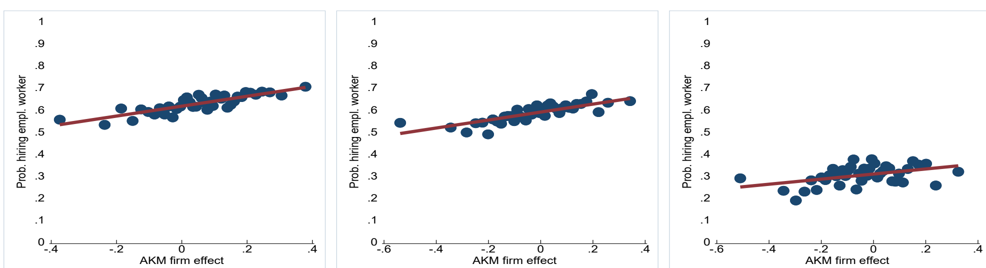
Notes: The figures show binscatter plots that relate the firm AKM fixed effect (IV) to the AKM fixed effect of the worker hired by this firm separately for each of the three channels “Postings”, “Networks”, or “Public Agency”. Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.

C.2 Clustering Small Firms

An alternative strategy to mitigate potential limited mobility bias involves grouping small firms into larger clusters. Specifically, we adopt the method outlined by Schmieder et al. (2023) and Bonhomme et al. (2019), where establishments with fewer than 10 employees are divided into 20 distinct clusters based on the similarity of their discretized empirical cumulative distribution functions of log wages, utilizing the K-means clustering algorithm. This approach helps alleviate limited mobility bias since small establishments frequently experience limited workforce mobility.

Figure C.4 shows binscatter plots that relate the firm's AKM fixed effect to the probability of using the channel or succeeding through the channel for one of the three channels. In all subplots, we can reproduce the patterns shown in the main text using the standard AKM approach. High-wage firms exhibit a greater propensity to utilize job postings for applicant searches, while lower-wage firms are more inclined to rely on networks and the public employment agency. Additionally, high-wage firms achieve a higher success rate in hiring through job postings but experience a lower success rate when using networks or the public agency, in contrast to low-wage firms.

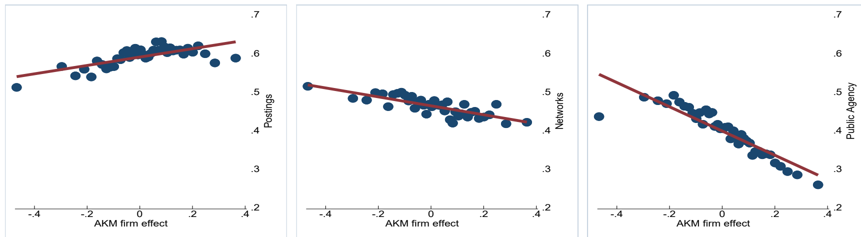
Figures C.5 and C.6 reaffirm that hiring through job postings corresponds to more poaching and attracts workers with higher wage ranks, particularly for firms positioned higher in the wage distribution. Poaching also enables workers to achieve more substantial enhancements in their employers' AKM rank compared to other search channels. Table C.1 reproduces the findings outlined in Table 2 from the main text, but this time with clusters specifically designed for small firms. Remarkably, we find that the effects of the channels are of similar magnitude in this scenario. Being recruited through job postings is associated with steeper job ladders compared to other channels.



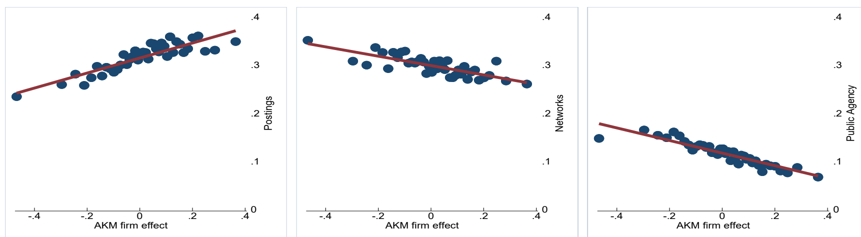
(a) Postings (b) Networks (c) Public Agency

Figure C.5: Probability of hiring an employed worker by AKM firm fixed effect (clustering of small firms)

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of hiring an employed worker separately for each of the three channels "Postings", "Networks", or "Public Agency". Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.



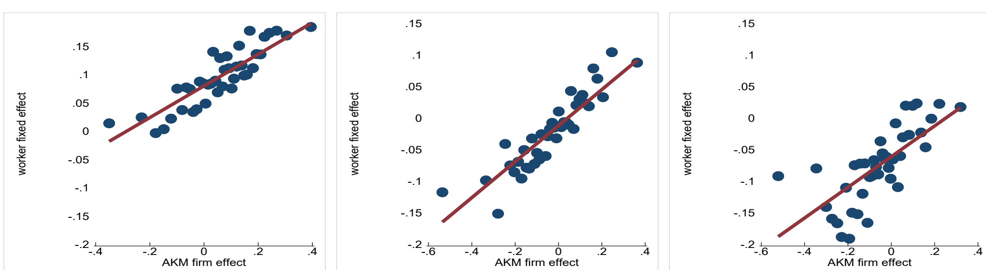
(a) Postings (Use) (b) Networks (Use) (c) Public Agency (Use)



(d) Postings (Success) (e) Networks (Success) (f) Public Agency (Success)

Figure C.4: Use and success of search channels by AKM firm fixed effect (clustering of small firms)

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of using the channel (top panels) or hiring through the channel (bottom panels) for one of the three channels "Postings" (left), "Networks" (middle), or "Public Agency" (right). Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.



(a) Postings (b) Networks (c) Public Agency

Figure C.6: Relationship between worker and firm AKM fixed effect by hiring channel (clustering of small firms)

Notes: The figures show binscatter plots that relate the firm AKM fixed effect to the AKM fixed effect of the worker hired by this firm separately for each of the three channels "Postings", "Networks", or "Public Agency". Controls: educational requirement (high school or less, vocational training, college/university degree), quadratic polynomial of firm age, six firm size categories (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints.

Table C.1: Change in firm effect at an EE transition by search channel (clustering of small firms)

	(1) △ firm effect	(2) △ firm effect
	w/o controls	worker controls
Reference=Postings		
Networks	-0.0261***	-0.0277***
	(0.0041)	(0.0044)
Public Agency	-0.0210***	-0.0284***
	(0.0065)	(0.0069)
Constant	0.0622***	0.2652***
	(0.0028)	(0.0253)
Observations	13,825	11,552
Adjusted R^2	0.0029	0.0206

Notes: EE means a direct employer-to-employer transition. Worker controls: dummy for change in occupation, dummy for change in hours, educational attainment (category), AKM person effect. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Model Appendix

D.1 Further Model Details

D.1.1 Wages

Write $W(x, \hat{y}, y)$ for the discounted income value of a worker who is employed in a firm with productivity y and either was previously employed at another firm with productivity $\hat{y} < y$ or received an outside offer from a sufficiently productive poaching firm with productivity $\hat{y} \leq y$. In both cases, the wage at firm y is negotiated such that[43]

$$W(x, \hat{y}, y) = \beta S(x, y) + (1 - \beta) S(x, \hat{y}) \ . \tag{D.1}$$

We further write $W(x, u, y)$ for the income value of a worker who is hired out of unemployment by firm y. The analogous surplus splitting then implies that

$$W(x, u, y) = \beta S(x, y) + (1 - \beta) U(x) \ . \tag{D.2}$$

[43]In the event where poaching and incumbent firms are equally productive, $y = \hat{y}$, the incumbent firm continues to employ the worker who then extracts the full match value, i.e., $W(x, y, y) = S(x, y)$.

An unemployed worker x will only accept a job at firm y, if match surplus $S(x,y) - U(x)$ is non-negative. Given that S is strictly increasing in y, the reservation productivity $R(x)$ of worker x satisfies the complementary-slackness condition

$$S(x, R(x)) \geq U(x) \quad , \quad R(x) \geq 0 \ . \tag{D.3}$$

The Bellman equation for the value of an employed worker is

$$\begin{aligned}[r + \delta(x)]W(x,\hat{y},y) =& w(x,\hat{y},y) + \delta(x)U(x) \qquad\qquad (\text{D.4}) \\ &+ \sum_c f^c(\theta^c)s^{c,e}(x)\int_{\hat{y}}^1 [\max(W(x,y,y'),W(x,y',y)) - W(x,\hat{y},y)]\pi^c(y')dy' \ .\end{aligned}$$

Here $w(x,\hat{y},y)$ denotes the wage that is negotiated with employer y. The worker receives flow income $w(x,\hat{y},y)$ and separates into unemployment at flow rate $\delta(x)$. At flow rate $f^c(\theta^c)s^{c,e}(x)$, the worker meets another firm via channel c which has productivity y' with probability $\pi^c(y')$. The worker's income value changes only if the productivity of the poaching firm exceeds $\hat{y}$. Then either $y' > y$ and the worker switches the job with continuation value $W(x,y,y')$, or $y' \leq y$ in which case the wage is renegotiated with the incumbent firm y, leaving the worker with value $W(x,y',y)$. The wage $w(x,u,y)$ that an unemployed worker negotiates with a firm y is obtained from a similar Bellman equation as in (D.4), with the only difference that the lower bound of integration is equal to the reservation productivity $R(x)$, reflecting that only outside offers y' above the reservation productivity can trigger either a wage renegotiation with the incumbent or a job-to-job transition.

Bellman equations (2) and (3) in the main text, together with the complementary-slackness condition (D.3), can be solved for value functions S , U and reservation productivities R, given tightness and firm distributions in all channels. Wages and worker value functions are then obtained from the surplus splitting conditions (D.1) and (D.2) and Bellman equation (D.4).

D.1.2 Recruiting Effort and Matching Probabilities

At any point in time in the stationary equilibrium, firm y maximizes the flow value

$$\sum_c \Bigg\{ - k^c(r^c) + q^c(\theta^c)r^c(1-\beta)\int_0^1 \Big[\max[S(x,y) - U(x), 0]\psi^c(x,u) + \int_0^y [S(x,y) - S(x,\hat{y})]\psi^c(x,\hat{y})d\hat{y}\Big]dx \Bigg\} \ ,$$

which is the difference between the profit value of the flow of new hires and the recruitment costs, summed over all channels. The first-order conditions of optimal effort choice are given by equations (4).

Write $r^c(y)$ for the solution of firm y's optimal search effort in channel c. The probability of a worker to meet with a firm with productivity y via channel c (conditional on such a meeting taking place) is

$$\pi^c(y) = \frac{r^c(y)\mu(y)}{\bar{r}^c} \ , \tag{D.5}$$

with aggregate recruiting intensity in channel c defined by

$$\bar{r}^c = \int_0^1 r^c(y)\mu(y)dy \ . \tag{D.6}$$

Likewise, the probabilities of a firm to meet a worker of ability x from either unemployment or from a job at a firm of type y via channel c (conditional on a meeting) are

$$\psi^c(x,u) = \frac{s^{c,u}(x)u(x)}{\bar{s}^c} \quad , \quad \psi^c(x,y) = \frac{s^{c,e}(x)n(x,y)}{\bar{s}^c} \ , \tag{D.7}$$

where $u(x)$ and $n(x,y)$ are stationary measures of unemployed and employed workers, and with aggregate worker search intensity in channel c defined by

$$\bar{s}^c = \int_0^1 \left[s^{c,u}(x)u(x) + \int_0^1 s^{c,e}(x)n(x,y)dy \right] dx \ . \tag{D.8}$$

Given aggregate search efficiency units on both sides of the labor market, tightness in channel c is

$$\theta^c = \frac{\bar{r}^c}{\bar{s}^c} \ . \tag{D.9}$$

Equation (4) and (D.5)–(D.9) jointly determine recruiting intensities, matching probabilities and tightness, given value functions S and U and steady-state measures of unemployed and employed workers.

D.1.3 Stationary Distribution

The stationary measure of workers of type x employed in a firm of type y, denoted $n(x, y)$, is obtained from equating outflows and inflows to this group:

$$n(x,y)\left[\delta(x)+\sum_c f^c(\theta^c)s^{c,e}(x)\int_y^1 \pi^c(y')dy'\right] = \sum_c f^c(\theta^c)\pi^c(y)\Big[u(x)s^{c,u}(x)\mathbb{I}_{y\geq R(x)} + \int_0^y n(x,\hat{y})s^{c,e}(x)d\hat{y}\Big] \ . \tag{D.10}$$

Matches (x, y) are destroyed either when the worker separates into unemployment or when the worker meets another firm of productivity greater than y through any search channel. Matches (x, y) with $y \geq R(x)$ are formed when an unemployed worker of ability x meets a firm of productivity y (flow rate $f^c(\theta^c)s^{c,u}(x)\pi^c(y)$ in channel c) or when worker x employed in a firm $\hat{y} < y$ meets firm y (flow rate $f^c(\theta^c)s^{c,e}(x)\pi^c(y)$ in channel c).

Unemployed are all workers without a job, i.e., the stationary measure of unemployed workers of ability x is[44]

$$u(x) = \lambda(x) - \int_0^1 n(x,y)dy \ . \tag{D.11}$$

Finally, let $\hat{n}(x, \hat{y}, y)$ denote the mass of workers earning wage $w(x, \hat{y}, y)$. Stationarity requires again that outflows to this group are equal to inflows:

$$\hat{n}(x,\hat{y},y)\left[\delta(x)+\sum_c f^c(\theta^c)s^{c,e}(x)\int_{\hat{y}}^1 \pi^c(y')dy'\right] = \sum_c f^c(\theta^c)s^{c,e}(x)\left\{n(x,\hat{y})\pi^c(y) + \left[\hat{n}(x,u,y)+\int_0^{\hat{y}}\hat{n}(x,\tilde{y},y)d\tilde{y}\right]\pi^c(\hat{y})\right\} , \tag{D.12}$$

for $\hat{y} \in [0, y)$ and

$$\hat{n}(x,u,y)\left[\delta(x)+\sum_c f^c(\theta^c)s^{c,e}(x)\int_{R(x)}^1 \pi^c(y')dy'\right] = u(x)\sum_c f^c(\theta^c)s^{c,u}(x)\pi^c(y)\mathbb{I}_{y\geq R(x)} \ . \tag{D.13}$$

D.1.4 Numerical Solution

For a given parameterization, we discretize x and y with N_x and N_y grid points, indexed $i = 1, \ldots, N_x$ for workers and $j = 1, \ldots, N_y$ for firms, and define all exogenous objects above

[44] It is straightforward to verify that (D.10) and (D.11) jointly imply that unemployment inflows equal outflows, $\int_0^1 n(x,y)\delta(x)dy = u(x)\sum_c f^c(\theta^c)s^{c,u}(x)\int_{R(x)}^1 \pi^c(y)dy$.

as vectors or matrices of dimensions N_x, N_y, or $N_x \times N_y$.

We first set tightness θ^c and matching probabilities $\pi^c \in \mathbb{R}^{N_y}$ in the three channels to arbitrary levels. Also fix the initial reservation productivity such that every worker accepts all jobs, i.e., discrete index $j^R(i) = 1$ for all workers $i = 1, \ldots, N_x$. Then we solve for equilibrium by iterating over the following two steps until convergence of θ^c, $\pi^c \in \mathbb{R}^{N_y}$ and $j^R \in \mathbb{R}^{N_x}$ is achieved.

Step 1

Solve for value functions S and U and stationary distribution measures n and u. This can be done by simple matrix inversion of the linear equations given by the Bellman equations (2), (3), and the stationarity conditions (D.10) and (D.11).

Step 2

Solve for tightness, matching probabilities and reservation productivities consistent with S, U, n and u. To do so, we obtain worker matching probabilities from search efficiencies and distribution measures from Step 1:

$$\psi_i^c(u) = \frac{s^c(x_i, u)u_i}{\bar{s}^c} \ , \ \psi_{ij}^c(e) = \frac{s^c(x_i, e)n_{ij}}{\bar{s}^c} \ ,$$

with aggregate search intensity in channel c

$$\bar{s}^c = \sum_i \left[s^c(x_i, u)u_i + s^c(x_i, e) \sum_j n_{ij} \right] \ .$$

Then we jointly solve the FOC for recruiting effort (4) with aggregate recruitment effort $\bar{r}^c = \bar{s}^c \theta^c$ for tightness in channel c, θ^c, and recruitment effort in channel c, r_j^c, from which we can back outmatching probabilities

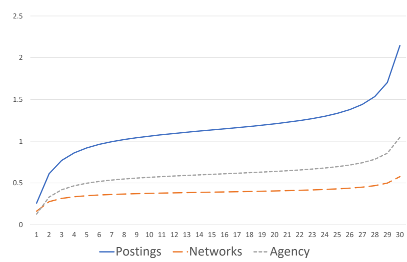
$$\pi_j^c = \frac{r_j^c \mu(y_j)}{\bar{s}^c \theta^c} \ .$$

Finally, set the reservation productivities to $j^R(i) = \min\{j | S_{ij} \geq U_i\}$.

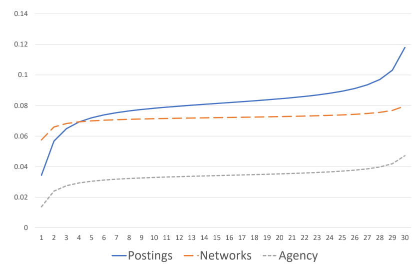
After convergence has been achieved, the remaining model equations can be solved for the wage distribution.

D.2 Costs and Benefits of Search Channels: Further Results

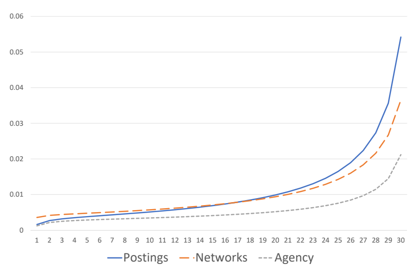
In this section we present we provide a more detailed view of the different recruitment outcomes firms have by using different search channels. In Section 3.4 of the main text we analyzed differences in recruitment outcomes across the three channels, focusing on the mean of the outcome across the firm productivity distribution and the ratio between the respective outcome variable at the 75th and 25th percentiles of the firm productivity distribution. Figure D.1 instead shows the estimated recruitment costs, meeting probabilities, hiring probabilities, shares of hires, profit per hire and average worker ability over the full firm productivity distribution.



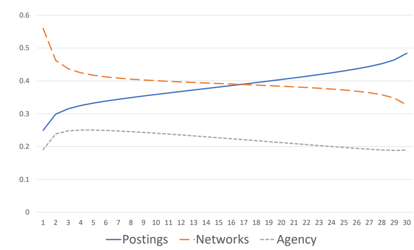
(a) Recruitment cost



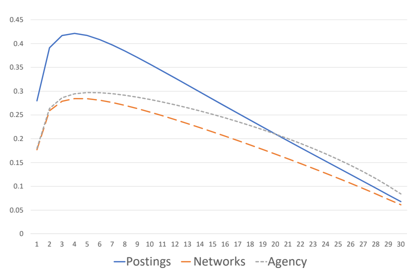
(b) Meeting probability



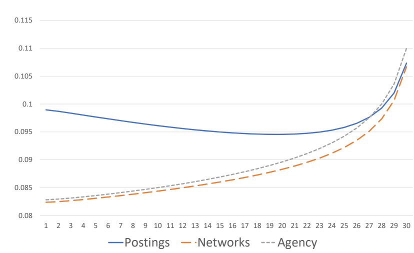
(c) Hiring probability



(d) Share of hires



(e) Profit per hire



(f) Average worker ability

Figure D.1: Recruitment outcomes by firm productivity type

Note: The horizontal axis shows the 30 indices of firm productivity y which have equal weight in the model parameterization.