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Carlos Carrillo-Tudela, Leo Kaas, Benjamin Lochner

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Matching through Search Channels

Abstract

Firms and workers predominately match via job postings, networks of personal contacts or the public employment agency, all of which help to ameliorate labor market frictions. In this paper we investigate the extent to which these search channels have differential effects on labor market outcomes. Using novel linked survey-administrative data we document that (i) low-wage firms and low-wage workers are more likely to match via networks or the public agency, while high-wage firms and high-wage workers succeed more often via job postings; (ii) job postings help firms the most in poaching and attracting high-wage workers and help workers the most in climbing the job ladder. To evaluate the implications of these findings for employment, wages and labor market sorting, we structurally estimate an equilibrium job ladder model featuring two-sided heterogeneity, multiple search channels and endogenous recruitment effort. The estimation reveals that networks are the most cost-effective channel, allowing firms to hire quickly, yet attracting workers of lower average ability. Job postings are the most costly channel, facilitate hiring workers of higher ability, and matter most for worker-firm sorting. Although the public employment agency provides the lowest hiring probability, its removal has sizeable consequences, with aggregate employment declining by at least 1.4 percent and rising bottom wage inequality.

JEL-Codes: E240, J230, J310, J630, J640.

Keywords: search channels, on-the-job search, recruitment effort, sorting wage dispersion.

Carlos Carrillo-Tudela
University of Essex / United Kingdom
cocarr@essex.ac.uk

Leo Kaas
Goethe University Frankfurt / Germany
kaas@wiwi.uni-frankfurt.de

Benjamin Lochner
University of Erlangen-Nuremberg (FAU) &
Institute for Employment Research (IAB) / Germany
benjamin.lochner@fau.de

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1 Introduction

The existence of labor market frictions makes the pairing of workers and firms a time-consuming and costly process which involves search and screening activities on both sides of the market. The use of job advertisements, business and social networks, as well as private and public employment agencies are common ways to deal with these frictions. For example, by posting their job openings, firms can reach a wide group of potential applicants across many locations. By using networks firms can approach suitable candidates, workers learn about job openings, and both gain more detailed information about each other prior to interview (see e.g. Mortensen and Vishwanath, 1994; Galenianos, 2014; Dustmann et al., 2016). Public employment agencies not only help firms and workers by providing job platforms, but also give bespoke advice to job seekers in their search process (see e.g. Crépon et al., 2013; Belot et al., 2019; Schiprowski, 2020). It remains unknown, however, how the firms' choices of these *search channels* impact the workers' labor market turnover and hence the ultimate allocation of heterogeneous workers into heterogeneous jobs.

The objective of this paper is to investigate the extent to which search channels have differential effects on the matching process between workers of different ability and firms of different productivity, and hence how they matter in shaping wage inequality, sorting and other aggregate labor market outcomes. We approach this question by obtaining new findings from linked survey-administrative data which we combine with a quantitative equilibrium model featuring two-sided heterogeneity and labor market frictions.

We begin our analysis by presenting evidence on the use and success of search channels and the resulting matching outcomes. To gain insights into the recruitment strategies of firms, we use the Job Vacancy Survey (JVS) of Germany's Institute for Employment Research (IAB) which collects detailed information about the recruitment process undertaken to fill the last vacancy in the surveyed firm. A crucial advantage of these data is that we are able to match the employer identity and, for 70 percent of the sample, the last person hired in the administrative Integrated Employment Biographies (IEB) of the IAB, which is a matched employer-employee dataset comprising the universe of workers registered with social security records. We further make use of a worker survey, the Panel Study Labour Market and Social Security (PASS) to obtain information about job search behavior of employed and non-employed job seekers. This survey, too, can be linked to the administrative employment and benefit recipient biographies.

To the best of our knowledge such combined data is unique and can give important insight on the relationship between firms' recruitment patterns, workers' job search strategies, and labor market outcomes at the match level. The administrative data allow us to obtain wage fixed effects (wage ranks) for both workers and firms, by estimating the two-way fixed effect regression first proposed by Abowd et al. (1999) (henceforth AKM) and following Card et al. (2013) in their application. The firm survey data give us information about the search channels used by different firms in the recruitment process and also about the search channel that ultimately led to the hired worker. Likewise, the worker survey provides information about the use of search channels by different workers, and through which channel they find a new job. Thus, we can study to what extent firms and workers of different wage ranks make use of search channels and how they help to generate matches between these different workers and firms. We focus on the three search channels which turn out to account for the vast majority of hires in our data: postings of jobs, networks of personal contacts, and the public employment agency.

While the number of search channels used does not differ systematically across the wage ranks of either workers or firms, a key finding is that high-wage firms use and succeed to hire more frequently via job postings and less frequently via personal networks or the public employment agency, in comparison to low-wage firms. Likewise, high-wage workers find jobs more often through job postings and less often through networks or the public employment agency, compared to low-wage workers who also make more frequent use of personal networks and of the public employment agency when seeking jobs. Search channels also matter for poaching and job ladder dynamics: For firms, job postings provide the highest probability to poach a worker from another firm. For workers, a job-to-job transition through job postings comes along with the largest steps on the job ladder as measured by the difference in wage ranks of the employers before and after the job move.

Further, search channels have a differential effect on sorting by the empirical wage ranks: Job postings allow firms to hire workers with higher wage ranks compared to other search channels, especially for firms higher up the wage distribution. Conversely, hiring through the public employment agency attracts workers at lower wage ranks, and unsurprisingly, this channel offers the lowest probability to poach a worker. Regarding match stability, a worker hired through the public employment agency is more likely to leave the job within the next two years, especially when this worker has a higher wage rank. In contrast, hiring through job postings increases match stability, but only for higher ranked firms and higher ranked workers. Networks generally lead to somewhat more stable matches, without differential effects across firm or worker ranks.

To interpret our empirical findings and to analyze the role of search channels for labor market sorting, employment, productivity and wages, we build an equilibrium search model with worker and firm heterogeneity which extends Cahuc et al. (2006) to include multiple search technologies and endogenous recruitment effort. Workers and firms potentially match through one of three channels: job postings, networks, and the public employment agency. Workers differ in ability and search on and off the job. The efficiency at which workers are able to utilize the three search channels may vary with their ability and employment status. Firms differ in productivity and decide the recruitment effort in each of the three channels, taking into account the distinct hiring probabilities and types of workers they expect to attract through each of the channels. The job-level production technology allows for complementarities between worker ability and firm productivity. Wages are negotiated between workers and firms upon hiring and renegotiated when a worker receives a credible outside offer. As a result, the wage depends on worker ability, firm productivity and rent sharing which reflects the bargaining history of the worker.

We estimate our model using information from the data described above. We identify the parameters governing matching efficiency, workers' search efficiencies and firms' recruitment costs in the three channels from the hiring and job-finding patterns across worker and firm wage percentiles together with information on recruitment costs that we also obtain from the JVS. Parameters describing the production technology and the worker ability and firm productivity distributions are identified from the distribution of wages and the wage variation across firms and workers as measured in matched panel data. Worker separations into unemployment and income during unemployment are allowed to vary with ability. These parameters are identified from employment-to-unemployment transition rates and unemployment-income replacement rates.

The estimation reveals that networks are the most cost-effective recruitment channel: It is least costly and comes with a high success probability, yet the average worker hired through networks has relatively low ability, especially in firms with low productivity. Job postings, on the other hand, are the most costly channel. Their benefit is that firms hire with high probability, especially when they are more productive, and that they attract more able workers. The public employment agency is less costly than postings, yet it attracts workers of lower ability and the hiring probability is also lower than in the other two channels. However, as firms hire predominately from unemployment through this channel, the employer rent is relatively large.

The estimated model exhibits a modest degree of worker-firm sorting with a correlation coefficient between worker ability and firm productivity of 18 percent. While sorting is partly explained by higher unemployment separation rates of low-ability workers, the estimation reveals that high-ability employed workers are more efficient in generating offers than low-ability employed workers, irrespective of the search channel. On the other hand, low-ability unemployed workers are better at generating offers through networks or the public employment agency than high-ability unemployed workers. Quantitatively, however, differences in search efficiency among *employed workers* account most for positive sorting along the job-finding margin, where the job postings channel plays the largest role. Higher job-finding rates of low-ability workers through networks or the public employment agency take only a negligible mitigating impact on sorting.

Finally, we use our model to analyze the role of the public employment agency for the labor market. To do so, we compare the benchmark estimated model to a counterfactual scenario in which the public employment agency is abolished. Our worker and firm survey data reveal that around half of all matches that are generated through the agency are obtained via the online job platform maintained by the agency, while the other half is obtained via the placement officers of the agency. Acknowledging that the public job platform can be readily substituted by private platforms, we allow workers to shift their search activity to the job postings channel to make up for the forgone meetings previously obtained through the public job platform. But even when workers are able to fully substitute the foregone meetings, the abolishment of the public employment agency has sizable consequences: Aggregate employment and output fall by 1.4 percent and 0.8 percent, respectively. The employment decline is strongest for workers at the bottom of the ability distribution (2.5 percent), yet still sizable for workers in the middle part of the distribution. Due to a composition effect, aggregate labor productivity increases. However, when workers at the bottom and middle of the ability distribution are employed, they end up in less productive firms, which ultimately widens wage inequality: the 90-50 and the 50-10 ratios increase by 3.3 and 1.2 percent, respectively. Thus, we conclude that the public employment agency matters decisively for aggregate and distributional labor market outcomes.

After briefly reviewing related literature, Section 2 describes the data and the main empirical findings. In Section 3 we present the equilibrium wage posting model, the model estimation and our quantitative results.

Related Literature

There is a larger literature that has explored the interpretation of AKM estimates for labor market sorting. Andrews et al. (2008), Eeckhout and Kircher (2011) and Lopes de Melo (2018) point out that the correlation between the estimated worker and firm fixed effects of an AKM regression generate a downwards biased measure of true labor market sorting. The key reason is that observed wages might not be a monotonic function of underlying firm or worker productivity. Theoretically this can occur due to search frictions and the presence of "foot-in-the-door" effect. The latter occurs when a worker accepts a lower starting wage than his current (per period) income. Examples of such an effect are abundant in wage posting models à la Burdett and Mortensen (1998). The sequential auction model proposed by Postel-Vinay and Robin (2002) is a prominent example which also applies to our framework. As a consequence several papers have proposed alternative methods to measure labor market sorting. Using structural models of the labor market, typically assuming search frictions, many have aimed at identifying the degree of complementarities in the production functions (see e.g. Hagedorn et al., 2017; Bagger and Lentz, 2019). A second approach has been to devise new reduced form ways to categories workers and firms (see e.g. Borovickova and Shimer, 2017; Bonhomme et al., 2019; Lentz et al., 2023). This paper builds on this literature and contributes by emphasizing the role of search channels in determining sorting in the presence of labor market frictions. Search channels are important as they reveal how firms and workers deal with the frictions that slow down match formation and impede perfect sorting. To the best of our knowledge we are the first to study such effects and do so in a comprehensive way.

Our paper also contributes to the growing theoretical literature interested in the role of firms' recruiting intensity on aggregate labor market outcomes. Recent work extends the canonical Diamond-Mortensen-Pissarides framework to feature multi-worker firms which choose recruitment effort as in Gavazza et al. (2018) or wages as in the competitive-search models of Kaas and Kircher (2015) and Schaal (2017). Selection cutoffs among heterogenous pools of applicants are also introduced in random search environments like the ones proposed by Baydur (2017) and Acharya and Wee (2020). Carrillo-Tudela et al. (2023) consider a model featuring these different dimensions of recruiting intensity which is informed by JVS data. In contrast, here we focus on the implications of firms' recruitment effort and the role played by distinct search channels in shaping labour market sorting, and aggregate employment and wage inequality.

There is also a large body of work which demonstrates that informal employment contacts based on individuals' social or professional networks have a strong influence on their labor market outcomes. Holzer (1988), for example, finds that 66 percent of young workers who accepted a job used informal search channels. Cappellari and Tatsiramos (2015) show that informal employment contacts have positive effects on workers' job finding rates, while Brown et al. (2016) show that such contacts lead to better job matches.[1] That workers hired through personal contacts earn higher wages and stay longer in the firm is consistent with the findings of Dustmann et al. (2016), among others. Lester et al. (2021) distinguish between referrals of family and friends and those of business contacts, showing that only the latter correlates with higher starting wages.

Theoretical frameworks that followed on from these findings formalize the idea that contacts help alleviate search frictions that arise from imperfect information about the location of jobs and workers and the idea that contacts help mitigate asymmetric information about the quality of applicants in the hiring process (see e.g. Topa, 2001; Montgomery, 1991; Galenianos, 2013). Information flows among the members of a given network lie at the heart of most of these theories. Others explore the impact of worker networks on wage inequality (see e.g. Mortensen and Vishwanath, 1994; Fontaine, 2008). Our paper presents novel evidence on the use of networks for matching outcomes and analyzes how the use of different search channels by firms and workers affects wage dispersion and sorting.

2 Empirical Patterns

2.1 Data

Our empirical work builds on firm and worker surveys which we link to administrative matched employer-employee data. All datasets are provided by Germany's Institute for Employment Research (IAB). We obtain information about recruitment strategies from the Job Vacancy Survey (JVS) which is a representative repeated cross-sectional survey of firms.[2] Its main purpose is to

[1]Topa (2001), among others, provide further evidence on the importance of search channels. See Ioannides and Loury (2004) and Brown et al. (2016) for a review of the literature.

[2]The JVS and all our empirical findings are based on establishments (i.e. regionally and economically delimited units, possibly consisting of multiple workplaces within the same region). To simplify terminology, we refer to "firms" instead of "establishments" throughout the paper.

measure the number of vacancies at these firms, over and above those that are officially reported at the Federal Employment Agency, and to obtain information about the firms' recruitment processes.[3] While the survey is conducted annually since 1989, firm IDs can be obtained and linked to administrative records only from the year 2010 onward. Given this matching restriction we focus on the years 2010-2016, for which we observe around 9,000-10,000 firms per year reporting recent recruitment activity.

The JVS 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 vacancy stock. Among those firms that reported recruitment activity within the last 12 months (68% of firms), the survey provides detailed information about the recruitment process pertaining to the last case of a successful hire.[4] 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 skill requirement and occupation. It also includes the age, education and previous employment status of the individual who ultimately filled the job. Although there is no direct information about whether the recorded information for the last case of a hire in the JVS corresponds to single vacancy job openings, we find evidence suggesting that this is indeed the case for the vast majority of hires (see Appendix A.1.2).

Regarding the job search behavior of workers we utilize the Panel Study "Labor Market and Social Security" (PASS). This is a household level survey oversampling households receiving unemployment transfers.[5] Established in the year 2006, this survey contains about 10,000 households including about 15,000 persons aged 15 or older. 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. Crucial for our purposes, household members (employed or non-employed) report whether they are currently looking for work. Conditional on workers reporting search activity during the last four weeks, they report the search channels used, applications sent, job interviews and some further job search information.

We link the JVS and PASS to administrative records of individual employment spells via firm IDs (JVS) and worker IDs (PASS). The administrative records are collected by the Federal Em-

[3]See Bossler et al. (2020a) for a data description and Bossler et al. (2020b) for a summary of recent studies using JVS data.

[4]Among recruiting firms 97% were successful in filling either all or a fraction of their vacancies, while the remainder 3% did not manage to fill any of their vacancies. Carrillo-Tudela et al. (2023) show that there are no meaningful differences in various characteristics (such as size, age or industry) between firms which fill either all or only a fraction of their job openings. This suggests that by focusing on recruiting firms that successfully hired workers, we are not introducing meaningful selection along these dimensions. The main difference between those firms that did not report any recruitment activity and those that did arises from their size distributions, where the former group is mostly composed by small firms with less than 20 employees. To make our JVS sample of hiring firms as representative as possible, we use the provided firm weights.

[5]The data combines a general population sample with a sample of benefit recipients. We apply the provided population weights to project the combined sample to the German residential population.

ployment Agency and available through the Integrated Employment Biographies (IEB). This data set encompasses the entire labor market spells of workers paying social security contributions in Germany since the year 1975 (prior to 1993, only West Germany is included in these data). Thus we can observe, for any particular day, all employed workers in JVS firms with information about their education, age, gender, nationality, occupation and daily earnings. Further, following the matching procedure developed in Lochner (2019), we are able to identify in the IEB around 70% of the last hires reported by JVS firms.[6] This implies that we observe the full employment and earnings biographies of JVS hires since they started paying social security contributions, as well as detailed information about the recruitment process that firms followed when hiring these workers. Similarly, the identification of workers surveyed by the PASS in the IEB data implies that we can observe their employment and earnings history since these workers started paying social security contributions, as well as the identities of their employers with information on their size, age and industry. Appendix A provides a more detailed discussion of these data sources and presents descriptive statistics of the firms surveyed in the JVS and their last hires as well as descriptive statistics of the workers surveyed in the PASS.

2.1.1 Search Channels

Central to our study is the information about the search channels used on both sides of the labor market and the channels which ultimately led to a match (successful channel). In particular, the JVS asks the (representative of the) recruiting firm "How did you search for applicants for this position?", for which more than one channel can be chosen and "Which of the search channels mentioned ultimately led to the vacancy being filled?" The questionnaire allows for several possible channels. We group all these possible channels into seven categories: (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 (see Appendix A.2 for details on the categories).

The first two columns of Table 1 show the use and success of search channels of firms surveyed in the JVS that reported a successful hire. On average, these firms use 1.9 channels, out of which postings, networks and the public employment agency are the most common ones. However, not all of them are equally successful: Job postings, networks and the public employment agency are most frequently reported as the channels through which the hired worker was contacted. Furthermore, the success rates (i.e., the ratios between the share in the second and the first column) of postings and networks by far exceed those of the other channels.

The last two columns of Table 1 report workers' search channel use and success. In the PASS,

[6] The identification is based on a discrete matching algorithm, which utilizes overlapping information such as the hiring date, workers' age, gender, and occupation in both the JVS and in the IEB. This matching procedure also confirms that multiple hires for the same job openings are a rare phenomenon. See Appendix A.1.2 for details.

actively searching workers report how they obtain information about jobs (channel use), while those workers who found a new job during the last year are asked how they had learned about the job (channel success). While the channel classification differs somewhat from the one in the JVS, the top three categories are very similar. On average, searching workers make use of 2.3 channels, where postings and networks dominate use and success, followed by the public employment agency.[7] Given the importance of postings, networks and the public employment agency, and to keep our empirical and theoretical analysis as clear as possible, we focus on the role of these three channels for the matching process.

Table 1: Use and success of search channels

	Firms (JVS)		Workers (PASS)	
Search channel	Use (%)	Successful (%)	Use (%)	Successful (%)
Postings	55.3	28.7	88.1	18.7
Networks	54.1	40.5	60.22	27.0
Public Agency	37.7	13.3	57.3	8.4
Unsolicited	18.7	8.0	-	-
Internal	14.5	5.3	-	-
Private Agent	6.1	2.6	12.1	2.2
Others	2.7	1.5	16.9	43.7
Total	**189.0**	**100.0**	**234.6**	**100.0**

Notes: The percentages of firms are taken from the section of the JVS about recruitment strategies at the last successful hire and are calculated using firm weights. Percentages of channel use of workers are taken from the job search section of the PASS which is answered by employed and non-employed workers reporting active search. Percentages of successful channels are taken from the spell section of the PASS where employed workers with a new job answer how they got to know about the job. Worker statistics are calculated using population weights.

2.1.2 Worker and Firm Heterogeneity

A key objective of our paper is to study the role of search channels for the matching process among heterogeneous workers and firms. To obtain an internally consistent way to rank both workers and firms, we decompose wages into fixed worker and firm effects. For this purpose, we follow Card et al. (2013) who estimate the two-way fixed effect regression proposed by Abowd et al. (1999) (henceforth AKM),

$$y_{it} = \alpha_i + \gamma_{J(i,t)} + \beta X_{it} + u_{it} \ , \tag{1}$$

[7] In Appendix A.2, we provide further details about the channel categories in the JVS and the PASS. For instance, the "Unsolicited" and "Internal" categories of the JVS shown in Table 1 are not available in the PASS and thus are included in the "Others" category. We also show the distributions of search channels for firms using hiring weights (instead of firm weights) and we report the use and success of search channels separately for employed and non-employed workers.

where y_{it} is the log real daily wage of worker i in year t. The coefficients α_i and γ_j are worker i and employer j fixed effects such that $j = J(i,t)$ describes worker i's employer in year t. X_{it} denotes a vector of worker covariates composed of a cubic polynomial in age, interacted with educational attainment and year dummies, and u_{it} is a residual term which captures both transitory wage changes and time-invariant match-specific wage differences. Firm fixed effects γ_j measure persistent wage differences across firms (which may stand for, e.g., compensating differentials, rent sharing or productivity differences), while worker fixed effects α_i reflect, among others, differences in schooling, innate ability or other time-invariant worker characteristics.

We estimate equation (1) for full-time workers of ages 20–60 and their employers using IEB data. To identify firm fixed effects, the sample is restricted to the largest connected set of firms which are linked through worker transitions. Note that we can only use full-time workers since the IEB data do not record hours worked. In case of multiple full-time job spells in the same year, $J(i,t)$ refers to the employer of worker i with the highest total earnings. Wages above the social security contribution threshold are imputed following standard procedures (see Card et al., 2013; Dustmann et al., 2009).

In our benchmark analysis we estimate (1) for the period 2010-2016 and match the resulting wage fixed effects to JVS firms, PASS workers and to those (identified) JVS hires who were hired on a full-time basis. To recover the fixed effects for PASS workers and workers identified as JVS hires after 2010 but for whom we could not obtain AKM fixed effects during 2010–2016, for instance because they were only part-time employed in this period, we estimate (1) for four separate earlier periods 1985–1992, 1993–1999, 1998–2004 and 2003–2010, and impute for each of these workers his/her most recent fixed effect estimate. To take into account changes in the wage structure over time, we standardize the estimates from earlier periods and transform them into the corresponding values of the 2010-2016 fixed effect distribution.[8] Thus, these fixed effects measure the contribution of a worker's time-invariant characteristics to log wages in relation to the average log wage in the 2010-16 period. Appendix A.3 presents and discusses further details about the AKM estimation and the results.

A potential concern with estimating the AKM fixed effects in the same period as the one used to measure the use of search channels is that the latter could be determining observed wages and hence the fixed effects. To address this concern we also estimate the firm and worker wage fixed effects using the aforementioned earlier periods. Appendix B.5 presents the results of this exercise, finding no meaningful change in the patterns relating the use of search channels to the AKM fixed effects presented below.[9] As an additional robustness exercise, when considering firm differences, we also

[8]Specifically, we calculate z-scores for fixed effects obtained from earlier time windows and invert them using the mean and standard deviation of the fixed effect distribution in the 2010-2016 period. Our findings are robust to leaving out observations with these recovered fixed effects.

[9]It is reasonable to assume that any differences in the estimates can be largely attributed to the fact that in this robustness exercise we do not capture those firms and workers that entered the labor market during the 2010-16

use the "poaching index" proposed by Bagger and Lentz (2019) instead of the AKM fixed effects. The poaching index ranks firms by the revealed preferences of workers who move between employers and is found to be positively correlated with the AKM firm effects (see Lochner and Schulz, 2022). The tables in Appendix B show very similar results when using the alternative ranking.

2.2 Search Channels Among Heterogeneous Workers and Firms

We now turn to investigate whether the probability of using a particular search channel as well as successfully matching through this channel correlates with firms' and workers' rank. In our firm-level analysis we estimate probability models in which we control for the AKM firm effects, the educational requirements of the job (high school or less, vocational education, university degree) as well as the firm's age, size, industry and whether financial, workforce and/or demand constraints were faced. For worker-level results, we control for a quadratic in worker age, gender, previous employment status, and one-digit occupation. Appendix B presents further results showing how firm and worker ranks correlate with their broader search behavior.

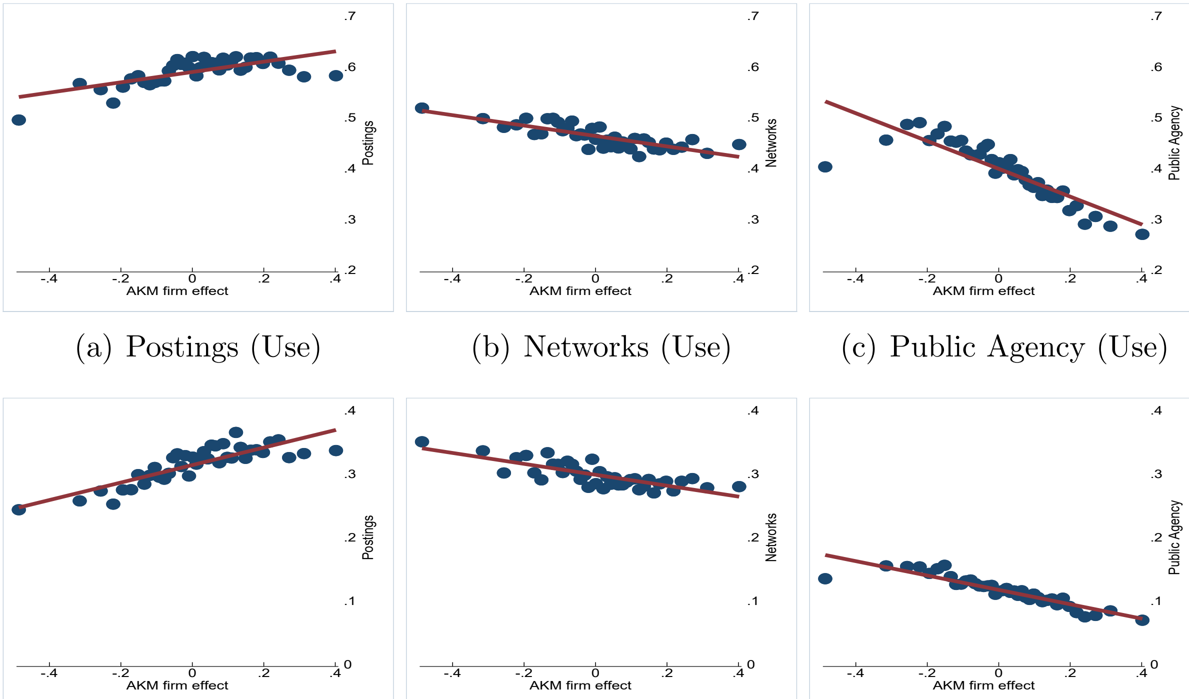
Figure 1 shows the relationship between a firm's AKM fixed effect and the estimated probabilities of either using a particular search channel or hiring through a particular search channel using the JVS. The plots depict important differences across firm types and search channels.[10] The top panels show that higher-wage firms are more likely to use job postings to search for applicants, while lower-wage firms are more likely to use networks and the public employment agency. The bottom panels demonstrate that similar conclusions hold when considering the probability that the hired worker was contacted through one of these channels: High-wage firms succeed to hire more often via job postings, and less often via networks or the public agency, compared to low-wage firms. Quantitatively, an increase of the firm fixed effect from the lowest to the highest bins shown in these graphs goes along with a 9.4 percentage point (pp) higher probability of using postings, a 9.5 pp lower probability of using networks, and a 25.4 pp lower probability of using the public agency. Likewise, the same increase of the firm fixed effect comes with a 13 pp higher probability of hiring through postings, but a 9.4 and 11.6 pp lower probability of hiring through networks and the public agency.

In terms of magnitudes, the differences in use and success probabilities are comparable to those that we observe between firm size categories or educational requirements of the job; see Table B.3 in Appendix B.3.1 which reports the coefficient estimates of the corresponding linear probability regressions.[11] These estimates show that firms have a higher probability of using or succeeding to

period, which reduces the number of observations.

[10]To establish the various binscatter plots in this section, we first residualize the AKM effects and the outcome variable using the respective controls. Next, we group the residualized AKM effects into equal-sized bins and compute the mean of the residualized AKM effects and the residualized outcome variable within each bin. We create scatterplots of these data points and fit OLS lines.

[11]Using an alternative probit specification leads to no meaningful differences in these conclusions.



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

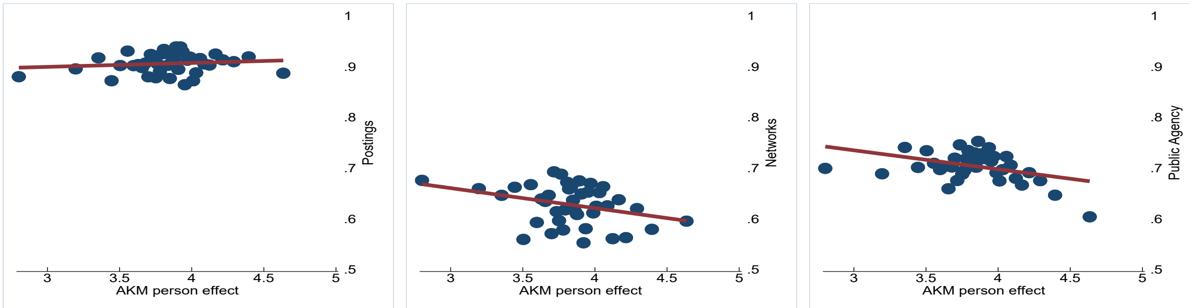
(d) Postings (Success) (e) Networks (Success) (f) Public Agency (Success)

Figure 1: Use and success of search channels by AKM firm fixed effect

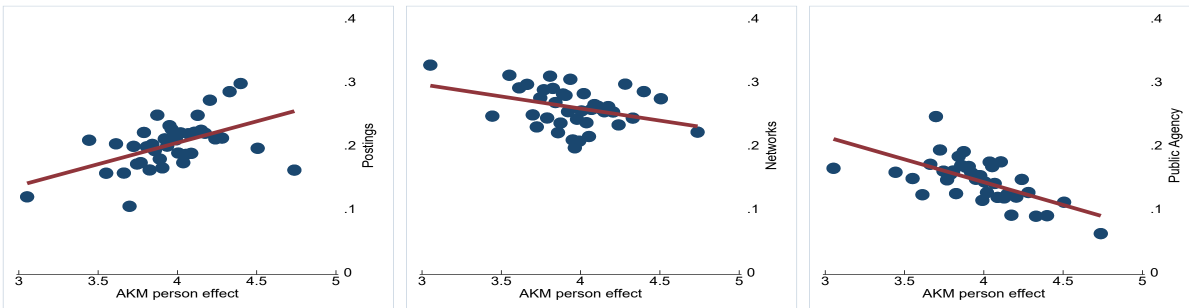
Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of using the channel (top panels) or hiring through the channel (bottom panels) for one of the three channels "Postings" (left), "Networks" (middle), or "Public Agency" (right). Controls: educational requirement (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.

hire through job postings when they want to fill higher skill jobs, whereas the probability of using or hiring through personal contacts and the public employment agency is higher when filling low-skill vacancies. Larger firms have a higher probability of using and succeeding to hire through job postings, while smaller firms are more likely to use personal networks. Larger firms are also more likely to use the public employment agency, but as compared to smaller firms their success in hiring is lower. The regression results thus show that the correlations between firm rank and the use and success of a given search channel are not driven by composition effects related to the educational requirements of the job opening nor the size, age or industry of the firm. Appendix B.3.2 includes an additional set of graphs which show the relationships between firm rank and channel use/success for several firm size and industry categories. All results are consistent with the patterns shown in Figure 1, further suggesting no meaningful composition effects.

Figure 2 shows the comparable relationships between a worker's AKM fixed effect and the estimated probabilities that the worker uses a search channel or that the worker found a job through



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



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

Figure 2: Use and success of search channels by AKM worker fixed effect

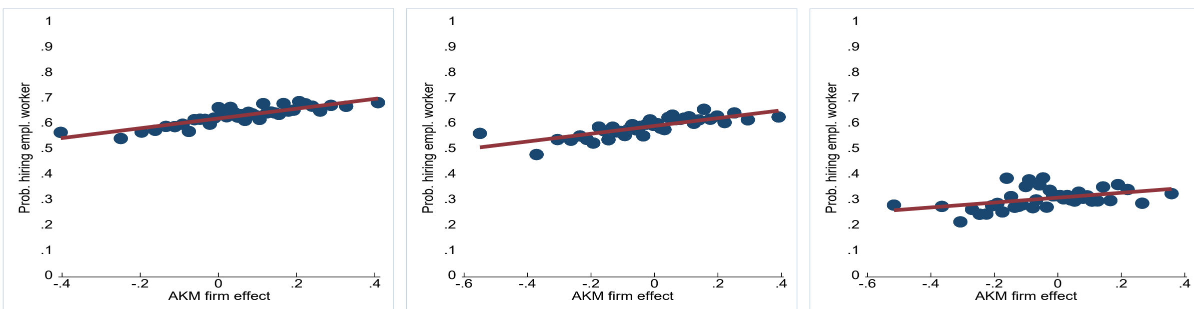
Notes: The figures show binscatter plots that relate the worker's AKM fixed effect to the probability of using the channel (top panels) or finding a job through the channel (bottom panels) for one of the three channels "Postings" (left), "Networks" (middle), or "Public Agency" (right). Controls: quadratic polynomial of worker age, gender, employment status (dep. employed, self-employed, unemployed, non-participation), one-digit occupation, and year dummies.

the respective channel using PASS data. In this case we condition on the worker's age, gender, employment status, and one-digit occupation. We observe that low-wage workers are more likely to use networks or the public employment agency compared to high-wage workers, and they are also more likely to find jobs through these channels (middle and right panels). Conversely, high-wage workers find jobs more often through job postings (lower left panel), while workers in all wage ranks make similar use of job postings when looking for jobs (upper left panel). An increase of the worker fixed effect from the lowest to the highest bins in these graphs goes along with a 7.8 pp reduction in the probability of using networks and a 7.4 pp reduction in the probability of using the public agency. Regarding job finding, the same increase of the worker fixed effect comes with a 13 pp higher probability of succeeding through postings, but 7.3 and 13.8 pp lower probabilities of succeeding through networks or the public agency.

The corresponding regression results are presented in Table B.4 in Appendix B.3.1. They show that unemployed workers make more use of networks and of the public employment agency compared to employed workers, with no statistically significant difference in the use of postings. While we find no systematic difference in the use of channels by age, we find that older workers are more likely to find a job through job postings. Women are more likely to use and succeed to find a job through job postings, but less likely to succeed through personal networks. Appendix B.3.2 presents an additional set of graphs showing the relationship between worker fixed effects and the channel use and success for several age and education categories. Once again we find that the patterns of Figure 2 are not driven by any of these subgroups.

Taken together the above results show that high-wage workers and high-wage firms match more often through job postings, while low-wage workers and low-wage firms match more often through networks or through the public agency. While these results point to an important role of search channels for labor market sorting, they do not contain information about match-level outcomes. We consider these in the following subsections.

2.3 Poaching and the Job Ladder



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

Figure 3: Probability of hiring an employed worker by AKM firm fixed effect

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". The same controls as in Figure 1 are applied.

We start our analysis of match-level outcomes by studying the relationship between the firm's successful search channel and the hired worker's previous employment status and the extent to which these channels help workers climb the job ladder. Figure 3 illustrates which search channels are more conducive to poach a worker (hire a worker who was previously employed) for different types of firms. Here we use information obtained from the JVS and control for the same job and firm characteristics as described in the previous section. The corresponding regression results are presented in Table B.5 in Appendix B.4.

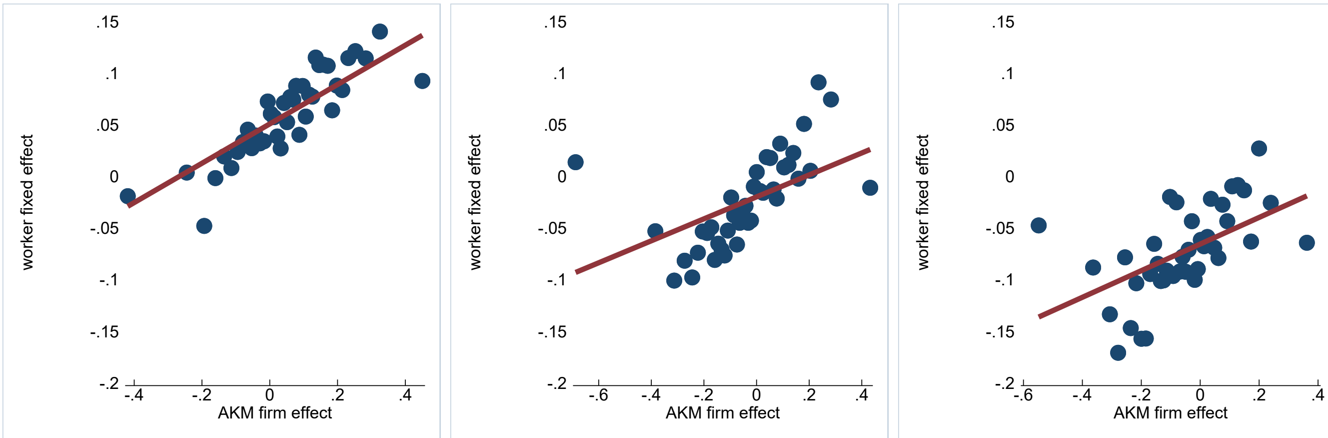
The estimates show that hiring through job postings or networks offer the highest probability of poaching a worker from another firm rather than hiring from non-employment. Reflecting the positive correlation between the AKM firm effect and the poaching index we observe in our data, the positive slopes of the depicted relationships show that higher-wage firms are more likely to poach a worker from another firm. However, we find that the probability of hiring an employed worker has a stronger increase with firm's wage rank when using job postings relative to networks. The public employment agency (unsurprisingly) offers the lowest probability that the hired worker was previously employed and the lowest increase in this probability with the AKM firm effect. Going from the lowest to the highest bin of the firm AKM fixed effect distribution results in an increase of the poaching probability of 17.9 pp for postings, 14.3 pp for networks, and 9.0 pp for the public employment agency.

Table 2: Change in firm effect at an EE transition by search channel

	(1) $\triangle$ firm effect	(2) $\triangle$ firm effect
	w/o controls	worker controls
Reference=Postings		
Networks	-0.0293***	-0.0308***
	(0.0046)	(0.0049)
Public Agency	-0.0204**	-0.0314***
	(0.0072)	(0.0077)
Constant	0.0580***	0.0666***
	(0.0032)	(0.0148)
mean $\triangle$ firm effect	0.0431	0.0457
st.d. $\triangle$ firm effect	0.257	0.2522
Observations	14,242	11,960
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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2 complements these results by investigating whether search channels facilitate the reallocation of workers into higher-paying firms through movement along the job ladder, using information on the identity of the hired workers into JVS firms and their previous employers. For this purpose, we regress the change of the AKM firm effect after an EE transition on the associated hiring channel. We consider two specifications, one without worker controls and the other adding the same worker controls as in the previous section. Our results show that on average workers climb the AKM firm rank after an EE transition. However, the magnitude at which they do so differs across search channels. If a worker is hired through networks or the public employment agency, the worker does not increase as much his position in the AKM firm rank as through jobs found via postings (the reference category). Without any worker controls, on average an EE transition goes along with an increase of the AKM firm effect of 4.3 percent. When transitioning through postings, the average



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

Figure 4: Relationship between worker and firm AKM fixed effect by hiring channel

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". The same controls as in Figure 1 are applied.

increase of the firm effect is 5.8 percent. It is only 2.9 percent when transitioning through networks and 3.8 percent when transitioning though the public agency. Adding worker controls in the second column of Table 2 confirms that the increase in the firm effect is highest for postings while it is about three percent lower for networks and the public agency.

These results suggest that hiring through job postings is associated with steeper job ladders for workers. Postings offer the greatest poaching probability for firms, especially for those higher up the wage distribution, and allow workers to experience larger improvements in their employers' AKM rank, relative to the other search channels.

2.4 Sorting and Match Stability

Next we investigate how the AKM fixed effect of the hired worker relates to the AKM fixed effect of the (hiring) firm, separately for each successful search channel. Figure 4 depicts these relationships, where we control for the aforementioned firm and job characteristics and Table B.6 in Appendix B.4 presents the estimates of the associated regressions. These estimates show a positive correlation between the firm and worker AKM ranks across the three channels. Thus all three search channels are conducive to the positive sorting between workers and firms when using AKM ranks (cf. Table A.7).[12]

[12]The slopes of the OLS lines in Figure 4 show that positive sorting is stronger when hiring through job postings than when hiring through the other two channels. In turn, hiring through networks generates stronger positive sorting than hiring through the public employment agency. However, these results should be interpreted with caution as the observations at the tails suggest some non-linearities.

The figures show that firms are able to hire higher ranked workers through job postings relative to hiring through the two other channels, where the public employment agency generates hires with the lowest fixed effects. Note that here we also control for educational requirements of the job, firm size and age, so that these results are not driven by composition effect based on these characteristics.[13]

Table 3: 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. The same controls as in Figure 1 are applied. 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 3 show that matches involving high-wage firms and high-wage workers are generally more stable. Hiring through job postings has no direct impact on match stability. However, we observe that match stability beyond two years and involving high-wage firms or high-wage workers are more stable when the match is formed via job postings. This suggests that the impact of job postings on the matching of workers and firms relative to the other channels is reinforced since these matches between high-wage workers and high-wage firms tend to be more

[13]Even when we do not control for educational requirements, the qualitative results are the same, while coefficients are generally larger, which suggests that workers sort by formal education in a similar way as they do in other (unobserved) skill dimensions. For instance, firms higher up in the wage distribution employ workers with on average higher educational requirements, and they achieve these hires more through job postings and less via networks or via the public employment agency.

stable. Hiring through networks is associated with more stable matches, consistent with previous evidence of the job referrals literature, but this probability does not seem to meaningfully differ across firm or worker wage ranks. In contrast, hiring via the public employment agency comes along with shorter match duration. Furthermore, the advantage for high-wage workers to be hired in a job that lasts longer than 24 months is almost completely offset when the match occurs via the public employment agency. Instead, the public employment agency helps low-wage workers to end up in relatively stable matches.

3 Quantitative Model

The evidence presented so far suggests that different search channels influence in important ways how different types of workers and firms form employment relationships. To understand the impact of these channels for labor market outcomes, we now present and estimate an equilibrium labor market model in which firms of different productivity hire workers of different ability via multiple matching technologies (search channels). Firms decide about recruitment effort, anticipating how likely it is to meet heterogeneous workers through the different search channels. Workers search on-the-job and reallocate across employers who respond to competing outside offers similar to Postel-Vinay and Robin (2002) and Cahuc et al. (2006). As in Lise et al. (2016) and Bagger and Lentz (2019), we allow for possible production complementarities between worker and firm permanent characteristics.

3.1 The Model

3.1.1 Environment

The model is set in continuous time and we consider a stationary equilibrium. There are fixed measures of firms and workers who are all infinitely lived, risk neutral and discount future incomes with interest rate r. Workers differ in fixed ability $x \in [0,1]$ with distribution measure $\lambda(x)$ such that the total measure is normalized to unity, $\int_0^1 \lambda(x)dx = 1$. Firms differ in permanent productivity $y \in [0,1]$ with distribution measure $\mu(y)$ so that the total measure of firms is $M = \int_0^1 \mu(y)dy$.

If a worker of ability x is employed at a firm of productivity y, the output of the job is $f(x,y)$. The production function f is strictly increasing in both x and y so that more able workers (more productive firms) have an absolute production advantage in comparison to less able workers (less productive firms). Firms operate linear production technologies which add up the output in all filled jobs. Therefore, the hiring of any particular worker impacts the firm's profit only through the job that this worker occupies, but it does not change the profits that the firm makes with any other worker, now or in the future. When unemployed, a worker of ability x receives income $b(x)$.

Firms and workers can potentially meet via different search channels $c \in C$ where C is a finite set. Following our empirical results, we consider the three channels "postings", "networks" and "public agency" in our quantitative analysis. Firms decide about recruitment effort r^c in channel c at flow cost $k^c(r^c)$ which is increasing and convex in r^c. A worker of ability x has search efficiency $s^{c,e}(x)$ in channel c while employed and $s^{c,u}(x)$ while unemployed. Dependence on x and on the current employment state captures that heterogeneous workers find jobs at different rates via search channel c. Worker search efficiency represents both the intensity of job search (such as time spent on search or the number of job applications) and the ability of the worker to generate contacts in the labor market. As our main interest is the recruitment decisions of firms, we leave workers' search efficiencies exogenous, thus keeping the model reasonably tractable.[14]

Within each search channel c, workers and firms meet randomly with congestion externalities on both sides. Specifically, a worker meets a random firm with flow rate $f^c(\theta^c)$ per unit of search efficiency in channel c, and a firm meets a random worker with flow rate $q^c(\theta^c) = f^c(\theta^c)/\theta^c$ per unit of recruitment effort in this channel. Worker meeting rates f^c are strictly concave and strictly increasing in the channel-specific market tightness θ^c which is the ratio between aggregate recruitment effort and aggregate worker search efficiency in channel c. This parsimonious specification emphasizes our focus on analyzing different search channels as vehicles that ameliorate information frictions about the availability of vacant jobs and searching workers, instead of screening frictions after the matching stage. We show that the differential search behavior of workers and firms leads to differences in the equilibrium composition of matches across search channels, thus impacting labor market sorting.

While job-to-job transitions are endogenous outcomes of recruitment effort and job acceptance decisions, workers may also separate into unemployment with exogenous flow rate $\delta(x)$. We allow for dependence on x to capture that in our data the probability of an employment to unemployment transition decreases with worker types.[15]

Wages are negotiated between the firm and the worker and are fixed over time until both parties agree to renegotiate. Such renegotiations happen if the worker receives a credible outside offer in which case the worker triggers a negotiation game with both the incumbent and the poaching firm. As in Bagger and Lentz (2019) and Dey and Flinn (2005), the outcome of this process is that the firm with the larger match value continues to employ the worker and that the worker takes the full

[14] A complication in matching models with two-sided endogenous search effort (in our model separate for each channel, with spillovers on the other channels) is the possibility of multiple equilibria arising from strategic complementarities of workers' and firms' search decisions.

[15] One can also specify the exogenous job destruction rate as $\delta(x, y)$ to capture any variation of job destruction across firm types. We focus on the variation across worker heterogeneity to reduce the set of parameters to estimate. As an extension to Table 3, when considering the probability that the hired worker separates into unemployment within the first 12 and 24 months on the job, we find that matches involving high-wage firms and high-wage workers are generally less likely to lead to unemployment within the first two years, irrespective of the search channel used to form the match; see Table B.7.

match value with the other, less productive firm as an outside option into the wage negotiation with the employing firm. The newly negotiated wage is set such that the worker receives the outside value plus share $\beta \in [0,1]$ of the surplus, whereas the employing firm receives share $1-\beta$ of the surplus. Likewise, if an unemployed worker negotiates with a firm, the unemployment value is the worker's outside option, and the wage is set with a similar splitting of the match surplus between the worker and the firm.

3.1.2 Value Functions and Equilibrium

We write $S(x,y)$ for the joint value of a match between a worker of ability x and a firm of productivity y. As will be seen below, our assumptions on f imply that S is strictly increasing in y. If a worker holds job offers from firms with productivities y and $y' > y$ (one being the incumbent, the other the poaching firm), the match value with the more productive firm y' is larger and therefore this firm continues to employ the worker, whereas the match value with the less productive firm $S(x,y)$ represents the worker's outside option in the wage negotiation with firm y'. Therefore, the wage is negotiated such that the worker obtains the surplus $\beta[S(x,y') - S(x,y)]$.

The joint value of a match (x,y) satisfies the Bellman equation

$$[r+\delta(x)]S(x,y) = f(x,y) + \delta(x)U(x) + \sum_c f^c(\theta^c)s^{c,e}(x)\beta \int_y^1 [S(x,y') - S(x,y)]\pi^c(y')dy' \ . \tag{2}$$

The match generates flow output $f(x,y)$ until a separation occurs in which case the firm is left with zero continuation value. At flow rate $\delta(x)$, the worker separates into unemployment with continuation value $U(x)$. At flow rate $f^c(\theta^c)s^{c,e}(x)$ the worker receives an offer from another firm via channel c. Here $\pi^c(y')$ is the endogenous probability to meet a firm of productivity y' in search channel c, conditional on such a meeting taking place. Only when the productivity of the poaching firm y' is larger than the productivity y of the incumbent, the worker quits and receives a value gain of $\beta[S(x,y') - S(x,y)]$. Because f is strictly increasing in y, standard arguments imply that the joint match value is strictly increasing in firm productivity.

The Bellman equation for the unemployment value is

$$rU(x) = b(x) + \sum_c f^c(\theta^c)s^{c,u}(x)\beta \int_{R(x)}^1 [S(x,y) - U(x)]\pi^c(y)dy \ . \tag{3}$$

An unemployed worker with ability x receives flow income $b(x)$ and meets a firm via channel c at flow rate $f^c(\theta^c)s^{c,u}(x)$. When this firm's productivity y exceeds the worker's reservation productivity $R(x)$, the worker accepts the job with a value gain equal to $\beta[S(x,y)-U(x)]$. Since S is increasing in y, the reservation productivity is defined by $S(x,R(x)) = U(x)$, or $R(x) = 0$ when $S(x,0) > U(x)$.

Given that the value of a firm is the sum of profit values in all filled jobs net of the recruitment costs, a firm maximizes its value in a stationary equilibrium if, at any point in time, recruitment effort in every search channel is chosen to maximize the difference between the profit value of the hires flow and the recruitment cost in that channel. Therefore, the first-order condition for recruitment effort r^c in channel c equates the marginal cost of effort to the marginal increase in the profit value of new hires. For a firm with productivity y this condition reads

$$k^{c'}(r^c) = q^c(\theta^c)(1-\beta)\int_0^1 \left[\max[S(x,y)-U(x),0]\psi^c(x,u) + \int_0^y [S(x,y)-S(x,\hat{y})]\psi^c(x,\hat{y})d\hat{y}\right] dx \ . \tag{4}$$

For a marginal increase of search effort in channel c, the firm generates additional meetings at flow rate $q^c(\theta^c)$ through this channel. Conditional on such a meeting taking place, $\psi^c(x,u)$ and $\psi^c(x,\hat{y})$ denote the endogenous probabilities that such a worker has ability x and comes either from unemployment or from another firm with productivity $\hat{y}$. The firm will only hire if the joint match value exceeds the previous match value of the worker in which case the firm's discounted profit value of the hire is equal to the share $(1-\beta)$ of the surplus.

Appendix C.1 contains further details about the model, specifying worker and firm matching probabilities $\pi^c(.)$, $\psi^c(.)$, and tightness θ^c in all channels c, wages, and stock-flow identities.

Definition: *A stationary equilibrium is a collection of value functions, wages, reservation productivities, recruitment effort, tightness, matching probabilities for all search channels, and a worker distribution over employment states consistent with (i) workers' job acceptance and quitting decisions with wage protocols based on surplus splitting; (ii) firms' recruitment effort decisions; (iii) stationary worker distribution.*

3.2 Calibration

We calibrate the model using simulated method of moments. We first describe the parameterization and then the calibration strategy. Data moments are obtained from the JVS, PASS and IEB and are motivated by the hiring and job-finding patterns documented in Section 2.

We use beta distributions to describe workers' abilities x (with parameters $\lambda_0, \lambda_1 > 0$) and firms' productivities y (with parameters $\mu_0, \mu_1 > 0$), and discretize the number of firm and worker types to 30. The production function is parameterized using a CES function such that match output is $f(x,y) = F_0\left(\alpha x^\rho + (1-\alpha)y^\rho\right)^{1/\rho}$ with parameters $F_0 > 0$, $\alpha \in [0,1]$, $0 \neq \rho \leq 1$.

Each search channel $c = p, n, a$ (i.e. postings, networks, agency) is characterised by a Cobb-Douglas matching function with efficiency parameter $m_0^c > 0$ and identical elasticity $\nu \in [0,1]$. Firms choose their recruitment intensity r^c using the cost function $k^c(r^c) = k_0^c(r^c)^{\zeta^c}$, with parameters $k_0^c > 0$ and $\zeta^c > 1$. Workers' search efficiencies are assumed to be linearly related to worker type x for each search channel and employment status. In particular, we set $s^{c,i}(x) = s_0^{c,i} + x(s_1^{c,i} - s_0^{c,i})$ where $i = e, u$ is employment status (i.e. employment, unemployment) and $s_0^{c,i} \geq 0$, $s_1^{c,i} \geq 0$ are parameters. This functional form is convenient to match job-finding patterns by worker type and search channel. We further simplify and make separations into unemployment linearly depend on worker type through $\delta(x) = \delta_0 + x(\delta_x - \delta_0)$. Unemployment income depends on worker type through $b(x) = f(x, b)$, where $b > 0$ is a home production parameter.

Together with the interest rate r and the bargaining parameter β, our model has 34 parameters we need to recover. The interest rate is set exogenously at 2% per annum such that, with a unit time equal to a month, $r = 0.00165$, and the matching function elasticity is set to $\nu = 0.5$, in line with standard parameterizations (see Petrongolo and Pissarides, 2001). All other parameters are calibrated jointly.

A key challenge for identification is that worker and firm types x and y are unobserved, so that we need to find appropriate proxy variables that can be readily computed in model simulations and that reflect the true worker and firm heterogeneity reasonably well. For this purpose, we follow an indirect inference approach and use wage fixed effects that are obtained from OLS panel regressions of log wages imposing uncorrelated worker and firm fixed effects, similar to Bagger and Lentz (2019) and Burdett et al. (2020). Specifically, we estimate first the wage regression

$$\ln w_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it} \ ,$$

on IEB data using OLS, where X_{it} is a polynomial in age, interacted with education and year dummies, and ε_{it} denote the wage residual. In a second step, the residuals are projected on firm-fixed effects,

$$\varepsilon_{it} = \gamma_{J(i,t)} + \eta_{it} \ ,$$

where $J(i, t)$ is worker i's employer in year t. Different from an AKM econometric model, this two-step OLS model can be easily estimated from simulations of our structural model. In particular, we follow a sample of workers (drawn from the stationary distribution) over a period of ten years and use spell transitions and wages to calculate the model counterparts of α_i and γ_j. To recover $\lambda_0, \lambda_1 > 0$ and $\mu_0, \mu_1 > 0$ we target the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} percentiles of the estimated α_i and γ_j distributions, respectively. In addition, we also target the same percentiles of the wage distribution obtained from w_{it}, to guarantee that the model replicates the wage distribution. We find that these 15 moments are also useful to inform the production function parameters and bargaining power. Parameter b is set to generate a 60% replacement rate.[16]

A second challenge is the separate identification of the matching function efficiency parameters, the cost functions parameters and the search efficiency parameters since they all affect firm hiring and worker job-finding rates. To aid this identification we use hiring cost information obtained from

[16]This replacement rate is obtained as the ratio between out-of-work cash benefits minus taxes over wages minus taxes for a worker, aged 40, who earns the average wage, where taxes include compulsory contributions to social insurance program less cash transfers (see Van Vliet and Caminada, 2012).

the JVS. In particular, during the years 2013 and 2014 firms reported the number of hours spent as well as all other monetary costs incurred when hiring the last worker. Based on this information, we build a measure of daily recruitment cost, separate for each successful search channel.[17]

After controlling for firm differences across industries, size, age and the educational requirements of the vacant jobs, we target the ratio between the average daily cost of using networks relative to using job postings (32.3%) and the average daily cost of using the public employment agency relative to postings (53.8%). We further find that daily recruitment costs (again residualized by firm and job characteristics) are increasing in firm fixed effects (OLS), although differentially across search channels. To help identifying the cost elasticities, we target the relative slopes of these relationships: Moving from low-wage to high-wage firms, the increase of network recruitment costs is only 19.5% of the increase of posting recruitment costs, while the increase of recruitment costs for the public employment agency is 45.2% of the increase in posting costs. Motivated by the relationships depicted in Figure 1, we also compute the probability that a newly hired worker was reached through job postings, the firm's employment network or the public employment agency. We target these probabilities by firm (OLS) fixed effect quintiles. The recruitment costs and hiring probability moments mainly help informing matching function and cost parameters $m_0^c > 0$, $k_0^c > 0$ and $\zeta^c > 1$.

To inform the worker search efficiency parameters, $s_0^{c,i}$, $s_1^{c,i}$, we compute the rate that a worker finds a new job through either job postings, networks or the public employment agency, and target these rates by worker (OLS) fixed effect quintiles. Here we separately target these relationships by EE and UE transitions to capture differences in employment status. Together this approach gives 49 moments to recover the 21 search and matching parameters. To additionally inform the two parameters governing separations into unemployment, we use the observed EU transition rate by worker fixed effect quintiles. Throughout this procedure, all transition rates are obtained from IEB data.[18]

3.3 Parameters and Model Fit

Figure 5 presents the model's fit relative to the observed (i) hiring probabilities by firm fixed effect quintiles (first row) and (ii) EE and UE transitions probabilities by worker fixed effect quintiles for each search channel (second and third rows). The figure shows that both in the model and data,

[17] Daily recruitment costs are calculated by dividing total recruitment costs by the number of days the firm reported searching, where total recruitment costs are the sum of monetary costs and recruitment hours multiplied with the average imputed wage of full-time employees within the firm. Since the JVS does not collect hiring costs separate for each channel, we calculate the flow cost per channel by using daily recruitment costs for those firms that only used one search channel (job postings, networks or the public employment agency). See Appendix B for further details.

[18] EE, UE and EU transition rates are calculated monthly by transforming the spell level data provided by the IEB. See Appendix A.1.3 for details.

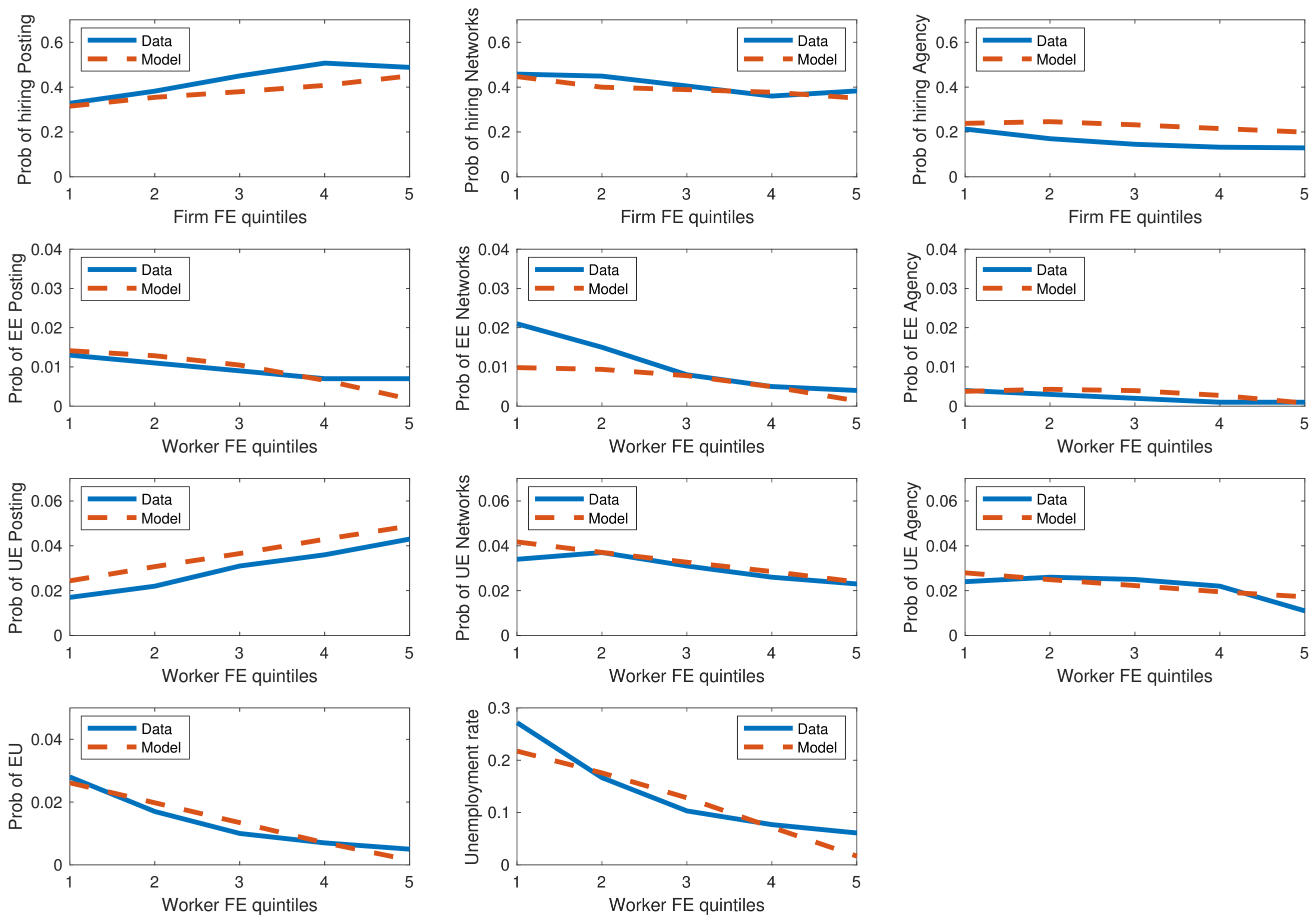


Figure 5: Hiring and worker flows by fixed effect quintiles

Notes: Worker and firm fixed effects are obtained from OLS wage regressions as described in Section 3.2 for IEB data, 2010–2016. The top rows show relationships between the probability that the last hire in the JVS was contacted through postings, networks, or the public agency, and firm fixed effects. The second and third rows show relationships between monthly EE and UE rates by channel (based on PASS and IEB data) and worker fixed effects. The fourth row shows monthly EU rates and unemployment rates by worker fixed effects.

higher-wage firms are more likely to hire a worker through job postings than lower-wage firms, while higher-wage firms are less likely to hire a worker through networks or the public employment agency than lower-wage firms. The data patterns are similar to our findings using AKM fixed effects as shown in Figure 1, where firms in higher AKM percentiles exhibit a larger hiring probability through postings and a lower one through networks and the public employment agency. We emphasize that our model is able to generate these relationships despite the restriction that recruitment costs do not depend on firm type y.

At the same time the model captures well the negative relationship between workers' EE transition rates and their fixed effects. Among the unemployed, the estimation is also successful at generating the upward-sloping relationship between worker fixed effects and the UE transition rate through job positing, and the downward-sloping relationships between worker fixed effects and UE transition rates through networks or the public employment agency. These findings are consistent with the relationships shown in Figure 2, where low-wage workers find jobs more frequently via networks and via the public agency compared to postings. When finding a job through job postings, Figure 2 shows that it is instead high-wage workers who find jobs more frequently. Figure 5 suggests that this combined effect is driven by UE transitions, a feature that is also verified when disaggregating the relationships in Figure 2 by type of transition. The last row of Figure 5 shows that the model generates the downward-sloping relationship between workers' fixed effects, EU transitions rates and unemployment rates observed in the data.

Table 4 shows that our model replicates the differences in recruitment costs across search channels, both regarding the levels and their relationships with firm fixed effects. Regarding levels, the flow cost of the public employment agency is about half of the flow cost of postings (136.6 euro er day), while the cost of networks is only about a third of the posting cost. Both in the data and in the model, the flow costs increase with the firm fixed effects (OLS), where the respective increase is steepest for the posting channel,[19] followed by the public employment agency (about 45 percent relative to postings) and networks (about 20 percent relative to postings).

Table 4: Recruitment cost differences between search channels

	Data		**Model**	
	Networks	Public agency	Networks	Public agency
Average cost (rel to postings, %)	32.3	53.8	30.8	51.1
Variation by firm FE (rel to postings, %)	19.5	45.2	19.7	46.1

Notes: See the main text and Appendix B for the calculation of daily (flow) recruitment costs in the data. The first row reports the ratio between daily recruitment costs in networks (public employment agency) relative to postings. The second row reports the slope of the relationship between daily recruitment costs and the firm fixed effect (OLS) for networks (public employment agency) in relation to the same slope for the postings channel.

Finally, Figure 6 shows the model's fit with respect to the distributions of firms' and workers' OLS fixed effects and log wages, all shown as cumulative density functions. As in the data, the model generates more dispersion across worker than firm fixed effects and hence is consistent with the relative dispersion observed when using instead the AKM fixed effects. However, the model generates a bit longer left tails as observed in the data. Given this caveat and the degree of overidentification we impose in our estimation procedure, the model matches well all three distributions overall. The model also matches the targeted average replacement rate, generating 60.1% relative to 60% in the data.

[19] A one-standard-deviation increase of the firm fixed effect implies a 23.3 euro increase of recruitment cost per day.

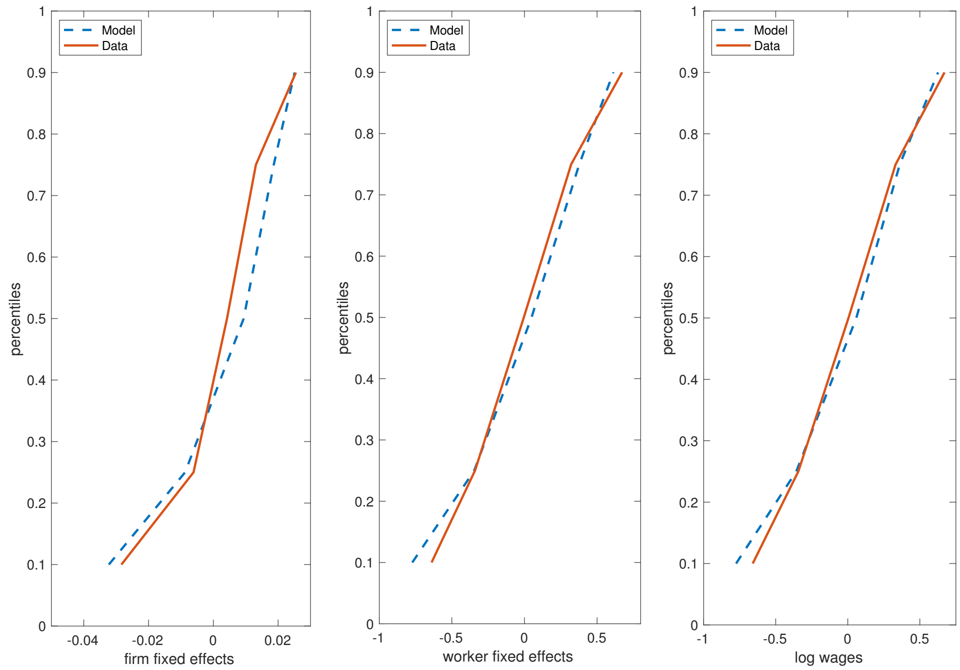


Figure 6: Firm and workers fixed effect and wage distributions

Notes: Worker and firm fixed effects are obtained from OLS wage regressions as described in Section 3.2 for IEB data, 2010–2016.

Table 5 presents the calibrated parameter values. The parameters governing the distributions of worker and firm types imply a unimodal and right-skewed shape for the worker and firm type density functions. In turn, the estimated production function is super-modular and hence a high-ability worker realizes a larger output increase when moving to a more productive firm than a low-ability worker does for the same job-to-job move. This result is consistent with a large literature that uses structural models (many similar to ours) to investigate production complementarities between workers and firms. The workers' bargaining parameter is estimated to be 80.6%, suggesting a relatively strong bargaining position among German workers.[20]

Regarding the implications of the estimated parameters for recruitment costs and matching technologies, we provide a discussion of the role of search channels for firms' recruitment policies in the next subsection. On the worker side, we observe that across all search channels, high-ability employed workers have higher search efficiencies than low-ability employed workers. This implies

[20] Cahuc et al. (2006) and Bagger and Lentz (2019) estimate lower values of this parameter on French and Danish data, respectively. In our model there is a tight relationship between the value of the bargaining parameter β and the home production parameter b. While our estimated value of β is consistent with a targeted replacement rate of 60%, targeting a higher replacement rate (possibly reflecting the value of leisure, home production, or higher government transfers to cohabiting/married individuals) implies a significantly lower estimated value of β. For example, targeting a replacement rate of 0.8 would imply a value of β=62% (and a slightly smaller value of ρ) that preserves the fit of the model in all other moments as described above as well as its main implications.

Table 5: Parameter values

Recruitment costs		**Search efficiency - employed**		**Distributions**	
k_0^p - postings	0.0779	$s_0^{p,e}$ - postings	2.7504	λ_0 - workers	2.2964
ζ^p	1.7158	$s_1^{p,e}$	5.3671	λ_1	14.5745
k_0^n - networks	4.0553	$s_0^{n,e}$ - networks	1.332	μ_0 - firms	2.9046
ζ^n	3.8882	$s_1^{n,e}$	3.082	μ_1	9.5074
k_0^a - pub. agency	0.3252	$s_0^{a,e}$ - pub. agency	2.7553	**Production function**	
ζ^a	1.7031	$s_1^{a,e}$	10.587	F_0	11.2535
Matching efficiency		**Search efficiency - unemployed**		α	0.9388
m_0^p	0.1289	$s_0^{p,u}$ - postings	0.9952	ρ	-3.286
m_0^n	0.1556	$s_1^{p,u}$	2.3525	**Wages**	
m_0^a	0.0755	$s_0^{n,u}$ - networks	1.2572	β - bargaining power	0.8061
EU transitions		$s_1^{n,u}$	0.6362	b - home production	0.0442
δ_0	0.0312	$s_0^{a,u}$ - pub. agency	5.567	**Others**	
δ_x	0.0009	$s_1^{a,u}$	2.982	r - interest rate	0.00165
				ν - matching function elasticity	0.5

that the model generates the negative relationship between EE transitions and worker fixed effects observed in the data (Figure 5) only through smaller job acceptance sets as high-ability workers move faster from low- to high-productivity firms.[21] Among the unemployed, the positive relationship between search efficiency and worker ability only holds through the job postings channel. In turn, this allows the model to reproduce the positive relationship between the UE rate through postings and worker fixed effects. When taking differences in matching efficiency and tightness between the three channels into account, we find that employed workers on average realize more meetings than non-employed workers, where the gap is largest through the job postings channel. This result is consistent with the observation of Faberman et al. (2022) that the employed are more efficient in job search than the non-employed.

3.4 Recruitment Costs and Benefits of Search Channels

In the model, all firms equate the marginal cost of recruiting through a given channel to the expected benefit of using that channel; see equation (4). There are important differences in worker composition, matching efficiency and recruiting cost parameters between the three channels that affect these costs and benefits in distinct ways.[22] Table 6 presents various statistics that shed light on the differences in recruitment outcomes across the three channels, where the left panel reports the mean of the outcome across the firm productivity distribution, and the right panel shows the ratio between the respective outcome variable at the 75th and 25th percentiles of the firm productivity

[21] Using a similar framework as in Cahuc et al. (2006), Bagger and Lentz (2019) propose a model where workers choose their search effort, but without different search channels. They also find that high-ability workers encounter firms more often than low-ability workers.

[22] The matching efficiency parameter is lowest for the public employment agency which suggests that this channel performs worst in its overall effectiveness of generating matches between workers and firms. However, this comparison is misleading because the firms' recruiting costs and the workers' search efficiencies also differ across channels, so that the overall effectiveness of search channels has to be evaluated on the basis of all these parameters.

distribution. Figure C.1 in Appendix C depicts the same variables over the full firm productivity distribution.

Table 6: Costs and benefits of recruitment channels

	Mean			**75-25 ratio**		
	Postings	Networks	Public agency	Postings	Networks	Public agency
Cost (% of aggregate output)	1.15	0.39	0.60	1.25	1.13	1.22
Meeting prob (%)	8.11	7.18	3.39	1.14	1.03	1.12
Hiring prob (%)	1.12	1.00	0.56	2.86	2.22	1.97
Profit per hire (rel to aggregate output)	0.264	0.194	0.224	0.435	0.510	0.616
Return	1.72	3.89	1.70	1	1	1
Average worker ability	0.097	0.088	0.089	0.982	1.077	1.096

Notes: The 75-25 ratio is the ratio between the respective outcome variable at the 75th and 25th percentile of the firm productivity distribution. "Profit per hire" is the discounted profit value of a worker hired through the channel, "return" is the expected discounted profit divided by the cost of using that channel, and "average worker ability" is the average value of x of newly hired workers through the respective channel.

In line with the calibration targets, the first row confirms that spending on job postings is about twice as large as spending on recruitment through the public employment agency and threefold larger than spending on recruitment through networks. It also shows that the spending gap between high and low productivity firms is larger for job postings than for the other two channels. Also targeted are the differences in hiring probabilities and their variation across high and low productivity firms, all shown in the third row.[23] The second row shows that the public employment agency generates fewer meetings than the other two channels. However, since this channel offers the largest likelihood of encountering a non-employed worker, it nevertheless provides firms with the largest acceptance rate (the ratio between hirings and meetings). Further, in comparison with the networks channel, the 75-25 ratio shows that high-productivity firms spend relatively more on the public employment agency which however does not generate relatively more hires in comparison to the networks or postings channels.

The fourth row of Table 6 reports the discounted profit value of a hire, separate for each channel. On average, this value is largest for the job postings channel and this is driven by firms in the lower half of the productivity distribution (see Figure C.1 in Appendix C.2). The 75–25 ratios reveal that these less productive firms generate larger profits irrespective of the channel because they hire more from non-employment and from lower rungs of the job ladder where the match surplus is larger. Job postings offer an additional advantage for less productive firms as they attract more able non-employed workers who are particularly effective in finding jobs through this channel. This is also reflected in the bottom row of the table which shows that the average worker ability of a newly hired worker through job postings is higher in firms at the 25th percentile compared to firms

[23]To be precise, our calibration strategy targets the hiring differences by firm wage fixed effects which correlate positively with the unobserved firm productivities in our model.

at the 75th percentile, the opposite of what is observed for networks or the public agency.[24] This is also an important reason why the average worker ability is highest when the match occurs via postings relative to the other channels.

The fifth row shows that, although networks exhibit the lowest profit per hires, this channel comes with the highest overall recruitment return which we define as the expected discounted profit of recruiting through a channel (i.e. the hiring flow multiplied with the discounted profit per hire) divided by the flow cost of using the channel. In fact, the value of that return is identical to the elasticity of the recruitment cost function.[25] Intuitively, the average worker hired through networks imposes a much lower cost for the firm than the average worker hired through the other two channels. In conclusion, networks are the most cost-effective channel, despite the observation that the hired workers are on average less able and yield lower profits than the workers hired through the job postings channel.

3.5 Labor Market Sorting

The degree to which heterogeneous workers and firms utilize search channels has implications for worker-firm sorting patterns. The different composition of worker and firm types by search channels comes about by search efficiency differences among heterogeneous workers and by differences in recruitment costs which together generate the distinct job-finding and hiring rate patterns illustrated in Figure 5.

Table 7: Labor market sorting and worker search efficiency

	Benchmark	**Identical worker search efficiency**			
		All channels	Postings	Networks	Public agency
Corr. coefficient	0.179	0.133	0.159	0.162	0.165
Change in %		−25.7	−10.9	−9.4	−7.5
(employed)		−24.7	−10.8	−8.1	−8.1
(non-employed)		−2.5	−0.8	−0.1	+0.3

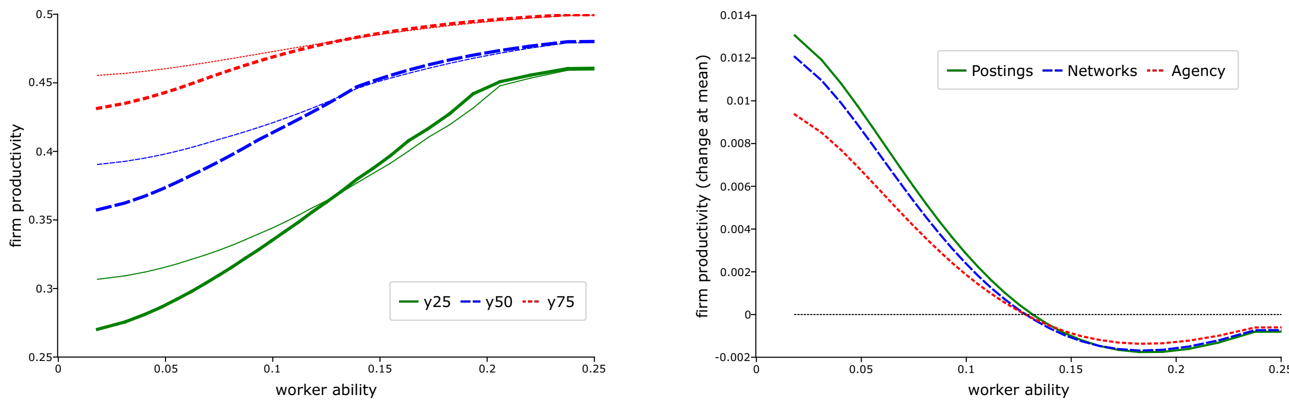
Notes: Worker search efficiencies are equalized to their respective means conditional on employment status (separately for each channel in the last three columns). In the last two rows, search efficiencies are equalized separately for employed/non-employed workers. In each of these experiments we solve for a new stationary equilibrium.

Our model generates moderate positive sorting, as measured by a correlation coefficient of 0.18 between worker ability x and firm productivity y. Table 7 shows that about a quarter of sorting stems from the fact that high- and low-ability workers search with different efficiencies.

[24]Figure C.1 reveals that at the very top of the firm productivity range the average workers ability reverses and starts increasing, achieving its highest value at the highest productivity firm.

[25]The return is calculated as the product between the right-hand side of equation (4) multiplied with recruitment effort r^c (i.e. the expected profit of the hires flow of the channel) divided by the cost $k^c(r^c)$ which is identical to the elasticity of k^c because of the first-order condition (4).

When we equalize worker search efficiencies in all channels to their respective means (conditional on employment status), the correlation coefficient between x and y falls to 0.13.[26] The bottom rows of the table indicate that the vast majority of this decline comes from heterogeneity in the search efficiency of employed workers: Since high-ability employed workers search with greater efficiency in all three search channels, they climb the job ladder faster so that they are matched more often with high-productivity firms. Heterogeneous job-finding of non-employed workers plays a rather minor role for labor market sorting in our model.[27]



(a) Labor market sorting

(b) Sorting effect of search channels

Figure 7: Impact of worker search efficiency on labor market sorting

Notes: Panel (a) shows the 25th, 50th and 75th percentiles of firm productivity by worker ability where the benchmark are the bold curves, and the counterfactual with equalized worker search efficiency are the thin curves. Panel (b) shows the changes of firm productivity at the mean when worker search efficiency is equalized separately for each channel.

Panel (a) of Figure 7 illustrates for each different employed worker ability three percentiles of their employer productivity distribution. Relative to the benchmark relationships shown by the bold curves, equalization of worker search efficiency increases the productivity rank of firms employing lower-ability workers, while it has only a modest negative effect on the productivity rank of firms employing high-ability workers, who are still able to climb the job ladder fast due to their lower separation rates. Hence, the sorting effect induced by differences in workers' search efficiency reported in Table 7 is driven by those in the bottom half of the ability distribution.[28]

Table 7 also presents the separate effects of equalising search efficiencies to their mean values in each of the three search channels. Worker-firm sorting decreases most when workers do not sort by

[26]The remaining degree of sorting stems from the model property that low-ability workers separate more quickly into non-employment, and hence fall off more frequently from the job ladder, compared to high-ability workers. When we additionally equate EU rates for all workers, the correlation coefficient drops to zero.

[27]In all the experiments shown in Table 7, we solve for a new stationary equilibrium. In particular, firms' recruitment effort responds to the counterfactual equalization of worker search efficiencies.

[28]Median worker ability in the calibrated model is $x = 0.122$.

ability in the postings channel, whereas the effect is weakest when search efficiencies are equalized in the public employment agency. In fact, the feature that low-ability, non-employed workers have greater search efficiency than high-ability, non-employed workers in the public employment agency has only a mild mitigating effect on sorting. Consistent with the pooled results, panel (b) of Figure 7 shows that changes in the average employer productivity are strongest for low-ability workers when their search efficiencies are equalised to the (higher) mean values, especially for job-to-job transitions that occur through the postings and networks channels.

3.6 The Role of the Public Employment Agency

A central objective of the public employment agency is to help job seekers, especially registered unemployed workers, to find employment. To this end the agency provides an online job portal and it supports job seekers individually through bespoke advice from placement officers who are based in local job centers that are jointly funded by the federal government and the municipalities. All over Germany there are about 300 local job centers employing over 42,000 staff with total administrative spending of over 6 bn euro in the year 2016.

A natural question is how these placement measures affect the labor market, namely aggregate employment, output, wage distributions and job-finding prospects of heterogeneous workers. To study this question, we use our model to analyze a counterfactual scenario in which the public employment agency is removed. Specifically, we set matching efficiency in this channel to zero and solve for a new stationary equilibrium where firms' recruitment effort in the other two channels expands, as it becomes easier to find and attract workers.

While the firms' endogenous responses are taken into account, our model treats workers' search efficiencies as fixed parameters which are meant to represent both search effort and the ability to generate job offers. We deal with this limitation by considering two polar scenarios: In the first, we assume that workers cannot generate additional meetings through the other two channels so that their search efficiencies in the job postings and networks channels are held constant. In the second scenario, we allow workers to increase their search efficiency in the job postings channel such that they obtain the same number of job offers that were generated via the online services of the public employment agency before its abolishment. The logic of this scenario is that the bespoke recommendations of the assigned placement officer cannot be easily substituted away, while the online job portal can potentially be substituted by private platforms to which workers may shift their search effort when the agency is closed down.[29] Using our survey data, we find that 48 percent of all job-finding events that occur via the public employment agency are obtained via its online services, while the rest is obtained via placement officers.[30] Therefore, we increase workers' search

[29]There is a growing literature that focuses on evaluating the effects on workers' re-employment probabilities of providing more targeted information to job seekers through their placement officers (Belot et al., 2019).

[30]See Table A.6 in the Appendix which breaks down the use and success of the two services of the public employ-

efficiencies in the job postings channel to make up for 50 percent of the forgone meetings, which we do separately by worker ability and employment status.[31]

Table 8: Labor market impact of an abolishment of the public employment agency

	Benchmark	**No public employment agency**	
		Without worker response	Worker response
Employment	0.878	0.853 (−2.81%)	0.866 (−1.37%)
Output	1.426	1.403 (−1.64%)	1.415 (−0.83%)
Productivity	1.625	1.644 (+1.20%)	1.634 (+0.54%)
90-50 wage ratio	1.773	1.753 (−1.09%)	1.831 (+3.28%)
50-10 wage ratio	2.291	2.319 (+1.21%)	2.319 (+1.21%)
Corr. coefficient	0.1778	0.1791 (+0.75%)	0.1785 (+0.39%)

Notes: Counterfactual model outcomes when match efficiency of the public employment agency is set to zero (percentage changes in brackets). The left column features no worker response, the right column allows for higher search efficiency in the postings channel; see the text for details.

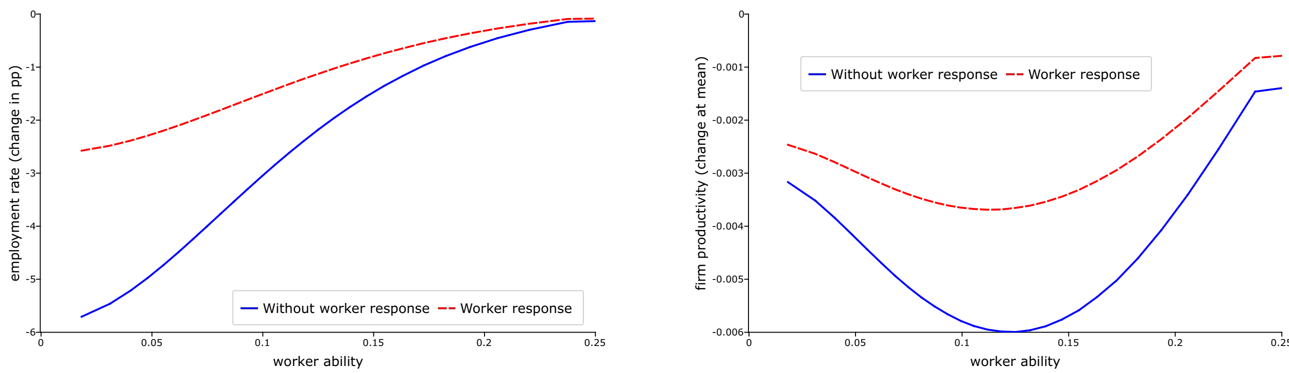
Table 8 shows the effect of shutting down the public employment agency under the two polar scenarios. The first two rows show that aggregate employment falls by 1.4–2.8 percent, and aggregate output declines by 0.8–1.6 percent, so that labor productivity increases by 0.5–1.2 percent. Behind these aggregate effects are the following observations: First, panel (a) of Figure 8 shows that employment declines predominately for low-ability workers, decreasing aggregate employment and increasing aggregate productivity through a composition effect. Second, panel (b) of Figure 8 shows that after the abolition of the public employment agency workers in the middle and at the bottom of the ability distribution end up working in firms which are on average less productive, decreasing aggregate output. Despite higher labor productivity, the output and employment losses due to the abolishment of the public employment agency are sizeable. For example, based on 2016 figures, the loss of output amounts to 20–40 bn euro and the decline of employment to 340–700 thousand workers.[32]

The remaining rows of Table 8 indicate that the removal of the public employment agency leads to an increase of bottom wage inequality as measured by the 50-10 ratio under both scenarios. Intuitively, output losses at the middle and bottom of the worker ability distribution, together with harmed employment chances for low-ability workers leads to a decline of wages at the bottom (cf. 8). For the same reason, worker-firm sorting increases modestly since more low-ability workers end up employed at less productive firms. When workers respond with higher search efficiency in

ment agency (online services and placement officers) for firms and workers.

[31] Private networks are plausibly a poor substitute for the services of the public employment agency. Nonetheless, we also consider alternative scenarios where the forgone meetings are (partly) recovered via the networks channel, without major changes to our conclusions.

[32] These estimates take into account that the three search channels covered here account for 80 percent of all hires in the German labor market (cf. Table A.4).



(a) Employment rate

(b) Firm productivity (mean)

Figure 8: Impact of the abolishment of the public employment agency on different workers

Notes: Change of the employment rate and firm productivity at the mean by worker ability. The solid curve features no worker response, the dashed curve allows higher search efficiency in the postings channel; see the text for details.

the postings channel, we also obtain an increase of top wage inequality as measured by the 90-50 ratio. In this case, those workers that succeed through postings also end up at higher rungs of the job ladder since the postings channel is used by a greater share of high-productivity firms, compared to the public employment agency prior to its removal, increasing top wage inequality.

4 Conclusions

Using linked survey-administrative data for Germany, we present new evidence on how workers and firms match via different search channels. We find that high-wage firms are more likely to hire through job postings, they are more likely to poach when using postings and more likely to hire a high-wage worker through this channel. Low-wage firms, in contrast, hire more frequently through personal networks and through the public agency. We document that high-wage workers find jobs more often via job postings and less often via networks or via the public agency, in comparison to low-wage workers. Job postings also permit workers to climb to higher-wage firms faster than networks or the public agency. Worker-firm matches that come about via job postings or networks are generally more stable.

To investigate the impact of search channels for sorting, wage inequality and aggregate labor market outcomes, we estimate an equilibrium job ladder model featuring the three search channels as separate matching technologies that are differentially populated by heterogeneous firms and workers. The estimation captures the hiring patterns for each search channel across firms and workers documented in our empirical analysis, as well as other key features of the labor market. We find that networks are the most cost-effective channel, allowing firms to hire quickly, yet attracting workers of lower average ability. Job postings are the most costly channel, facilitate hiring workers of higher ability, and matter most for worker-firm sorting. The public employment agency provides the lowest hiring probability. Its removal, however, would imply that aggregate output declines by at least 0.8 percent, employment declines by at least 1.4 percent and bottom wage inequality increases by 1.2 percent.

Our analysis focuses on the role of job postings, networks and the public employment agency as vehicles that ameliorate search frictions. These search channels, however, also play a role in reducing screening frictions about the workers' and firms' type. For example, Montgomery (1991) presents a theory in which referrals allow firms to obtain a better signal of the applicant's suitability for a job. In many cases job postings also specify certain key characteristics firms are looking for in applicants, allowing employers to focus their recruitment effort. By guiding job seekers to jobs that better suit their skills, placement officers in public employment agencies also help both side of the market in identifying a suitable match. In our model, the efficiency parameter of the channel-specific matching function captures these dimensions in a reduced form. Nevertheless, it remains important to further explore how these search channels shape labor market sorting and wage inequality through an explicit analysis of their role in reducing information frictions. We leave this topic for future research.

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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.1.1 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 B.5.1), 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 statistics of the full IEB. The second column shows statistics for all firms in the IEB that 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 B.3.2 shows that our main empirical results do not meaningfully change when we condition on firm size. Section B.5.2 further shows that using hiring weights does not meaningfully change our results.

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.

Table A.2 reports descriptive statistics for the various JVS samples. 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 third and fifth column show that we can identify worker effects more frequently in larger firms. 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.

A.1.2 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.1.3 Additional Moments

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

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.

who experience an employment to unemployment transition (from one month to another) divided by the stock of employed workers in a given month.

A.2 Search Channels: Further Descriptive Statistics

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.

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.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.

Table A.5 shows that the same conclusion arises when separating the sample into employed and non-employed workers.

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)

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**

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**

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.3 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.[33] The correlation coefficients between α_i and γ_j are very similar in both 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).[34] Further, the reported correlation between worker and firm fixed effects is also higher

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

[34]Applying the bias correction as described in Andrews et al. (2012), the variance of the firm (person) fixed effect is 2.5% (4%) lower after the correction. The corresponding correlation between the fixed effects is 35% as compared to 33% in our AKM regression. In addition, Lochner et al. (2020) show that the bias is relatively constant over time. Song et al. (2019) draw a similar conclusion using U.S. data.

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 labour 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 labour 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 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 relative 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.[35] We highlight the importance of controlling for

[35] 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

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 (1–10 (reference), 11–25, 26–50, 51–100, 101-1000, and >1000 employees), one-digit industry codes, and financial, demand and workforce constraints. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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 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 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.

Calculation of Daily Recruitment Costs

In Section 3.2 we use information on recruitment cost as part of our calibration strategy. For the identification of the parameters that determine the flow recruitment costs separate for each search

to construct target moments as part of our calibration strategy in Section 3.2 and described these further in the next subsection.

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 those firms that only used postings have on average very similar characteristics as those that use two or more channels, those 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.

B.2 Workers' Search Strategies

We now investigate to what extent the search behavior of workers correlates with their relative 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 active 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 Survey of Consumer Expectations.

Tables B.1 and B.2 show that the average number of search channels used by either firms or

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

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 now show 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

B.3.1 Regression Tables

Table B.3 echoes the results presented in Figure 1, where we show that higher AKM ranked firms exhibit a higher probability of using and hiring through job postings, while lower ranked firms have a higher probability of using and hiring through networks or the public employment agency. The top panel of Table B.3 shows these results using a linear probability model controlling for the educational requirements of the job (high school or less, vocational education, university degree) as well as the firm's 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. 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. The bottom panel of Table B.3 presents a similar set of results from estimating the same regression but now using the poaching index instead of the AKM fixed effect.

Table B.4 echoes the results from Figure 2, where we show that higher AKM ranked workers have a higher probability of finding employment through job postings, while lower ranked workers

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

have a higher probability of using and finding a job through networks or the public employment agency. Note that here we also find that there are no differential effect across the AKM rank of a worker on the use of job postings.

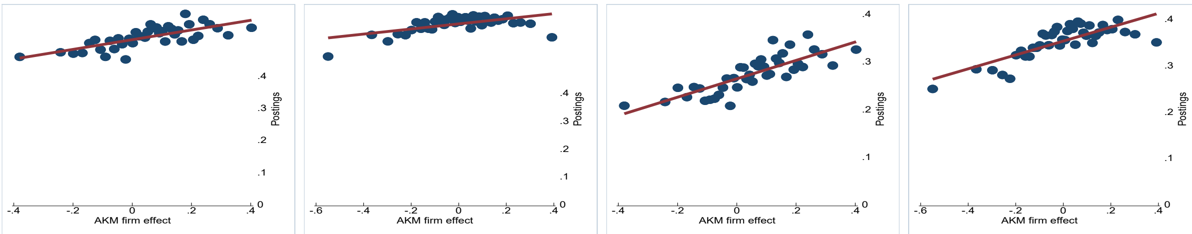
Table B.4: Search channels and worker types

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

B.3.2 By Firm and Worker Characteristics

We now show that higher ranked firms exhibit a higher probability of using and succeeding in hiring through job postings and a lower probability of using and succeeding in hiring through networks and the public employment agency even when we analyze these relationships within industry and firm size categories. Figure B.1 aggregates industries into two sectors: manufacturing and services. The first two columns show the correlation between the probability of use and the firm AKM rank, while the second two columns show the correlation between the probability of hiring through a given channel and the firm AKM rank. Figures B.2 and B.3 aggregate firms into three size classes: small (1-10 employees), medium (10-100 employees) and large (more than 100). Figure B.2 first considers within each of these categories the relationship between probability of use and the AKM rank, while Figure B.3 considers the probability of hiring a worker through a given channel and the AKM rank.

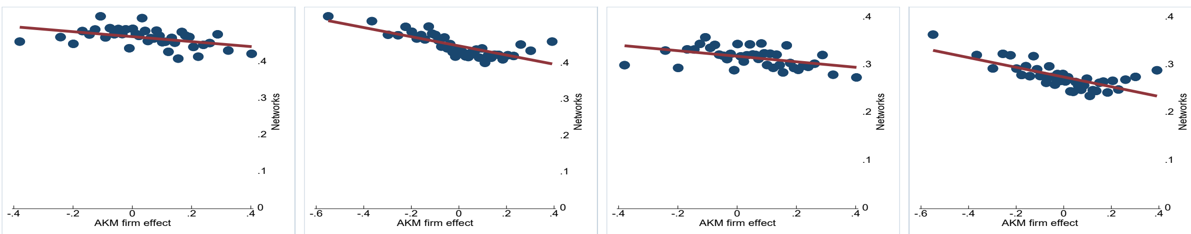


(a) Manufacturing: Postings (Use)

(b) Services: Postings (Use)

(c) Manufacturing: Postings (Success)

(d) Services: Postings (Success)

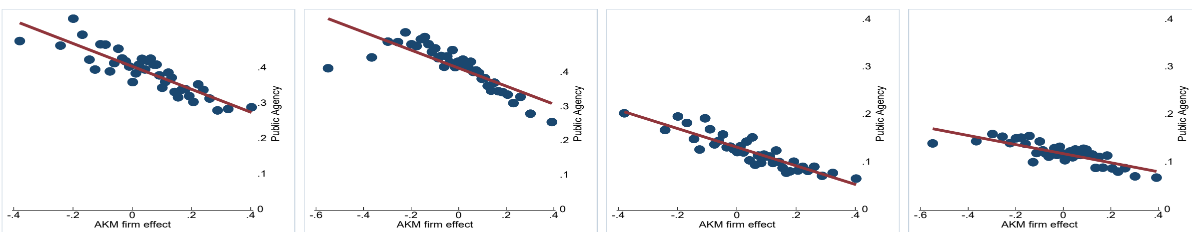


(e) Manufacturing: Networks (Use)

(f) Services: Networks (Use)

(g) Manufacturing: Networks (Success)

(h) Services: Networks (Success)



(i) Manufacturing: Public Agency (Use)

(j) Services: Public Agency (Use)

(k) Manufacturing: Public Agency (Success)

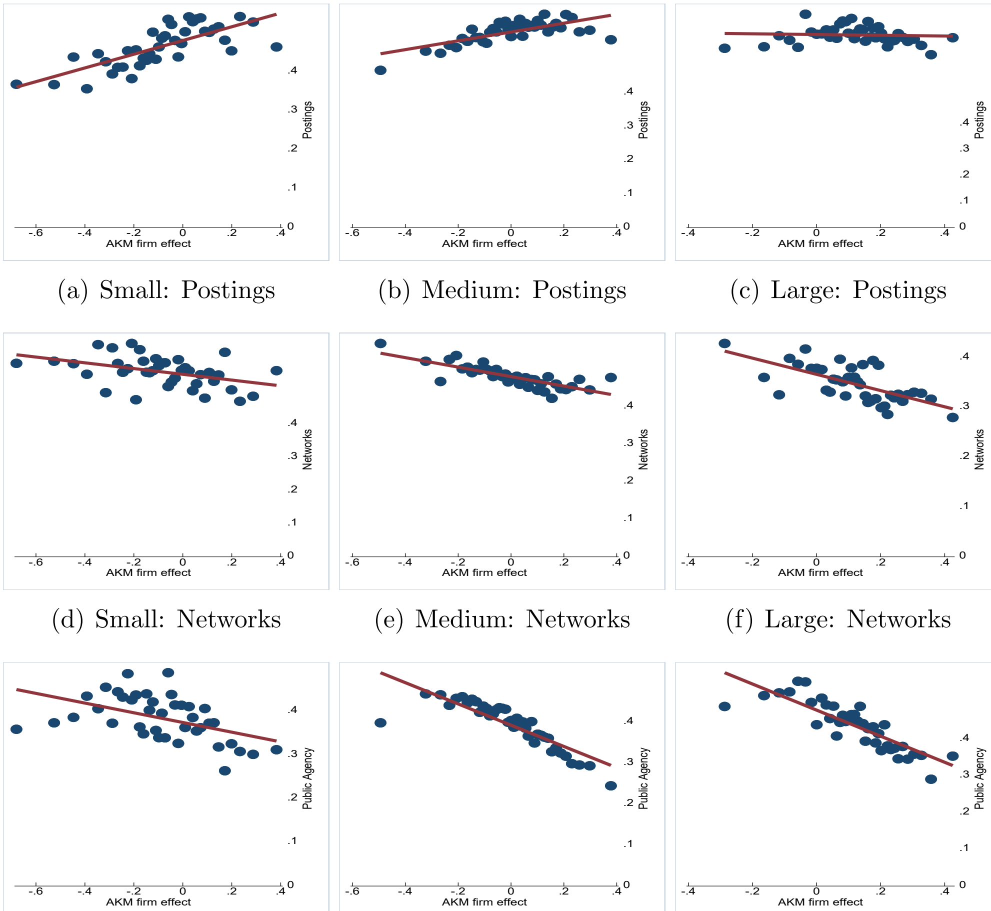
(l) Services: Public Agency (Success)

Figure B.1: Use and success of search channels by AKM firm fixed effect and sector

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of using (left) and succeeding (right) through the channel. "Manufacturing" include two-digit WZ2008 industry codes 10-44, "Services" include industry codes 45-99. The same controls as in Figure 1 are applied.

We now consider the relationships between the probability of use and success of channels with workers' AKM ranking within age and education groups. We divide workers into three age categories: young (less than 30 years of age), middle aged (between 30-50 years of age) and older (above 50 years of age) workers. We also consider three education categories: low (no vocational training/university degree), medium (vocational training) and high (university degree or equivalent educational attainment).

Figure B.4 considers the probability of use of search channels with age groups. The aggregate relationship depicted in Figure 2.a in the main text showed a weakly positive but not statistically significant relationship between the AKM rank of workers and the probability of using job postings. Figure B.4 shows that behind this weak correlation, young and middle aged workers exhibit a negative relationship between the AKM rank and the use of job postings, while for older workers



(a) Small: Postings (b) Medium: Postings (c) Large: Postings

(d) Small: Networks (e) Medium: Networks (f) Large: Networks

(g) Small: Public Agency (h) Medium: Public Agency (i) Large: Public Agency

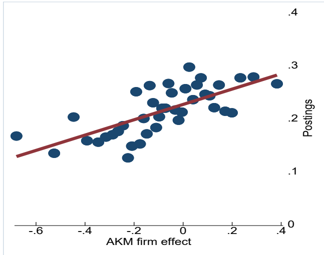
Figure B.2: Use of search channels by AKM firm fixed effect and firm size

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of using the channel. "Small" refers to firms with 1-10 workers, "medium" refers to firms with 11-100 workers, and "large" refers to firms with more than 100 workers. The same controls as in Figure 1 are applied.

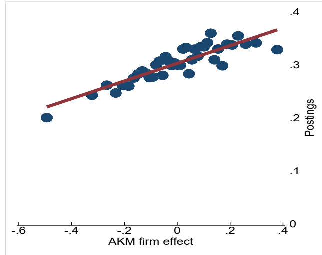
this relation is positive. However, across all age groups we observe a negative correlation between the probability of using networks or the public employment agency and the AKM rank documented in the pooled relationships depicted in Figure 2.

Figure B.5 shows that the correlation between the probability of finding a job through each of the three search channels and the AKM rank of a worker for each age category follows the same patterns as the pooled relationships. Namely, positive for postings and negative for networks and the public employment agency.

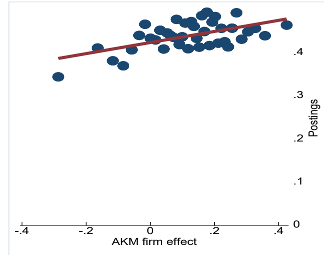
Figures B.6 and B.7 present the relationship between the probability of use and success of each the three search channels and the AKM rank of workers within the three education categories described above. For the low educated group we find a positive relationship between the use of postings and the AKM rank, while for the other two education categories we observe a negative



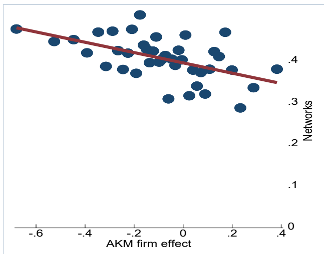
(a) Small: Postings



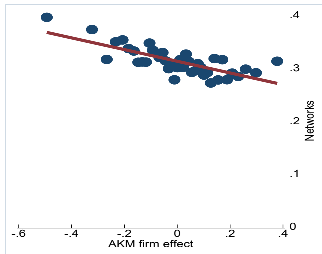
(b) Medium: Postings



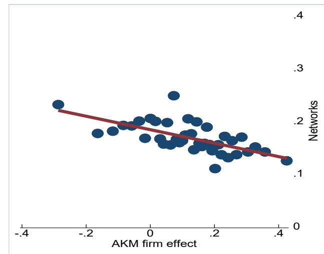
(c) Large: Postings



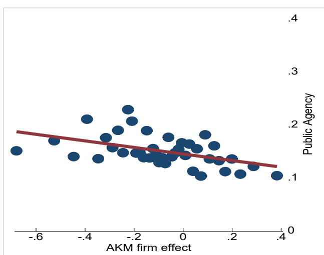
(d) Small: Networks



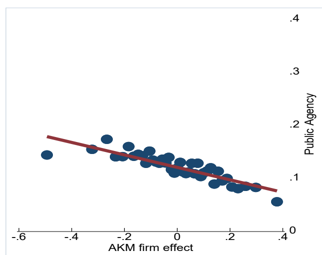
(e) Medium: Networks



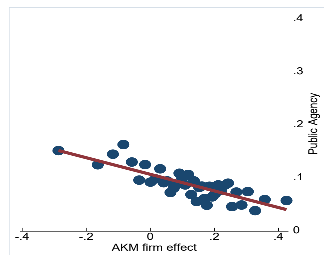
(f) Large: Networks



(g) Small: Public Agency



(h) Medium: Public Agency



(i) Large: Public Agency

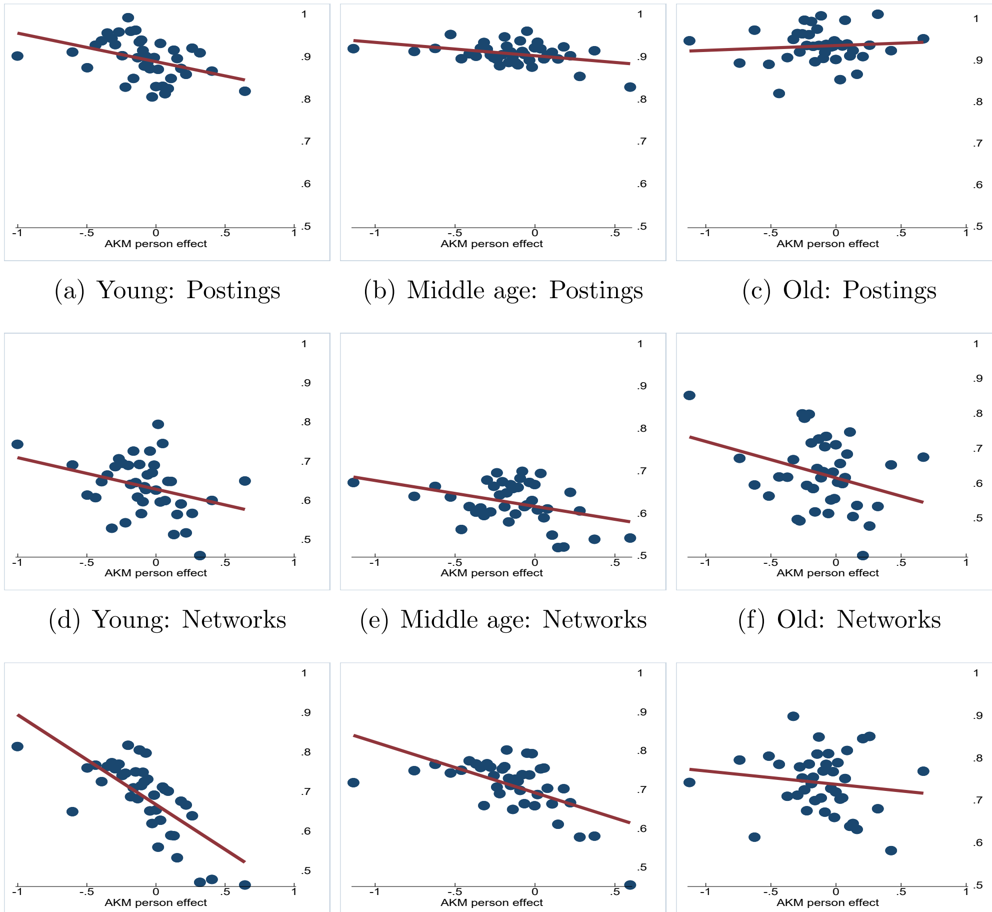
Figure B.3: Success of search channels by AKM firm fixed effect and firm size

Notes: The figures show binscatter plots that relate the firm's AKM fixed effect to the probability of succeeding to hire through the channel. "Small" refers to firms with 1-10 workers, "medium" refers to firms with 11-100 workers, and "large" refers to firms with more than 100 workers. The same controls as in Figure 1 are applied.

relation. For networks and the public employment agency we observe a negative correlation, consistent with the pooled relationships of Figure 2. In terms of probability of job finding through either of the three search channels, Figure B.7 shows positive relationships with the AKM rank when considering postings, but negative relationships when considering networks and the public employment agency, consistent with the pooled relationships of Figure 2.

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.



(a) Young: Postings (b) Middle age: Postings (c) Old: Postings

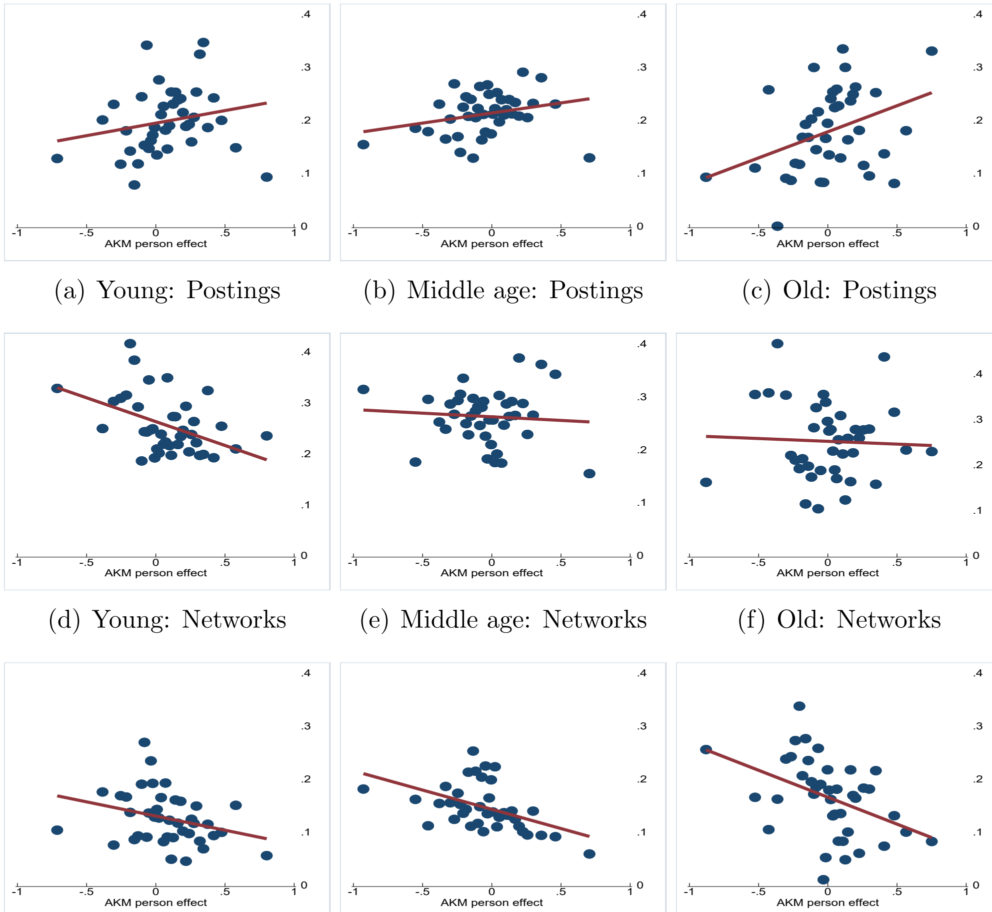
(d) Young: Networks (e) Middle age: Networks (f) Old: Networks

(g) Young: Public Agency (h) Middle age: Public Agency (i) Old: Public Agency

Figure B.4: Use of search channels by AKM worker fixed effect and worker age

Notes: The figures show binscatter plots that relate the worker's AKM fixed effect to the probability of using the channel. "Young" includes workers younger than 30, "middle age" includes workers aged 30-50, and "old" includes workers older than 50. The same controls as in Figure 2 are applied.

First we regress a linear probability model where the dependent variable takes the value of one when the hired worker was employed before and zero otherwise, and estimate regressions for each successful search channel separately, comparing the effects of the respective search channel relative to the rest (as done above in the previous tables). Complementing Figure 3, Table B.5 shows that hiring through job postings or networks of personal contacts increases the probability that the new hire comes from another firm rather than from non-employment. Higher-wage firms also are more likely to poach, reflecting the positive correlation between the AKM firm effect and the poaching index we observe in our data as discussed above. The interaction term shows that the probability of hiring an employed worker increases faster with the AKM firm effect when the hire occurs through a job postings relative to personal networks and the public employment agency, where we find (unsurprisingly) a lower probability that the worker was previously employed.



(a) Young: Postings (b) Middle age: Postings (c) Old: Postings

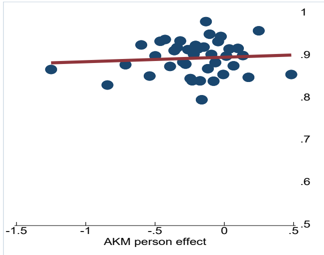
(d) Young: Networks (e) Middle age: Networks (f) Old: Networks

(g) Young: Public Agency (h) Middle age: Public Agency (i) Old: Public Agency

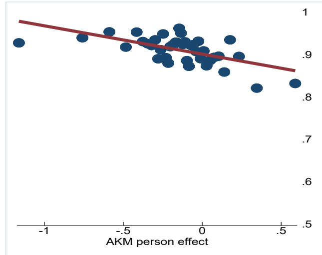
Figure B.5: Success of search channels by AKM worker fixed effect and worker age

Notes: The figures show binscatter plots that relate the worker's AKM fixed effect to the probability of succeeding through the channel. "Young" includes workers younger than 30, "middle age" includes workers aged 30-50, and "old" includes workers older than 50. The same controls as in Figure 2 are applied.

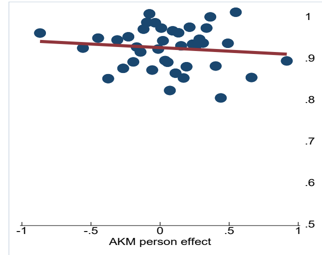
Table B.6 complements Figure 4 in the main text. This table reports the results from regressing the AKM fixed effect of the hired worker on the AKM fixed effect of the new employer, the search channel used to contact the worker and the interaction between them. The estimates show a positive relationship 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 increases by about 25%, but decreases by about 40% 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



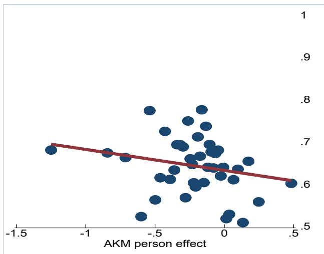
(a) Low: Postings



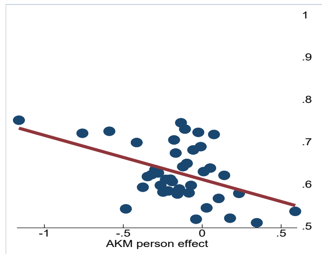
(b) Medium: Postings



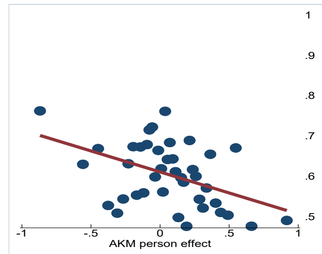
(c) High: Postings



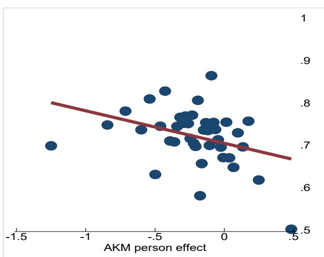
(d) Low: Networks



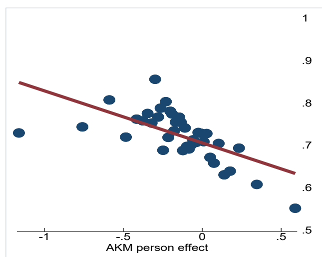
(e) Medium: Networks



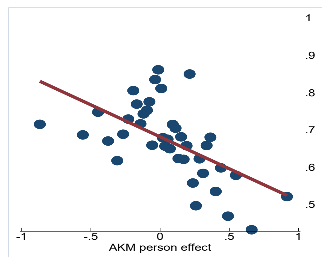
(f) High: Networks



(g) Low: Public Agency



(h) Medium: Public Agency



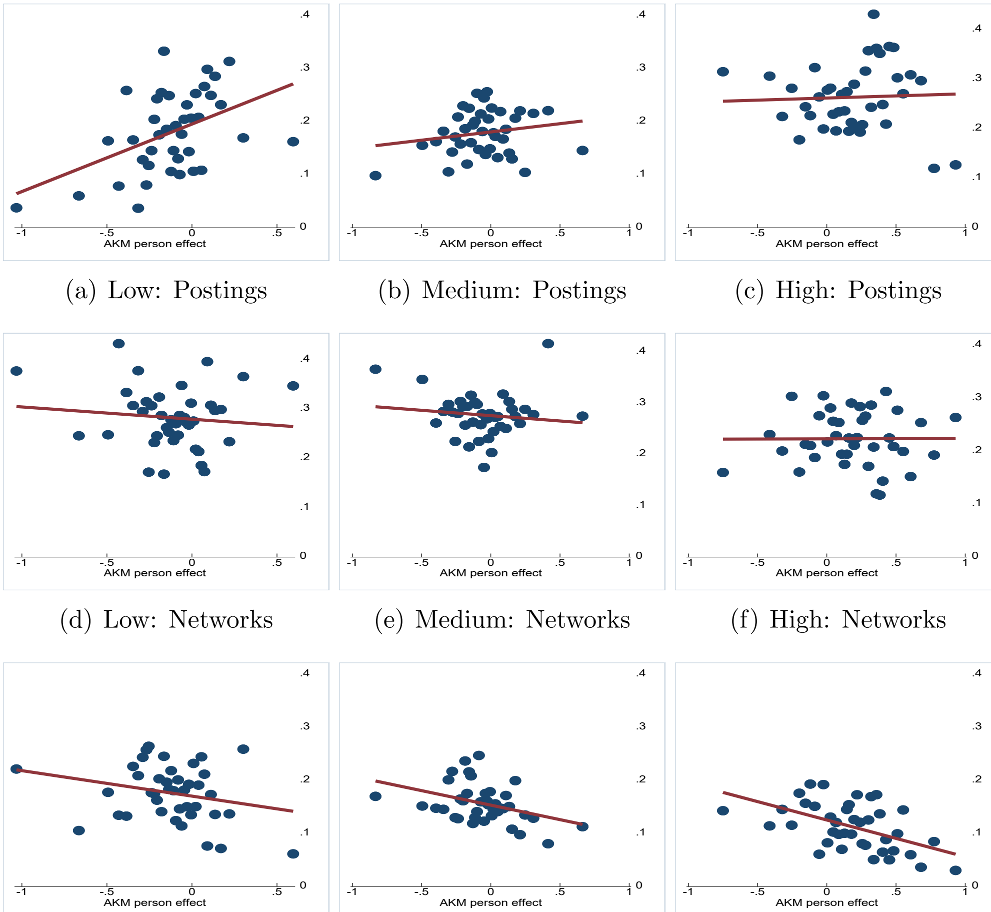
(i) High: Public Agency

Figure B.6: Use of search channels by AKM worker fixed effect and worker education

Notes: The figures show binscatter plots that relate the worker's AKM fixed effect to the probability of using the channel. "Low" includes workers with no vocational training/ university degree, "medium" includes workers with vocational training, and "high" includes workers with a university degree or equivalent educational attainment. The same controls as in Figure 2 are applied.

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.

Finally, we complement the results about match stability shown in Table 3 by investigating 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 the main text, 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.



(a) Low: Postings (b) Medium: Postings (c) High: Postings

(d) Low: Networks (e) Medium: Networks (f) High: Networks

(g) Low: Public Agency (h) Medium: Public Agency (i) High: Public Agency

Figure B.7: Success of search channels by AKM worker fixed effect and worker education

Notes: The figures show binscatter plots that relate the worker's AKM fixed effect to the probability of succeeding to hire through the channel. "Low" includes workers with no vocational training/ university degree, "medium" includes workers with vocational training, and "high" includes workers with an university degree or equivalent educational attainment. The same controls as in Figure 2 are applied.

B.5 Robustness Analysis

B.5.1 Alternative AKM Fixed Effects

In this section we show the results from regressions using AKM firm and worker effects from a time period previous to our sample period. Specifically, we estimate the AKM model as described in Section A.3 of this appendix and the main text for the period 2003-2010 and transfer the resulting fixed effects to the firm and workers in our sample period 2010-2016. Tables B.8, B.9, B.10, B.11 and B.12 show the results, replicating earlier Tables B.1, B.3, B.4, B.5, and B.6. These results show that the conclusions that emerge from using fixed effects from the period 2010-2016 or from 2003-2010 are very similar.

Specifically, Table B.8 shows that high-ranked firms attract more applicants and more suitable

Table B.5: Search channels and poaching

	Prob. hiring emp. 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. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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). The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

applicants, but are more selective than lower-ranked firms. Higher-ranked firms also spend more hours and money in the recruitment process, however they use fewer search channels. Table B.9 shows that hiring through job postings or networks of personal contacts increases the probability of poaching. Hiring through personal contacts and the public employment agency lowers the probability of poaching relative to hiring through job postings. Table B.10 confirms that hiring through job postings enhances the positive correlation between the hired worker AKM fixed effect and that of his/her employer more than hiring through personal networks and the public employment agency.

Finally, Tables B.11 and B.12 shows that our conclusion that higher-ranked firms and workers are matched predominately through postings relative to personal networks and the public agency is unaffected from using alternative firm fixed effects (those from previous years).

Table B.7: 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. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: 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	-0.050***	0.954***	6.305***	633.365***	3.813***	-0.034*	-0.617
	(0.008)	(0.108)	(0.449)	(131.088)	(0.750)	(0.018)	(1.553)
Vocational training	-0.072***	0.354***	3.289***	354.834***	4.591***	0.079***	15.034***
	(0.005)	(0.065)	(0.269)	(77.668)	(0.411)	(0.012)	(0.920)
University degree	-0.115***	0.935***	7.150***	1543.012***	12.119***	0.162***	32.989***
	(0.006)	(0.079)	(0.329)	(97.111)	(0.526)	(0.015)	(1.114)
st.d. AKM firm effect	0.206	0.206	0.206	0.210	0.207	0.222	0.207
No. Obs.	48164	49410	51607	6190	19083	75008	48534
Adj. R^2	0.041	0.095	0.088	0.101	0.054	0.375	0.049

Notes: All columns are OLS regressions with different dependent variables. Further controls: 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. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B.5.2 Using Hiring Weights

In this section we further investigate the robustness of our results by using hiring weights as an alternative to firm weights or not using any weights in the JVS. Using alternative weights is important as those firms that have been successful in hiring at least part of their vacancies, and are the ones which provide information about the last case of a hire, tend to be larger firms. Tables B.13, B.14, B.15, and B.16 show, however, that the results presented in the main text are robust when

Table B.9: Search channels and poaching

	Prob. hiring emp. worker		
	Posting	Networks	Public agency
AKM firm effect	0.081***	0.128***	0.089***
	(0.011)	(0.012)	(0.011)
Successful search channel	0.127***	0.110***	-0.232***
	(0.004)	(0.004)	(0.006)
Search channel × AKM firm effect	0.022	-0.077***	-0.070**
	(0.021)	(0.020)	(0.030)
Observations	63027	63027	63027
Adj. R^2	0.048	0.044	0.056

Notes: Linear probability regressions where the outcome is one if the hired worker was previously employed and zero otherwise. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.10: Relationship between AKM worker and firm fixed effects and the successful channel

	Hired worker AKM fixed effect		
	Posting	Networks	Public agency
AKM firm effect	0.169***	0.155***	0.175***
	(0.021)	(0.022)	(0.019)
Successful search channel	0.008	0.016**	-0.028***
	(0.007)	(0.007)	(0.010)
Search channel × AKM firm effect	0.019	-0.027	-0.093*
	(0.036)	(0.034)	(0.048)
Observations	9977	9977	9977
Adj. R^2	0.150	0.150	0.151

Notes: The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11: Search channels and firm types

	Use of search channel			Successful channel		
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM firm effect	0.073***	-0.063***	-0.172***	0.097***	-0.056***	-0.090***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.007)
Vocational training	0.089***	-0.090***	0.026***	0.094***	-0.086***	0.002
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.004)
College degree	0.193***	-0.120***	-0.050***	0.192***	-0.122***	-0.041***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
No. Obs.	61198	61198	61198	57290	57290	57290
Adj. R^2	0.106	0.056	0.052	0.075	0.071	0.017

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 same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

using hiring weights.

Table B.12: Search channels and worker types

	Use of search channel			Successful channel		
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM person effect	0.014*	-0.034*	-0.021*	0.033***	-0.053***	-0.062***
	(0.008)	(0.018)	(0.013)	(0.012)	(0.013)	(0.010)
dep.empl.=reference						
self-empl.	0.034*	0.021	-0.008	-0.063***	0.020	-0.081***
	(0.021)	(0.034)	(0.032)	(0.023)	(0.025)	(0.020)
unempl.	0.060***	0.057***	0.273***	0.016	0.011	0.072***
	(0.007)	(0.013)	(0.011)	(0.010)	(0.011)	(0.009)
non-part.	0.026*	0.042	0.046*	-0.015	-0.056**	-0.037**
	(0.015)	(0.029)	(0.024)	(0.020)	(0.022)	(0.018)
Observations	9963	9963	9963	8408	8408	8408
Adjusted R^2	0.012	0.003	0.075	0.002	0.005	0.018

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 same controls as in Figure 2 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.13: 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	-0.1099***	1.2218***	9.3633***	1479.1243***	7.8431***	-0.1480***	15.0843***
	(0.0091)	(0.1410)	(0.5440)	(167.5835)	(0.8775)	(0.0287)	(1.7303)
Vocational training	-0.0394***	-0.4176***	1.1801***	302.9464***	4.2156***	0.0173	20.2415***
	(0.0041)	(0.0634)	(0.2442)	(70.7053)	(0.3705)	(0.0129)	(0.7698)
University degree	-0.0750***	0.1370	5.9690***	1819.1182***	11.7480***	0.0955***	39.4056***
	(0.0054)	(0.0846)	(0.3268)	(98.1314)	(0.5124)	(0.0173)	(1.0179)
No. Obs.	46119	47278	49224	6114	19313	60095	46593
Adj. R^2	0.0454	0.0896	0.0919	0.1709	0.0555	0.1826	0.0631

Notes: All columns are OLS regressions with different dependent variables using the provided hiring weights. Further controls: 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. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14: Search channels and poaching

	Prob. hiring emp. worker		
	Posting	Networks	Public agency
AKM firm effect	0.184***	0.267***	0.193***
	(0.014)	(0.014)	(0.013)
Successful search channel	0.098***	0.110***	-0.243***
	(0.004)	(0.005)	(0.006)
Search channel × AKM firm effect	0.090***	-0.130***	-0.035
	(0.021)	(0.022)	(0.031)
Observations	59297	59297	59297
Adj. R^2	0.069	0.070	0.085

Notes: Linear probability regressions with the provided hiring weights where the outcome is one if the hired worker was previously employed and zero otherwise. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.15: Search channels and firm types

	Use of search channel			Successful channel		
	Postings	Networks	Public agency	Postings	Networks	Public agency
AKM firm effect	0.020*	-0.098***	-0.290***	0.106***	-0.077***	-0.149***
	(0.010)	(0.012)	(0.012)	(0.012)	(0.011)	(0.009)
Vocational training	0.077***	-0.124***	0.040***	0.098***	-0.111***	0.067***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
College degree	0.148***	-0.116***	-0.074***	0.193***	-0.117***	-0.006
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.005)
No. Obs.	57824	57824	57824	54473	54473	54473
Adj. R^2	0.128	0.055	0.100	0.066	0.076	0.032

Notes: All regressions are linear probability models with the provided hiring weights where the outcome is one if the particular channel is used (left panel) or successful (right panel) and zero otherwise. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.16: Relationship between AKM worker and firm fixed effects and the successful channel

	Hired worker AKM fixed effect		
	Posting	Networks	Public agency
AKM firm effect	0.109***	0.210***	0.186***
	(0.014)	(0.014)	(0.013)
Successful search channel	0.006***	0.114***	-0.035***
	(0.005)	(0.005)	(0.006)
Search channel × AKM firm effect	0.202***	-0.108***	-0.139***
	(0.021)	(0.022)	(0.032)
Observations	23192	23192	23192
Adj. R^2	0.232	0.230	0.230

Notes: OLS regressions with the provided hiring weights. The same controls as in Figure 1 are applied. Standard errors in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C Model Appendix

C.1 Further Model Details

C.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[36]

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

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

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

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

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

The Bellman equation for the value of an employed worker is

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

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 (C.4), with the only difference that the lower bound of integration is equal

[36] 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. $W(x, y, y) = S(x, y)$.

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 (C.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 (C.1) and (C.2) and Bellman equation (C.4).

C.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

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

with aggregate recruiting intensity in channel c defined by

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

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

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

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

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

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

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

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

C.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:

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

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[37]

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

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:

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

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

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

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

C.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 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 (C.10) and (C.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

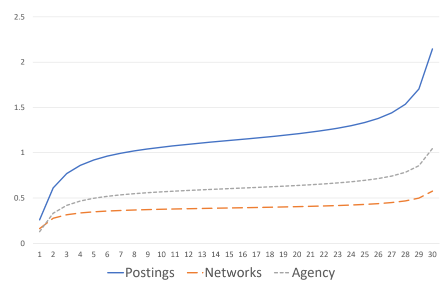
$$\pi_j^c = \frac{r_j^c \mu(y_j)}{\bar{s}^c\theta^c} \ .$$

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

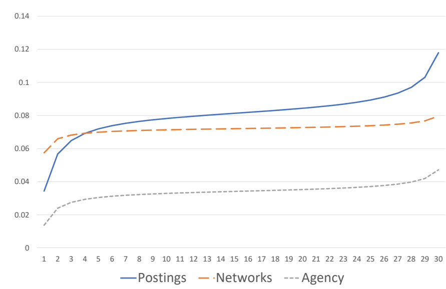
After convergence has been achieved, the remaining model equations can be solved for the wage distribution.

C.2 Recruitment Costs and Benefits of Search Channels: Further Results

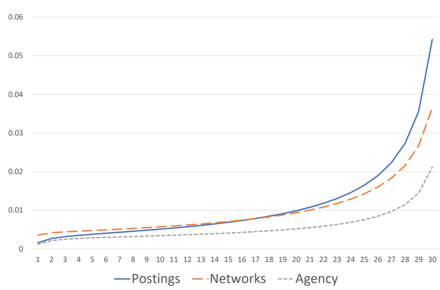
In this section we present we provide a more detailed view of the different recruitment outcomes firms have by using different search channels. In Section 3.4 of the main text we analysed differences in recruitment outcomes across the three channels, focusing on the mean of the outcome across the firm productivity distribution and the ratio between the respective outcome variable at the 75th and 25th percentiles of the firm productivity distribution. Figure C.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.



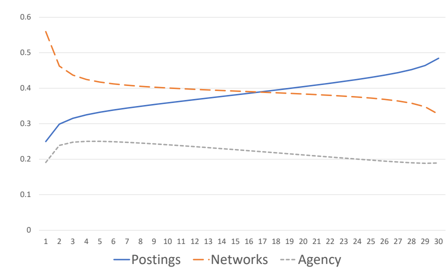
(a) Recruitment cost



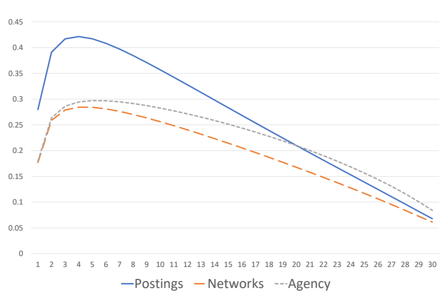
(b) Meeting probability



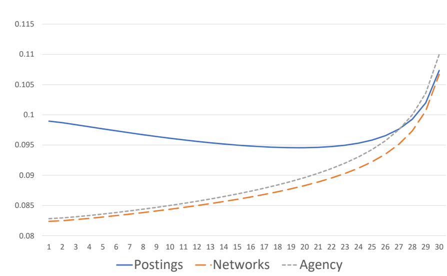
(c) Hiring probability



(d) Share of hires



(e) Profit per hire



(f) Average worker ability

Figure C.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.