Recruitment Policies, Job-Filling Rates and Matching Efficiency*

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Abstract

Recruitment intensity is important for the matching process in the labor market. Using unique linked survey-administrative data, we investigate the relationships between hiring and recruitment policies at the establishment level. Faster hiring goes along with higher search effort, lower hiring standards and more generous wages. We develop a directed search model that links these patterns to the employment adjustments of heterogenous firms. The model provides a novel structural decomposition of the matching function that we use to evaluate the relative importance of these recruitment policies at the aggregate level. The calibrated model shows that hiring standards play an important role in explaining differences in matching efficiency across labor markets defined as region/skill cross products and for the impact of labor market policy, whereas search effort and wage policies play only a minor role.

JEL classification: E24; J23; J63
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1 Introduction

Recent evidence documents substantial and systematic variation in job-filling rates across firms. This is hard to reconcile with a standard aggregate matching function which stipulates that the job-filling rate is a function of the vacancy-unemployment ratio (labor market tightness) in the relevant labor market but is otherwise unrelated to the characteristics of the firm. Differences in job-filling rates are particularly large with respect to the firms' employment growth and hiring rates; firms that hire more do so by filling their vacant jobs faster (see Davis et al., 2013). Such variation matters for matching efficiency: changes in aggregate recruiting intensity can account for a persistent shift of the Beveridge curve in the aftermath of the Great Recession (see e.g. Gavazza et al., 2018). Due to a lack of appropriate micro data, relatively little is known about firms' efforts to make their recruitment process more effective. As a consequence, standard labor market theories focus on the firms' decisions to create jobs, while taking recruitment behavior and its impact on matching efficiency as exogenous model parameters. These limitations make it difficult to evaluate which hiring practices are more sensitive to labor market interventions, leaving policymakers with little guidance on how best to improve the effectiveness of policies that aim to improve the job-finding prospects of unemployed workers.

Different mechanisms can possibly explain why some firms hire faster than others. Expanding firms may invest more in search or screening intensity and hence fill jobs more quickly (e.g. Gavazza et al., 2018), they may pay higher wages (or offer more attractive non-pecuniary job benefits) to attract more workers (e.g. Kaas and Kircher, 2015), or they may reduce their hiring standards (e.g. Sedlacek, 2014). Other explanations, unrelated to the choices of firms, can be measurement issues due to time aggregation (since the vacancy stock is observed infrequently, some hiring occurs without a reported vacancy) or composition effects (for instance, firms that grow faster may be those firms that create jobs with lower skill requirements that are easier to fill). Without detailed information about the recruitment process or about specific characteristics of the hired workers, previous work has not been able to assess which of these channels is responsible for the observed variation in job-filling rates and ultimately in matching efficiency.

This paper uses unique linked survey-administrative data and a structural model analysis to quantify the role of different dimensions of recruitment for hiring and matching efficiency. We distinguish between three broad measures of recruiting intensity: search effort, wage generosity and hiring standards. First, we present new evidence showing that all three measures are important for hiring at the micro level: Firms with larger hiring rates exert greater search effort, offer more generous starting wages and become less selective. Second, in order to understand the impact of recruiting intensity on aggregate matching efficiency, we propose and quantitatively assess an equilibrium search-and-matching model of the labor market where differential job-filling rates result from optimal recruitment decisions of heterogeneous firms. A key feature of the model is that it provides a novel structural decomposition of the matching function in terms of the three recruitment margins. Third, we use our model to assess the role of recruitment for labor market reforms that aim at improving workers' job-finding prospects. This allows us to gauge which dimensions of firms' hiring policies are most responsive to labor market policy.

To describe the empirical patterns, we link an annual vacancy survey of German establishments (Job Vacancy Survey, JVS) to administrative matched employer-employee data (Integrated Employment Biographies, IEB) for the period 2010–2017.[1] The linking of these data is novel and crucial for our purposes. The JVS contains information on the stock of vacancies at the day of interview, which is further broken down into three skill levels. From the administrative data, we measure the hires flow in the period after the interview. This permits us to calculate the *vacancy yield* (hires per vacancy) as a proxy of the monthly job-filling rate, in a similar fashion as Davis et al. (2013) do using the Job Openings and Labor Turnover Survey (JOLTS) for the U.S. In line with the U.S. data, we verify that most of the observed variation in hiring rates arises from the vacancy yields margin; that is, establishments fill a greater portion of their vacancies when they hire more. This is a robust relationship that holds after controlling for establishment size, age and industry (see also Mongey and Violante, 2020; Mueller et al., 2020). We also examine whether the observed characteristics of new hires, such as previous employment status, age or gender vary systematically with employment growth of the hiring establishment, which could potentially contribute to variation of vacancy yields. We find little evidence in favor of composition effects on these dimensions.

Differently from the data used in the aforementioned contributions, the JVS contains information about the establishment's recruitment behavior and outcome. This information can be connected to the factual hiring patterns of the establishment from the administrative data. Using both data sets, we construct separate indices capturing each establishment's search effort, wage generosity and hiring standards. These indices build on direct information from the survey, and also utilize wage information for all new hires from IEB data. In this way we capture different aspects of an establishment's recruitment policies at a given point in time. We demonstrate that establishments indeed make use of all three recruitment margins: All standardized indices vary with the hiring rate of an establishment in a systematic way even after controlling for a wide range of job and establishment characteristics.

To rationalize these establishment-level patterns and to link them to aggregate labor market outcomes, we build a tractable directed search model similar to Moen (1997) and Garibaldi and Moen (2010) in which multi-worker firms operate a constant-returns technology and adjust their vacancy postings, wage policies, search effort and reservation match-specific productivity (hiring standards) in response to idiosyncratic productivity shocks. We characterize the unique equilibrium and show that firms with more productive projects post more vacancies, exert more search effort, offer more generous wages and set lower hiring standards, all of which contribute to larger hiring rates. Aggregating over firms, the model can then generate the observed positive

[1] For ease of exposition, in what follows we will use the terms firms and establishments interchangeably.

relationship between hiring rates and vacancy yields where the latter is an endogenous outcome of all three recruitment policies. Moreover, aggregate matching efficiency is an endogenous outcome rather than an exogenous model parameter.

The model is calibrated using the evidence from our data via simulation method of moments. We exploit cross-sectional variation at the establishment level and by constructing 36 "local labor markets" based on the cross-product of three skill levels and twelve regions for the 2010–2017 period. The model is able to quantitatively reproduce market-specific wages, unemployment and job-finding rates, as well as the cross-sectional relationships between search effort, wage generosity, hiring standards and vacancy yields to the variation in hiring rates across establishments that we document empirically. The model is also consistent with the observed variation in unemployment rates, job-finding rates, vacancy yields and labor market tightness between local labor markets.

Using the model-implied decomposition of the matching function, we find that most of the variation of matching efficiency across local markets comes from the creation of jobs (market tightness) and from hiring standards. However, firms in tighter labor markets are more selective which in turn reduces matching efficiency. This arises as in tighter labor markets unemployed workers have better job-finding prospects and hence higher reservation wages; therefore firms become more selective as they need to offer sufficiently high wages to fill their positions. This feature matters when comparing labor markets both across the skill and the geographic dimensions.

Variation of search effort has a positive, but quantitatively less important effect on matching efficiency, although we observe a stronger impact of search effort in high-skill labor markets. Since we consider segmented local labor markets, only the dispersion of wages, but not the average wage level, contributes to matching efficiency. Indeed, wage dispersion per se reduces matching efficiency, but the degree of wage dispersion is small in our calibrated model and hence contributes very little to the variation of matching efficiency.[2] This implication is consistent with the observation that in our data wage dispersion varies little across local labor markets.

Finally, to investigate the role of labor market policy for job-finding rates through its effects on recruitment, we consider the impact of a reduction of unemployment benefits, mimicking one aspect of the Hartz labor market reforms that were implemented in the mid 2000s in Germany. Similar to our results for matching efficiency, the creation of jobs (market tightness) and hiring standards are the two dominant forces that raise the job-finding rate in response to the policy change. But this time the two factors go in the same direction: As unemployment income is reduced and workers' reservation wages become lower, firms create more vacancies *and* reduce their hiring standards, both of which contribute to an increase of the job-finding rate. The selectivity margin accounts for over a quarter of the increase in the job-finding rate for the whole labor market. As in the data, this margin is more prominent for the low-skill labor market, where it is responsible for a third

[2] A higher wage *level* does not increase matching efficiency in our model essentially because workers' search intensity is exogenous. The *dispersion* of wages reduces matching efficiency since it induces dispersion of job queues in different submarkets. If job queues are more dispersed, concavity of the matching function implies that the number of aggregate matches is lower which follows from Jensen's inequality.

of the increase of the job-finding rate. The importance of vacancy creation and the selectivity margin provide a natural explanation for the findings of Carrillo-Tudela et al. (2021), who show that job-finding rates increase the most in low-skill labor markets after the implementation of the Hartz reforms.

To further show the importance of hiring standards, we evaluate the same reduction of unemployment benefits, but this time not allowing firms to adjust their selectivity margin. This exercise now leads to a much more subdued increase in the job-finding rate, especially for the lower skilled workers. Ignoring the firms' choice of hiring standards would thus lead to vastly distinct policy conclusions. This is important as the majority of the literature that evaluates the Hartz reforms does not consider this margin.

Related Literature. Our paper contributes to a large and growing literature that documents the several aspects of firms' recruitment policies. Early examples are Barron and Bishop (1985) and Barron et al. (1985), who investigate the determinants of the extensive and intensive margins of employer search effort in the hiring process. They use information from the Employer Opportunity Pilot Project (EOPP) in the U.S. about the number of applicants, interviews, job offers, hours involved in processing and screening applications and several job and employer characteristics. Like the JVS, the EOPP data provides information that arises from the last newly hired worker. Unlike the JVS, however, it is much smaller, covers a much shorter time span, does not have information about the usage of search channels or the geographic scope of search (which are direct measures of search effort) and cannot be linked with matched employer-employee administrative data or with the employers' job or worker flow rates.

Several other studies also use EOPP data to explore the implications of hiring standards and offered wages on the probability of filling a vacancy. Burdett and Cunningham (1998) find that as employers increase their hiring standards by requiring greater experience and education from their applicants, the probability of filling their vacancies decreases.[3] Faberman and Menzio (2017) relate the wage offered to the probability of filling a vacancy, finding that higher wage offers go together with longer vacancy durations, seemingly contradicting the predictions of the standard competitive search model. However, Marinescu and Wolthoff (2020) show using U.S. vacancy data from a private online platform that a positive relation arises between posted wages and the number of applicants (and hence higher job-filling rates) when one controls for job titles as they reflect better hierarchy, experience, and the level of specialization of jobs.[4] Mueller et al. (2020) use administrative data on Austrian public employment agencies and link it to matched employer-

[3]See also Van Ours and Ridder (1992) for evidence on vacancy durations using Dutch data. More recently, Modestino et al. (2020) use data from online job postings and find that education and experience requirements increased during the Great Recession, especially in labor markets with lower vacancy-unemployment ratios.

[4]Using online Chilean vacancy data, Banfi and Villena-Roldan (2019) find that a positive relationship between offered wages and the number of applications holds even for job ads where wages are revealed "implicitly" through wage-bracket filters. Belot et al. (2022) find a similar positive relationship between posted wages and applications using a field experiment among job seekers.

employee administrative data, finding a positive relation between job-filling rates and starting wages. Our study is not restricted to vacancies posted at specific public or private job boards, and it uses detailed information on recruitment strategies beyond starting wages. Thus, our results complement and extend the existing literature.

Davis et al. (2012, 2013) using JOLTS micro data were the first who described the "hockey stick" relationships between establishment growth, hiring rates and vacancy yields. We go beyond these patterns and investigate to what extent different recruitment policies are associated with faster hiring. Lochner et al. (2021) also use the JVS and study how particular measures of employer search effort and hiring standards vary across the establishment growth distribution. Our paper links the JVS with matched employer-employee data which allows us to construct broader measures of recruitment policies, including the effects of employers wage generosity, and to relate them to the variation of hiring rates.[5] Further, we quantitatively assess the implications of wages, search effort and hiring standards for matching efficiency and labor market policy within an equilibrium search-and-matching model.

There is also a growing theoretical literature interested in the role of firms' recruiting intensity on aggregate labor market outcomes and on the micro-level relationships uncovered by Davis et al. (2013). Recent work extends the canonical Diamond-Mortensen-Pissarides framework to feature multi-worker firms which chose search effort as in Gavazza et al. (2018) and Leduc and Liu (2020) or wages as in the competitive-search models of Kaas and Kircher (2015) and Schaal (2017). Selection cutoffs among heterogenous pools of applicants (hiring standards) are also introduced in random search environments like the ones proposed by Acharya and Wee (2020), Baydur (2017), Chugh and Merkl (2016), Sedlacek (2014) and Villena-Roldan (2012). Our paper proposes a unified framework to study these three different measures of recruiting intensity and to quantify them in accordance with our empirical findings. A competitive search environment is helpful as it provides an intuitive and simple way through which changes in posted wages have a direct effect on a firm's hiring and job-filling rates.[6] In this sense our model is close in spirit to Wolthoff (2018) who also considers these different recruitment policies and uses EOPP data for calibration of his model. The key differences are that we explicitly consider firm dynamics, investigate how these policies affect hiring of multi-worker firms and how they matter for aggregate matching efficiency and labor market policy.

[5] JVS data have also been used, for instance, by Davis et al. (2014), Ehrenfried and Holzner (2019) and Mercan and Schoefer (2020). None of these papers study the role of different recruitment policies for hiring or link the JVS to the administrative data which is crucial for our research.

[6] Although this is also possible in an extended version of the random search environment with on-the-job search proposed by Mortensen (1998), it would needlessly complicate the analysis. Further, we find little evidence that establishments meaningfully change their hiring policies when they hire an employed relative to an unemployed worker, suggesting that for our purpose adding on-the-job search is not of first order.

2 Empirical Findings

2.1 Data

Our first data source is the Job Vacancy Survey (JVS) of the Institute for Employment Research (IAB) which is a representative cross-sectional survey of establishments in Germany (for a data description, see Bossler et al., 2019). The main purpose of the survey is to measure the number of vacancies at these establishments, over and above those that are officially reported at the Federal Employment Agency, and to obtain information about their recruitment processes. While the survey is conducted annually since 1989, establishment IDs can be obtained and linked to administrative records only from the year 2010 onward. Given this matching restriction we focus on the years 2010–2017, for which we observe around 13,000-15,000 establishments per year.

The JVS survey is conducted in the last quarter of a year and consists of two parts. The first part contains general information about the establishment, including employment, location, industry, and whether the establishment was facing financial, demand and/or workforce restrictions. This part of the survey also contains the current stock of vacancies (defined as "open positions to be filled immediately or to the next possible date"), broken down by three levels of education requirements (no formal education, vocational training, and university degree). The second part provides information about the recruitment behavior among the surveyed establishment.

Surveyed establishments can be categories into three separate groups: (i) those that reported not engaging in any recruitment activity during the last 12 months (32% of establishments); (ii) those that reported recruitment activity but were unsuccessful in filling all of their available job openings in the last 12 months (2% of establishments); and (iii) those that reported recruitment activity and filled all or some of their openings in the last 12 months (66% of establishments). All establishments 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. We use this information when constructing our JVS-based recruitment measures.[7] Besides several questions about the hiring process that we further describe below, the survey includes information about the hired person (age, education, previous employment status, monthly starting wage) and a few general questions about the job (occupation, permanent/temporary, replacement hire). It is important to note that in the vast majority of cases, the recorded information for the last case of a hire in the JVS corresponds to single vacancy job openings.[8] Tables 10 and 11 in Appendix A present the main summary

[7]Establishments with an unsuccessful hire are asked to provide information about why they did not manage to fill their vacancy. However, this information is not very useful to construct our recruitment measures as it does not encompass details of the recruitment process other than the number of search channels employed in advertising the job opening.

[8]Carrillo-Tudela et al. (2022) are able to identify the worker hired in the JVS in the IEB administrative data using the matching procedure developed in Lochner (2019). They are also able to identify any additional hires that could arise from the same job opening by using the establishment 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

statistics of our JVS sample. Table 12 in the same appendix shows that there are no meaningful differences in various characteristics (such as size, age or industry) between establishments which fill either all or only a fraction of their job openings. This suggests that by focusing on successful hires, we are not introducing meaningful selection along these dimensions.

Our second data source is the Integrated Employment Biographies (IEB) which is the administrative record of all workers paying social security contributions. These data provide information on individuals' daily earnings and employment histories as well as their education, age, gender, nationality, occupations and the type of employment contract (full-time vs. part-time). We make use of information about the employment biographies of all workers employed in one of the establishments surveyed in the JVS during 2010–2017. The link between JVS and IEB data is crucial for our aims as it allow us to utilize information on hiring standards and wage policies in recruiting establishments from administrative records; see Appendix A for summary statistics and details on the data linking process.

2.2 Variation in Vacancy Yields

Before turning to recruitment strategies, we first demonstrate that most of the variation in hiring rates across firms is accounted for by the *vacancy yield*, which is a direct measure of recruiting intensity obtained from vacancy stock and hires flow data. These findings are consistent with those of Davis et al. (2013) for the U.S. based on the Job Openings and Labor Turnover Survey (JOLTS).

Variation in the hiring rate (hires H divided by employment E) arises from variation in the vacancy rate (vacancies V divided by E) and the vacancy yield (H divided by V) as implied by the equation

$$\frac{H}{E} = \frac{V}{E} \times \frac{H}{V} \ . \tag{1}$$

We measure reported vacancies from the JVS and hires following the 30 days after the day of interview from the administrative IEB data.[9] Employment is calculated as the average of the employment stock at the beginning and end of the 30-day period.

Figure 1 shows vacancy rates and vacancy yields by hiring rates, where establishment-level observations are pooled in bins of monthly employment growth. In line with results for the U.S. using JOLTS data,[10] the lion share of hiring rate variation is accounted for by the vacancy yield:

2010-2017 one can find additional hires in the administrative data that share the same establishment 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 establishments (over 500 employees).

[9]We use 30-day intervals here to be consistent with the U.S. results using monthly JOLTS data. Further, hires exclude employer returns. That is, we do not count as part of hires all those workers who return to their previous employer after a non-employment spell shorter than three months.

[10]For comparable graphs to our Figure 1, see Figure 1 in Mongey and Violante (2020) and Figure IX in Davis

As monthly hiring rates increase from close to zero up to 30%, the vacancy rate roughly doubles, whereas the vacancy yield goes up by a factor around eight.[11] A log variance decomposition of equation (1) confirms that the vacancy yield accounts for 84% of the hiring rate variability across the pooled observations in Figure 1.

The red diamonds in both graphs show the same outcome variables conditional on industry, establishment size and age, which demonstrates that the observed patterns are not induced by a changing compositions of establishment in these dimensions. In Appendix A, we report the relationships between the variables shown in Figure 1 and employment growth rates, confirming similar "hockey-stick" relationships between employment growth and the vacancy yield as shown in Figure V of Davis et al. (2013) for JOLTS data.[12]

In conclusion, variation in hiring rates appear to be predominately accounted for by the vacancy yield margin rather than differences in vacancy rates. Investigating whether employers tend to hire different groups of workers, we find little evidence in favor of such composition effects. Faster-growing establishments hire slightly more from unemployment (rather than from another employer) and relatively more females. There is no evidence, however, that these establishments hire more workers without German citizenship, above 50 years of age or from long-term unemployment, groups which are considered to be disadvantaged in the labor market (see Figure 11 in Appendix A).

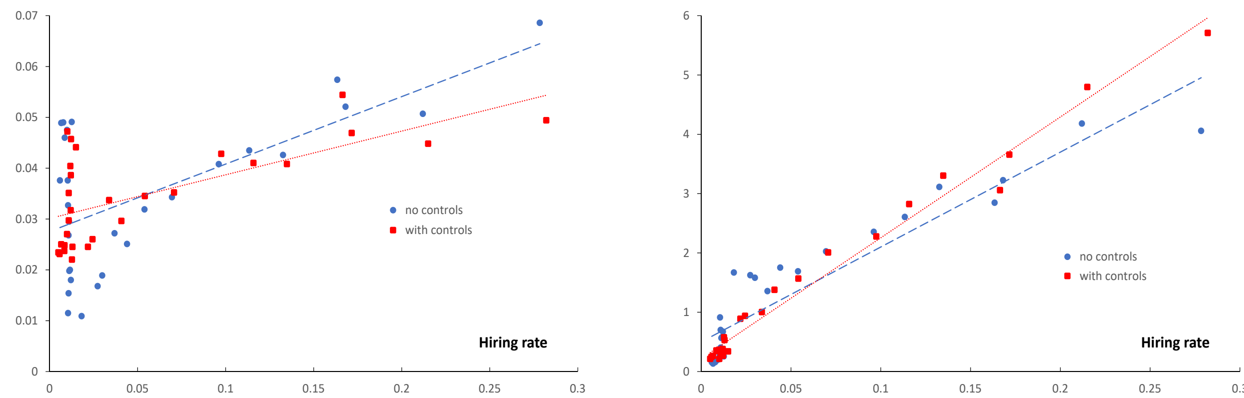
2.3 Hiring Rates and Recruitment Policies

The previous findings indicate that stronger hiring activity goes along with higher vacancy yields, which may indicate greater recruiting intensity on the side of firms. We now turn to our main empirical findings. We are interested in measuring the relationship between the establishment's hiring rate and its wage policy, hiring standards and the search effort exerted when filling a position. We focus on these recruitment policies as they have been separately highlighted before as the main

et al. (2013).

[11] Note that values of the vacancy yield above one point to a common measurement issue in such data. For instance, at the interview date establishments may not report any vacancies, while in the 30 days following the interview positive hires are recorded. Aside from misreporting, this can arise, for example, as some establishments had their job offers accepted before the JVS interview date but the new hire started work after the interview date. Another reason could be that a job became vacant after the interview date and was filled sufficiently quickly within the 30-day interval after the JVS interview. Davis et al. (2013) show that one way to deal with such time aggregation issues is to estimate the daily job-filling rate from an underlying daily vacancy "birth and death" process. Appendix A.2 provides the results of this exercise for our data, showing that similar relationships arise for daily fill rates. We also consider the subsample with positive vacancies, where the vacancy yield can be calculated at the establishment level, and show that it also varies strongly with employment growth. Finally, using a statistical model of the daily hiring process, Davis et al. (2013) also show that a mechanical luck effect cannot explain the strong relationship between vacancy yields and establishment growth.

[12] Different from the monthly JOLTS, the annual JVS has no panel dimension, so that we cannot replicate the fixed-effects regressions of Davis et al. (2013). We also remark that vacancy rates are larger for JVS establishments with negative employment growth in comparison to JOLTS data. Despite such differences, the main conclusion is the same: vacancy yields vary systematically and significantly with the establishments' employment growth and hiring rates.



(a) Vacancy Rate

(b) Vacancy Yield

Figure 1: Vacancy rate and vacancy yield by hiring rate

Notes: Hiring rates H/E (30 days post interview) and vacancy rates V/E are weighted averages in 29 bins of employment growth (30 days post interview), ranging from -30% to +30% with smaller bin widths around zero growth. For each bin, the vacancy yield H/V is calculated as the ratio between the hiring rate and the vacancy rate, which is equivalent to dividing total weighed hires by total weighted vacancies in a growth bin. Blue circles (dashed slopes) are unconditional means, red squares (dotted slopes) are conditional on industry, size and age. Specifically, hiring rates and vacancy rates are regressed on dummies for the 29 growth bins, one-digit industry, six size classes and five age classes. Then, the estimated coefficients on the bin dummies are shifted to the unconditional means, and vacancy yields are calculated as before.

instruments employers have at their disposal to increase their hiring (see the literature discussed in the introduction). We use questions in the JVS about the last case of a hire that pertain to these aspects of the hiring policy, as well as wage information obtained from the administrative IEB data to construct measures relating to the employer's wage and hiring standards policies.

To investigate the relation between hiring rates and recruitment policies, we construct the establishment's hiring rate based on a 90-day period around the date of interview. We choose a longer interval than for the calculation of vacancy yields (Figure 1) for two reasons: First, in many establishments, especially in smaller ones, there are not enough hires in administrative data during short time spans so that we cannot construct meaningful measures for wage and hiring standards policies based on IEB data. Second, a longer interval smoothes out short-term fluctuations and hence better reflects the establishment's actual hiring policies at the time the interview takes place.[13]

A potential concern with the recruitment information obtained from JVS data is that it reflects only the last case of a hire. Indeed, the underlying assumption is that the reported recruitment

[13]We re-computed the relationships depicted in Figure 1 using 90-day intervals and find no meaningful change in our conclusions; see Figure 10 in Appendix A.

behavior, especially after controlling for characteristics of the specific job, is sufficiently representative of the establishment's recruitment policy in the period under consideration. To mitigate any "survivorship bias" arising from this feature of the data, we use as outcome variables several recruitment measures and regress them on establishment and job level variables. In particular, we analyze the extent to which faster hiring goes along with specific recruitment policies across establishments by regressing various recruitment policy variables on 13 bin dummies for the establishment's 90-day hiring rate, ranging from zero to intervals up to 25% and taking hiring rates near zero as the baseline category.[14] In addition, we also consider specifications where we control for year, establishment characteristics (industry, five size categories, and establishment age) and job characteristics (1-digit occupation, three levels of skill requirements, dummies for long-term experience and leadership requirements, and a dummy for a newly created job).

Another potential concern is the extent to which measurement error pollutes the JVS recruitment measures we use here. Measurement error could arise, for example, due to a recall error from the employee responding the survey.[15] Other biases may result from the lag between the interview date and the date of the last hire which is generally longer in smaller, low-turnover establishments. When we additionally control for this time lag, our results do not change in a meaningful way (see Figure 16 in Appendix A).

To further temper concerns arising from the data collection process used in the JVS, we utilize the IEB data in order to obtain alternative measures of an establishment's wage generosity and hiring standards that are based on administrative data. With the IEB data we can construct such measures on the basis of all new hires and existing workers at a given establishment. Below we show that both data sets provide a very similar picture. We then use these data to construct unified measures of wage generosity and hiring standards. Our measure of search effort, however, must rely exclusively on information drawn from the JVS.

Figures 2–4 depict the estimated relationships between several recruitment measures from JVS and IEB data and hiring rates, while Table 13 in Appendix A reports standard errors for the estimated coefficients, many of which are significantly different from zero at the 1% or 5% level. In Appendix A we also show that our results remain similar when we either remove the smallest establishments (those with less than 20 employees), observations with zero hires or observations with negative employment growth from the sample. The presence of small establishments may be a concern because they can never have small and positive hiring rates and often hire no worker at all.[16] Shrinking establishments may also hire differently or face different constraints in the labor market. Our results show, however, that neither of these modifications alters our main conclusions.

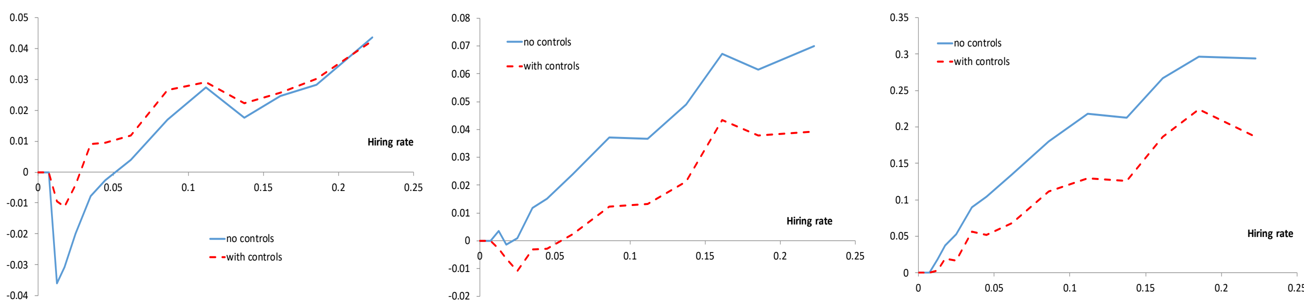
[14]Recall that for these regressions we use establishments that were either fully or partially successful in filling all of their vacancies. Any bias from not considering establishments that did not manage to fill any of their open positions is likely to be small as these represent only a small proportion of all hiring establishments in our sample.

[15]Other potential problems can be associated to non-response issues for which appropriate weights are provided (see Brenzel et al., 2016, for details).

[16]For instance, the lowest positive hiring rate of an establishment with 20 workers is 4.9%.

Wage generosity

To measure the generosity of an employer's wage policy at the hiring stage, we first make use of JVS information on whether the employer had to pay more than expected to make a hire. Let $\hat{w}_{jt}^{JVS}$ denote this *wage concessions* variable which takes the value of one if establishment j at time t had to pay more than expected and zero otherwise. Figure 2.a shows the relationship (with and without controls) between $\hat{w}_{jt}^{JVS}$ and the hiring rates. Relative to establishments with a zero hiring rate, those that exhibit hiring rates over 20% are 4.5% more likely to make a wage concession. This increased probability is comparable to the effects of establishment size and to wage concession differentials across industries (when using them as part of the controls).



(a) JVS - Wage Concessions (b) IEB - Wage Premium (c) JVS+IEB - Wage Generosity

Figure 2: Wage generosity and hiring rates

Notes: Each indicator is regressed on bin dummies of the establishment's hiring rate with the category near zero as reference. The solid (blue) curves show the coefficients when no further controls are applied, the dashed (red) curves also control for year, establishment characteristics (industry, 5 size categories, age and age^2) and job characteristics (1-digit occupation, 3 levels of skill requirements, dummies for long-term experience and leadership requirements, and a dummy for a newly created job).

Next we use IEB data to determine whether an employer hired workers on wages that were larger than those predicted by a standard wage equation. Specifically, we use data on the employment spells of all workers that were employed in one of the JVS establishments in our sample between 2005–2018. For all prime-age (ages 23 to 55), male full-time workers, we estimate

$$\ln w_{it} = f_i + g_{j(i)} + \delta_t + \beta X_{it} + \eta_{it} \ , \qquad (2)$$

where f_i denotes a worker fixed effect, $g_{j(i)}$ an establishment fixed effect, δ_t a time trend, X_{it} a vector of worker observable characteristics (quadratic on experience, quadratic on tenure and dummies for education and occupational group) and η_{it} white noise. We define our *wage premium* measure by the average residual wage of current hires in a given establishment (H_{jt}):[17]

$$\hat{w}_{jt}^{IEB} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} \eta_{it} \ .$$

The wage premium is the difference between the average wage paid to new hires at time t and the predicted average wage that the very same workers (with the same observed and unobserved characteristics) would normally earn in the same establishment.[18] Figure 2.b shows the relationship (with and without controls) between $\hat{w}_{jt}^{IEB}$ and the hiring rate. Here we observe that the wage premium increases by 4 or 7 log points between establishments with a hiring rate of 20-25% relative to those with a zero hiring rate. The difference in these estimates arises mainly due to the effects of establishment size and industry composition.[19]

Given that $\hat{w}_{jt}^{JVS}$ and $\hat{w}_{jt}^{IEB}$ should be measuring different aspects of employers' wage policies, we construct a combined *wage generosity* measure $\hat{w}_{jt}$ as the average of the standardized values of $\hat{w}_{jt}^{JVS}$ and $\hat{w}_{jt}^{IEB}$ where we standardize $\hat{w}_{jt}$ again so that it has unit variance. Figure 2.c shows the positive relationship between $\hat{w}_{jt}$ and establishment hiring rates. The difference in the estimates with and without controls once again arises due to the impact of establishment size and industry effects.

Hiring standards

The JVS provides information on two aspects that shed light on employers' hiring standards. Employers are asked whether they eventually hired a worker whose (i) qualification or (ii) experience is at or below the level usually expected for the vacant position. These are indicator variables which take the value of one if the hired worker's qualification (or experience) matches the job requirements and zero if it does not.[20] Figures 3.a and 3.b show the relationship between the

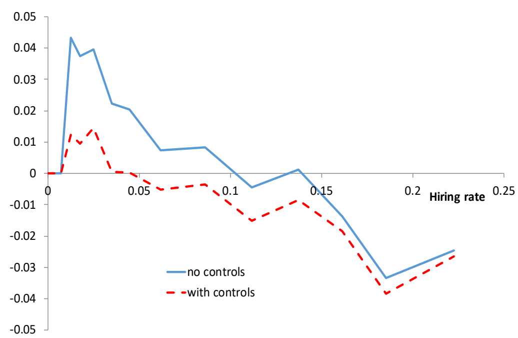
[17] H_{jt} are all hires (excluding employer returns) during the 90-day interval around the JVS interview as described above.

[18] Thus, our wage premium measures variation of temporary wage policies as opposed to permanent wage differences across establishment as measured by the fixed effect. In fact, the establishment fixed effect correlates negatively with hiring rates, reflecting that low-wage establishments have higher turnover.

[19] Another explanation for a positive relation between our wage premium and the hiring rates may be that fast-growing establishments pay higher wages to *all their workers* in a reaction to positive productivity shocks. To examine this possibility, we repeat the above exercise using incumbent workers instead of new hires. This exercise shows, however, a nearly flat relationship between the wage premium of incumbents relative to their establishments' hiring rates. In particular, we find that the wage premium increases by 0.003 or 0.004 log points (depending on whether controls are added) between establishments with a 25% hiring rate and those with a zero hiring rate, suggesting that this explanation is not supported by our data.

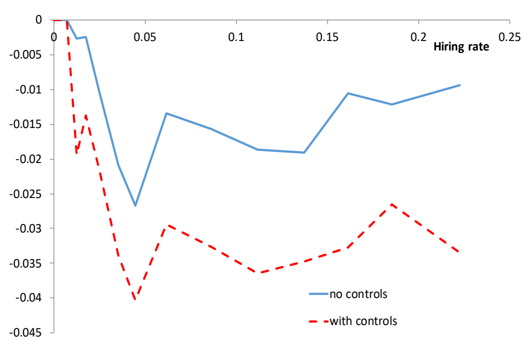
[20] The JVS also provides information on the total number of individuals who applied to the vacancy associated with the last successful hire as well as how many of them were deemed suitable. Although these variables have been used as selectivity measures elsewhere (see e.g. Lochner et al., 2021), we have not taken them into account as they appear to be strongly influenced by establishments' search efforts and posted wages (see e.g. Belot et al., 2022; Banfi and Villena-Roldan, 2019; Marinescu and Wolthoff, 2020). Hence, it is not a priori clear to what extent they convey information about an establishment's hiring standards, search effort or wage generosity.

establishments' hiring rates and the extent to which the worker fits the job requirements in terms of qualification and experience. A negative relation implies that lowering hiring standards go together with larger hiring rates. In particular, we find that establishments with higher hiring rates are about 3–4% more likely to apply lower hiring standards, relative to those establishments with zero hires. The difference in the estimates with and without controls arises in this case from the effect of employment size, rendering the estimated coefficients for establishments with the lower hiring rates insignificant (cf. Table 13), but hardly affecting the coefficients at higher rates.

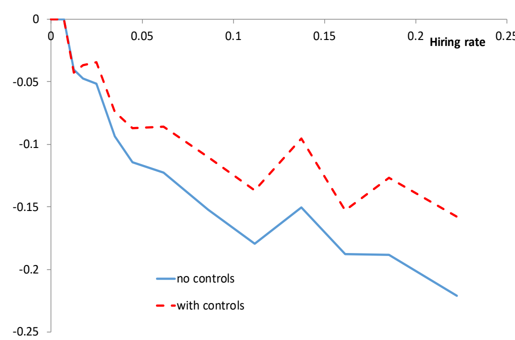


(a) JVS - No experience mismatch

(b) JVS - No qualification mismatch



(c) IEB - Selectivity



(d) IEB+JVS - Hiring Standards

Figure 3: Hiring standards and hiring rates

Notes: Each indicator is regressed on bin dummies of the establishment's hiring rate with the category near zero as reference. The solid (blue) curves show the coefficients when no further controls are applied, the dashed (red) curves also control for year, establishment characteristics (industry, 5 size categories, age and age^2) and job characteristics (1-digit occupation, 3 levels of skill requirements, dummies for long-term experience and leadership requirements, and a dummy for a newly created job).

To complement these measures, we use the wage equation (2) on IEB data and define an alternative selectivity measure as the difference between the average fixed effect of new hires (H_{jt}) and the average fixed effect among incumbent workers (N_{jt}) in establishment j at time t:

$$s_{jt}^{IEB} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} f_i - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} f_i.$$

A higher value of s_{jt}^{IEB} implies stricter hiring standards: establishment j hires workers with larger fixed effects in period t as compared to the fixed effects of the existing workforce in this establishment.[21] Figure 3.c shows the relationship between this measure and the establishments' hiring rates. If one interprets the fixed effects as worker ability, then employers who hire more also hire relatively less able workers by about 3–4 log points. Once again the difference between the estimates with and without controls mainly results from the effect of controlling for establishment size.

Figure 3.d shows the combined effect of the standardized values of the qualification and experience mismatch variables and the selectivity measure s_{jt}^{IEB} when averaged to derive a single, standardized measure of employers' *hiring standards* s_{jt}. This index confirms the previous results: establishments that hire faster are more likely to reduce standards.

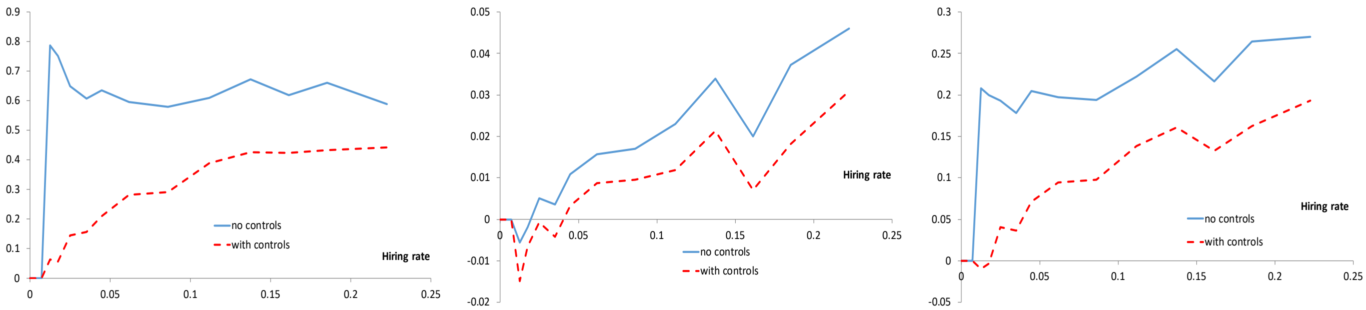
Search effort

To measure employers' search effort in the hiring process we rely exclusively on JVS data. Employers are asked to report the number of search channels utilized in their attempts to fill their (last) vacancies. They were also asked about whether their search was restricted to the local or national labor market or they extended their search to the international market. We use answers to these questions to construct our measures of employer search effort, where the former is computed as the number of channels and the latter is an indicator variable that takes the value of one if the search was international and zero otherwise.[22]

Figure 4.a and 4.b show the relationships between these two measures of search effort and the establishment's hiring rate. Establishments that exhibit hiring rates over 20% use about 0.4 more search channels and are 3–5% more likely to search internationally than those establishments

[21] Alternatively, we can define the selectivity measure based on observable worker characteristics (education and occupation) by calculating the difference between the averages of $\beta X_{it}^{ed/occ}$ for new hires and incumbent workers. The negative relationship between hiring rates and these alternative selectivity measures remains intact. Likewise, when we define the selectivity measure based on unobservable *and* observable worker characteristics by calculating the difference between the averages of $f_i + \beta X_{it}$ for new hires and incumbent workers, we obtain similar results. Finally, when we build a selectivity index based on match fixed effects, our results are almost the same; see Appendix A.6 for all these robustness exercises.

[22] For the years 2013, 2014 and 2017, the JVS provides information on the number of hours allocated to recruiting the most recent hire, which could be used as an additional measure of search effort. Estimating such a measure (as either total hours or hours per applicant) on hiring rates yields a positive relationship, but this is statistically insignificant. More recruitment hours could also reflect intentions to hire more selectively and hence pertain to the aspects discussed above rather than to search effort. Given this ambiguity and the lack of explanatory power, we did not include this information.



(a) JVS - No. Search Channels (b) JVS - Geographical Search (c) JVS - Search Effort

Figure 4: Search effort and hiring rates

Notes: Each indicator is regressed on bin dummies of the establishment's hiring rate with the category near zero as reference. The solid (blue) curves show the coefficients when no further controls are applied, the dashed (red) curves also control for year, establishment characteristics (industry, 5 size categories, age and age^2) and job characteristics (1-digit occupation, 3 levels of skill requirements, dummies for long-term experience and leadership requirements, and a dummy for a newly created job).

with zero hiring rates. Figure 4.c shows the combined effect of the standardised values of these two variables after averaging them to obtain a single, standardized *search effort* measure, e_{jt}. All these measures show that larger hiring rates go together with higher search effort. Once again the differences between the estimates with and without controls are mostly due to the size composition.

Summary

The main takeaway of the above results is the clear relationship between establishments' hiring rates and their degree of (i) wage generosity (positive), (ii) hiring standards (negative) and (iii) search effort (positive). Using the three standardized indices $\hat{w}$, s and e, shown in the last graphs in Figures 2–4, we can compare their respective quantitative responses to hiring rate variation. With the aforementioned controls taken into account, we find that the slope of the wage generosity index to the hiring rate is 1.01, the slope of the hiring standards index is -0.60, and the slope of search effort is 0.91. That is, when the hiring rate increases by ten percentage points, wage generosity (search effort) goes up by 0.1 (0.091, resp.) standard deviations, and hiring standards decrease by 0.06 standard deviations. Therefore, at the micro level of individual establishments all three recruiting intensity measures respond to the hiring rate, but wage generosity and search effort appear the more responsive measures to hiring rates (in comparison to their respective overall dispersion across establishments).

Using these establishment-level results we now turn to investigate the quantitative importance of the aforementioned recruitment measures for aggregate matching efficiency and for the effects of labor market policy. To this aim we develop a parsimonious directed search model of firm dynamics in which employers simultaneously adjust their posted wages, hiring standards and search effort to fill their open positions. When we calibrate the model in Section 4, the responsiveness of each recruitment index in the model will target its empirical counterpart.

3 The Model

Environment

Time is continuous and the economy is in steady state. There is a measure $\bar{L}$ of risk-neutral, infinitely-lived and identical workers. There is also a unit mass of risk-neutral firms which exit the economy at exogenous rate δ. To keep the stock of firms constant, a mass δ of new firms enter the economy per unit time. Both firms and workers maximize their respective expected discounted value of payments, where they discount future income with common interest rate r.

A firm is a collection of multiple projects, each of which employs multiple workers. Labor productivity in a generic project is denoted by p and remains constant over time. Firms face expansion opportunities as new projects become available at exogenous Poisson rate χ. Firms then draw the new project's productivity from distribution Π with support $P \subset \mathbb{R}_+$. Entrant firms draw initial project productivity from the same distribution. Each project operates under a constant-returns-to-scale technology in which labor is the only input.

A simplifying assumption is that firms only hire workers for their most recent project, while they continue to operate their older projects with previously hired workers. Further, workers in older projects cannot be shifted to newer projects in the same firm, possibly due to the specificity of workers' tasks in each project.[23] With these assumptions, our model permits a tractable characterization of firm policies in the presence of firm-specific shocks, while separations (specified below) are kept exogenous.

At any point in time, firms decide how many workers to hire in their newest project and hence how many vacancies to create. Opening a measure $V \geq 0$ of vacancies involves a flow cost $c_V(V)$, where c_V satisfies $c_V' > 0$ and $c_V'' > 0$. Additionally, for every posted vacancy the firm chooses search effort $e \geq 0$ at cost $c_e(.)$ with $c_e' > 0$, $c_e'' > 0$, $c_e(0) = 0$. Thus the total number of "effective vacancies" opened by a firm is eV and involves total flow costs $c_V(V) + V \cdot c_e(e)$. Similar to the recruitment cost function used by Gavazza et al. (2018), the cost per vacancy is additively separable in two components: the first $(c_V(V)/V)$ is increasing in the number of vacancies which indicates that opening a larger number of new jobs is more costly at the margin. The second component $c_e(e)$ reflects the per-vacancy cost of recruitment effort. This separability facilitates the analytic characterization of recruitment policies at the end of this section.

[23] Evidence in favor of this assumption is the small extent to which we observe a vacancy being filled by a worker already employed in the same establishment opening this vacancy. In the JVS we find that the proportion of internal hires is 6%.

We assume that only unemployed workers search for jobs.[24] Upon meeting, the worker-firm pair draws match-specific productivity $x \sim G(.)$ with support X. If the worker is hired at a firm with current productivity p, the flow output of the match is $p \cdot x$ for the duration of the match.[25]

In addition to firm exit at rate δ, continuing firms draw a job destruction shock at Poisson rate ν. If such a shock arrives, the firm exogenously separates from a fraction ψ of all its workers, both in new and in existing projects, where ψ is drawn from distribution Ψ with mean $\bar{\psi}$. This assumption allows us to capture that in the data declining firms exhibit positive (but small) hiring rates. Each individual worker then separates into unemployment at Poisson rate $s \equiv \delta + \nu\bar{\psi}$. While unemployed, workers receive flow income b.

Search is competitive as in Moen (1997). Workers search for long-term contracts posted by firms. Workers and firms understand that contracts with a higher present value of wages attract more job seekers, and hence have a higher job-filling rate and a lower job-finding rate. Unemployed workers and firms with vacant jobs then meet in submarkets that are differentiated by their present values of wage payments. In a given submarket, a vacancy with search effort e meets a worker with flow probability $e \cdot m(\lambda)$, where λ denotes the measure of workers per unit of effective vacancies in the submarket, and $m(.)$ is an increasing and concave reduced-form meeting function satisfying $m(0) = 0$. Flow consistency implies that a worker in this submarket meets a firm with flow probability $m(\lambda)/\lambda$.

The contracts posted by firms entail a hiring threshold $\tilde{x}$ and constant wages (for each realisation of $x \geq \tilde{x}$) denoted by $w(x)$.[26] Workers observe these contract postings and choose in which submarket to search.

Firm and Worker Decisions

Given the stationarity of the environment, standard recursive arguments imply that the expected profit value of a job with productivity p filled with a worker with match-specific productivity x and earning a wage $w(x)$ is

$$J(p, x, w(x)) = \frac{px - w(x)}{r + s} \ .$$

[24] This assumption is motivated by the JVS evidence showing no meaningful variation of the hiring composition by employment status with the establishment's growth rate (see Figure 11.a). See the conclusions of this paper for further discussion.

[25] To keep the analysis as tractable as possible, we assume that workers are ex-ante homogenous, while ex-post heterogeneity arises from match-specific productivities. This creates a potential tension with our main IEB selectivity measure which builds on worker fixed effects. However, we emphasize that our results are similar when we use an IEB selectivity measure based on match fixed effects. Even quantitatively, the relationship between the hiring rate and the different selectivity indices are almost the same, so that the choice of the index matters little for the calibration of our model (see Appendix A.6).

[26] Wage schedules are indeterminate in this model with risk-neutral workers and firms. This concerns both the variation with tenure and variation with match productivity x. Limited commitment on either side of the market restricts the set of feasible wage schedules. See Appendix B for further discussion.

A firm with current productivity p decides the vacancy stock V, search effort per vacancy e, and contract posting $(\tilde{x}, w(.))$, for which it expects a flow meeting rate $m(\lambda)$ per effective vacancy eV. The objective of the firm is to maximize the expected flow profit value of this recruitment policy which is given by

$$eVm(\lambda) \int_{\tilde{x}} J(p, x, w(x)) \; dG(x) - c_V(V) - Vc_e(e) \; .$$

Per unit time, the firm meets $eVm(\lambda)$ workers of which it hires all those whose match productivity exceed $\tilde{x}$ in which case the firm realizes the discounted profit value $J(p, x, w(x))$. The flow cost of this recruitment policy is $c_V(V) + Vc_e(e)$. Since firms operate linear production technologies, the optimal recruitment policy depends on current productivity p and is independent of the size of the firm.

The firm understands that the meeting rate $m(\lambda)$ varies with the terms of the posted contract since workers choose search strategies optimally given the set of available contracts offered by all firms. Let $W^e(w)$ denote the expected discounted income of an employed worker earning wage w, and let W^u be the expected discounted income of an unemployed worker. The discounted surplus value of a worker earning wage w can be expressed by

$$W^e(w) - W^u = \frac{w - rW^u}{r + s} \; .$$

The value of an unemployed worker searching in a submarket with posting $(\tilde{x}, w(.))$ and meeting rate $m(\lambda)/\lambda$ satisfies $rW^u = b + \bar{\rho}(\tilde{x}, w, \lambda)$ where the worker's expected flow value from search in this submarket is the product of the flow meeting probability $m(\lambda)/\lambda$ and the expected income gain,

$$\bar{\rho}(\tilde{x}, w, \lambda) \equiv \frac{m(\lambda)}{\lambda} \int_{\tilde{x}} [W^e(w(x)) - W^u] dG(x) \; . \tag{3}$$

Workers decide in which submarkets to search. Given that workers are homogeneous, this implies equal search values in all active submarkets.

Equilibrium Definition and Properties

A *stationary competitive search equilibrium* describes vacancies V_p, search effort per vacancy e_p, job postings $(\tilde{x}_p, w_p(x)) \in Z \equiv X \times \mathbb{R}_+^X$ for all firms with current productivity $p \in P$, queue lengths (i.e., job seekers per effective vacancy) in submarkets for different postings, defined by $\Lambda : Z \to \mathbb{R}_+$, a search value of unemployed workers ρ, and unemployment rate u such that

1. Firms maximize expected profits: For all $p \in P$, vacancies V_p, search effort e_p and job postings $(\tilde{x}_p, w_p)$ solve the problem

$$\max_{V,e,\tilde{x},w,\lambda} eVm(\lambda) \int_{\tilde{x}} \frac{px - w(x)}{r + s} \; dG(x) - c_V(V) - Vc_e(e) \tag{4}$$

subject to $\lambda = \Lambda(\tilde{x}, w)$.

2. Workers search optimally: For all postings $(\tilde{x}, w) \in Z$ and $\lambda = \Lambda(\tilde{x}, w)$,

$$\bar{\rho}(\tilde{x}, w, \lambda) \leq \rho \quad , \quad \lambda \geq 0 \ , \tag{5}$$

with complementary slackness (choice of submarkets). Furthermore,

$$\int V_p e_p \lambda_p \ d\Pi(p) \leq u\bar{L} \quad , \quad \rho \geq 0 \ , \tag{6}$$

with complementary slackness (labor market participation).

3. Stationary unemployment (stock-flow consistency):

$$(1-u)\bar{L}s = \int (1 - G(\tilde{x}_p)) m(\lambda_p) e_p V_p \ d\Pi(p) \ . \tag{7}$$

Optimal search requires that workers receive the same expected search value in all submarkets which they visit ($\lambda > 0$) which is entailed in the complementary-slackness condition (5). It further necessitates that unemployed workers search in some submarket if they can obtain positive surplus, $\rho > 0$; otherwise unemployed workers are indifferent between search and inactivity. This is specified in the complementary-slackness condition (6) where the left-hand side is aggregate unemployment ($V_p e_p \lambda_p$ unemployed workers search for employment in firms with productivity p which constitute measure $d\Pi(p)$) and the right-hand side is aggregate non-employment. Condition (7) says that unemployment inflows (= separations, left-hand side) are equal to outflows (= hires, right-hand side).

Conditions (6) and (7) can be combined to

$$\int \frac{H_p}{s} + V_p e_p \lambda_p \ d\Pi(p) \leq \bar{L} \ , \tag{8}$$

where

$$H_p = (1 - G(\tilde{x}_p)) m(\lambda_p) e_p V_p \tag{9}$$

is the flow of hires of firms with current productivity p. H_p/s is aggregate employment in all projects with productivity p, and $V_p e_p \lambda_p$ are unemployed workers searching for jobs with productivity p. Hence inequality (8) says that employment and unemployment together do not exceed the measure of workers $\bar{L}$, and they are equal to $\bar{L}$ if all non-employed workers search which is the case if the expected value of search is positive, $\rho > 0$. In this case, ρ is implicitly pinned down by equation (8), hence it depends on labor demand (i.e., the distribution of vacancies, search effort and hiring standards) as well as on labor supply $\bar{L}$. Any change of aggregate market conditions, for instance a uniform increase of productivity across all projects, changes the equilibrium values of V_p, e_p, $\tilde{x}_p$ and λ_p, and therefore impacts the search value ρ.[27]

Because of $c_e(0) = 0 = m(0)$, firms will either not hire and choose $e = \lambda = 0$, or they aim to attract $\lambda = \Lambda(\tilde{x}, w) > 0$ job seekers per effective vacancy. In the latter case, posted wages must satisfy

$$\frac{m(\lambda)}{\lambda} \int_{\tilde{x}} \frac{w(x) - b - \rho}{r + s} \, dG(x) = \rho \tag{10}$$

to make sure that unemployed workers are attracted to these vacancies, see condition (5) together with (3).

The job-filling rate of a firm with project productivity p is

$$q_p \equiv \frac{H_p}{V_p} = e_p \cdot m(\lambda_p) \cdot (1 - G(\tilde{x}_p)) \ . \tag{11}$$

Variation in job-filling rates are accounted for by three factors: search effort e, wages as reflected through λ, and hiring standards as measured by the threshold $\tilde{x}$.

Firm Dynamics

In the cross-section of firms, job-filling rates and recruitment policies vary by the current productivity p of the firm. They can be related to employment growth and hiring rates, thus generating the theoretical counterparts of the empirical relationships identified in the previous section. The dynamics of firms is driven by three forces: (i) firms enter and exit with flow probability δ; (ii) firms draw new projects with altered productivity with flow probability χ; (iii) firms draw job destruction shocks with flow probability ν. In all cases firms adjust their workforce, but upward adjustments are not instantaneous due to convex vacancy and search effort costs.

While a firm's hires flow depends on the productivity of the current project, job destruction is exogenous and follows a jump process. Thus, employment N_t in a firm with current productivity p adjusts according to

$$dN_t = H_p dt - dQ_t^{\nu} \psi_t N_t \ ,$$

where Q_t^{ν} is the Poisson process of job destruction with arrival rate ν, and ψ_t (the fraction of destroyed jobs) is randomly drawn from distribution Ψ.

Characterization of Recruitment Policies

Substitute (10) into (4) to rewrite the firm's problem:

$$\max_{V,e,\tilde{x},\lambda} V \cdot \left\{ em(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s} \, dG(x) - e\lambda\rho - c_e(e) \right\} - c_V(V) \ . \tag{12}$$

[27] Using standard arguments, it can be verified that the competitive search equilibrium is constrained efficient. That is, vacancies, search effort, hiring thresholds and the allocation of workers and effective vacancies across submarkets maximize the discounted value of aggregate output net of costs.

The first-order conditions are:

$$p\tilde{x} = b + \rho \ , \tag{13}$$

$$c_e'(e) = m(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s} \ dG(x) - \lambda\rho \ , \tag{14}$$

$$\rho = m'(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s} \ dG(x) \ , \tag{15}$$

$$c_V'(V) = em(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s} \ dG(x) - e\lambda\rho - c_e(e) \ . \tag{16}$$

Equation (13) says that job surplus is zero for the worker who is hired at the margin. This condition implies a negative relationship between the firm's current productivity p and the hiring threshold $\tilde{x}$. Combining (14) and (15) gives

$$c_e'(e) = \rho \frac{m(\lambda) - \lambda m'(\lambda)}{m'(\lambda)} \ , \tag{17}$$

which implies that the queue length λ (and hence wage offers) and search effort e are positively related in the cross-section of firms. Conditions (13) and (15) give rise to

$$\rho = m'(\lambda) \frac{b + \rho}{r + s} \int_{\tilde{x}} \frac{x}{\tilde{x}} - 1 \ dG(x) \ . \tag{18}$$

This equation says that across firms worker queues λ and hiring thresholds $\tilde{x}$ are negatively related. In other words, firms which are less selective in hiring also pay higher wages to workers with similar productivity. Finally, substitute (14) into (16) to obtain

$$c_V'(V) = ec_e'(e) - c_e(e) \ . \tag{19}$$

This condition implies that search effort e and vacancies V are positively related across firms.

Therefore, firms with higher current productivity (i) post more vacancies, (ii) are willing to accept lower hiring standards, (iii) exert higher search effort, and (iv) set wages so as to attract more workers.[28] Consequently, all three factors in equation (11) which contribute to job-filling rates q_p are positively correlated: Higher search effort e_p goes together with a higher meeting rate per effective vacancy $m(\lambda_p)$ and with a larger hiring probability conditional on a meeting, $1 - G(\tilde{x}_p)$.[29] The respective percentage contributions to the variation of job-filling rates can be

[28]This result uses the additive separable specification of recruitment costs $c_e(e)V + c_V(V)$. It can be extended to a more general convex cost function $C(e, V)$ if the upper bound on the cross derivative $C_{eV} \leq C_e/V$ holds.

[29]This feature is consistent with what we find in JVS data: Establishments that exert more search effort also have lower hiring standards and pay more generous wages (see Appendix A.4). The perfect correlation between these factors in our model is an artefact of the assumption that all heterogeneity stems from differences in productivity p; it would be broken if firms also differ in, e.g., effort costs or match-specific productivity distributions.

written

$$\frac{dq}{q} = \frac{de}{e} + \frac{m'(\lambda)\lambda}{m(\lambda)} \cdot \frac{d\lambda}{\lambda} - \frac{G'(\tilde{x})\tilde{x}}{1 - G(\tilde{x})} \cdot \frac{d\tilde{x}}{\tilde{x}} \ . \tag{20}$$

Using the policy functions derived above, this can be further expressed

$$\frac{dq}{q} = \frac{dp}{p}(1 - \varepsilon_{\hat{G},\tilde{x}}) \Big\{ \underbrace{\frac{1}{(1 - \varepsilon_{m,\lambda})\varepsilon_{c'_e,e}}}_{=\text{search effort}} + \underbrace{\frac{\varepsilon_{m,\lambda}}{-\varepsilon_{m',\lambda}}}_{=\text{wages}} + \underbrace{\frac{G'(\tilde{x})\tilde{x}}{(1 - G(\tilde{x}))(1 - \varepsilon_{\hat{G},\tilde{x}})}}_{=\text{hiring standards}} \Big\} \ , \tag{21}$$

where $\varepsilon_{f,z}$ denotes the elasticity of function f with respect to variable z, and $\hat{G}(\tilde{x}) \equiv \int_{\tilde{x}} x - \tilde{x} \, dG(x)$. This decomposition shows how the functional forms of the meeting function m, the search cost function c_e, and the distribution of match-specific productivity G determine the respective contributions of search effort, wages and hiring standards for the overall recruiting intensity of firms.

4 Quantitative Analysis

How does recruitment behavior contribute to variation of aggregate matching efficiency? Does recruiting intensity matter for the impact of labor market policy? To answer these questions, we parameterize our model and calibrate its parameters to match selected statistics of the German labor market and the evidence presented above.

We explore variation across different local labor markets. That is, we consider 12 regions (i.e. German states where smaller states are merged to neighboring states) and three skill levels (no formal education, vocational training, and college degree) which gives rise to 36 labor markets. We believe that these labor markets are sufficiently segmented so that we can safely abstract from mobility across them.[30] We further abstract from complementarities in production between different skill groups. With these assumptions, our model economy describes a given local labor market in which heterogeneous firms apply different recruitment policies in order to hire homogeneous workers. Most of the model parameters are calibrated uniformly for all local markets, while others are market-specific in order to capture the observed cross-sectional variation in unemployment rates, job-finding rates and wages.

All data targets are based on averages over the period 2010–2017 where we obtain employment, unemployment, vacancies, the number of establishments (employing workers of the given skill), monthly unemployment-to-employment (UE) flows and the mean wage for all markets. We measure the job-finding rate as the monthly UE flow divided by the unemployment stock. To have a model-consistent measure of the vacancy yield, we define the vacancy yield as hires from

[30] In particular, most metropolitan areas are contained in one of the 12 regions. Moreover, the skill groups are based on education acquired early in life so that workers usually do not move between them. The reported vacancies in the JVS are differentiated according to the same classification.

unemployment (UE flow) divided by the vacancy stock. Figure 5 shows the relationship between labor market tightness (vacancies divided by unemployment), job-finding rates and vacancy yields across the 36 labor markets. Labor markets for low-skilled workers are less tight than labor markets for medium- and high-skilled workers, and these markets have lower job-finding rates and higher vacancy yields. Likewise, there are increasing (decreasing) relationships between tightness and the job-finding rate (vacancy yield) across regions. In principle, these patterns are consistent with a standard reduced-form matching function uniformly applied for all labor markets (plus noise). We use our model to explore to what extent variation in the recruitment policies amplifies or mitigates these empirical relationships.

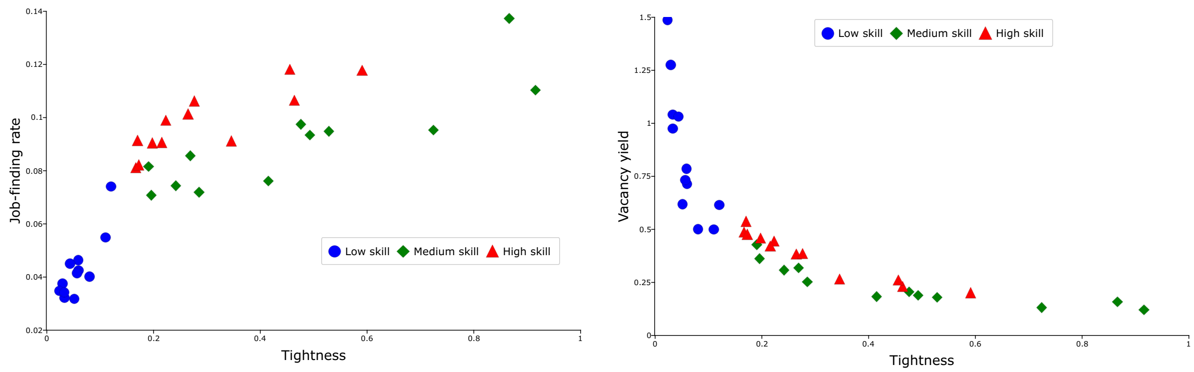


Figure 5: Market tightness, job-finding rates and vacancy yields in 36 (region×skill) labor markets in Germany (2010–2017)

4.1 Calibration Strategy

We set a month as our unit time and let the meeting function follow a Cobb-Douglas specification, $m_0\lambda^\mu$ with $\mu \in (0,1)$. The recruitment and vacancy cost functions are given by $c_e e^\gamma$ and $c_V V^\Phi$ with elasticity parameters $\gamma > 1$ and $\Phi > 1$. Match-specific productivity is assumed to be Pareto distributed, $G(x) = 1 - (x_0/x)^\alpha$ for $x \geq x_0$, where $\alpha > 1$, while project productivities are distributed with cumulative distribution $\Pi(p) = (p/\bar{p})^\eta$ for $p \in [0, \bar{p}]$, with $\eta > 0$. These functional forms are convenient as they imply that the firms' policies $\tilde{x}_p$, λ_p, V_p and e_p, as well as several aggregate model statistics (in particular, means and standard deviations of various outcome variables) can be all obtained in closed form (see Appendix B for details).

In our model, a firm's hires flow H_p is entirely determined by its recruitment policies via equation (9) which gives rise to a too tight relationship between recruitment and hires in comparison to the data. To rationalize the empirical micro-level relationships presented in Section 2, we augment our model with idiosyncratic hiring shocks which are orthogonal to firm characteristics and change the actual hires during a time interval of length T (a 90-day interval in our model, see below) according to $\hat{H}_p^T = e^{\sigma\varepsilon - \sigma^2/2} H_p T$, where ε is a standard normally distributed random variable and

$\sigma > 0$ controls the variance of hiring shocks. These shocks neither impact the optimal policies of risk-neutral firms, nor do they matter for our decomposition of aggregate matching efficiency.[31]

We choose a calibration strategy where only few parameters are set specific for each labor market, indexed by $m = 1, \ldots, 36$, while the other parameters are shared by all labor markets. To recover these parameters we follow a two-step procedure in which we split the parameters between an inner and outer loop. Given values for the outer loop parameters, we can directly calibrate those in the inner loop such that their values solve a non-linear system of equations, matching exactly the targeted moments. We then iterate on the values of the outer loop parameters using a simulation minimum distance procedure until convergence, adjusting the inner loop parameters at each iteration.

The inner loop contains all the market-specific parameters and a few of the global parameters. Market-specific parameters are $\bar{L}_m$ (labor force in relation to the number of establishments), ν_m and δ_m (job destruction in continuing and exiting firms), $\bar{p}_m$ and η_m (upper bound and shape of the productivity distribution) and b_m (unemployment income). $\bar{L}_m$ is set directly to the corresponding data value. The total separation rate $s_m = \delta_m + \nu_m \bar{\psi}$ is set to match the steady-state unemployment rate u_m in market m.[32] If f_m is the job-finding rate in this market, stock-flow consistency implies $s_m = u_m f_m/(1 - u_m)$.[33] In all markets, we attribute one-third of separations to exits and two-thirds to separations for continuing establishments, consistent with Fuchs and Weyh (2010) who find that one third of destroyed jobs in the German labor market are at exiting establishments.

Parameters $\bar{p}_m$ and b_m are set to match average wages and job-finding rates in market m. Here we can utilize the closed-form expressions obtained in Appendix B. Specifically, the mean wage in market m is

$$\bar{w}_m = (b_m + \rho_m)\frac{\alpha + \mu - 1}{\alpha - 1} \ , \tag{22}$$

and the job-finding rate is

$$f_m = \frac{\rho_m(r + s_m)(\alpha - 1)}{\mu(b_m + \rho_m)} \ , \tag{23}$$

[31] Common to other multi-worker firm models, our model applies the law of large numbers at the firm level so that each firm perfectly foresees the fraction of vacancies it fills in a given period. One interpretation of the hiring shocks is the uncertainty of the hiring process which may be especially important for small and medium-sized firms. For instance, if a firm has two vacant positions and anticipates a quarterly fill rate of 50%, it may not hire exactly one worker every quarter, but instead expects a distribution over $n \in \mathbb{Z}_+$ successful hires. Firms with more vacancies may face similar uncertainty. We introduce these hiring shocks to match the cross-sectional relationships in Figure 6.a-c below (see footnote 36 for further discussion).

[32] In recent work, Bilal (2021) finds that the separation rate accounts for the majority of the geographic variation of unemployment rates in France and in the U.S. Replicating his decomposition in our data reveals that the separation rate (job-finding rate) accounts for 61% (39%) of unemployment rate variation across the 36 labor markets which are differentiated by region and skill. Also consistent with the evidence of Kuhn et al. (2022) for geographic variation across commuting zones in Germany, the vacancy yield (job-filling rate) is higher in labor markets with high unemployment (low tightness), see Figure 5 and Table 2.

[33] Imposing steady state for each market is innocuous. Accounting for the fact that employment growth rates g_m across the 36 markets during 2010-2017 are different, we set $s'_m = u_m f_m/(1 - u_m) - g_m$ and obtain very similar results.

where ρ_m is the value of workers' search, an endogenous variable defined in Section 3. With $(\bar{w}_m, f_m)$ set to their data values, (22) and (23) are solved uniquely for b_m and ρ_m. Then, the closed-form expressions for aggregate unemployment U_m and aggregate employment $E_m = H_m/s_m$ in market m (see Appendix B) are used to solve the aggregate resource condition $U_m + E_m = \bar{L}_m$ for the upper bound of productivity $\bar{p}_m$ in market m. Intuitively, higher productivity $\bar{p}_m$ increases the demand for labor in market m (more vacancies and higher recruiting intensity) which raises the job-finding rate and the workers' search value. Formally, f_m increases in ρ_m which itself increases in $\bar{p}_m$. Therefore, job-finding rates and mean wages uniquely identify b_m and $\bar{p}_m$.

Given the upper bound of productivity $\bar{p}_m$, the shape parameter η_m controls the dispersion of productivity, and thereby the dispersion of recruitment policies, within a local market. To capture cross-market differences in recruitment activity, we set η_m to match the empirical coefficient of variation (CV) of search costs per vacant job that we measure in our JVS data. Empirically, the CV of search costs correlates negatively with job-finding rates across markets and is larger in low-skill labor markets than in medium- or high-skill markets.[34] Our calibration strategy captures this systematic variation between markets and allows us to investigate its impact on matching efficiency.

The remaining parameters are shared by all labor markets. The interest rate $r = 0.34\%$ corresponds to an annual real interest rate of 4%. The distribution of destroyed jobs Ψ, conditional on a job destruction shock, is set to the empirical monthly job destruction distribution with mean 5.74%.

The elasticity of the meeting function μ (together with the Pareto parameter α) controls the level of wages relative to unemployment income, see equation (22). Given a value for α, μ is set to match an average replacement rate of 46%, consistent with the level of unemployment income after the Hartz labor market reforms (cf. Krebs and Scheffel, 2013). Utilizing the functional form for aggregate vacancies in Appendix B, the scale of the vacancy cost function c_V is set to match the average number of vacancies per establishments, given all other model parameters.

Three further global parameters x_0 (lower bound of match productivity), c_e (search effort scale parameter), and m_0 (scale parameter of the meeting function) cannot be identified separately from the scale of productivity $\bar{p}_m$. This is because all model statistics (unemployment, vacancies, hires, etc.) depend on the product $c_e^{-1}\left(m_0 x_0^{\alpha} \bar{p}_m^{\alpha}\right)^{\gamma/(1-\mu)}$, which implies that any change in the parameters x_0, c_e and m_0 scales up or down the productivity parameters $\bar{p}_m$ in the same proportion in all local markets. For the same reason, the global values of x_0, c_e and m_0 do not matter for any of the decomposition results that we present below; hence their values can be normalized without impacting our results.[35]

This leaves five global parameters to be jointly estimated in the outer loop of the calibration:

[34] Search costs are calculated as the sum of the total hours wage bill of the staff involved in recruitment and monetary cost incurred through e.g. advertising and interviewing, among other reasons. See Appendix A.7 for the cross-market correlations of the mean and the CV of search costs with the job-finding rate.

[35] See Appendix B for details and further discussion.

the elasticities of search costs and vacancy costs, $\gamma > 1$ and $\Phi > 1$, the Pareto shape parameter $\alpha > 1$ for match-specific productivity, the standard deviation of idiosyncratic hiring shocks $\sigma > 0$, and the arrival rate of productivity shocks χ. During the estimation, all inner loop parameters are recalibrated to match their respective calibration targets as explained above, with the exception of the interest rate which remains constant throughout.

Parameters γ, α and σ jointly determine how strongly search effort, wages, and hiring standards respond to the variation of hiring rates across firms. This is a consequence of equation (21) which shows how the variability of recruitment policies responds to the elasticities of match productivity (via α), search costs (via γ), and the meeting function (μ). The latter elasticity is already calibrated from (22) to match the average replacement rate. We calibrate γ, α and σ to reflect the variation of standardized recruitment indices $\hat{w}$, s and e with firm-level hiring rates, as shown in the last graphs of Figures 2–4 in Section 2. Idiosyncratic hiring shocks help to make these relationships in the model flatter as required by the data.[36]

To generate outcome variables comparable to those in the data, we simulate the model for a sample of hiring firms over a 90-day period in each of the 36 labor markets and then use the three factors in decomposition (11), observed in the middle of this period, for the respective contributions of effort e_p, wage generosity $m(\lambda_p)$ and hiring standards $G(\tilde{x}_p)$. Then, we standardize all three model-generated outcome variables (uniformly for all 36 markets) and calculate averages of the standardized indices for each of 13 bins of 90-day hiring rates (after applying the lognormally distributed hiring shocks) ranging from 0% to 25%. Based on those model-generated data points for each index, we calculate the slope of every index with respect to the hiring rate. The results summarized at the end of Section 2.3 show that the standardized wage index reacts somewhat stronger than the standardized effort index (slope 1.01 versus 0.91), whereas the standardized hiring standards index reacts less than the effort index (slope -0.60). Given that hiring standards in the model are based on match-specific selectivity, we use the selectivity index based on match-specific effects whose slope with the hiring rate is -0.54 (see footnote 25 and Appendix A.6).

The convexity parameter of vacancy costs Φ controls to what extent firms use vacancy postings to increase their hiring rate. Larger values of Φ make highly productive firms less willing to post more vacancies and rather resort to increase their vacancy yield (cf. Kaas and Kircher, 2015; Gavazza et al., 2018; Mueller et al., 2020). That is, parameter Φ controls the slope of the relationship between hiring rates and the vacancy yield. To obtain this slope in the model, we again simulate a cross-section of firms over 30-day intervals in all 36 labor markets and calculate averages of vacancy yields and hiring rates in each of 29 bins of firm growth rates ranging from -30% to 30%. The slope of the vacancy yield-hiring relation is then targeted to the one observed

[36] In the absence of idiosyncratic hiring shocks ($\sigma = 0$), the slopes of all recruitment indicators with respect to the hiring rate are too steep. Still, the two parameters γ and α can be calibrated to match the variation of wage generosity and hiring standards ($\hat{w}$ and s) *in relation to* the variation of search effort e, although not their absolute variation with hiring rates. Our main results are very similar with such an alternative calibration.

in the data as shown in Figure 1.b based on the averages not controlled for firm size (16.0).[37]

Finally, the arrival rate of productivity shocks χ matters for the frequency of employment adjustments and is set to target that 80% of establishments have monthly employment growth rates in the interval $[-0.01, +0.01]$.

4.2 Fit of the Model

Table 1 shows the values of calibrated parameters and calibration targets. The bottom five rows of the table shows that the model matches the data targets used for estimation of the last five parameters well. All other data targets are matched exactly since they identify the corresponding parameters uniquely, as described above.

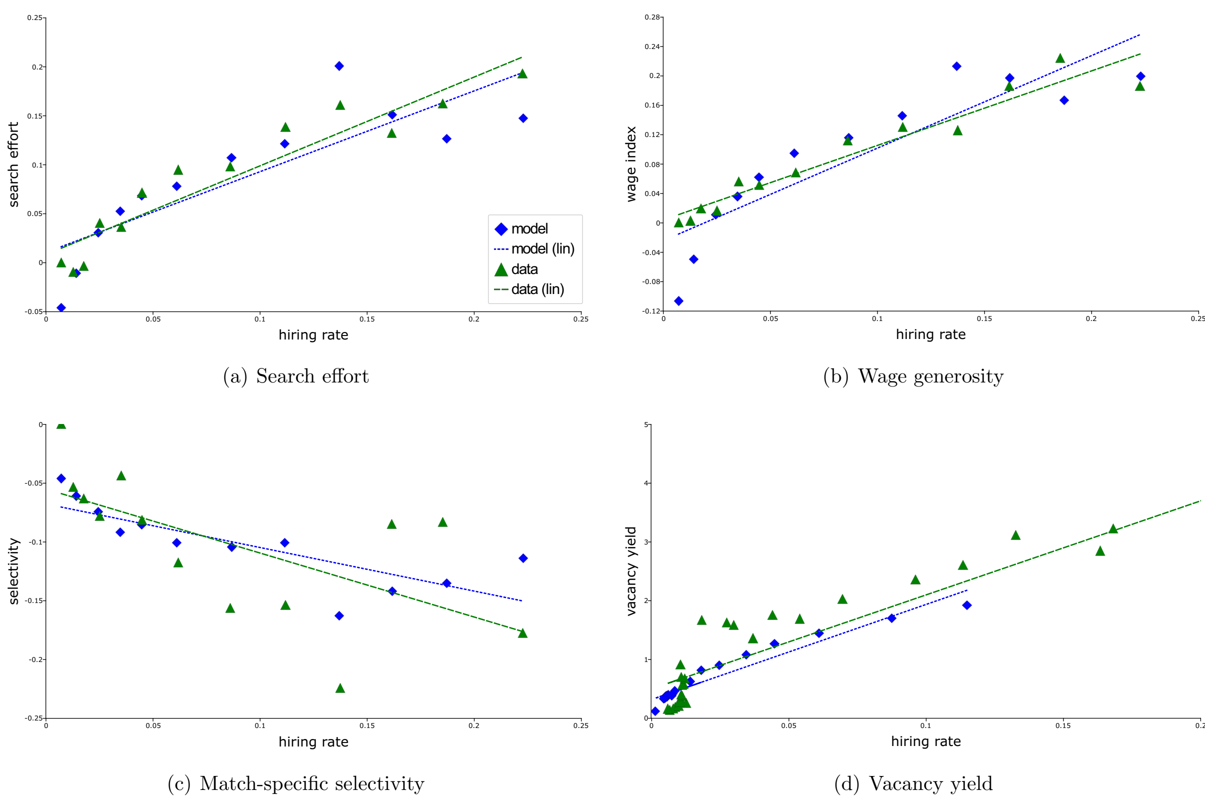
Table 1: Calibrated parameters and targets used for estimation

(a) Market-specific parameters (inner loop)			
Parameter		Mean Value	Explanation/Target
Labor force (normalized)	$\bar{L}_m$	7.11	Workers per establishment
Job destr. arrival rate	ν_m	9.3%	Unemployment rates
Exit rate	δ_m	0.27%	1/3 of separations due to exit
Productivity upper bound	$\bar{p}_m$	308.3	Job-finding rates
Productivity shape	η_m	1.20	CV search costs
Unemployment income	b_m	0.49	Wages (mean normalized to 1)
(b) Global parameters (inner loop)			
Parameter		Value	Explanation/Target
Interest rate	r	0.34%	4% annual real rate
Mean job destruction	$\bar{\psi}$	0.0574	Job destruction distribution
Vacancy cost scale	c_V	7,548.1	0.12 vacancies per establishment
Matching fct. elasticity	μ	0.121	Average replacement rate 46%
Matching fct. scale	m_0	0.01	Normalized (see text)
Search effort scale	c_e	1.0	Normalized (see text)
Match prod. Pareto scale	x_0	0.01	Normalized (see text)
(c) Global parameters (outer loop)			
Parameter		Value	Explanation/Target
Vacancy cost elasticity	Φ	5.89	Slope vacancy yield wrt hiring rate
Search effort elasticity	γ	4.19	Slope search effort wrt hiring rate
Match prod. Pareto shape	α	3.16	Slope hiring standards wrt hiring rate
Std.dev. hiring shocks	σ	2.26	Slope wages wrt hiring rate
Arrival rate prod. shocks	χ	1.11	Employment growth $[-0.01, 0.01]$
(d) Targets for estimation			
Statistics		Data	Model
Slope vacancy yield wrt hiring rate		16.0	15.8
Slope search effort wrt hiring rate		0.91	0.88
Slope selectivity wrt hiring rate		-0.54	-0.39
Slope wages wrt hiring rate		1.01	1.30
Share employment growth $[-0.01, 0.01]$		0.80	0.82

Figure 6 shows how our model replicates the main relationships between recruitment indicators

[37] In the simulations of our continuous-time model, we use a five-day period length to discretize time steps. When aggregating hires over 30-day periods, this procedure takes time aggregation bias into account, such as the hiring of workers during the 30-day period into jobs that were not posted at the beginning of the period.

and hiring rates presented in Section 2, where the linear approximations illustrate the targeted slopes shown in the bottom half of Table 1. Panels (a)-(c) demonstrate that search effort and wage generosity are increasing in the firm's hiring rate, while selectivity (based on match quality) is decreasing. As in the data, the slope is largest for the standardized wage generosity index and lowest for the selectivity index, although the model somewhat overshoots the former and undershoots the latter, while it matches the search effort relationship well.[38] Panel (d) shows that the model generates the steep positive relationship between the hiring rate and the vacancy yield. We further mention that our model generates similar hockey-stick relationships between hiring rates, vacancy yields, vacancy rates and employment growth, as shown in the data in Figure 7.b-d of Appendix A.1. Among shrinking firms, hiring rates and vacancy yields are similarly low (hiring rates around 1% and vacancy yields below 0.5), while our model underpredicts vacancy rates which are relatively high in JVS data, also in comparison to the U.S. JOLTS data.



(a) Search effort

(b) Wage generosity

(c) Match-specific selectivity

(d) Vacancy yield

Figure 6: Model fit: Recruitment indicators and hiring rates

Notes: Panels (a)-(c) show the three recruitment indicators in bins of 90-day hiring rates. Panel (d) shows hiring rates and vacancy yields in bins of 30-day employment growth. The data are triangles with dashed linear approximation (green). Model simulations are diamonds with dotted linear approximation (blue).

While our model is able to replicate firm dynamics and their variation of recruitment policies, it is not well suited to generate empirical firm size distributions which would require persistent

[38]The means of the model indices are adjusted to their counterparts in the data. This shift is innocuous, given that the data represent differences to the reference category of zero hires.

differences in technology or productivity. In fact, in our calibrated model all firms employ less than 50 workers, where the relatively larger firms are those that spent a longer time in the market with a history of high productivity draws. Nonetheless, when we compare firms with less than 20 and more than 20 employees, we find similar differences in most dimensions. In particular, the relatively larger firms have lower hiring rates and larger vacancy yields, both in the data and in the model. Likewise, search effort (wage generosity) in larger firms is higher by about 0.1 (0.05) standard deviations in the data and in the model. Regarding hiring standards, we obtain opposite signs, but there the gap between these two size classes is smaller (0.02-0.03 standard deviations). A thorough exploration of the role of firm size for recruitment behavior is beyond the scope of this paper.

Before turning to the cross-market decomposition analysis, we show in Table 2 that our model matches relatively well the correlations between key labor market outcomes across the 36 markets. Note that our model exactly matches unemployment rates and job-finding rates in each market, so that the high correlation between these two variables is the same as in the data. Labor markets with higher unemployment have lower vacancy-unemployment ratios and higher vacancy yields. Further, the positive (negative) relationships between tightness and the job-finding rate (vacancy yield) shown in Figure 5 is reproduced in our model. The explanation why our model generates these patterns is as follows: average firm productivity (which is equal to $\eta_m p_m/(1+\eta_m)$) is higher in markets with high job-finding rates. This follows from the identification of market-specific parameters as described in the previous subsection. In more productive markets, firms create more vacancies, while unemployment is lower, so market tightness is higher. On the other hand, the aggregate vacancy yield (which is identical to the job-finding rate divided by tightness) is lower.

Table 2: Model fit: Cross-market correlations

	Data				**Model**			
	u	f	q	θ	u	f	q	θ
u	1.000				1.000			
f	-0.902	1.000			-0.902	1.000		
q	0.874	-0.789	1.000		0.541	-0.511	1.000	
θ	-0.680	0.808	-0.750	1.000	-0.701	0.800	-0.778	1.000

Notes: Correlation matrix for the unemployment rate (u), job-finding rate (f), vacancy yield (q) and labor market tightness (θ) across the 36 (region×skill) labor markets in Germany (2010–2017).

4.3 Variation of Matching Efficiency

We now analyze how the different margins of recruiting intensity contribute to the variation of matching efficiency across local labor markets.

Our calibrated model permits an exact decomposition of matching efficiency. We present this decomposition in terms of the job-finding rate (hires per unemployed worker) since this variable is of particular interest for the policy experiments of the next subsection and is also targeted in our calibration. Dividing the job-finding rate by market tightness delivers an equivalent decomposition of the vacancy yield (specifically, hires *from unemployment* per vacancy as defined here). These results are presented and discussed in Appendix B.2.

Since aggregate hires in a labor market are $H = \int H_p \, d\Pi(p) = \int (1 - G(\tilde{x}_p)) m(\lambda_p) e_p V_p \, d\Pi(p)$, the job-finding rate in this market can be decomposed as follows:

$$\frac{H}{U} = \underbrace{m_0 \Big(\frac{\bar{V}}{U}\Big)^{1-\mu}}_{\text{Tightness}} \cdot \underbrace{\bar{e}^{1-\mu}}_{\substack{\equiv m_E \\ \text{Search effort}}} \cdot \underbrace{\frac{\bar{m}}{m(\bar{\lambda})}}_{\substack{\equiv m_W \\ \text{Wage dispersion}}} \cdot \underbrace{\int (1 - G(\tilde{x}_p)) \frac{m(\lambda_p) e_p V_p}{\bar{m} \bar{e} \bar{V}} \, d\Pi(p)}_{\substack{\equiv m_S \\ \text{Selectivity}}} \tag{24}$$

where

$$\bar{V} \equiv \int V_p \, d\Pi(p) \quad , \quad \bar{e} \equiv \int e_p \frac{V_p}{\bar{V}} \, d\Pi(p) \quad , \quad \bar{m} \equiv \int m(\lambda_p) \frac{e_p V_p}{\bar{e} \bar{V}} \, d\Pi(p) \quad \text{and} \quad \bar{\lambda} \equiv \frac{U}{\bar{e} \bar{V}} \, .$$

$\bar{V}$ are aggregate vacancies, $\bar{e}$ is a vacancy-weighted aggregate measure of search effort, and $\bar{m}$ is an average of the worker-firm meeting rate weighted by effective vacancies eV. $\bar{\lambda}$ is the inverse of effective labor market tightness (i.e. unemployment divided by effective vacancies).

Equation (24) shows how the job-finding rate depends on four factors. The first one is a standard matching function relationship which links labor market tightness (i.e. the vacancy-unemployment ratio) to meetings per job seeker, an increasing and concave relationship. The other three factors contribute to matching efficiency: m_E measures the contribution of search effort to matching efficiency, while m_S captures the contribution of selectivity.

m_W is a "wage dispersion" term which reflects different wage policies in heterogenous firms. The numerator $\bar{m}$ is a weighted measure of worker-firm meetings, whereas the denominator $m(\bar{\lambda})$ is the meeting rate at average effective market tightness $\bar{\lambda}$. If wage policies in all firms were identical ($\lambda_p = \bar{\lambda}$), m_W would be exactly equal to one. If wage policies differ, this term is smaller than one due to the strict concavity of the meeting function (Jensen's inequality). Thus, dispersion of wages (in a competitive search model) reduces matching efficiency (cf. Kaas and Kircher, 2015). The average value of m_W is 0.965, so that dispersion is responsible for the loss of about 3.5% of worker-job matches.

We emphasize the distinction between the firm-level decomposition of job-filling rates and the decomposition of aggregate matching efficiency presented here. At the micro level, higher wages attract more workers, thus allowing the firm to fill more vacancies, and indeed this is an important mechanism for understanding recruitment intensity as we demonstrated before. At the aggregate level, however, the level of the (average) wage in the market has no impact on matching efficiency in this model.[39] Only the dispersion of wages matters to the extent that the number of matches is lower when workers and firms match in markets with different queue lengths.

Using our decomposition, we can explore the interplay of labor market tightness, search effort, wage dispersion and selectivity for the variation of job-finding rates across labor markets. The variance of the (log) job-finding rate is 0.184. Table 3 shows the covariance matrix of all (log) terms in equation (24). A first observation is that most of the variation of the job-finding rate comes from labor market tightness and from selectivity, whereas search effort and wage dispersion play a much smaller role for cross-market differences in job-finding rates. Second, the selectivity term m_S correlates negatively with market tightness: Firms in tighter labor markets are more selective which in turn reduces matching efficiency.

Table 3: Covariances across local labor markets

Total variance job-f. rate 0.18406	Tightness	Search effort	Wage dispersion	Selectivity
Tightness	0.65722	0.03177	0.00168	-0.38241
Search effort	0.03177	0.00417	0.00009	-0.01349
Wage dispersion	0.00168	0.00009	0.00002	-0.00107
Selectivity	-0.38241	-0.01349	-0.00107	0.24953

Notes: Covariance matrix of logged variables. Summation over all terms adds up to the variance of the logged job-finding rate (0.184).

These observations are also reflected in Table 4 whose first row shows the contribution of the four terms to the total cross-market variance of the job-finding rate. Across all 36 labor markets, market tightness and hiring selectivity are the two dominant forces in accounting for the variation of job-finding rates. However, these two forces work against each other: tighter labor markets have more selective firms, which then dampens the job-finding rate. Search effort m_E has a positive, but quantitatively smaller impact on variation of job-finding rates, while the contribution of the wage dispersion term is negligible. In Appendix A.7, we report cross-market correlations between the job-finding rate and the means of our three recruitment indicators within each market. Consistent with the model findings, hiring standards and search effort correlate positively with job-finding rates.

The intuition why hiring standards reduce matching efficiency in tighter markets is as follows: Local labor markets differ in their maximum firm productivity $\bar{p}_m$ and in the reservation wages of workers, $b_m + \rho_m$, which are calibrated to match wages and job-finding rates. Labor markets with higher job-finding rates (such as high-skill ones) also tend to have higher wages and higher reservation wages. In fact, productivity and reservation wages correlate strongly with job-finding

[39] In a richer model, where also workers' search intensity is endogenous, a higher average wage could possibly induce workers to search harder, thus impacting matching efficiency. Such an indirect channel is absent in our model.

rates (correlation coefficients around 0.7), but productivity differences are less pronounced (the standard deviation of reservation wages is about twice as large). By optimality condition (13), firms in markets with high productivity and high reservation wages become more selective as they need to offer sufficiently high wages to fill their positions, which ultimately reduces matching efficiency.

Table 4: Relative contributions to the variation of job-finding rates across local labor markets

	Variance JFR	Tightness	Search effort	Wage dispersion	Selectivity
Total	0.184	167.4%	12.2%	0.4%	-80.1%
Low skill	0.059	142.4%	3.8%	0.1%	-46.2%
Medium skill	0.038	222.2%	-1.3%	0.4%	-121.2%
High skill	0.016	207.4%	20.0%	2.8%	-130.2%

Notes: The first row shows the percentage contribution to the total variance of the log job finding rate (summation over the rows or columns in Table 3. The bottom three rows repeat this calculation for the variation across the 12 regions separate by skill level.

The wage dispersion term hardly matters for the cross-market variation of job-finding rates. While wage dispersion generally reduces matching efficiency, its variation matters little for differences between the 36 labor markets. This result is consistent with our data, where we find little cross-market variation of measured wage dispersion.[40] Nonetheless, we challenge our finding with robustness checks in subsection 4.5 regarding our calibration of productivity dispersion and the meeting function elasticity which impact the importance of the wage-dispersion term in equation (24). We further conduct robustness experiments regarding the elasticities of the cost functions for vacancies (parameter Φ) and search effort (parameter γ), both of which matter for the contributions of vacancies and effort for firm-level and aggregate outcomes.

We further explore to what extent variation across regions or across skill groups is driven by the different margins. Regarding variation across the 12 *regional* labor markets, the bottom three rows in Table 4 report the percentage contributions of the three channels to the variance of job-finding rates, separate for each of the three skill groups. Evidently, the cross-regional variance of the job-finding rate for each skill group is smaller than the total variance (first column of the table). Again, tightness and selectivity account for the lion share in cross-regional differences in job-finding rates, and they work in opposite directions: regions with tighter markets have more selective firms. Search effort and wage dispersion (to a lesser extent) contribute to matching efficiency mostly in high-skill labor markets.

Variation across skill groups is reported in Table 5. Medium- and high-skill labor markets

[40] When computing the coefficient of variation for (log) wages in each market we find that cross-market differences in this coefficient are small. The standard deviation of the distribution of market-specific coefficients of variation is 0.03. When controlling for skill levels we find that among the low-skill markets the standard deviation is 0.01, while for medium- and high-skill markets the standard deviation is 0.0045 and 0.0068, respectively.

have job-finding rates which are around 123% (80 log points) larger than those in low skill labor markets. Much of this gap is accounted for by differences in labor market tightness, especially for high-skilled workers (2nd column). But also in high-skill labor markets, firms are considerably more selective, which reduces matching efficiency as compared to markets for low-skilled workers (4th column). Search effort accounts for a small but positive difference in job-finding rates across skill groups, while the contribution of the wage-dispersion term is tiny.

Table 5: Average log differences to low-skill labor markets

	JFR	Tightness	Search effort	Wage dispersion	Selectivity
Medium skill	0.760	0.822	0.134	0.001	-0.198
High skill	0.846	1.707	0.100	0.004	-0.965

4.4 The Role of Recruiting Intensity for Labor Market Policy

Since recruitment strategies depend on the economic environment, it is important to understand how the different margins of firms' hiring policies respond to changes in labor market policy. It is well known that the German labor market experienced a major transition in the last two decades during which the harmonized unemployment rate declined from over 11% in 2005 to just over 3% in 2019. There is quite some literature discussing the role of different economic events and policy reforms for this transition. Particularly the Hartz labor market reforms, which consist of different policy measures, and their impact on the decline of unemployment have been analyzed extensively in the academic literature (see Krause and Uhlig, 2012; Krebs and Scheffel, 2013; Dustmann et al., 2014; Hochmuth et al., 2021; Carrillo-Tudela et al., 2021, among others).

A major part of these reforms concerns a significant reduction of government transfers to the unemployed, especially for long-term unemployed workers (Hartz IV). There are different ways how changes in unemployment income (UI) affect the labor market. Besides potential implications for the job-separation rate (see Hartung et al., 2018), most of the literature focuses on the role of the UI system on the job-finding rate which operate either via the search intensity margin of workers or via the job-creation decisions of firms.

Although our model, with exogenous separations and with no search intensity margin on the side of workers, cannot comprehensively analyze these various channels, it is well-suited to explore to what extent the different margins of recruiting intensity, in addition to the creation of jobs, contribute to changes in job-finding rates in response to changes of UI. To this end, we conduct a simple experiment where we compare the stationary equilibrium of our calibrated model with a UI replacement rate of 46% (post-Hartz period) to the stationary equilibrium of our model with a higher pre-Hartz reform replacement rate of 57% (cf. Krebs and Scheffel, 2013). For the latter economy we increase unemployment income levels b_m in all local labor markets in the same proportion to market-specific wages, leaving all other parameters unchanged.

Table 6 shows how the job-finding rate changes between the two scenarios. The first column reports the log change of the job-finding rate in response to the decline of unemployment income from 57% to 46%. On average, the job-finding rate increases by 0.317 log points (37%). Across skill groups, the increase is strongest for the low-skilled (0.554 log points, 74%) and weakest for the high-skilled (0.161 log points, 17%). The larger increase of the job-finding rate in low-skill labor markets is consistent with the findings in Carrillo-Tudela et al. (2021), whose data work implies that in low-skill labor markets the job-finding rate increased by 30.3%, while the job finding rates in medium and high skill markets increased by 25.1% and 9.8%, respectively, when comparing the 2000-2005 to the 2010-2014 period.

Table 6: Impact of a decrease of the replacement rate from 57% to 46%

	JFR	Tightness	Search effort	Selectivity
Total	0.317	0.223	0.007	0.086
Low skill	0.554	0.346	0.021	0.187
Medium skill	0.234	0.189	0.001	0.044
High skill	0.161	0.135	0.000	0.026

Note: The table shows the changes of the reported variables in log points. The first row is averaged over all local labor markets, the bottom three rows are averaged over regions, separately for each skill group.

The remaining columns of the table build again on equation (24) which gives an exact decomposition of the log change of the job-finding rate (in each local market) into the sum of log changes of four components: market tightness plus three margins of recruiting intensity. The wage dispersion term m_W does not contribute to policy changes. While the level of wages (and reservation wages) falls on average by 2.7% with lower UI,[41] the dispersion across firms within any local labor market is unchanged in our model. Therefore, this term does not contribute to the change of the job-finding rate and is not reported in the table.

Table 6 shows that the job-creation margin (tightness) is responsible for over 70% of the increase of the job-finding rate (22.3 log points), while the rest is mostly accounted for by the selectivity margin (8.6 log points). Search effort plays a minor role. With lower UI and firm productivity unchanged, hiring thresholds are lower, see condition (13). At the same time, it becomes more attractive to create jobs and exert higher search effort. This is the reason why tightness and effort increase, while firms become less selective.

Across skill groups, job creation remains the strongest contributor, but the selectivity margin is relatively more important for the low skilled where it accounts for one third of the increase

[41] The relatively small response of reservation wages to unemployment benefit changes is consistent with empirical findings; see Krueger and Mueller (2016) and references therein.

of the job-finding rate and less important for the high skilled where it accounts for only 16%. Especially in low-skill labor markets, firms reduce their hiring standards in response to a decrease of unemployment income which has a quantitatively significant impact on the job-finding rate.

Table 7: Impact of a decrease of the replacement rate without selectivity adjustment

	JFR	Tightness	Search effort
Total	0.124	0.105	0.019
Low skill	0.159	0.122	0.037
Medium skill	0.119	0.106	0.013
High skill	0.094	0.086	0.008

Ignoring the selectivity margin in a labor market model may lead to substantially different policy conclusions. To observe this, we conduct the same policy experiment but now we exogenously fix the firms' hiring thresholds at their steady-state equilibrium levels with the pre-Hartz replacement ratio. When unemployment income is cut to the lower level, firms optimally adjust their vacancy postings, search effort and wage policies, whereas they are assumed to hire the same types of workers. Table 7 shows that in this alternative model the job-finding rate increases by merely 12.9 log points on average. The increase is still largest in low-skill markets, although the absence of the selectivity margin has the sharpest impact on the policy impact for low-skill workers. The absence of hiring standards has an important, indirect dampening effect on the job-finding rate via market tightness: Since workers with low match quality do not find jobs when UI benefits are reduced, these workers remain in the unemployment pool which reduces job-finding chances for all job seekers (the standard labor market congestion externality). This explains why the contribution of market tightness is much smaller (especially in low-skill labor markets) in comparison to Table 6. On the other hand, higher search effort contributes a bit more to better job-finding prospects since firms resort to this margin in response to a greater match surplus.

4.5 Robustness

Our calibrated model attributes a major role to hiring selectivity, both for aggregate matching efficiency and for the labor market responses to policy changes. At the same time, the impact of firms' search effort is relatively small, and differences in wage dispersion across labor markets have only a negligible impact on matching efficiency. We now examine the robustness of these results. First, both estimated cost function elasticities Φ and γ are relatively large, so that it can be conjectured that our model generates larger responses of vacancy postings and effort for lower values of these parameters. Second, the estimated elasticity of the meeting function and the cross-market variation of productivity dispersion is rather low which may contribute to the negligible role of the wage dispersion term.

In each of the four experiments, we recalibrate the inner loop parameters so that the model continues to match the cross-market variation of job-finding rates and other targets, but we do not reestimate the remaining outer loop parameters. Table 8 shows how the decomposition of the job-finding rate changes under the alternative parameterizations, and Table 9 shows the robustness of the policy experiment of the last subsection.

Table 8: Robustness: Decomposition of job-finding rate variation for different parameterizations

	Tightness	Search effort	Wage dispersion	Selectivity
Benchmark	167.4%	12.2%	0.39%	-80.1%
$\gamma = 1.5$	167.4%	30.6%	0.03%	-98.1%
$\Phi = 1.5$	196.4%	3.6%	0.01%	-100.1%
$\mu = 0.3$	133.4%	9.8%	0.66%	-43.8%
High $\sigma(\eta_m)$	193.2%	10.6%	1.30%	-105.1%

Reducing the elasticity of the effort cost function to $\gamma = 1.5$ raises the slope of the search effort relationship in Figure 6.a by 25%, while the slope of the selectivity relationship in Figure 6.c falls further. At the aggregate level, the contribution of search effort for matching efficiency goes up by 18 percentage points and search effort also plays a much more prominent role for higher job-finding rates in response to a cut in unemployment income; see the second rows in Tables 8 and 9.

When we decrease the elasticity of the vacancy cost function to $\Phi = 1.5$, we fail to generate the vacancy yield relationship in Figure 6.d (the slope falls from 15.8 to 3.9).[42] As firms' vacancy postings become more sensitive to shocks, tightness is also more responsive to productivity differences across labor markets, thus raising its significance for job-finding rate differences even further (see the third row of Table 8).

Table 9: Robustness: Impact of a lower replacement ratio for different parameterizations

	JFR	Tightness	Search effort	Selectivity
Benchmark	0.317	0.223	0.007	0.086
$\gamma = 1.5$	0.243	0.053	0.088	0.102
$\Phi = 1.5$	0.213	0.084	0.017	0.112
$\mu = 0.3$	0.163	0.090	0.002	0.071
High $\sigma(\eta_m)$	0.317	0.223	0.007	0.086

[42] Low values of this elasticity typically fail to generate the steep relationship between the vacancy yield and employment growth; see Kaas and Kircher (2015) and Mueller et al. (2020) for related results. In our model, this low value of Φ also fails to replicate the large slope in Figure 7.d but it matches the slope in Figure 9 (see Appendix A.2) which is based on the smaller sample with non-zero vacancy firms.

When the elasticity of the meeting function increases from 0.12 to 0.3, our model fails to target the unemployment replacement rate.[43] Since larger values of μ increase the congestion externality on the firms' side, their vacancy responses are muted which shows up in the fourth rows of Tables 8 and 9.

Finally, the contribution of the wage dispersion term for matching efficiency remains small even if we increase the standard deviation of the productivity shape parameters η_m by factor five (leaving the mean unchanged). This experiment increases the contribution of tightness and selectivity in Table 8 even further while increasing the wage-dispersion term only little, and it has no effect on the policy results.

To sum up, in all these experiments hiring selectivity remains the dominant recruitment factor for matching efficiency and it plays an important role for the labor market effects of UI policy.

5 Conclusions

In this paper we use novel survey and administrative data for Germany and document that different dimensions of recruiting intensity, namely wage policies, search effort and hiring standards, vary systematically with an establishment's hiring rate. This result is robust after controlling for a wide range of employer and job characteristics. We propose a directed search model with heterogeneous multi-worker firms in order to analyze the mechanisms behind these patterns and to evaluate the role of recruitment policies for matching efficiency and for the impact of labor market policy.

In our quantitative analysis, we calibrate the model such that it replicates the main microeconomic relationships that we document in our empirical analysis and we verify that the model fits several facts about the cross-market variation of job-finding rates, vacancy yields and indicators of recruitment policies. A key feature of our model is that it provides a structural decomposition of the aggregate job-finding rate in terms of labor market tightness and the three recruitment policies. Most of the variation of the job-finding rate across local labor markets is driven by market tightness and hiring standards which turn out to operate in opposite directions: Tighter markets go together with stricter hiring standards which reduces matching efficiency. This feature occurs both across the skill and geographic dimensions. Search effort only plays an important quantitative role for matching efficiency in high-skill labor markets, whereas it matters much less in lower- or medium-skill markets.

These features suggest heterogenous effects when considering the impact of labor market policies on employers' recruiting intensity and ultimately on the re-employment chances of the unemployed. To investigate this further we conduct a simple experiment that mimics the drastic change in unemployment benefits as implemented in Germany during the Hartz labor market reforms. We find that the increase of the job-finding rate can be attributed mainly to two factors: higher

[43] Specifically, matching average wages and job-finding rates requires negative values of b for values of μ above 0.2 (given the estimated values of the other parameters).

vacancy creation and reductions in hiring standards where the latter response is particularly stark in low-skill labor markets. This result supports the finding of Carrillo-Tudela et al. (2021) who document that the reduction in unemployment after the Hartz reforms was largely due to workers moving from non-employment into low-skill part-time jobs which, as part of the reforms, also became much cheaper for employers to set-up and offer.

Our model focuses on the hiring policies of firms, abstracting from heterogeneity among workers. In our quantitative analysis, worker characteristics are reflected in those parameters governing cross-market differences in job-finding rates, wages and turnover (i.e., productivity, unemployment income, and separation rates). However, it may be that worker characteristics interact in important ways with the firms' incentives to use specific recruitment margins. To explore this possibility, we obtain statistics about worker observable characteristics such as gender, age, experience or foreign nationality, both for recent hires and for the total workforce. Across our region-skill markets, there are indeed some notable differences in these dimensions. Yet, most of these characteristics do not correlate strongly with our recruitment indicators, with only few exceptions. For example, firms' search effort is lower in markets with more female workers, while firms are more selective in those markets where recent hires are more often older or female. The extent to which recruitment behavior matters for labor market outcomes of particular groups of workers is an important topic for future research; see Lochner and Merkl (2022) for recent work on gender-specific hiring policies using JVS data.

A further limitation is that our model abstracts from job-to-job transitions which we motivate by our own evidence showing no systematic relationship between employment growth and the share of hires poached from other employers. Yet, the fact that faster-growing establishments are both less selective and offer higher wages may have offsetting effects on the respective shares of hires from employment and unemployment. Indeed, when we include the share of hires from non-employment into our main regressions of recruitment indicators, we find that establishments that hire more from non-employment have both lower wage premia and lower hiring standards. Understanding the role of these separate mechanisms for labor market turnover and sorting is another interesting issue to be studied in future work (see also Carrillo-Tudela et al., 2022).

Appendix

A. Data Appendix

For our analyses we use survey and administrative data of the Institute for Employment Research (IAB). The Integrated Employment Biographies (IEB) administrative data are processed and kept by IAB according to German Social Code III. There are certain legal restrictions due to the protection of data privacy. The data contain sensitive information and therefore are subject to the confidentiality regulations of the German Social Code (Book I, Section 35, Paragraph 1).[44] To access the Job Vacancy Survey (JVS) data one needs to follow an application process detailed in https://www.iab.de/en/befragungen/stellenangebot.aspx.

The IEB data provides employment records of all workers paying social security contributions with the exception of civil servants (Beamte). The IEB therefore covers around 80% of the workforce. These data provide information on individuals' daily earnings and daily employment histories as well as their education, age, gender, nationality, occupations and the type of employment contract (full-time vs. part-time). In addition these data provide the identity of a worker's current employer through a unique establishment identifier. This identifier is used to aggregate workers with the same employer identifier and obtain the characteristics of any establishment's workforce at any point in time (measured in days). Since it encompasses the universe of private-sector workers in Germany, the IEB can be used to derive the employment dynamics of each establishment; i.e. employment growth, hiring, separation, job creation and job destruction rates, among others.

Crucially, the JVS identifies the surveyed establishment using the same identifier as the IEB. Therefore the identifier also allows us to link all the worker information from the IEB to the establishment information provided by the survey. As mentioned in the main text, the first section of the JVS provides general information about the establishment, including employment, location, industry, and whether the establishment was facing financial, demand and/or workforce restrictions. This part of the survey also contains the current stock of vacancies (defined as "open positions to be filled immediately or to the next possible date"), broken down by three levels of education requirements (no formal education, vocational training, and university degree). The second part provides information about the recruitment behavior among the surveyed establishment.

The ability to identify JVS establishments in the IEB data then allows us to compute the number of new hires and total employment (and hence the hiring rate) for each JVS establishment at a daily basis. Since we know the date at which each establishment was interviewed in the JVS, we construct the hiring rate of each establishment around the JVS interview date and analyze it together with the information provided in the survey. We link the JVS and IEB data for the

[44]The data are held by the Institute for Employment Research (IAB), Regensburger Str. 104, 90478 Nuremberg, Germany. To access the data for replication purposes, please get in contact with Hermann Gartner (hermann.gartner@iab.de).

period 2010–2017 due to legal restrictions that forbid the link for earlier years. The data obtained from linking the IEB and the JVS, however, is not publicly available.

A.1 Summary Statistics

Table 10 presents the main characteristics of our sample. In particular, the vast majority of the establishments in the JVS are small with less than 20 employees and about 50% of them are in the trade and retail sector or provide commercial or social services.[45] Establishments are also more likely to report they face workforce or demand restrictions than financial restrictions.

Table 10: Sample characteristics (JVS and IEB)

	No. Obs	Mean	Std. Dev.		No. Obs	Mean	Std. Dev.
Establishments (JVS)							
Age (years)	68,440	17.366	12.473	*Industry distribution*	68,681		
Size distribution	68,681			Manufacturing		0.083	0.139
< 20		0.698	0.459	Natural Resources		0.060	0.131
$20 - 49$		0.176	0.381	Construction		0.107	0.309
$50 - 199$		0.103	0.304	Trade and retail		0.184	0.388
$200 - 499$		0.016	0.126	Hospitality		0.075	0.264
500+		0.007	0.084	Commercial services		0.173	0.378
Restrictions	68,681			Transport, communication		0.059	0.235
Demand		0.117	0.322	Other private & public services		0.063	0.244
Financial		0.046	0.209	Social services		0.160	0.367
Workforce		0.169	0.375	Other services		0.158	0.186
Jobs (JVS)							
Qualification requirements	57,432			Number of applications	50,356	13.333	19.741
Unskilled		0.168	0.374	Number of suitable applicants	47,773	3.839	4.479
Vocational training/Tech College		0.639	0.480	Number of interviews	22,767	3.517	3.051
Bachelor/Master/PhD		0.194	0.395	Paid higher wage than expected	72,709	0.116	0.321
Experience	59,785			Accepted lower experience	72,709	0.095	0.293
Long-term exp.		0.360	0.480	Accepted lower qualification	72,709	0.079	0.270
Leadership exp.		0.084	0.278	Number of channels	68,945	2.965	1.974
Vacancy duration (days)	49,049	59.503	59.273	Recruitment international	63,005	0.038	0.191
Workers (IEB)							
Education	54,519,822			*Labor market experience*	54,519,822		
Unskilled		0.103	0.304	Potential exp. (years)		17.741	10.856
Vocational training/Tech College		0.710	0.454	Establishment tenure (years)		7.424	8.590
Bachelor/Master/PhD		0.187	0.390				

Note: All statistics are based on establishment-year (worker-year, resp.) observations.

In terms of the last filled job the majority of establishments require a vocational training, while long-term experience is also a common job requirement. These vacancies are typically filled in two months. Table 11 reports variation in average vacancy durations across skill categories, where low skill represents jobs for workers who have not completed post-school education, medium skill represents jobs which require vocational training; and high skill are jobs that require a university

[45]The manufacturing category encompasses (i) Nutrition, textiles, clothing, furniture; (ii) Wood, paper, printing, publishing; (iii) Chemistry, plastics, glass, construction materials; and (iv) Machines, electronics, vehicles industries. The natural resources category encompasses the (i) Agriculture, forestry, fishing; (ii) Metal, metal products; and (iii) Energy, mining industries. The other services category encompasses (i) Finance, insurance; and (ii) Public administration industries.

degree. Low-skill vacancies are filled in about a month and a half and high-skill vacancies in about two-and-a-half months. Table 10 shows that establishments end up receiving an average of 13 applications for their vacancies, but Table 11 shows there is large variation across skill categories where low-skill vacancies receive on average 10 applications and high-skill ones receive on average 20 applications. Employers end up interviewing on average about only one quarter of these applicants. Once again Table 11 reports large variation across skill categories such that establishments end up interviewing about 40% of the applicants for low-skill vacancies but only 20% of applicants for high-skill ones. In terms of the usage of recruitment policies, Table 10 shows that about 10% of all establishments in our sample report using wages and/or lowering hiring standards to fill their jobs with large variation across skill categories, where 20% of employers end up offering a higher wage when filling high-skill jobs but only 7% of them when filling low-skill ones.

Table 11: Sample characteristics by skill group (JVS)

	Low skill			**Medium skill**			**High skill**		
	Mean	St. dev.	N	Mean	St. dev.	N	Mean	St. dev.	N
Vacancy duration (days)	43.915	54.167	5,874	59.387	59.145	32,986	73.173	60.248	9,127
Number of applicants	9.793	16.278	5,917	12.392	18.506	34,214	19.562	24.663	9,296
Number of suitable applicants	3.459	4.381	5,533	3.628	4.213	32,487	4.856	5.217	8,928
Number of interviews	3.750	3.688	3159	3.330	2.863	15,131	3.849	2.921	4,069
Paid higher wage than expected	0.075	0.263	7,798	0.152	0.359	41,746	0.155	0.362	10,952
Accepted lower experience	0.096	0.294	7,798	0.110	0.313	41,746	0.083	0.276	10,952
Accepted lower qualification	0.089	0.284	7,798	0.098	0.298	41,746	0.048	0.215	10,952
Number of search channels	3.414	2.389	7,534	3.405	2.123	40,321	3.611	2.015	10,709
Recruitment international	0.085	0.279	7,142	0.039	0.195	36,118	0.088	0.283	9,261

Worker information from the IEB is presented at the bottom of Table 10. It refers to the education and experience characteristics of those workers who were employed in JVS establishments during the sample period. Overall, this information suggests that workers employed in JVS establishments exhibit education and experience characteristics that are similar to those found in the general labor force.

Table 12 evaluates the extent on selection from using recruitment information in those establishments which were fully or partially successful in filling all of their job openings during the last 12 months. The top two rows show that the majority of establishments interviewed engaged in search/recruitment activities and 81% of them managed to fill all of their vacancies, while only 3% were totally unsuccessful.

The remainder of the table shows that establishments that were fully or partially successful in filling their vacancies seem not to differ meaningfully in size, age, industry composition, growth rate and demand and financial restriction. The only differing characteristic is workforce restrictions, which is expected. This suggests that our focus on successful hires does not introduce meaningful selection along the aforementioned dimensions.

When comparing establishments that engaged in recruitment activities relative to those that did not, however, we do observe selection on size. Among the latter, the size distribution is heavily biased towards smaller establishments with around 75% of its mass concentrated in establishments with less than 20 employees. We also find that these are more often shrinking establishments, with an average growth rate of -0.014. Establishments without recent recruitment activity are also more likely not to report any vacancy at the time of interview in comparison to recruiting establishments. Unsurprisingly, non-recruiting establishments are also more likely to have zero hires in administrative data in the 90-day interval around the time of interview. We do not observe meaningful differences in other dimensions.

We also observe selection based on size and employment growth when comparing establishments that were fully/partially successful in hiring relative to those that did not manage to fill any open position. Again this type of selection should not play a major role in our conclusions as the totally unsuccessful recruiting establishments represent a very small proportion among establishments reporting recruitment activity.

A.2 Hiring rates, vacancy yields and vacancy rates by employment growth

Figure 1 shows the relationships between hiring rates, vacancy yields and vacancy rates where these variables are averages of employment growth bins (with and without controls). Here we present the underlying relationships of the three variables with employment growth. We measure the establishment's employment growth rate over 30-day intervals after the JVS interview, using average size at the beginning and at the end of the interval in the denominator (cf. Davis et al., 1998). We partition these monthly employment growth rates into 29 bins around zero. Figure 7.a shows the distribution of monthly employment growth, where 58.2% (38,767 observations) of establishments exhibit zero growth, 24.4% (16,269 observations) exhibit negative growth and 17.4% (11,564 observations) positive growth.

Figure 7.b shows the variation of hiring rates across employment growth bins, where the hiring rate is defined as hires in interval $[t0, t1]$ divided by average employment. Formally, the hiring rate of an establishment is $\frac{H_{t0,t1}}{0.5(E_{t0}+E_{t1})}$ where $t0$ is the day of interview and $t1$ is 30 days after that. Each point on the solid curve shows an employment-weighted average in a particular growth bin. This graph exhibits a very similar pattern as related graphs based on JOLTS data (e.g. Davis et al., 2013): the hiring rate is essentially flat for shrinking establishments which still hire to replace some of its workers, but high and steeply increasing in employment growth in expanding establishments. Note again that we remove employer returns from hires and separations which gives rise to somewhat smaller worker flow rates (and larger spikes at inaction) compared to other data sources. In addition to the bin averages, the dashed curve shows the regression coefficients on bin dummies where we include controls for industry and establishment size and age.

Figure 7.c shows the variation of vacancy rates, defined as vacancies reported at the interview

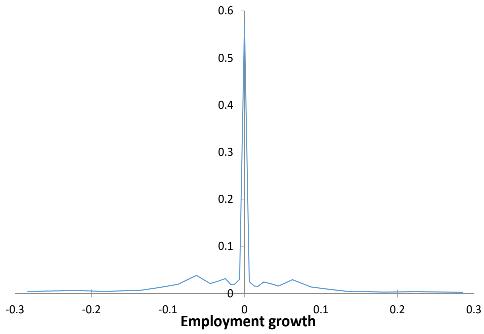
Table 12: Characteristics of recruiting and non-recruiting establishments

	Recruiting Establishments			Non-recruiting
	Filled all	Filled some	Filled none	Establishments
Overall proportions	55.47	10.89	2.1	31.54
Proportion of rec. estab.	81.03	15.91	3.07	n.a.
Firm size				
< 20	33.89	33.24	79.21	76.4
20-49	30.1	30.89	16.11	15.08
50-199	23.19	22.84	4.14	5.95
200-499	7.48	7.34	0.31	1.57
500 +	5.35	5.69	0.23	0.99
Industry				
Agriculture, forestry, fishing	4.36	4.2	5.45	4.88
Nutrition, textiles, clothing, furniture	4.37	4.26	5.14	4.19
Wood, paper, printing, publishing	4.05	2.97	3.95	5.04
Chemistry, plastics, glass, construction materials	4.6	3.67	4.03	3.9
Metal, metal products	4.42	5.14	7.21	3.79
Machines, electronics, vehicles	5.47	6.21	7.02	4.84
Energy, mining	5.33	2.29	3.22	7.59
Construction	3.86	6.09	8.94	3.49
Trade and retail	4.09	4.57	5.18	4.87
Hospitality	4.15	6.41	4.22	3.02
Commercial services	4.69	6.18	5.26	4.04
Finance, insurance	3.26	1.62	3.8	4.54
Transport, communication	16.17	21.47	16.76	15.89
Other private & public services	11.99	7.99	7.36	12.64
Public administration	12.38	13.48	10.86	10.03
Social services	6.81	3.45	1.61	7.24
Age (years)	20.49	19.16	18.27	19.17
Growth rate	0.067	0.063	-0.029	-0.014
Zero reported vacancies	70.6	37.8	55.2	93.8
Zero hires (90d around interview)	33.8	29.7	61.9	69.3
Restrictions				
Demand	0.102	0.120	0.151	0.131
Finance	0.043	0.062	0.071	0.040
Workforce	0.117	0.460	0.405	0.030

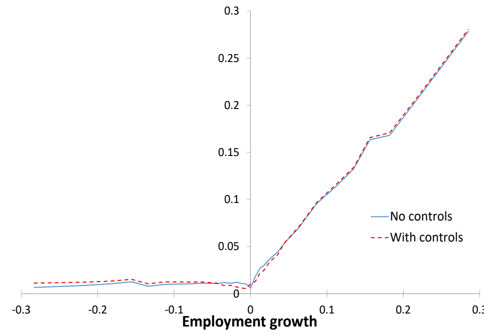
Note: Recruiting (non-recruiting) establishments are those which report some (no) recruiting activity during the last 12 months.

date V_{t0} divided by average employment at $t0$ and $t1$, again as a weighted average for each growth bin. Vacancy rates increase from around 2% for stable establishments to over 5% for establishments that grow by more than 20% when not using any controls. When using establishment size, age and industry controls, however, vacancy rates appear much more similar, fluctuating between 3% and 4% across shrinking, stable and expanding establishments.

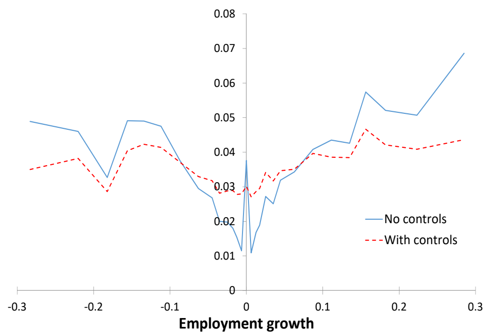
Figure 7.d shows the variation of vacancy yields across employment growth bins where, following (1), we define the vacancy yield for every growth bin as the ratio between the hiring rate and the vacancy rate in that bin which is equivalent to dividing total hires of all establishments in



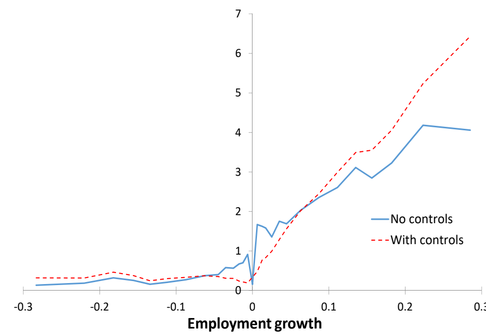
(a) Employment Growth Distribution



(b) Hiring Rate



(c) Vacancy Rate



(d) Vacancy Yield

Figure 7: Variation by 30-day establishment growth

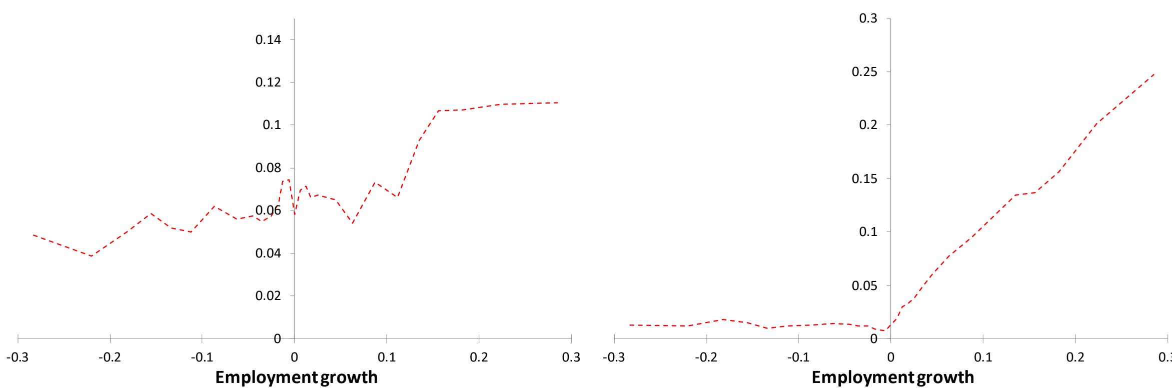
a particular growth bin by the total vacancies of these establishments. As found in JOLTS data (cf. Figure V of Davis et al., 2013), there is considerable variation of vacancy yields across growth bins in our data. While vacancy yields are flat in the negative growth range, they increase steeply in the positive range, from values below one to over four (without controls) or six (with controls).

Time aggregation in vacancy yields

The monthly vacancy yield depicted in Figure 7.d shows values greater than one, possibly as a result of time aggregation. To deal with this measurement issue we follow the method proposed by Davis et al. (2013). They estimate the daily job-filling rate during period t, f_t, by assuming an underlying birth-death process for vacancies. Using the resulting system of equations some algebra shows that f_t solves

$$H_t = f_t\left[v_{t-1}\sum_{s=1}^{\tau}(1-f_t-\delta_t+\delta_t f_t)^{s-1}+\sum_{s=1}^{\tau}(\tau-s)(1-f_t-\delta_t+\delta_t f_t)^{s-1}\frac{v_t-(1-f_t-\delta_t+\delta_t f_t)^{\tau}v_{t-1}}{\sum_{s=1}^{\tau}(1-f_t-\delta_t+\delta_t f_t)^{s-1}}\right], \tag{25}$$

where H_t denotes the number of hires during the period, v_{t-1} and v_t denote the number of vacancies at the end of periods $t-1$ and t, δ_t denotes the rate at which vacancies posted during the period and τ is the number of days in the period. Davis et al. (2013) use monthly JOLTS data to solve for the job-filling rate. In our case, however, we can only use quarterly data. We obtain the necessary information from the follow-up surveys that complement the yearly (main) JVS. These follow-up surveys are implemented in each of the subsequent three quarters and aim at generating a short panel, albeit composed of a much smaller set of participating establishments. These surveys only contain a small number of questions drawn from the first part of the main survey, which includes for each quarter establishments' total hires, vacancy stocks and their number of fail vacancies.



(a) Based on (25)

(b) Based on steady state (see text)

Figure 8: Daily-job filling rate and establishment growth

The left panel of Figure 8 shows the estimated daily job-filling rate relative to employment growth when using equation (25). The "hockey-stick" relationship of Figure 7.d remains but the relationship appears much noisier. This likely arises as the follow-up surveys are based on a much smaller number of establishments and since the time span between interview is relatively long. An alternative way to estimate the daily job-filling rates is by using the steady state version of equation (25). Davis et al. (2013) argue that this alternative provides a very good approximation to the daily job-filling rate implied by (25), when estimated using monthly data and a much larger sample (relative to the one provided by the JVS follow-up surveys). The key advantage for us is that it is much less demanding on our data as it implies that f is given by

$$f = \frac{H}{v\tau}. \tag{26}$$

The right panel of Figure 8 shows the resulting relationship between the daily job-filling rate relative to employment growth. Note that in this case, the "hockey-stick" appears much stronger and in line with the findings of Davis et al. (2013).

Non-zero vacancy observations

Another explanation for large vacancy yields is that some hiring firms do not report vacancies at the beginning of the period where hires are recorded. Davis et al. (2013) note that in JOLTS data 42% of hires occur in establishments reporting zero vacancies at the end of the previous month. In our data too, many establishments do not report vacancies (cf. Table 12) which prevents us from calculating vacancy yields at the establishment level for the full sample. However, even when we restrict the sample to positive vacancy observations, an increasing relationship between employment growth and the vacancy yield remains, both with and without controls for industry, size and age; see Figure 9. Further, the vacancy yield variation is sizable (albeit smaller than in Figure 7.d), increasing from around 0.2 to 1.2-1.5 as employment growth increases from zero to 30%.

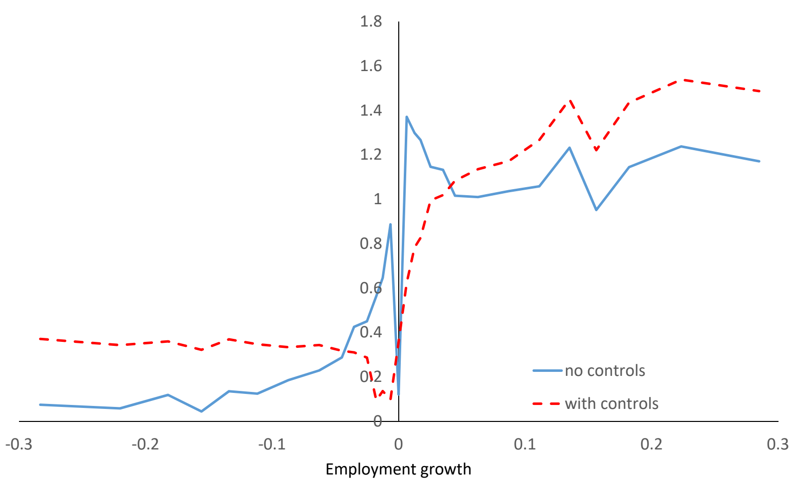
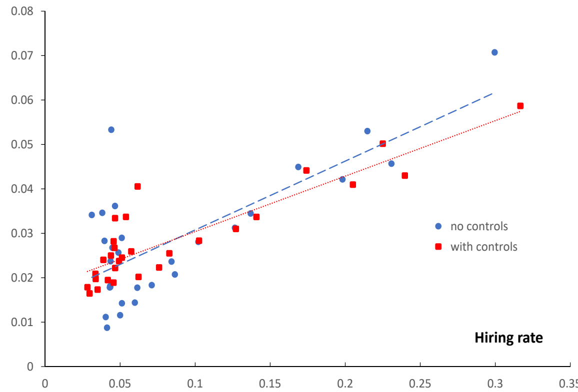


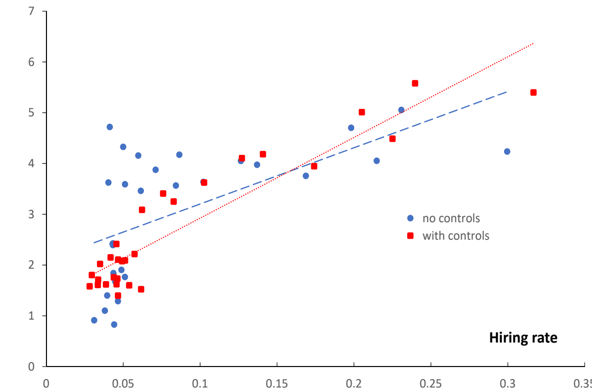
Figure 9: Vacancy yield versus employment growth (non-zero vacancy observations)

90-day intervals

Since our recruitment indicators based on IEB data use 90-day intervals of hires in administrative data, we also verify whether the relationships between hiring rates, vacancy rates and vacancy yields shown in Figure 1 for 30-day periods are robust to 90-day intervals. Figure 10 shows that this is indeed the case: The vacancy yield accounts for the majority of hiring rate variation, both unconditional and when controls for industry, establishment size and age are applied.



(a) Vacancy Rate



(b) Vacancy Yield

Figure 10: Vacancy rate and vacancy yield by hiring rate (90-day intervals)

Notes: See the notes to Figure 1 for explanations.

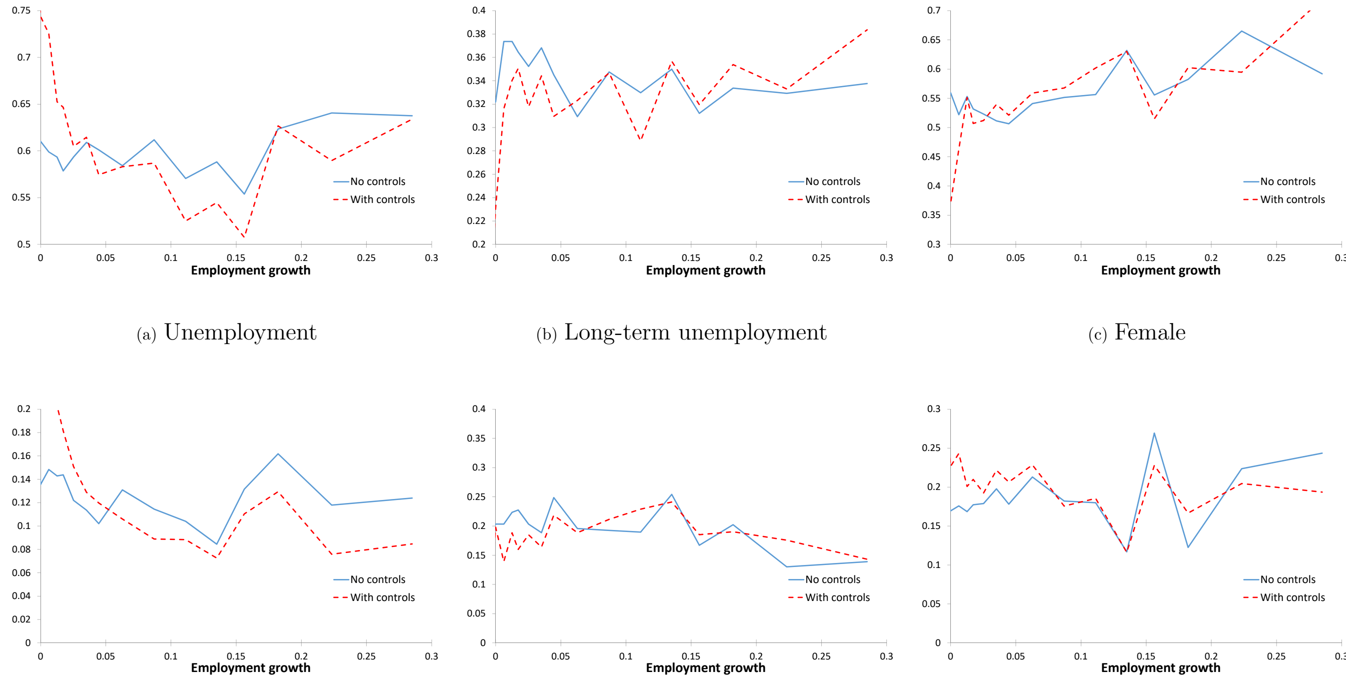
A.3 Composition of Hires

Figure 11 shows to what extent the composition of hires changes when the establishment's employment growth rate varies from zero to 30%. We separately show how the share of hires from unemployment or from long-term unemployment, the share of female or foreign hires, and the shares of young (under age 25) and older (ages over 50) varies with the establishment's employment growth. When applying controls for size, age and industry, fast-growing establishments hire slightly more long-term unemployed workers and more females. There is no evidence, however, that these establishments hire more unemployed workers, more foreign workers, or workers in specific age groups.

A.4 Relationship Between Hiring Rates and Recruitment Policies

Regression coefficients. Table 13 presents the regression coefficients of the hiring rate that are behind Figures 2-4. The first column of each regression reports the hiring rate coefficients without further controls; the second column reports the coefficients also controlling for year dummies, establishments' industry, (five) size categories, age, the job's 1-digit occupation, three levels of skill requirements, dummies for long-term experience and leadership requirements, and a dummy for whether this was a newly created job or not. In all cases we use the hiring bin close to zero as the baseline category.

Complementarities between recruitment measures. Establishments typically make use of multiple recruitment policies. In particular, we find that about 80% of expanding establishments



(a) Unemployment (b) Long-term unemployment (c) Female

(d) Foreign (e) Under 25 (f) Over 50

Figure 11: Shares of hires by 30-day establishment growth

that report hiring a worker with lower qualifications also report hiring a worker with lower experience than expected. About 20% of those that reported reducing hiring standard also report paying more than expected. The more search channels establishments use, the more frequently they report paying more than expected (the fraction increases monotonically from 9% for establishments using only one channel up to 55% for those that use 12 channels). A similar relationship holds for establishments that report reducing hiring standards (6% in establishments using one channel and 36% in establishments using 12 channels).

Further, we find that establishment that grow faster use more intensively all three measures. This result is obtained by ranking each the standardized measures of wage generosity, hiring standards and search effort within each establishment growth bin. Computing their product and then the average of this product within each growth bin, reveals an increasing relationship between the joint usage of these measures and establishment growth.

A.5 Robustness of the Main Empirical Relationships

The relationships between the establishment hiring rate and the three main recruitment indices $\hat{w}$, s, e (as defined in Section 2) are neither driven by observations with zero hires, zero vacancies, by establishments with less than 20 workers or by establishments with negative employment growth. This is shown in Figures 12–15 which replicate the main insights presented in Figures 2-4: Establishments with larger hiring rates exert more effort, pay more generous wages and reduce their

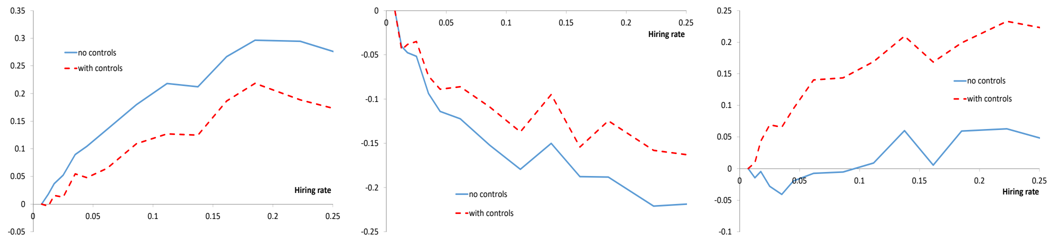
Table 13: Recruitment policies and hiring rates - Regression coefficients

Hiring bin (max)	**Wage concessions**		**IEB - Wage premium**		**Wage generosity**		**Number of channels**		**Geographic Search**	
0.015	-0.036***	-0.0094	0.0036	-0.003	0.018	0.0026	0.7869***	0.0625	-0.0056	-0.0149***
	(.0084)	(.0093)	(.0118)	(.013)	(.0368)	(.0387)	(.0522)	(.0558)	(.0054)	(.0059)
0.02	-0.0308***	-0.0112	-0.0014	-0.0065	0.037	0.0193	0.7512***	0.0557	-0.0019	-0.0065
	(.0074)	(.0083)	(.0113)	(.0125)	(.0352)	(.0372)	(.0461)	(.0498)	(.0047)	(.0053)
0.03	-0.0199***	-0.0042	0.0008	-0.0109	0.0523	0.0162	0.6479***	0.1454***	0.005	-0.0007
	(.0052)	(.0058)	(.0102)	(.0113)	(.0319)	(.0337)	(.0324)	(.0351)	(.0033)	(.0037)
0.04	-0.0077	0.0091	0.0117	-0.0032	0.0897***	0.0561*	0.6078***	0.1574***	0.0035	-0.0042
	(.0051)	(.0057)	(.0102)	(.0114)	(.0319)	(.034)	(.0318)	(.0344)	(.0033)	(.0036)
0.05	-0.0026	0.0095	0.0151	-0.0028	0.1045***	0.0515	0.6348***	0.2096***	0.0108***	0.0032
	(.0054)	(.006)	(.0103)	(.0116)	(.0323)	(.0346)	(.0338)	(.036)	(.0035)	(.0038)
0.075	0.004	0.0118***	0.0239**	0.0023	0.135***	0.0682**	0.5945***	0.281***	0.0157***	0.0088***
	(.004)	(.0044)	(.0097)	(.0111)	(.0305)	(.0331)	(.0251)	(.0266)	(.0026)	(.0028)
0.1	0.017***	0.0266***	0.0371***	0.0122	0.1799***	0.1116***	0.5782***	0.2905***	0.017***	0.0095***
	(.0048)	(.0052)	(.01)	(.0115)	(.0315)	(.0343)	(.0299)	(.0313)	(.0031)	(.0033)
0.125	0.0275***	0.0291***	0.0366***	0.0133	0.2181***	0.1299***	0.6091***	0.3878***	0.0229***	0.0118***
	(.0053)	(.0058)	(.0103)	(.012)	(.0324)	(.0356)	(.0334)	(.0347)	(.0034)	(.0037)
0.15	0.0176***	0.0223***	0.049***	0.0212*	0.2122***	0.1258***	0.6725***	0.4256***	0.034***	0.0214***
	(.0068)	(.0074)	(.011)	(.0128)	(.0346)	(.038)	(.0423)	(.0441)	(.0043)	(.0047)
0.175	0.0246***	0.0258***	0.0672***	0.0434***	0.2667***	0.1862***	0.6198***	0.4234***	0.02***	0.007
	(.0076)	(.0082)	(.0114)	(.0133)	(.0361)	(.0397)	(.0474)	(.0491)	(.0049)	(.0052)
0.2	0.0282***	0.0302***	0.0615***	0.0378***	0.2964***	0.2241***	0.6595***	0.4332***	0.0372***	0.0182***
	(.0092)	(.0099)	(.0124)	(.0145)	(.0393)	(.0433)	(.0571)	(.0589)	(.0058)	(.0062)
0.25	0.0436***	0.0425***	0.07***	0.0393***	0.2944***	0.186***	0.5891***	0.4422***	0.046***	0.0309***
	(.0072)	(.0079)	(.0112)	(.0133)	(.0357)	(.0396)	(.0453)	(.047)	(.0046)	(.005)
Controls		X		X		X		X		X
Constant	0.1108***	0.0442***	-0.0995*** *	-0.0557***	-0.1578***	-0.1237**	2.5305***	0.9029***	0.0255***	0.0527***
	(.0022)	(.0137)	(.0092)	(.0205)	(.0287)	(.0609)	(.014)	(.0823)	(.0014)	(.0087)
R2	0.003	0.0515	0.0097	0.0206	0.0152	0.0471	0.0217	0.1033	0.0054	0.0406
N obs	68681	59268	29637	22626	25788	22626	65209	57347	59365	51242

Hiring bin (max)	**Search effort**		**Qualification Mismatch**		**Experience Mismatch**		**IEB - Selectivity**		**Selectivity (JVS+IEB)**	
0.015	0.2083***	-0.0098	-0.0435***	-0.0075	-0.0433***	-0.0124	-0.0027	-0.0194	-0.0405	-0.0426
	(.0199)	(.0212)	(.007)	(.0079)	(.0076)	(.0087)	(.0116)	(.0129)	(.0348)	(.0373)
0.02	0.2***	-0.0037	-0.0377***	-0.0031	-0.0374***	-0.0096	-0.0024	-0.0138	-0.0476	-0.0367
	(.0176)	(.0189)	(.0062)	(.0071)	(.0067)	(.0077)	(.0111)	(.0124)	(.0333)	(.0358)
0.03	0.1932***	0.0402***	-0.0388***	-0.0113**	-0.0396***	-0.0145***	-0.0103	-0.0215*	-0.0517*	-0.0345
	(.0123)	(.0133)	(.0043)	(.005)	(.0047)	(.0054)	(.01)	(.0113)	(.0302)	(.0325)
0.04	0.1781***	0.0364***	-0.0265***	-0.0013	-0.0224***	-0.0004	-0.0209**	-0.0339***	-0.0937***	-0.0739**
	(.0121)	(.0131)	(.0043)	(.0049)	(.0047)	(.0053)	(.01)	(.0114)	(.0302)	(.0328)
0.05	0.2048***	0.0712***	-0.016***	0.0052	-0.0203***	-0.0003	-0.0267***	-0.0403***	-0.114***	-0.0872***
	(.0129)	(.0137)	(.0045)	(.0051)	(.0049)	(.0056)	(.0101)	(.0116)	(.0306)	(.0334)
0.075	0.1972***	0.0947***	-0.0133***	0.0015	-0.0073**	0.0052	-0.0134	-0.0294***	-0.1223***	-0.0861***
	(.0095)	(.0101)	(.0034)	(.0038)	(.0036)	(.0041)	(.0096)	(.011)	(.0288)	(.0319)
0.1	0.1939***	0.0979***	-0.0039	0.0098**	-0.0083*	0.0036	-0.0157	-0.0326***	-0.1522***	-0.1103***
	(.0114)	(.0119)	(.004)	(.0044)	(.0044)	(.0049)	(.0099)	(.0115)	(.0298)	(.0331)
0.125	0.2219***	0.1382***	0.0072	0.0209***	0.0045	0.0151***	-0.0187*	-0.0364***	-0.1794***	-0.1369***
	(.0127)	(.0132)	(.0045)	(.0049)	(.0049)	(.0054)	(.0101)	(.0119)	(.0307)	(.0344)
0.15	0.255***	0.1607***	0.0019	0.0135**	-0.0012	0.0085	-0.0191*	-0.0347***	-0.1501***	-0.0954***
	(.0161)	(.0167)	(.0057)	(.0063)	(.0062)	(.0069)	(.0108)	(.0127)	(.0328)	(.0367)
0.175	0.2162***	0.1322***	0.017***	0.0256***	0.0138**	0.0184**	-0.0105	-0.0327**	-0.1877***	-0.1525***
	(.018)	(.0186)	(.0064)	(.007)	(.0069)	(.0076)	(.0113)	(.0133)	(.0343)	(.0384)
0.2	0.2643***	0.1621***	0.0173**	0.0227***	0.0334***	0.0384***	-0.0121	-0.0265*	-0.1882***	-0.1268***
	(.0218)	(.0224)	(.0077)	(.0084)	(.0084)	(.0092)	(.0123)	(.0145)	(.0374)	(.0419)
0.25	0.27***	0.1931***	0.0248***	0.0256***	0.0246***	0.0266***	-0.0094	-0.0335**	-0.221***	-0.1578***
	(.0172)	(.0178)	(.0061)	(.0067)	(.0066)	(.0073)	(.0111)	(.0133)	(.034)	(.0383)
Controls		X		X		X		X		X
Constant	-0.1796***	-0.5947***	0.0854***	0.0773***	0.1010***	0.0888***	-0.0449***	-0.0009	0.1458***	0.1103*
	(.0053)	(.0313)	(.0019)	(.0117)	(.002)	(.0127)	(.009)	(.0205)	(.0271)	(.0591)
R2	0.0182	0.1007	0.0039	0.0199	0.0031	0.0149	0.0003	0.007	0.0056	0.0158
N obs	65209	57347	68681	59268	68681	59268	29144	22343	25446	22343

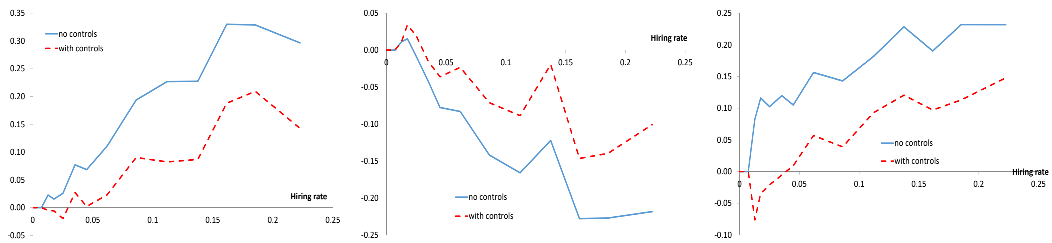
Notes: Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

hiring standards. Furthermore, our findings do not change in a meaningful way when we control for the time lag between the interview date and the date of the last hire, which may possibly vary across establishments with different hiring policies; see Figure 16.



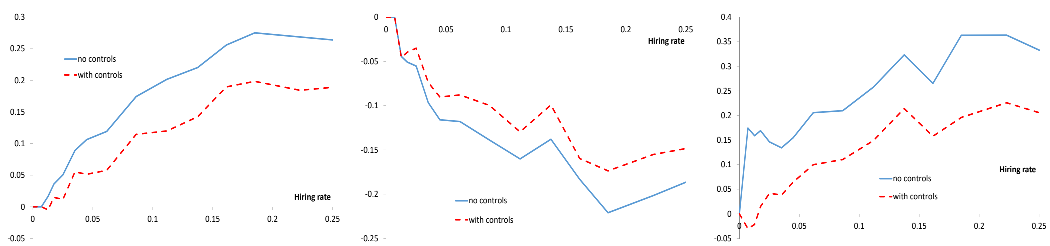
(a) Wage generosity (b) Hiring standards (c) Search effort

Figure 12: Variation of the main recruitment indices (with zero hires observations removed).



(a) Wage generosity (b) Hiring standards (c) Search effort

Figure 13: Variation of the main recruitment indices (with zero vacancy observations removed).



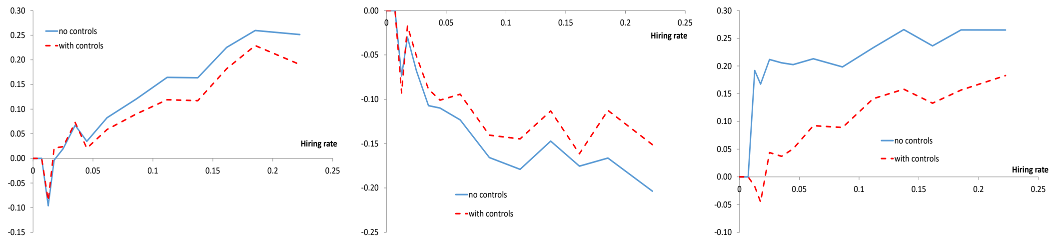
(a) Wage generosity (b) Hiring standards (c) Search effort

Figure 14: Variation of the main recruitment indices (only establishments with 20+ workers).

A.6 Alternative Selectivity Measures

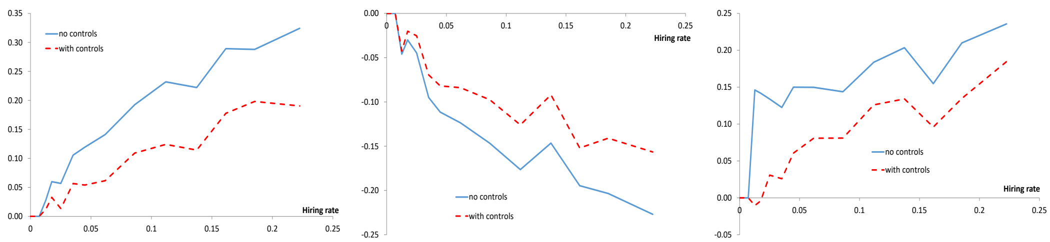
Our wage-based measure of selectivity builds on the difference between the fixed effects of new hires and those of incumbent workers. Thus it compares fixed (unobserved) worker characteristics. Here we show that our results are robust when we consider other measures of selectivity that either build on observed worker characteristics or on match-specific effects.

First, we ask if the composition of hires shifts towards workers with lower education or working in lower-paid occupations. Here we build on the wage equation (2) (with education and occupation controls) and calculate for each worker/year observation (i, t) education and occupation wage



(a) Wage generosity (b) Hiring standards (c) Search effort

Figure 15: Variation of the main recruitment indices (only non-shrinking establishments).



(a) Wage generosity (b) Hiring standards (c) Search effort

Figure 16: Variation of the main recruitment indices (with controls for the time lag).

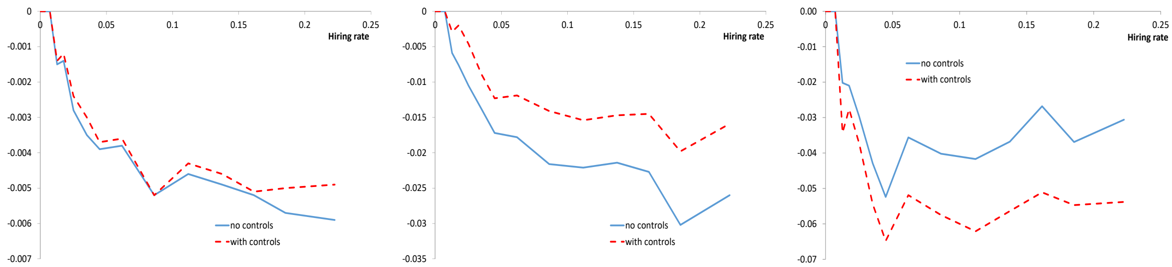
effects $ed_{it} = \beta^{ed} X_{it}^{ed}$, $occ_{it} = \beta^{occ} X_{it}^{occ}$. Then we calculate education and occupation selectivity indices

$$s_{jt}^{ed} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} ed_{it} - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} ed_{it} \ ,$$
$$s_{jt}^{occ} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} occ_{it} - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} occ_{it} \ .$$

Analogous to our selectivity measure s_{jt}^{IEB}, a higher value of s_{jt}^{ed} (s_{jt}^{occ}) means stricter educational (occupational) hiring standards: Relative to the existing workforce, new hires have higher education (work in higher remunerated occupations). When we regress these alternative measures on the establishment's hiring rate (with or without controls), our main negative relationship remains intact, see panels (a) and (b) of Figure 17. Panel (c) obtains a similar finding when our selectivity index is calculated on all observable and unobservable worker characteristics ("full selectivity"),

$$s_{jt}^{Full} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} [f_i + \beta X_{it}] - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} [f_i + \beta X_{it}] \ .$$

While all these IEB selectivity indicators are based on observed or unobserved worker effects,



(a) Occupation Selectivity (b) Education Selectivity (c) Full Selectivity

Figure 17: Alternative IEB selectivity indicators.

we also examine a selectivity indicator variable which is based on match fixed effects. To this end, we include a match effect m_{ij}, in addition to the worker effect f_i,[46] to our wage regression (2) and then calculate a match-level selectivity index

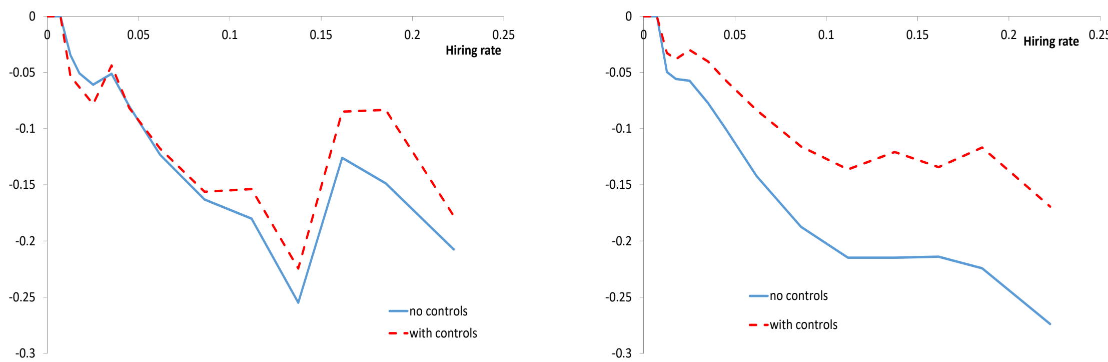
$$s_{jt}^{ME} = \frac{1}{H_{jt}} \sum_{i \in H_{jt}} m_{ij} - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} m_{ij}.$$

If s_{jt}^{ME} is higher, firm j in period t hires workers whose match quality (as measured by the match fixed effects) is larger relative to the match quality of incumbent workers, i.e. the firm is more selective with respect to match quality. Figure 18 shows that our results remain robust when we use this alternative selectivity index. Panel (a) shows the negative relationship of s^{ME} and the establishment's hiring rate, panel (b) confirms a similar result for a combined index which builds on s^{ME} and the two JVS questions on qualification and experience mismatch. Note that the outcome variable in both of these graphs is standardized and that the slope of each index with respect to the hiring rate is similar to the one of the original combined index in Figure 3.d. Specifically, using the controlled relationships in Figure 18, we obtain a slope of -0.544 in panel (a) and -0.675 in panel (b), whereas the slope in Figure 3 is -0.605.

A.7 Variation Across Local Labor Markets

Next to the micro-level relationships between recruitment policies and hiring presented in Section 2, we show here how recruitment indicators correlate with aggregate labor market outcomes across labor markets. To do so, we consider the 36 labor markets segmented by geography and skill that we use in our quantitative model analysis. The first three columns of Table 14 show the correlations between the three main recruitment indicators (means of the standardized index in every market), the job-finding rate f and the unemployment rate u. While wage-generosity does

[46] The inclusion of the establishment fixed effect g_j does not matter for this exercise as it is differenced out in the index s_{jt}^{ME}.



(a) IEB - Selectivity (Match Effects) (b) IEB+JVS Hiring Standards (Match Effects)

Figure 18: Selectivity indicators based on match quality.

not vary systematically with these labor-market indicators, search effort and hiring standards are larger in labor markets with a high job-finding rate and low unemployment. The latter result is consistent with our quantitative finding that firms apply stricter hiring standards in labor markets where job-finding rates are higher. The last two columns of the table show the correlations between the two labor market indicators and the mean and the coefficient of variation (CV) of search costs. In labor markets with high job-finding rates (low unemployment), firms spend more on recruitment and the variation of search costs across firms is smaller. Note that we use the latter variable to calibrate the market-specific parameters controlling the dispersion of recruitment policies.

Table 14: Correlations between recruitment indicators and labor market outcomes across local labor markets

	Wage generosity	Hiring standards	Search effort	Search costs (Mean)	Search costs (CV)
f	0.042	0.414	0.393	0.724	-0.428
u	0.064	-0.524	-0.280	-0.684	0.298

Notes: Correlations between the job-finding rate (f), the unemployment rate (u), and recruitment indicators across the 36 (region$\times$skill) labor markets in Germany (2010–2017).

B. Model Appendix

B.1 Closed-Form Model Solutions

For the parameterization used in Section 4, there are closed-form expressions for the firms' policy variables:

$$
\begin{aligned}
\tilde{x}_p &= (b+\rho)p^{-1} \ , \\
\lambda_p &= \Big[\frac{\mu m_0 (b+\rho)^{1-\alpha} x_0^\alpha p^\alpha}{(r+s)\rho(\alpha-1)}\Big]^{1/(1-\mu)} \ , \\
e_p &= \Big[\frac{\rho(1-\mu)}{c_e \gamma \mu}\Big]^{1/(\gamma-1)} \cdot \lambda_p^{1/(\gamma-1)} \ , \\
V_p &= \Big[\frac{c_e(\gamma-1)}{c_V \Phi}\Big]^{1/(\Phi-1)} \cdot e_p^{\gamma/(\Phi-1)} \ .
\end{aligned}
$$

We can further obtain closed-form expressions for a number of cross-sectional statistics where we make use of the following result.

Lemma: Let $X_p = Ap^\beta$, for some parameters A, β, and let p be distributed with cdf $\Pi(p) = (p/\bar{p})^\eta$. Then the mean and the variance of X_p are

$$
\mathbb{E}(X_p) = \frac{A\eta}{\beta+\eta}\bar{p}^\beta \qquad , \qquad var(X_p) = \frac{\beta^2}{(2\beta+\eta)\eta}\mathbb{E}(X_p)^2 \ .
$$

Using this lemma and the above expressions, we obtain cross-sectional statistics for the means of vacancies V_p, hires $H_p = m(\lambda_p)(1-G(\tilde{x}_p))e_p V_p$ and vacancy yields H_p/V_p (all within a given local labor market):

$$
\begin{aligned}
\mathbb{E}(V_p) =& \Big(\frac{c_e(\gamma-1)}{c_V\Phi}\Big)^{\frac{1}{\Phi-1}} \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e \gamma}\Big)^{\frac{\gamma}{(\Phi-1)(\gamma-1)}} \cdot \Big(\frac{m_0\mu(b+\rho)^{1-\alpha}x_0^\alpha}{\rho(r+s)(\alpha-1)}\Big)^{\frac{\gamma}{(\Phi-1)(\gamma-1)(1-\mu)}} \cdot \\
& \frac{\eta}{\eta + \frac{\alpha\gamma}{(\Phi-1)(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma}{(\Phi-1)(\gamma-1)(1-\mu)}} \ , \\
\mathbb{E}(H_p) =& m_0(\frac{x_0}{b+\rho})^\alpha \cdot \Big(\frac{c_e(\gamma-1)}{c_V\Phi}\Big)^{\frac{1}{\Phi-1}} \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e \gamma}\Big)^{\frac{\Phi+\gamma-1}{(\Phi-1)(\gamma-1)}} \cdot \Big(\frac{m_0\mu(b+\rho)^{1-\alpha}x_0^\alpha}{\rho(r+s)(\alpha-1)}\Big)^{\frac{\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}-1} \cdot \\
& \frac{\eta}{\eta + \frac{\alpha\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}} \ , \\
\mathbb{E}(H_p/V_p) =& m_0(\frac{x_0}{b+\rho})^\alpha \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e \gamma}\Big)^{\frac{1}{\gamma-1}} \cdot \Big(\frac{m_0\mu(b+\rho)^{1-\alpha}x_0^\alpha}{\rho(r+s)(\alpha-1)}\Big)^{\frac{1-\mu+\mu\gamma}{(\gamma-1)(1-\mu)}} \cdot \frac{\eta}{\eta + \frac{\alpha\gamma}{(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma}{(\gamma-1)(1-\mu)}} \ .
\end{aligned}
$$

Integrating over $V_p e_p \lambda_p$ for all firms, we further obtain an expression for aggregate unemployment

$$
U = \Big(\frac{c_e(\gamma-1)}{c_V\Phi}\Big)^{\frac{1}{\Phi-1}} \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e \gamma}\Big)^{\frac{\Phi+\gamma-1}{(\Phi-1)(\gamma-1)}} \cdot \Big(\frac{m_0\mu(b+\rho)^{1-\alpha}x_0^\alpha}{\rho(r+s)(\alpha-1)}\Big)^{\frac{\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}} \cdot
$$

$$
\frac{\eta}{\eta + \frac{\alpha\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma\Phi}{(\Phi-1)(\gamma-1)(1-\mu)}} \ .
$$

We can also obtain closed-form expressions for the mean and variance of search costs that we use to calculate the coefficient of variation, one of our moments for model estimation:

$$\mathbb{E}(c_e e_p^\gamma) = c_e \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e \gamma}\Big)^{\frac{\gamma}{\gamma-1}} \cdot \Big(\frac{m_0 \mu (b+\rho)^{1-\alpha} x_0^\alpha}{\rho(r+s)(\alpha-1)}\Big)^{\frac{\gamma}{(\gamma-1)(1-\mu)}} \cdot \frac{\eta}{\eta + \frac{\alpha\gamma}{(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma}{(\gamma-1)(1-\mu)}} \ ,$$

$$\mathrm{var}(c_e e_p^\gamma) = \Big(\frac{\alpha\gamma}{(\gamma-1)(1-\mu)}\Big)^2 \cdot \frac{1}{\eta(\eta + \frac{2\alpha\gamma}{(\gamma-1)(1-\mu)})} \cdot \mathbb{E}(c_e e_p^\gamma)^2 \ .$$

The above expressions make clear that parameters c_e, m_0, x_0 and $\bar{p}$ affect the means of all these variables in the same way, so that they cannot be separately identified from aggregate statistics. Indeed, all four expressions above depend on these parameters through the term

$$c_e^{-1} \Big(m_0 x_0^\alpha \bar{p}^\alpha\Big)^{\frac{\gamma}{1-\mu}} \ .$$

Hence, parameters c_e, m_0, x_0 and $\bar{p}$ influence the vacancy yield, aggregate vacancies, aggregate unemployment and aggregate hires with the same log-linear proportions, so that only one of these parameters can be identified from the above data targets. To obtain intuition for this result, a lower value of x_0 (less productive workers on the job) requires a higher productivity of firms $\bar{p}$ to generate the same number of hires, unemployment, vacancy yield etc. A lower efficiency of the meeting technology m_0 requires a higher value of $(x_0\bar{p})^\alpha$ to compensate for a lower meeting rate with a higher selection probability so as to end up with the same number of hires, unemployment, vacancy yield, etc. The reason why c_e cannot be separately identified is that a higher value of c_e reduces recruitment effort e, and thus hires, unemployment etc. in the same proportion as a decrease of either m_0 or $(x_0\bar{p})^\alpha$ would do.

Because employment in projects of productivity p is H_p/s, aggregate employment is simply $\mathbb{E}(H_p)/s$. The job-finding rate is given by aggregate hires per unemployed worker which simplifies to

$$\frac{\mathbb{E}(H_p)}{U} = \frac{\rho(r+s)(\alpha-1)}{\mu(b+\rho)} \ .$$

Regarding wages, the model neither pins down wage-tenure profiles nor the variation of wages across workers within the same firm. Assuming that individual wages are constant over time, they need to satisfy (see (10) and (15))

$$\rho(r+s) = \frac{m(\lambda_p)}{\lambda_p} \int_{\tilde{x}_p} w(x) - b - \rho \; dG(x) = m'(\lambda_p) \int_{\tilde{x}_p} px - b - \rho \; dG(x) \ .$$

One wage schedule which is compatible with this condition and which also satisfies the limited commitment constraint that neither the firm nor the worker would dissolve the contract ex-post is

$$w_p(x) = (1-\mu)(b+\rho) + \mu p x \ ,$$

where μ is the constant elasticity of the meeting function.[47] Because expected match-specific productivity is $\mathbb{E}(x|p) = \alpha\tilde{x}_p/(\alpha-1)$, the mean wage in projects with productivity p is

$$\mathbb{E}(w|p) = (b+\rho)\frac{\alpha+\mu-1}{\alpha-1} \ .$$

Output per worker (productivity) in such a project is

$$\mathbb{E}(px|p) = (b+\rho)\frac{\alpha}{\alpha-1} \ .$$

Because more productive projects employ less productive workers, average productivity and wages in all projects (and all firms) are identical.

B.2 Vacancy Yield Decompositions

In Section 4.3 we show how the three recruitment margins contribute to matching efficiency using a decomposition of the job-finding rate. Here we present the equivalent results based on the decomposition of the vacancy yield. Dividing equation (24) by market tightness $\bar{V}/U$ we obtain the vacancy yield as a product of four terms:

$$\frac{H}{\bar{V}} = \underbrace{m_0\Big(\frac{\bar{V}}{U}\Big)^{-\mu}}_{\text{Tightness}} \cdot \underbrace{\bar{e}^{1-\mu}}_{\substack{\equiv m_E \\ \text{Search effort}}} \cdot \underbrace{\frac{\bar{m}}{m(\bar{\lambda})}}_{\substack{\equiv m_W \\ \text{Wage dispersion}}} \cdot \underbrace{\int (1-G(\tilde{x}_p))\frac{m(\lambda_p)e_pV_p}{\bar{m}\bar{e}\bar{V}}\, d\Pi(p)}_{\substack{\equiv m_S \\ \text{Selectivity}}} \ . \tag{27}$$

Note that the contribution of the three matching efficiency terms m_E, m_W and m_S is the same as in the decomposition of the job-finding rate. In contrast, the first term depends negatively on market tightness simply because firms are less likely to meet workers in tighter labor markets.

Table 15 presents the covariance matrix for the logged variables in equation (27), while Tables 16 and 17 show the decompositions of the vacancy yield, paralleling the corresponding tables in Section 4.3. The most notable difference in Table 15 is that the sign of the tightness term is reversed and that this term is also much smaller which is due to the low calibrated value of the meeting function elasticity μ.

For the same reason, differences in market tightness are less important for cross-market differences in vacancy yields as shown in Table 16, while selectivity shows up as the most important driving force. Markets with high vacancy yields have both lower tightness and less selective firms.

[47] If the firm would provide perfect insurance to its applicants against realization of x, it would offer the same wage to all workers which is then $w(x) = w = (b+\rho)(\alpha+\mu-1)/(\alpha-1)$. Alternatively, the log-linear schedule $w(x) = px(\alpha+\mu-1)/\alpha$ also satisfies the above condition. Both alternatives either violate limited-commitment constraints on either the worker (who prefers to quit when $w < b+\rho$) or the firm (which prefers to layoff the worker ex-post if $w > px$).

Table 15: Covariances across local labor markets

Total variance vac. yield 0.33327	Tightness	Search effort	Wage dispersion	Selectivity
Tightness	0.01245	-0.00437	-0.00023	0.05263
Search effort	-0.00437	0.00417	0.00009	-0.01349
Wage dispersion	-0.00023	0.00009	0.00002	-0.00107
Selectivity	0.05263	-0.01349	-0.00107	0.24953

Notes: Covariance matrix of logged variables. Summation over all terms adds up to the variance of the logged vacancy yield (0.33327).

Since firms in tighter markets also exert more effort, the search effort term shows up with a negative sign, but its overall contribution is small, similar to the equivalent table for the job-finding rate decomposition.

Table 16: Relative contributions to the variation of vacancy yields across local labor markets

	Variance VY	Tightness	Search effort	Wage dispersion	Selectivity
Total	0.333	18.1%	-4.1%	0.4%	86.3%
Low skill	0.052	20.5%	-10.6%	-0.2%	90.3%
Medium skill	0.192	15.7%	0.7%	-0.1%	83.7%
High skill	0.061	16.3%	-3.1%	-1.0%	87.9%

Notes: The first row shows the percentage contribution to the total variance of the log vacancy yield (summation over the rows or columns in Table 15. The bottom three rows repeat this calculation for the variation across the 12 regions separate by skill level.

Regarding differences between skills, Table 17 shows that vacancy yields are lower in medium- and high-skill markets compared to low-skill markets. The model explains these differences through greater market tightness and more selective firms. However, firms also exert greater search effort when hiring skilled workers, which mitigates the gap in vacancy yields.

Table 17: Average log differences to low-skill labor markets

	VY	Tightness	Search effort	Wage dispersion	Selectivity
Medium skill	-0.176	-0.113	0.134	0.001	-0.198
High skill	-1.095	-0.235	0.100	0.004	-0.965

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