Carrillo-Tudela, Carlos; Gartner, Hermann; Kaas, Leo

Working Paper

Recruitment policies, job-filling rates and matching efficiency

IAB-Discussion Paper, No. 15/2020

Provided in Cooperation with:
Institute for Employment Research (IAB)

Suggested Citation: Carrillo-Tudela, Carlos; Gartner, Hermann; Kaas, Leo (2020) : Recruitment policies, job-filling rates and matching efficiency, IAB-Discussion Paper, No. 15/2020, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg

This Version is available at:
https://hdl.handle.net/10419/222400

INSTITUTE FOR EMPLOYMENT RESEARCH
The Research Institute of the Federal Employment Agency

IAB-DISCUSSION PAPER

Articles on labour market issues

15|2020 Recruitment Policies, Job-Filling Rates and Matching Efficiency

Carlos Carrillo-Tudela, Hermann Gartner, Leo Kaas

Recruitment Policies, Job-Filling Rates and Matching Efficiency

Carlos Carrillo-Tudela (University of Essex)
Hermann Gartner (IAB Nuremberg and Friedrich-Alexander University Erlangen-Nuremberg)
Leo Kaas (Goethe University Frankfurt)

Mit der Reihe „IAB-Discussion Paper“ will das Forschungsinstitut der Bundesagentur für Arbeit den Dialog mit der externen Wissenschaft intensivieren. Durch die rasche Verbreitung von Forschungsergebnissen über das Internet soll noch vor Drucklegung Kritik angeregt und Qualität gesichert werden.

The “IAB-Discussion Paper” is published by the research institute of the German Federal Employment Agency in order to intensify the dialogue with the scientific community. The prompt publi-cation of the latest research results via the internet intends to stimulate criticism and to ensure research quality at an early stage before printing.

Contents

List of Figures

Abstract

Recruitment behavior is important for the matching process in the labor market. Using unique linked survey-administrative data, we explore the relationships between hiring and recruitment policies. Faster hiring goes along with higher search effort, lower hiring standards and more generous wages. To analyze the mechanisms behind these patterns, we develop a directed search model in which firms use different recruitment margins in response to productivity shocks. The calibrated model points to an important role of hiring standards for matching efficiency and for the impact of labor market policy, whereas search effort and wage policies play only a minor role.

Zusammenfassung

Für das Matching am Arbeitsmarkt spielt das Rekrutierungsverhalten der Betriebe eine zentrale Rolle. Um zu untersuchen, wie das Rekrutierungsverhalten mit der Zahl der Einstellungen zusammen hängt, verknüpfen wir die IAB-Stellenerhebung mit administrativen Daten. Es zeigt sich: Mehr Einstellungen sind mit mehr Suchaufwand verbunden, mit großzügigeren Löhnen und mit geringeren Anforderungen an die Arbeitsuchenden. Um zu analysieren, welcher Mechanismus diesem Muster zugrunde liegt, entwickeln wir ein Modell mit zielgerichteter Suche. Betriebe können dabei bei Produktivitätsschocks ihr Rekrutierungsverhalten über mehrere Stellschrauben anpassen. Im kalibrierten Modell erweist sich das Anforderungsnieveau als wichtigste Stellschraube für die Auswirkung auf die Matching-Effizienz und für die Wirksamkeit von Arbeitsmarktpolitik. Suchaufwand und die Lohnpolitik spielen demgegenüber eine kleinere Rolle.

JEL

E24; J23; J63

Keywords

Vacancies; Recruitment; Labor market matching

Acknowledgements

We thank Alex Clymo, Melvyn Coles, Steven Davis, Pedro Gomes, Rafael Lopez de Melo, Simon Mongey, Ctirad Slavik, Gianluca Violante, and seminar and conference audiences at Essex SaM workshop, IAB Nuremberg, Macro-SaM Marrakech workshop, Essex-Frankfurt SaM workshop, IZA Workshop: Heterogeneity and the Labor Market (Bonn), SaM Virtual Congress, Aarhus, Birbeck, Tilburg and Uppsala for their comments and discussions. Hermann Gartner and Leo Kaas thank the German Research Foundation (grant GA 2737/2 and KA 1519/10) for financial support. An earlier version of this paper circulated under the title "Understanding Vacancy Yields - Evidence from German Data".

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/Faberman/Haltiwanger, 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/Mongey/Violante, 2018). While there is a great amount of work documenting the effectiveness of workers' job search efforts, 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 their policies.

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/Mongey/Violante, 2018), they may pay higher wages (or offer more attractive non-pecuniary job benefits) to attract more workers (e.g. Kaas/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, it is difficult to assess which of these channels are responsible for the observed variation in job-filling rates and ultimately in matching efficiency.

In this paper we investigate the following aspects of recruiting intensity: (i) the extent to which firms use search effort, wage generosity and hiring standards to hire faster; (ii) the impact of these recruitment margins on matching efficiency; (iii) the impact that labor market policy has on these recruitment margins and through them on job-finding rates. We do this by first presenting new evidence on how search effort, wage generosity and hiring standards vary with hiring and job-filling rates. In order to understand the economic mechanisms behind these relationships and their impact on matching efficiency, we propose and quantitatively assess an equilibrium search-and-matching model of the labor market where dif-

ferential hiring rates are determined by vacancy creation, search effort, wage generosity and hiring standards decisions. Our findings show an important role of employers' hiring standards for matching efficiency and labor market policies that aim at increasing workers' job finding prospects, whereas employers' search effort and wage generosity only play a minor role.

To describe the empirical patterns, we analyze data from the Job Vacancy Survey (JVS), an annual survey of German establishments, which we link to administrative matched employer-employee data (Integrated Employment Biographies, IEB) for the period 2010–2017. 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/Faberman/Haltiwanger (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 along the establishment growth distribution arises from the vacancy yields margin; that is, establishment that grow faster hire more per vacancy. This is a robust relationship that holds after controlling for establishment size, age and industry (see also Mongey/Violante, 2020). We also examine whether the observed characteristics of new hires, such as previous employment status, age or gender vary systematically with the establishments' growth rates, 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 for the last case of a hire. This information can be connected to the factual hiring patterns of the establishment from the linked administrative data. We construct separate indices capturing each establishment's search effort, wage generosity and hiring standards. These indices build on direct information from the survey, but also utilize wage information for all new hires during the same period 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. Concerning variation of vacancy yields across local labor markets and over time to investigate aggregate labor market outcomes, we find that together all three recruitment measures contribute in a similar proportion as labor market tightness to the variation in vacancy yields, pointing to their importance in determining matching efficiency.

To investigate the mechanisms behind these patterns, we build a tractable directed search model similar to Moen (1997) and Garibaldi/Moen (2010) in which multi-worker firms oper-

ate multiple projects with 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 relationship between firm growth and vacancy yields where the latter is an endogenous outcome of all three recruitment policies.

A key feature of our model is that it provides a novel structural decomposition of the aggregate job-finding rate in terms of labor market tightness, on the one hand, and the three recruitment policies on the other. This decomposition allows us to quantitatively investigate how recruitment behavior contributes to matching efficiency. It also allows us to evaluate the equilibrium effects of labor market policy on the firms' recruitment behavior and, thus, on the rate at which unemployed workers find jobs.

The model is calibrated using the evidence from the JVS and IEB data as well as data on worker flows to inform the main structural parameters. We exploit cross-sectional variation in the data 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 reproduce market-specific (average) wages, unemployment and job-finding rates, as well as the cross-sectional relationships between vacancy yields and establishment growth, and the relative responsiveness of search effort, wage generosity and hiring standards to the variation in hiring rates across establishments that we document empirically. The model is also consistent with the observed variation in vacancy yields, labor market tightness, search effort and hiring standards across local labor markets.

Using the model-implied decomposition of the matching function, we find that most of the variation of the job-finding rate 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, more productive labor markets unemployed workers have higher reservation wages and hence firms must become more selective when they offer sufficiently high wages to fill their positions. This feature matters when comparing labor markets both across the skill and the geographic dimensions. It is also consistent with the observation that job-finding rates, average wages and hiring standards are positively correlated across local labor markets in the data.

Variation of search effort has a positive, but quantitatively less important effect on job-finding rates, although we observe a more prominent 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 does not differ between markets in our model and hence does not contribute to the variation of matching efficiency.[1] This implication is consistent with the observation that in our data wage dispersion (measured by the coefficient of variation) varies little across local labor markets, particularly when controlling for skill levels.

Finally, to investigate the role of labor market policy for job-finding rates through its effects on recruitment measures, 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. Our calibrated model shows that job-finding rates increased the most in low-skill labor markets. Similar to our findings for matching efficiency, the creation of jobs (market tightness) and hiring standards are the two dominant forces that shift 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 about a quarter of the increase in the job-finding rate for the whole labor market. For the low-skill labor market, this margin is even more prominent where it is responsible for a third of the increase of the job-finding rate. On the other hand, changes of search effort or wage dispersion do not matter much for the aggregate policy effects. The importances of vacancy creation and the selectivity margin provide a natural explanation for the findings of Carrillo-Tudela/Launov/Robin (2020), who show that job-finding rates increase the most in low-skill labor markets after the implementation of the Hartz reforms.

Related Literature

Our paper contributes to a large and growing literature that documents the several aspects of firms' recruitment policies. Early examples are Barron/Bishop (1985) and Barron/Bishop/Dunkelberg (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

[1] 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.

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/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.[2] Faberman/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/Wolthoff (2020) show using online U.S. vacancy data 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.[3] Further, Kettemann/Mueller/Zweimueller (2018) use administrative data on Austrian job centres and link it to matched employer-employee administrative data, finding a positive relation between vacancy filling rates and starting wages. Our results complement these findings, showing that lower hiring standards, more generous wage policies and higher search effort all go together with larger hiring rates.

Davis/Faberman/Haltiwanger (2012, 2013) using JOLTS micro data were the first who described the "hockey stick" relationships between establishment growth, hiring rates and vacancy yields. We verify that such relationships are similar in our German data and we investigate to what extent different recruitment policies help firms hire faster. Lochner et al. (2020) 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 vacancy yields and hiring rates. 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/Faberman/Haltiwanger (2013). Recent work extends the canonical Diamond-Mortensen-Pissarides framework to feature multi-worker firms which chose search effort as in Gavazza/Mongey/Violante (2018) and Leduc/Liu (2017) or wages as in the competitive-search models of Kaas/Kircher (2015) and Schaal (2017). Selection cutoffs among heterogenous pools of applicants (hiring standards) are also introduced in random search environments like the ones

[2] See also Van Ours/Ridder (1992) for evidence on vacancy durations using Dutch data.

[3] Using online Chilean vacancy data, Banfi/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/Kircher/Mueller (2018) find a similar positive relationship between posted wages and applications using a field experiment among job seekers.

proposed by Acharya/Wee (2020), Baydur (2017), Chugh/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.[4] 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 job-filling rates in multi-worker firms and how they matter for aggregate matching efficiency and labor market policy.

[4] 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 complicated 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 primary 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 the recruitment processes of these establishments. 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 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 of the survey contains detailed information about the recruitment behavior of the surveyed establishment. For that purpose, information about the last case of a successful hire within the last 12 months is collected. Not all surveyed establishments hired a worker in the last 12 months (or did not fill this part of the survey for other reasons). Thus we have information about the recruitment behavior for a subsample of around 9,000-10,000 establishments per year. 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 about 90 percent of the cases, the recorded information for the last case of a hire corresponds to single vacancy job openings.[5] Appendix A presents the main summary statistics of our JVS

[5] Carrillo-Tudela et al. (2020) are able to identify the worker hired in the JVS in the IAB 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 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 percent 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 percent. Further, nearly all of these multiple

sample. Note that by design of the survey, the search event is finished before the date of interview.

We can link the JVS to the administrative records of individual employment spells which are collected by the Federal Employment Agency (*Integrated Employment Biographies*, IEB).[6] Thus we can observe, for any particular day, all employed workers in JVS establishments (with information about education, age, gender, nationality and daily earnings), and thus infer their hires and separations during any arbitrary time interval.[7] We measure vacancy rates, hiring rates and employment growth rates over intervals of 30 days after the day of interview. This allows us to calculate a measure of the *vacancy yield* (hires divided by the stock of vacancies at the beginning of the period), hence analogously to the monthly vacancy yield that Davis/Faberman/Haltiwanger (2013) consider using data from the Job Openings and Labor Turnover Survey (JOLTS).

2.2 Variation in Hiring Rates and Vacancy Yields

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 decomposition

$$\frac{H}{E} = \frac{V}{E} \times \frac{H}{V} \,. \tag{2.1}$$

We present the variation of each of these components across employment growth bins. This approach allows us to somewhat mitigate a common measurement problem in such data: at the interview date many establishments report no vacancies, while in the 30 days following the interview positive hires are recorded.[8] We measure the employment growth rate over 30-day intervals using average size at the beginning and at the end of the interval in the denominator (cf. Davis/Haltiwanger/Schuh, 1998). We partition these monthly employment growth rates into 29 bins around zero.[9] We remove those (typically small) establishments which grow or shrink by more than 30 percent during the interval. Figure 1.a shows the distribution of

hires in many of the regressions discussed below.

[6] The IEB data set encompasses the universe of establishments in Germany that have at least one employee paying social security contributions. Summary statistics about worker characteristics in the merged sample are presented in Appendix A.

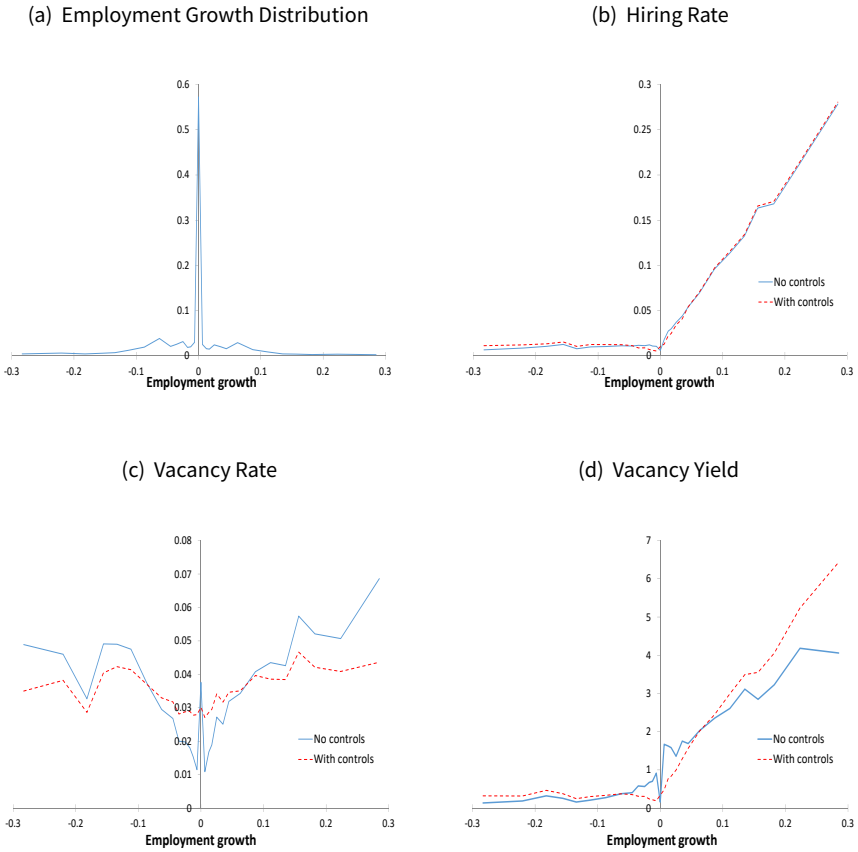
[7] We exclude employer returns from hires and separations. That is, we do not count as part of hires or separations all those workers whose employment spell is interrupted for a period less than three months and who return to their previous employers.

[8] Aside from misreporting, this can arise, for example, as some establishments posted vacancies, 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 vacancy was posted after the interview date and was filled sufficiently quickly within the 30-day interval after the JVS interview. Our data do not allow us to explore these possibilities.

[9] Next to a mass point at zero, we use 28 symmetric bins with positive and negative growth rates where intervals closer to zero are smaller.

monthly employment growth, where 58.2 percent (38,767 observations) of establishments exhibit zero growth, 24.4 percent (16,269 observations) exhibit negative growth and 17.4 percent (11,564 observations) positive growth.

Figure 1: Variation by 30-day establishment growth



Source: Own calculation.

Figure 1.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/Faberman/Haltiwanger, 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. We do this in order to illustrate

that these patterns are not merely induced by a changing industry or establishment size/age compositions across bins of establishment growth.

Figure 1.c shows the variation of vacancy rates, defined as vacancies reported at the interview 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 two percent for stable establishments to over five percent for establishments that grow by more than 20 percent 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 percent across shrinking, stable and expanding establishments.

Figure 1.d shows the variation of vacancy yields across employment growth bins where, following (2.1), 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 particular growth bin by the total vacancies of these establishments. As found in JOLTS data, 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). In conclusion, variation in hiring rates across growth bins is predominately accounted for by the vacancy yield margin rather than differences in vacancy rates.

Investigating whether expanding 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 6 in Appendix A).

2.3 Recruitment Policies and Hiring Rates

The previous findings indicate that larger employment expansions go along with higher job-filling rates. In the following we shed light on how these establishments achieve faster hiring. In particular, we are interested in 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 elsewhere as the main instruments employers have at their disposal to increase their hiring (see e.g. Gavazza/Mongey/Violante, 2018; Kaas/Kircher, 2015; Sedlacek, 2014). 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 measure 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.[10]

To analyze to what extent faster hiring goes along with specific recruitment policies across establishments, we regress various recruitment policy variables on 15 bin dummies for the establishment's 90-day hiring rate, ranging from a mass point at zero to intervals up to 25 percent. Next to these relationships, 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). We show in Appendix A that our results are similar when we remove the smallest establishments (those with less than 20 employees) or observations with zero hires from the sample. The presence of small establishments may be a concern because they can never have small and positive hiring rates.[11]

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 behavior, especially after controlling for characteristics of the specific job, is sufficiently representative of the establishment's recruitment policy in the period under consideration. Another potential concern is the extent to which measurement error pollutes the JVS recruitment measures we use here.[12] To somewhat temper these concerns, 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 sets 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.

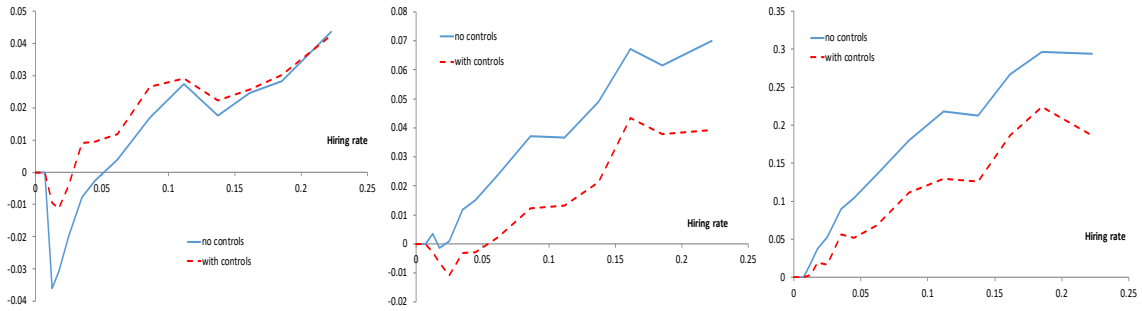
[10] We also re-computed the relationships depicted in Figure 1 using 90-day intervals and find no meaningful change in our conclusions.

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

[12] Measurement error in the JVS could, for example, arise due to a recall error from the employee responding the survey. Other potential problems can be associated to non-response issues for which appropriate weights are provided (see Brenzel et al., 2016: for details).

Figure 2: Wage generosity and hiring rates

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



Source: Own calculation.

Wage generosity

To measure the generosity of an employer's wage policy at the hiring stage, the JVS provides 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. It illustrates that establishments which hire more also had to make more wage concessions.

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 (age 23 to 55), male full-time workers, we estimate

$$\ln w_{it} = f_i + g_{j(i)} + \delta_t + \beta X_{it} + \eta_{it} \,, \tag{2.2}$$

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}):[13]

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

[13] H_{jt} are all hires during the 90-day interval around the last case of hiring in the JVS as described above.

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 firm. Figure 2.b shows the relationship (with and without controls) between $\hat{w}_{jt}^{IEB}$ and the hiring rates. Here we observe that establishments which hire more paid on average higher wages to their new hires relative to these workers' predicted wages. Given than $\hat{w}_{jt}^{JVS}$ and $\hat{w}_{jt}^{IEB}$ might measure different aspects of employers' wage policies, we construct a combined *wage generosity* measure $\hat{w}_{jt}$ as the weighted 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.[14]

Hiring standards

The JVS provides information on two aspects that shed light on employers' hiring standards. Employers are asked directly whether they eventually hired a worker whose (i) qualification or (ii) experience is 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 otherwise. Figures 3.a and 3.b show the relationship between the 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 goes together with higher hiring rates. Relative to those establishments with low hiring rates, establishments with larger hiring rates apply lower hiring standards.

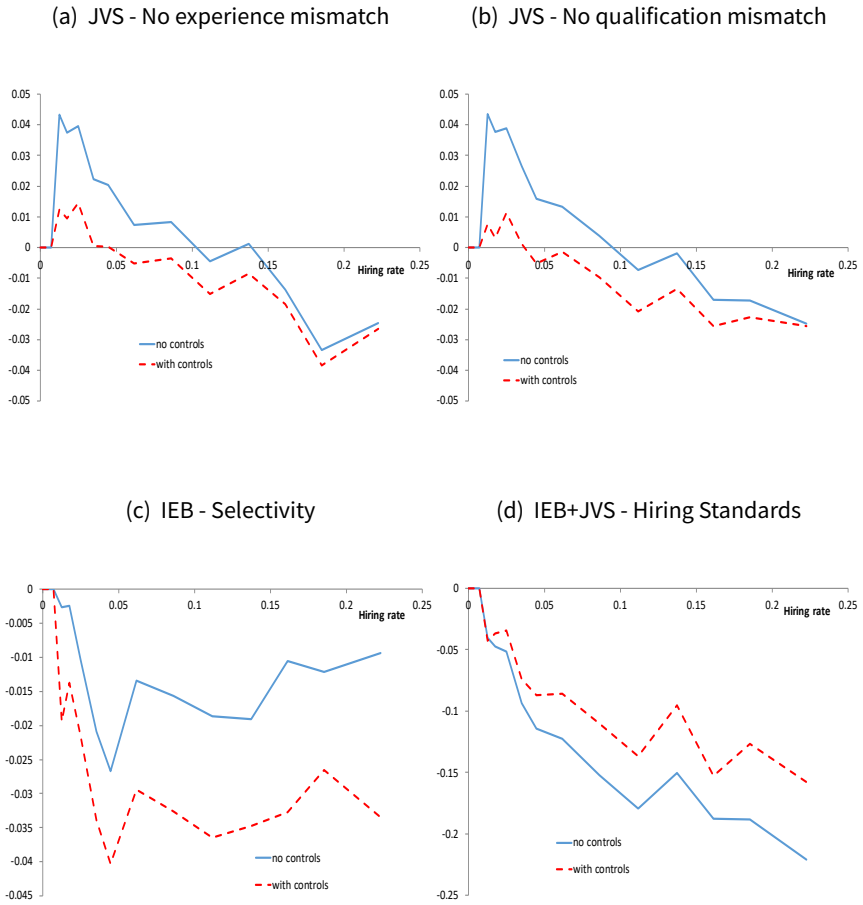
To complement these measures, we use the wage equation (2.2) on IEB data and define an alternative selectivity measure as the difference between the average fixed effect of new hires (H_{jt}) and the average fixed effect among the rest of the workforce (N_{jt}) in establishment j at time t:

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

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. 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. 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'

[14] In Appendix A we report the values of the estimated coefficients shown in Figures 2–4, many of which are significantly different from zero at the 1 or 5 percent level. We take the reference category to be the case of a zero hiring rate.

Figure 3: Hiring standards and hiring rates



Source: Own calculation.

hiring standards s_{jt}.

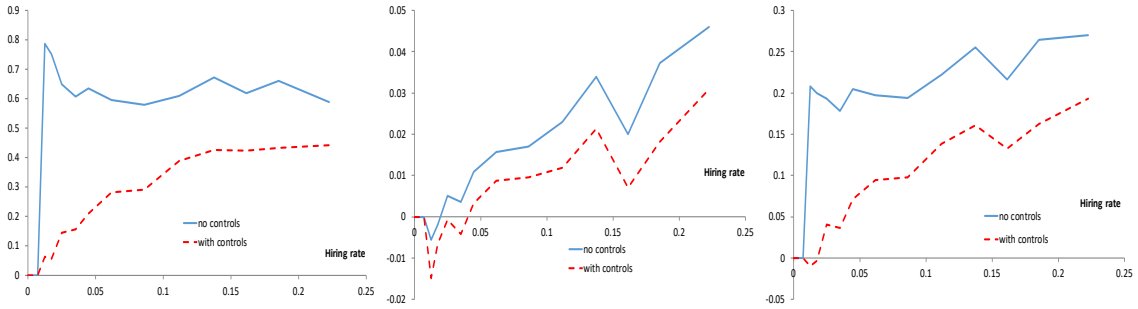
Search effort

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. Figure 4.a shows the relationship between the number of search channels used by an establishment and its

hiring rate; while Figure 4.b shows the relationship between the geographical extent of the establishment's search and its hiring rate. Figure 4.c then 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 goes together with higher search effort.

Figure 4: Search effort and hiring rates

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



Source: Own calculation.

Relative responsiveness of the recruitment indices across establishments

The above results show clear relationships 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 0.997, the slope of the hiring standards index is -0.544, and the slope of search effort is 0.884. That is, when the hiring increases by ten percentage points, wage generosity (search effort) goes up by 0.100 (0.088, resp.) standard deviations, and hiring standards decrease by 0.054 standard deviations. Therefore, 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 variations across establishments).

2.4 Vacancy Yields Across Labor Markets

After exploring the micro-level relationships between recruitment policies and hiring, we now examine to what extent recruiting intensity matters for aggregate labor market outcomes.

Specifically, we analyze how the three recruitment indices contribute to the variation of vacancy yields across labor markets and over time. To do so, we consider 36 labor markets segmented by geography and skill which are based on the aforementioned three job skill requirements obtained from the JVS and on 12 German regions.[15] Over the period 2010–2017, these are 288 observations (region$\times$skill$\times$year). We regress the vacancy yield (hires per vacancy) on market tightness (vacancy-unemployment ratio) and on the mean values of each of the three standardized recruitment indices introduced above.

Table 1: Vacancy yields across labor markets

OLS	(1)	(2)	(3)	(4)	(5)	(6)
θ - Market tightness	-0.948***	-0.856***	-0.894***	-0.805***	-0.835***	-0.845***
	(0.230)	(0.227)	(0.224)	(0.225)	(0.228)	(0.225)
Search Effort			0.812***			0.753***
			(0.266)			(0.267)
Hiring Standards				-1.014***		-0.920**
				(0.376)		(0.376)
Wage Generosity					0.250	0.002
					(0.287)	(0.288)
Constant	1.972***	2.574***	2.571***	2.572***	2.537***	2.570***
R^2	0.053	0.095	0.122	0.115	0.113	0.146
Year dum.	N	Y	Y	Y	Y	Y
N obs	288	288	288	288	288	288

*** $p < 0.001$; ** $p < 0.05$; * $p < 0.10$. Standard errors in parenthesis.

Source: Own calculation.

Table 1 shows the coefficients of OLS regressions. The first two columns report only the correlations between labor market tightness and vacancy yields, with and without year dummies. Columns (3) to (5) include in isolation the correlations between market-specific averages of our three recruitment measures and the vacancy yields. Column (6) then considers the impact of all recruitment measures together. We find that tighter labor markets have lower vacancy yields, consistent with a standard matching function. The coefficients for wage generosity and search effort are positive and the one for hiring standards is negative. They are statistically significantly different from zero for search effort and higher standards, but not for the wage generosity index, suggesting little variation of average wage generosity across local labor markets.

To investigate these measures' relative impact in explaining the variation of vacancy yields, we compare the fit of the OLS regression across columns (3) to (5) relative to column (2). We find that all three recruitment measures have a similar impact in increasing the R^2. Noting that θ on its own without the year dummies (column (1)) generates an $R^2 = 0.053$, column (6) then suggests that together our recruitment measures contribute in explaining the variability of vacancy yields across local markets in a similar magnitude as labor market tightness. This shows a prominent role of recruiting intensity for matching efficiency to which we return in Section 4. In Appendix A we also show that a similar conclusion holds when controlling for market (i.e. skill$\times$region) fixed effects.

[15] The regions are based on the 16 states (*Bundesländer*) where we merge the city states Berlin, Bremen and Hamburg, as well as Saarland to their respective neighboring states.

3 The Model

We now develop a parsimonious search and matching model where firms have different margins to fill vacancies. Consistent with our empirical patterns, these margins are wage policies, search effort, and hiring standards. In the next section we use this model to quantify the impact of these margins for the variation in matching efficiency and for the effectiveness of labor market policy.

Environment

Time is continuous and the economy is in steady state. There is 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 finite set $P \subset \mathbb{R}_+$ with probabilities π_p, $p \in P$.[16] 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. This simplification captures that expanding establishments (the focus of our paper) hire workers externally into new positions.[17] It also allows us to keep separations exogenous and hence permits a tractable characterization of firm policies in the presence of firm-specific shocks.

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

[16] In principle the new draw of p could be correlated with the productivity of the last project to capture possibly persistence of the firm's management and/or innovation capabilities. To keep the theory as parsimonious as possible, we assume uncorrelated productivity draws.

[17] 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 percent.

$c_V(V)$, 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 $c_V(V)+V \cdot c_e(e)$.

We assume that only unemployed workers search for jobs.[18] Upon meeting, the worker-firm pair draws a match-specific productivity $x \sim G(.)$ with support X. If the worker is hired at a firm with current project productivity p, the flow output of the match is $p \cdot x$ for the duration of the match. In addition to firm exit at rate δ, employed workers exogenously separate from firms into unemployment at Poisson rate s, hence the total separation rate is $s + \delta$. 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 matching 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 $w(x)$.[19] 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

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

A firm with current project 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

[18] This assumption is motivated by the JVS evidence showing no meaningful difference in the hiring behavior of expanding establishments with respect to the previous employment status of its new hires (see Figure 6.a).

[19] 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 details.

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 project productivity p only 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 can then be expressed by

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

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 given by

$$\bar{\rho}(\tilde{x}, w, \lambda) \equiv \frac{m(\lambda)}{\lambda}\int_{\tilde{x}} [W^e(w(x)) - W^u]dG(x)\,. \tag{3.1}$$

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 project 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

$$\max_{V,e,\tilde{x},w,\lambda} eVm(\lambda)\int_{\tilde{x}} \frac{px - w(x)}{r+s+\delta}\,dG(x) - c_V(V) - Vc_e(e) \tag{3.2}$$

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

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

$$\bar{\rho}(\tilde{x}, w, \lambda) \leq \rho \quad , \quad \lambda \geq 0 \,, \tag{3.3}$$

with complementary slackness (choice of submarkets). Furthermore,

$$\sum_{p \in P} \pi_p V_p e_p \lambda_p \leq u\bar{L} \quad , \quad \rho \geq 0 \,, \tag{3.4}$$

with complementary slackness (labor market participation).

3. Stationary unemployment (stock-flow consistency):

$$(1-u)\bar{L}(s+\delta) = \sum_{p \in P} \pi_p (1 - G(\tilde{x}_p)) m(\lambda_p) e_p V_p \,. \tag{3.5}$$

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 (3.3). 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 (3.4) where the left-hand side is aggregate unemployment ($V_p e_p \lambda_p$ unemployed workers search for employment in firms with current productivity p which constitute measure π_p) and the right-hand side is aggregate non-employment. Condition (3.5) says that unemployment inflows (= separations, left-hand side) are equal to outflows (= hires, right-hand side).

Conditions (3.4) and (3.5) can be combined to

$$\sum_{p \in P} \pi_p \left(\frac{H_p}{s+\delta} + V_p e_p \lambda_p \right) \leq \bar{L} \,, \tag{3.6}$$

where $H_p = (1 - G(\tilde{x}_p)) m(\lambda_p) e_p V_p$ is the flow of hires of firms with current project productivity p. $H_p/(s+\delta)$ is aggregate employment in all projects with productivity p, and $V_p e_p \lambda_p$ are unemployed workers searching for jobs at firms with current project productivity p. Hence inequality (3.6) 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 (3.6), 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.[20]

[20] 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.

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

$$\frac{m(\lambda)}{\lambda} \int_{\tilde{x}} \frac{w(x) - b - \rho}{r + s + \delta} \, dG(x) = \rho \tag{3.7}$$

to make sure that unemployed workers are attracted to these vacancies, see condition (3.3) together with (3.1).

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

$$q_p \equiv \frac{H_p}{V_p} = e_p \cdot m(\lambda_p) \cdot (1 - G(\tilde{x}_p)) \, . \tag{3.8}$$

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 productivity p. They can be related to firms' 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 two forces: (i) new firms enter with flow probability δ, and (ii) existing firms draw new project productivities with flow probability χ. In both cases firms adjust their workforce, but they do not do so instantaneously due to convex vacancy and search effort costs.

While a firm's hires flow depends on the productivity of the current project, the separation rate is constant. Thus, employment in a firm with project productivity p and size N adjusts according to

$$\dot{N} = H_p - sN \, .$$

Therefore, the firm's employment growth rate $\dot{N}/N$ varies with the hiring rate H_p/N according to $\dot{N}/N = H_p/N - s$. The cross-sectional relationships between firm growth $\dot{N}/N$, hiring rates H_p/N, vacancy rates V_p/N and job-filling rates q_p depend on the joint distribution of project productivity p and employment N. Write $\Psi_p(N)$ for the cumulative distribution of firms by employment size, conditional on current project productivity p, and let $\Psi(N) \equiv \sum_{p \in P} \pi_p \Psi_p(N)$ be the mass of firms with employment less than or equal to N. In steady state, these distributions satisfy

$$\delta(1 - \Psi_p(N)) + \chi(\Psi(N) - \Psi_p(N)) = \Psi_p'(N)(H_p - sN) \, , \tag{3.9}$$

for all $p \in P$ and $N \geq 0$.[21] This system of differential equations can be solved subject to the boundary conditions $\Psi_p(0) = 0$ and $\Psi_p(\bar{N}) = 1$, where $\bar{N} = H_{\bar{p}}/s$ is the employment that a firm with maximal productivity $\bar{p} = \max\{p \in P\}$ would reach in the absence of shocks.[22]

Characterization of Recruitment Policies

Substitute (3.7) into (3.2) to rewrite the firm's problem:

$$\max_{V,e,\tilde{x},\lambda} V \cdot \left\{ em(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s + \delta} \, dG(x) - e\lambda\rho - c_e(e) \right\} - c_V(V) \, . \tag{3.10}$$

The first-order conditions are

$$p\tilde{x} = b + \rho \, , \tag{3.11}$$

$$c_e'(e) = m(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s + \delta} \, dG(x) - \lambda\rho \, , \tag{3.12}$$

$$\rho = m'(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s + \delta} \, dG(x) \, , \tag{3.13}$$

$$c_V'(V) = em(\lambda) \int_{\tilde{x}} \frac{px - b - \rho}{r + s + \delta} \, dG(x) - e\lambda\rho - c_e(e) \, . \tag{3.14}$$

Equation (3.11) 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 project productivity p and the hiring threshold $\tilde{x}$. Combining (3.12) and (3.13) gives

$$c_e'(e) = \rho \frac{m(\lambda) - \lambda m'(\lambda)}{m'(\lambda)} \, , \tag{3.15}$$

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 (3.11) and (3.13) give rise to

$$\rho = m'(\lambda) \frac{b + \rho}{r + s + \delta} \int_{\tilde{x}} \frac{x}{\tilde{x}} - 1 \, dG(x) \, . \tag{3.16}$$

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 work-

[21] Consider the mass of firms with employment up to N and project productivity p, which is $\pi_p \Psi_p(N)$. The inflow into this group is $\delta\pi_p + \chi\pi_p\Psi(N) + \pi_p\Psi_p'(N)\max(0, sN - H_p)$ (i.e. entrants plus firms drawing new productivity p plus firms contracting in size just above N). The outflow of this group is $\delta\pi_p\Psi_p(N) + \chi\pi_p\Psi_p(N) + \pi_p\Psi_p'(N)\max(0, H_p - sN)$ (i.e. exits plus firms drawing new productivity plus firms growing in size just below N). Equating inflows and outflows and canceling π_p gives equation (3.9).

[22] $\Psi_p(.)$ may not be differentiable at $N = H_p/s$ which complicates the numerical solution of this system of differential equations. We obtain a numeric solution by solving for the invariant distribution of the Markov process describing the dynamics of firms over discrete time intervals dt on finite state space $P \times \mathcal{N}$ where $\mathcal{N}$ is a discrete grid of $[0, \bar{N}]$.

ers with similar productivity. Finally, substitute (3.12) into (3.17) to obtain

$$c'_V(V) = ec'_e(e) - c_e(e)\,. \tag{3.17}$$

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

Therefore, we can conclude that firms with higher current project productivity p (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.[23] To the extent that project productivity p is the only source of heterogeneity between firms (as assumed in this model), all three factors in equation (3.8) which contribute to job-filling rates q_p are positively correlated: Firms with more productive projects have higher search effort e_p, a higher meeting rate per effective vacancy $m(\lambda_p)$ and a larger hiring probability conditional on a meeting, $1 - G(\tilde{x}_p)$.[24] The respective percentage contributions to the variation of job-filling rates can be written

$$\frac{dq}{q} = \frac{de}{e} + \frac{m'(\lambda)\lambda}{m(\lambda)} \cdot \frac{d\lambda}{\lambda} - \frac{G'(\tilde{x})\tilde{x}}{1 - G(\tilde{x})} \cdot \frac{d\tilde{x}}{\tilde{x}}\,. \tag{3.18}$$

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

$$\frac{dq}{q} = \frac{dp}{p}(1 - \varepsilon_{\Psi,\tilde{x}})\Big\{ \underbrace{\frac{1}{(1 - \varepsilon_{m,\lambda})\varepsilon_{c'_e,e}}}_{=\text{search effort}} + \underbrace{\frac{(1 - \varepsilon_{\Phi,\tilde{x}})\varepsilon_{m,\lambda}}{-\varepsilon_{m',\lambda}}}_{=\text{wages}} + \underbrace{\frac{G'(\tilde{x})\tilde{x}}{(1 - G(\tilde{x}))(1 - \varepsilon_{\Psi,\tilde{x}})}}_{=\text{hiring standards}} \Big\}\,, \tag{3.19}$$

where $\varepsilon_{f,z}$ denotes the elasticity of a function f with respect to variable z, and $\Psi(\tilde{x}) \equiv \int_{\tilde{x}} x - \tilde{x}\, dG(x)$. This decomposition shows how the functional forms of the matching 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.

[23] This generalizes Kaas/Kircher (2015) who show that firms use both more vacancy postings and higher wage offers when they hire faster.

[24] 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.

4 Quantitative Analysis

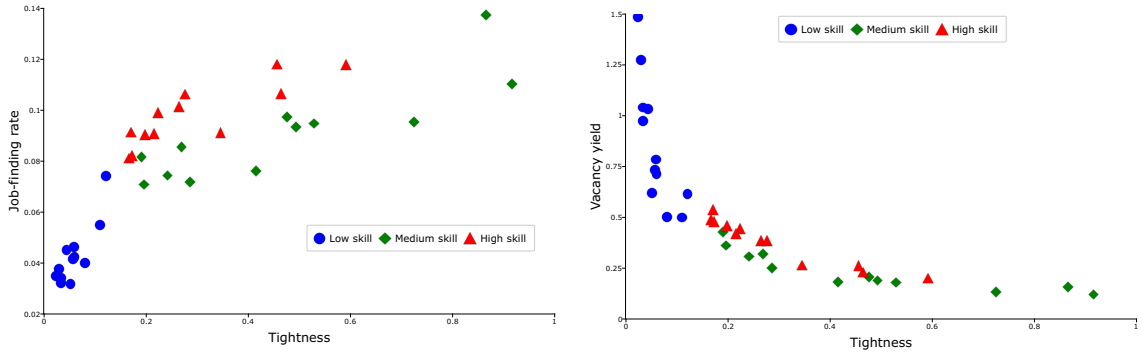
How does recruitment behavior contribute to the cross-sectional variation of matching efficiency? Does recruiting intensity matter for the impact of labor market policy? To answer these questions, we parameterize our model and calibrate its parameters to match selected statistics of the German labor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

We explore variation across different local labor markets which are segmented in the same way as in Section 2. 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.[25] We further abstract from complementarities in production between different skill groups. With these assumptions, our model describes a given local labor market. 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 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.

[25] In particular, most metropolitan areas are contained 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.

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



Source: Own calculation.

4.1 Calibration Strategy

We set a month as our unit time and let the matching 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 $\eta > 0$.[26] Our parameterization ensures that all firms face a non-trivial selection decision. That is, the bounds on the two productivity distributions must be set such that hiring thresholds are interior for all firms, which requires $\bar{p}x_0 < b + \rho$. 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).

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. Market-specific parameters are $\bar{L}_m$ (labor force in relation to the number of establishments), s_m and δ_m (separations in continuing and exiting firms), $\bar{p}_m$ (upper bound of the productivity distribution) and b_m (unemployment income). $\bar{L}_m$ is set directly to the corresponding data value. The total separation rate is set to match the steady-state unemployment rate u_m in market m. If f_m is the job-finding rate in this market, stock-flow consistency implies $s_m + \delta_m = \frac{u_m}{1-u_m} f_m$. In all markets, we attribute one-third of separations to exits and two-thirds to separations for continuing establishments, consistent with Fuchs/Weyh (2010)

[26] While a discrete distribution simplifies notation in the previous section, we assume a particular functional form of a continuous distribution here in order to obtain closed-form expressions for many outcome variables which simplifies the algebra.

who find that one third of destroyed jobs in the German labor market are at exiting establishments.

Given all other model 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

$$\bar{w}_m = (b_m + \rho_m)\frac{\alpha + \mu - 1}{\alpha - 1}\,, \tag{4.1}$$

and the job-finding rate is

$$f_m = \frac{\rho_m(r + s_m + \delta_m)(\alpha - 1)}{\mu(b_m + \rho_m)}\,, \tag{4.2}$$

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, (4.1) and (4.2) are solved uniquely for b_m and ρ_m. Then, the closed-form expressions for aggregate unemployment U_m and aggregate employment $E_m = H_m/(s_m + \delta_m)$ 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 wages uniquely identify b_m and $\bar{p}_m$.

The remaining parameters are shared by all labor markets. The interest rate $r = 0.34$ percent corresponds to an annual real interest rate of 4 percent. The matching function elasticity μ (together with the Pareto parameter α) controls the level of wages relative to unemployment income, see equation (4.1). Given a value for α, μ can be set directly to match an average replacement rate of 46 percent, consistent with the level of unemployment income after the Hartz labor market reforms (cf. Krebs/Scheffel, 2013). Utilizing the functional form for aggregate vacancies in Appendix B, the scale of the vacancy cost function c_V can also be set directly 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 (matching function scale parameter) 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 $c_e^{-1}\left(m_0 x_0^{\alpha}\bar{p}_m^{\alpha}\right)^{\frac{\gamma}{1-\mu}}$. This implies that any change in the parameters x_0, c_e and m_0 would scale 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 normalised without impacting our results.[27]

This leaves five global parameters to be jointly estimated: the elasticities of search costs and vacancy costs, $\gamma > 1$ and $\Phi > 1$, the Pareto shape parameter $\alpha > 1$ for match-specific productivity, the shape parameter of the project productivity distribution $\eta > 0$, and the arrival rate of project productivity shocks χ.

Parameters γ and α determine in which proportion firms use search effort, wages, and hiring standards to increase their job-filling rate. This is a consequence of decomposition (3.19) which shows how variation of job-filling rates (by project productivity) is decomposed into the three recruiting margins. This decomposition crucially responds to the elasticities of match productivity, search costs, and the matching function. The latter elasticity is already calibrated from (4.1) to match the average replacement rate. We calibrate γ and α to reflect the relative variation of standardized recruitment indices $\hat{w}$, s and e, as shown in the last graphs of Figures 2–4 in Section 2. To generate outcome variables comparable to those in the data, we simulate the model for a sample of firms over a 90-day hiring period in each of the 36 labor markets and then use the three factors in decomposition (3.8), 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 15 bins of 90-day hiring rates ranging from 0 to 30 percent. Based on those 15 model-generated data points for each index, we calculate the slope of every index with respect to the hiring rate. Our empirical results suggest that the standardized wage index reacts somewhat stronger than the standardized effort index (with relative slope 1.127), whereas the standardized hiring index reacts less than the effort index (relative slope -0.615). Our model targets these relative slopes.[28]

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/Kircher, 2015; Gavazza/Mongey/Violante, 2018; Kettemann/Mueller/Zweimueller, 2018). That is, parameter Φ controls the slope of the hockey-stick relationship between firm growth 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 in each of 15 bins of firm growth rates ranging from 0 to 30 percent. The slope of the vacancy yield-growth relation is then targeted to the one observed in the data as shown in Figure 1.d based

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

[28] Given that all variation of recruitment indices and hires in the model comes from differences in firm productivity (within a market) or from differences in market-specific parameters (across markets), our model generates too much variability of the three indices with hiring rates as compared to those observed in Figures 2–4. Therefore we cannot target the absolute slopes of the relationships between recruitment indices and hiring rates. Nonetheless, most of the variation in the model (and in the data) takes place within local labor market (see the comparison below).

on the averages not controlled for firm size (11.5).

Finally, the two parameters for the productivity distribution η (shape of the density) and χ (arrival rate of productivity shocks) matter for the frequency and size of the firms' employment adjustments. We target that 80 percent of establishments have monthly employment growth rates in the interval $[-0.01, +0.01]$ and 3.6 percent of establishments grow by more than 10 percent.

4.2 Fit of the Model

Table 2 shows the values of calibrated parameters and calibration targets. The bottom five rows of the table compare how the model matches the data targets used for estimation of the last five parameters. All other data targets are matched exactly since they identify the corresponding parameters uniquely, as described above. The model fit is rather good, with the exception of the share of monthly employment growth rates above 10 percent which is somewhat underestimated by the model. Besides capturing the slope of the vacancy yield with respect to employment growth, our model also generates the hockey-stick relationships between hiring rates and establishment growth (Figure 1.b) and, by implication, a moderate variation of the vacancy rate.

In terms of non-targeted moments, the model also does well in several dimensions. Based on Monte Carlo simulations for each local labor market, we construct standardized indices for search effort, wage generosity and hiring standards as described in the previous subsection. Three key features stand out. First, similar to their empirical counterparts, we find that in the model most of the variation of these indices happens within local labor markets. Precisely, a variance decomposition reveals that the between-market component accounts for only 0.2 percent (effort), 1.0 percent (wage generosity) and (3.0 percent) of the total variance in the model. In the data, the between-market variance is also rather small (0.4 percent–1.0 percent).

Table 3 shows how local-market averages of job-finding rates and vacancy yields correlate with market tightness and the three standardized recruitment indices, all of them averaged for each local labor market. Here the model shows that job-finding rates correlate positively with labor market tightness, search effort and hiring standards, in line with the data. Likewise, both in the data and in the model, the vacancy yield correlates negatively with tightness and hiring standards while the correlation with search effort is zero in the data and small in the model. On the other hand, the model does not reproduce the weak correlations between wage generosity, job-finding rates and vacancy yields that we observe in the data.[29]

[29] Note again that our model only targets (and perfectly matches) the job-finding rates in all labor markets,

Table 2: Calibrated parameters and targets used for estimation

Market-specific parameters			
Parameter		Mean Value	Explanation/Target
Labor force (normalized)	$\bar{L}_m$	7.1	Workers per establishment
Separation rate	s_m	0.54%	Unemployment rates
Exit rate	δ_m	0.27%	1/3 of separations due to exit
Productivity upper bound	$\bar{p}_m$	1045.5	Job-finding rates
Unemployment income	b_m	0.38	Wages (mean normalized to 1)
Global parameters (directly calibrated)			
Parameter		Value	Explanation/Target
Interest rate	r	0.34%	4% annual real rate
Vacancy cost scale	c_V	515,257	0.12 vacancies per establishment
Matching fct. elasticity	μ	0.054	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)
Global parameters (estimated)			
Parameter		Value	Explanation/Target
Vacancy cost elasticity	Φ	10.25	Slope vacancy yield wrt emp. growth
Search effort elasticity	γ	7.86	Relative slope wages/effort
Match prod. Pareto shape	α	1.97	Relative slope hiring standards/effort
Arrival rate prod. shocks	χ	0.34	Employment growth $[-0.01, 0.01]$
Productivity shape	η	0.15	Employment growth $> 10\%$
Targets for estimation			
Statistics		Data	Model
Relative slope wages/effort		1.13	1.13
Relative slope hiring standards/effort		-0.62	-0.62
Slope vacancy yield wrt emp. growth		11.5	11.3
Share employment growth $[-0.01, 0.01]$		0.80	0.81
Share employment growth > 0.1		0.036	0.007

Source: Own calculation.

To compare to what extent all three recruitment indicators affect vacancy yields, we regress the vacancy yield on tightness, search effort, hiring standards and wage generosity. The regression coefficients that we obtain are smaller than those obtained in the data (see specification (6) in Table 1), but the relative order is similar. Hiring standards have the strongest (negative) relation to the vacancy yield (-0.437 compared to -0.920 in Table 1), followed by search effort (0.148 compared to 0.75). Wage generosity has the smallest impact on vacancy yields in the data and in the model (0.056 compared to 0.002).

4.3 Variation of Matching Efficiency

We now analyze how recruiting intensity contributes to the variation of matching efficiency across local labor markets. We do not explore variation over time because our model is set in steady state and the period in which our data are obtained (2010-2017) is rather short.

but it does not target the cross-market variation of any of the other variables specified in Table 3. However, all model-generated variables correlate positively with their data counterparts, with the only exception of search effort where the correlation is zero.

Table 3: Cross-market correlations

	Data		Model	
	Job-finding rate	Vacancy yield	Job-finding rate	Vacancy yield
Job-finding rate	1.0	-0.789	1.0	-0.593
Vacancy yield	-0.789	1.0	-0.593	1.0
Tightness	0.808	-0.750	0.804	-0.843
Search effort	0.393	0.004	0.769	-0.215
Hiring standards	0.414	-0.369	0.627	-0.997
Wage generosity	0.042	0.129	-0.896	0.865

Source: Own calculation.

Our calibrated model permits an exact decomposition of matching efficiency. Since aggregate hires in a labor markets 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:[30]

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

Search effort | Wage dispersion | Selectivity

(4.3)

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 (4.3) shows how the job-finding rate depends on four factors. The first one is the standard matching function which links labor market tightness (i.e. the vacancy-unemployment ratio) to matches 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, m_S captures the contribution of selectivity and m_W is a "wage dispersion" term which reflects different wage policies in heterogenous firms.[31] The numerator $\bar{m}$

[30] Multiplication of this equation by $U/\bar{V}$ delivers an equivalent decomposition of the vacancy yield in the definition of this section (hires *from unemployment* per vacancy). We report the decomposition of the job-finding rate since our model targets this outcome variable and since it is especially of interest for the policy experiment of the next subsection.

[31] Note that the three terms m_E, m_W and m_S are different from the recruitment indices that we construct earlier (based on Monte-Carlo simulations mimicking their data counterparts, see subsection 4.1). However, m_E correlates positively with the search effort index, and m_S correlates negatively with the hiring standards index (i.e. there are less matches if hiring standards are stricter). Since the cross-market variance of m_W is zero, it does not correlate with the wage generosity index.

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 matching function (Jensen's inequality). Thus, dispersion of wages (in a competitive search model) reduces matching efficiency (cf. Kaas/Kircher, 2015). In our calibrated model, only m_E and m_S vary across local labor markets, but m_W is constant and equal to 0.93. That is, wage dispersion reduces matching efficiency, but it does so uniformly across labor markets. This implication is to a large extent consistent with our data, where we find little cross-market variation of measured wage dispersion.[32]

We can now explore to what extent labor market tightness, search effort and selectivity contribute to variation of job-finding rates across labor markets. The variance of the (log) job-finding rate is 0.184. Table 4 shows the covariance matrix of all (log) terms in (4.3) with the exception of m_W as it is constant across markets. Most of the variation of the total job-finding rate comes from labor market tightness and from selectivity. Variation of search effort plays only a minor role. Note that the selectivity term m_S correlates negatively with tightness. In other words, firms in tighter labor markets are more selective which reduces matching efficiency.

Table 4: Covariances across local labor markets

Total variance 0.184	Tightness	Search effort	Selectivity
Tightness	0.689	0.018	-0.395
Search effort	0.018	0.002	-0.006
Selectivity	-0.395	-0.006	0.259

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

These observations are also reflected in Table 5 whose first row shows the contribution of the three 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. Note that this finding is consistent with Table 3 which shows that job-finding rates and the hiring-standards index are *positively* correlated (both in the data and in the model). Finally, search effort m_E has a positive, but quantitatively small impact on variation of job-finding rates.

The intuition why hiring standards reduce matching efficiency in tighter markets is as fol-

[32] 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.

lows: Local labor markets essentially 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) tend to have higher productivity $\bar{p}_m$, and this is the reason why firms create more vacancies and hence market tightness is larger. However, these more productive markets also have higher reservation wages and the ratio between the two objects, $\bar{p}_m/(b_m + \rho_m)$, is *lower* in tighter markets. By optimality condition (3.11), this implies that firms must become more selective as they offer sufficiently high wages to fill their positions, which ultimately reduces matching efficiency.

Table 5: Relative contributions to the variation of job-finding rates across local labor markets

	Variance JFR	Tightness	Search effort	Selectivity
Total	0.184	169.6%	7.3%	-76.9%
Low skill	0.059	150.1%	2.4%	-52.5%
Medium skill	0.038	233.4%	-1.1%	-132.3%
High skill	0.015	175.0%	10.3%	-85.3%

Source: Own calculation.

Effort plays a rather small quantitative role compared to the other two margins because of the relatively large estimated value of the effort cost elasticity γ. However, even when we reduce this parameter substantially to $\gamma = 2$, the contribution of search effort to the variation of job-finding rates increases to 29 percent, while tightness and selectivity remain the two most important margins for the variation of job-finding rates across markets.

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 5 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 contributes to matching efficiency mostly in high-skill labor markets.

Variation across skill groups is reported in Table 6. Medium- and high-skill labor markets have job-finding rates which are around 123 percent (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.

Table 6: Average log differences to low-skill labor markets

	JFR	Tightness	Search effort	Selectivity
Medium skill	0.76	0.81	0.08	-0.13
High skill	0.85	1.74	0.06	-0.95

Source: Own calculation.

4.4 The Role of Recruiting Intensity for Labor Market Policy

Because recruiting intensity responds to the economic environment, it is important to understand how the different margins of firms' hiring policies react 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 eleven percent in 2005 to just over three percent 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/Uhlig, 2012; Krebs/Scheffel, 2013; Dustmann et al., 2014; Hochmuth et al., 2019; Carrillo-Tudela/Launov/Robin, 2020: 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/Jung/Kuhn, 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 percent (post-Hartz period) to the stationary equilibrium of our model with a higher pre-Hartz reform replacement rate of 57 percent (cf. Krebs/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 7 shows how job-finding rates change between the two scenarios. The first column shows the log change of the job-finding rate in response to the decline of unemployment

income from 57 to 46 percent. On average, the job-finding rate increases by 27.4 log points (32 percent). Across skill groups, the increase is strongest for the low-skilled (43.2 log points, 54 percent) and weakest for the high-skilled (16.1 log points, 17 percent). The larger increases in job-finding rates in low-skill labor markets is consistent with the findings in Carrillo-Tudela/ Launov/Robin (2020), whose data work implies that in low-skill labor markets the job-finding rate increased by 30.3 percent, while the job finding rates in medium and high skill markets increased by 25.1 percent and 9.8 percent, respectively, when comparing the 2000-2005 to the 2010-2014 period.

Table 7: Impact of a decrease of the replacement rate from 57 to 46 percent

	JFR	Tightness	Search effort	Selectivity
Total	0.274	0.211	0.002	0.063
Low skill	0.432	0.290	0.007	0.135
Medium skill	0.229	0.198	0.001	0.031
High skill	0.161	0.146	0.000	0.015

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. Source: Own calculation.

The remaining columns of the table build again on equation (4.3) 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 falls on average by 3.1 percent with lower UI, the dispersion across firms within the local labor markets is unchanged.

Table 7 shows that the job-creation margin (tightness) is responsible for about three quarters of the increase of the job-finding rate (21.1) log points, while the rest is accounted for by the selectivity margin (6.3 log points). Search effort plays only a negligible role. With lower UI and firm productivity unchanged, hiring thresholds are lower (see condition (3.11)). 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 about a third of the increase in the job-finding rate and less relevant for the high skilled where it accounts for less than ten percent of the increase of the job-finding rate. 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.

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. Further, across local labor markets, defined as the cross-product between three skill groups and 12 geographic regions, we find that these three recruitment margins contribute significantly to the variation of vacancy yields. 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, in particular about the relative sensitivities of search effort, wage generosity and hiring standards across hiring establishment. Then we verify that the model fits several facts about the cross-market variation of job-finding rates, vacancy yields and aggregate 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 does not matter much 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 propose a simple exercise 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 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/Launov/Robin (2020) 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.

References

Acharya, Sushant; Wee, Shu Lin (2020): Rational Inattention in Hiring Decisions. In: American Economic Journal: Macroeconomics, Vol. 12, No. 1, p. 1–40.

Banfi, Stefano; Villena-Roldan, Benjamin (2019): Do High-Wage Jobs Attract more Applicants? Directed Search Evidence from the Online Labor Market. In: Journal of Labor Economics, Vol. 37, No. 3, p. 715–746.

Barron, John M; Bishop, John (1985): Extensive search, intensive search, and hiring costs: New evidence on employer hiring activity. In: Economic Inquiry, Vol. 23, No. 3, p. 363–382.

Barron, John M.; Bishop, John; Dunkelberg, William C. (1985): Employer Search: The Interviewing and Hiring of New Employees. In: Review of Economics and Statistics, Vol. 67, No. 1, p. 43–52.

Baydur, Ismail (2017): Worker Selection, Hiring, and Vacancies. In: American Economic Journal: Macroeconomics, Vol. 9, No. 1, p. 88–127.

Belot, Michelle; Kircher, Philip; Mueller, Paul (2018): How Wage Annnouncements Affect Job Search - a Field Experiment. In: Working Paper in Economics, 739, University of Gothenburg.

Bossler, Mario; Gartner, Hermann; Kubis, Alexander; Küfner, Benjamin; Rothe, Thomas (2019): The IAB Job Vacancy Survey - Establishment Survey on Labour Demand and Recruitment Processes, Waves 2000 to 2016 and Subsequent Quarters 2006 to 2017, fDZ-Datenreport 03/2019, IAB Nuremberg.

Brenzel, Hanna; Czepek, Judith; Kiesl, Hans; Kriechel, Ben; Kubis, Alexander; Moczall, Andreas; Rebien, Martina; Roettger, Christoff; Szameitat, Joerg; Warning, Anja; Weber, Enzo (2016): Revision of the IAB Job Vancancy Survey: Backgrounds, methods and results, iAB-Forschungsbericht 4/2016.

Burdett, Kenneth; Cunningham, Elizabeth J (1998): Toward a theory of vacancies. In: Journal of Labor Economics, Vol. 16, No. 3, p. 445–478.

Carrillo-Tudela, Carlos; Gartner, Herman; Kaas, Leo; Lochner, Benjamin (2020): Sorting Through Search Channels.

Carrillo-Tudela, Carlos; Launov, Andrey; Robin, Jean-Marc (2020): The Fall in German Unemployment: A Flow Approach. In: Centre for Economic Policy Research, dP12846.

Chugh, Sanjay K; Merkl, Christian (2016): Efficiency and Labor Market Dynamics in a Model of Labor Selection. In: International Economic Review, Vol. 57, No. 4, p. 1371–1404.

Davis, Steven J; Faberman, R Jason; Haltiwanger, John C (2013): The Establishment–Level Behavior of Vacancies and Hiring. In: Quarterly Journal of Economics, Vol. 128, p. 581–622.

Davis, Steven J; Faberman, R Jason; Haltiwanger, John C (2012): Recruiting intensity during and after the Great Recession: National and industry evidence. In: American Economic Review, Vol. 102, No. 3, p. 584–88.

Davis, Steven J; Haltiwanger, John C; Schuh, Scott (1998): Job creation and destruction. MIT Press.

Dustmann, Christian; Fitzenberger, Bernd; Schönberg, Uta; Spitz-Oener, Alexandra (2014): From sick man of Europe to economic superstar: Germany's resurgent economy. In: Journal of Economic Perspectives, Vol. 28, No. 1, p. 167–88.

Faberman, R Jason; Menzio, Guido (2017): Evidence on the relationship between recruiting and the starting wage. In: Labour Economics, Vol. 50, p. 67–79.

Fuchs, Michaela; Weyh, Antje (2010): The Determinants of Job Creation and Destruction: Plant-Level Evidence for Eastern and Western Germany. In: Empirica, Vol. 37, No. 4, p. 425–444.

Garibaldi, Pietro; Moen, Espen R (2010): Job to job movements in a simple search model. In: American Economic Review, Vol. 100, No. 2, p. 343–47.

Gavazza, Alessandro; Mongey, Simon; Violante, Giovanni (2018): Aggregate Recruiting Intensity. In: American Economic Review, Vol. 108, No. 8, p. 2088–2127.

Hartung, Benjamin; Jung, Philip; Kuhn, Moritz (2018): What hides behind the German labor market miracle? Unemployment insurance reforms and labor market dynamics. CESifo Discussion Paper 7379.

Hochmuth, Brigitte; Kohlbrecher, Britta; Merkl, Christian; Gartner, Hermann (2019): Hartz IV and the Decline of German Unemployment: A Macroeconomic Evaluation. Working papers, Friedrich Alexander-Universität Nürnberg Erlangen.

Kaas, Leo; Kircher, Philipp (2015): Efficient Firm Dynamics in a Frictional Labor Market. In: American Economic Review, Vol. 105, No. 10, p. 3030–60.

Kettemann, Andreas; Mueller, Andreas I; Zweimueller, Josef (2018): Wages, Workers and Vacancy Durations: Evidence from Linked Data, working Paper.

Krause, Michael U.; Uhlig, Harald (2012): Transitions in the German labor market: Structure and crisis. In: Journal of Monetary Economics, Vol. 59, No. 1, p. 64–79.

Krebs, Tom; Scheffel, Martin (2013): Macroeconomic evaluation of labor market reform in Germany. In: IMF Economic Review, Vol. 61, No. 4, p. 664–701.

Leduc, Sylvain; Liu, Zheng (2017): The Weak Job Recovery in a Macro Model of Search and Recruiting Intensity, federal Reserve Bank of San Francisco Working Paper 2016-09.

Lochner, Ben (2019): A simple algorithm to link “last hires” from the Job Vacancy Survey to administrative records, fDZ-Methodenreport 06/2019, IAB Nuremberg.

Lochner, Benjamin; Merkl, Christian; Stuber, Heiko; Gürtzgen, Nicole (2020): A Note on Recruiting Intensity and Hiring Practices: Cross-Sectional and Time-Series Evidence, mimeo.

Marinescu, Ioana; Wolthoff, Ronald (2020): Opening the Black Box of the Matching Function: the Power of Words. In: Journal of Labor Economics, Vol. 38, No. 2, p. 535–568.

Moen, Espen R (1997): Competitive search equilibrium. In: Journal of Political Economy, Vol. 105, No. 2, p. 385–411.

Mongey, Simon; Violante, Gianluca (2020): Macro Recruiting Intensity from Micro Data. In: NBER Working Paper, 26231.

Mortensen, Dale (1998): Equilibrium Unemployment with Wage Posting: Burdett-Mortensen Meet Pissarides. In: CLMSR Working paper 98-14, Aarhus University.

Schaal, Eduoard (2017): Uncertainty and Unemployment. In: Econometrica, Vol. 85, No. 6, p. 1675–1721.

Sedlacek, Petr (2014): Match Efficiency and Firms’ Hiring Standards. In: Journal of Monetary Economics, Vol. 62, p. 123–133.

Van Ours, Jan; Ridder, Geert (1992): Vacancies and the recruitment of new employees. In: Journal of Labor Economics, Vol. 10, No. 2, p. 138–155.

Villena-Roldan, Benjamin (2012): Aggregate Implications of Employer Search and Recuitment Selection, center for Applied Economics (CEA) Working Paper 272.

Wolthoff, Ronald (2018): Applications and Interviews: Firms’ Recruitment Decisions in a Frictional Labor Market. In: The Review of Economic Studies, Vol. 85, No. 2, p. 1313–1351.

Appendix

A. Data Appendix

For our analyses we use survey and administrative data of the Institute for Employment Research (IAB). The 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).[33]

A.1 Summary Statistics

Table 8 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 percent of them are in the trade and retail sector or provide commercial or social services.[34] Establishments are also more likely to report they face workforce or demand restrictions than financial restrictions.

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 9 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 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 8 shows that establishments end up receiving an average of 13 applications for their vacancies, but Table 9 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 we observe large variation across skill categories such that establishments end up interviewing about 40 percent of the applicants for low-skill vacancies but only 20 percent of applicants for high-skill ones.

[33] 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).

[34] 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.

Table 8: 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				

Source: Own calculation.

In terms of the usage of recruitment policies, Table 8 shows that about 10 percent 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 percent of employers end up offering a higher wage when filling high-skill jobs but only 7 percent of them when filling low-skill ones. Although not shown in these tables, we find that about 80 percent of establishments that report hiring a worker with lower qualifications also report hiring a worker with lower experience than expected. Among those establishments who report reducing hiring standard about 20 percent of them also report paying more than expected. Establishments use about three search channels on average with little variation across skill categories. The more search channels they use, the more frequently they report to pay more than expected (the fraction increases monotonically from 9 percent for establishments using only one channel up to 55 percent for those that use 12 channels). A similar relationship holds for reducing hiring standards (6 percent in establishments using one channel and 36 percent in establishments using 12 channels).

Worker information from the IEB is presented at the bottom of Table 8. 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 9: Sample characteristics by skill group (JVS)

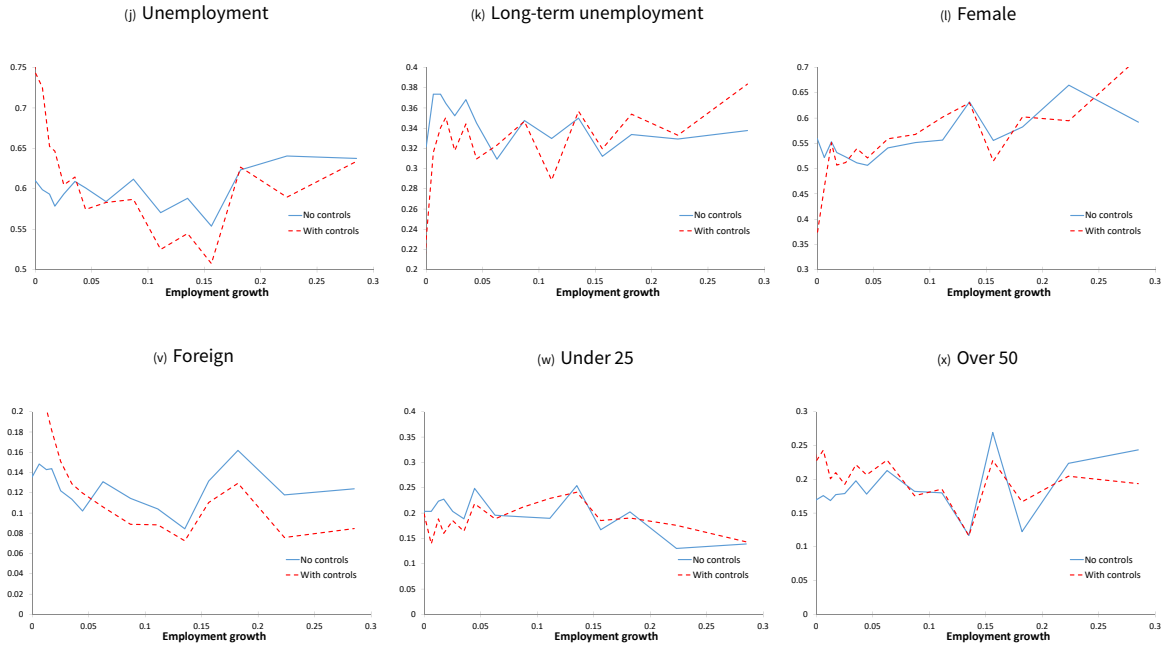
	Low skill			Medium skill			High skill		
	Mean	St. dev.	N	Mean	St. dev.	N	Mean	St. dev.	N
Vacancy duration (days)	43.915	54.167	5,874	59.387	59.145	32,986	73.173	60.248	9,127
Number of applicants	9.793	16.278	5,917	12.392	18.506	34,214	19.562	24.663	9,296
Number of suitable applicants	3.459	4.381	5,533	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

Source: Own calculation.

A.2 Composition of Hires

Figure 6 shows to what extent the composition of hires changes when the establishment's employment growth rate varies from zero to 30 percent. Fast-growing establishments hire slightly more unemployed workers and more females. There is no evidence, however, that these establishments hire more foreign workers, workers above 50 years of age or from long-term unemployed.

Figure 6: Shares of hires by 30-day establishment growth



Source: Own calculation.

A.3 Relationship Between Hiring Rates and Recruitment Policies in the JVS

Regression coefficients.

Table 10 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 zero hiring bin as the baseline category.

Table 10: Recruitment policies and hiring rates - Regression coefficients

	Wage concessions		IEB - Wage premium		Wage generosity		Number of channels		Geographic Search	
Hiring bin (max)										
0.015	-0.036***	-0.0094	0.0036	-0.003	0.018	0.0026	0.7869***	0.0625	-0.0056	-0.0149***
0.02	-0.0308***	-0.0112	-0.0014	-0.0065	0.037	0.0193	0.7512***	0.0557	-0.0019	-0.0065
0.03	-0.0199***	-0.0042	0.0008	-0.0109	0.0523	0.0162	0.6479***	0.1454***	0.005	-0.0007
0.04	-0.0077	0.0091	0.0117	-0.0032	0.0897***	0.0561*	0.6078***	0.1574***	0.0035	-0.0042
0.05	-0.0026	0.0095	0.0151	-0.0028	0.1045***	0.0515	0.6348***	0.2096***	0.0108***	0.0032
0.075	0.004	0.0118***	0.0239**	0.0023	0.135***	0.0682**	0.5945***	0.281***	0.0157***	0.0088***
0.1	0.017***	0.0266***	0.0371***	0.0122	0.1799***	0.1116***	0.5782***	0.2905***	0.017***	0.0095***
0.125	0.0275***	0.0291***	0.0366***	0.0133	0.2181***	0.1299***	0.6091***	0.3878***	0.0229***	0.0118***
0.15	0.0176***	0.0223***	0.049***	0.0212*	0.2122***	0.1258***	0.6725***	0.4256***	0.034***	0.0214***
0.175	0.0246***	0.0258***	0.0672***	0.0434***	0.2667***	0.1862***	0.6198***	0.4234***	0.02***	0.007
0.2	0.0282***	0.0302***	0.0615***	0.0378***	0.2964***	0.2241***	0.6595***	0.4332***	0.0372***	0.0182***
0.25	0.0436***	0.0425***	0.07***	0.0393***	0.2944***	0.186***	0.5891***	0.4422***	0.046***	0.0309***
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***
R^2	0.003	0.0515	0.0097	0.0206	0.0152	0.0471	0.0217	0.1033	0.0054	0.0406
N obs	68,681	59,268	29,637	22,626	25,788	22,626	65,209	57,347	59,365	51,242

	Search effort		Qualification Mismatch		Experience Mismatch		IEB - Selectivity		Selectivity (JVS+IEB)	
Hiring bin (max)										
0.015	0.2083***	-0.0098	-0.0435***	-0.0075	-0.0433***	-0.0124	-0.0027	-0.0194	-0.0405	-0.0426
0.02	0.2***	-0.0037	-0.0377***	-0.0031	-0.0374***	-0.0096	-0.0024	-0.0138	-0.0476	-0.0367
0.03	0.1932***	0.0402***	-0.0388***	-0.0113**	-0.0396***	-0.0145***	-0.0103	-0.0215*	-0.0517*	-0.0345
0.04	0.1781***	0.0364***	-0.0265***	-0.0013	-0.0224***	-0.0004	-0.0209**	-0.0339***	-0.0937***	-0.0739**
0.05	0.2048***	0.0712***	-0.016***	0.0052	-0.0203***	-0.0003	-0.0267***	-0.0403***	-0.114***	-0.0872***
0.075	0.1972***	0.0947***	-0.0133***	0.0015	-0.0073**	0.0052	-0.0134	-0.0294***	-0.1223***	-0.0861***
0.1	0.1939***	0.0979***	-0.0039	0.0098***	-0.0083*	0.0036	-0.0157	-0.0326***	-0.1522***	-0.1103***
0.125	0.2219***	0.1382***	0.0072	0.0209***	0.0045	0.0151***	-0.0187*	-0.0364***	-0.1794***	-0.1369***
0.15	0.255***	0.1607***	0.0019	0.0135**	-0.0012	0.0085	-0.0191*	-0.0347***	-0.1501***	-0.0954***
0.175	0.2162***	0.1322***	0.017***	0.0256***	0.0138**	0.0184**	-0.0105	-0.0327**	-0.1877***	-0.1525***
0.2	0.2643***	0.1621***	0.0173**	0.0227***	0.0334***	0.0384***	-0.0121	-0.0265*	-0.1882***	-0.1268***
0.25	0.27***	0.1931***	0.0248***	0.0256***	0.0246***	0.0266***	-0.0094	-0.0335**	-0.221***	-0.1578
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*
R^2	0.0182	0.1007	0.0039	0.0199	0.0031	0.0149	0.0003	0.007	0.0056	0.0158
N obs	65,209	57,347	68,681	59,268	68,681	59,268	29,144	22,343	25,446	22,343

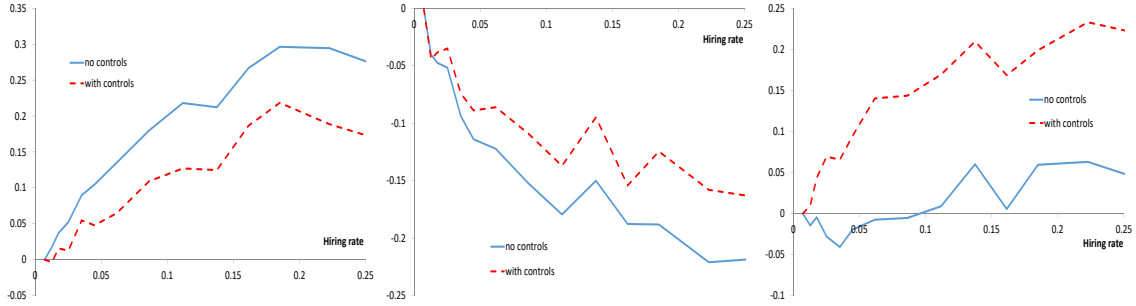
*Note: *-significant at a 10%, **-significant at a 5%, ***-significant at a 1%.* Source: Own calculation.

Excluding zero hires and removing the smallest establishments.

Figure 7 and Figure 8 show the relationships between the establishment hiring rate and the three main recruitment indices $\hat{w}$, s, e as defined in Section 2, where we either exclude all observations with zero hires or where we remove the smaller establishments with less than 20 workers. The main insights presented in Figures 2-4 remain: Establishments with larger hiring rates exert more effort, pay more generous wages and reduce their hiring standards.

Figure 7: Variation of the main recruitment indices (with zero hires observations removed).

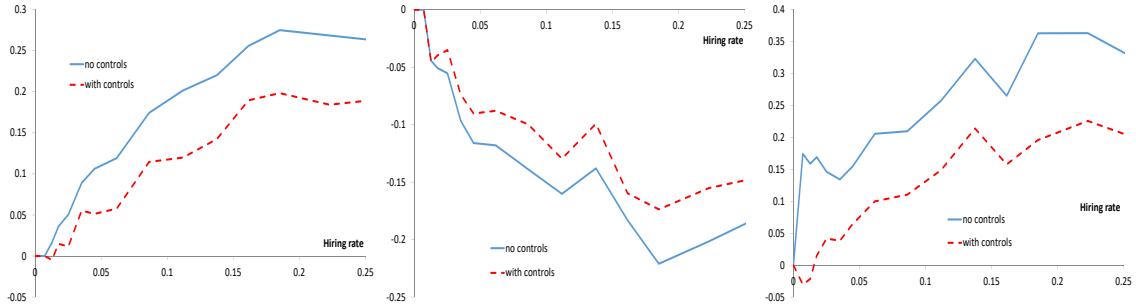
(j) Wage generosity (k) Hiring standards (l) Search effort



Source: Own calculation.

Figure 8: Variation of the main recruitment indices (only establishments with $20+$ workers).

(j) Wage generosity (k) Hiring standards (l) Search effort



Source: Own calculation.

A.4 Vacancy Yields Across Labor Markets

The results presented in Table 1 show using OLS regressions of vacancy yields across labor markets that coefficients on wage generosity and search effort are positive while the one on hiring standards is negative. These relationships are statistically significant for search effort and higher standards, but not for wage generosity. Table 11 shows that a similar conclusion arises when controlling for market (i.e. skill$\times$region) fixed effects. Here, however, the relationship between search effort and vacancy yields across markets is somewhat less strong. Further, comparing the coefficients of determination across columns, a similar picture arises as with the OLS regressions, where all three measures improve the fit of the fixed effects regression in a similar magnitude as labor market tightness which on its own generates an $R^2 = 0.056$.

Table 11: Vacancy yields across labor markets

Fixed effects						
θ - Market tightness	-1.637***	-1.427***	-1.406***	-1.411***	-1.435***	-1.396***
	(0.335)	(0.338)	(0.326)	(0.337)	(0.339)	(0.329)
Search Effort			0.550***			0.406
			(0.246)			(0.249)
Hiring Standards				-1.237***		-1.140***
				(0.376)		(0.329)
Wage Generosity					0.388	0.165
					(0.250)	(0.254)
Constant	2.238***	2.754***	2.737***	2.767***	2.710***	2.734***
R^2	0.056	0.113	0.136	0.134	0.132	0.151
Year dum.	N	Y	Y	Y	Y	Y
N obs	288	288	288	288	288	288

*** $p < 0.001$; ** $p < 0.05$; * $p < 0.10$. Standard errors in parenthesis.

Source: Own calculation.

B. Closed-Form Model Solutions

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

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

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):

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

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

$$\mathbb{E}(H_p/V_p) = m_0\big(\frac{x_0}{b+\rho}\big)^{\alpha} \cdot \Big(\frac{\rho(1-\mu)}{\mu c_e\gamma}\Big)^{\frac{1}{\gamma-1}} \cdot \Big(\frac{m_0\mu(b+\rho)^{1-\alpha}x_0^{\alpha}}{\rho(r+s+\delta)(\alpha-1)}\Big)^{\frac{1-\mu+\mu\gamma}{(\gamma-1)(1-\mu)}} \cdot \frac{\eta}{\eta+\frac{\alpha\gamma}{(\gamma-1)(1-\mu)}} \cdot \bar{p}^{\frac{\alpha\gamma}{(\gamma-1)(1-\mu)}}.$$

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

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

The above expressions make clear that parameters c_e, m_0, x_0 and $\bar{p}$ affect the means of 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 matching efficiency 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 $H_p/(s+\delta)$, aggregate employment is simply $\mathbb{E}(H_p)/(s+\delta)$. The job-finding rate is given by aggregate hires per unemployed worker which simplifies to

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

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 (3.7) and (3.13))

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

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 matching function elasticity.[35] 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.

[35] 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 $w > px$).

Imprint

IAB-Discussion Paper 15|2020

Publication Date
25 May 2020

Publisher
Institute for Employment Research
of the Federal Employment Agency
Regensburger Straße 104
90478 Nürnberg
Germany

Download
http://doku.iab.de/discussionpapers/2020/dp1520.pdf

All publications in the series "IAB-Discusssion Paper" can be downloaded from
https://www.iab.de/en/publikationen/discussionpaper.aspx

Website
www.iab.de/en

Corresponding author
Hermann Gartner
Phone +49 911 179 3386
E-Mail Hermann.Gartner@iab.de