A Note on Recruiting Intensity and Hiring Practices: Cross-Sectional and Time-Series Evidence *

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Abstract

Using the German IAB Job Vacancy Survey, we look into the black box of recruiting intensity and hiring practices from the employers' perspective. Our paper evaluates three important channels for hiring, namely vacancy posting, the selectivity of hiring (labor selection), and the number of search channels. In line with our theoretical framework, all these hiring channels are procyclical over the business cycle. While vacancy posting and labor selection show a U-shape over the employment growth distribution, the number of search channels tends to be upward sloping in terms of employment growth. We argue that growing establishments react to positive firm-specific productivity shocks by using all three channels more actively. Furthermore, we connect the fact that shrinking establishments post more vacancies and are less selective than establishments with a constant workforce to churn triggered by employment-to-employment transitions.

Keywords: recruiting intensity, vacancies, labor selection, administrative data, survey data
JEL Classifications: E24, J63

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1 Introduction

In the canonical search and matching model (Mortensen and Pissarides, 1994), firms exclusively rely on the number of posted vacancies to adjust the number of hires. Through the aggregate matching function, the search and matching model contains a tight link between the number of posted vacancies and the number of hires. Davis et al. (2013, p. 590) argue that standard theory misses important other channels: In addition to the vacancy margin, firms may also vary their recruiting intensity, i.e. "(...) employers rely on a mix of recruiting and hiring practices that differ in propensity to involve a measured vacancy and in vacancy duration." In a similar vein, based on a structural model, Gavazza et al. (2018) show that firms' recruiting intensity is strongly procyclical over the business cycle. Both articles document that recruiting intensity is very important for explaining cross-sectional and time-series patterns in the United States (e.g., the collapse of hiring during the Great Recession).

While Davis et al. (2013) and Gavazza et al. (2018) quantify the role of recruiting intensity for job-filling rates from the residual of a generalized matching function, there is no direct evidence for the behavior of these margins in the United States. The behavior of vacancy yields[1] over the employment distribution and over time are known. By contrast, the exact channels for these patterns remain a black box. What are the instruments —other than vacancies— that firms use? How strongly do firms vary these instruments in the cross section (e.g., along the employment growth distribution) and over time (i.e., along the business cycle)? Answers to these questions are important for economic modelers, both to get the micro-foundations and the transmission mechanisms right. These are crucial prerequisites for meaningful counterfactual policy exercises and welfare statements.

Our paper starts by presenting a simple multi-worker firm optimization problem where firms can use three hiring margins. Although we do not solve for the full heterogeneous equilibrium, the firm optimization is a useful tool for measuring different recruiting channels in the data and for showing how firms should respond to different shocks. In our model, firms post vacancies in order to attract applicants and they choose an effort level at which they want to advertise these vacancies. Following Gavazza et al. (2018), we assume that both vacancies and effort are subject to a convex cost function. In addition, firms choose the fraction of applicants they want to hire. Following Chugh and Merkl (2016), applicants draw from an idiosyncratic training cost distribution. Firms choose an endogenous training cost cutoff and thereby endogenously determine their selectivity. Firms that are hit by a positive aggregate or firm-specific shock post more vacancies, increase their recruiting effort and are less selective. As we assume a decreasing returns

[1] For an analysis of vacancy yields in Germany, see Carrillo-Tudela et al. (2018) and Carrillo-Tudela et al. (2020).

to labor production function, firms that (involuntarily) lose a fraction of workers face an increase of their marginal product and thereby increase their hiring activity in all three dimensions. Against the background of these model predictions, we analyze whether we can find similar patterns in the data.

Given the lack of suitable survey datasets for the United States[2], our paper uses the German IAB Job Vacancy Survey (JVS) to look into the black box of recruiting intensity and hiring practices. The JVS is a representative annual cross-sectional survey of up to 14,000 establishments (Moczall et al., 2015). Establishments are asked about the number of hires, separations and vacancies in a particular year. In addition, they provide detailed information on their most recent hire (such as the used search channels or the number of suitable applicants). Furthermore, we are the first to complement the data from the JVS with administrative information from the Administrative Wage and Labor Market Flow Panel (AWFP) which contains job flows, worker flows, and wage information for the universe of German establishments (Stüber and Seth, 2019).[3] Our paper uses empirical indicators for firms' recruiting intensity and for their selectivity. For recruiting intensity, we use a normalized measure for the number of search channels that establishments used for their most recent hire. For selectivity, we use the inverse of the number of suitable applicants for the vacancy of the most recent hire (see Hochmuth et al., 2019). A firm that hires a larger fraction of suitable applicants is considered to be less selective.
In line with our theoretical predictions, the vacancy rate, the selection rate and the number of search channels all move procyclically over the business cycle. In a recession, establishments post fewer vacancies and use fewer search channels. The development of the used number of search channels over time is in line with the idea of endogenous recruiting intensity by Davis et al. (2013) and Gavazza et al. (2018).

We document that the number of search channels tends to be upward sloping over the employment growth distribution (although not monotonically), which can be explained by firm-specific productivity shocks. In addition, we show that both the vacancy rate and the selection rate show a U-shape over the employment growth distribution. Through the lens of our model the upward sloping path in the positive part of the employment growth distribution can be explained by positive firm-specific productivity shocks.

At first sight, it appears to be a certain challenge to explain why (faster) shrinking establishments post more vacancies and are less selective than establishments with a constant workforce. In terms of firm-specific productivity shocks, this behavior cannot be rationalized. However, we show that there is a connection between the negative part of

[2]The 1980 Employment Opportunity Pilot Project is a notable exception for a firm survey (see for example Barron et al., 1985). However, the survey is quite outdated and it is purely cross-sectional. Recently, the Survey of Consumer Expectations documents search behavior (see Faberman et al., 2017). However, this survey asks individuals, while the IAB Job Vacancy Survey asks establishments.

[3]Carrillo-Tudela et al. (2020) recently linked the JVS with the Integrated Employment Biographies at the establishment level. They use the linked dataset to analyze vacancy yields, recruiting intensity and hiring standards.

the employment growth distribution and churn. Bachmann et al. (2017) document that churn (worker flows beyond job flows) follows a U-shaped pattern over the employment growth distribution, which is similar to the U-shape for vacancy rates and selection that we find. They identify employment-to-employment transitions as the underlying reason for this pattern. By linking the three hiring margins to churn and employment-to-employment transitions[4], we can show that there is a positive connection between churn as well as employment-to-employment transitions and these three margins. From a theoretical perspective this can be rationalized in terms firms with a decreasing returns to labor production function that increase their marginal product when they lose workers (on an involuntary basis). In this case, they will increase their hiring efforts in all three dimensions.

2 Firms' Decisions with Three Hiring Margins

This section serves two purposes. First, by setting up firms' optimization problem with three hiring margins and by deriving optimality conditions, we derive hypotheses how firms react to different type of firm-specific and aggregate shocks. Second, the model structure will be useful when defining suitable measures for selectivity and recruiting intensity in the data.

We assume an environment where firms are subject to search frictions, produce under decreasing returns and have two additional hiring margins at hands. Besides vacancy posting, they can adjust their search effort and change their selectivity.

As in Elsby and Michaels (2013), we assume that firms produce with a decreasing returns to scale technology and labor as the only input. Under decreasing returns, firms with different productivities and different sizes can coexist in an undirected search environment.

When hiring new workers, firms have to post vacancies in order to get in contact with workers. Search is random (i.e., undirected). We assume that there is an aggregate contact function. As in Gavazza et al. (2018), firms face a vacancy posting cost function $g\left(e_{it}, v_{it}, n_{it}\right)$, which is increasing and convex in search effort e_{it} and in the number of vacancies v_{it} ($\partial g/\partial e_{it} = g_{e_{it}} > 0$, $\partial^2 g/\partial e_{it}^2 > 0$, $\partial g/\partial v_{it} = g_{v_{it}} > 0$, $\partial^2 g/\partial v_{it}^2 > 0$).[5] The underlying idea is that firms can choose an optimal number of vacancies. Small workforce adjustments are less costly than large workforce adjustments. In addition, firms can choose how intensively they advertise these vacancies. More effort increases the

[4] We use the merged JVS and AWFP data to show the connection between employment-to-employment transitions to other establishments (as a proxy for involuntary worker losses from the establishment's perspective) and the three hiring margins.

[5] Gavazza et al. (2018) show that the per vacancy cost function needs to be a function of effort and vacancies relative to the workforce at the firm level (with a specific functional form) in order to obtain a loglinear relation between the firm's job-filling rate and vacancy rate.

probability of making a contact, but it is more costly.

As in Chugh and Merkl (2016) and Kohlbrecher et al. (2016), we assume that worker-firm pairs draw a realization from an idiosyncratic training cost distribution upon contact. The training cost realization is drawn from a stable density function $f(\varepsilon)$, which is i.i.d. across workers and time. Firms choose up to which training cost realization $\tilde{\varepsilon}_{it}$ they want to select workers and thereby select a certain fraction of applicants for hiring, namely $\eta_{it} = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon$.

The sequence of decisions is as follows: At the beginning of each period, aggregate and firm-specific shocks realize. Next, firms decide how many vacancies to post (v_{it}) and at which intensity (e_{it}). Workers and firms get in contact with one another according to an undirected contact function, where $q_t = C_t/V_t^*$ represents the probability of getting in contact with a worker when posting a vacancy. C_t are economy-wide contacts and V_t^* are economy-wide effective vacancies at the aggregate level ($V_t^* = \int e_{it} v_{it} di$). Note that q_t is a market outcome, which depends on the contact function, the behavior of other firms and thereby market tightness. Finally, workers and firms draw an idiosyncratic training cost shock ε_{it} and the firms chooses a fraction of workers η_{it} to be hired.

Multi-worker firms maximize the following profit function

$$E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[\ a_{it} n_{it}^{\alpha} - w_{it}^{I}(1-\phi) n_{i,t-1} - g\left(e_{it}, v_{it}, n_{it}\right) - e_{it} v_{it} q_t \eta_{it} (\bar{w}_{it} + \bar{H}_{it}) \ \right] \right\}, \tag{1}$$

subject to the firm-specific employment stock (n_{it}) and the firm's selection rate for workers:

$$n_{it} = (1-\phi) n_{i,t-1} + e_{it} v_{it} q_t \eta_{it}, \tag{2}$$

where employment consists of workers that remain in the firm from the past period and new matches. New matches consist of effective vacancies at the firm level ($v_{it}^* = e_{it} v_{it}$) multiplied with the probability of making a contact and the selection rate (η_{it}).

a_{it} stands for firm-specific productivity (which may be subject to firm-specific and aggregate shocks), w_{it}^I is the wage for incumbent workers (who do not require any training)[6], ϕ is the exogenous separation rate. α determines the curvature of the production function (with $0 < \alpha \leq 1$) and δ is the discount factor.

We define the average wage for new matches and the average training costs as

$$\bar{w}_{it} = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{it}} w(\varepsilon) f(\varepsilon) d\varepsilon}{\eta_{it}}, \tag{3}$$

[6]As we only solve the firm optimization, we do not have to take a stance on wage formation. As usual with search frictions, the model could be closed with individual Nash bargaining, wage posting or collective wage determination mechanisms.

$$\bar{H}_{it} = \frac{\int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon}{\eta_{it}}. \tag{4}$$

Maximizing the profit function (see Appendix A for details) yields the following three conditions. They represent the three hiring margins that firms have at hands.

Vacancy posting condition:

$$\frac{g_{v_{it}}}{e_{it} q_t \eta_{it}} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - (\bar{w}_{it} + \bar{H}_{it}) + (1-\phi)\, \delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{5}$$

Selection condition:

$$\tilde{\varepsilon}_{it} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - w\left(\tilde{\varepsilon}_{it}\right) + (1-\phi)\, \delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{6}$$

where $w\left(\tilde{\varepsilon}_{it}\right)$ is the wage of the marginal entrant.

Effort condition:

$$\frac{g_{e_{it}}}{v_{it} q_t \eta_{it}} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - (\bar{w}_{it} + \bar{H}_{it}) + (1-\phi)\, \delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{7}$$

The model is a useful accounting tool for analyzing important mechanisms in the data. Let's start by looking at the business cycle dynamics in the model. A boom is associated with an increase of the marginal product of labor ($MPL_t = \alpha a_{it} n_{it}^{\alpha-1}$) and the future present value of a match.[7] In booms, firms have an incentive to post more vacancies (and thereby increase $g_{v_{it}}$), as the right hand side of equation (5) increases.

As the selection equation (6) contains the marginal product and the same future terms, firms are willing to accept larger training costs $\tilde{\varepsilon}_{it}$ in a boom. In different words, firms are less selective and select a larger fraction of applicants.

In similar vein, the model predicts an increase in firms' hiring effort (recruiting intensity) in booms. The right hand side of vacancy posting equation (7) is exactly the same as the right hand side of the job-creation equation (5). Thus, firms will increase $g_{e_{it}}$. Note that both an increase in vacancies and in effort generate more contacts. Thus, the relative use of these two instrument depends on the underlying convexity of the cost function for these two instruments.

To sum up, our model predicts a positive comovement of vacancy posting, selection and recruiting effort over the business cycle. However, we do not expect a one-to-one movement. First, while the average present value is relevant for the job-creation condition, it is the present value of a marginal worker for the selection condition (compare equations (5) and (6)). Second, both the vacancy posting function and the training cost distribution

[7] In Real Business Cycle models, aggregate productivity would increase. In a New Keynesian Model, the relative price of labor would increase (which has an observationally equivalent effect).

have curvature. Third, the convexity of the vacancy posting function with respect to vacancies and effort may be different.

So far, we have discussed aggregate productivity shocks. However, we expect a very similar behavior under firm-specific productivity shocks. Whenever a firm is hit by a positive firm-specific productivity shock, it has an incentive to post more vacancies, to be less selective and to invest more effort. Thus, to the extent that positive employment growth is driven by firm-specific productivity shocks, we expect a positive comovement between employment growth, vacancy posting, the selection rate and recruiting intensity along the employment growth distribution.

Finally, it is also worthwhile thinking about a situation where firms lose a large fraction of their workforce, e.g. because these workers leave to a different firm (which could be modelled by an increase in the exogenous separation rate ϕ). In this case, firm-specific employment n_{it} will drop and the marginal product increases. This has similar effects as a positive productivity shock. Firms will post more vacancies, be less selective and provide more effort. We will discuss this scenario when we analyze churn and employment-to-employment transitions in the empirical part.

3 Data Description and Empirical Methodology

3.1 Data Sources

Our primary data source is the IAB Job Vacancy Survey (JVS, see Moczall et al., 2015). The JVS is a representative survey among German establishments from all sectors and from all establishment size classes. It is a repeated cross-section, covering up to around 14,000 establishments per year. The survey is ideal for our analysis as it collects data on a variety of topics with regard to the hiring process of German establishments (e.g., the number of vacancies on the establishment level). The main questionnaire, which is conducted in every fourth quarter of a year additionally inquires information about the most recent new hire including information on job characteristics such as the exact job requirements, the search channel, the search duration, the exact hiring date, individual hire attributes such as gender, age, as well as match-specific characteristics like educational qualification, wage bargaining, and, in some waves, the hourly wage. For our analysis, we use the JVS from 1992–2017 (due to the reunification in Germany). Our estimation sample consists of 257,865 (establishment-year) observations. Descriptive statistics on our main variables are shown in Table B.1 in the Appendix B.1.

In addition, we link the JVS to administrative data, the Administrative Wage and Labor Market Flow Panel (AWFP, see Stüber and Seth, 2019). The AWFP is a dataset on labor market flows and stocks for the universe of German establishments. It contains data on job flows, worker flows, and wages for each establishment. The AWFP comprises partitions of the labor force according to selected employee characteristics (e.g., education) and for some sub-groups of employees (e.g., newly hired workers). For our analysis, we use the AWFP at the quarterly frequency for the years 2010–2014.[8] Our linked dataset consists of 61,021 (establishment-Q4) observations. Descriptive statistics on our main variables are shown in Table B.2 in the Appendix B.2.

3.2 Measures of Hiring Margins

Our empirical goal is to analyze how the hiring margins from the model behave in the data. Our first measure is the vacancy rate. Establishments report their contemporaneous number of vacant positions. From this, we calculate the vacancy rate as in Davis et al. (2013). The vacancy rate in period t is the number of vacancies in period t divided by the sum of vacancies and the average employment stock in $t-1$ and t.

As a second measure, we require a measure for search effort at the establishment level. We use the number of adopted search channels, which is also often used as a measure for individuals' job search effort.[9] The JVS reports the number of search channels establishments used for their most recent hire. The survey contains several channels that can be chosen (e.g., newspapers, own website, internet platforms, Federal Employment Agency, social media, and internal posting). As the number of options varies over the years, we follow Bossler et al. (2018) and group the number of channels into six time-consistent categories: 1) direct ads (newspapers, own website, commercial job boards, social media), 2) contact to the Federal Employment Agency, 3) private job services, 4) unsolicited applications, 5) internal vacancies, and 6) other channels.

The third measure is hiring selectivity. As proposed by Hochmuth et al. (2019), we use the inverse of the number of suitable applicants as a proxy of how "picky" establishments are in selecting new hires. This measure corresponds to our theoretical framework. Remember that multi-worker firms have to post vacancies at a certain effort level and thereby obtain a certain number of applicants. All these applicants draw a training cost realization from a time-invariant training cost distribution. Firms choose a certain fraction of these applicants (depending on the aggregate state of the economy and firm-specific shocks). In our model, the number of hires ($e_{it}v_{it}q_t\eta_{it}$) divided by the contacts ($e_{it}v_{it}q_t$) would correspond to the selection rate η_{it}.

As we do not have any information on the overall number of contacts at the estab-

[8]The IAB has the permission to link the JVS data to administrative data of the IAB only since 2010. Therefore we cannot link earlier years.

[9]See for example van den Berg and van der Klaauw (2019). An alternative would be to look at vacancy durations. However, whether longer vacancy durations reflect more or less search effort is, in general, ambiguous. The reason is that vacancy durations may consist both of periods during which firms wait for applications and selection periods (see Ours and Ridder, 1993). As a further alternative indicator one may exploit information on hours spent searching. However, in the JVS this information is available only from 2014 onwards.

lishment level, we rely on the most recent hire and define the selection rate as the inverse of the number of suitable applicants. This is a good proxy to the extent that the number of suitable applicants for the most recent hire is representative for the establishment.
Note that we choose suitable applicants instead of overall applicants for the definition of the empirical selection rate because the former corresponds better to our model. Our model does not contain any skill dimension, i.e. in contrast to the data it is excluded that somebody applies to a job and does not fulfill the requirements (e.g., university degree).

Our measures for recruiting intensity (search effort) and selectivity (selection rate) are nicely aligned. They are both based on information for the case of the most recent hire at the establishment level.

3.3 Regression Approach

We closely follow Davis et al. (2013, see Section III.C) and estimate the relationship of the hiring margins and employment growth at the establishment level in a nonparametric manner. First, we partition the employment growth rates into an extensive set of bins. We use narrow bins in areas where growth rates are very small and then gradually widen the bins in thinner parts of the distribution. Second, we run OLS regressions of the variables of our interest on the bin dummies and controls variables. By default, we control for heterogeneities in industry and establishment size. When we refer to the number of search channels, we additionally control for job requirements. When we refer to the selection rate, we additionally control for job requirements and the number of search channels. The latter is important because an establishment may attract more suitable applicants by increasing its effort. By controlling for the number of search channels, we exclude that our results for labor selection are distorted by this margin.

The bin dummy coefficients allow us to recover the nonparametric relationship of the hiring margins and the employment growth rates.[10] For visual clarity, we use a centered, five-bin moving average to smooth our estimation results.
We separately run these regressions for boom and recession periods as well as on all available periods. To detect booms (recessions) on the labor market, we filter the annual aggregate unemployment rate using a Hodrick-Prescott filter with a smoothing parameter of 6.25 (Ravn and Uhlig, 2002).[11] We define a boom (recession) as cyclical unemployment below (above) the 25^{th} (75^{th}) percentile. Note that we define booms and recessions based on the labor market state because we are interested whether establishments act in a tight or slack environment.[12]

[10] To restore the grand employment-weighted means, we add an equal amount to each bin dummy coefficient as in Davis et al. (2013).

[11] See Figure B.1 in Appendix B.3 for the filtered unemployment time series. Results are robust when we use a smoothing parameter 100 instead.

[12] While unemployment and GDP are generally strongly negatively correlated, our definition makes a major difference during the Great Recession where German unemployment barely increased and thus

4 Cross-Sectional and Time-Series Behavior

It is well known that hires and separations show a hockey stick behavior over the employment growth distribution in the United States (Davis et al., 2013). We show in the Appendix C that this also holds for Germany.

By contrast, due to a lack of suitable datasets, there is little knowledge on the cross-sectional behavior of different hiring margins. Therefore, this section shows how vacancies, selection and recruiting intensity behave over the employment growth distribution and depending on the business cycle for Germany. In addition, we analyze the time series behavior of these different margins. To generate the following graphs, we rely on the regression approach described in Section 3.3.

Figure 1 follows Davis et al. (2013)[13] and shows the vacancy rate over the employment growth distribution. In line with our model predictions, growing establishments post more vacancies than establishments with a constant workforce. However, shrinking establishments also post more vacancies than establishments with a constant workforce. Note that the vacancy behavior on the left-hand side of the employment growth distribution is different from the United States where vacancies in the negative part of the employment growth distribution are relatively flat (see Davis et al., 2013). We will discuss this behavior in more detail in the next section.

Furthermore, Figure 1 shows that the average vacancy rate is smaller in slack labor markets than in tight labor markets. This is in line with our model that contains elements from the canonical search and matching model (Mortensen and Pissarides, 1994). Due to smaller expected profits, fewer vacancies are posted in a recession.

In the canonical search and matching model, searching workers and searching firms get in contact with one another and a constant fraction of workers or all of them are hired. However, in reality, workers and firms (or establishments) meet for an interview and not all interviews turn into matches. The rate at which a contact turns into a match may differ in the cross section and over time.

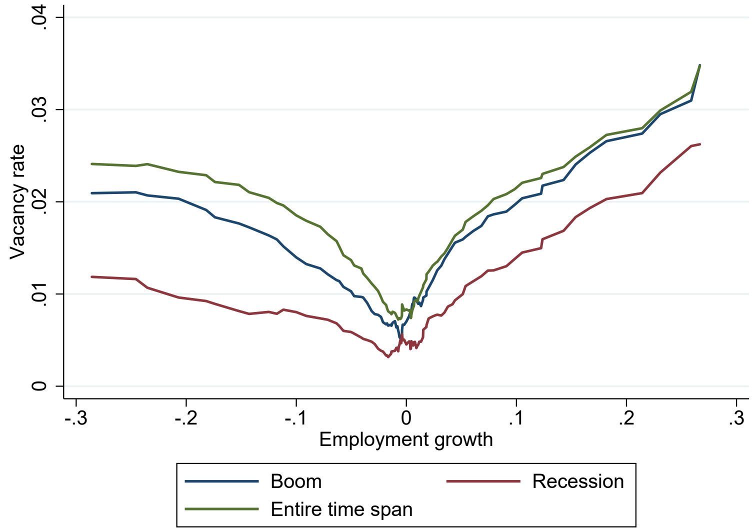
Let's think about our empirical indicator for selectivity through the lens of our theoretical model (for a detailed discussion see Section 3), where multi-worker firms post vacancies, get in contact with workers and then select a certain fraction of these applicants. Assume a firm selects 50% of applicants in our model. This would mean that there were two applicants for the most recent hire. Therefore, we use the inverse of the number of suitable applicants (labor selection rate) for the most recent hire as a measure for selectivity.[14] If there are more suitable applicants per hire, this means that the firm gets more selective (i.e., the selection rate falls). Note that we have chosen the number

establishments did not act in a particularly slack labor market. We use the harmonized annual unemployment rate from the OECD (2020).

[13] Carrillo-Tudela et al. (2018) and Carrillo-Tudela et al. (2020) show a similar figure for Germany.

[14] This measure was proposed by Hochmuth et al. (2019).

Figure 1: Vacancy rate and employment growth



Note: The vacancy rate is defined as the number of vacancies divided by the sum of the number of vacancies and the average employment stock. We use the establishment size and a set of industry dummies as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

of *suitable* applicants as our proxy because we assume that this means that firms have already screened the applications or interviewed the candidates (i.e., in terms of the model, they have drawn an idiosyncratic training cost realization). As a robustness check, we use the inverse of the overall number of applicants (which is also asked for in the JVS) as selection rate. We show in the Appendix D that our results are robust when using this alternative measure.

Figure 2 documents that the labor selection rate shows a U-shaped pattern along the employment growth distribution. Shrinking and growing establishments select a larger fraction of workers than establishments with a constant workforce.

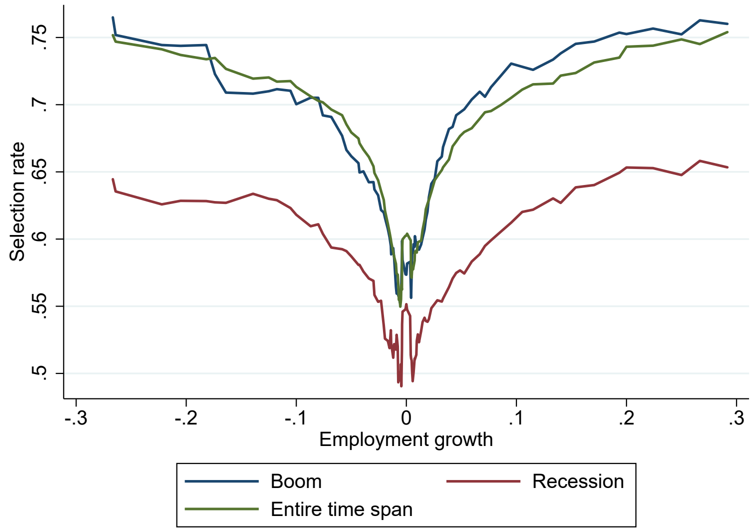
Several points are worthwhile emphasizing in this context: First, the increasing selection rate in the positive part of the employment growth distribution is in line with our predictions from the model. The pattern is also in line with Baydur (2017) who shows that growing firms become less selective, i.e. they have a higher selection rate. However, the falling selection rate in the negative part of the employment growth distribution is not in line with his model.

Second, comparing Figures 1 and 2, it is remarkable that both the pattern for vacancies and labor selection are U-shaped over the employment growth distribution. This is line with our model that predicts a strong positive comovement of these two variables.

Third, as mentioned above, it is important to stress that Figure 2 was generated by controlling for the number of search channels. Therefore the U-shape is not driven by differential use of channels over the employment growth distribution.

Fourth, we will argue in Section 5 that the behavior of the selection rate in the

Figure 2: Selection rate and employment growth



Note: The selection rate is defined as the inverse of the number of suitable applicants. We use the establishment size, a set of industry and job requirement dummies, and the number of search channels as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

negative part of the employment distribution may be related to churn and employment-to-employment transitions.

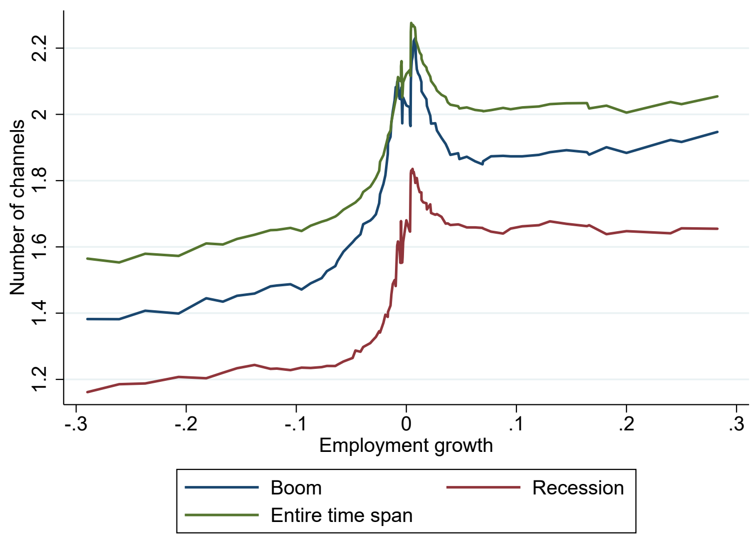
Fifth, Figure 2 also shows that the labor selection rate is a lot smaller in recessions than in booms. This is in line with our model prediction and confirms results by Hochmuth et al. (2019) who construct aggregate time series (on the sectoral, state, and national level) based on the JVS. They show that labor selection is strongly procyclical over the business cycle. However, they do not analyze the cross-sectional dimension.

Finally, it is worthwhile discussing potential other channels that could drive the U-shape in Figure 2. Through the lens of an undirected search model with a contact function, the patterns can be rationalized. But could there be other mechanisms that drive the patterns in the data? A high selection rate for fast-growing and fast-shrinking establishment corresponds to a small number of suitable applicants for the most recent hire. From a layman's perspective, this may be an indicator that they both have difficulties to attract a sufficient number of suitable applicants. But through this perspective, it is difficult to explain why this should be the case for shrinking establishments (that may be less attractive for applicants) as well as growing establishments (that may be very attractive). It is important to note that our paper establishes new stylized facts that are in line with an undirected search model with three hiring margins. Future research may come up with alternative mechanisms that are equally in line with the data.

Besides changing the number of vacancies and their selectivity, establishments can change their recruiting intensity. The JVS asks establishments about the number of channels they used for their most recent hire. The survey contains several channels that can be chosen (e.g., newspapers, own website, internet platforms, Federal Employment Agency, social media, and internal posting).[15]

Figure 3 shows an upward-sloping pattern of the number of search channels along the employment growth distribution (although not monotonically).[16] In contrast to the vacancy rate and the selection rate, the behavior of recruiting intensity is not U-shaped. However, the pattern that growing establishments use recruiting intensity more than shrinking firms is in line with our expectations. It is also worth emphasizing that the number of search channels varies substantially over the employment growth distribution. It almost doubles when we go from the negative to the positive part of the employment growth distribution.

Figure 3: Number of search channels and employment growth



Note: The number channels are the sum of search channels used by the establishments for their most recent hire. We use the establishment size and a set of industry and job requirement dummies as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

As expected through the lens of our model, Figure 3 shows that the number of search channels is procyclical. These results are in line with Davis et al. (2013) and Gavazza et al. (2018). In recessions, the number of channels falls significantly along the entire employment growth distribution. Thus, establishments reduce the number of search channels in recessions because expected profits are smaller. Through the lens of a standard search and matching model, this may generate a decline in aggregate matching

[15] As the number of options varies over the years, we use a normalized measure for the number of channels. We group the number of channels into six time-consistent accumulations: 1) direct ads (newspapers, own website, commercial job boards, social media), 2) contact to the Federal Employment Agency, 3) private job services, 4) unsolicited applications, 5) internal vacancies, and 6) other channels. Note that other normalization approaches do not alter the observed patterns qualitatively.

[16] Note that some establishments report that they used no search channels at all and these are included in Figure 3 because we want to mirror the entire growth distribution. These cases add up to on average 15 percent of all observations (share is only available from 2000 onwards).

efficiency (as search channels are omitted in the standard matching function). See Section 6 for a further discussion.

To sum up, the number of search channels tends to be upward sloping over the employment growth distribution and the vacancy rate and the selection rate show a U-shaped pattern. These are so far undocumented dimensions of recruiting intensity and hiring practices, which are useful benchmarks for theoretical models. In the next step, we connect these facts to worker churn and employment-to-employment transitions at the establishment level.

5 Worker Churn and Employment-to-Employment Transitions

Our model framework can easily explain the upward-sloping part of the vacancy rate and selection rate in the positive part of the employment growth distribution (based on firm-specific productivity shocks). By contrast, the curvature for shrinking establishments is less straightforward to explain. Therefore, we refer to work by Bachmann et al. (2017) who analyze churn for Germany. They show that worker churn is a U-shaped function of employment growth, which is procyclical over the business cycle (replicated, based on the JVS, in Figure E.1 in Appendix E). Interestingly, the vacancy rate and the selection rate show a very similar shape over the employment growth distribution (recall Figures 1 and 2).

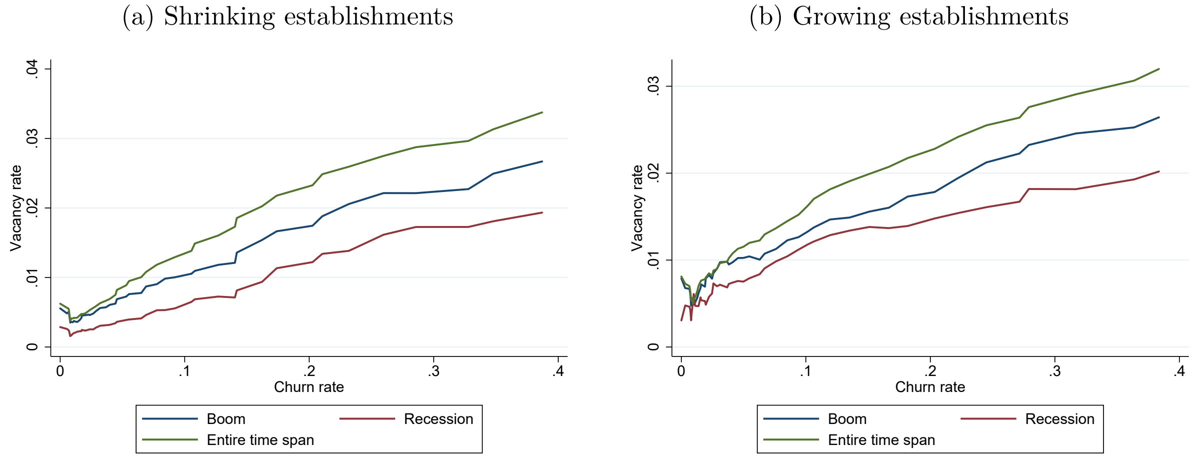
Worker churn (CH_{it}) is defined as the sum of establishments' hirings (H_{it}) in excess of job creation (JC_{it}) and their separations (S_{it}) in excess of job destruction (JD_{it}):

$$CH_{it} = (H_{it} - JC_{it}) + (S_{it} - JD_{it}) \tag{8}$$

To illustrate this, assume a firm that shrinks from 10 to 9 workers in a given period ($JD = 1$). If the firm hires 1 workers ($H = 1$) and separates from 2 workers ($S = 2$) during the same period, we would count a churn of 2 workers ($CH = 2$). Put differently, for shrinking establishments, we observe churn whenever they hire. Obviously, hiring requires vacancy posting, selection and search effort. Thus, we connect churn behavior to hiring practices.[17] It is worth emphasizing that churn may be driven by different reasons. Consider a shrinking establishment that churns. The establishment may be firing workers (say, production workers) and may be replacing them with better suitable workers (say, automation specialists). Alternatively, in the process of downsizing the establishment

[17] More generally, the churn rate is twice the hiring rate for shrinking establishments. For growing establishments, the churn rate is twice the separation rate.

Figure 4: Vacancy rate as a function of churn.



Note: The vacancy rate is defined as the number of vacancies divided by the sum of the number of vacancies and the average employment stock. The churn rate is defined as CH_{it} divided by the average employment stock. We use the establishment size and a set of industry dummies as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

may be losing more workers than desired (or other workers than those desired).[18]

To gain insights about the potential interaction between churn and hiring practices, we plot vacancies, search channels, and labor selection as a function of churn. For clarity, we show the churn rate for shrinking (establishments that hire despite shrinking) and growing establishments (establishments that separate despite growing and thereby have to hire more).[19]

Figure 4 shows that the vacancy rate is an upward-sloping function of churn. Figure 5 illustrates the positive connection between churn and selection. Figure 6 shows that the relationship between churn and the number of channels is less clear. Overall, these findings suggest that the U-shaped pattern of the labor selection and vacancy rate may be connected to the churn pattern over the employment growth distribution.

Bachmann et al. (2017) argue that employment-to-employment transitions are a key driver for churn. Note that employment-to-employment transitions can be considered as a proxy for involuntary worker losses from the establishment's perspective. Based on the JVS, we do not know where workers move to after leaving a establishment. However, by linking the Vacancy Survey with the AWFP, we can see whether the workers who left the firm moved into unemployment[20] or into employment.

Figure 7 shows the connection between employment-to-employment transitions, churn

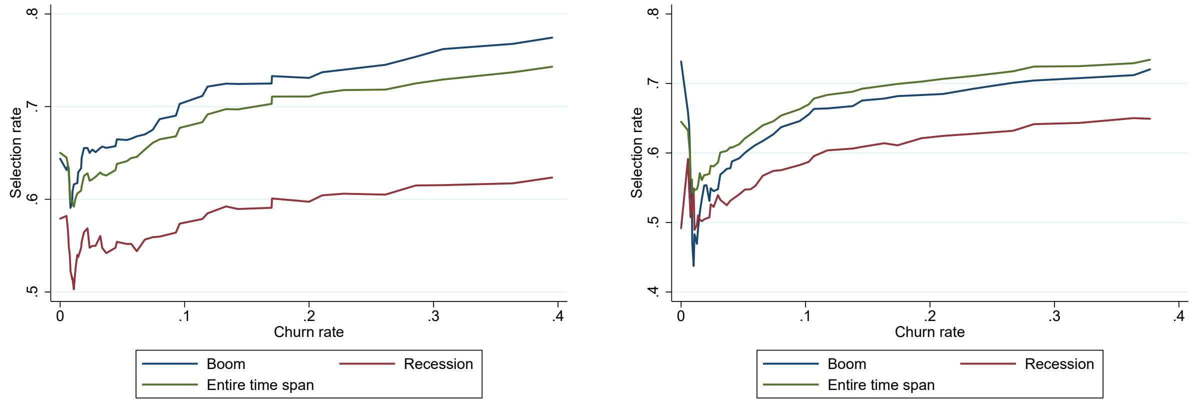
[18] Bachmann et al. (2017) show that worker churn arises from workers with similar work skills being churned and that churn is unlikely to reflect reorganization at the establishment level.

[19] The churn rate is normalized by dividing it by the average employment stock in $t-1$ and t. It ranges from zero to two. We exclude outliers with churn rates above 2 (about 2% of our sample) because these are either due to misreporting or intra-period churn.

[20] We count flows into non-employment as flows into unemployment.

Figure 5: Selection rate as a function of churn

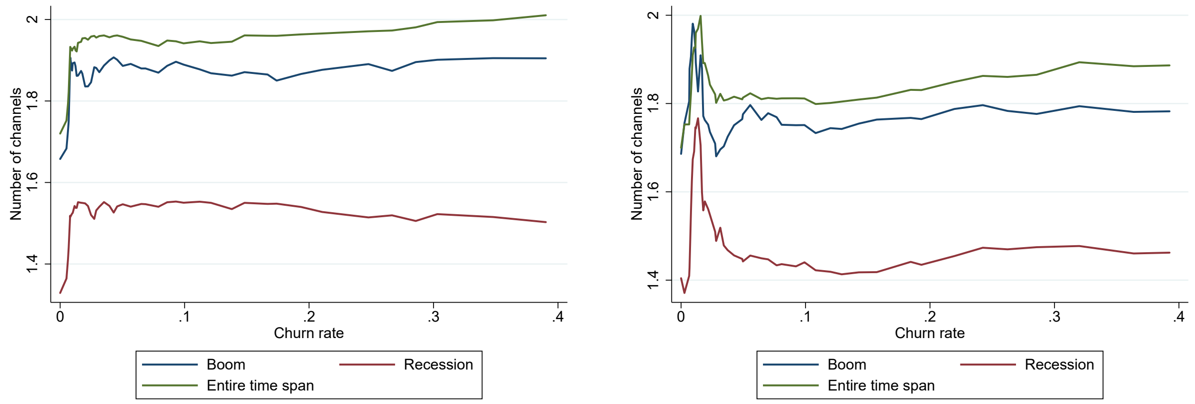
(a) Shrinking establishments (b) Growing establishments



Note: The selection rate is defined as the inverse of the number of suitable applicants. The churn rate is defined as CH_{it} divided by the average employment stock. We use the establishment size, a set of industry and job requirement dummies, and the number of search channels as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

Figure 6: Number of channels as a function of churn

(a) Shrinking establishments (b) Growing establishments

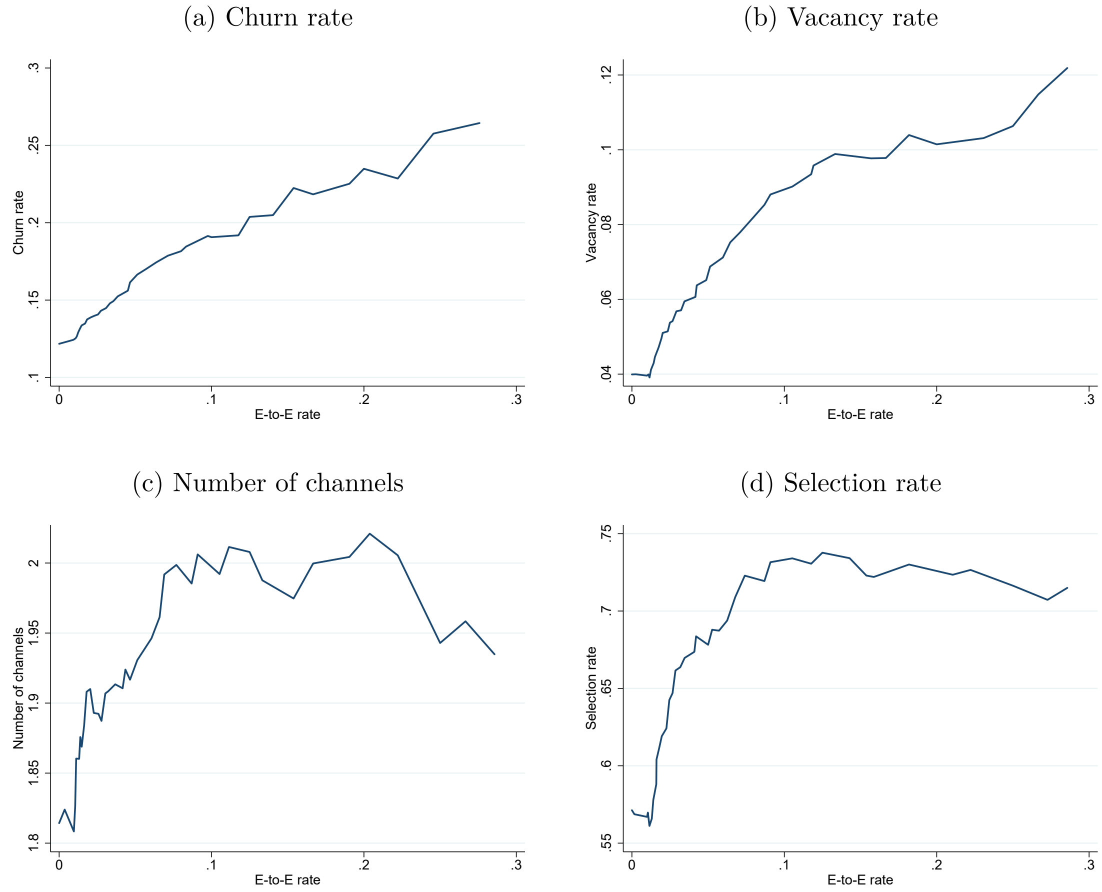


Note: The number channels are the sum of search channels used by the establishments for their most recent hire. The churn rate is defined as CH_{it} divided by the average employment stock. We use the establishment size and a set of industry and job requirement dummies as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

and the three hiring margins:[21] The upper left panel illustrates that there is an almost a linear one-to-one connection between employment-to-employment transitions and churn. The other three panels show the connection between employment-to-employment transitions and vacancy rates, search channels as well as labor selection. Basically, higher employment-to-employment flows are associated with larger vacancy rates and, except

[21] Note that we are legally allowed to merge the JVS and the AWFP only for the years 2010 to 2014. Due to this short time horizon, we cannot show the behavior over time (i.e., booms and recessions as in the previous sections).

Figure 7: Churn rate, vacancy rate, number of channels, and labor selection rate as a function of the Employment-to-Employment outflow rate



Note: The churn rate is defined as CH_{it} divided by the average employment stock. The vacancy rate is defined as the number of vacancies divided by the sum of the number of vacancies and the average employment stock. The number channels are the sum of search channels used by the establishments for their most recent hire. The selection rate is defined as the inverse of the number of suitable applicants. The E-to-E rate is the number of workers poached by other establishments divided by the average employment stock. We use the establishment size (Panel a, b, c, and d), a set of industry dummies (Panel a, b, c, and d), a set of job requirement dummies (Panel c and d), and the number of search channels (Panel d) as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey, AWFP.

for very large employment-to-employment transition rates, with larger selection rates and more search effort. Apparently, establishments try to compensate for lost workers by posting more vacancies and by being less selective.

As discussed in Section 2, higher vacancy posting, a higher selection rate and more recruiting effort in case of employment-to-employment transitions can be rationalized by decreasing returns. A lower employment level increases the marginal product and thereby gives an incentive to establishments to hire more workers.

Against this background, it is now straightforward to provide a potential explanation for the U-shape of the vacancy rate and selection rate over the employment growth distribution. Faster shrinking establishments face larger churn (as they lost a large fraction of workers to other establishments). Thus, they increase their vacancy posting and their selection rate to increase their workforce.

6 Summary and Perspectives

This paper uses the IAB Job Vacancy Survey (and its linkage to the AWFP) to establish new facts on how establishments use vacancy postings, the number of search channels, and the selection rate over the employment growth distribution and over time. This is an important reference point for future theory development. Although we do this exercise for Germany due to data availability, we believe that we also obtain valid guidance for other countries. Many patterns (such as the hockey stick behavior of hiring and separations along the employment growth distribution, see Appendix C) are similar in Germany and for instance in the United States.

In the cross-sectional dimension, our paper shows the connection between the employment growth distribution and different hiring margins. While fast-shrinking and fast-growing establishments show similar vacancy rates, fast-growing establishments have a much larger hiring rate. This may be explained by a larger recruiting intensity of fast-growing establishments. We interpret these findings as direct evidence for endogenous recruiting intensity as put forward by Gavazza et al. (2018).

In addition, we find evidence that a larger employment growth rate is associated with a larger labor selection rate (in the positive part of the employment growth distribution). This is in line with the model by Baydur (2017), who shows that faster-growing establishments become less selective. However, our empirical exercise also documents

Figure 8: Number of channels and labor market tightness

(a) time series, normalized around 1 (b) time series, HP-filtered

Note: In Panel (a), the time series are normalized around 1. In Panel (b) the time series are HP-filtered with $\lambda = 6.25$. Source: IAB Job Vacancy Survey, OECD.

cross-sectional patterns that standard labor market models have not yet incorporated.

Fast-shrinking establishments tend to show larger vacancy rates and selection rates than establishments with a constant workforce. We argue that this phenomenon is related to churn. Fast-shrinking establishments lose more workers than they would like to. These establishments initiate replacement hires by posting more vacancies and select a larger fraction of workers. Churn patterns in the cross section and over the business cycle are extensively documented in Bachmann et al. (2017). Our paper connects this phenomenon to different hiring channels and thereby provides interesting additional stylized facts for on-the-job-search models.

In the time dimension, our paper documents that vacancy posting, the number of search channels and labor selection are all procyclical. This is in line with Davis et al. (2013) and Gavazza et al. (2018). Figure 8 shows that the number of search channels is strongly procyclical in Germany. Market tightness and the number of search channels have a correlation of 0.72 (for both levels and the Hodrick-Prescott filtered cyclical components).

To the best of our knowledge, nobody has directly linked the behavior of search channels and its role for aggregate matching, which we identify as an important topic for future research. For the United States, Mongey and Violante (2019) construct an aggregate measure of recruiting intensity and find that its procyclicality is driven by firms cutting back on recruiting effort in slack labor markets. However, the labor market experience during the Great Recession was remarkably different in Germany compared to the United States. As market tightness did not drop substantially, we do not have a similar natural experiment for analyzing the change of matching efficiency due to a drop of search channels.

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A Model Derivations

Firms maximize the intertemporal Lagrangian, where λ_{it} is the Lagrange multiplier.

$$L = E_0 \left\{ \sum_{t=0}^{\infty} \delta^t \left[\begin{array}{c} a_{it} n_{it}^{\alpha} - w_{it}^{I}(1-\phi) n_{i,t-1} - g\left(e_{it}, v_{it}, n_{it}\right) - e_{it} v_{it} q_t \eta_{it} (\bar{w}_{it} + \bar{H}_{it}) \\ + \lambda_{it}\left(n_{it} - (1-\phi) n_{i,t-1} - e_{it} v_{it} q_t \eta_{it}\right) \end{array} \right] \right\} \tag{A.1}$$

The firm maximizes this condition with respect to n_{it}, v_{it}, $\tilde{\varepsilon}_{it}$, and e_{it}:

$$\frac{\partial L}{\partial n_{it}} = \alpha a_{it} n_{it}^{\alpha-1} - (1-\phi)\delta E_t w_{it+1}^{I} - g_{n_{it}} + \lambda_{it} - (1-\phi)\,\delta E_t \lambda_{it+1} = 0 \tag{A.2}$$

$$\frac{\partial L}{\partial v_{it}} = -g_{v_{it}} - e_{it} q_t \eta_{it} (\bar{w}_{it} + \bar{H}_{it}) - \lambda_{it} e_{it} q_t \eta_{it} = 0 \tag{A.3}$$

$$\frac{\partial L}{\partial \tilde{\varepsilon}_{it}} = -e_{it} v_{it} q_t \left[w\left(\tilde{\varepsilon}_{it}\right) f\left(\tilde{\varepsilon}_{it}\right) + \tilde{\varepsilon}_{it} f\left(\tilde{\varepsilon}_{it}\right) \right] - \lambda_{it} e_{it} v_{it} q_t f\left(\tilde{\varepsilon}_{it}\right) = 0 \tag{A.4}$$

In the previous equation, we use that $\frac{\partial \int_{-\infty}^{\tilde{\varepsilon}_{it}} w(\varepsilon) f(\varepsilon) d\varepsilon}{\partial \tilde{\varepsilon}_{it}} = w\left(\tilde{\varepsilon}_{it}\right) f\left(\tilde{\varepsilon}_{it}\right)$, $\frac{\partial \int_{-\infty}^{\tilde{\varepsilon}_{it}} \varepsilon f(\varepsilon) d\varepsilon}{\partial \tilde{\varepsilon}_{it}} = \tilde{\varepsilon}_{it} f\left(\tilde{\varepsilon}_{it}\right)$, $\frac{\partial \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon) d\varepsilon}{\partial \tilde{\varepsilon}_{it}} = f\left(\tilde{\varepsilon}_{it}\right)$.

$$\frac{\partial L}{\partial e_{it}} = -g_{e_{it}} - v_{it} q_t \eta_{it} (\bar{w}_{it} + \bar{H}_{it}) - \lambda_{it}\left(v_{it} q_t \eta_{it}\right) = 0 \tag{A.5}$$

Simplifying equation (A.4), we obtain:

$$\lambda_{it} = -w\left(\tilde{\varepsilon}_{it}\right) - \tilde{\varepsilon}_{it} \tag{A.6}$$

Simplifying equation (A.3):

$$\lambda_{it} = -\frac{g_{v_{it}}}{e_{it} q_t \eta_{it}} - (\bar{w}_{it} + \bar{H}_{it}) \tag{A.7}$$

Combining (A.6) and (A.7), we obtain

$$\frac{g_{v_{it}}}{e_{it} q_t \eta_{it}} = \left(w\left(\tilde{\varepsilon}_{it}\right) - \bar{w}_{it}\right) - \left(\bar{H}_{it} - \tilde{\varepsilon}_{it}\right) \tag{A.8}$$

Next, we substitute (A.7) into (A.2) and rearrange terms:

$$\frac{g_{v_{it}}}{e_{it} q_t \eta_{it}} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - (\bar{w}_{it} + \bar{H}_{it}) + (1-\phi)\,\delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{A.9}$$

This equation shows the vacancy posting condition. Vacancies are posted up to the point where the average costs of creating a job (left hand side) are equal to average expected returns of a job (right hand side).

By substituting (A.8) into (A.9), we obtain the selection condition:

$$\tilde{\varepsilon}_{it} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - w\left(\tilde{\varepsilon}_{it}\right) + (1-\phi)\,\delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{A.10}$$

This condition states that workers are selected up to the point where the marginal training costs, $\tilde{\varepsilon}_{it}$, are equal to the expected returns of the marginal worker.

Next, let's substitute (A.6) into equation (A.5) and simplify:

$$- g_{e_{it}} - v_{it} q_t \eta_{it} (\bar{w}_{it} + \bar{H}_{it}) + \left(w\left(\tilde{\varepsilon}_{it}\right) + \tilde{\varepsilon}_{it}\right)\left(v_{it} q_t \eta_{it}\right) = 0 \tag{A.11}$$

$$\frac{g_{e_{it}}}{v_{it} q_t \eta_{it}} = -(\bar{w}_{it} + \bar{H}_{it}) + \left(w\left(\tilde{\varepsilon}_{it}\right) + \tilde{\varepsilon}_{it}\right) \tag{A.12}$$

Using equations (A.8) and (A.9), we obtain:

$$\frac{g_{e_{it}}}{v_{it} q_t \eta_{it}} = \alpha a_{it} n_{it}^{\alpha-1} - g_{n_{it}} - (\bar{w}_{it} + \bar{H}_{it}) + (1-\phi)\,\delta E_t \left(\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}} + \bar{w}_{it+1} - w_{it+1}^{I} + \bar{H}_{it+1} \right) \tag{A.13}$$

This is the optimal effort conditions. It states that firms will change their effort up to the point where the costs equal the expected returns.

B Data Description

B.1 The IAB Job Vacancy Survey

Table B.1: Descriptive statistics, JVS (from 1992–2017)

Variable	Mean	SD	Min	Max
Vacancy rate	0.01	0.05	0	0.95
Hiring rate	0.09	0.13	0	1.29
Churn rate	0.11	0.22	0	2
Selection rate	0.51	0.46	0	1
Number of channels	1.04	1.18	0	7

Note: The table describes variables from the IAB Job Vacancy Survey (JVS) from 1992–2017, unweighted, on a yearly frequency. Our estimation sample consists of 257,865 establishments-year observations.

B.2 The Administrative Wage and Labor Market Flow Panel

Table B.2: Descriptive statistics, JVS and AWFP (from 2010–2014)

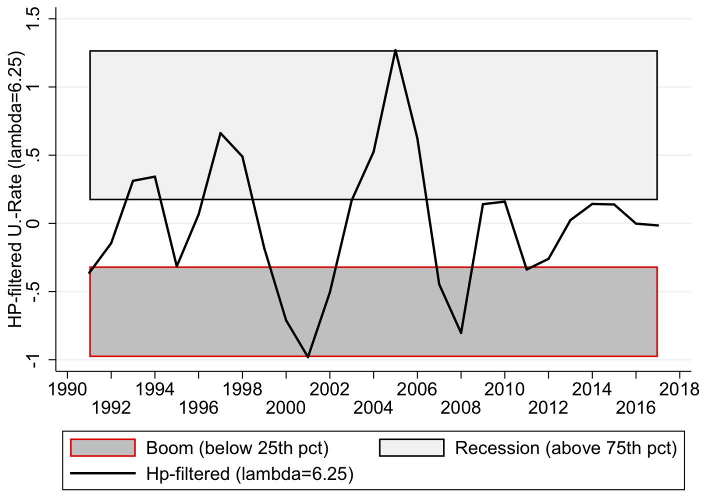
Variable	Mean	SD	Min	Max
Vacancy rate	0.03	0.09	0	1
Hiring rate	0.03	0.07	0	1
Churn rate	0.04	0.10	0	2
Selection rate	0.57	0.36	0	1
Number of channels	1.33	1.31	0	7

Note: The table describes variables from the IAB Vacancy Survey (JVS) linked to the Administrative Wage and Labor Market Flow Panel (AWFP) from 2010–2014, unweighted, on a quarterly frequency. Our estimation sample consists of 61,021 establishment-Q4 observations.

B.3 Aggregate Unemployment

We use the HP-filtered (lambda of 6.25) annual harmonized unemployment rate in order to define booms and recessions.

Figure B.1: Aggregate unemployment and business cycle definition



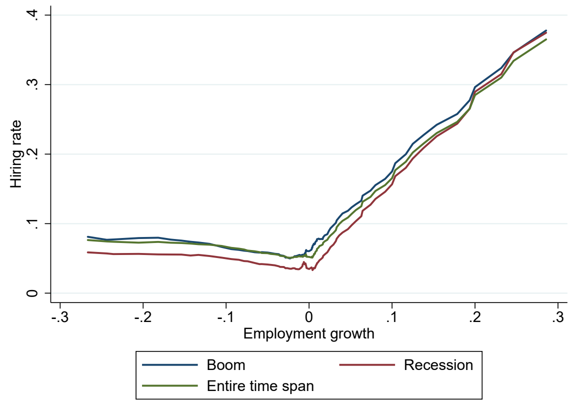
Source: OECD.

C Hockey Sticks

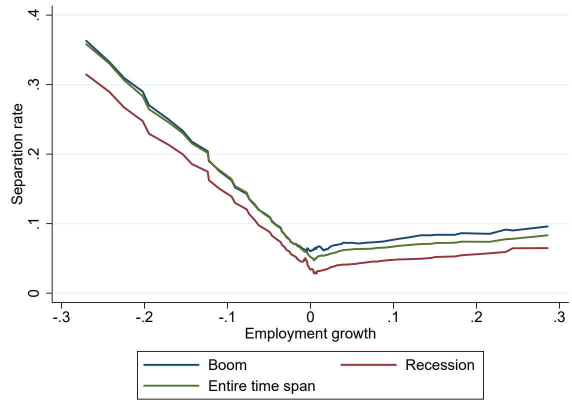
Davis et al. (2013) document for the United States that worker flows —hires and separations— are (inverted) hockey stick functions of employment growth. Based on the AWFP, Bachmann et al. (2017) show that the same pattern holds true for West Germany. To assess the validity of the annual JVS (relative to the administrative AWFP) in this dimension, we generate a similar picture. Figure C.1 displays the hiring rate (HR) and the separation rate (SR) over the employment growth distribution in booms and recessions. As in Davis et al. (2013), the HR (SR) is calculated as hires (separations) in t divided by the average employment stock in $t-1$ and t. Not surprisingly, growing establishments hire workers and shrinking establishments separate from workers. However, shrinking establishments also hire workers and growing establishments also separate workers and thereby generate churn (see Section 4).[22] Along the entire employment growth distribution, the hiring rate and the separation rate increases in booms relative to recessions.

Figure C.1: Worker flows and employment growth

(a) Hiring rate



(b) Separation rate



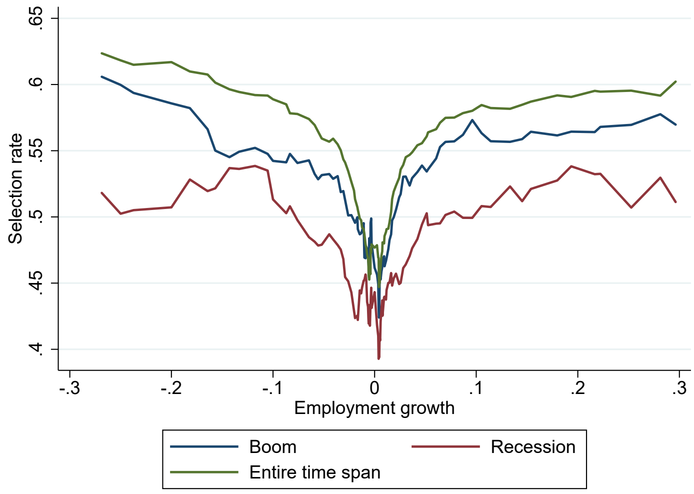
Note: The hiring rate is defined as the number of hired workers divided by the average employment stock. The separation rate is defined as the number of workers leaving the establishment divided by the average employment stock. We use the establishment size and a set of industry dummies as control variables. The regression approach is explained in Section 3.3. Source: IAB Job Vacancy Survey.

[22]These patterns based on the JVS are very similar to prior findings based on administrative data, see Bachmann et al. (2017).

D Robustness Checks

As a robustness check, we use the inverse of the number of all applications from the case of the most recent hiring to construct an alternative selection rate. Figure D.1 shows the result. As discussed in Section 4, our main results with respect to the selectivity of establishments are unaltered.

Figure D.1: Alternative selection rate and employment growth



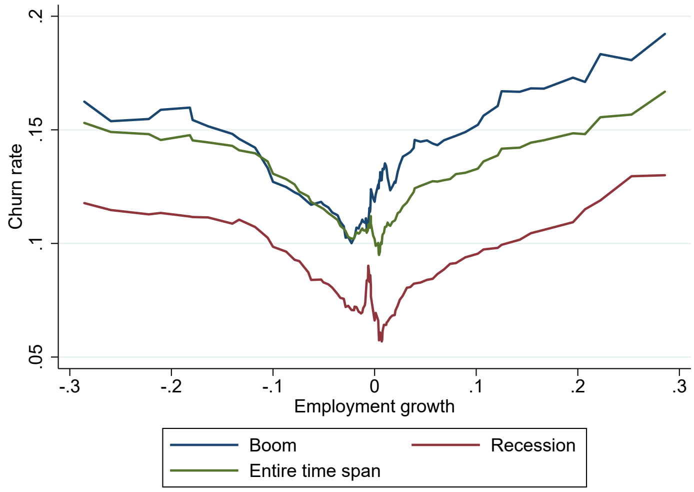
Note: The selection rate is defined as the inverse of the number of all applications. We use the establishment size, a set of industry and job requirement dummies, and the number of search channels as control variables. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

E Worker Churn

In the JVS, establishments are directly asked about the number of new hires, the number of workers who left, and the stock of workers. Figure E.1 shows churn over the employment growth distribution.

Figure E.1: Worker churn rate and employment growth



Note: The churn rate is defined as CH_{it} divided by the average employment stock. We use the establishment size and a set of industry dummies as control variables. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.