

DISCUSSION PAPER SERIES

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Cross-Sectional and Time-Series Evidence**

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Benjamin Lochner

University of Erlangen-Nuremberg and IAB

Christian Merkl

University of Erlangen-Nuremberg and IZA

Heiko Stüber

University of Erlangen-Nuremberg, IAB and IZA

Nicole Gürtzgen

IAB, University of Regensburg and ZEW

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IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

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

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—through the lens of an undirected search model. Vacancy posting and labor selection show a U-shape over the employment growth distribution. The number of search channels is also upward sloping for growing establishments, but relatively flat for shrinking establishments. We argue that growing establishments react to positive establishment-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 those with a constant workforce to churn triggered by employment-to-employment transitions. In line with our theoretical framework, all three hiring margins are procyclical over the business cycle.

JEL Classification: E24, J63

Keywords: recruiting intensity, vacancies, labor selection,
administrative data, survey data

Corresponding author:

Benjamin Lochner
University of Erlangen-Nuremberg (FAU)
Lange Gasse 20
90403 Nuremberg
Germany
E-mail: Benjamin.Lochner@fau.de

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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 different hiring margins in the United States. The behavior of vacancy yields over the employment distribution and over time are known.¹ By contrast, the exact drivers for these vacancy yields 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 agent equilibrium, firms' optimality conditions are a useful tool for measuring different recruiting channels in the data and for hypothesizing 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.² Firms choose an endogenous training cost cutoff and thereby endogenously determine their selectivity. We derive three hypotheses from our model. First, firms that are hit by a positive firm-specific productivity shock post more vacancies, increase their search effort,

¹[Carrillo-Tudela et al. \(2020\)](#) analyze vacancy yields for Germany.

²[Sedláček \(2014\)](#) proposes a model in a similar spirit.

and are less selective. Second, as we assume a decreasing returns to labor production function, firms that (unexpectedly) lose a fraction of workers face an increase of their marginal product and thereby increase their hiring activity in all three dimensions. Third, we expect all three hiring margins to be procyclical over the business cycle. In a boom, firms' profits and their incentive to hire more workers increase. Thereby, they use all three margins more intensively. These three hypotheses guide our data analysis.

Given the lack of suitable survey data for the United States³, our paper uses the German IAB-Stellenerhebung (IAB Job Vacancy Survey, JVS henceforth) 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 establishments⁴ (Moczall et al., 2015). These 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). From the JVS, we construct empirical indicators for establishments' 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 utilize information on the number of suitable applicants for an establishment's most recent hire. An establishment that hires a large fraction of suitable applicants is considered to be less selective than an establishment that hires a small fraction of suitable applicants. As in Hochmuth et al. (2019), we thus use the inverse of the number of suitable applicants for the the most recent hire.

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 establishments in Germany (Stüber and Seth, 2018). Carrillo-Tudela et al. (2020) recently linked the JVS with the Integrated Employment Biographies of the IAB at the establishment level. Using the variation across local labor markets, they analyze vacancy yields, recruiting intensity, and matching efficiency. Among other things, they show that the recruiting intensity matters for matching efficiency. Later, we argue that their paper is complementary to ours in various dimensions.

Our paper documents the following three important facts: First, we show that the number of search channels is upward sloping in the positive part of the employment growth distribution. By contrast, it is relatively flat in the negative part of the employment growth distribution. These cross-sectional facts for search channels can be explained by

³The 1980 Employment Opportunity Pilot Project is a notable exception for a firm survey (see for example Barron et al., 1985). However, the survey is outdated and it is purely cross-sectional (one point in time). 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.

⁴We use firm and establishment interchangeably. While models usually refer to firms, the data used for the analyses is establishment data.

establishment-specific productivity shocks. Larger positive productivity shock stimulate establishments' employment growth and thereby give an incentive to establishments to increase their recruiting intensity.

Second, 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 again be explained by positive firm-specific productivity shocks. But why do (faster) shrinking firms post more vacancies and are less selective than firms with a constant workforce? [Bachmann et al. \(2020\)](#) show that faster shrinking establishments are subject to more worker churn than establishments with a constant workforce. Intuitively, establishments in the negative part of the employment growth distribution lose more workers than expected and thereby have to hire new workers to adjust to their desired size. In different words, they lose workers and hire workers within the same period (within a given skill group and more so, the more they shrink). Therefore, our paper establishes a link between worker churn and hiring margins. We show that faster shrinking establishments post on average more vacancies and select a larger fraction of workers than establishments with a constant workforce in order to accomplish their necessary replacement hirings.⁵ As [Bachmann et al. \(2020\)](#) show a strong comovement between churn and employment-to-employment transitions, we link the three hiring margins to employment-to-employment transitions, showing a positive connection. From a theoretical perspective this can be rationalized by firms with a decreasing returns to labor production function that increase their marginal product when they lose workers (on an involuntary basis).

Third, 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 slack labor market establishments post fewer vacancies, use fewer search channels, and are less selective than in a tight labor market. The development of the used number of search channels over time is in line with procyclical recruiting intensity, as argued by [Davis et al. \(2013\)](#) and [Gavazza et al. \(2018\)](#).

2 Firm Model 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 obtain three hypotheses how firms react to different types 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. They pro-

⁵Using the JVS, [Mercan and Schoefer \(2020\)](#) show that replacement hiring is a significant share among all hiring in Germany.

duce under decreasing returns and have three 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.

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 $g(e_{it}, v_{it}, n_{it})$, which depends on firm-specific effort e_{it} , vacancies v_{it} , and employment n_{it} . The cost function is increasing and convex in search effort and in the number of vacancies ($\partial g/\partial e_{it} = g_{e_{it}} > 0$, $\partial^2 g/\partial e_{it}^2 > 0$, $\partial g/\partial v_{it} = g_{v_{it}} > 0$, $\partial^2 g/\partial v_{it}^2 > 0$).⁶ Small workforce adjustments are less costly than large workforce adjustments.

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 decide whether or not a certain contact is suitable for hiring. They 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 $\eta_{it} = \int_{-\infty}^{\tilde{\varepsilon}_{it}} f(\varepsilon)d\varepsilon$.

As we assume an idiosyncratic shock that is purely transitory, it is unrelated to systematic productivity differentials connected to occupations or skills. This is important when we link our model to the data. Note that our approach is different from the approach of [Carrillo-Tudela et al. \(2020\)](#), who model permanent idiosyncratic productivity draws and link them to the data.⁷

The sequence of decisions in our model is as follows: Both the firm-specific productivity (a_{it}) and the firm-specific separation rate (ϕ_{it}) are stochastic. At the beginning of each period, aggregate and firm-specific shocks realize. Firms can adjust their recruiting behavior in response to these shocks. Next, firms decide how many vacancies (v_{it}) to post 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 firm chooses a fraction of workers η_{it} to be hired.

Multi-worker firms maximize the following profit function

⁶[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 log-linear relation between the firm's job-filling rate and vacancy rate.

⁷For a detailed discussion of positive and normative differences between a temporary and a permanent idiosyncratic shock see [Merkl and van Rens \(2019\)](#).

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

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

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

Employment consists of workers that remain in the firm from the past period and new matches. Employment relationships from the past period are subject to exogenous separation rate shocks (ϕ_{it}). As the separation rate shock hits at the beginning of the period, firms can adjust their recruiting behavior in response to these shocks.⁸ New matches consist of effective vacancies at the firm level ($v_{it}^* = e_{it} v_{it}$) multiplied with the probability of making a contact (q_{it}) and the selection rate (η_{it}).

a_{it} denotes 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).⁹ α determines the curvature of the production function (with $0 < \alpha < 1$) and δ is the discount factor.

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

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

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

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:

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

⁸Note that our assumption is different from the typical way of modelling endogenous separations (with a match-specific productivity shocks). We aim at modelling a shock that is exogenous and unexpected to the firm.

⁹As 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.

Selection condition:

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

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

Effort condition:

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

All three hiring margins are a function of the the marginal product of labor ($MPL_{it} = \alpha a_{it} n_{it}^{\alpha-1}$) and the expected future value of a match. The latter includes the expected future marginal products of labor (which can be seen when substituting $\frac{g_{v_{it+1}}}{e_{it+1} q_{t+1} \eta_{it+1}}$ by iterating equation 5 forward) and the cost difference between incumbent workers (with zero training costs and wage w_{it+1}^I) and new workers (with average expected wage costs and training costs, $\bar{w}_{it+1} + \bar{H}_{it+1}$).

When firms are hit by a positive idiosyncratic productivity shock, a_{it} , the marginal product of labor increases. Thus, the right hand side in all three equations increases. Firms will post more vacancies, increase the cutoff point for selection (i.e. select a larger fraction of applicants) and raise their recruiting effort. In different words, according to our model all three margins show a positive comovement with idiosyncratic productivity. In the JVS, we do not have any information on establishments' productivity or revenues. However, we expect that establishments with positive productivity shocks are growing establishments. Therefore, our *first hypothesis* is that all three hiring margins are positively correlated with employment growth in the positive part of the employment growth distribution.

With decreasing returns to labor, there is an optimal firm size. In steady state, every firm faces an optimal firm size \bar{n}_i , which depends on the firm-specific steady state productivity a_i . Whenever a firm is hit by an unexpected large positive idiosyncratic separation rate shock, the beginning-of-period firm size drops below its optimum and the marginal product of labor increases. In this case, our model predicts that all three hiring margins will increase. However, firms will not immediately compensate for the lost workers. They will only do so gradually due to convex adjustment costs, $g(e_{it}, v_{it}, n_{it})$. Thus, as *second hypothesis* we expect a positive connection between the size of unexpected establishment-specific separations and all three hiring margins.

Similar to establishment-specific productivity, we do not directly observe whether there is unexpected loss of workers. Therefore, we will use two proxies in our empirical analysis. Our first proxy is worker churn, which shows up whenever an establishment hires and separates from workers within a short time period. Whenever a establishment is hit by a large separation rate shock and starts replacing some of these workers within

the same period, we observe churn. [Bachmann et al. \(2020\)](#) show in a different model context that stochastic separations are important for explaining worker churn patterns in Germany. We complement their results from the hiring side. As a second proxy for unexpected worker separations, we use the employment-to-employment transition rate, which we obtain by linking the JVS to administrative data from the AWFP (i.e. the share of workers that leave an establishment and immediately start working in another establishment without touching unemployment).

Finally, as a *third hypothesis*, we expect a positive comovement of aggregate productivity (or the business cycle more generally) with vacancies, selection, and establishments' search effort. When aggregate productivity increases, this increases the whole distribution of marginal products and thereby the optimal establishment size. Note, however, that there may be additional equilibrium effects at work about which our simple firm optimization problem remains silent.

3 Data Description and Empirical Methodology

3.1 Data Sources

Our primary data source is the IAB-Stellenerhebung (IAB Job Vacancy Survey, JVS, see [Moczall et al., 2015](#)). The JVS is a representative survey among establishments in Germany 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. Among other things, the main questionnaire, which is conducted in every fourth quarter of a year, asks establishments about the number of vacancies on the establishment level. The JVS additionally inquires information about the most recent new hire including information on job characteristics such as the exact job requirements, the search channels, 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 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, 2018](#)). The AWFP is a dataset on labor market flows and stocks for the universe of establishments in Germany.¹⁰ It

¹⁰The FDZ-AWFP (see, [Stüber and Seth, 2019](#)), a 50% random sample of the AWFP, and an AWFP extension for the JVS (see, [Stüber et al., 2020](#)) are available at the Research Data Centre (FDZ) of the German Federal Employment Agency at the IAB.

contains data on job flows, worker flows, and wages for each establishment. For our analysis we use the AWFPP at the quarterly frequency for the years 2010–2014.¹¹ Our linked dataset consists of 61,021 (establishment-Q4) observations. Descriptive statistics on our main variables are shown in Table B.2 in Appendix B.2.

3.2 Measures of Hiring Margins

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

Second, 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.¹² The JVS reports the search channels establishments used for their most recent hire (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. Since we do not have any information on the overall number of contacts at the establishment level, we rely on information about the most recent hire. 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, where multi-worker firms have to post vacancies at a certain effort level and thereby obtain a certain number of applicants. All these applicants then 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} . The underlying assumption is that most recent hires are representative for all hires

¹¹The IAB has the permission to link the JVS data to administrative data of the IAB only since 2010. Therefore we cannot link earlier years.

¹²See 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 onward.

(after controlling for observables). When firms answer how many suitable applicants they had for a given position, we expect that these are applicants that had suitable skills, suitable experience, etc. However, firms still have to choose the candidate that fits best for the position (i.e. the one with the lowest training costs in terms of our model). Accordingly, we choose the number of *suitable* applicants (and not the overall number of applicants) for our measure for selectivity 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).¹³ Thus, our empirical approach is in line with the model, which does not contain any skill dimension.¹⁴

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 and occupations. When we refer to the selection rate, we additionally control for job requirements, occupations, 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 rule out 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.¹⁵ For visual clarity, we use a centered, moving average to smooth our estimation results.

We separately run these regressions for boom and recession periods as well as for 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](#)).¹⁶ We define a boom (recession) as cyclical unemployment

¹³As 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 Appendix D that our results are robust when using this alternative measure.

¹⁴Note that our selectivity measure is different from [Carrillo-Tudela et al. \(2020\)](#). They use a permanent productivity draw in their model, i.e. a component that is much more related to skills and reflected in wage formation. Their work and our work are thus complementary and shows that both dimensions of selection matter in the data.

¹⁵To restore the grand employment-weighted means, we add an equal amount to each bin dummy coefficient as in [Davis et al. \(2013\)](#).

¹⁶See Figure B.1 in Appendix B.3 for the filtered unemployment time series. Results are robust when we use a smoothing parameter 100 instead.

below (above) the 25th (75th) 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.¹⁷

4 Cross-Sectional 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). A similar hockey stick behavior was also documented for Germany by various papers (see e.g., Bachmann et al., 2020; Bossler and Upward, 2016; Carrillo-Tudela et al., 2020). We replicate the hockey stick behavior based on the JVS in Appendix C.

By contrast, due to a lack of suitable datasets, there is little knowledge on the cross-sectional behavior of different hiring margins (for a recent exception see Carrillo-Tudela et al., 2020). Therefore, this section shows how vacancies, selection, and recruiting intensity behave over the employment growth distribution. To generate the following graphs, we rely on the variable definitions in Section 3.2 and the regression approach described in Section 3.3.

4.1 Hiring Margins and Employment Growth

Figure 1 shows the behavior of the vacancy rate, the selection rate, and the number of search channels over the employment growth distribution. Vacancies and labor selection show a U-shaped behavior. The number of search channels is upward sloping in the positive part of the employment distribution, but relatively flat in the negative part of the employment growth distribution.

Vacancy Rate

The upward sloping behavior of vacancies in the positive part of the employment growth distribution in Figure 1a is in line with our first hypothesis.¹⁸ The behavior can be easily rationalized by a search and matching model (Mortensen and Pissarides, 1994). Whenever (expected) profits increase, which would be the case under positive idiosyncratic productivity shocks, firms start posting more vacancies.

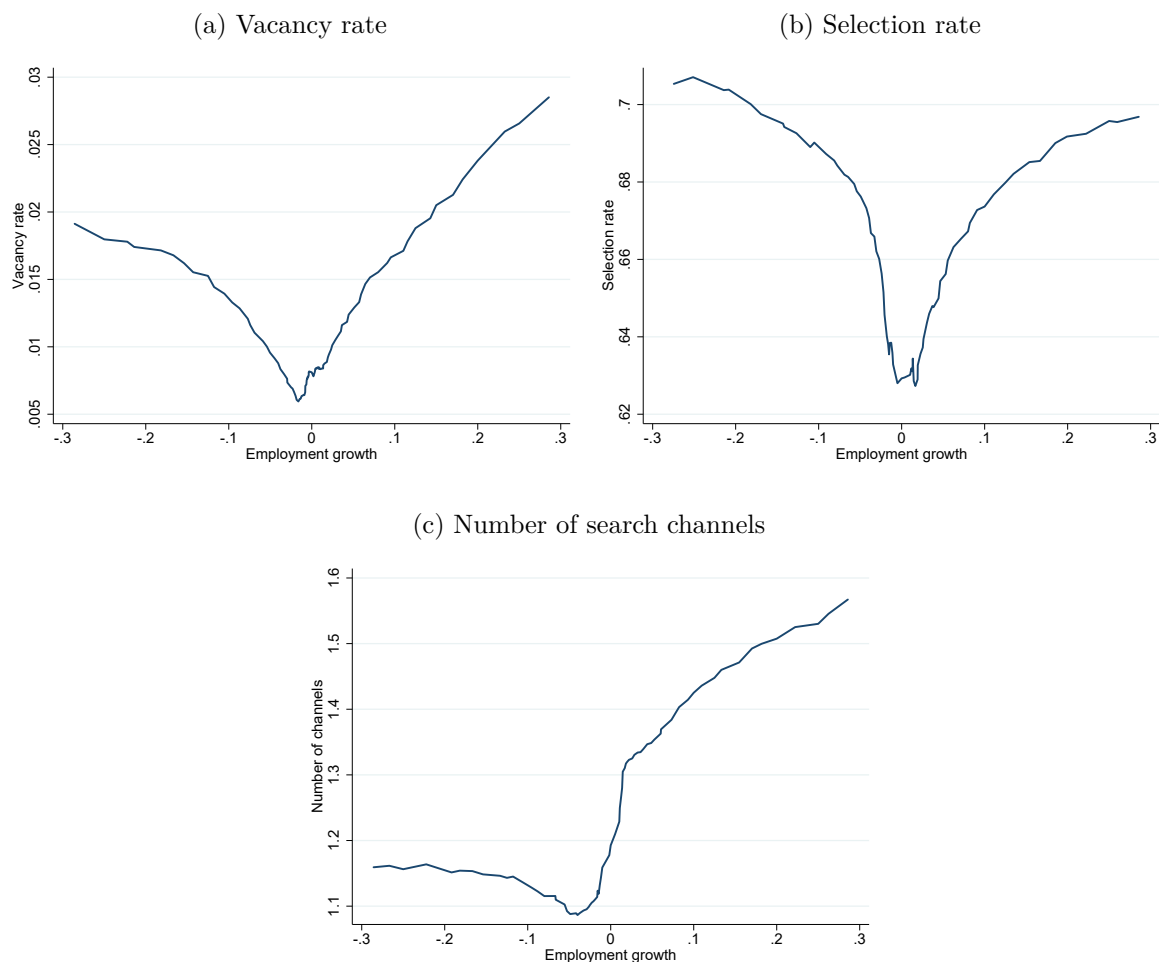
It is, however, more difficult to explain that shrinking establishments post more vacancies than establishments with a constant workforce. In Section 4.2, we discuss the

¹⁷While unemployment and GDP are generally strongly negatively correlated, our definition makes a major difference during the Great Recession where unemployment in Germany barely increased and thus establishments did not act in a particularly slack labor market. We use the harmonized annual unemployment rate from the OECD (2020).

¹⁸Davis et al. (2013) and Carrillo-Tudela et al. (2020) show similar figures for the United States and Germany, respectively.

left-hand side of the vacancy distribution in more detail. 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](#)).

Figure 1: Hiring margins 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 in $t - 1$ and t . The selection rate is defined as the inverse of the number of suitable applicants for the most recent hire. The number channels are the sum of search channels used by the establishments for their most recent hire. Control variables: a) dummies for establishment size and industry, b) as a) and dummies for job requirements, occupations and the number of search channels, c) as a) and dummies for job requirements and occupations. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

Labor Selection Rate

While firms only use the vacancy margin for hiring in the standard search and matching model, our model allows firms to vary the degree of selectivity. Conceptionally, workers and firms (or establishments) meet for an interview and not all interviews turn into matches. Through the lens of our theoretical model (Section 2), if a firm has two suitable applicants for the most recent hire, it selects 50% of these applicants. If it has three suitable applicants, the selection rate is 33%. Therefore, we follow [Hochmuth et al.](#)

(2019) and use the inverse of the number of suitable applicants (selection rate) for the most recent hire as a measure for selectivity. In different words, whenever there are more suitable applicants per hire, this means that the firm is more selective (i.e., the selection rate falls). Recall Section 3.2 for a detailed discussion of our selection measure.

Figure 1b documents that the labor selection rate shows a U-shaped pattern along the employment growth distribution (similar to the vacancy rate). 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 positive idiosyncratic productivity shocks. Baydur (2017) 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 and is discussed in Section 4.2.

Second, it is important to stress that Figure 1b was generated by controlling for the number of search channels (as the use of more channels may attract more suitable applicants per vacancy). Therefore the U-shape is not driven by differential use of channels over the employment growth distribution.

Finally, it is worthwhile discussing potential other theoretical mechanisms that could drive the U-shape in Figure 1b. A high selection rate for fast-growing and fast-shrinking establishment corresponds to a small number of suitable applicants for the most recent hire. This may be an indicator that both shrinking and growing firms have difficulties to attract a sufficient number of suitable applicants. Through the lens of a directed search model, it appears plausible that shrinking firms may be less attractive for applicants. Thereby, they may attract fewer applicants, which leads to a higher selection rate. However, it appears unlikely that a directed search mechanism generates fewer applicants for growing establishments (which may actually 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.

Number of Search Channels

In addition to changing the number of vacancies and their selectivity, establishments can change their recruiting intensity. The JVS asks establishments about the number of search 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).¹⁹

Figure 1c shows that there is a positive slope for the number of used channels in the

¹⁹Recall Section 3.2 for details. Other normalization approaches, such as the proportion of search channels used, do not alter our results qualitatively.

positive part of the employment growth distribution.²⁰ In contrast to the vacancy rate and selection, recruiting intensity is not (strongly) downward sloping in the negative part of the employment distribution. The discovered pattern that growing establishments use recruiting intensity more than shrinking firms is in line with the pattern generated by idiosyncratic productivity shocks.

In a nutshell, the vacancy rate, the selection rate, and the number of search channels are all upward sloping in the positive part of the employment growth distribution. The first model hypothesis explains the upward-sloping part of all three hiring margins in the positive part of the employment growth distribution based on firm-specific productivity shocks. We connect the behavior in the negative part of the employment growth to churn in the next section.

4.2 Hiring Margins and Worker Churn

In order to explain the behavior of hiring margins in the negative part of the employment distribution, we refer to our second hypothesis from our model and to work by [Bachmann et al. \(2020\)](#) who analyze worker churn for Germany. They show that worker churn is a U-shaped function of employment growth (replicated, based on the JVS, in Figure 2). Interestingly, the vacancy rate and the selection rate show a very similar shape over the employment growth distribution as worker churn (recall Figures 1a and 1b). According to our second hypothesis, the behavior in the negative part of the employment growth distribution may be connected to unexpected loss of workers, which would depress employment below the optimal firm-specific level and therefore stimulate hiring. We use two measures to analyze this connection, namely worker churn and employment-to-employment transitions.

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}):

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

where JC_{it} is defined as establishments' positive job turnover and JD_{it} as establishments' absolute negative JT_{it} , with ($JT_{it} = H_{it} - S_{it}$):

$$JC_{it} = \begin{cases} JT_{it}, & \text{if } JT_{it} > 0 \\ 0, & \text{otherwise} \end{cases} \quad (9)$$

²⁰Note that some establishments report that they used no search channels at all. These establishments are included in Figure 1c because we want to mirror the entire growth distribution. These cases add up to on average 15 percent of all observations.

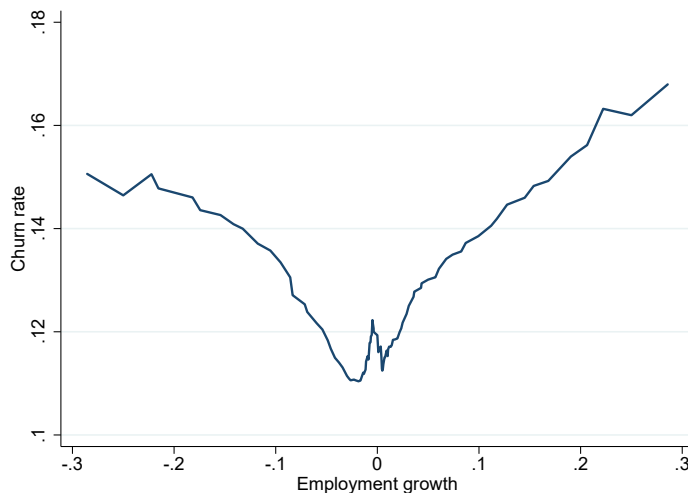
and

$$JD_{it} = \begin{cases} \text{abs}(JT_{it}), & \text{if } JT_{it} < 0 \\ 0, & \text{otherwise.} \end{cases} \quad (10)$$

More generally, the worker churn rate is twice the hiring rate for shrinking establishments. For growing establishments, the churn rate is twice the separation rate.²¹

To illustrate this, assume an establishment that shrinks from 10 to 9 workers in a given period ($JD = 1$). If the establishment hires 1 worker ($H = 1$) and separates from 2 workers ($S = 2$) during the same period, we would count a churn of 2 workers ($CH = 2$), i.e. churn is a measure for the number of hires/separations beyond what would have been necessary for the actual workforce adjustment. Put differently, for shrinking establishments, we observe worker churn whenever they hire within the same period when they separate from workers. Obviously, hiring requires vacancy posting, selection, and search effort, even though establishments shrink. Thus, we connect worker churn behavior to hiring practices.

Figure 2: Worker churn rate and employment growth



Note: The churn rate is defined as CH_{it} divided by the average employment stock in $t - 1$ and t . Control variables: dummies for establishment size and industry. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

Figure 2 shows a U-shaped behavior for churn. Fast-shrinking and fast-growing establishments churn most. This means that shrinking establishments hire more workers than establishments with a constant workforce.

To gain insights about the potential interaction between worker churn and hiring practices, we plot vacancies, search channels, and labor selection as a function of worker churn (see Appendix E). For clarity, we show the worker churn rate for shrinking (establishments that hire despite shrinking) and growing establishments (establishments that

²¹The churn rate is calculated following Davis et al. (2013), using as the denominator the average employment stock in $t - 1$ and t .

separate despite growing and thereby have to hire more).²² Figure E.1 shows that the vacancy rate is an upward-sloping function of worker churn. Figure E.2 illustrates the positive connection between worker churn and selection (although there is some noise for very low churn). Figure E.3 shows a positive connection between worker churn and the number of channels. Overall, these findings suggest that the U-shaped pattern of the labor selection and vacancy rate may be connected to the worker churn pattern over the employment growth distribution.

Bachmann et al. (2020) show that there is a strong positive comovement between employment-to-employment transitions and worker churn. Note that employment-to-employment transitions (i.e. workers that work at another establishment in the next period without touching the pool of unemployment) 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 JVS with the AWFPP, we can see whether the workers who left the firm moved into unemployment²³ or into employment.

Figure 3 shows the connection between employment-to-employment transitions, worker churn, and the three hiring margins:²⁴ The upper left panel illustrates that there is an almost linear one-to-one connection between employment-to-employment transitions and worker churn. The other three panels show the connection between employment-to-employment transitions and vacancy rates, search channels, and labor selection. Basically, higher employment-to-employment flows are associated with larger vacancy rates, with larger selection rates, and more search effort. Establishments try to compensate for lost workers by posting more vacancies, by providing more search effort, and by being less selective.²⁵

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 (losing a large fraction of workers to other establishments). Thus, as their marginal product increases (through the lens of our model), they increase their vacancy posting and their selection rate to compensate for part of the lost workers and to do replacement hiring.²⁶

²²The 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.

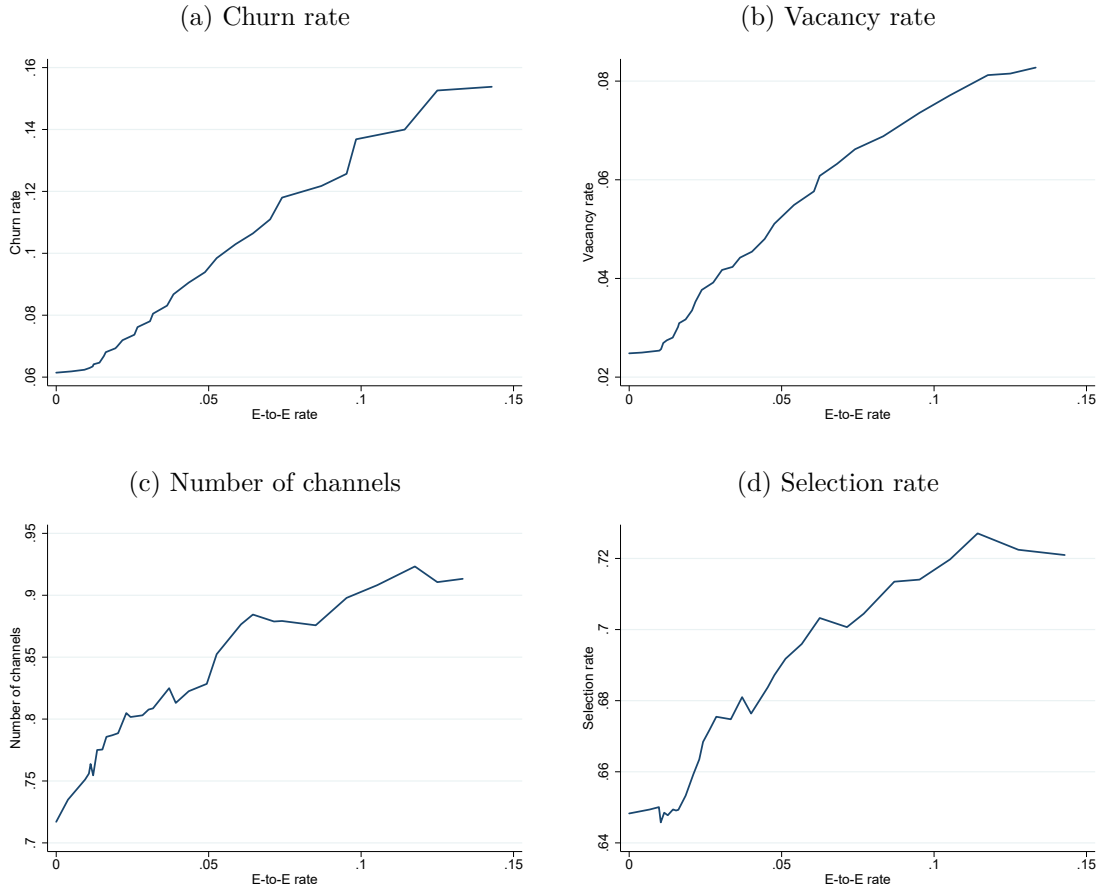
²³We count flows into non-employment as flows into unemployment.

²⁴Note that we are legally allowed to merge the JVS and the AWFPP 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 next section).

²⁵Mercan and Schoefer (2020) show that quits trigger vacancies. These vacancies generate other vacancies through replacement hiring — the so-called vacancy chain.

²⁶The curvature of churn appears to be different in Germany than in the United States. Davis et al. (2013) show that the hiring rate is relatively flat in the negative part of the employment distribution in the United States, in particular when controlling for fixed effects. This is different in Germany and thereby provides a potential explanation for the (differing) downward sloping vacancy rate in the negative

Figure 3: Worker 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 in $t - 1$ and t . 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.

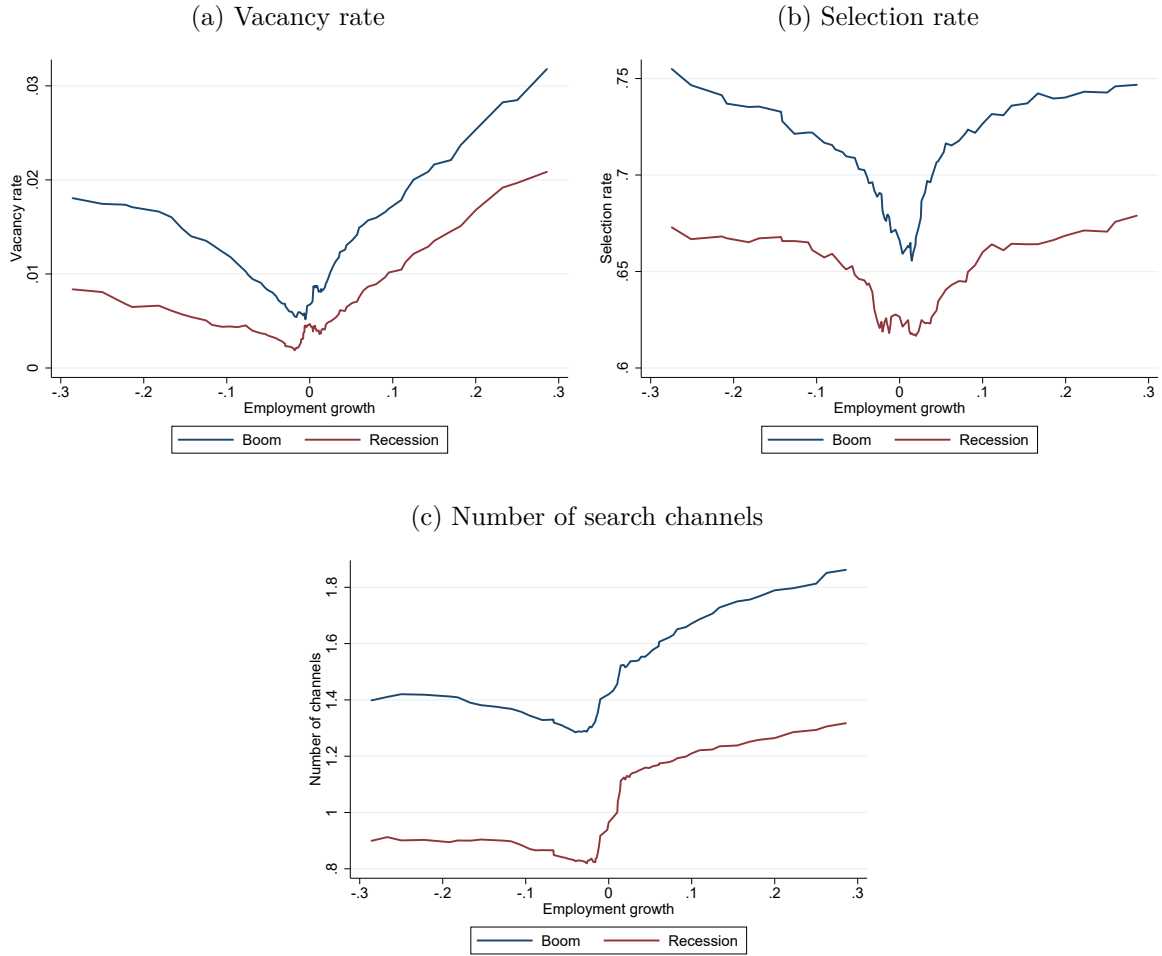
Sources: IAB Job Vacancy Survey and Administrative Wage and Labor Market Flow Panel.

5 Time Series Behavior

This section analyzes the time-series dimension of all three hiring margins. It provides plots of the cross-sectional distribution for all three margins (as defined in Section 3.2) for labor market recessions and booms. Further, it addresses our third hypothesis: we expect a positive comovement of aggregate productivity (or the business cycle more generally) with vacancies, selection, and establishments' search effort.

Figure 4a 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). In a recession, due to a smaller expected marginal product of labor, fewer vacancies are posted. The part of the employment growth distribution.

Figure 4: Hiring margins 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 in $t - 1$ and t . The selection rate is defined as the inverse of the number of suitable applicants for the most recent hire. The number channels are the sum of search channels used by the establishments for their most recent hire. Control variables: a) dummies for establishment size and industry, b) as a) and dummies for job requirements, occupations, and the number of search channels, c) as a) and dummies for job requirements and occupations. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

procyclicality of vacancies over the business cycle is a well-known phenomenon for Germany (see e.g. [Gartner et al., 2012](#)). We establish the fact that the vacancy distribution (over employment growth) shifts up pretty uniformly in a boom relative to a recession.

Figure 4b 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. We establish the fact that the selection rate distribution (over employment growth) shifts up pretty uniformly in a boom relative to a recession. Thus, vacancies and the selection rate do behave very similarly in the cross-sectional and in the time-series dimension.

As expected through the lens of our model, Figure 4c 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 booms, the number of channels increases significantly along the entire employment growth distribution. Thus, in recessions 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 efficiency (as search channels are omitted in the standard matching function). In the next section, we construct a time series for the number of channels, compare it to the dynamics of market tightness, and discuss the potential role for matching efficiency.

6 Perspectives

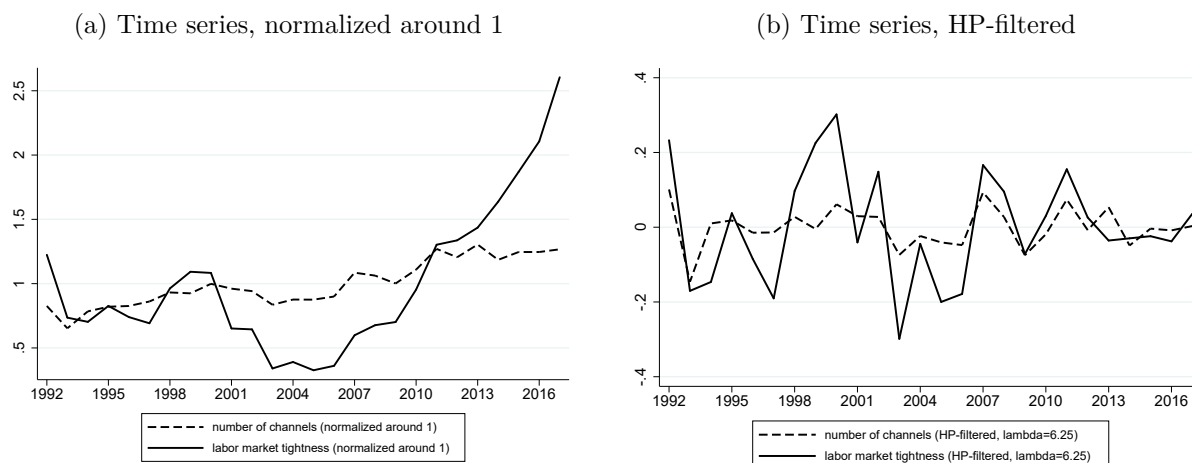
Our paper uses the IAB Job Vacancy Survey (and its linkage to the AWFPP) to establish facts on how establishments use vacancy postings, the number of search channels, and the selection rate over the employment growth distribution and over time. This is an important reference point for future theory development. 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) 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 (see [Appendix C](#)). This may be due to the larger number of search channels used by fast-growing establishments. We interpret these findings as 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 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 worker 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. Worker churn patterns in the cross section and over the business cycle for Germany are documented in [Bachmann et al. \(2020\)](#). 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 5 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).

Figure 5: Number of channels and labor market tightness



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

Sources: IAB Job Vacancy Survey and OECD.

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 in 2009 was remarkably different in Germany compared to the United States. As market tightness did not drop substantially during the Great Recession in Germany, there is no similar natural experiment for analyzing the change of aggregate matching efficiency due to a drop of aggregate search channels.

By contrast, in 2020 Germany faces a significant drop of market tightness due to Covid-19, which may affect all three hiring margins. This may be exploited to analyze the implications on aggregate matching efficiency. As such an investigation requires the availability of more recent data on different hiring margins, we leave this for future research.

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A Model Derivations

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

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

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

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

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

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

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

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

Simplifying equation (A.4), we obtain:

$$\lambda_{it} = -w(\tilde{\varepsilon}_{it}) - \tilde{\varepsilon}_{it} \quad (\text{A.6})$$

Simplifying equation (A.3):

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

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

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

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

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

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:

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

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:

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

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

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

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

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

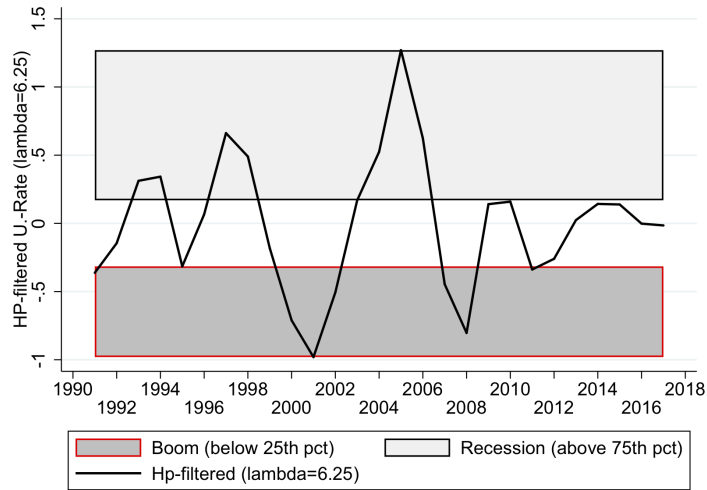
Table B.2: Descriptive statistics, JVS and AWFP (from 2010–2014)

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

Figure B.1: Aggregate unemployment and business cycle definition

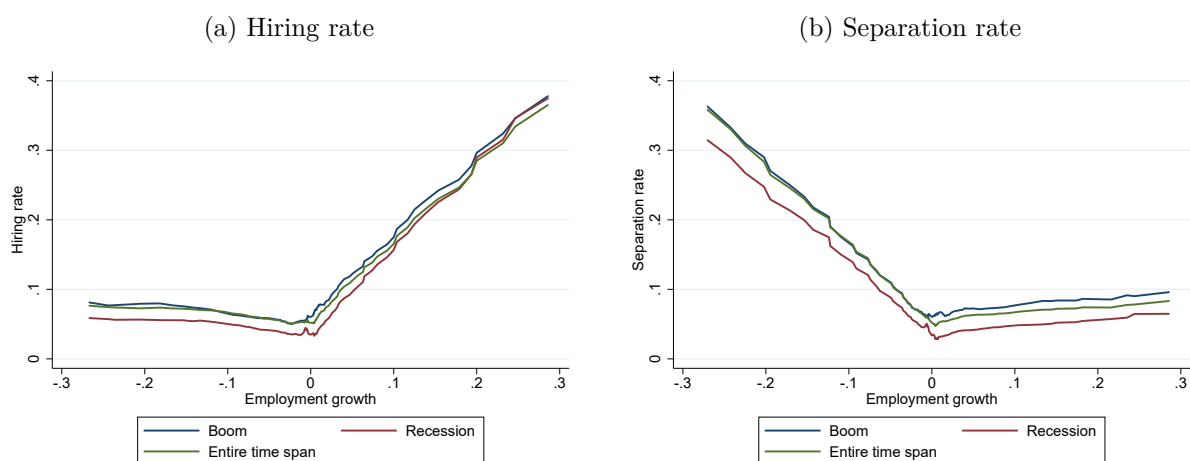


Note: We use the HP-filtered (lambda of 6.25) annual harmonized unemployment rate in order to define booms and recessions.
Source: OECD.

C Hockey Sticks

Davis et al. (2013) document for the United States that worker flows are (inverted) hockey stick functions of employment growth. Based on the AAFP, Bachmann et al. (2020) show that the same pattern holds true for West Germany. To assess the validity of the annual JVS (relative to the administrative AAFP) 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). These patterns based on the JVS are very similar to prior findings based on administrative data, see Bachmann et al. (2020). 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



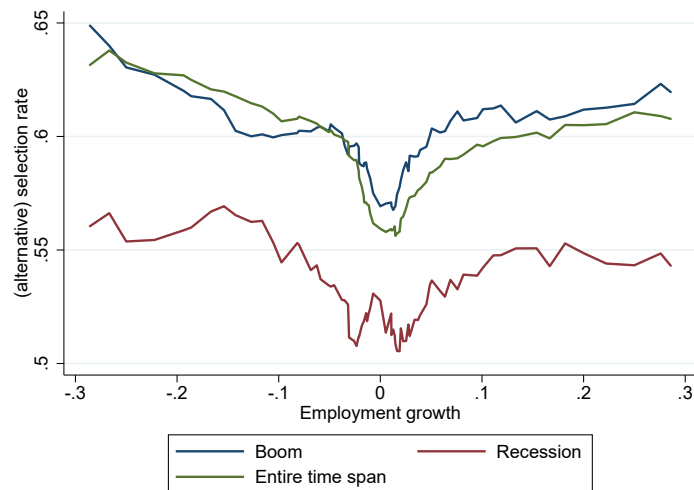
Note: The hiring rate is defined as the number of hired workers divided by the average employment stock in $t - 1$ and t . The separation rate is defined as the number of workers leaving the establishment divided by the average employment stock. Control variables: dummies for establishment size and industry. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

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

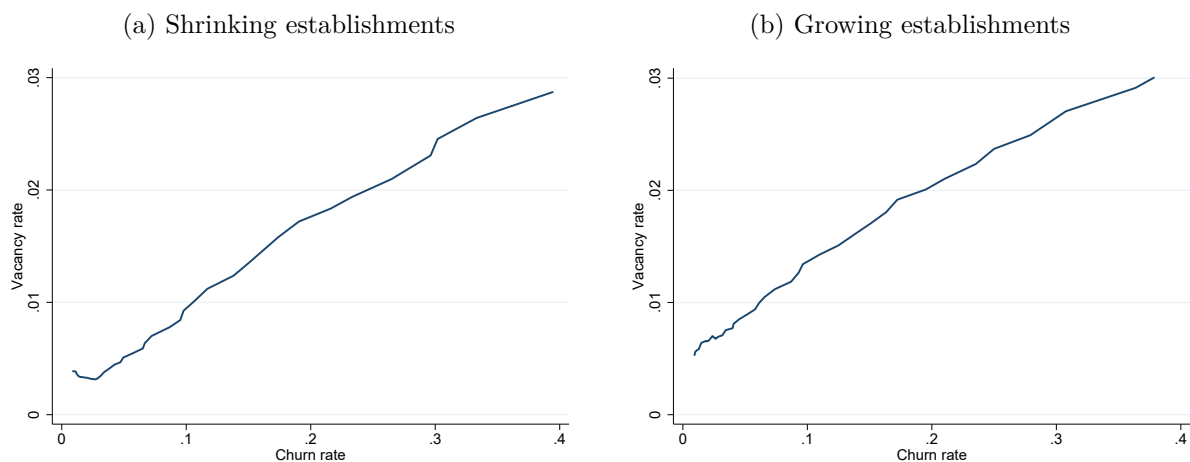


Note: The selection rate is defined as the inverse of the number of all applications. Control variables: dummies for establishment size, industry, job requirements, and occupations. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

E Further Figures

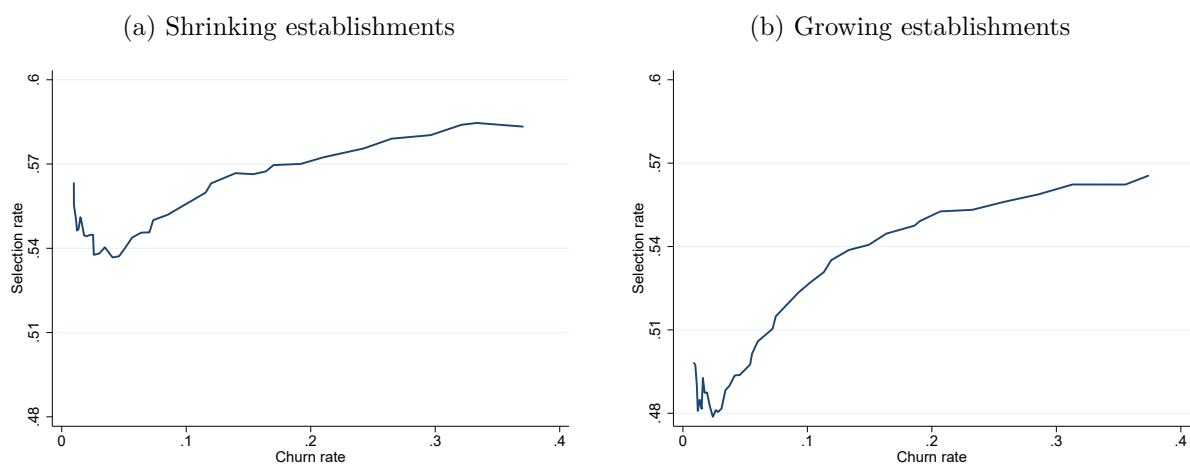
Figure E.1: Vacancy rate as a function of worker churn.



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 in $t - 1$ and t . The churn rate is defined as CH_{it} divided by the average employment stock. Control variables: dummies for establishment size and industry. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

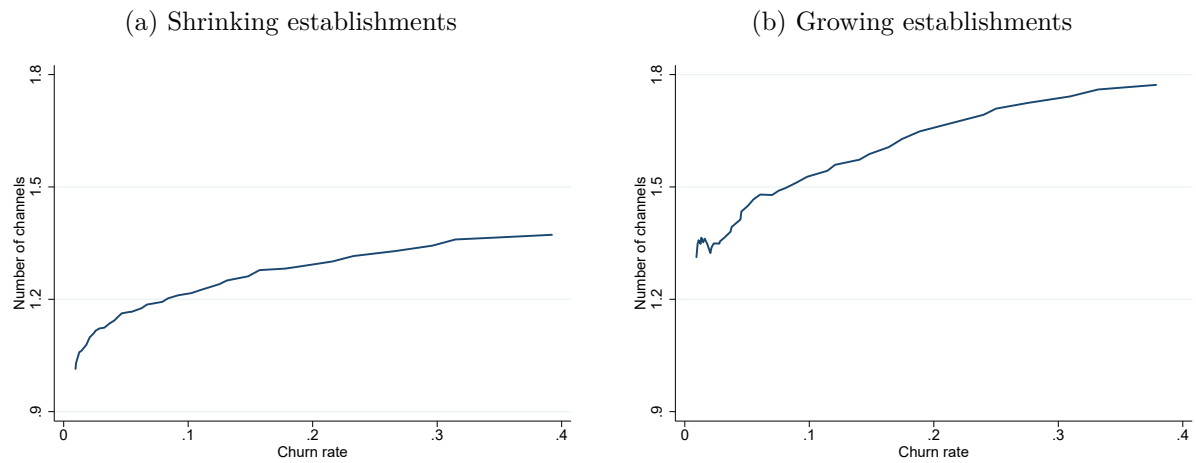
Figure E.2: Selection rate as a function of worker churn



Note: The selection rate is defined as the inverse of the number of suitable applicants for the most recent hire. The churn rate is defined as CH_{it} divided by the average employment stock in $t - 1$ and t . Control variables: dummies for establishment size, industry, job requirements, occupations, and the number of search channels. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.

Figure E.3: Number of channels as a function of worker churn



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 in $t - 1$ and t . Control variables: dummies for establishment size, industry, job requirements, and occupations. The regression approach is explained in Section 3.3.

Source: IAB Job Vacancy Survey.