

 **Discussion Papers
in Economics**

No. 04/2019

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

Ben Lochner
FAU Erlangen-Nürnberg

Christian Merkl
FAU Erlangen-Nürnberg

Heiko Stüber
FAU Erlangen-Nürnberg

Nicole Gürtzgen
FAU Erlangen-Nürnberg

ISSN 1867-6707

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

Ben Lochner¹, Christian Merkl², Heiko Stüber³, and Nicole Görtzgen⁴

¹*University of Erlangen-Nuremberg (FAU) and Institute for Employment Research (IAB)*

²*University of Erlangen-Nuremberg (FAU) and Institute of Labor Economics (IZA)*

³*University of Erlangen-Nuremberg (FAU), Institute for Employment Research (IAB), and
Institute of Labor Economics (IZA)*

⁴*Institute for Employment Research (IAB) and European Economic Research (ZEW)*

July 11, 2019

Abstract

Using the IAB Job Vacancy Survey for Germany, we look into the black box of recruiting intensity and hiring practices. Our paper shows three important channels for hiring, namely vacancy posting, the selectivity of hiring (labor selection), and the number of search channels. 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 shrinking plants post more vacancies and are less selective than plants with a constant workforce because they react to churn triggered by employment-to-employment transitions to other plants. Furthermore, in line with economic theory, vacancy posting, labor selection, and the number of search channels are procyclical over the business cycle. Our paper is the first to link the the Job Vacancy Survey and the Administrative Wage and Labor Market Flow Panel to document the interaction between hiring practices and employment-to-employment transitions to other plants.

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

*We thank Brigitte Hochmuth and Britta Kohlbrecher for excellent comments.

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. While the behavior of vacancy yields over the employment distribution and over time are known, the exact channels for these patterns remain a black box.¹ 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.

Given the lack of suitable survey datasets for the United States, 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 ([Moczzall 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 last hire (such as the used search channels or the number of suitable applicants).

We are the first to merge the JVS with the Administrative Wage and Labor Market Flow Panel (AWFP), which contains job flows, worker flows, and wage information for the universe of German plants ([Stüber and Seth, 2017](#)). The AWFP complements the information from the JVS, by differentiating workers flows based on their destination

¹The 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.

labor market states.²

Our paper starts by documenting that German establishments (henceforth plants for short) show a similar hockey stick behavior for hires and separations over the employment growth distribution as firms in the United States. Despite an asymmetric hiring rate pattern over the employment growth distribution, the vacancy rate shows a symmetric U-shape over the employment growth distribution. Against the background of search and matching theory, these two facts can only be reconciled by considering additional hiring practices. We show that the number of search channels tends to be upward sloping over the employment growth distribution. In different words, while both shrinking and growing plants have a higher vacancy rate than plants with a constant workforce, growing plants use more search channels (e.g., newspapers, internet, employment agency, social media) than shrinking plants. This higher recruiting intensity appears to make growing plants more effective in terms of hires per vacancy, i.e. they have a higher vacancy yield.

Over the business cycle, both the vacancy rate and the number of search channels move procyclically. In a recession, plants post fewer vacancies and use fewer search channels. The behavior of the used number of search channels in the cross section and over time is in line with the idea of endogenous recruiting intensity by [Davis et al. \(2013\)](#) and [Gavazza et al. \(2018\)](#).

Furthermore, we document that the share of suitable applicants hired (labor selection) shows a U-shape over the employment growth distribution. Selection is procyclical over the business cycle. The latter is in line with [Hochmuth et al. \(2019\)](#) and [Kohlbrecher et al. \(2016\)](#). They show in a search and matching model with labor selection that firms become more selective in a recession (i.e. they select a smaller fraction of applicants).

In addition, our paper connects different hiring margins to worker churn (i.e. worker flows in excess of job flows). We find that all three hiring margins (vacancies, search channels, and labor selection) comove positively with churn.

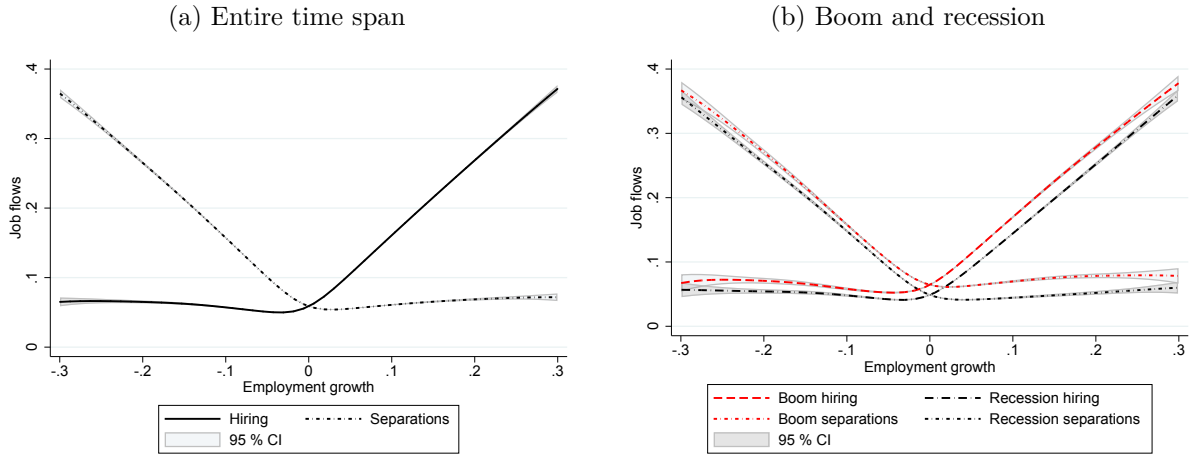
Finally, we use the merged JVS and AWF data to show the connection between employment-to-employment transitions to other plants (as a proxy for involuntary worker losses from the plant's perspective) and recruiting intensity. Interestingly, it appears that plants react to more employment-to-employment transitions to other plants by posting more vacancies and by being less selective.

2 Vacancies, Hiring, and Separations

[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 AWF data, [Bachmann et al. \(2017\)](#) show that the same pattern holds true for West Germany. To

²For further information on the JVS, the AWF data, and the merged data please refer to Appendix A.

Figure 1: Worker flows and employment growth



Note: Left panel shows hiring and separations over the entire time span. Right panel shows hiring and separations in booms and recession.

to assess the validity of the annual JVS (relative to the administrative AWF) in this dimension, we generate a similar picture. Figure 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 .³ 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](#)).⁴ We define a boom (recession) as cyclical unemployment below (above) the 25th (75th) percentile. Note that we define booms and recessions based on the labor market state because we are interested whether plants act in a tight or slack environment.⁵

Figure 1 shows (inverted) hockey stick function for hires and separations along the employment growth distribution. Not surprisingly, growing plants hire workers and shrinking plants separate from workers. However, shrinking plants also hire workers and growing plants also separate workers and thereby generate churn (see Section 4).⁶ Along the entire employment growth distribution, the hiring rate and the separation rate increases in booms relative to recessions (see Figure 1, right panel).

While the hockey stick behavior and cyclicity of hires and separations are well-known facts ([Davis et al., 2013](#)), there is little knowledge on the underlying channels that

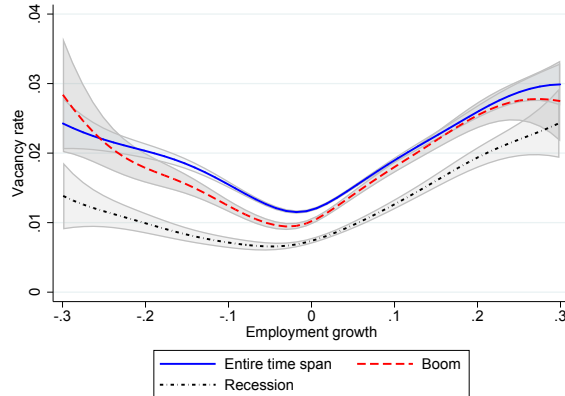
³All graphs in this paper are generated by running a kernel smoothed local linear regression with bandwidth of 0.05. All patterns are qualitatively robust to halving or doubling the bandwidth.

⁴See Figure 11 in Appendix A.3 for the filtered unemployment time series. Results are robust when we use a smoothing parameter 100 instead.

⁵While 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 plants did not act in a particularly slack labor market.

⁶These patterns based on the JVS are very similar to prior findings based on administrative data, see [Bachmann et al. \(2017\)](#).

Figure 2: Vacancy rate and employment growth



drive hiring. Figure 2 shows the vacancy rate over the employment growth distribution.⁷ Interestingly, both shrinking and growing plants post more vacancies than plants with a constant workforce. Comparing Figures 1 and 2, it is visible that growing plants are more successful in terms of hires per vacancy (i.e. they have a higher vacancy yield) than shrinking plants. We will analyze potential reasons in the next section.

Furthermore, Figure 2 shows that the average vacancy rate is smaller in recessions than in booms. This is in line with the canonical search and matching model (Mortensen and Pissarides, 1994), where fewer vacancies are posted in a recession (due to smaller expected profits). In the search and matching model there is a tight link between the number of vacancies and hires.

As the JVS is a repeated cross section, our paper cannot control for time-invariant plant heterogeneity. However, Appendix 2 shows that the most important patterns also hold for different size categories as well as manufacturing and services.

3 Recruiting Intensity and Hiring Practices

Besides changing the number of vacancies, plants can change their recruiting intensity.⁸ The JVS asks plants about the number of channels they used for their last 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).⁹

⁷As in Davis et al. (2013), we define the vacancy rate as the number of vacancies divided by the sum of vacancies and the average employment stock in $t - 1$ and t .

⁸We focus on the number of used search channels and labor selection. Other channels that we have looked at appear to be not important. Results are available on request.

⁹As 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

Figure 3: Search channels at the plant level over employment growth

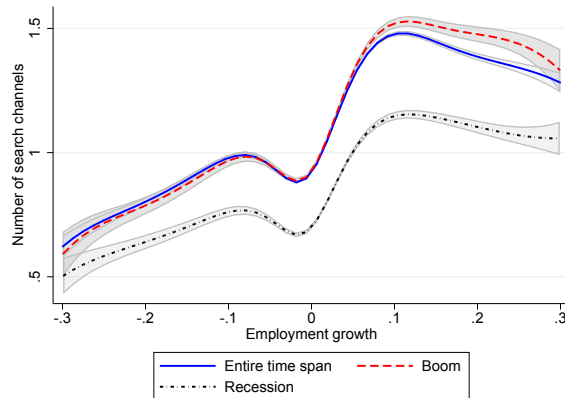


Figure 3 shows an upward-sloping pattern of the number of search channels along the employment growth distribution (although not monotonically).¹⁰ This provides an explanation why growing plants hire a larger fraction of workers than shrinking plants (although they show similar vacancy rates). In different words: We find that growing firms have higher vacancy yields and use more search channels. This is in line with the idea by [Davis et al. \(2013\)](#) and [Gavazza et al. \(2018\)](#) that recruiting intensity is important in the cross section.

It is also worth emphasizing that the number of search channels varies substantially over the employment growth distribution. It increases almost by factor three when we compare plants with a growth rate of -30% to those with a growth rate of +30%.

Due to the repeated cross-sectional nature of the JVS, we cannot control for time-invariant plant characteristics. However, in [Appendix B](#), we check whether the upward-sloping pattern for the number of search channels is robust across sectors and size categories. While the quantitative nature and curvature are sector and size dependent, the broad picture remains.

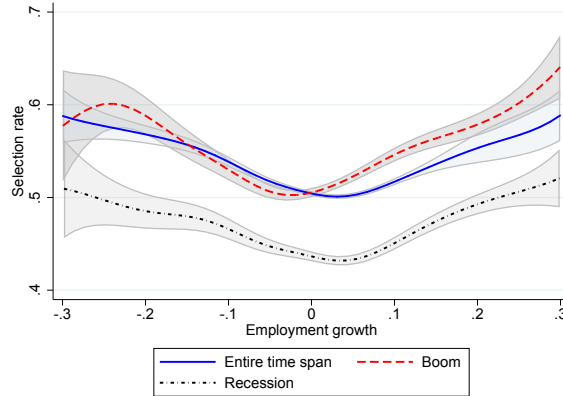
Our results are also in line with [Davis et al. \(2013\)](#) and [Gavazza et al. \(2018\)](#) in the time dimension. Figure 3 shows that the number of search channels is procyclical. In recessions, the number of channels falls significantly along the entire employment growth distribution. Thus, in addition to posting a smaller number of vacancies in recessions, plants also reduce the number of search channels. 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 canonical search and matching model, searching workers and searching firms

other normalization approaches do not alter the observed patterns qualitatively.

¹⁰Note that some plants 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).

Figure 4: Labor selection rate and employment growth



get in contact with one another and a constant fraction of workers (or all of them) is hired. However, in reality, workers and firms (or plants) 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.

Hochmuth et al. (2019) propose the inverse of the number of suitable applicants (labor selection rate) for the last hire as a proxy for selectivity. Through the lens of a random search-and-matching model, a higher labor selection rate means that plants are less selective. Hochmuth et al. (2019) construct aggregate time series (on the sectoral, state, and national level) based on the JVS to show that labor selection is strongly procyclical over the business cycle. Figure 4 confirms this result. It shows that the labor selection rate is a lot smaller in recessions than in booms.

In addition, Figure 4 documents that labor selection rate shows a U-shaped pattern along the employment growth distribution. Shrinking and growing plants select a larger fraction of workers than plants with a constant workforce.

The increasing selection rate in the positive part of the employment growth distribution in Figure 4 can be explained by the framework of Baydur (2017), where growing firms become less selective. However, the falling selection rate in the negative part of the employment growth distribution would not be in line with his model. We argue in Section 5 that this fact may be related to churn and employment-to-employment transitions.

The selection rate (Figure 4) and the vacancy rate (Figure 2) show a very similar pattern in the cross section and over the business cycle. Kohlbrecher et al. (2016) provide a theoretical foundation for the similar pattern over the business cycle. In a search and matching model with labor selection, firms reduce vacancies and lower their selection rate in recessions, i.e. there is a tight connection between these two margins.

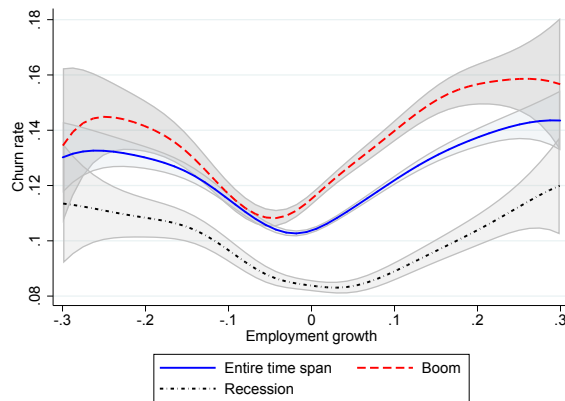
Overall, the number of search channels tends to be upward sloping over the employment growth distribution. The selection rate shows a U-shaped pattern. These are two

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 at the plant level.

4 Worker Churn

In the JVS, plants are directly asked about the number of new hires, the number of workers who left, and the stock of workers. We define worker churn as the sum of inflows and outflows minus job creation or job destruction. The churn rate is normalized by dividing it by the average employment stock in $t - 1$ and t . The churn rate ranges from zero to two.¹¹ Below, we analyze how churn and different recruiting intensity measures interact.

Figure 5: Worker churn rate and employment growth



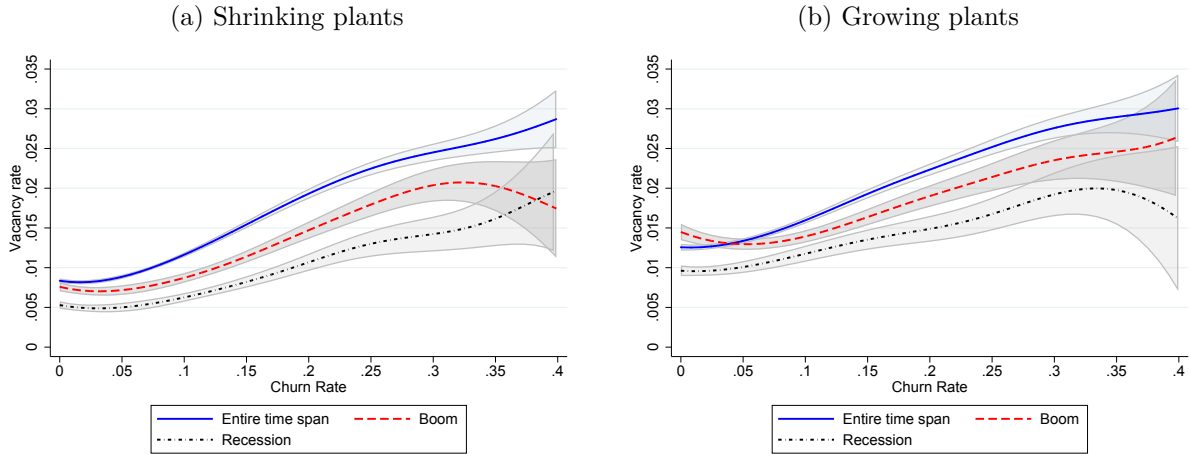
From [Bachmann et al. \(2017\)](#), we know that worker churn is a U-shaped function of employment growth, which is procyclical over the business cycle (replicated in Figure 5 based on the JVS). Growing plants may be invest less time/effort into screening new workers. Therefore, they may be more likely to separate from a larger fraction of initial hires, which would lead to a larger churning rate in growing firms.¹² Interestingly, the vacancy rate, the selection rate and the churn rate all show a very similar (relatively symmetric) shape over the employment growth distribution (recall Figures 2 and 4).

Next, we plot vacancies, search channels, and labor selection as a function of churn. To gain further insights into the interactions of these variables, we separate between shrinking and growing plants. Figure 6 shows that the vacancy rate is an upward-sloping

¹¹We exclude outliers with churn rates above 2 (about 2% of our sample) because these are either due to misreporting or intra-period churn.

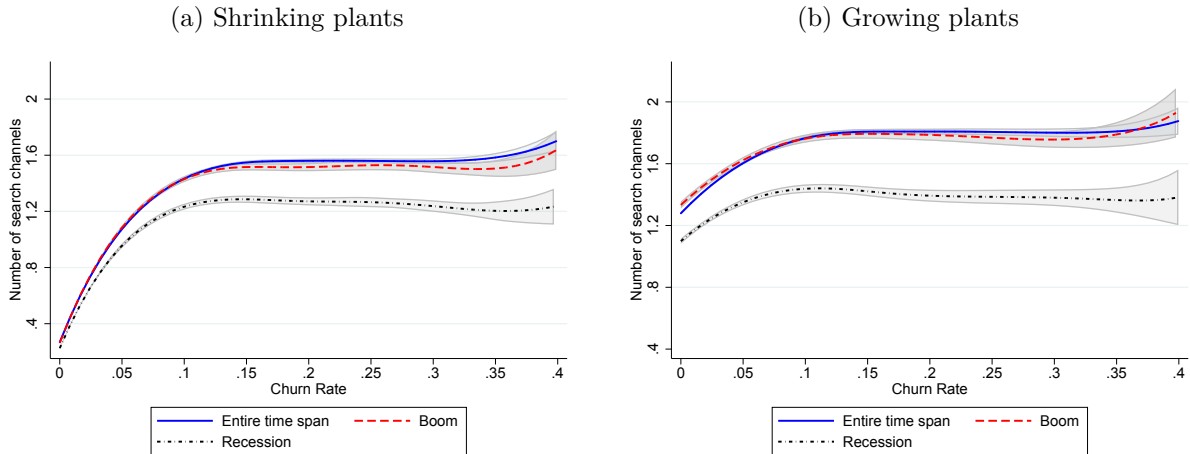
¹²[Bachmann et al. \(2017\)](#) show in an updated version of their paper that worker churn arises from workers with similar work skills being churned and that churn is unlikely to reflect reorganization at the plant level.

Figure 6: Vacancy rate as a function of churn.



function of churn. Figure 7 shows that there is a positive relationship between churn and the number of channels used. Figure 8 illustrates the positive connection between churn and selection. More churn is associated with larger recruiting efforts (vacancies, channels, and labor selection), although the relationship is not completely monotonic. Overall, these findings suggest that the U-shaped patterns of the labor selection and vacancy rate may be explained by the churn pattern over the employment growth distribution. The churn pattern, however, seems to contribute less to explaining the overall cross-sectional pattern of the number of search channels.

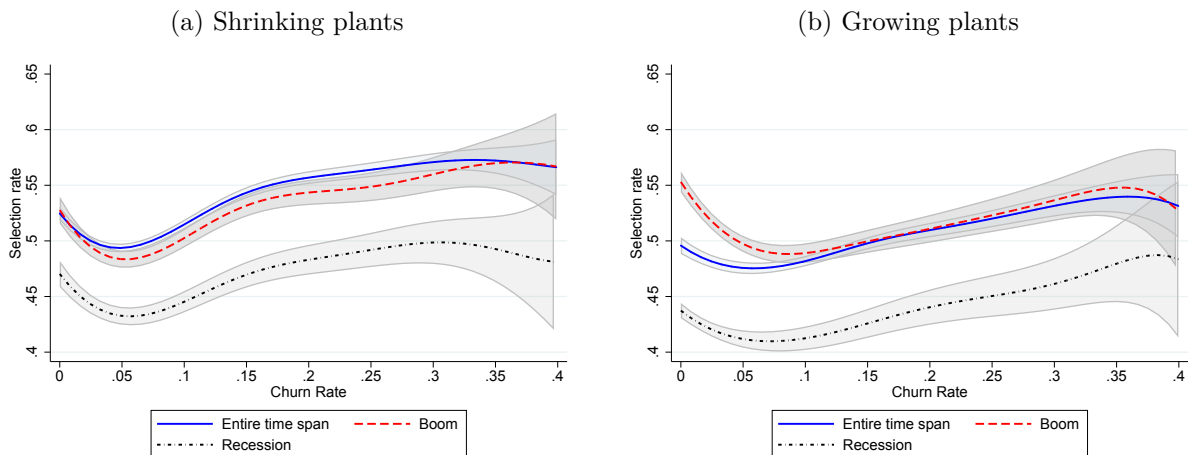
Figure 7: Number of channels as a function of churn



5 Job-to-Job Transitions

In the previous section, we have analyzed the connection between worker churn on the one hand and vacancies, search channels and selection on the other hand. In this context, it is worth emphasizing that churn may be driven by different reasons. Consider a shrinking plant that churns. The plant may be firing workers (say, production workers) and may be

Figure 8: Selection rate as a function of churn



replacing them with better suitable workers (say, automation specialists). Alternatively, in the process of downsizing the plant may be losing more workers than desired (or other workers than those desired).

Bachmann et al. (2017) argue that job-to-job transitions are a key driver for churn (they can be considered as a proxy for involuntary worker losses from the plant’s perspective). Based on the JVS, we do not know where workers move to after leaving a plant. By linking the Vacancy Survey with the AWFPP, we can see whether the workers who left the firm moved into unemployment¹³ or into employment.

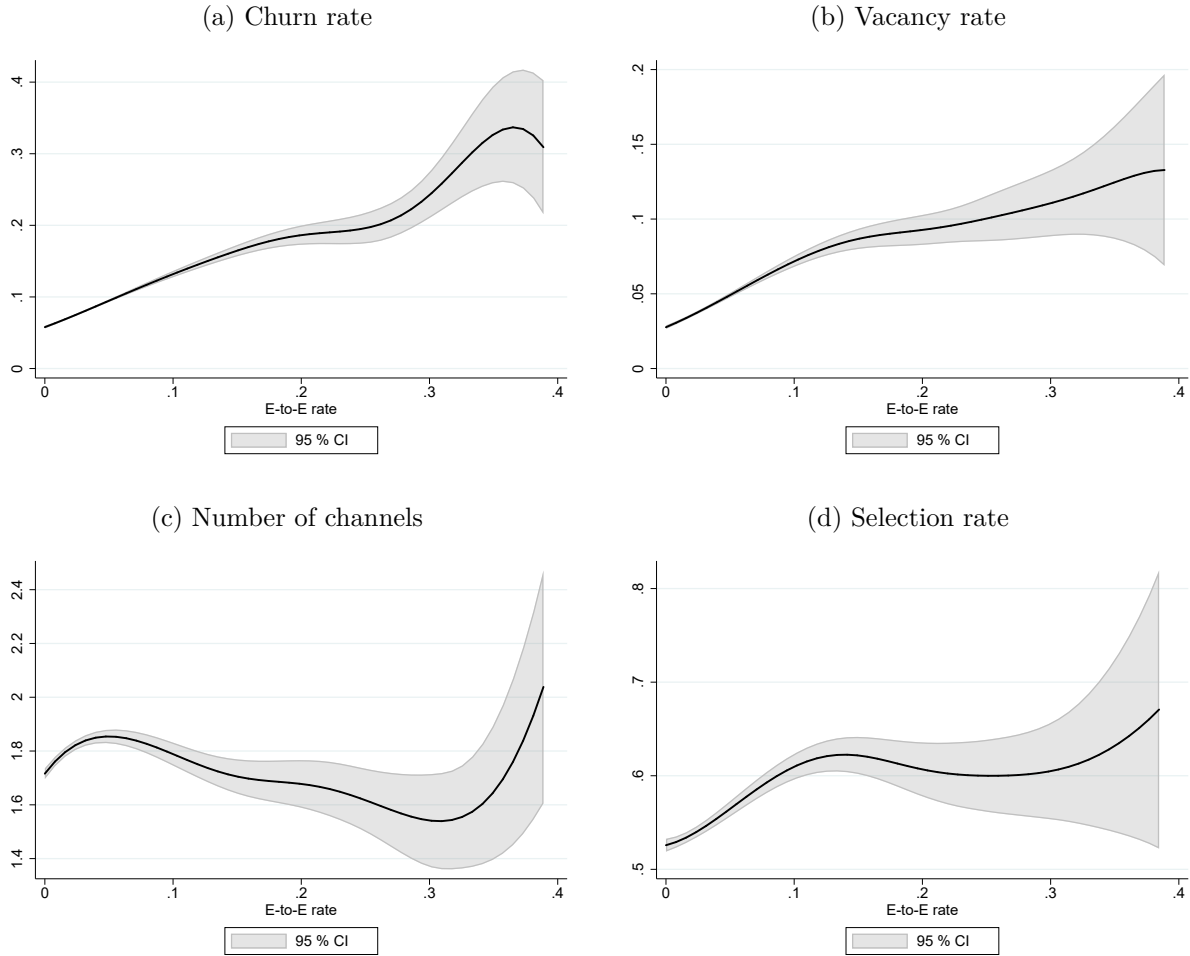
Figure 9 shows several interesting facts: First, the upper left panel illustrates that there is an almost a linear one-to-one connection between employment-to-employment transitions and churn. This confirms the findings by Bachmann et al. (2017). The other three panels show the connection between employment-to-employment transitions and vacancy rates, search channels as well as labor selection. Basically, higher employment-to-employment flows are associated with larger vacancy rates and larger selection rates. Apparently, plants try to compensate for these worker losses by posting more vacancies and by being less selective. By contrast, the pattern is less clear for the number of search channels.

As documented before, vacancy rates and the selection rates move very closely together (Kohlbrecher et al., 2016). By contrast, the number of search channels seems to be the hiring instrument of choice for growing plants (and less for shrinking plants that try to compensate for worker losses).

Note 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 previous sections).

¹³We count flows into non-employment as flows into unemployment.

Figure 9: Churn rate, vacancy rate, number of channels, and labor selection rate as a function of the Employment-to-Employment outflow rate



Note: Churn rate (upper left panel), vacancy rate (upper right panel), number of channels (lower left panel), labor selection rate (lower right panel) and employment-to-employment outflows (E-to-E).

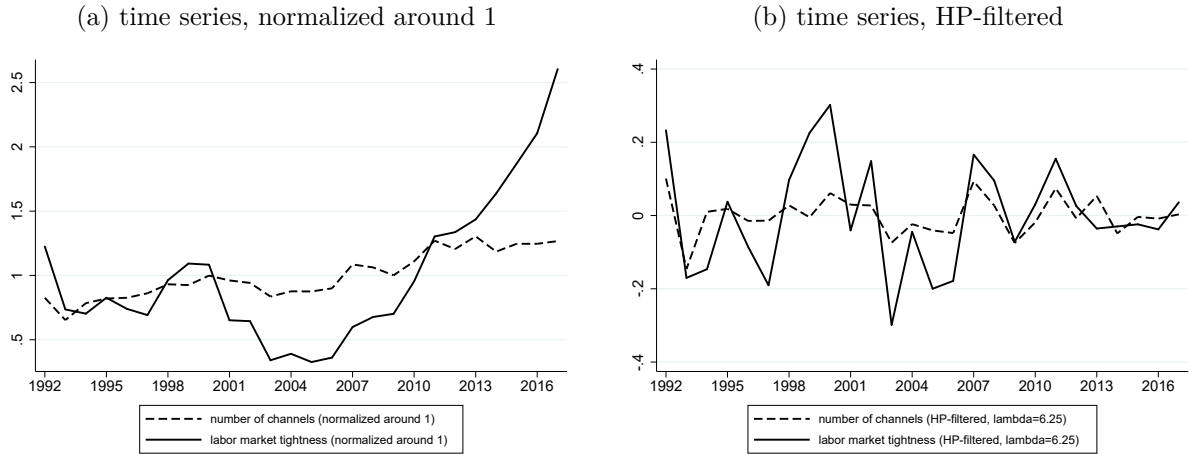
6 Connection to Theory and Outlook

Our paper documents the cross-sectional and time-series dimension of recruiting intensity and hiring practices. This section summarizes the key results through the lens of random search and matching models.

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 plants show similar vacancy rates, fast-growing plants have a much larger hiring rate and thereby larger vacancy yields. We argue that this may be explained by a larger recruiting intensity of fast-growing plants. On average, plants with a 30% employment growth rate use almost three times as many search channels as plants with a -30% employment growth rate. This is 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

Figure 10: Number of channels and labor market tightness



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 plants become less selective.

However, our empirical exercise also documents cross-sectional patterns that standard labor market models have not yet incorporated. Fast-shrinking plants tend to show larger vacancy rates and selection rates than plants with a constant workforce. We argue that this phenomenon appears to be related to churn. Fast-shrinking plants lose more workers than they would like to. These plants 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. \(2013\)](#), [Gavazza et al. \(2018\)](#) and [Hochmuth et al. \(2019\)](#). To 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. Figure 10 plots the number of search channels over time and market tightness. The two time series have a correlation of 0.72 (for both levels and the Hodrick-Prescott filtered cyclical components).

7 Conclusion

This paper uses the JVS (and its linkage to the AWFPP) to establish new facts on how plants 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 the United States. Many patterns (such as the hockey stick behavior of hiring and separations along the employment growth distribution) are similar in Germany and in the United States.

We document that the number of search channels and the selection rate play an important role for plant's hiring practices. We also analyze the connection between worker churn and hiring practices. Vacancies and selection seem to be particularly important for replacing lost workers, while the number of search channels seems to be of particular importance for growing plants.

References

- Bachmann, Rüdiger, Christian Bayer, Christian Merkl, Stefan Seth, Heiko Stüber, and Felix Wellschmied (2017) “Worker Churn and Employment Growth at the Establishment Level,” *CEPR Discussion Paper, No. 12343*.
- Barron, John, John Bishop, and William C. Dunkelberg (1985) “Employer Search: The Interviewing and Hiring of New Employees,” *The Review of Economics and Statistics*, Vol. 67, pp. 43–52.
- Baydur, Ismail (2017) “Worker Selection, Hiring, and Vacancies,” *American Economic Journal: Macroeconomics*, Vol. 9, pp. 88–127.
- Davis, Steven J., R. Jason Faberman, and John C. Haltiwanger (2013) “The Establishment-Level Behavior of Vacancies and Hiring,” *The Quarterly Journal of Economics*, Vol. 128, pp. 581–622.
- Faberman, R. Jason, Andreas I. Mueller, Ayşegül Şahin, and Giorgio Topa (2017) “Job Search Behavior among the Employed and Non-Employed,” *National Bureau of Economic Research Working Paper, 23731*.
- Gavazza, Alessandro, Simon Mongey, and Giovanni L. Violante (2018) “Aggregate Recruiting Intensity,” *American Economic Review*, Vol. 108, pp. 2088–2127.
- Hochmuth, Brigitte, Britta Kohlbrecher, Christian Merkl, and Hermann Gartner (2019) “Hartz IV and the Decline of German Unemployment: A Macroeconomic Evaluation,” *IZA Discussion Paper, 12260*.
- Kohlbrecher, Britta, Christian Merkl, and Daniela Nordmeier (2016) “Revisiting the matching function,” *Journal of Economic Dynamics and Control*, Vol. 69, pp. 350 – 374.
- Moczall, Andreas, Anne Müller, Martina Rebien, and Kurt Vogler-Ludwig (2015) “The IAB Job Vacancy Survey. Establishment Survey on Job Vacancies and Recruitment Processes. Waves 2000 to 2013 and Subsequent Quarters from 2006,” , FDZ Datenreport 04/2015, Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg.
- Mortensen, Dale T. and Christopher A. Pissarides (1994) “Job Creation and Job Destruction in the Theory of Unemployment,” *The Review of Economic Studies*, Vol. 61, pp. 397–415.
- Ravn, Morten O. and Harald Uhlig (2002) “On Adjusting the Hodrick-Prescott Filter for the Frequency of Observations,” *The Review of Economics and Statistics*, Vol. 84, pp. 371–376.

Stüber, Heiko and Stefan Seth (2017) “The Administrative Wage and Labor Market Flow Panel,” *FAU Discussion Papers in Economics*, No. 01-2017.

A Data Description

A.1 The IAB Job Vacancy Survey

The IAB Job Vacancy Survey (JVS, see [Moczall et al., 2015](#)) is a representative survey among German establishments (henceforth plants for short) from all sectors and from all plant size classes. The JVS is a repeated cross-section, covering up to around 14,000 plants per year. The survey started in 1989 and is currently available up to 2017. The survey collects data on a variety of topics with regard to the hiring process of German plants. It identifies the number of vacancies on the German labor market, including those vacancies that are not reported to the Federal Employment Agency — Germany’s public employment service. The main questionnaire, which is conducted in every fourth quarter of a year, collects information about the number and structure of vacancies, future labor demand, about the current economic situation, and the expected development of participating plants. A major part of the survey inquires information about the last new hire of a plant. Plants are asked whether or not they filled a position during the last 12 months. If they did, they are further asked about certain job characteristics such for example the exact job requirements, the search channel, the search duration, and the exact hiring date. Furthermore, plants report certain 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 (plants-year) observations. Descriptive statistics on our main variables are shown in Table 1.

Table 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, on a yearly frequency. Our estimation sample consists of 257,865 plants-year observations.

A.2 The Administrative Wage and Labor Market Flow Panel

The Administrative Wage and Labor Market Flow Panel (AWFP, see [Stüber and Seth, 2017](#)) is a dataset on labor market flows and stocks for the universe of German establishments (henceforth plants for short). It contains data on job flows, worker flows, and wages for each plant. In addition, the AWFP contains this information for 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). The AWFP covers the time period 1975—2014 and is available on the annual and the quarterly frequency.

For our analysis, we use the AWFP on the quarterly frequency for the years 2010–2014. Since the main questionnaire of the JVS is conducted in every fourth quarter, we link it to the fourth quarter of the AWFP. Our linked dataset consists of 61,021 (plant-Q4) observations. Descriptive statistics on our main variables are shown in [Table 2](#).

Table 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, on a quarterly frequency. Our estimation sample consists of 61,021 plant-Q4 observations.

A.3 Aggregate Unemployment

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

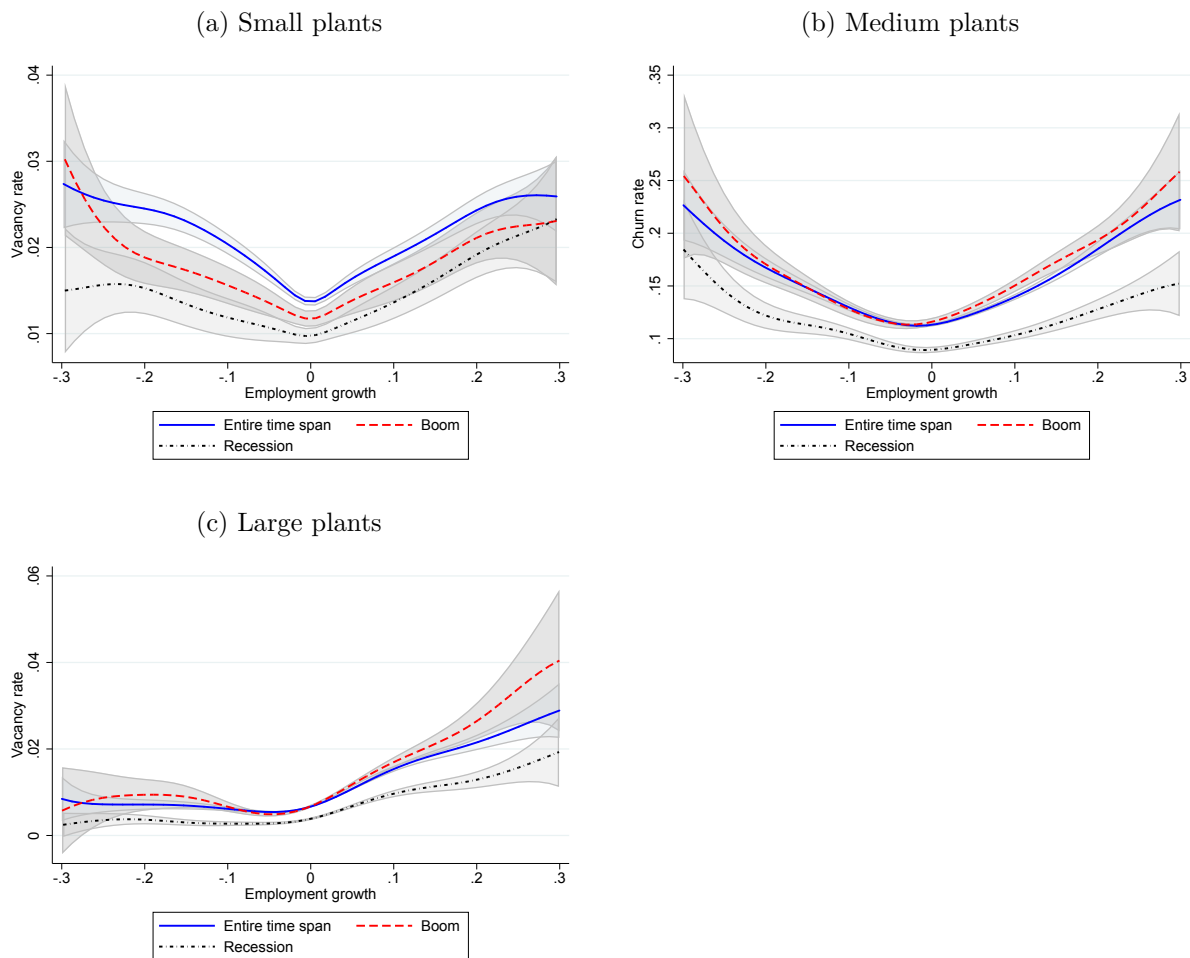
Figure 11: Aggregate unemployment and business cycle definition



B Robustness Checks

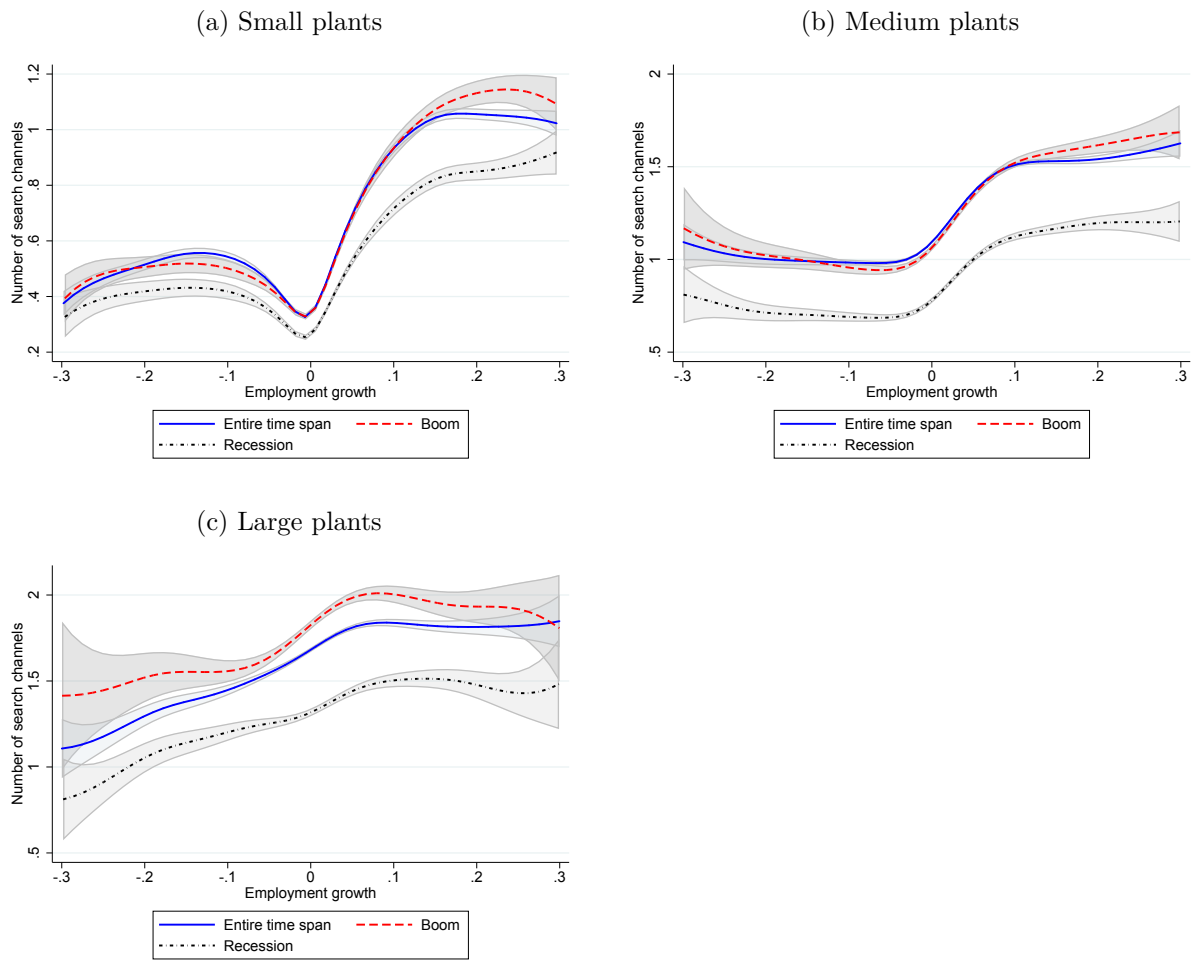
B.1 Size categories

Figure 12: Vacancy rate and employment growth



Note: Small plants have up to 10 employees, medium plants have 11–100 employees, large plants have more than 100 employees.

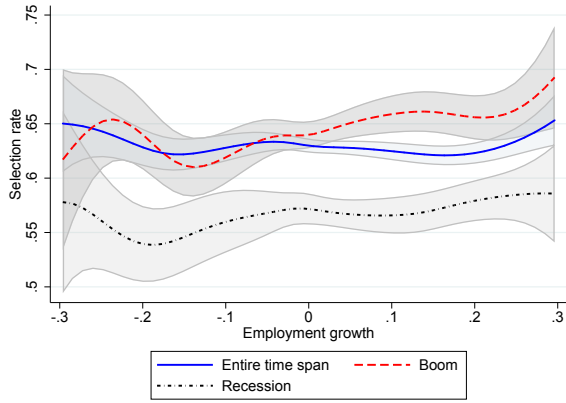
Figure 13: Number of search channels and employment growth



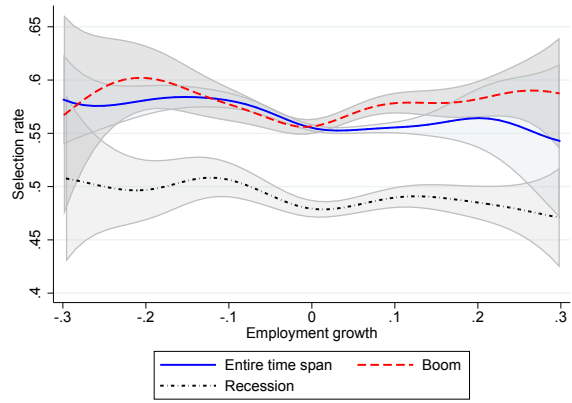
Note: Small plants have up to 10 employees, medium plants have 11–100 employees, large plants have more than 100 employees.

Figure 14: Selection rate and employment growth

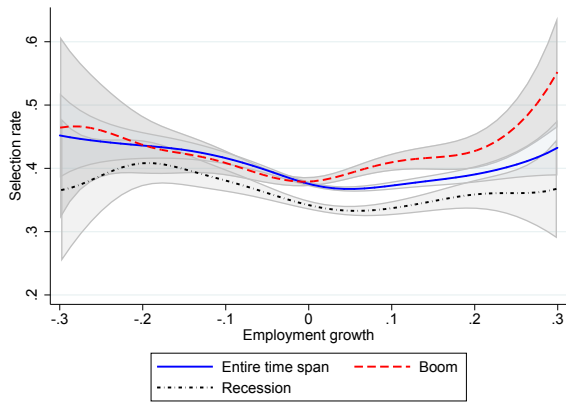
(a) Small plants



(b) Medium plants

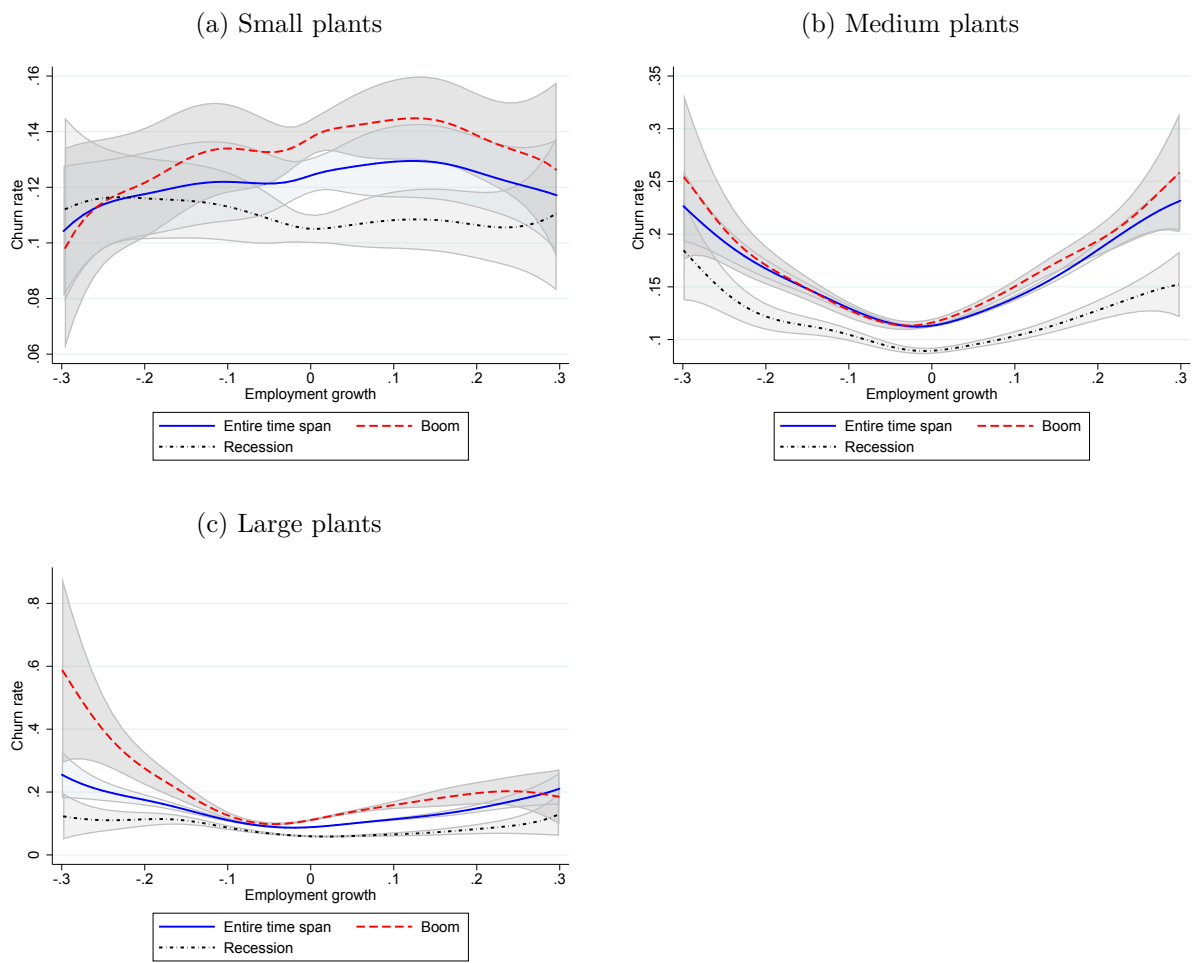


(c) Large plants



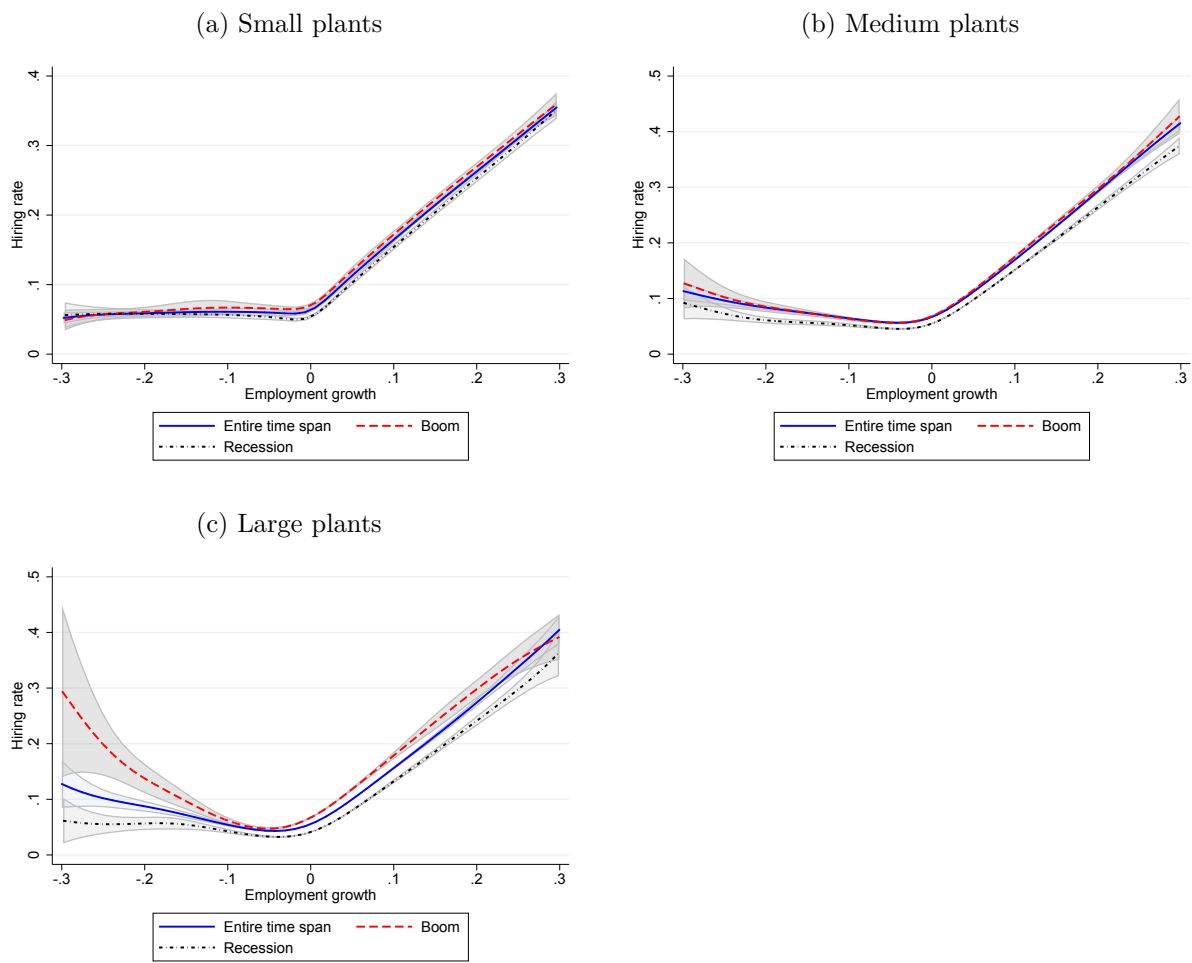
Note: Small plants have up to 10 employees, medium plants have 11–100 employees, large plants have more than 100 employees.

Figure 15: Churn rate and employment growth



Note: Small plants have up to 10 employees, medium plants have 11–100 employees, large plants have more than 100 employees.

Figure 16: Hiring rate and employment growth



Note: Small plants have up to 10 employees, medium plants have 11–100 employees, large plants have more than 100 employees.

B.2 Sectors

Figure 17: Vacancy rate and employment growth

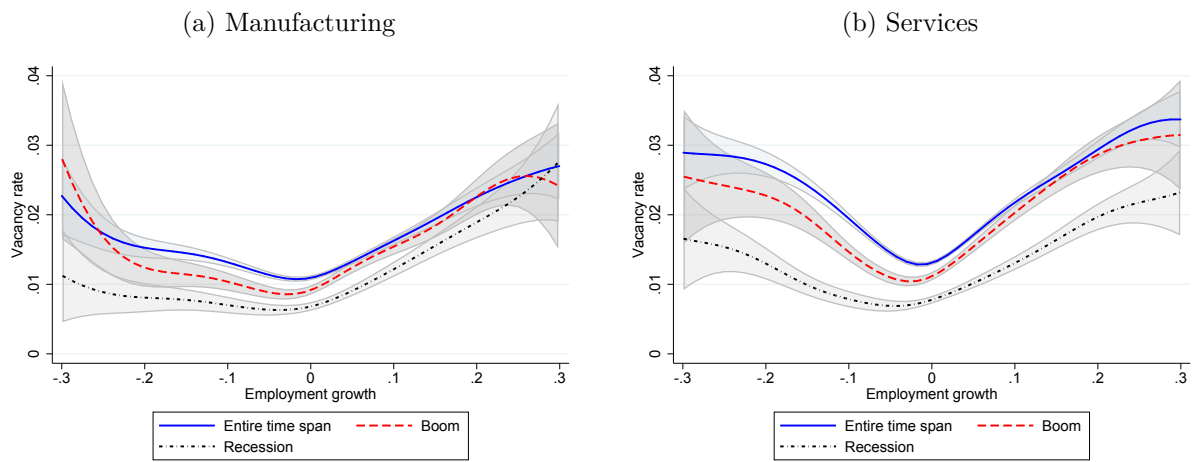


Figure 18: Number of search channels and employment growth

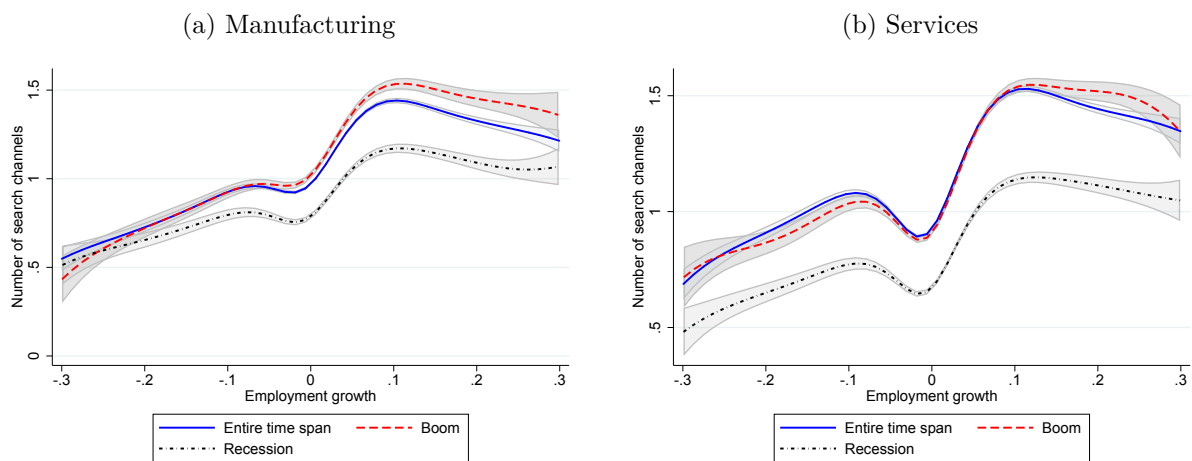


Figure 19: Selection rate and employment growth

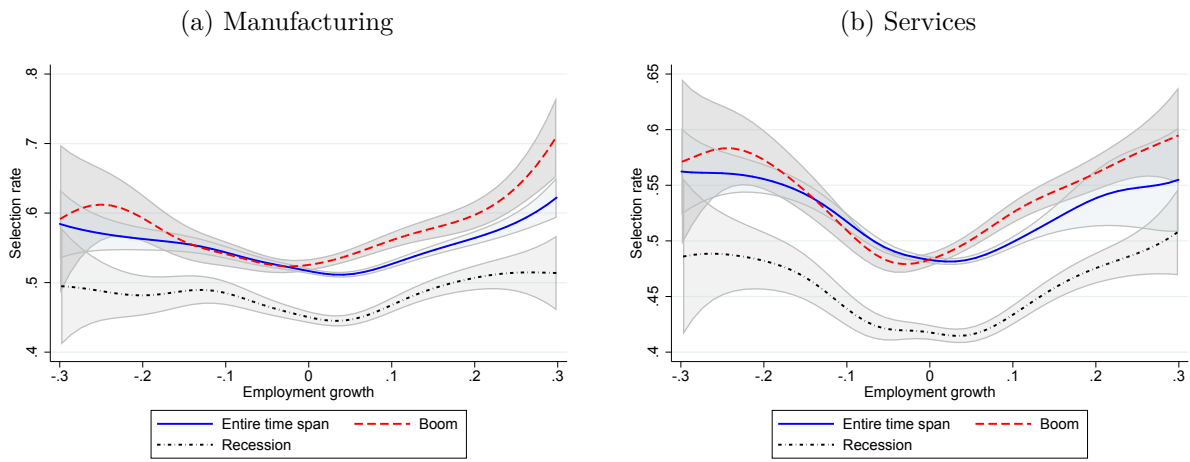


Figure 20: Churn rate and employment growth

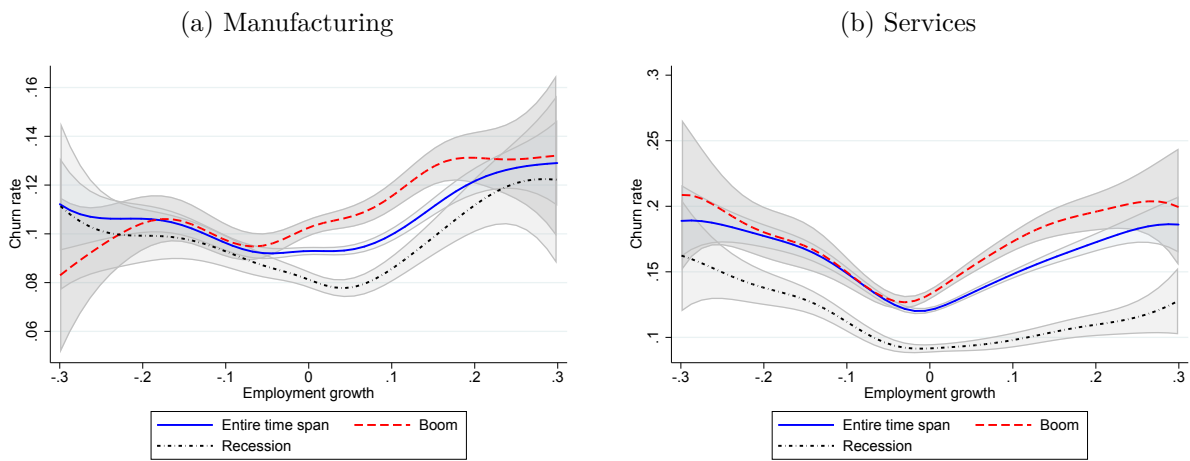


Figure 21: Hiring rate and employment growth

