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## Worker Churn and Employment Growth at the Establishment Level

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# Worker Churn and Employment Growth at the Establishment Level

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## Abstract

We study the relationship between employment growth and worker flows in excess of job flows (churn) at the establishment level using the new German *AWFP* dataset spanning from 1975–2014. Churn is large along the entire employment growth distribution and most pronounced at rapidly adjusting establishments. We find that the patterns of churn along the employment growth distribution can be explained by separation rate shocks. These shocks become larger on average during boom periods leading to procyclical worker churn. Distinguishing between separations into non-employment and to other establishments, we find that the latter drive all procyclical churn. The increase in incidences of separations to other establishments and hiring from other establishments is almost uniform along the entire employment growth distribution during a boom.

**Key Words:** job flows, worker flows, churn, job-to-job transitions, aggregate fluctuations

**JEL Classification:** E32, J23, J63

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# 1 Introduction

Many establishments hire and separate simultaneously. This leads to worker turnover in the economy that is larger than what would be necessary to accommodate observed job creation and destruction (see Burgess et al. (2000) and Davis et al. (2006, 2012)). These worker flows in excess of job flows, in short worker churn, are quantitatively large and increase substantially during booms.

In this paper, we use micro data to study the relationship between establishment growth (job creation and destruction) and worker churn. Our analysis offers new insights into the sources of worker reallocation, the frictions establishments face when adjusting employment, and the way business cycles propagate through endogenous worker reallocation.

For our analysis, we use the new Administrative Wage and Labor Market Flow Panel (*AWFP*) for Germany. The data comprises the entire universe of German establishments from 1975–2014 at the quarterly frequency. It allows us to link establishment growth to hiring decisions (from other establishments and non-employment) and separation decisions (to other establishments and non-employment). In comparison to the US data, aggregate job and worker flows are about half the size in Germany. In both countries, worker turnover is almost twice as large as job turnover. What is more, flow rates have similar cyclical properties in the two countries.<sup>1</sup> The aggregate separation rate is procyclical, the job destruction rate is countercyclical, and the hiring rate is more procyclical than the job creation rate. Moreover, worker flows are more volatile than job flows leading to procyclical worker churn in the aggregate.

In the cross-section, the churning rate is lowest for establishments that do not change their number of workers. It grows in absolute employment growth, i.e, rapidly shrinking and rapidly growing establishments have the highest churning rate. In other words, establishments that decrease the number of workers often also hire. On average, they hire more than establishments with a constant work force. Equivalently, establishments that increase the number of workers often also separate from some workers. On average, they separate from more workers than establishments with a stable number of workers.

This observation cannot be explained with simple models of employment dynamics, where establishments face a constant separation rate and make employment adjustments in reaction to idiosyncratic productivity shocks. In such a framework, rapidly shrinking establishments are at or above their employment target and thus have no incentives to hire any workers. In fact, in such a setup, churn is highest for establishments with a constant number of workers where every hire is a replacement of an exogenous and predictable separation.

The fact that rapidly shrinking establishments also hire substantial numbers of workers implies that these establishments separate from more workers than they had planned or had foreseen. We interpret this as stochastic separation rate shocks to the establishment. These separation rate shocks, in addition to productivity shocks are an important source of uncertainty for establishments and drive short-term employment fluctuations. If it takes time to hire, establishments will try to rehire the separations they expect in excess of their desired employment changes. When sepa-

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<sup>1</sup>Davis et al. (2012) provide a comprehensive overview for the US data.

rations realize below this value, the establishment grows. If more separations than anticipated happen, the establishment shrinks. Since this expectation error is by definition unrelated to the desired plant growth, it can produce large average churning rate in fast growing or shrinking establishments. Stochastic separations from the point of view of the establishment may reflect that workers find better employment opportunities outside the given establishment, or that the establishment learns that some of its workers are not a good match.

Next, we study the cyclical properties of worker churn. During booms, relative to recessions, the churning rate becomes larger along the entire employment growth distribution. From a statistical perspective, cyclical movements in the employment growth distribution do not contribute to cyclical movements in the aggregate churning rate. This property of churn is remarkably different from the underlying worker flows. Davis et al. (2012) show that worker flows follow a "hockey-stick" -like behavior over the employment growth distribution that we confirm in the German data. As a result, both cyclical shifts in the employment growth distribution and shifts in worker flows conditional on the employment growth distribution contribute to aggregate worker flow rates (but not to the aggregate churning rate).

Through the lens of our model, separation shocks become on average larger during a boom. Our data allows us to decompose separations (and hires) into those going to other establishments and those going to non-employment. We find that separations (and hires) to other establishments shift up along the employment growth distribution in a parallel fashion during a boom (relative to a recession). Worker transition rates through the non-employment pool show no such cyclical behavior. Using again a statistical model, we show that cyclical aggregate worker churn is almost identical to the procyclical job-to-job transition rate. What is more, after subtracting job-to-job transitions from hires and separations, worker flows have the same cyclical properties as job flows. The hiring rate from non-employment is almost identical to the job creation rate. Similarly, the separation rate into non-employment is almost identical to the job destruction rate which means that the separation rate becomes countercyclical once we subtract the job-to-job transition rate.

These findings also contribute to a recent literature that debates the link of observable establishment characteristics with cyclical hiring and separation decisions and resulting establishment growth. We show that cyclical job-to-job transitions (both hiring and separations) are not systematically linked to establishment *growth*. Moscarini and Postel-Vinay (2012, 2013) develop a framework that links establishment *size* to cyclical job-to-job transitions. Large firms grow during booms on expense of small firms by poaching workers from small firms in a procyclical way. Haltiwanger et al. (2015) question such poaching behavior, and show that establishment *pay* is a better predictor for cyclical employment growth and poaching patterns.

Our findings lend support to theories that stress job-to-job transitions as means of procyclical worker reallocation (for example, Moscarini and Postel-Vinay (2013), Schaal (2015), and Fujita and Nakajima (2016)). These theories suggest that during a boom, workers systematically reallocate from low to high productivity establishments. At the same time, our results suggest that we require more heterogeneity than implied by a common ranking (productivity) of establishments by all workers. In common-rank models, highly ranked establishments have low separation rates (and

hence churning rates) on average. As higher ranked establishments grow more during a boom than during recessions, the composition of high growth establishments shifts towards high rank and hence low churn establishments. Therefore, in common-rank models, one observes during booms that churn increases at the low end of the employment growth distribution by more than at the upper end. Our data by contrast shows that separations to other establishments and hence churn shifts up equally across the employment growth distribution during a boom. Therefore, while our results suggest that workers climb the job ladder faster in booms, they also suggest that the ranking of establishments across the ladder is worker specific.

The remainder is organized as follows. Section 2 introduces the new *AWFP* dataset and explains the main concepts that we use to analyze the data. Section 3 analyzes aggregate job and workers flow dynamics. Section 4 links churn to establishment growth in the cross-section. Section 5 studies the cyclical dynamics in the churning rate. Section 6 connects our empirical finding to models of procyclical labor reallocation and Section 7 concludes.

## 2 Dataset and Variables Definitions

### 2.1 The Administrative Wage and Labor Market Flow Panel

The new Administrative Wage and Labor Market Flow Panel (*AWFP*) measures employment, labor flows, and wage data<sup>2</sup> for the universe of German establishments (*Betriebe*) for the years 1975–2014.

The *AWFP*'s main data source is the Employment History (*Beschäftigten Historik*, BeH) of the Institute for Employment Research (IAB). The BeH is an individual-level dataset covering all workers in Germany subject to social security.<sup>3</sup> The information in the BeH originates from the German notification procedure for social security. Essentially, this procedure requires employers to keep the social security agencies informed about their employees by reporting any start or end of employment and by (at least) annually confirming existing employment relationships.

From the BeH, the *AWFP* aggregates the worker and job flow information to the establishment level such that an establishment becomes the observational unit.<sup>4</sup> To ensure consistency over time, most variables in the *AWFP* — and all variables used in the paper — are calculated on a 'regular worker' basis. In the *AWFP* a person is defined as a 'regular worker' when she is employed full-time and belongs to one of the following person groups: 'employees subject to social security without special features', 'seamen' or 'maritime pilots'. Therefore (marginal) part-time employees, employees in partial retirement, interns, etc. are not counted as regular-workers.

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<sup>2</sup>Merkel and Stüber (2016) use the *AWFP* to analyze the effects of different wage dynamics on labor flows.

<sup>3</sup>Marginal part-time workers (*geringfügig Beschäftigte*) are included since 1999. The main types of employees not covered by the BeH are civil servants (*Beamte*), military personnel, and the self-employed.

<sup>4</sup>Before this aggregation, the data on individuals are subjected to numerous validation procedures. Further details on the dataset are described in Seth and Stüber (2017). Conceptual differences between the *AWFP* and US Data are discussed in appendix A.1.

The *AWFP* covers the time period 1975–2014 (West-Germany until 1992 and the re-unified Germany thereafter). It is available at an annual and a quarterly frequency. For our analysis, we use the *AWFP* at the quarterly frequency and drop all establishments that are on the territory of former East-Germany and Berlin to avoid a break in the series.<sup>5</sup> For further information on the dataset we refer the reader to the *AWFP* data report (Seth and Stüber (2017)).

## 2.2 Variables Definitions

In the *AWFP*, a worker is considered to be working for a given establishment (henceforth plant) in a given quarter when she is employed at this plant at the end of the quarter.<sup>6</sup> This definition yields the number of jobs at a plant at the end of a quarter ( $J_t$ ), the number of hires<sup>7</sup> ( $H_t$ ) at a plant, as well as the number of separations<sup>8</sup> ( $S_t$ ). These are the time series from the *AWFP* from which almost all data series in our paper are constructed.<sup>9</sup>

Using the basic data, we compute the net job flow,  $JF_t = J_t - J_{t-1}$ . When a plant decreases employment ( $JF_t < 0$ ) within a quarter, we count this as job destruction,  $JD_t$ . When employment increases ( $JF_t > 0$ ), we count this as job creation,  $JC_t$ . A plant may hire and separate from workers within the same quarter. We have  $H_t \geq JC_t \geq 0$  and  $S_t \geq JD_t \geq 0$  for each plant in each quarter.

Part of our analysis deals with differences in plant-level behavior given the amount of employment growth at the plant. For this purpose, we first aggregate the plant-level data to 21 employment growth categories/bins. Figure XVI in Appendix A.3 provides the time averaged employment share in each of these categories.

We allow each employment growth category to have its own seasonal component and compute seasonally adjusted series, using the X-12 ARIMA CENSUS procedure.<sup>10</sup> To derive the aggregate series for West Germany, we finally sum over the seasonal adjusted series for all employment growth categories.

Given either the aggregated stock/flow data or the stock/flow data by employment growth category, we define flow rates. We use the average of contemporaneous and lagged end-of-quarter employment as the denominator:

$$N_t = [J_t + J_{t-1}]/2.$$

For example, the hiring rate is given by:

$$HR_t = \frac{H_t}{N_t}. \quad (1)$$

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<sup>5</sup>A previous discussion paper (Bachmann et al. (2013)) used the *ELFLOP* dataset (see Bachmann et al. (2011)), the precursor of the *AWFP*.

<sup>6</sup>It turns out that most workers leave or join a plant at the end, respectively the beginning of a quarter.

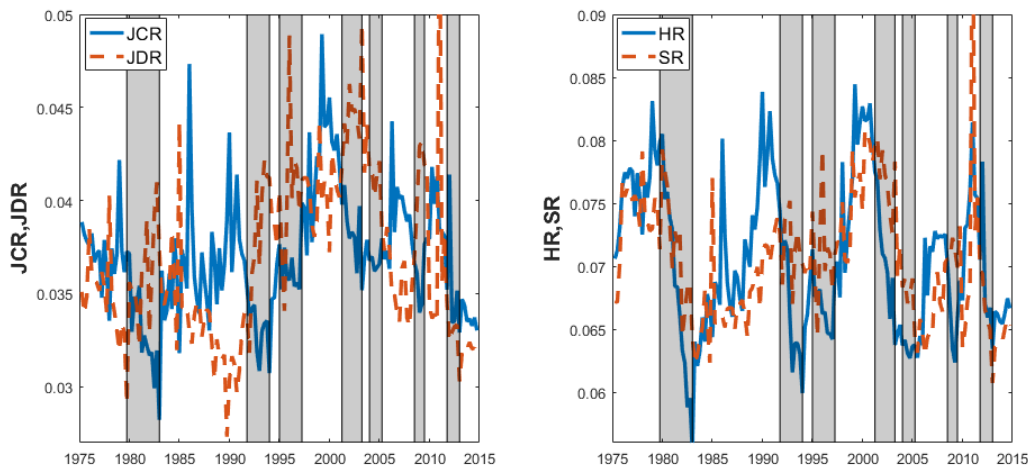
<sup>7</sup>A worker that has not been working for that plant at the end of the previous quarter.

<sup>8</sup>A worker that has been working for the plant at the end of the previous quarter.

<sup>9</sup>For some analysis we use data packages of the *AWFP* that provide a decomposition of inflows and outflows according to their source and destination, respectively.

<sup>10</sup>By allowing for series-specific seasonality, we want to ensure consistency for each variable for the sum of all individual categories and the aggregate series of West Germany.

Figure I: Job and Worker Flows



Note: the left panel displays job flows. *JCR*: job creation rate, *JDR*: job destruction rate. The right panel displays worker flows. *HR*: hiring rate, *SR*: separation rate. All rates are de-seasonalized and obtained as the cyclical component from the HP(100,000)-filter. West German plants only. The gray shaded areas represent periods of at least 5 consecutive quarters of unemployment growth.

The separation rate (*SR*), the job-creation rate (*JCR*), and the job-destruction rate (*JDR*) are defined analogously. Using the numerator  $N_t$ , as defined above, implies that all rates are bound in the interval  $[-2, 2]$  with endpoints corresponding to the death and birth of plants.<sup>11</sup>

Most of our analysis deals with fluctuations at the business cycle frequency. To measure the stage of the business cycle, we use the aggregate unemployment rate for West-Germany.<sup>12</sup> If not otherwise stated, we compute the cyclical component for the aggregate or disaggregate-by-employment-growth-rate employing an HP-filter for the series with a smoothing parameter of 100,000 (following Shimer (2005)). Consequently, the cyclical components have the interpretation of a deviation from a slowly moving non-linear trend. Given that unemployment and flows are already expressed as rates, we define the cyclical components as absolute deviations from the trend, i.e., they have to be interpreted as percentage point deviations.

### 3 Aggregate Job and Worker Flows

In this section, we show job and workers flows in Germany and their dynamics. Figure I displays the (unfiltered, but seasonally adjusted) job and worker flows over time. The gray shaded areas represent periods of at least 5 consecutive quarters of unemployment growth. The time average quarterly job creation and destruction rate are both around 3.7%.<sup>13</sup> Worker flows are substantially larger. The time average

<sup>11</sup>See Davis et al. (1996) for a more thorough discussion regarding the properties of this measure.

<sup>12</sup>Cyclical unemployment has a strong negative correlation with GDP (-0.71).

<sup>13</sup>It is by chance that the time average flow rates are almost equal.

Table 1: Job and Worker Flows

	<i>Mean</i>	<i>SD</i>	<i>AC</i> (1)	Correlation with $U_{t+j}$				
				$j = -2$	$-1$	$0$	$+1$	$+2$
<b>JCR</b>	3.69%	0.29%	0.52	0.19*	0.08	-0.04	-0.17*	-0.28*
<b>JDR</b>	3.69%	0.36%	0.40	-0.02	0.05	0.15	0.23*	0.29*
<b>HR</b>	7.06%	0.57%	0.82	-0.26*	-0.40*	-0.53*	-0.64*	-0.72*
<b>SR</b>	7.06%	0.47%	0.47	-0.46*	-0.50*	-0.51*	-0.50*	-0.48*

Note: the table displays the properties of the HP(100,000)-filtered rates. *JCR*: job creation rate, *JDR*: job destruction rate, *HR*: hiring rate, *SR*: separation rate. *SD*: standard deviation, *AC*(1): first order auto correlation. A \* indicates significance at the 5% level obtained by non-parametric block-bootstrapping with a block length of 20.

quarterly hiring and separation rate are both around 7.1%. Those time average flows are yet larger in the US, where time average quarterly job flows are around 7.1% and time average worker flow rates are around 11.8%.<sup>14</sup>

The upper panel in Table 1 displays summary statistics of the cyclical component of the job flow rates. The job creation rate is somewhat more persistent but fluctuates less than the job destruction rate. The job creation rate moves counter to the unemployment rate, particularly at leads of unemployment. In contrast, the job destruction rate moves together with the unemployment rate. The bottom panel in Table 1 displays summary statistics of the hiring and the separation rate. Worker flows are more persistent than job flows and more volatile. Moreover, both rates are procyclical. Taken together, early in a boom (recession), job creation is high (low) and job destruction is low (high). However, worker flows stay high (low) throughout the boom (recession). The fact that the hiring rate rises more than the job creation rate during a boom is made possible by a procyclical separation rate.

Table 2 shows that these relationships lead to the following somewhat complex correlation structure between job and worker flows: The job creation and destruction rate are negatively correlated. Job creation rate and hiring rate, and the job destruction rate and the separation rate are positively correlated. Nonetheless, the hiring and separation rate are also positively correlated.

## 4 Understanding Worker Churn

The previous section showed that the flow of workers (worker turnover) in Germany is about twice as high as is required for the observed job turnover. The same pattern has been shown for the US (Burgess et al. (2000) and more recently Lazear and

<sup>14</sup>See tables 4 and 5 in Appendix A.1 for a comparison to US data.

Table 2: Correlations of Job and Worker Flows

	JCR	JDR	HR
<b>JDR</b>	−0.32*		
<b>HR</b>	0.81*	−0.29*	
<b>SR</b>	0.12	0.61*	0.49*

Note: the table displays correlation coefficients of HP(100,000)-filtered job and worker flow rates. A \* indicates significance at the 5% level obtained by non-parametric block-bootstrapping with a block length of 20.

Spletzer (2012) and Lazear and McCue (2017)). Burgess et al. (2000) introduce a measure that quantifies the amount of worker flows in excess of job flows at the plant level, called worker churn:

$$CH_t = (H_t - JC_t) + (S_t - JD_t). \quad (2)$$

Intuitively, churn occurs because non growing plants hire workers, and growing plants separate from workers. On average, churn is around 7% of employment each quarter. Figure II displays the rate of churn across the employment growth distribution. It shows a U-shaped pattern in employment growth. The larger the absolute rate of employment change, the more a plant churns workers. Importantly, this pattern is not driven by small plants, where small numbers of worker flows imply large flow rates.<sup>15</sup> In other words, growing plants not only hire a large fraction of their workforce, but they also separate from a significant number of workers and they separate from more workers than plants with a constant workforce. Vice versa, plants that shrink hire workers and they hire more than plants with a constant work force.

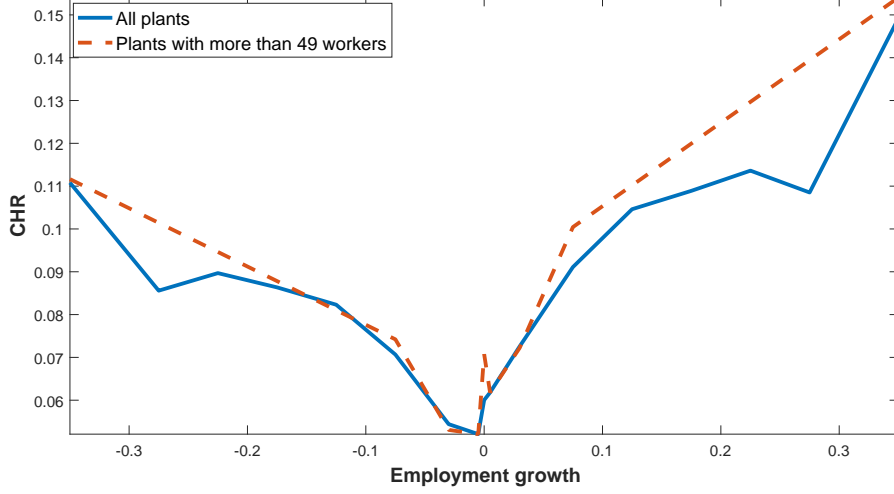
This is surprising and as we will show next is hard to explain with simple models of employment adjustments by plants but requires that plants do not have full control over the number of workers they employ.

#### 4.1 Quadratic Hiring Costs

For this purpose, we start off with a basic model of employment dynamics at the plant level. Our basic setup consist of plants that face a decreasing returns to scale

<sup>15</sup>Note, for expositional reasons, we abstract from plants shrinking more than  $-0.4$  or growing more than  $0.4$ . Figure XVI in Appendix A.3 shows that these plants contribute little to overall employment. To understand their importance for the aggregate churning rate, we compute the churning rate resulting from the churn of plants growing in the interval  $[-0.4, 0.4]$ . Figure XVII in Appendix A.3 shows that the resulting churning rate is basically identical to the aggregate churning rate (interval  $[-2, 2]$ ).

Figure II: Churning Rate and Employment Growth



Note: The figure displays the churning rate,  $CHR_{it} = \frac{H_{it} - JC_{it} + S_{it} - JD_{it}}{(E_{it} + E_{it-1})/2}$ , as a function of the plant specific employment growth rate. Plants are grouped in 17 employment growth categories. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. West German plants only. Pooled data, de-seasonalized by growth category, quarterly frequency, 1975Q1 - 2014Q4. The red dashed line displays the churning rate for plants with at least 50 employees.

production function in employment, shocks to idiosyncratic productivity, exogenous separations and quadratic costs of hiring.

In detail, let plant  $i$  produce output  $Y$  at time  $t$  according to the following decreasing returns to scale production function:

$$Y_{it} = z_{it} E_{it}^{\alpha}, \quad (3)$$

where  $E_{it}$  is the employment level,  $z_{it}$  is idiosyncratic productivity and  $\alpha$  (with  $0 < \alpha < 1$ ) is the curvature of the production function. Productivity follows an  $AR(1)$  process in logs:

$$\log z_{it} = (1 - \rho)\mu + \rho \log z_{it-1} + \epsilon_{it}, \quad \epsilon_{it} \sim N(0, \sigma_{\epsilon}^2). \quad (4)$$

At the beginning of a period, workers separate from the plant at a constant rate  $s$ . The firm actively adjusts its workforce by  $H_{it} \in \mathbb{R}$  workers such that the number of workers at firm  $i$  evolves according to

$$E_{it} = (1 - s)E_{it-1} + H_{it}. \quad (5)$$

If  $H_{it} > 0$ , then this active adjustment is counted as “hires”. If  $H_{it} \leq 0$ , we count the active adjustment as additional separations. The plant decides on  $H_{it}$  after observing its productivity, i.e. it has full command over the number of workers used in production and no planning lag. Adjusting the number of workers is subject to quadratic adjustment costs:  $c_{it} = \psi H_{it}^2$ . Plants choose hiring to maximize the sum of expected profits which they discount at rate  $r$  given a wage rate  $w$ .

It is straightforward to see that for negative employment growth rates smaller than  $-s$ , there is no hiring and thus the churn is zero – different to the data. For employment growth rates larger than  $-s$ , firms re-hire the workforce lost through separations. Yet, as separations are a fixed fraction of employment, the model cannot produce the fact that fast growing plants not only hire more, but also separate more from workers. We use the same definitions of rates in the model as in the data, i.e., based on the average employment between two adjacent periods. Therefore, the separation rate, as measured,  $s \frac{E_{it-1}}{(E_{it-1}+E_{it})/2}$ , and analogously the churn rate declines in plant growth.

To obtain a quantitative impression of the difference between model and data, we calibrate the model and display the churn rates by employment growth in Figure III. The parameters of this simple model are the wage,  $w$ , the returns to scale,  $\alpha$ , the quarterly interest rate  $r$ , the mean of the productivity process,  $\mu$ , the autocorrelation,  $\rho$ , the standard deviation of productivity shocks,  $\sigma_z$ , the separation rate,  $s$ , and the adjustment cost parameter,  $\psi$ .

We assume a quarterly interest rate of 0.01, set  $\alpha = 0.6$ , and normalize the wage to  $w = 1$ . We set  $\rho$  to 0.9675 as estimated by Bachmann and Bayer (2014) and use  $\mu$  to match an average plant size in our data of 12.6. We obtain the other three parameters,  $\sigma_z$ ,  $s$ ,  $\psi$ , from an equally weighted simulated minimum distance estimator. Our moments are the aggregate separation rate and the churning rate at the sixteen employment growth categories.<sup>16</sup> Column (2) in Table 3 displays the estimated parameters.

Figure III compares the churning rate over the employment growth distribution in the model and the data. The model fails to generate any churn at rapidly shrinking plants. These plants experience negative productivity shocks and desire to shrink; thus, they do not hire any workers. Plants with positive productivity shocks desire to grow. The churn at these plants is basically given by the exogenous separation rate  $s$ . Convex adjustment costs turn out to be of little importance to understand churn in the present framework.

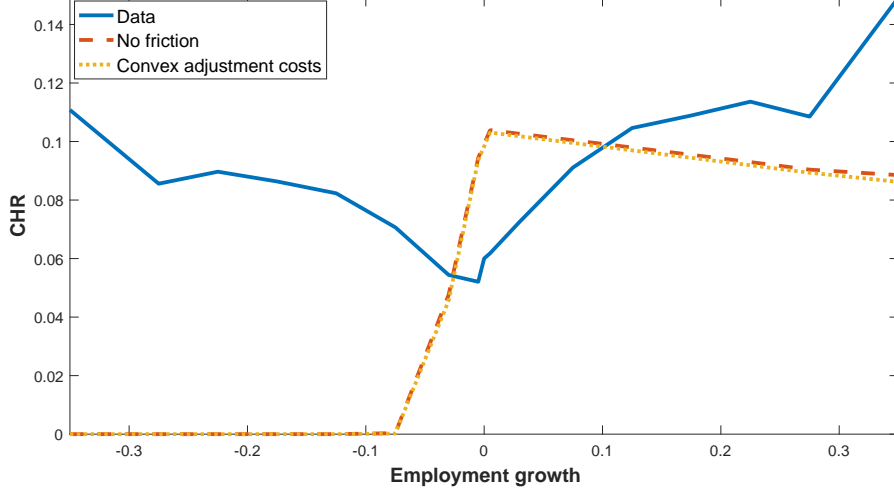
## 4.2 Separation shocks

Large churn at rapidly shrinking plants suggests that more workers separate from these plants than they desire - hence they rehire. Conversely it implies that plants shrink *because* workers separate as opposed to workers separating because plants want to shrink. These separations may result from workers finding a better employment opportunity. However, it does not mean that all separations must be worker initiated. They may as well be initiated by plants, which may fire workers after new information about certain workers has arrived (e.g. a lower match quality).

To understand how important these stochastic separations are for churning, we extend our model of employment dynamics to feature stochastic separations. For clarity, we assume that all plants have a common productivity level  $\mu$ . Similar to the structure of productivity shocks, we assume that the separation rate follows a

<sup>16</sup>We have in total 17 employment growth categories. However, given our assumption of a continuous shock distribution and convex adjustment costs, constant employment is a zero probability event.

Figure III: Churning in a model with only productivity shocks



Note: The figure displays the churning rate as a function of the plant specific employment growth rate. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. The blue solid line refers to the empirical churning rates for the West-German sample 1975-2014. The yellow dotted line, *convex adjustment costs*, refers to the optimal hiring policy of plants in a model with productivity shocks and convex adjustment costs. The red dashed line, *No friction*, refers to the same model but adjustment costs are set to zero.

(truncated) log-normal distribution:

$$\log s \sim \mathcal{N}(\mu_s, \sigma_s^2).$$

It is straightforward to see how churn arises at shrinking plants in this framework. Plants lose workers and they rehire. Without any adjustment costs, plants would have zero employment growth. Adjustment costs yield that plants only rehire a part of their workforce lost. Since the marginal benefit from rehiring increase more than linearly in the distance from optimal employment, plants that lose many workers rehire a larger fraction of these worker losses. Hence, churn is larger for largely shrinking plants. These plants had large separation shocks and they lean more strongly against the wind than plants with small shocks.

Conversely, positive employment growth arises because a plant having had large separation shocks in the past has a too low employment stock, rehires and thus grows. Fast growing plants are now either plants with little separation in the current period, or plants with particularly small employment stock to start with. This implies that the larger employment growth, the larger the fraction of plants with both a lot of hiring and a lot of separations.

Thereby, a calibrated version of the model can replicate the U-shape of churning rates in plant growth. We set again the quarterly interest rate to 0.01,  $\alpha = 0.6$ , and normalize the wage to  $w = 1$ . The remaining parameters of the model are the level of productivity,  $\mu$ , the adjustment costs,  $\psi$ , the location parameter of the separation rate shocks,  $\mu_s$ , and the dispersion parameter,  $\sigma_s$ . As before, we choose  $\mu$  to match

Table 3: Parameter Estimates

	Convex costs		Time-to-hire		
	Productivity shocks	Separation shocks	Average	Recession	Boom
$\mu$ %	1.48	1.67	1.52	1.50	1.53
$\sigma_\epsilon$ %	0.06	—	—	—	—
$\mu_s$	—	−3.44	−3.22	−3.26	−2.99
$\sigma_s$	—	0.70	1.08	1.20	1.00
$\psi$ %	0.78	300.10	—	—	—

Note: The table displays the parameter estimates for the different models of churn and employment growth.  $\mu$ : Mean of log-productivity.  $\sigma_\epsilon$ : Standard deviation of log-productivity shocks.  $\mu_s$ : Mean of log-separation rate shocks.  $\sigma_s$ : Standard deviation of log-separation rate shocks.  $\psi$ : Scaling parameter of quadratic hiring costs.

the average plant size in the data and obtain the other parameters by a minimum distance estimation.

Figure IV compares the model implied churning rate to the data. After a large separation rate shock, plants want to re-hire their work force. Resulting from the quadratic adjustment costs, they stretch out this re-hiring process over several periods, with the most re-hiring taking place in the first period. As a result, churn is large at rapidly shrinking plants, and small at growing plants.

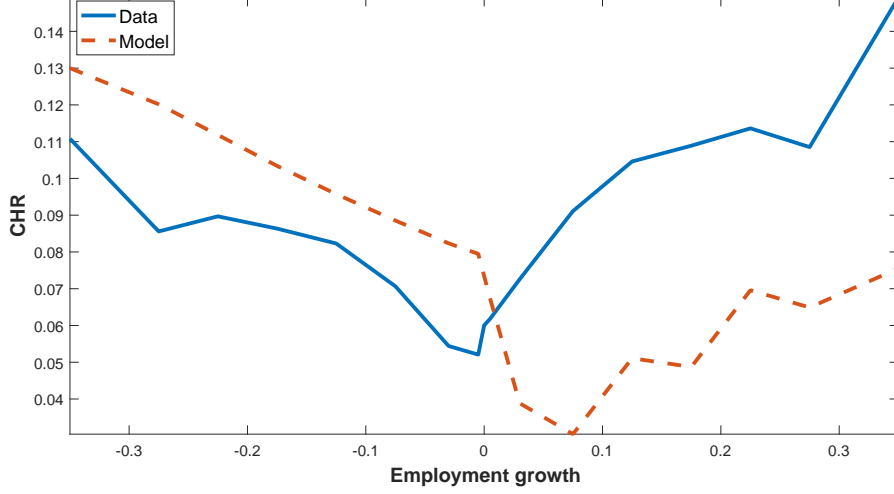
### 4.3 Time-to-Hire

While the separation shocks taken together with costs of employment adjustment can generate the U-shape of churning rates, the estimated adjustment costs are unrealistically large (see third column in Table 3). The model needs to bring down rehiring rates in order to match the level of churning and at the same time make sure that the employment growth distribution fits the data. Effectively, the model seeks to make current hiring and current separations independent.

A similar, but maybe better suited, friction to achieve this decoupling of current hiring and current separations is when hiring decisions are taken based on information of the preceding period. Then hiring and separations become decoupled by assumption.

To be more specific, let's assume that hiring decisions take place before the separation rate shock occurs. Plants, therefore, make mistakes in planning their employ-

Figure IV: Churning in a model with only separation shocks



Note: The figure displays the churning rate as a function of the plant specific employment growth rate. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. The blue solid line refers to the empirical churning rates for the West-German sample 1975-2014. The red dashed line, “model”, refers to the optimal hiring policy of plants in a model with quadratic adjustment costs and stochastic separations.

ment stock. The plant chooses to hire  $H_{it}$  to maximize:

$$\max_{H_{it}} \left\{ \mathbf{E}_{t-1} \{ z_{it} E_{it}^\alpha - w E_{it} \} \right\} \quad (6)$$

$$E_{it} = (1 - s_{it})(E_{it-1} + H_{it}), \quad \log s_{it} \sim \mathcal{N}(\mu_s, \sigma_s^2).$$

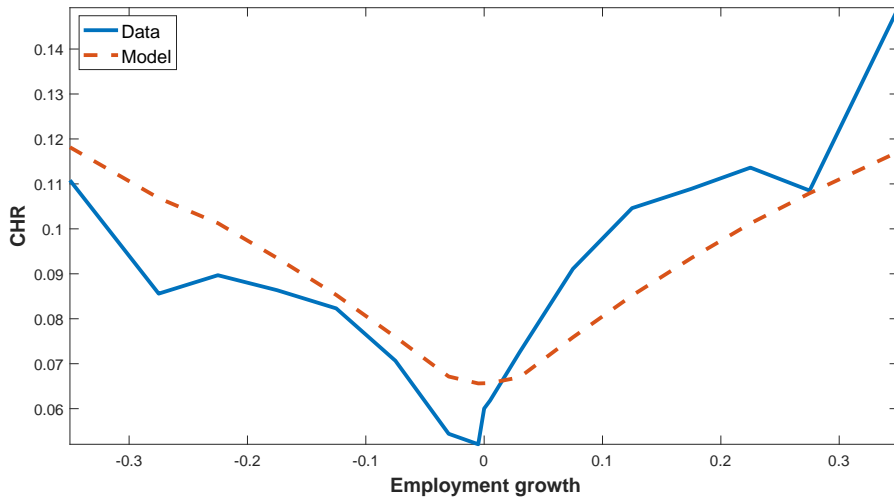
Crucially, optimal employment choices independent of last periods realized employment level,  $E_{it-1}$ . Therefore, plants with the largest employment growth are those who experienced large separation rates in the past. Yet, this does not mean that they necessarily have low separation rates today. On the contrary, plants with many hires tend to have many separations,  $s(E_{it-1} + H_{it})$ , and thus churn.

We calibrate the model under our maintained assumptions of  $r = 0.01$ ,  $\alpha = 0.6$ , and  $w = 1$ , calibrating the mean log plant productivity,  $\mu$ , the location parameter of the separation rate shocks,  $\mu_s$ , and the dispersion parameter,  $\sigma_s$ . Again, we use  $\mu$  to match the average plant size in the data and obtain the remaining parameters by a simulated minimum distance estimator. Figure V shows that the model is able to replicate the U-shaped pattern of the churning rate. Particularly, churn is largest at rapidly growing and shrinking plants.

Table 3 shows the resulting parameters. The implied uncertainty about separations is substantial. Within the 90% confidence interval, the separation rate ranges from 1 to 18 percent on a quarterly basis.<sup>17</sup>

<sup>17</sup>Key to have large churn at rapidly growing and shrinking plants are large separation rate shocks. the log-normal distribution assumption is not critical for our results. Results are similar when replacing the log-normal by an exponential distribution.

Figure V: Churning in a model with time-to-hire, stochastic separation, and productivity shocks



Note: The figure displays the churning rate as a function of the plant specific employment growth rate. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. The blue solid line refers to the empirical churning rates for the West-German sample 1975-2014. The red dashed line, “model”, refers to the optimal hiring policy of plants as described by model (6).

## 5 Understanding Cyclical Churn

So far, our analysis has focused on the time average churning rate. Yet, as highlighted for the US by Burgess et al. (2000) and Lazear and Spletzer (2012), churn is particularly large during boom periods. The left panel of Figure VI highlights the same phenomenon in our data. It plots the aggregate churning rate alongside the cyclical component of the unemployment rate. Churn fluctuates substantially in a procyclical way; its correlation with unemployment is  $-0.72$ . During times of low unemployment, it is about 3 percentage points higher than during times of high unemployment.

Figure VII shows the cyclical dynamics of the churning rate for the entire employment growth rate distribution. In constructing the figure, we pool the ten quarters with the lowest cyclical unemployment rate (boom) and the highest cyclical unemployment rate (recession). Table 6 in Appendix A.3 displays further summary statistics of the cyclical dynamics of the churning rate for each individual employment growth category. Both the table and Figure VII show that across the employment growth distribution, churn moves counter the unemployment rate. Moreover, in absolute value, the rise during booms is similar across the distribution. The only exception are rapidly growing plants, but the employment share at these plants is close to acyclical.

We use our model of time to build with separation shocks to estimate how these shocks must be varying over the business cycle. Table 3 shows that separation rate shocks are on average larger during booms, but their dispersion is somewhat larger

Figure VI: Churning Rate

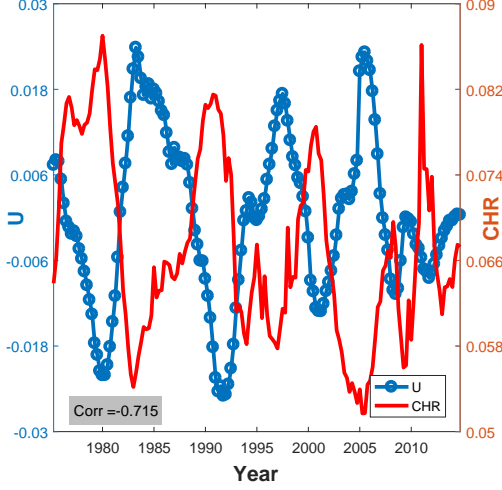
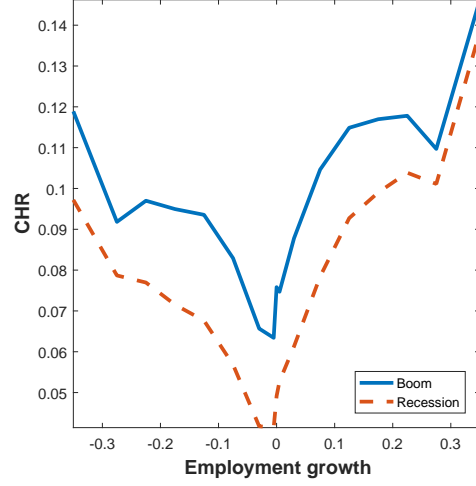


Figure VII: Churn and Plant Growth



Note: Left figure: The blue marked line is the HP(100,000)-filtered unemployment rate. The red straight line is the churning rate. Right figure: The churning rate across the employment growth distribution. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. The blue straight line is the average churning rate in the ten quarters with the lowest HP(100,000)-filtered unemployment rate (boom). The red dashed line is the average churning rate in the highest HP(100,000)-filtered unemployment rate (recession).

during recessions. In fact, losing more than 20 percent of the workforce is more likely during recessions than during booms; but this event occurs in less than 9 percent of all cases. Put differently, the typical firm faces more separations during a boom, but shocks in the very right tail are larger during recessions. One example of such an event would be organizational restructuring that changes the desired mix of employees.

Given the importance of separation rate shocks for short run employment dynamics of firms that we estimate, this result is particularly interesting in light of the discussion about the role of uncertainty in business cycles. There, typically it is assumed that productivity shocks are more dispersed in recessions. Here, we find that the number of employees fluctuates more in recessions because of more dispersed separation rate shocks.

### 5.1 A Statistical Model of Procyclical Churn

Before discussing the sources of higher separations during booms, we discuss, in a statistical sense, what drives cyclical movements in the aggregate churning rate. More specifically, we quantify the relative importance of two channels. First, the parallel shift of the churning rate over the cycle (Figure VII). Second, the employment growth distribution shifts over the cycle; thereby, interacts with the U-shaped pattern of the churning rate (Figure II). Let  $chr(j)_t$  be the churning rate of the  $j$ -th employment

growth category/bin. Note that

$$CHR_t = \sum_{j=1}^J chr(j)_t \underbrace{\frac{n_t(j)}{N_t}}_{ec_t(j)}, \quad (7)$$

where  $ec_t(j)$  is the share of overall employment in an employment growth rate bin. In order to understand the importance of the two channels of cyclical churn, consider the following statistical models:

$$\begin{aligned} CHR_t^{D-fix} &= \sum_{j=1}^J chr_t(j) \overline{ec(j)} \\ CHR_t^{f-fix} &= \sum_{j=1}^J \overline{chr(j)} ec_t(j), \end{aligned} \quad (8)$$

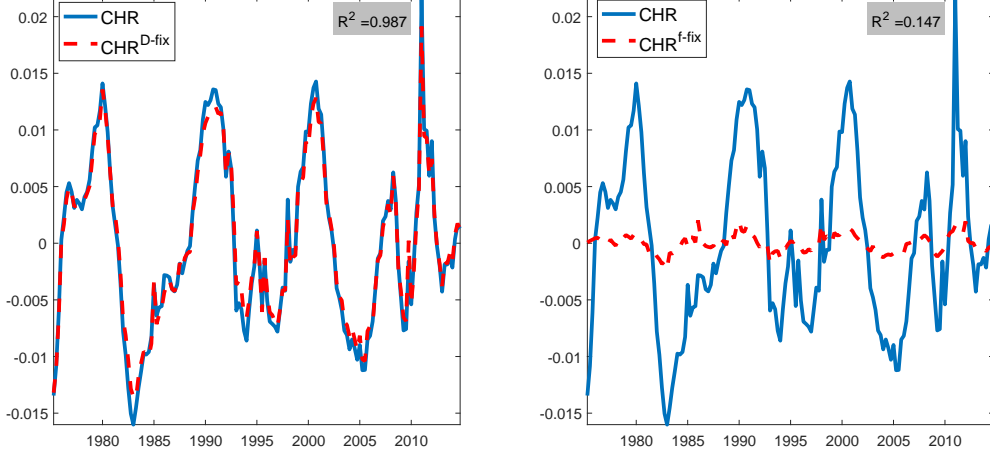
where  $\bar{x}$  denote time-mean values of employment shares and churning rates, respectively. According to the first model, churn is procyclical because plants at all employment growth categories increase their churn during a boom (cyclical movements in  $chr(j)$ ). Cyclical changes in the employment growth distribution do not contribute to churn. According to the second model, churn is procyclical because the employment growth distribution shifts during booms towards employment growth categories with higher average churning rates (cyclical movements in  $ec_t(j)$ ). Given the behavior of the churning rate, this latter channel would be potentially large, if booms were characterized by a shift away from marginally adjusting plants towards rapidly adjusting plants. In this case, not only would procyclical job flows lead to procyclical worker flows, but the change in the employment growth distribution would also contribute to increasing worker flows.

Figure VIII displays the cyclical component of  $CHR_t^{D-fix}$  and  $CHR_t^{f-fix}$  along with the cyclical churning rate. The churning rate with fixed employment shares is almost identical to the aggregate churning rate. Moreover, the churning rate with fixed growth-specific churning rates explains almost none of the aggregate dynamics in the churning rate. Put differently, to understand aggregate procyclical churn, it is not necessary to jointly study the dynamics in the employment growth distribution and conditional worker flows.

Davis et al. (2012), using US data, study how well different statistical models can explain aggregate movements in worker flow rates. In contrast to our finding for the churning rate, they find that both cyclical movements in the employment growth distribution and cyclical shifts in growth-specific worker flows are important to understand cyclical movements in the hiring and separation rate. Figure IX provides a graphical explanation for the difference. The churning rate relative to worker flows, is almost constant across the employment growth distribution. Particularly, worker flows show the "hockey-stick" behavior described in Davis et al. (2012).

We close this section explaining how our results are related to the statistical models studied by Davis et al. (2012). Using the notations from above, their first model relates the hiring and separation rate to cyclical movements in the employment growth distribution:

Figure VIII: Contributions to Cyclical Churning



Note: The blue solid lines refer to the empirical churning rates for the West-German sample. The red dashed lines decompose the churning rate into the components described by model (8).  $R^2$ : share of the churning rate explained by rate  $x_t$  computed as  $1 - (\sum (CHR_t - x_t)^2 / (\sum CHR_t^2))$ . All series are cyclical component of the HP(100,000)-filter.

$$HR_t^{f-fix} = \sum_{j=1}^J \overline{hr(j)} ec_t(j); \quad SR_t^{f-fix} = \sum_{j=1}^J \overline{sr(j)} ec_t(j). \quad (9)$$

We show in Appendix A.2 that this model, similar to the findings of Davis et al. (2012), explains about half of movements in the hiring rate<sup>18</sup>, but less of the separation rate. We also consider a second model where worker flows move procyclical because for a given amount of employment adjustment, at least some plants increase their worker turnover in booms relative to recessions:

$$HR_t^{D-fix} = \sum_{j=1}^J \overline{hr_t(j) ec(j)}; \quad SR_t^{D-fix} = \sum_{j=1}^J \overline{sr_t(j) ec(j)}. \quad (10)$$

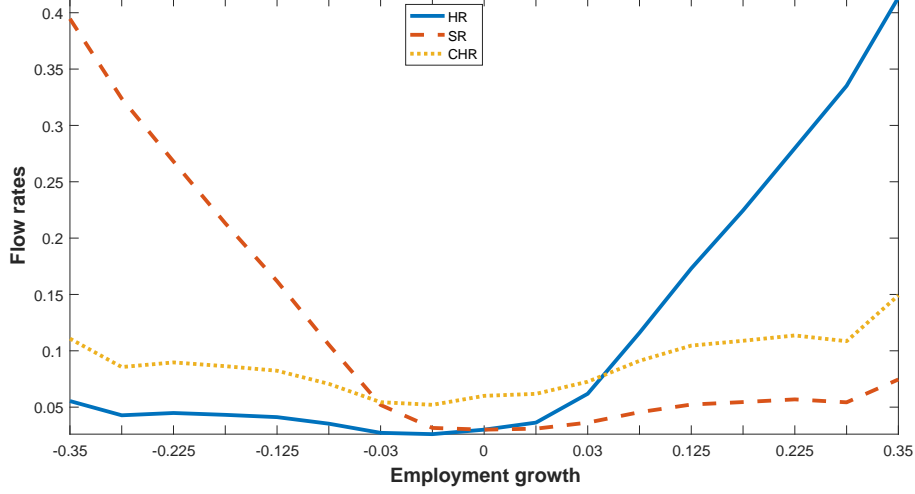
Obviously, when the hiring rate changes without an associated change in job flows, the separation rate needs to change one to one with the hiring rate:  $HR_t^{D-fix} = SR_t^{D-fix}$ . This observation makes the link between our analysis of the churning rate and the statistical models studied by Davis et al. (2012) explicit:

$$CHR \approx 2HR^{D-fix} \approx 2SR^{D-fix}. \quad (11)$$

How well do these statistical models explain worker flows? In Appendix A.2 we replicate the finding of Davis et al. (2012) that

<sup>18</sup>Computed as  $1 - \frac{\sum (HR_t - X_t)^2}{\sum (HR_t/2)^2}$ , where  $x_t$  is the counterfactual series.

Figure IX: Flows and Employment Growth



Note: The figure displays time averaged flow rates by employment growth for the West-German sample 1975-2014. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. The blue solid line is the hiring rate, the red dashed line the separation rate, and the yellow dotted line the churning rate.

$$HR_t \approx HR_t^{f-fix} + HR_t^{D-fix}, \quad (12)$$

$$SR_t \approx SR_t^{f-fix} + SR_t^{D-fix}. \quad (13)$$

This aggregation result is consistent with the result we show in Figure VIII. The close to uniform churning along the (for business cycles relevant part of the) employment growth distribution assures that it is not necessary to study the interaction between dynamics in the employment growth distribution and conditional worker flows.

## 5.2 Sources of Procyclical Churn

As shown above, procyclical churn is linked to rising separations during booms. To understand the reason for these separations, we differentiate separations (hires) based on their destination (source). In our data, we have information whether a separating worker is employed the next quarter at a different plant. Denote such separations as job-to-job transitions, *JTJ*. We decompose total worker flows as those resulting from job-to-job transitions, and those resulting from non-employment transitions:

$$HR_t = JTJR_t + HR^{N-emp} \text{ and } SR_t = JTJR_t + SR^{N-emp}, \quad (14)$$

where  $HR^{N-emp}$  denotes the hiring rate from non-employment and  $SR^{N-emp}$  denotes the separation rate into non-employment. Figures X and XI shows how separations split up into flows to other employment and non-employment and how new hires

Figure X: Job to Job Transitions

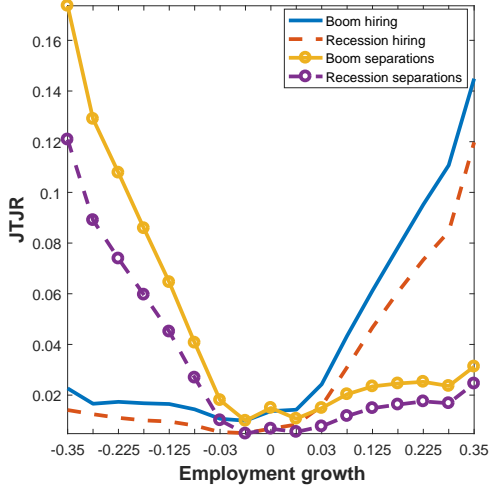
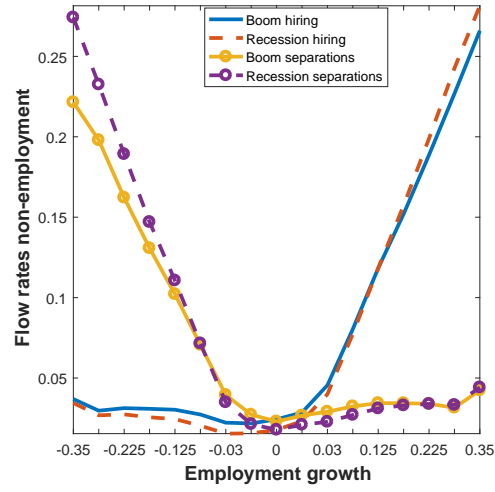


Figure XI: Non-employment



Note: The figure displays time averaged flow rates by employment growth for the West-German sample. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. Left figure: The separation and hiring rate from employment in the ten quarters with the lowest HP(100,000)-filtered unemployment rate (boom) and the highest (recession). Right figure: The separation and hiring rate from non-employment in the ten quarters with the lowest HP(100,000)-filtered unemployment rate (boom) and the highest (recession).

split into hires from employment and non-employment. During booms, the separation (hiring) rate into (from) employment shifts up in an almost parallel fashion over the employment growth distribution. Put differently, along the employment growth distribution, during a boom, more workers leave plants to work for another plant and plants increase their hiring from other plants. At the same time, the separation rate into non-employment and the hiring rate from non-employment show much less cyclical dynamics. On the contrary, rapidly shrinking plants separate significantly more into non-employment, and rapidly growing plants hire more from non-employment during recessions. Only inactive plants slightly increase hiring from and separations to non-employment during booms. Consequently the aggregate movements in churn are driven by the dynamics of job-to-job transitions.

## 6 Theory and Evidence

How do our results relate to the existing theoretical and empirical literature on labor market flows? Models with a one-to-one link between worker and job flows (such as Mortensen and Pissarides (1994)) miss the large amount of procyclical churn. We show that these cyclical dynamics in worker churn result from changes in job-to-job transitions, not changes in the rate workers are churned through non-employment.

A recent literature links observable plant characteristics to cyclical job-to-job transitions and resulting plant growth. Moscarini and Postel-Vinay (2012, 2013) develop a framework where large firms grow during booms on expense of small firms

by poaching workers from small firms in a procyclical way. Haltiwanger et al. (2015) question such poaching behavior, and show that plant pay is a better predictor for cyclical employment growth patterns.

Several recent works interpret these observable plant differences as representing underlying plant productivity. Moscarini and Postel-Vinay (2013), Schaal (2015), and Fujita and Nakajima (2016) all develop theories where during times of high production potential, vacancy posting is high, and workers flow from low- to high-productivity firms. Our findings support the idea of using job-to-job transitions as the key cyclical worker reallocation mechanism.

At the same time, our findings do not support the idea that the bulk of procyclical job-to-job transitions is driven by a common ranking (productivity) of plants for all workers; thereby a systematic reallocation of workers from low to high productivity plants during booms. In such a set-up, highly ranked plants have low separation rates (and churning rates) on average. Moreover, during a boom, higher ranked plants grow more than during recessions. Therefore, we should observe that during booms, the separation rate (and churning rate) increases by more at shrinking plants than at growing plants. As shown above, we find no evidence of this. We therefore view our empirical evidence as one for job-ladders, where booms foster reallocation of workers, climbing up their job ladder. Yet, they are not in line with workers having a common ranking across plants.

## 7 Conclusion

This paper studies the link between worker churn and establishment growth using a newly assembled plant-level dataset from Germany. We show that churn occurs along the entire employment growth distribution; most pronounced at rapidly adjusting plants. Stochastic separation rate shocks that lead to planning errors by establishments do a good job in explaining cross-sectional churn behavior.

These separation rate shocks become larger in booms leading to procyclical churn along the entire employment growth distribution. Rising separation rates represent workers reallocating to other establishments, not into non-employment. Again, separations (and hiring) to (from) other establishments rises by a similar amount along the entire employment growth distribution.

This uniform behavior along the employment growth distribution is at odds with the idea that booms are times where workers systematically reallocate to plants which are desired by all workers. One promising way to rationalize churn across the employment growth distribution may be found in theories that stress the presence of match quality, as in Barlevy (2002), instead of productivity differences between plants. This match quality may also be time varying because of idiosyncratic productivity shocks. Gulyas (2016) shows some evidence that the desired workforce composition may change when plants grow or shrink in sizes.

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## A Appendices

### A.1 Conceptual Differences between the *AWFP* and US Data

The *AWFP* allows us to link job and worker flows. A major obstacle for studying this link in the United States is the availability of data sets that provide information on establishment characteristics, worker flows, and job flows. The most suited US data source is the *Job Openings and Labor Turnover Survey (JOLTS)*, used by Davis et al. (2006, 2012), sampling 16,000 establishments in the US on a monthly basis. However, *JOLTS* only started in 2001, providing data on at most two full business cycles.<sup>19</sup> By contrast, the German *AWFP*, contains quarterly information on job and worker flows of all full-time employees working for all German establishments from 1975–2014. This allows us to systematically study the response of job and worker flows and their interaction.<sup>20</sup>

For our comparison with the US, we obtain seasonally adjusted US quarterly job flows from the Business Employment Dynamics (*BED*) data for the period of 1992–2014. *BED* contains information on the universe of US establishments, excluding household employment, governmental employees, the self-employed, and small farm workers. The *BED* data does not contain information on worker flows. Therefore, we obtain seasonally adjusted worker flows from *JOLTS* for the years 2001–2014. *JOLTS* samples every month 16,000 establishments from the universe of US establishments with the exception of agriculture and private households. We aggregate the monthly flows to the quarterly frequency.

Figure XII compares German job and worker flows to those in the US. Job and worker flows are substantially larger in the US than in Germany. Average quarterly job flows in Germany are 0.036, compared to 0.071 in the US. Similarly, the average worker flow rate in Germany is 0.070, compared to 0.118 in the US. The second major difference between the countries is that job flows show a negative trend in the US over time, but no such trend is present in Germany. Davis et al. (2010) provide a discussion of the decreasing job flow volatility in the US. Hyatt and Spletzer (2015) show that about half of the decrease can be explained by a decrease in the amount of jobs lasting less than a quarter, which are not similarly important in Germany as in the United States.

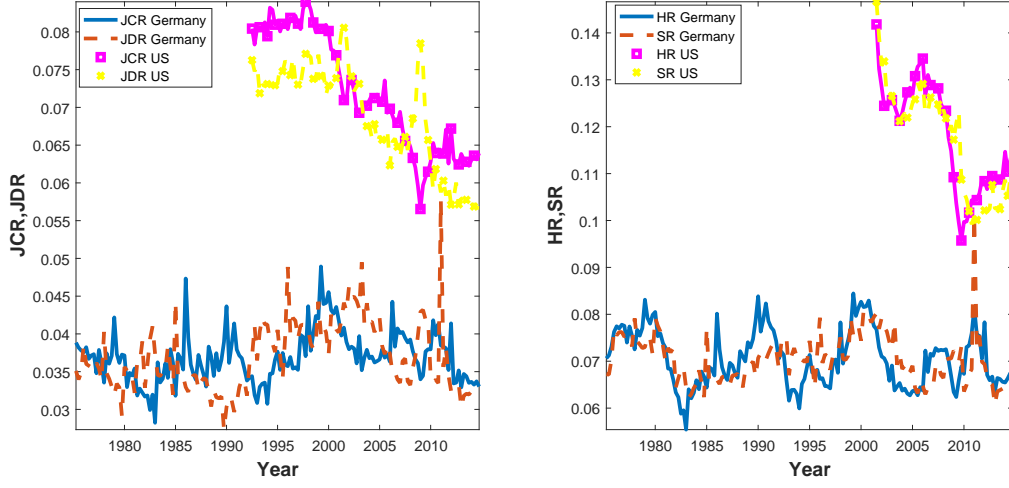
Table 4 displays the cyclical properties of job flow rates in the US. The cyclical volatility of the job-creation rate, *JCR*, and the the job-destruction rate, *JDR*, are similar in the two countries. Remember that both flow rates are substantially lower

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<sup>19</sup>Abowd and Vilhuber (2011) present stylized facts from the *Longitudinal Employer-Household Dynamics (LEHD)*. This data covers at least 30 percent of US employment since 1993; however, it is not publicly available.

<sup>20</sup>The two concepts of establishments are not quite the same. In the US, an establishment is a single physical location where business is conducted or where services or industrial operations are performed. In our dataset, each firms' production unit located in a county (Kreis) receives an establishment identifier based on an industry classification. When each production unit within a county has a different industry classification, or a firms' production unit are located in different counties, the two definitions coincide. When a firm has more than one production unit within the same county that are classified by the same industry, they may receive the same establishment identifier. The employer may decide; however, to have different identifiers assigned (see Dunderl et al. (2006)).

Figure XII: Job and Worker Flows in the US and Germany



Note: The figure displays job and worker flows in Germany and the US. *JCR*: job creation rate, *JDR*: job destruction rate, *HR*: hiring rate, *SR*: separation rate.

in Germany. As a result, these flow rates are more than 50 percent more volatile in Germany when using log deviations. Using log deviations, the *JCR* and *JDR* are 2.5 and 3.7 times more volatile than output in the US. We find for Germany ratios of 4.3 and 5.4, respectively. This reflects that the Shimer (2005) puzzle is even more evident in Germany compared to the US when looking at the job finding rate from unemployment and vacancies (see Gartner et al. (2012) and Jung and Kuhn (2014)).

Table 5 computes the correlations between job and worker flows in US data. As in the German data, the job creation and destruction rate are negatively correlated, and the hiring and separation rate are positively correlated. Moreover, the job creation rate is positively correlated with the hiring rate, and the job destruction rate is positively correlated with the separation rate.

Table 4: Job and Worker Flows in the US and Germany

					Correlation with $U_{t+j}$		
		<i>Mean</i>	<i>SD</i>	<i>AC</i> (1)	$j = -2$	$j = 0$	$j = +2$
<b>JCR</b>	GER	3.69%	0.29%	0.52	0.19*	-0.04	-0.28*
<b>JCR</b>	US	7.16%	0.27%	0.81	-0.16	-0.45*	-0.63*
<b>JDR</b>	GER	3.69%	0.36%	0.40	-0.02	0.15	0.29*
<b>JDR</b>	US	6.84%	0.34%	0.81	-0.32*	0.02	0.30*
<b>HR</b>	GER	7.06%	0.57%	0.82	-0.26*	-0.53*	-0.27*
<b>HR</b>	US	11.82%	0.82%	0.93	-0.63*	-0.87*	-0.94*
<b>SR</b>	GER	7.06%	0.47%	0.47	-0.46*	-0.51*	-0.48*
<b>SR</b>	US	11.68%	0.67%	0.87	-0.91*	-0.86*	-0.68*

Note: the table displays the properties of the HP(100,000)-filtered job and worker flow rates. *SD*: standard deviation, *AC*(1): first order auto correlation. A \* indicates significance at the 5% level obtained by non-parametric block-bootstrapping with a block length of 20.

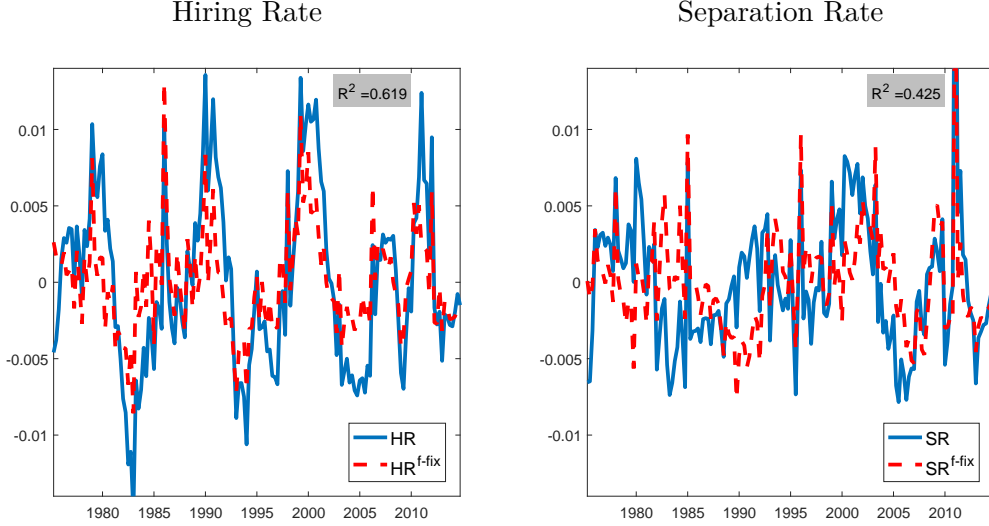
Table 5: Correlations of Job and Worker Flows in the US

	<b>JCR</b>	<b>JDR</b>	<b>HR</b>
<b>JDR</b>	-0.75*		
<b>HR</b>	0.64*	-0.44*	
<b>SR</b>	0.08	0.25	0.71*

Note: the table displays correlation coefficients of HP(100,000)-filtered job and worker flow rates. A \* indicates significance at the 5% level obtained by non-parametric block-bootstrapping with a block length of 20.

## A.2 Relationship with Davis et al. (2012)

Figure XIII: Fixed Worker Flow Rates Over the Cycle



Note: The blue solid lines refer to the empirical hiring and separation rate for the West-German sample. The red dashed lines display the corresponding synthetic series described by model (15).  $R^2$ : share of hiring (separation) rate explained by rate  $x_t$  computed as  $1 - (\sum (HR_t - x_t)^2 / (\sum HR_t^2))$ . All series are HP(100,000)-filtered.

This section compares our findings to Davis et al. (2012) closely following their approach. The most widely used framework to understand worker flows are variants of the Mortensen and Pissarides (1994) model. In this framework, all worker flows result from job flows, a characteristic which Davis et al. (2012) label the "iron link" between job and worker flows. To understand the aggregate implications of these models, we study the following statistical model:

$$HR_t^{f-fix} = \sum_{j=1}^J \overline{hr(j)} ec_t(j) \quad (15)$$

$$SR_t^{f-fix} = \sum_{j=1}^J \overline{sr(j)} ec_t(j),$$

where  $\bar{x}$  denote time-mean values of variable  $x$ . According to this model, given some establishments' employment growth, worker flows do not vary over time. Therefore, cyclical changes in worker flow rates result from cyclical shifts in the employment growth distribution only. The specification is more general than the pure "iron link", because we allow shrinking establishments to have positive hires and growing establishments to have positive separations. Moreover, we allow the series to have a time varying trend component.

Figure XIII plots the synthetic flow rates from our statistical model against the true hires and separation rate. Job flows explain a substantial fraction of cyclical

worker flows. Movements of the employment growth distribution capture all major movements in the hiring rate. In a statistical sense, the synthetic series explains 64% of the movements in the hiring rate. For the separation rate, the synthetic series with fixed conditional flow rates explains 43%. Let us now consider a second statistical model:

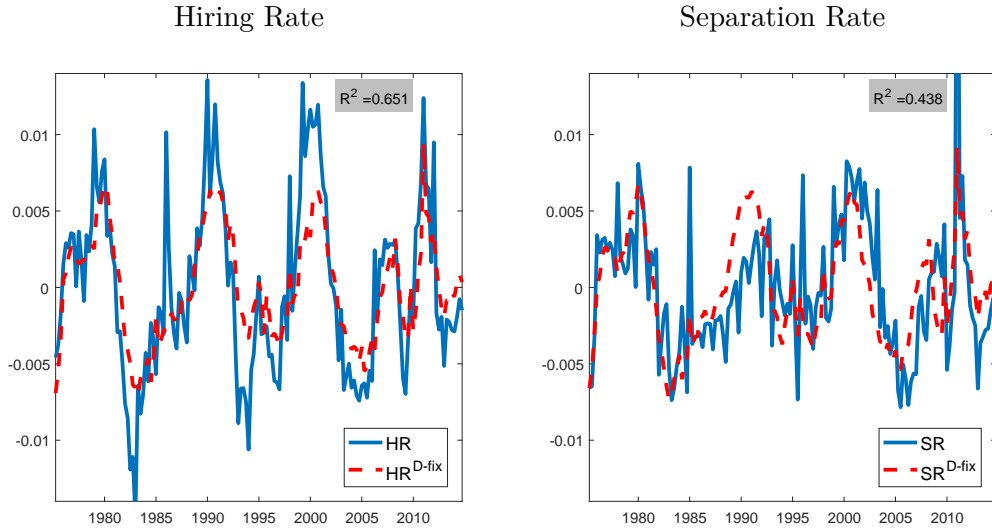
$$HR_t^{D-fix} = \sum_{j=1}^J hr_t(j) \overline{ec(j)} \quad (16)$$

$$SR_t^{D-fix} = \sum_{j=1}^J sr_t(j) \overline{ec(j)}.$$

According to this model, worker flows move procyclical because for a given amount of employment adjustment, at least some establishments increase their worker turnover in booms relative to recessions.

Figure XIV displays the resulting synthetic series from this exercise. The series are a quite good fit for the realized rates. The synthetic series explains 65% of the hiring rate. The hiring rate is not sufficiently volatile, but the timing of periods with high and low rates is almost identical. The statistical model explains 44% of the separation rate. Taken together, in a statistical sense, the model with the fixed employment growth distribution and the model with the fixed conditional worker flows explain similar amounts of the volatility in aggregate worker flow rates. However, particularly for the separation rate, the model with the fixed employment growth distribution

Figure XIV: Components of the Hires and Separation Rate over the Cycle



Note: The blue solid lines refer to the empirical hiring and separation rate for the West-German sample. The red dashed lines display the corresponding synthetic series described by model (16).  $R^2$ : share of hiring (separation) rate explained by rate  $x_t$  computed as  $1 - (\sum (HR_t - x_t)^2 / (\sum HR_t^2))$ . All series are HP(100,000)-filtered.

explains mainly major changes in the rate, and the model with fixed conditional flows explains quarter to quarter spikes.

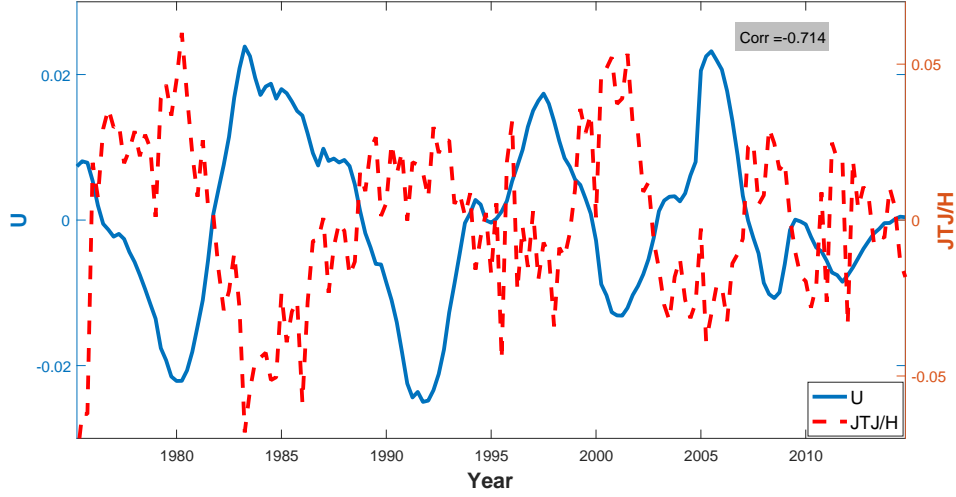
### A.3 Further Tables and Figures

Table 6: Dynamics of the Churning Rate

growth rate	<i>mean</i>	<i>SD</i>	<i>AC</i> (1)	<i>CorrU</i>
-2 to -0.75	3.00%	0.53%	-0.17	-0.02
-0.75 to -0.4	7.77%	0.59%	0.58	-0.66*
-0.4 to -0.3	11.11%	1.31%	0.66	-0.70*
-0.3 to -0.25	8.56%	0.82%	0.76	-0.68*
-0.25 to -0.2	8.98%	0.91%	0.84	-0.71*
-0.2 to -0.15	8.65%	1.03%	0.86	-0.69*
-0.15 to -0.1	8.25%	1.14%	0.87	-0.66*
-0.1 to -0.05	7.12%	1.05%	0.93	-0.68*
-0.05 to -0.01	5.49%	0.83%	0.92	-0.72*
-0.01 to 0	5.22%	0.63%	0.85	-0.75*
0	6.06%	0.66%	0.90	-0.84*
0 to 0.01	6.15%	0.59%	0.76	-0.79*
0.01 to 0.05	7.20%	0.69%	0.88	-0.83*
0.05 to 0.1	9.03%	0.82%	0.83	-0.75*
0.1 to 0.15	10.39%	0.89%	0.76	-0.65*
0.15 to 0.2	10.84%	0.90%	0.77	-0.55*
0.2 to 0.25	11.33%	0.89%	0.66	-0.52*
0.25 to 0.3	10.83%	0.84%	0.55	-0.40*
0.3 to 0.4	14.88%	1.43%	0.34	-0.31*
0.4 to 0.75	10.01%	0.71%	0.44	-0.39*
0.75 to 2	3.88%	0.34%	0.32	-0.23

Note: the table displays the HP(100,000)-filtered churning rate over the employment growth distribution. Mean: non-filtered time-average churning rate, *SD*: standard deviation, *AC*(1) autocorrelation coefficient, *CorrU*: correlation with unemployment. A \* indicates significance at the 5% level obtained by non-parametric block-bootstrapping with a block length of 20.

Figure XV: Job-to-Job Transitions



Notes: the figure displays for the West-German sample the share of hires explained by job-to-job transitions and the unemployment rate. All series are the cyclical component of the HP(100,000)-filter.

Figure XVI: Growth Distribution

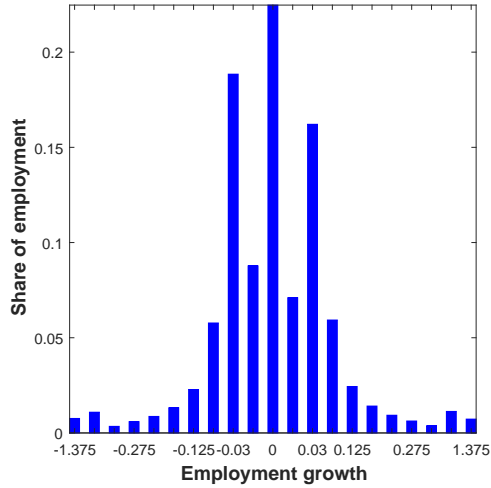
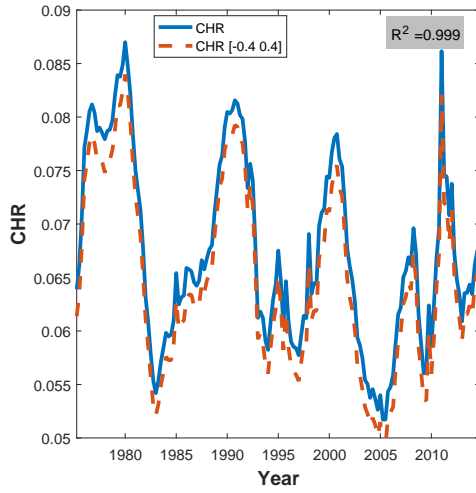


Figure XVII: Churning rate  $[-0.4, 0.4]$

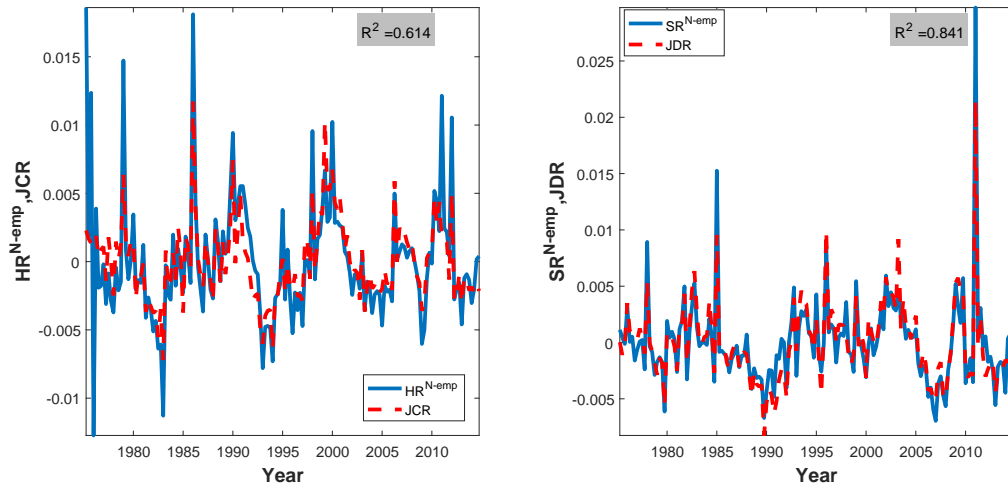


Note: Left figure: The time-average employment share for West-Germany (1975-2014) for each employment growth category. We represent the employment growth category by its midpoint as an estimate of the average growth in that category. Right figure: The blue straight line is the churning rate. The red dashed line is the churning rate resulting from churn occurring in employment growth categories  $[-0.4, 0.4]$ .  $R^2$ : share of churning rate explained by rate  $x_t$  computed as  $1 - (\sum (CHR_t - x_t)^2) / (\sum CHR_t^2)$ .

Figure XVIII: Flows from Non-Employment and Job Flows

(A) HR without JTJ

(B) SR without JTJ



Note: The blue solid lines refer to the empirical hiring rate from non-employment (left) and separation rate to non-employment (right) in West-Germany. The red dashed line is the corresponding job creation rate (left) and job destruction rate (right).  $R^2$ : share of hiring (separation) rate from (to) non-employment explained by rate  $x_t$  computed as  $1 - (\sum (HR_t^{N-emp} - x_t)^2 / (\sum HR_t^{N-emp^2}))$ . All series are HP(100,000)-filtered.