Job and Worker Flows: New Stylized Facts for Germany

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Abstract

We study the relationship between cyclical job and worker flows at the establishment level using the new German *AWFP* dataset spanning from 1975–2014. We find that worker turnover moves more procyclical than job turnover. This procyclical worker churn takes place along the entire employment growth distribution of establishments. We show that these procyclical conditional worker flows result almost exclusively from job-to-job transitions. Growing establishments fuel their employment growth by poaching workers from other establishments as the boom matures. At the same time, non-growing establishments replace these workers by hiring from other establishments and non-employment.

Key Words: Job flows, Worker flows, Aggregate fluctuations
JEL Classification: E32, J23, J63

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1 Introduction

Workers predominantly reallocate during booms (see Davis et al. (2006)). It is tempting to understand this as a result of job flows: during booms establishments post more vacancies as productivity increases and workers flow more quickly from unemployment to employment leading to job creation. However, Burgess et al. (2000) and, more recently, Davis et al. (2006, 2012) and Lazear and Spletzer (2012) show that worker flows increase substantial more than job flows during booms. In other words, the churn of workers across establishments increases in booms. Understanding the reasons behind this procyclical behavior of worker reallocation in excess of job reallocation can inform us on how business cycles propagate through endogenous worker reallocation.

This paper uses the new Administrative Wage and Labor Market Flow Panel (*AWFP*) for Germany to establish several new stylized facts for labor market flows over the business cycle. The dataset comprises the entire universe of German establishments from 1975–2014 at the business cycle frequency. Although we analyze the connection between worker flows and job flows from a pure statistical perspective, the paper is theory driven. The questions we ask are motivated by recent labor market flow models and the answers we provide serve as a relevant benchmark for theoretical modelers.

We find that aggregate job and worker flow behavior in Germany — though smaller than in the US on average — shows very similar cyclical properties to US data.[1] The job creation rate is procyclical and the job destruction rate is countercylical. Inspecting the micro-data, a boom (relative to a recession) is characterized by more establishments (modestly) growing and fewer establishments being inactive or decreasing their workforce. Worker flows, namely the hires and separation rate are strongly procyclical.

More procyclical worker flows than job flows implies aggregate procyclical worker churn (as defined by Burgess et al. (2000)). Using the micro-data, we show that churn is of a similar magnitude along the employment growth distribution, particular those parts that change over the business cycle. What is more, the cyclical properties of churn are stable along the employment growth distribution. As a consequence, from a statistical perspective, cyclical movements in the employment growth distribution do not contribute to cyclical movements in the aggregate churning rate.

Turning to the source of these procyclical excess worker flows, our data allows us to quantitatively link two phenomena studied separately thus far: procyclical job-to-job transition and worker churn.[2] We find that job-to-job transitions explain quantitatively the entire cyclicality in worker churn. In addition, we show that cyclical movements in the job creation rate result from cyclical movements in the hires rate from non-employment. Cyclical movements

[1] Davis et al. (2012) provide a comprehensive overview for the US data.

[2] The former is usually measured in worker surveys, the latter in firm surveys.

in the job destruction rate result from cyclical movements in the separation rate to non-employment.

Recent literature studies cyclical employment growth and hiring behavior by establishment (or firm) characteristics. Moscarini and Postel-Vinay (2012) find that employment growth at large firms is more cyclical than at small firms. Motivated by this finding, Moscarini and Postel-Vinay (2013), Schaal (2015), and Fujita and Nakajima (2016) build structural on-the-job search models where high-productivity (large) firms poach workers from low-productivity (small) firms in a procyclical way. Empirically, Haltiwanger et al. (2015) find no relationship between establishment size and procyclical job-to-job transitions. Instead, they show that establishment pay is a key determinant for poaching behavior. We add to this literature by demonstrating a link between the source of cyclical hiring and the employment growth distribution. Non-growing establishments increase hiring from employment and non-employment during booms. By contrast, growing establishments increase only hiring from employment.

How well do on-the-job search models explain the stylized facts we present? Schaal (2015) shows that in a model where wages are linked to productivity, churn in general is small and particularly non-existing at shrinking establishments. Positive vacancy creation costs create an inaction region implying that slowly shrinking establishments have no desire to hire workers. Moreover, rapidly shrinking establishments result from negative idiosyncratic productivity shocks that provide no incentives for hiring. In contrast, our results show that shrinking establishments find it profitable to replace part of their exiting workforce leading to a constant average churning rate along the employment growth distribution. Moreover, shrinking establishments find it profitable (and are able) to hire from other establishments in a procyclical way. Thus, either hiring costs need to small for these establishments, or worker heterogeneity leads to a large desire to change the workforce after a negative productivity shock.

The aggregate job and worker flows from the *AWFP* used in our paper will be available online (see Seth and Stüber (2017)) and can be used for estimations or calibrations by other researchers.

The rest of the paper 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 job and workers flow dynamics. Section 4 relates procyclical "excess worker turnover" (churn) to the employment growth distribution of establishments and addresses the reasons for churn. Section 5 connects the empirical insights from sections 3 and 4 to labor market flow theory and section 6 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[3] 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 liable to social security.[4] 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.[5] 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 full-time employed and belongs to one of the following person groups: 'employees s.t. social security without special features', 'seamen' or 'maritime pilots'. Therefore (marginal) part-time employees, employees in partial retirement, interns etc. are not accounted for as regular workers. All stocks and flows in the AWFP are generally calculated on a regular worker basis.

The *AWFP* covers the time period 1975–2014 (West Germany until 1992 and the re-unified Germany thereafter). It is available at a yearly and quarterly frequency. For our analysis, we use the *AWFP* on 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.[6] For further information on the dataset please refer to the *AWFP* data report (Seth and Stüber (2017)).

[3]Merkl and Stüber (2016) use the *AWFP* to analyze the effects of different wage dynamics on labor flows.

[4]Marginal part-time workers (*geringfügig Beschäftigte*) are included since 1999. The main types of employees not covered are public officials (*Beamte*), military personnel, and the self-employed.

[5]Before this aggregation, the data on individuals are subjected to numerous validation procedures. Job and worker flow disaggregated by sub-categories of workers are available as well, but for the present paper we only exploit information for the total job and worker flows at the establishment level. 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.

[6]A previous discussion paper (Bachmann et al. (2013)) used the *ELFLOP* dataset (see Bachmann et al. (2011)), the precursor of the *AWFP*.

2.2 Variable Definitions

In the *AWFP* data, 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.[7] This definition yields the number of jobs at a plant at the end of a quarter (J_t), the number of hires[8] (H_t) at a plant, as well as the number of separations[9] (S_t). These are the time series from the *AWFP* from which all other data are constructed for our paper.

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 fire workers within the same quarter. We refer to the sum of hires and separations as worker turnover (gross worker flow), WT_t. We have $H_t \geq JC_t$ and $S_t \geq JD_t$ 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 aggregate the plant-level data to 13 employment growth categories/bins.[10]

We allow each employment growth category to have an individual specific seasonal component and compute seasonally adjusted series, using the X-12 ARIMA CENSUS procedure.[11] To derive the aggregate series for West Germany, we finally aggregate 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 as denominator the average of contemporaneous and lagged end-of-quarter employment:

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

For example, the hires rate reads:

$$HR_t = \frac{H_t}{N_t}. \tag{1}$$

The separation rate (SR), the job-creation rate (JCR), and the job-destruction rate (JDR) are defined equivalently. Using the numerator N_t, as defined above,

[7] It turns out that most workers leave or join a plant at the end respectively beginning of a quarter.

[8] A worker that has not been working for that plant at the end of the previous quarter.

[9] A worker that has been working for the plant at the end of the previous quarter.

[10] The categories are: plants shrinking by > 0.75, 0.40–0.75, 0.10–0.40, 0.05–0.10, 0.01–0.05, 0–0.01, plants leaving employment unchanged and plants that grow by > 0.75, 0.40–0.75, 0.10–0.40, 0.05–0.10, 0.01–0.05, 0–0.01. We calculate the employment growth rate as: $\frac{J_t - J_{t-1}}{(J_t + J_{t-1})/2} = \frac{JF_t}{N_t}$. Please note the discussion on the definition and interpretation of rates at the end of this subsection. Figure XII in Appendix A.3 shows the time averaged employment share in each of the categories.

[11] 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.

implies that all rates are bounded in the interval $[-2, 2]$ with endpoints corresponding to death and birth of plants.[12]

Most of our analysis deals with fluctuations at business cycle frequency. To measure the stage of the business cycle, we use the aggregate unemployment rate for West Germany.[13] If not otherwise stated, we compute the cyclical component for the aggregate or employment growth category series employing a HP-filter for the series with a smoothing parameter of $100,000$ (following Shimer (2005)). Consequently, the cyclical components have the interpretation of a deviations 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 aggregate dynamics of job and workers flows in Germany. 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. Quarterly job flow and worker flow rates are around 3.6% and 7.0%, respectively.[14] The two rates are negatively correlated. During times of rising unemployment, job creation is low and job destruction is high. In contrast, worker flows co-move over time. Both rates fall during times of unemployment growth.

The upper panel in Table 1 displays summary statistics of the cyclical component of the job flow rates. The job creation rate, JCR, is somewhat more persistent but fluctuates less than the job destruction rate, JDR.

Figure II shows how shifts in the entire employment growth distribution create these cyclical movements in job flow rates. The figure displays the employment share of each employment growth bin in a boom relative to a recession. In constructing the figure, we average over the ten quarters with the highest positive and negative deviation from trend unemployment.[15] During a boom (relative to a recession), employment shares shift towards growing plants in the range of 0.01 to 0.4 and away from plants being inactive, or weakly decreasing their workforce. The share of employment at rapidly growing and contracting plants ($\approx$ plant entry and exit) is countercyclical.

The bottom panel in Table 1 displays summary statistics of the hires rate

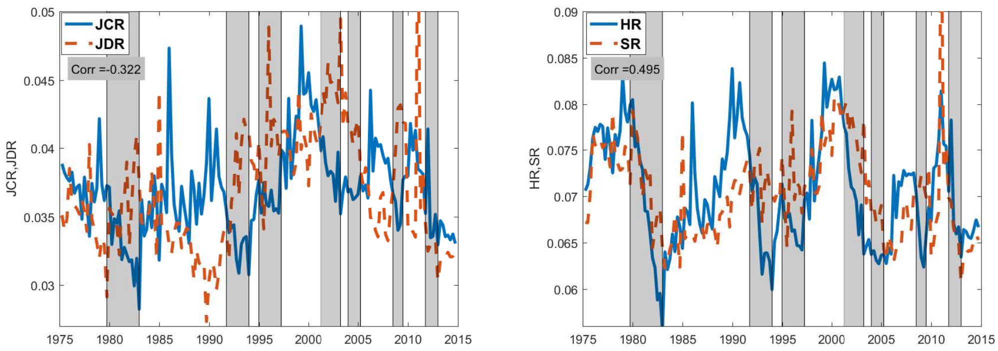
[12]See Davis et al. (1996) for a more thorough discussion regarding the properties of this measure. Most importantly, the measure allows for consistent aggregation.

[13]Cyclical unemployment has a strong negative correlation with GDP (-0.71).

[14]Those flows are substantially larger in the US. Average quarterly job flows are 7.1% and average worker flow rates are 11.8%. However, Table 3 in appendix A.1 shows that the cyclical component of job and worker flows behaves very similarly in the US.

[15]The amount of selected quarters is of little importance.

Figure I: Job and Worker Flows



Note: the top panel displays job flows. JCR: job creation rate, JDR: job destruction rate. The bottom panel displays worker flows. HR: hires rate, SR: separation rate. All rates are the cyclical component from a HP-filter.

and the separation rate. Worker flows are more persistent than job flows and more volatile. Moreover, both rates move procyclical. Put differently, during a boom (relative to a recession), the hires rate rises more than the job creation rate which is made possible by a procyclical separation rate.

4 Understanding Cyclical Worker Flows

Similar o our findings above, Burgess et al. (2000) and recently Lazear and Spletzer (2012) show that worker turnover in excess of job turnover, worker churn, is strongly procyclical in the US. In this section, we study these excess worker flows along the entire employment growth distribution. Moreover, we show that this procyclical worker churn results from job-to-job transitions.[16]

4.1 Churn and the Employment Growth Distribution

Burgess et al. (2000) introduce a measure that quantifies the amount of worker flows in excess of job flows at the plant, worker churn:

$$CH_t = (H_t - JC_t) - (S_t - JD_t).$$

Intuitively, churn occurs because non growing plants hire workers, and growing plants separate from workers. Figure III plots the churning rate, $CHR_t = \frac{CH_t}{N_t}$, alongside the cyclical component of the unemployment rate. Churning is substantial, between 5.6% and 8.5% of employment per quarter. Moreover, it moves procyclical (with GDP); its correlation with unemployment is -0.72.

[16]Supporting this finding, Davis et al. (2012) use *JOLTS* data showing that lay-offs are countercyclical, but quits are procyclical.

Table 1: Job Flows

	SD	$AC(1)$	Correlation to U_{t+j}				
			$j=-2$	-1	0	$+1$	$+2$
JCR	0.29%	0.52	0.19	0.08	-0.04	-0.17	-0.28
JDR	0.36%	0.4	-0.02	0.05	0.15	0.23	0.29
HR	0.57%	0.82	-0.26	-0.4	-0.53	-0.64	-0.72
SR	0.47%	0.47	-0.46	-0.5	-0.51	-0.5	-0.48

Note: the table displays the properties of the HP-filtered rates. JCR: job creation rate, JDR: job destruction rate, HR: hires rate, SR: separation rate. SD: standard deviation, $AC(1)$: first order auto correlation.

Our data allows us to study the churning rate across the entire employment growth distribution. Let $chr(j)_t$ be the churning rate of the j-th employment growth category/bin. Note that

$$CHR_t = \sum_{j=1}^{J} chr(j)_t \underbrace{\frac{n_t(j)}{N_t}}_{ec_t(j)}, \tag{2}$$

where $ec_t(j)$ is the share of overall employment in the respective bin.

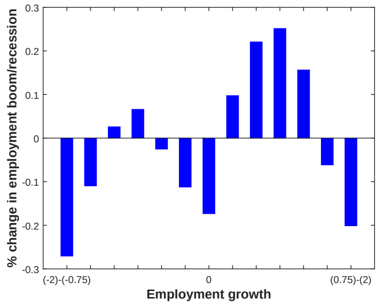
Churn can be procyclical for two reasons: first, conditional on plants' employment growth, plants' have higher conditional worker flows during booms (cyclical movements in $chr(j)$). Second, during booms, the distribution of plants may shift towards plant with higher churning rates (cyclical movements in $ec_t(j)$). In order to understand the importance of the latter, consider the following statistical model:

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

where $\overline{ec(j)}$ denote time-mean values of employment shares. According to this model, churn is procyclical because plants at all employment growth categories increase their churn during a boom. Cyclical changes in the employment growth distribution do not contribute to churn.

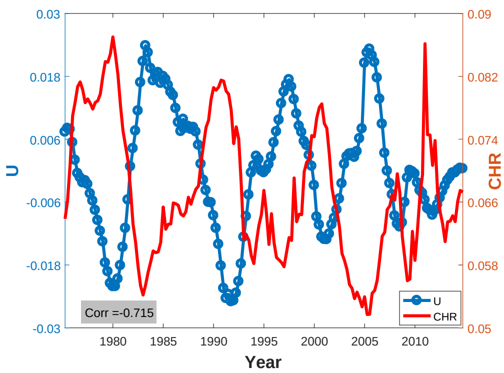
Figure IV displays the cyclical component of CHR_t^{D-fix}. The churning rate with fixed employment shares is almost identical to the aggregate churning rate.

Figure II: Employment Growth Distribution over the Cycle



Note: the categories are: -0.75: plants shrinking by more than 0.75; -0.75–0.4: plants shrinking by 0.4 to 0.75; -0.4–0.1: plants shrinking by 0.1 to 0.4; -0.1–0.05: plants shrinking by 0.05 to 0.1; -0.05–0.01: plants shrinking by 0.01 to 0.05; -0.01–0: plants shrinking by 0 to 0.01; 0: plants leaving employment unchanged; 0.75: plants expanding by more than 0.75; 0.4–0.75: plants expanding by 0.4 to 0.75; 0.1–0.4: plants expanding by 0.1 to 0.4; 0.05–0.1: plants expanding by 0.05 to 0.1; 0.01–0.05: plants expanding by 0.01 to 0.05; 0–0.01: plants expanding by 0 to 0.01. To calculate the figures, we take the statistics of the ten quarters with the highest negative deviation of unemployment from trend relative to the ten quarters with the highest positive deviation of unemployment from trend.

Figure III: Churning Rate

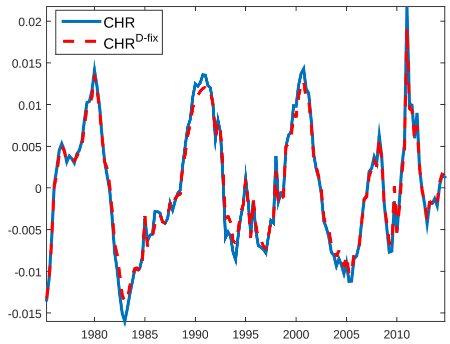


Note: U: HP-filtered unemployment rate, CHR: churning rate.

Put differently, to understand procyclical churn, it is not necessary to jointly study dynamics in the employment growth distribution and conditional worker flows. To understand this restriction, consider the following example where the restriction would not hold: assume that booms were characterized by a a shift away from marginally adjusting plants towards rapidly adjusting plants, and excessive worker flows were higher in the latter. 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.

To understand why the restriction holds in the data, Table 2 displays the cyclical dynamics of the churning rate for each individual employment growth

Figure IV: Churning with fixed Employment Distribution



Note: CHR: churning rate, CHR^{D-fix}: churning rate with fixed employment shares. All series are cyclical component of the HP-filter.

category. Across the employment growth distribution, churn is large and moves counter the unemployment rate. Moreover, in absolute value, the rise during booms is similar across the distribution. The only exceptions to this pattern are rapidly growing and shrinking plants. However, recall from figure II that most cyclical dynamics of the employment growth distribution take place in the interval $[-0.01, 0.4]$.

We close this section relating our finding to those of Davis et al. (2012). Using US data, they study how well different statistical models can explain aggregate movements in worker flow rates. Using the notations from above, their first model relates the hires and separation rate to cyclical movements in the employment growth distribution:

$$HR_t^{f-fix} = \sum_{j=1}^{J} \overline{hr(j)} ec_t(j) \qquad SEPR_t^{f-fix} = \sum_{j=1}^{J} \overline{sr(j)} ec_t(j).$$

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 hires rate, but little of the separation rate. Similar to them, let us 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:

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

Obviously, when the hires rate changes without an associated change in job flows, the separation rate needs to change one to one with the hires rate: $HR_t^{D-fix} = SR_t^{D-fix}$. This observation makes the link between our analysis

Table 2: Dynamics of the Churning Rate

growth rate	$mean$	SD	$AC(1)$	$CorrU$
-2 to -0.75	3%	0.53%	-0.17	-0.02
-0.75 to -0.4	7.77%	0.59%	0.58	-0.66
-0.4 to -0.1	8.69%	1%	0.91	-0.71
-0.1 to -0.05	7.12%	1.05%	0.93	-0.67
-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%	0.9	-0.84
0 to 0.01	6.15%	0.59%	0.76	-0.79
0.01 to 0.05	7.2%	0.69%	0.88	-0.83
0.05 to 0.1	9.03%	0.82%	0.83	-0.75
0.1 to 0.4	11.00%	0.84%	0.79	-0.59
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 cyclical dynamics of the churning rate over the employment growth distribution. Mean: average churning rate, SD: standard deviation, $AC(1)$ autocorrelation coefficient, $CorrU$: correlation with unemployment.

of the churning rate and the statistical models studied by Davis et al. (2012) explicit:

$$CHR \approx 2HR^{D-fix} \approx 2SR^{D-fix}.$$

How well do these statistical models do together in explaining worker flows? We replicate in the appendix the finding of Davis et al. (2012) that

$$\begin{aligned} HR_t \approx & HR_t^{f-fix} + HR_t^{D-fix}, \\ SR_t \approx & SR_t^{f-fix} + SR_t^{D-fix}. \end{aligned}$$

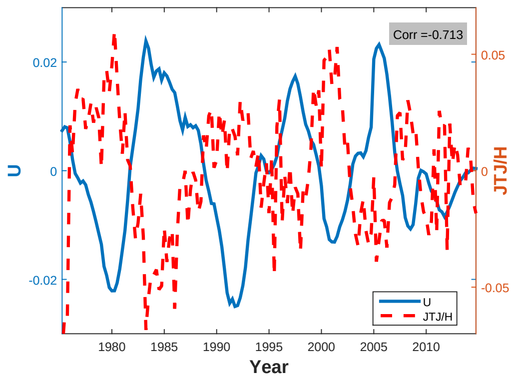
This aggregation result is nothing but our assumption in (2). The uniform churning along the employment growth distribution assures that cyclical changes in the employment growth distribution are irrelevant for cyclical changes in excess worker flows.

4.2 Job-to-Job Transitions and Procyclical Churn

The last sections identified a common component in the hire and separation rate that moves strongly procyclical conditional on plants' employment growth.

We have not addressed the reasons for these excessive worker turnover during booms yet. In our data, we have information whether a newly hired worker was employed the quarter before at a different plant. Denote such hires as job-to-job transition, JTJ. To understand how JTJ lead to churn, consider a simple example. When one plant hires a worker from a different plant, and this second plant replaces the worker by a hire from non-employment, we have: $JC = 1$, $JD = 0$, $H = 2$, $S = 1$, and $CH = 2$.

Figure V: Job-to-Job Transitions

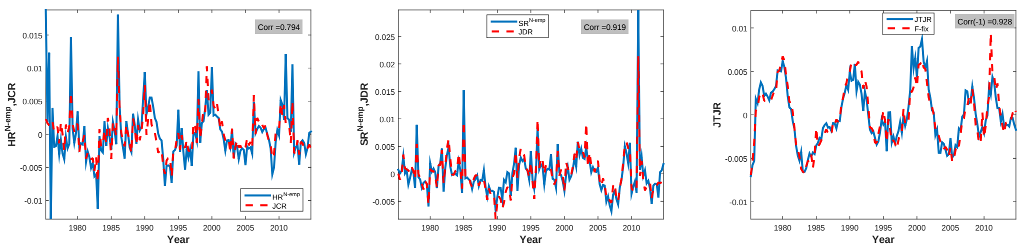


Notes: the figure displays the HP-filtered share of hires explained by job-to-job transitions.

Figure V plots the cyclical component of the share of hires explained by job-to-job transitions. When unemployment is 2 percentage points above trend, the share of hires explained by job-to-job transitions is 5 percentage points below trend. The reverse is true when unemployment is below trend. Thus, procyclical job-to-job transitions may indeed explain procyclical churn.

Figure VI: Worker Flows

(A) HR without JTJ (B) SR without JTJ (C) JTJR



Note: panels (A) and (B) displays the HP-filtered hires and separation rate net of job-to-job (JTJ) transitions (straight), and the job creation rate (JCR) and job destruction rate (JDR) — both dashed. Panel (C) displays the JTJ transition rate ($JTJR$) and half the churning rate ($CHR/2$).

To understand this relationship better, we decompose total worker flows as those resulting from job-to-job transitions, and those resulting from non-employment:

$$HR_t = JTJR_t + HR^{N-emp} \text{ and } SR_t = JTJR_t + SEPR^{N-emp},$$

where HR^{N-emp} denotes the hires rate from non-employment and SR^{N-emp} denotes the separation rate into non-employment. Consider a model where the cyclical component in job-to-job transitions leads to no cyclical movements in job creation or destruction, but is pure churn. Under this hypothesis, the following would hold:

$$\begin{aligned} JTJR_t &= \frac{CHR_t}{2} \\ HR^{N-emp} &= JCR_t \\ SR^{N-emp} &= JDR_t. \end{aligned}$$

Intuitively, two conditions must be met for this model to perform well. First, there may be no other reason for procyclical churn, but job-to-job transitions. For example, consider a theory of learning about match quality as in Pries and Rogerson (2005). Plants would have higher churn during booms, because an increase in the hires rate leads to more layoff of workers. Second, plants losing workers due to job-to-job transitions must be able to replace them, i.e., the vacancy yield is high. Put differently, plants may not fuel their growth during booms on the "expense" of other plants. Instead, plants whose workers are poached must find it profitable to replace them during booms, i.e., by hiring from other plants or from the non-employment pool.

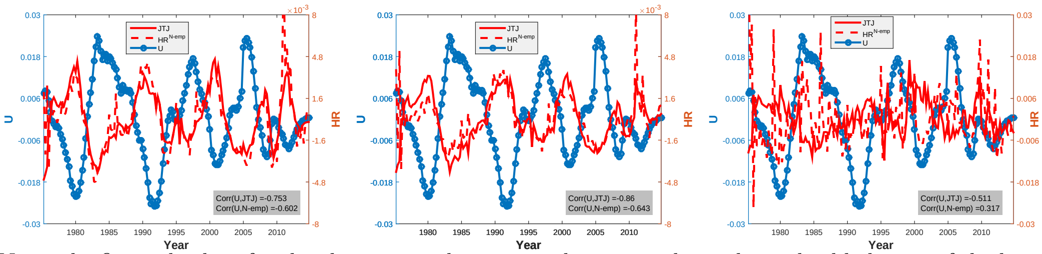
Figure VI shows that the model performs extremely well. Cyclical dynamics in worker flows resulting from non-employment transitions coincide almost completely with the cyclical dynamics of job flow rates. The correlation between the worker and job flow series are between 0.8 and 0.9, and the volatilities are similar. This also implies that the separation rate becomes countercyclical once we control for job-to-job transitions. The last panel displays the cyclical component of the churning rate ($\frac{CHR}{2}$) and the job-to-job transition rate. Little surprising, the two line up nicely, too.

Moscarini and Postel-Vinay (2012) argue that large firms have more procyclical employment growth than small firms. In Moscarini and Postel-Vinay (2013) they explain this fact by large firms systematically poaching workers from small firms in a procyclical way. Haltiwanger et al. (2015) show that such poaching behavior does not take place, and that plant pay is a better predictor for cyclical employment growth patterns. We close this section by linking sources of cyclical hiring and the employment growth distribution.

It turns out that shrinking plants behave very similar among them, and so do growing plants. Thus, to reduce notation, we classify plants into only

Figure VII: Employment Growth and Source of Hiring

(A) Shrinking (B) No Change (C) Increase



Note: the figure displays for shrinking, non-adjusting, and growing plants the cyclical behavior of the hires rate from employment (JTJ) and non-employment (HR^{N-emp}). U: unemployment.

three employment growth categories (shrinking, constant, growing). Each category hires about 45 percent of its employment from other plants. Figure VII plots for each category the two cyclical components of the hires rate. Non-growing plants, particularly shrinking plants, have procyclical hires from both employment and non-employment. For example, in 1980, the hires rate was 1 percentage point above trend at shrinking plants. An increase in job-to-job transition flows contributed about 60 percent to this rise, and an increase in hiring from unemployment contributed the remaining 40 percent. Put differently, during booms, non-growing plants replace their workers by hiring more workers from non-employment and from employment. This pattern is different for growing plants. The last panel in figure VII shows that employment growth during booms is mostly fueled from more job-to-job transitions. The hires rate from non-employment is actually slightly larger during recessions than during booms.

5 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 demonstrate that these cyclical dynamics in worker churn result from changes in job-to-job transition, not changes in the rate workers are churned through unemployment.

Recent advances in on-the-job-search theories stress that during times of high production potential, vacancy posting is high, and workers flow from low- to high-productivity firms. Motivated by the finding of Moscarini and Postel-Vinay (2012), Moscarini and Postel-Vinay (2013) propose a model where (permanently) low-productivity (small) firms face increasing separation rates during booms because of procyclical poaching behavior of high-productivity (large) firms. Schaal (2015) and Fujita and Nakajima (2016) introduce firm specific shocks into on-the-job search model to better match the employment growth distribution from the data.

How well does an on-the-job search mechanism explain procyclical worker churn? Schaal (2015) shows that a model where wages are linked to productivity implies almost no churn for growing plants. The rational is simple, growing plants are on average high-productivity (pay high wages); therefore, they face little separations. Fujita and Nakajima (2016) assumes all plants pay a common wage, implying that growing plants also lose workers due to job-to-job transitions. The latter are procyclical, resulting in procyclical churn.

Neither model is able to rationalize churn; thus, neither procyclical churn, at shrinking plants. Why do these models fail to create churn at shrinking plants? Positive vacancy creation costs create an inaction region implying that slowly shrinking plants have no desire to hire workers. Moreover, plants that shrink rapidly do so because of negative idiosyncratic productivity shocks; thus, have no incentives to hire workers, either. By contrast, in the data, churn is close to uniform and strongly procyclical across the employment growth distribution. This links back to our finding that studying shifts in this distribution is quantitatively unimportant for understanding procyclical churn. Naturally, this restriction is violated in the above mentioned models: during booms the economy shifts towards more growing plants which have higher churning rates.

Procyclical churn at shrinking plants is also key to understand the cyclical behavior of job flows. Fujita and Nakajima (2016) show that without hiring at shrinking plants, a procyclical job-to-job transition rate leads naturally to rising job creation and destruction in booms; some plants grow at the expense of others. Our stylized facts shows that this is not born out by the data. The reason is that shrinking plants find it profitable to replace some departing workers by new hires, and do so particularly during booms. We provide some intuition for the procyclical hiring behavior of non-growing plants. Hiring from employment requires offering better work contracts than hiring from non-employment. Growing plants appear to be able to do so; they fuel their growth by poaching workers during booms. By contrast, non-growing plants replace the rise in departing workers partly by raising hiring from non-employment.

6 Conclusion

This paper studies the causes of procyclical worker flows using a newly assembled plant-level dataset from Germany. We show that cyclical changes in job flows, explain at most half of the cyclical movements in worker flows. Instead, persistent procyclical churn is key to understand the business cycle behavior of worker flows.

We establish a set of robust data characteristics that we believe a theory of procyclical churn should address. First, across the employment growth distribution, the magnitude of churn and its rise during booms is similar. Second, procyclical churn is almost completely driven by procyclical job-to-job transitions.

Moscarini and Postel-Vinay (2013), Schaal (2015), and Fujita and Nakajima (2016) all develop theories of procyclical job-to-job transitions resulting from productivity differences between firms. Yet, all of these theories have difficulty explaining our stylized facts. Particularly, these theories fail to rationalize churn in general, and procyclical churn in particular at shrinking plants. Yet, we show that this is a robust feature of the data with implications for cyclical worker and job flows.

One promising way to rationalize churn across the employment growth distribution may be theories that stress the presence of mismatch, as in Barlevy (2002), instead of productivity differences between plants. An alternative way is to note that the desired workforce composition may change when plants up (down) sizes. Gulyas (2016) shows some evidence for such a mechanism in German data.

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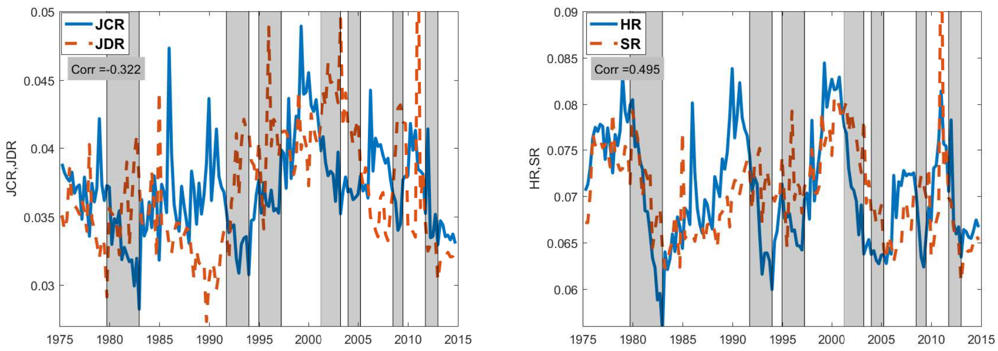
A Appendices

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

We are the first to use the new *AWFP* dataset for the business cycle analysis of labor market flows which allows us to link job and worker flows. A major obstacle for studying this link in the United States is the availability of datasets 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 on a monthly basis 16,000 establishments in the US. However, *JOLTS* only started

Figure VIII: Job and Worker Flows



Notes: The figure displays job and worker flows in Germany and the US.

in 2001, providing data on at most two full business cycle.[17] 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.[18]

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, most agricultural employment and governmental employees. 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 quarterly frequency.

Figure VIII 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.

[17]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.

[18]The two concepts of establishments are not identical. 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 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 Dundler et al. (2006)).

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 3: US Job and Worker Flows

			Correlation to U_{t+j}				
	SD	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
JCR	0.27%	0.81	-0.16	-0.31	-0.45	-0.55	-0.63
JDR	0.34%	0.81	-0.32	-0.16	0.02	0.18	0.3
HR	0.82%	0.93	-0.63	-0.77	-0.87	-0.92	-0.94
SR	0.67%	0.87	-0.91	-0.92	-0.86	-0.78	-0.68

Note: the top panel displays job flows. JCR: job creation rate, JDR: job destruction rate. The bottom panel displays worker flows. HR: hires rate, SR: separation rate. All rates are the cyclical component from a HP-filter.

Table 3 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 remarkable similar in the two countries. Remember that both flow rates are substantially lower 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.

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

This section compares our findings to Davis et al. (2012) closely following their approach. The most widely 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:

$$HR_t^{f-fix} = \sum_{j=1}^{J} \overline{hr(j)} ec_t(j) - TR_t$$
$$SEPR_t^{f-fix} = \sum_{j=1}^{J} \overline{sr(j)} ec_t(j) - TR_t,$$

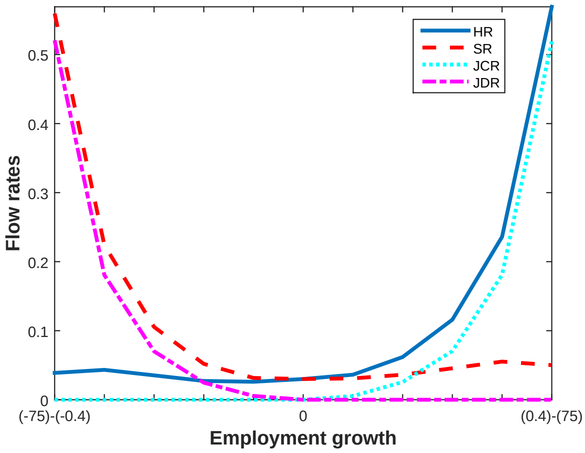
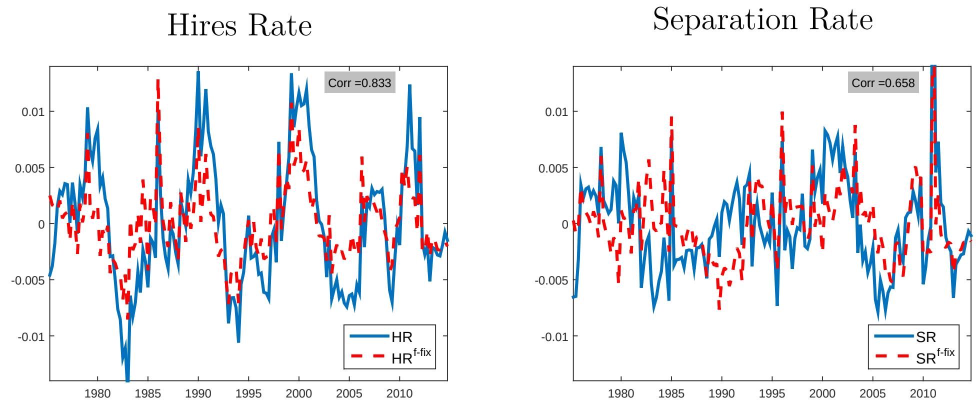


Figure IX: Flows and employment growth

where $\overline{x}$ 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. Davis et al. (2012) show that this is a key characteristic in the US labor market and figure IX shows it to be also true in Germany. Moreover, we allow the series to have a time varying trend component TR_t.

Figure X 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 hires rate. The contemporaneous correlation between the two series is 0.83. For the separation rate, the synthetic series with fixed conditional flow rates shows a correlation of 66 percent with the actual separation rate series. Let us now consider a second statistical model:

Figure X: Fixed Worker Flow Rates Over the Cycle

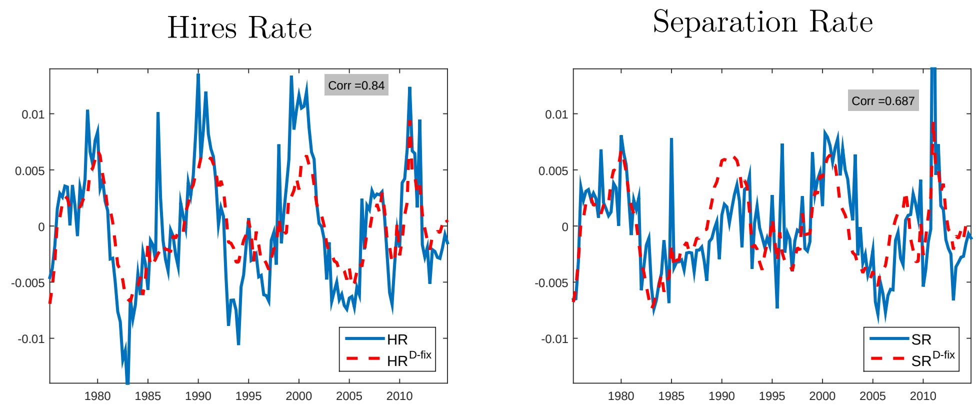


Note: the figure displays the cyclical component of the hires rate (HR) and separation rate (SR) — both solid — together with the synthetic ones implied when holding the flow rates conditional on establishment growth constant (dashed).

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

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 XI: Components of the Hires and Separation Rate over the Cycle



Note: the figure displays the cyclical component of the hires and separation rates (solid) and the synthetic ones implied when holding the distribution of establishment employment growth fixed (dashed).

Figure XI displays the resulting synthetic series from this exercise. The series are a quite good fit for the realized rates. Conditional on job flows, cyclical worker flows are highly autocorrelated and strongly procyclical. The hires rate is not sufficiently volatile, but the timing of periods with high and low rates is almost identical. For the separation rate, the peaks and troughs of the two rates are almost identical. The correlation between the raw and synthetic series is 84 percent for the hires rate and 69 percent for the separation rate.

A.3 Further Figures

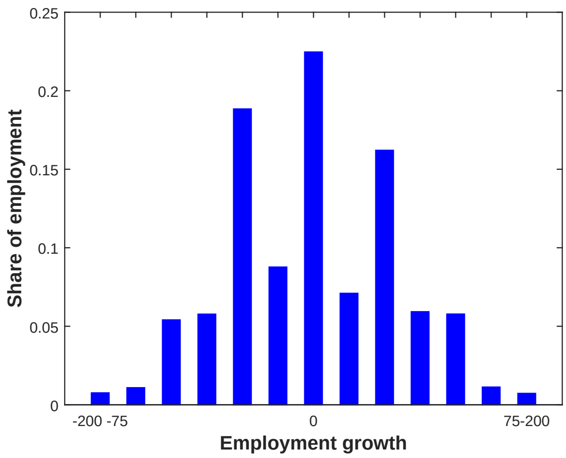


Figure XII: Average Growth Distribution