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ABSTRACT

Cyclicality of Job and Worker Flows: New Data and a New Set of Stylized Facts*

We study the relationship between cyclical job and worker flows at the plant level using a new data set spanning from 1976-2006. We find that procyclical labor demand explains relatively little of procyclical worker flows. Instead, all plants in the employment growth distribution increase their worker turnover during booms. We also find that cyclical changes in the employment growth distribution are mostly driven by plants moving from inactivity to a growing labor force during booms. Consequently, increased labor turnover at growing plants is the main quantitative driver behind increased labor turnover during booms. We argue that on the job search models are able to capture non-parallel shifts in the employment growth distribution and procyclical conditional worker flows for a range of the growth distribution. Yet, they fail to rationalize procyclical accession rates for all shrinking and procylical separation rates for all growing plants.

JEL Classification: E32, J23, J63

Keywords: job flows, worker flows, aggregate fluctuations

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1 Introduction

Modern labor markets are characterized by large worker turnover. In the US, more than 3 percent of workers are employed at a job that they did not hold the month before and more than 3 percent separate from their current job each months (see Davis et al. (2006)). Moreover, the job turnover rate is strongly procyclical with most reallocations taking place during booms. Understanding the role labor demand plays in these large flows teaches us important aspects of the labor market. Do workers simply change jobs because their old job is no longer available, or do they find better jobs? Similarly, do jobs cease to exist after workers separate, or do plants replace workers, possibly increasing the match quality? Is rising worker reallocation during booms simply reflecting rising job reallocation? And do firms adjust their workforce differently during booms and recessions?

A major obstacle for answering these basic questions is the availability of data sets that provide information on plant characteristics, worker flows and labor demand. The most suited US data source is the *Job Openings and Labor Turnover Survey* (JOLTS), sampling on a monthly basis 16000 establishments in the US. However, JOLTS only started in 2001, providing data on at most one full business cycle.

In this paper, we introduce a new data set, the German *Establishment Labor Flow Panel, ELFLOP*, containing quarterly information on job and worker flows of all employees working within the universe of German establishments. The new data set currently covers the period $1975-2006$ and allows us to systematically study the response of job and worker flows and their interaction to aggregate shocks.

Consistent with Davis et al. (2006) and Davis et al. (2011), we find that job flows can explain 50 percent of worker flows in the cross-section, and that plants from the entire growth distribution hire and separate from workers:

1. For both positive and negative net employment growth, plants hire and separate from workers. Worker flows are twice as large as job flows.

2. Accessions of workers are almost flat for negative net employment growth and separations from workers are almost flat for positive net employment growth.

Our analysis reveals the following stylized facts for the link between job and worker flows over the business-cycle:

3. Job and worker flow rates are about 50% smaller and somewhat more volatile in Germany than in the US. The correlation with the cycle is comparable.

4. The job creation rate is procyclical, the job destruction rate is weakly countercyclical. Both are leading the cycle.

5. The accession and the separation rate are strongly procyclical.

6. The distribution of plants' employment growth shifts over the cycle in a non-parallel fashion. Most notably, rapidly growing plants (likely entering plants) have countercyclical employment shares and plants contracting at intermediate ranges have procyclical shares. The countercyclical job destruction rate is mostly explained by rapidly shrinking plants (likely plant closures).

7. Conditional on plants' employment growth, the accession and separation rate are procyclical for each plant category.

8. Most business cycle dynamics in worker flows can be explained by plants changing accession and separation behavior conditional on employment growth. Shifts in the distribution of employment growth explain some variations in the accession rate and very little in the separation rate. Contrary, spikes in worker flows at higher frequencies are predominantly explained by changes in the employment growth distribution

9. Systematic cyclical variations in excess worker flows are predominantly explained by plants that increase employment.

While this paper mostly descriptive in aiming at establishing business cycle facts, the choice of questions we look at is theory driven. Indeed, our business cycle facts directly speak to the main mechanisms of employment flow models. The mostly common used framework to study worker flows in steady state and their cyclical dynamics are variants of the Mortensen and Pissarides (1994) model where all worker flows result from labor demand, e.i., job flows. Stylized fact 1 implies that such models can explain at most half of all worker flows. Beyond this level effect, these theories cannot address the full cyclical behavior in these flows (stylized fact 7).

Recent advances in on-the-job-search theories allow for systematic differences between worker and job flows. These theories stress that during times of high production potential, vacancy posting is high, and workers flow from low to high productive plants. How well does an on the job search mechanism in explaining cyclical dynamics of worker flows? In general, such models can generate non-parallel shifts in the distribution of employment growth. Less productive plants face increasing separation rates during booms because of procyclical poaching behavior of high productive plants. Therefore, these plants shrink during booms and grow during recessions[1]. While the mechanism is partly in line with our stylized fact 7 it fails to rationalize procyclical accession rates of shrinking plants and procyclcial separation rates of growing plants.

Our stylized facts 7 and 8 may suggest that theories implying procyclical conditional worker flows are observationally identical, and that keeping track of the employment growth distribution carries little additional insights. Stylized fact 9 shows that this is not the case. The non-parallel shift in the employment growth distribution with most changes occurring in the right side of the distribution leads expanding plants to be the main quantitative driver of procyclical worker flows.

Some of our findings contrast with (older) conclusions drawn by Davis et al. (2006) for the US and Bellmann et al. (2011) for Germany, but align with some of the (newer) findings presented in Davis et al. (2011). The first two contributions conclude that changes in the employment growth distribution are the major driving force behind the cyclical behavior of worker flows. Davis et al. (2011) argue that these flows are mainly driven by changes in plant behavior conditional on employment growth, but changes in the employment growth distribution are still quantitatively important. We argue that the different conclusions are mainly driven by different approaches. Bellmann et al. (2011) use a regression based approach and we argue

[1]See Schaal (2011) and Moscarini and Postel-Vinay (2011).

that their findings do not warrant their strong conclusion. With regard to Davis et al. (2006) and Davis et al. (2011) we argue that in their data, changes in the employment growth distribution mainly pick up seasonal changes and other high frequency movements in worker flows, especially for the separation rate, and not changes at business cycle frequency. The richness of our data allows us to map the data into the frequency domain. The correlation between the procyclical worker flows and the cyclical changes in the employment growth distribution is much higher at frequencies under one and a half year than it is between 2 and 8 years, the standard frequency for business cycle movements. The opposite is true when looking at the correlation between cyclical worker flows and worker flows conditional on employment growth.

Overall the differences in conclusions that the other authors arrive at are partly driven by the data limitations that they face: short time series and subsamples instead of the universe of plants. This shows the importance to build from comprehensive micro data. The new *ELFLOP* data set introduced in this paper allows us to do so for the German labor market.

The rest of the paper is organized as follows: The next section introduces the data set and explains our main concepts that we use to analyze the data. The following section presents stylized facts about aggregate job and worker flows in Germany on business cycle frequency and compares the flow rates to US data. Thereafter, we present a series of recent structural interpretations for worker flows. We look at the behavior of the employment growth distribution over the business cycle and changes in worker flows conditional on plant growth, constantly comparing the existing theories against the data. The last section concludes.

2 Data

2.1 Data Source

2.1.1 The Establishment Labor Flow Panel

The basis of our analysis forms the *Establishment Labor Flow Panel* (*ELFLOP*), a data set we compiled and that measures employment and labor flow data for the universe of German establishments. *ELFLOP* covers the time period 1975-2006 (West Germany until 1992-II the re-unified Germany thereafter, but regional information is available). We drop all establishments that are on the territory of former Eastern-Germany and Berlin to avoid a break in the series. All data is available at a quarterly frequency. The data used to produce *ELFLOP* originate 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 annually confirming existing employment relationships.

The *Forschungsdatenzentrum der Bundesagentur für Arbeit* (German Bureau of Labor) uses the data collected through the notification procedure as input for its BLH (Employees And Benefits-Recipients History File), which in turn is *ELFLOP*'s data source. The BLH is an individual-level data set covering all workers in Germany liable to social security. The main types of employees not covered are public officials (*Beamte*), military personell and the self-employed. Also, marginal part-time workers (less than 15h/week and below 315€monthly income) are only included in the BLH since 1999. To ensure consistency over time, all variables are therefore calculated on a *regular worker* basis: apprentices and interns, marginal part-time workers, workers in partial retirement (and a few other groups of minor importance) are being excluded from the data[2].

From the BLH files, *ELFLOP* aggregates the worker and job flow information to

[2]Also, workers working below 15 hours a week and earning less than roughly 315€(in 1999, lower values before) were exempt from social security taxation (geringfügige Beschäftigung) and hence not recorded. Since 1999 these workers are recorded as well in the data but as a separate category. We exclude these workers from the analysis.

the plant level, such that a plant becomes the observational unit. Job and worker flow disaggregated by sub-categories of workers are available in the micro data as well, but for the present paper we only exploit information for the aggregate job and worker flows at the plant level. Similarly, plant information (industry, age, location, workforce composition, average salary, etc.) is available as part of the micro data. Again in the present paper we do not exploit these data dimensions. Further details on the data set are described in Bachmann et al. (2011).

2.1.2 US Data

We compare our aggregate job and worker flows to US plant level data in Section 3[3]. Unfortunately, a dataset as comprehensive as *ELFLOP* does not exist for the US. We obtain seasonally adjusted US quarterly job flows from the *Business Employment Dynamics* (*BED*) data provided by Davis et al. (2006) for the period of 1990-2005. *BED* job gains and job losses contain information on the universe of US establishments, excluding household employment, most agricultural employment and governmental employees.

Unfortunately, the *BED* data does not contain information on worker flows. Therefore, we obtain seasonally adjusted worker flows from the *Job Openings and Labor Turnover Survey* (*JOLTS*) for the years 2001-2012 first quarter. *JOLTS* samples every month 16000 establishments from the universe of US plants with the exception of agriculture and private households. We aggregate the monthly flows to quarterly frequency.

[3]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 data set, each firm's 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 firm's 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)).

2.2 Stock Concepts, Data Cleaning and Aggregation

In the *ELFLOP* data, a worker is considered to be working for a given establishment (*Betrieb*), or short: plant, in a given quarter when she has been employed at this plant at the end of the quarter[4]. This definition yields the number of jobs at a plant at the end of a quarter, the number of hires (accession ACC) of a plant (a worker that has not been working for that plant at the end of the previous quarter), as well as the number of separations (SEP) (a worker that has been working for the firm at the end of the previous quarter). These are the basic data from which all other data are constructed.

We compute beginning of quarter, *EB*, and end of quarter employment, *EE*, for each plant. When a plant decreases employment by N within a quarter, we count this as N job destructions, *JD*. When employment increases by N, we count N job creations, *JC*. The sum of the two is job turnover. A plant may hire and fire workers within the same quarter and we refer to the sum of accessions and separations as worker turnover. We have $ACC \geq JC$ and $SEP \geq JD$ for each establishment 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 $J = 11$ employment growth categories[5].

We allow each growth category to have an individual specific seasonal component and compute seasonally adjusted series, using the *X-12 ARIMA CENSUS* procedure[6]. The raw data suffers from several worker reclassifications resulting from changes in the social security system and and outliers resulting from labor disputes during which workers were laid off for short periods of time as result of a strike. We adjust every series using a semi-parametric approach described in Appendix A. To derive the aggregate series for West-Germany, we finally aggregate over the seasonal

[4]It is relatively rare to observe workers leaving a job before the end of a month in the data. In facts most workers leave or join a plant at the end reps. beginning of a quarter.

[5]The categories are: plants shrinking by 75, $10-75$, $5-10$, $1-5$, $0-1$ percent, plants leaving employment unchanged and plants that grow by by 75, $10-75$, $5-10$, $1-5$, $0-1$ percent.

[6]Allowing for series specific seasonality may be surprising. We want to insure consistency for each variable for the sum of all individual categories and the aggregate series of West-Germany. Hence, we allow for individual specific seasonality and aggregate afterwards to the level of West-Germany.

adjusted series for all J employment growth categories.

Given the aggregated stock/flow data, we define flow *rates*. We use as denominator the average of end-of-quarter employment and beginning-of-quarter employment:

$$EM_t = [EE_t + EB_t]/2.$$

For example, the accession rate hence reads:

$$ACCR_t = \frac{ACC_t}{EM_t}. \tag{1}$$

All other rates are defined analogously. The measure implies that all rates are bounded in the interval $[-2, 2]$ with endpoints corresponding to death and birth of plants[7].

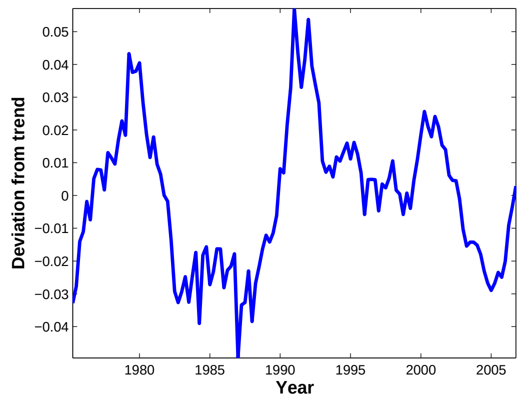
Our analysis deals with fluctuations at business cycle frequency. We compute the cyclical component for the aggregate series employing a HP-filter for the log series with a smoothing parameter of 10^5. Consequently, the cyclical components have the interpretation of a percentage deviations from a slowly moving trend.

2.3 Business Cycles in Germany

Figure I plots our cyclical measure GDP. There are several boom and bust cycles in the sample period. At the beginning of the sample, Germany was still recuperating from the first oil price shock and moved into a subsequent boom at the end of the 70's. The boom began to level off in 1979 (*second oil crisis*), leading into a subsequent long lasting recession that reached its trough (with regard to GDP) around 1987 (*Black Monday*). The economy moved afterwards into the post-reunification boom at the beginning of the 90's, which lasted until the mid 90's. The following years see unemployment peaking around 1998, until the economy moved into the boom at the beginning of the 2000's. Around 2002 unemployment was on the rise again, until two years before the end of the sample period the economy bettered again. Hence,

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

Figure I: Cyclical Measure



Notes: The deviation of GDP from its trend component.

our dataset provides us with almost four complete business cycles.

3 Cyclicality of Job and Worker Flows in Germany and the US

This section presents cyclical dynamics of job and worker flows in Germany. In Section 5.2 we compare our results to those found by previous studies conducted on US data. Therefore, we additionally compare our results for Germany to US data to assure that differences are not driven by labor markets that function very differently[8]. This section establishes that while job and worker flows are lower in Germany, their cyclical dynamics are similar to the US. Additionally, we investigate how (un)important difference in industry and size structure of plants are for the differences across countries. Appendix B, provides the details for the latter comparison.

Table 1 displays the cyclical properties of job flow rates in Germany to the US. The *job-creation rate, JCR,* is about half the size in Germany compared to the US, and its cyclical volatility is about twice as large. Similarly to the *JCR*, the *job-*

[8]Keep in mind that contrary to *ELFLOP*, neither *JOLTS*, nor the *BED* cover all sectors. We report all rates based on the respective data sample.

Table 1: Job Flow Rates

					Correlation to GDP_{t+j}				
		mean	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
Creation Rate	GER	3.7%	8.1%	0.57	-0.02	0.06	0.19	0.27	0.33
	US	7.9%	3.4%	0.82	0.03	0.12	0.20	0.28	0.34
Destruction Rate	GER	3.3%	8.0%	0.60	0.13	0.01	-0.11	-0.19	-0.23
	US	7.6%	5.2%	0.80	0.48	0.36	0.24	0.21	0.19

Notes: Germany: *ELFLOP* 1975-2006, US: BLS 1990-2005, SD: standard deviation of log rate, AC(1): first order autocorrelation, Mean: average seasonally adjusted rate. The bottom panel of the table displays correlation of the flow rates with GDP.

destruction rate, JDR, is about twice as large in the US compared to Germany and about 40% less volatile[9]. 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 Jung and Kuhn (2011) and Gartner et al. (2009)). The *JCR* and *JDR* are 1.7 and 2.6 times more volatile than output in the US. We find for Germany ratios of 3.7 and 3.7, respectively. Likely, differences in volatilities of cross-country labor demand, especially job creation, appear to be linked to differences in the cyclicality of the job finding rate and vacancy posting behavior, cf. Jung and Kuhn (2011).

This observation leads to a related point about relative volatilities of the *JCR* and *JDR*. Campbell and Fisher (2000) argue that the higher volatility of *JDR* relative to *JCR* is an equilibrium outcome with proportional hiring and firing costs and show that the volatilities are non-monotone in these costs (first increase then decrease). Hence, the relative low volatility of JDR in Germany must result from

[9]The numbers imply that job turnover is somewhat more than twice as large in the US compared to Germany. This is roughly in line, yet somewhat larger, to the estimates provided by Davis and Haltiwanger (1999) based on yearly data (see their Table 5).

non-proportional hiring and firing costs (e.g. time-costs or firing costs increasing during recessions). Moreover, the high absolute volatilities challenge the conventional wisdom of high firing costs in Germany, as discussed in Jung and Kuhn (2011).

Despite being more volatile in Germany, the correlation of the *JCR* with GDP is almost identical across the two countries. The correlation becomes weaker as the boom matures and is acyclical already two quarters after the peak of *GDP*. The *JDR* is close to acyclical in Germany, turning slightly countercyclical at leads of GDP. Contrary, we find a slightly procyclical rate in the US, especially at lags of GDP[10].

Table 2: Worker Flows

					Correlation to GDP_{t+j}				
		mean	*SD*	*AC*(1)	$j=-2$	-1	0	$+1$	$+2$
Accession Rate	GER	7.2%	8.5%	0.86	0.35	0.45	0.56	0.61	0.64
	US	12.0%	6.2%	0.92	0.47	0.57	0.64	0.68	0.68
Separation Rate	GER	6.8%	5.9%	0.74	0.64	0.65	0.65	0.63	0.61
	US	12.0%	4.9%	0.87	0.66	0.59	0.50	0.43	0.36

See Notes to Table 1.

Table 2 establishes that worker flows are twice as large in the US compared to Germany[11]. The *accession rate, ACCR,* is as volatile as the *JCR* and *JDR* in Germany, and the separation rate is less volatile. Worker flows are more volatile than job flows in the US, especially the *ACCR*. The *ACCR* is strongly procyclical in both

[10] Fujita and Nakajima (2009) report a slightly countercyclical rate. The difference arises because they use a HP smoothing parameter of 1600.

[11] Our job and worker flows imply an annualized rate that is about twice as large as the one reported by Bellmann et al. (2011) for a sub-sample of our data (see their Table 2). Our separation rate matches that reported by Jung and Kuhn (2011) (see their Table 1).

countries and slightly leading the cycle. Similarly, the separation rate is procyclical in both countries. It is lagging the cycle in the US, but no such tendency is observable for Germany. One needs to be careful with such interpretations; however, because we observe only one cycle in the US.

Table 3: Turnover Rates

					Correlation to GDP_{t+j}				
		mean	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
Job Turnover Rate	GER	6.9%	4.2%	0.43	0.10	0.06	0.09	0.11	0.14
	US	15.6%	3.2%	0.81	0.41	0.36	0.30	0.33	0.34
Worker Turnover Rate	GER	14.0%	6.6%	0.88	0.51	0.59	0.65	0.68	0.69
	US	24.0%	5.0%	0.91	0.62	0.64	0.64	0.64	0.60

See Notes to Table 1.

Let us define job-, respectively worker-turnover rates as:

$$TOR_t^J = \frac{JC_t + JD_t}{EM_t}, \qquad TOR_t^W = \frac{ACC_t + SEP_t}{EM_t}$$

Table 3 summarizes the cyclical dynamics of these flows. Turnover rates are both larger in the US compared to Germany and less cyclical volatile. Resulting from the slightly procyclical JCR in the US, the US job-turnover rate is more procyclical in the US than in Germany. Worker turnover is strongly positively correlated with all lags and leads of GDP in both countries.

Of course some of the differences are also driven by plants being of different size and the industry composition not being the same in Germany and the US. In Appendix B we show that Germany has a relatively large employment share in manufacturing and that job flows are lower in manufacturing than in services.

Therefore some part of the difference might be due to composition. Yet, we cannot do an industry by industry comparison, as for the US flow data by industry is only available to us at the annual frequency and for job flows only. Instead, we create synthetic series of aggregate worker and job flows for Germany, where we weight industries and size classes with their average employment share in the US (1977-2006). Table 4 displays the results , and details can be found in Appendix B for a discussion of the data and the way we construct the series controlling for composition. We find that the job-creation rate and accession rates on average would go up by 1/5 in Germany, while the separation rate would go up by roughly 1/10 and the job destruction rate would remain unchanged[12]. More importantly, the business cycle behavior of the synthetic rates coincides with the actual ones.

4 Plant Employment Growth and Worker Flows in the Cross-Section

This section studies the role job flows play in explaining worker flows in the cross-section. More specifically, we ask how worker flows change, conditional on a plant's employment growth. We discretize the plant distribution into J growth bins. Summing over all quarters, we compute for each employment growth type the mean worker flow rates.

Figure II shows the accession and separation rate conditional on the job creation and destruction rate. The cross sectional relationship is very similar to the one presented in Davis et al. (2006) for the US (compare their Figure 6)[13]. The stylized facts from the figure are: Separations increase almost one to one with job destruc-

[12] Of course these synthetic rates do not respect the constraint that aggregate labor supply imposes. Since we do not see a corresponding increase in job-destruction moving from the actual to the synthetic rates, the higher synthetic job-creation rate reflects merely the trend growth of services over the sample period. In addition to the quantifiable differences we try to correct for in the Table 4, there remain differences between the two data sources in defying a plant and defining a job (recall ELFLOP excludes marginal part time workers, which are often production helpers with short tenure).

[13] Bellmann et al. (2011) present similar evidence for a subsample of German plants.

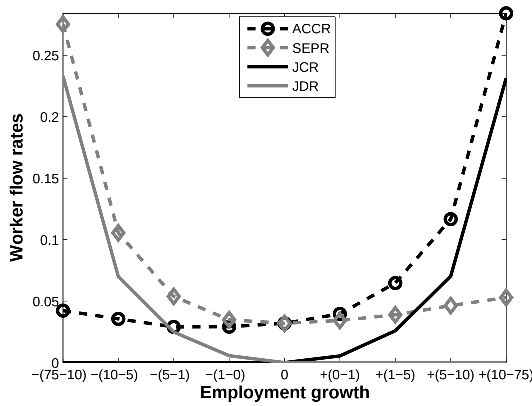
Table 4: Flow Rates controlling for Industry and Size

	type	*mean*	*SD*	*AC*(1)	Correlation to GDP_{t+j} $j=-2$	-1	0	$+1$	$+2$
Creation Rate	real	3.8%	8.7%	0.63	-0.02	0.08	0.21	0.30	0.35
	syn	4.6%	8.3%	0.68	0.09	0.19	0.29	0.38	0.42
Destruction Rate	real	3.6%	8.8%	0.66	0.13	-0.02	-0.15	-0.23	-0.27
	syn	3.5%	8.3%	0.60	0.19	0.05	-0.07	-0.15	-0.19
Accession Rate	real	7.3%	9.2%	0.88	0.34	0.44	0.54	0.61	0.64
	syn	8.7%	9.5%	0.90	0.39	0.49	0.57	0.63	0.66
Separation Rate	real	7.1%	5.8%	0.72	0.67	0.66	0.63	0.61	0.60
	syn	7.6%	6.9%	0.80	0.65	0.66	0.66	0.65	0.64

Notes: Germany: *ELFLOP* 1977-2006, US: *BDS* 1977-2006, N: Share of plants, EMP: Share of employment, JC: Share of job creation, JD: Share of job destruction, $\hat{JCR}$: Yearly job creation rate using as denominator march employment, $\hat{JDR}$: Yearly job destruction rate using as denominator march employment. Data excludes the primary sector, as data on size-industry cells is too thin there, the public service sector and households. "syn" refers to synthetic rates that enforce an average sectoral/size composition for the German data as in the US data from which Tables 1-3 are calculated.

tion and accessions increase almost one to one with job creation. Hence, growing plants rely preliminary on extended hiring, while shrinking plants do so preliminary by separating with existing employees. Second, accessions and separations are visible at all employment growth categories. Put differently, not all worker flows result from job flows. Third, the separations rate increase again slightly to the right of the zero employment growth category and the same is true to the left for the accession rate. Theories that emphasis the importance of learning over match quality can rationalize an increasing separation rate at rapidly growing plants. Pries and Rogerson (2005) use a set-up where a match learns about its production potential over time and separation from unpromising matches is endogenous. Rapidly growing plants have relatively many new workers with unknown production potential, leading to

Figure II: Worker Flows and Employment Growth



Notes: The figure displays job and worker flows for plants that shrink by $10-75$, $5-10$, $1-5$, $0-1$ percent and for plants that grow by by $10-75$, $5-10$, $1-5$, $0-1$ percent.

large separations at these plants. While not able to generate a U-shape pattern in the separation rate, Schaal (2011) shows that on-the-job search models[14] can create a positive separation rate for growing plants. These plants are faced by workers switching to more productive plants, but are able to overcompensate these separations by accessions from less productive plants and out of unemployment. Yet, these models fail to create any significant accessions for shrinking plants because vacancy posting costs make it unattractive to replace workers. Menzio and Moen (2008) propose a model that carries some promise with this regard. They show that plants hit by a negative productivity shock may find it optimal to replace their high tenured workers with low tenured workers to reduce wage costs.

5 The Link between Cyclical Job and Worker Flows

Table 3 shows that most worker turnover is preliminary taking place in booms. However, it is silent why this is so. This section and the following one provides evi-

[14]Other examples for models studying aspects of on-the-job search in steady state are Faberman and Nágipal (2008) and Garibaldi and Moen (2010).

dence from our data that helps us to discriminate among different theories of worker turnover. More specifically, we ask whether the procyclical component of worker flows can be explained by cyclical shifts in the distribution of plants' employment growth levels, or by cyclical shifts in accession and separation flows conditional on plant growth.

5.1 Theories of Job and Worker Flows and Conceptual Issues

One view of the cyclicality of labor market flows is that they result from cyclical labor demand, e.g., job flows. The most widely used explanation within this view are variations of the Mortensen and Pissarides (1994) model. This model takes an extreme view where a firm is composed of one job and hence, all labor-market flows result from job flows. Worker flows are procyclical because the distribution of employment growth shifts to the right during a boom. The simplest way to break the link between worker and job flows is to think of a firm operating with linear production technology and introduce an exogenous separation probability, in which case some worker flows result from replacement hires.

Barlevy (2002) and Shi (2011) proposes theories where aggregate fluctuations drive the profitability to open vacancies and workers have the opportunity to search on the job. There is only match specific productivity, making the notion of replacement hiring inoperative. Moscarini and Postel-Vinay (2011) provide a model where firms operate under linear production technology, but differ in fixed idiosyncratic productivity. Workers can search on the job and job-to-job transitions rise in a boom, providing an explanation for the procyclical worker flows. Moreover, the model implies an endogenous distribution of plant growth rates. Schaal (2011) allows for firms with concave production functions and stochastic idiosyncratic productivities with on the job search. His model gives rise to rich dynamics in the employment growth distribution of plants[15].

[15] Kaas and Kircher (2011) provide a model where concave production technology interacts with convex vacancy posting costs. However, they abstract from on the job search.

5.2 Plants' Employment Growth and Worker Flows over the Business Cycle

To generate data that can be compared to the models' predictions, we decompose changes in worker flows into changes that result from a change in the distribution of job flows and into dynamic changes of plant behavior conditional on job flows. To demonstrate the basic concept, we closely follow Davis et al. (2011). Denote any worker flow rate in period t as F_t. Moreover, discretize the plant distribution into J growth bins. Denote by $f_t(j)$ and $h_t(j)$ the mean flow rate and the employment share at plants of type j, respectively. Obviously

$$F_t = \sum_{j=1}^{J} f_t(j) h_t(j)$$

Let us now focus on the cyclical behavior of the plant growth distribution and conditional plant behavior. Our goal is to quantify the contribution of each for aggregate worker flows. We opt for the following notation: Let capital letters, denote aggregate variables, e.g., $ACCR_t$ is the aggregate accession rate at each period t. Moreover, let lower case letters denote the conditional mean of the j-th employment growth category, e.g., $accr_t(j)$ is the accession rate of firms in the j-th employment growth category at time t.

Using these definitions and using (1), we can rewrite the aggregate rate as:

$$ACCR_t = \sum_{j=1}^{J} accr_t(j) \underbrace{\frac{em_t(j)}{EM_t}}_{ec_t(j)} \tag{2}$$

The equation highlights that changes in aggregate rates must result from changes in employment growth specific rates, or changes in the distribution of employment growth. Before quantifying the contribution of each component for the aggregate worker flow rates, it is instructive to consider the cyclical behavior of each subcomponent. Therefore, we apply our standard HP-filter to each of the J series of $ec_t(j)$,

$accr_t(j)$ and $sepr_t(j)$.

Table 5: Dynamics of the Employment Growth Distribution (Share of Employment)

				Correlation to GDP_{t+j}				
growth rate	*mean*	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
-200% to -75%	0.6%	11.7%	0.58	-0.24	-0.31	-0.39	-0.44	-0.45
-75% to -10%	6.3%	8.3%	0.52	0.32	0.23	0.12	0.03	-0.01
-10% to -5%	6.0%	10.9%	0.70	0.40	0.26	0.15	0.06	0.03
-5% to -1%	19.8%	11.6%	0.80	0.13	0.00	-0.10	-0.15	-0.18
-1% to 0%	8.6%	9.3%	0.34	-0.27	-0.28	-0.33	-0.36	-0.36
0%	21.1%	4.1%	0.85	-0.56	-0.61	-0.62	-0.64	-0.64
0% to 1%	6.9%	11.4%	0.36	-0.14	-0.04	0.00	0.04	0.01
1% to 5%	16.7%	12.6%	0.82	0.00	0.13	0.23	0.28	0.30
5% to 10%	6.3%	12.6%	0.77	0.08	0.22	0.33	0.41	0.46
10% to 75%	7.0%	9.2%	0.56	0.10	0.19	0.31	0.40	0.46
75% to 200%	0.7%	9.9%	0.43	-0.20	-0.22	-0.14	-0.11	-0.06

Notes: See Table 1. The table refers to the share of employment in of plants in the respective growth categories as fraction of total employment $ec_t(j)$.

5.2.1 The Employment Growth Distribution

We begin by looking at the cyclical properties of the employment growth distribution. Table 5 shows the complex dynamics of the various $ec_t(j)$. The share of workers at plants increasing employment is procyclical in all categories, except for plants growing by more than 75% ($\approx$ entrants). Interestingly, also plants that decrease employment by $5-75\%$ have a (weakly) procyclical employment share. By contrast, the employment share of not actively adjusting plants (between -5%[16] and 0%) is counter-cyclical. So is the employment share at strongly shrinking plants ($\approx$ exiters,

[16] Reflecting exogenous break-ups

Table 6: Dynamics of the Employment Growth Distribution (Share of Plants)

				Correlation to GDP_{t+j}				
growth rate	*mean*	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
-200% to -75%	2.9%	5.6%	0.68	-0.25	-0.30	-0.38	-0.41	-0.46
-75% to -10%	10.0%	5.1%	0.51	0.49	0.44	0.37	0.31	0.25
-10% to -5%	2.3%	6.0%	0.64	0.59	0.50	0.42	0.33	0.27
-5% to -1%	2.2%	5.8%	0.71	0.20	0.08	-0.02	-0.09	-0.15
-1% to 0%	0.2%	6.5%	0.46	-0.24	-0.29	-0.34	-0.37	-0.39
0%	62.7%	1.7%	0.79	-0.60	-0.63	-0.65	-0.67	-0.66
0% to 1%	0.2%	7.1%	0.25	-0.01	0.08	0.10	0.14	0.15
1% to 5%	1.9%	5.8%	0.74	0.29	0.43	0.50	0.58	0.59
5% to 10%	2.3%	6.9%	0.83	0.44	0.57	0.64	0.71	0.74
10% to 75%	10.7%	6.3%	0.76	0.39	0.47	0.53	0.59	0.62
75% to 200%	4.5%	5.6%	0.44	-0.07	-0.04	0.05	0.11	0.17

Notes: See Table 1. The table refers to the share plants in the respective growth categories as fraction of total plants.

$< -75\%$ employment growth). Overall, the table suggests that during booms there is more job reallocation between ongoing firms, more firms being actively adjusting their labor force, while the average entrant and exiter in a boom is smaller[17]. Table 6 shows that we find the same dynamics (maybe a fortiori) when looking at shares of plants in an employment growth category, instead of employment shares[18].

5.2.2 Conditional Worker Flow Rates

Table 7 shows the dynamics of $accr_t(j)$. Table 8 analogously displays the statistics for $sepr_t(j)$. The all worker flow rates are procyclical in each category of plant growth. Put differently, conditional on each plant growth category, plants hire and separate from more workers in booms.

In relative, i.e. log, terms the business cycle volatility of the accession rate is up to a factor of 5 times higher at shrinking plants relative to expanding plants and vice versa for the separation rate. Going into more detail, one sees that the accession rate looses its connection to the cycle to quite some extent for firms expanding by more than 10% and again symmetrically the separation rate is less cyclical for plants shrinking by more than 10%. One reason may be the relative scarcity of labor during booms. At any rate, the result puts considerable restrictions on models that explain part of worker flows by on-the-job search. As discussed earlier, the models of Schaal (2011) and Moscarini and Postel-Vinay (2011) fail to generate any significant accessions for plants that contract in the cross-section. Our results show that this problem becomes even more severe over the business cycle. The least productive plants are shrinking most rapidly and find it difficult to hire new workers because the labor market becomes more tight leading to a declining accession rate. Vice versa, these theories seem well suited to explain the procyclical behavior of the separation rate at rapidly shrinking plants. Those plants are low productive plants that are

[17] Hence, (in Germany) the overall increase in the job destruction rate during recessions is induced by very narrowly defined plant categories. The results also align with the finding of Davis et al. (2005), who show that the mean of the employment growth distribution is a relatively poor predictor for aggregate worker flows.

[18] Now, the fraction of plants contracting by 5-75% is strongly procyclical. The fraction of entering firms is roughly the same.

Table 7: Dynamics of the Accession Rate

				Correlation to GDP_{t+j}				
growth rate	*mean*	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
-200% to -75%	2.1%	8.4%	0.50	0.28	0.31	0.36	0.37	0.37
-75% to -10%	4.2%	10.4%	0.91	0.50	0.60	0.68	0.70	0.68
-10% to -5%	3.6%	14.1%	0.94	0.45	0.57	0.65	0.69	0.69
-5% to -1%	2.9%	14.3%	0.95	0.49	0.59	0.65	0.68	0.68
-1% to 0%	2.9%	11.6%	0.88	0.56	0.64	0.69	0.71	0.69
0%	3.2%	10.9%	0.94	0.62	0.70	0.75	0.77	0.77
0% to 1%	4.0%	8.5%	0.79	0.64	0.69	0.72	0.73	0.72
1% to 5%	6.4%	6.1%	0.91	0.61	0.66	0.71	0.73	0.72
5% to 10%	11.6%	3.6%	0.93	0.58	0.67	0.73	0.76	0.76
10% to 75%	28.4%	1.7%	0.27	0.18	0.17	0.19	0.15	0.21
75% to 200%	164.7%	1.7%	0.19	0.39	0.41	0.32	0.33	0.31

Notes: See Table 1. The table refers to the accession rate in plants in the respective growth categories.

faced by high worker attrition because of high job-to-job transitions during booms. Yet, the models have again difficulties in explaining why the separation rate is most cyclical at fast growing plants.

Figure III summarizes all the above findings in graphical form. It displays the procyclical conditional worker flows and the change in the employment growth distribution. In constructing the figure, we average over the five quarters with the highest positive and negative deviation from GDP trend. The left panel highlights that conditional worker flows shift up in a boom relatively to a recession. For the accession rate, the difference is most pronounced for shrinking plants. The accession rate at plants decreasing employment by more than 5 percent is by more than 25 percent higher during booms relative to recessions. Similarly, the difference in the separation rate is more pronounced at growing plants. Rapidly growing plants see their sepa-

Table 8: Dynamics of the Separation Rate

growth rate	*mean*	*SD*	*AC*(1)	Correlation to GDP_{t+j}: $j=-2$	-1	0	$+1$	$+2$
-200% to -75%	151.9%	1.7%	-0.02	0.07	0.10	0.17	0.20	0.18
-75% to -10%	27.5%	2.2%	0.56	-0.01	0.12	0.20	0.24	0.26
-10% to -5%	10.6%	4.8%	0.91	0.44	0.56	0.64	0.68	0.68
-5% to -1%	5.4%	8.0%	0.94	0.53	0.62	0.68	0.70	0.69
-1% to 0%	3.5%	9.6%	0.87	0.58	0.65	0.69	0.72	0.69
0%	3.2%	10.9%	0.94	0.62	0.70	0.75	0.77	0.77
0% to 1%	3.4%	9.7%	0.80	0.64	0.68	0.72	0.73	0.71
1% to 5%	3.9%	9.8%	0.93	0.63	0.68	0.72	0.74	0.73
5% to 10%	4.6%	9.3%	0.93	0.57	0.66	0.72	0.75	0.75
10% to 75%	5.3%	7.8%	0.84	0.49	0.61	0.68	0.72	0.73
75% to 200%	2.0%	8.4%	0.38	0.20	0.26	0.35	0.40	0.42

Notes: See Table 1. The table refers to the separation rate in plants in the respective growth categories.

ration rate increasing by 20 percent during booms relative to recessions. The right panel shows the difference in the distribution of employment shares over the different employment growth categories. Differences at plants shrinking by 1-75 percent are small and almost negligible, representing their close to acyclical employment shares. During a recession the share of inactive plants increases and employment shares at growing plants decrease.

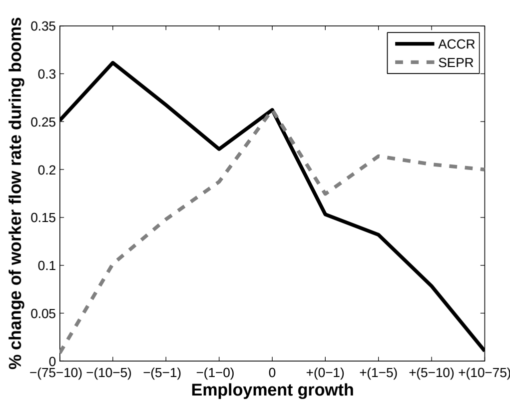
5.2.3 Decomposing Aggregate Worker Flows

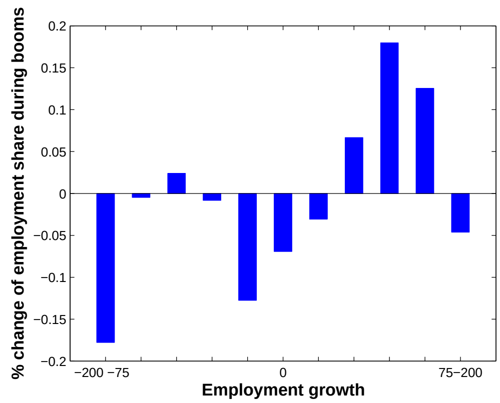
The correlations that we presented so far are silent to the question of the quantitative importance of changes in the cross sectional distribution of employment over growth categories ($ec_t(j)$) for explaining changes in worker flows. To address this formally, recall that an aggregate flow rate can be written as the sum of products of conditional

Figure III

Worker Flows

Employment Growth Distribution





Notes: -75%: Plants shrinking by more than 75%, $-75-10\%$: Plants shrinking by 10 to 75% , $-10-5\%$: Plants shrinking by 5 to 10%, $-5-1\%$: Plants shrinking by 1 to 5%, $-1-0\%$: Plants shrinking by 0 to 1%, 0%: Plants leaving employment unchanged, 75%: Plants expanding by more than 75%, $10-75\%$: Plants expanding by 10 to 75% , $5-10\%$: Plants expanding by 5 to 10%, $1-5\%$: Plants expanding by 1 to 5%, $0-1\%$: Plants expanding by 0 to 1%. To calculate the figures, we take the statistics of the five quarters with the highest positive deviation of GDP from trend relative to the five quarters with the highest negative deviation of GDP from trend.

flows and employment shares:

$$F_t = \sum_{j=1}^{J} f_t(j) ec_t(j)$$

Now, let $\overline{x}$ denote time-mean values of variable x, e.g., $\overline{accr(j)}$ is the mean accession rate over time in growth category j. Then, using these definitions we can decompose movements in the aggregate rate into two synthetic series such that:

$$F_t - \overline{F} \approx \underbrace{\sum_{j=1}^{J} \left[f_t(j) - \overline{f(j)} \right] \overline{ec(j)}}_{=:F^{D-fix}} \quad + \quad \underbrace{\sum_{j=1}^{J} \overline{f(j)} \left[ec_t(j) - \overline{ec(j)} \right]}_{=:F^{f-fix}} \tag{3}$$

In this vein, we construct series of implied worker flows, where we fix the distribution of employment growth ($\overline{ec(j)}$) and the behavior of plants conditional on employment growth ($\overline{f(j)}$):

$$ACCR_t^{D-fix} = \sum_{j=1}^{J} accr_t(j)\overline{ec(j)} \qquad ACCR_t^{f-fix} = \sum_{j=1}^{J} \overline{accr(j)}ec_t(j)$$
$$SEPR_t^{D-fix} = \sum_{j=1}^{J} sepr_t(j)\overline{ec(j)} \qquad SEPR_t^{f-fix} = \sum_{j=1}^{J} \overline{sepr(j)}ec_t(j)$$

The two flow rates on the left ask how worker flow rates would look like when keeping the distribution of employment growth at their sample mean, *D-fix*. The two worker flow rates on the right ask how the aggregate had looked like keeping the flow rates conditional on plant growth at their sample means, *f-fix*, and vary the employment growth distribution[19].

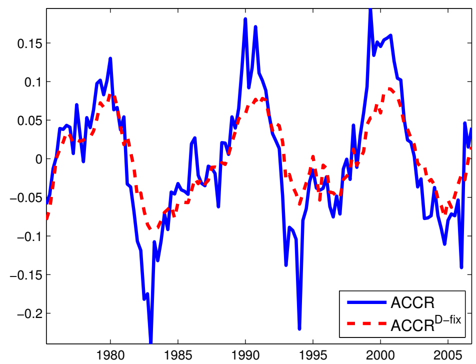
Figure IV shows the results from this exercise. The realized accession and separation rate and the rates that keeps the employment growth distribution constant *(D-fix)* are a quite good fit for the realized rates. The accession rate is not sufficiently volatile, but the timing of periods with high and low rates is almost identical. The fit for the separation rate appears even better. The peaks and troughs of the two rates are almost identical, and the synthetic rate only fails to capture higher frequency movements. Recall from Tables 7 and 8 that plants change accession and separation behavior almost uniformly across the employment growth distribution. As a result, one can predict changes in the aggregate flows quite well by changes in conditional plant behavior, the correlation between the raw and synthetic accession rate series is 87.5%, yet the variance of the synthetic one is only 34% of the variance of the raw accession rate series. For the separation rate, we obtain a correlation of 79.7% between raw and synthetic series with the variance of the synthetic series being 85%

[19]Due to the length of our sample, it is unavoidable to allow worker flows to have a trend component. We construct the fixed distribution and fixed flow rates series from the raw data and detrend all (constructed) aggregate series afterwards using an HP-filter. Using HP-filtering at each series separately implies that aggregation does not need to hold any longer. However, we find that the resulting error is practically zero for both rates, i.e. for the cyclical component $F_t \approx F_t^{D-fix} + F_t^{f-fix}$ still holds.

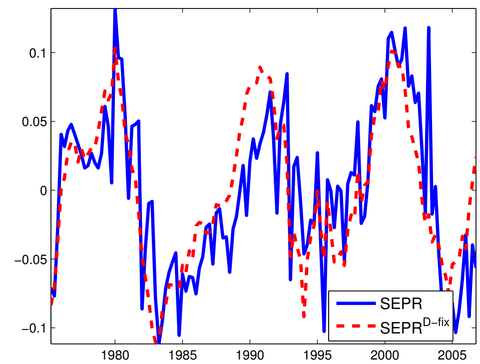
Figure IV: Components of the Accession and Separation Rate over the Cycle

(A) Fix Employment Growth Distribution

Accession Rate

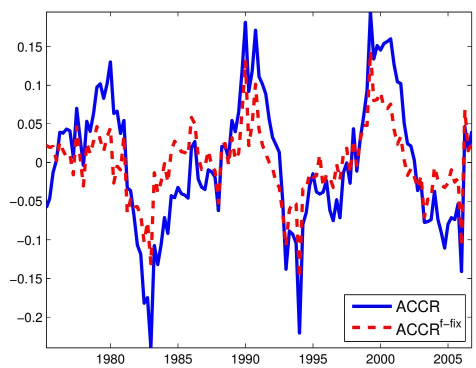


Separation Rate

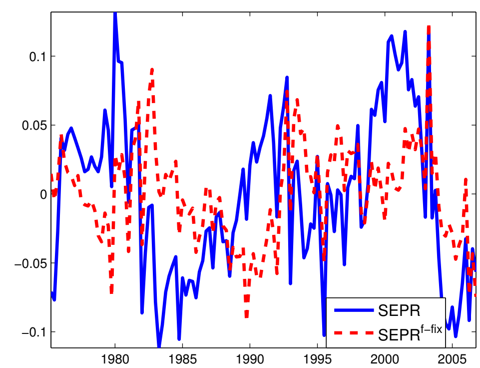


(B) Fix Conditional Flow Rates

Accession Rate



Separation Rate



Notes: *Panel A* displays the cyclical component of the accession and separation rates (solid) and the synthetic ones implied when holding the distribution of plant employment growth fixed (dashed). *Panel B* displays the cyclical component of the accession and separation rates (solid) together with the synthetic ones implied when holding the flow rates conditional on plant growth constant (dashed).

of the one for the actual separation rate series.

The lower two panels in Figure IV show the results for the synthetic series obtained from holding conditional worker flows constant at their sample averages and varying the employment composition over the employment growth distribution. The employment growth distribution explains parts of the overall shape in the accession rate. It fails in predicting the rise at the end of the 70's and the downturn at the mid 2000's, but it captures all other major movements. In fact, the correlation is with 80% almost as large as for the other synthetic series, just the volatility is with only 30% of the actual accession rate series[20]. For the separation rate however, the synthetic series with fixed conditional flow rates shows only a correlation of 41% with the actual separation rate series and the variance of the synthetic series amounts only to 38.8% of the original series[21]. Table 9 summarizes the covariance structure of the actual and the two synthetic series.

In addition, the table also shows the analogue results for band-pass (cf., Baxter and King (1999)) filtered series that allow to focus on movements at business cycle (2-8 years) and below business cycle frequency (< 2 years). Since the filter is not linear, the filtered actual series is no longer equal to the sum of the two filtered synthetic series. Overall, the movements in the employment growth distribution explain particularly strongly the below-business-cycle-frequency movements in worker flows. Conversely movements in the conditional flow rates are particularly important in explaining movements at business-cycle frequency, especially for the separation rate.

5.2.4 Comparing the Results to Existing Studies

Our conclusions are in contrast to the one drawn by Davis et al. (2006) for the US and Bellmann et al. (2011) for Germany and differ in some respects to the ones drawn by Davis et al. (2011) for the US. We can explain much of these differences by the different methods that are applied to reach the conclusion.

Bellmann et al. (2011) use a bi-annual 1% sub-sample of German plants between 1993-2009. Using a regression based approach, they find that the relationship between the amount of hires (separations) and the individual employment growth (Figure II) is relatively stable over time and conclude from this that changes in the employment growth distribution must cause the changes in separation and hires over the cycle. Our Figure III shows that the relationship does shift up in a boom, but

[20]The remainder 26% is explained by positive comovement of the two synthetic series.

[21]Again the (here negative) remainder is explained by the (here negative) covariance of the two synthetic separation series.

Table 9: Variance and covariance structure of actual and synthetic worker flow series

	Frequency					
	All		Business Cycle		High	
	rel. var.	correl.	rel. var.	correl.	rel. var.	correl.
Accession						
Fix Distribution	34%	88%	24%	90%	10%	23%
Fix conditional flows	31%	87%	36%	93%	94%	95%
Separation						
Fix Distribution	85%	79%	124%	72%	10%	67%
Fix conditional flows	39%	41%	64%	22%	68%	96%

Notes: The table displays correlations and relative volatilities between the raw worker flow rates and synthetic worker flow rates.
Fix Distribution / *Fix conditional flows*: Synthetic worker flow rate with constant employment growth distribution and with constant conditional worker flows, respectively. *Business Cycle:* Frequency between 2 and 8 years. *High:* Frequency between .5 and 1.5 years. *All:* HP(10^5)-filtered series.

one may miss this shift with a low sample size[22]. Indeed, their result would imply that Tables 7 and 8 show no correlation to the cycle.

Davis et al. (2006) use monthly seasonally non-adjusted JOLTS data between Jan. 2001 and Jan. 2004. They find that changes in the employment growth distribution

[22]Davis et al. (2005) and Davis et al. (2011) show that from eyballing this relationship is very stable in the US, too. However, changes in the cross sectional distribution can only account for 40% of the changes in the accession and separation rate.

explain 38% of movements in aggregate hires and 42% of movements in aggregate separations. They conclude that *"[...] business cycle swings mainly involve shifts in the distribution of employer growth [...]"*. Two issues arise with their conclusion: First, they leave a large fraction of variation unexplained, making an assesment of their conclusion difficult. Second, they use a short sample period coupled with monthly seasonally non-adjusted data. In Appendix C, we show that non-seasonal adjustment of the data leads to a larger role played by changes in the employment growth distribution. This finding supports our earlier notion that changes in the employment growth distribution are the main driver behind higher frequency spikes in worker flows.

Finally, Davis et al. (2011) overcome some of the shortcomings in Davis et al. (2006). They use quarterly seasonally non-adjusted JOLTS data from 2001-2010. Their analysis proceeds in several steps. First, they regress movements in worker flow rates on dummies of the employment growth distribution. They find a R^2 of 0.54 and 0.47 for the accession and separation rate, respectively. Afterwards, they seasonally adjust the predicted and the realized rates and show that the seasonally adjusted predicted rates do a poor job in explaining aggregate worker flows, especially it fails almost completely to explain the separation rate. We take this evidence as supportive for our earlier finding that changes in the employment growth distribution do a good job in predicting high frequency fluctuations, but they contribute little to fluctuations in the separation rate at business cycle frequency. The authors proceed and allow in their regressions for several cyclical indicators, meaning that the cycle can shift plant behavior conditional on employment growth. The fit of the seasonally adjusted realized and predicted worker flows becomes quite well, which leans support to our findings in Figure IV. The authors do one more exercise to evaluate the importance of the cross sectional distribution. They first regress raw worker flows only on cyclical indicators, omitting the employment growth distribution. They find a R^2 of 0.81 and 0.65 for the accession and separation rate, respectively. The predictive power goes close to one when they keep the employment growth distribution constant. They conclude that keeping track of the employment growth distribution is important to account for dynamics in worker flows. We speculate that the increase in predictive power is mainly due to the ability to explain higher frequency spikes in worker flow rates.

6 Churning

The last section established that conditional worker flows shift up almost monotonically during booms and that cyclical worker flows are mainly explained by this parallel shift. However, we also established that the employment growth distribution shifts in a non-parallel fashion over the cycle, which gives potentially rise to very different quantitative importances of the parallel shift over the employment growth distribution. This section quantifies the relative importance of different plant types in explaining cyclical differences in job and worker flows. To keep the analysis tractable, we aggregate the plant growth distribution into expanding plants, constant plants and shrinking plants in each period. This section evolves around the notion of churn, e.g., the excess of worker over job flows:

$$CH_t = (ACC_t - JC_t) + (SEP_t - JD_t).$$

6.1 Churning over the Business Cycle

Following Lazear and Spletzer (2011), note that churn at expanding plants, $CH(E)_t$, at non adjusting plants, $CH(Z)_t$, and at shrinking plants, $CH(S)_t$, is given by:

$$CH_t = CH(E)_t + CH(Z)_t + CH(C)_t.$$

$$CH(E)_t = 2SEP(E)_t; \quad CH(S)_t = 2ACC(C)_t; \quad CH(Z)_t = 2SEP(Z)_t = 2ACC(Z)_t$$

Put differently, churn can be procyclical when plants that leave employment unchanged increase their worker turnover during booms, shrinking plants hire more during booms, or because expanding plants separate from more workers during booms.

Let us express the amount of churn relative to employment (the churning rate):

$$CHR_t = \frac{CH_t}{EM_t} \qquad CHR(E)_t = \frac{CH(E)_t}{em(E)_t}$$
$$CHR(Z)_t = \frac{CH(Z)_t}{em(Z)_t} \qquad CHR(S)_t = \frac{CH(S)_t}{em(S)_t}.$$

Moreover, define for $k \in [E, Z, S]$: $ec(k)_t = \frac{em(k)_t}{EM_t}$. Obviously,

$$CHR_t = \sum_{k \in \{R,Z,S\}} CHR(k)_t \, ec(k)_t.$$

Table 10: Churning

				Correlation to GDP_{t+j}				
	mean	*SD*	$AC(1)$	$j=-2$	-1	0	$+1$	$+2$
Churning rate	7.1%	11.3%	0.96	0.55	0.65	0.71	0.74	0.74
Churning rate(E)	8.3%	9.1%	0.93	0.60	0.68	0.74	0.76	0.76
Churning rate(Z)	6.4%	10.9%	0.94	0.62	0.70	0.75	0.77	0.77
Churning rate(S)	6.4%	12.9%	0.95	0.51	0.61	0.67	0.70	0.69

Notes: CHR: Churning rate, $CHR(E)$: Churning rate at expanding plants, $CHR(Z)$: Churning rate at constant plants, $CHR(S)$: Churning rate at shrinking plants. See also notes to Table 1.

Table 10 displays the cyclical dynamics of these rates. The churning rate at expanding plants has a somewhat higher sample average, but there are little differences to the other rates at business cycle frequency[23]. All series are strongly procyclical[24],

[23] Alda et al. (2005) report for Germany that the churning rate is twice as high at plants that leave their employment unchanged relative to shrinking plants, with expanding plants being in the middle. However, their dataset is only a small subsample of ours and covers only the year 1999.

[24] Burgess et al. (2000) also find a procyclical churning rate for the state of Maryland from 1985-1994.

and have similar business cycle volatilities. The correlations to GDP are somewhat more pronounced early in a boom, but remain strong throughout it. This reflects basically our earlier results in Tables 7 and 8.

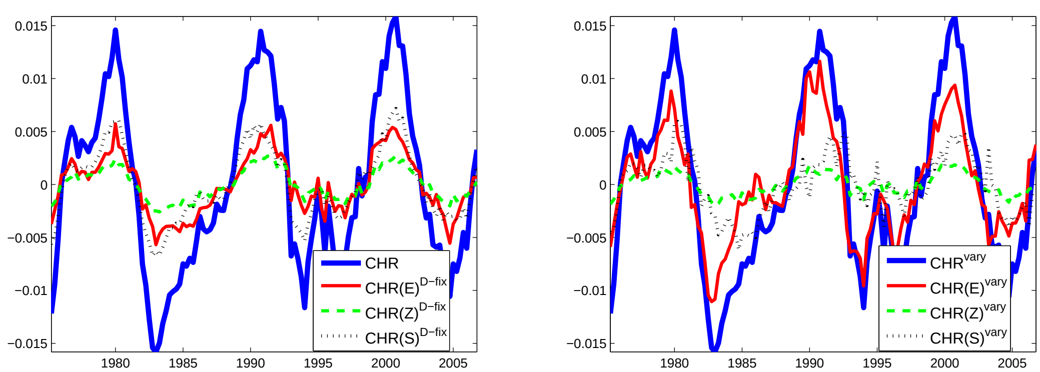
While the churning rates have very similar cyclical properties, cyclical changes in $ec(k)_t$ may imply that the quantitative effect of the sub-categories on the cyclical changes in the aggregate churning rate may be very different. Similarly to above, we define (disaggregated) synthetic churning rates

$$CHR_t^{D-fix}(k) = CHR(k)_t \, \overline{ec(k)}; \qquad CHR_t^{vary}(k) = CHR(k)_t \, ec(k)_t,$$

i.e., the churning rate of type k when its employment share is at its sample mean and when it is allowed to vary. Again, we look at the detrended series.

Figure V: Cyclical Dynamics in the Churning Rate

(A) Constant Employment (B) Varying Employment



Notes: CHR^{vary}: Cyclical component of the churning rate with varying employment share, $CHR(x)^{D-fix}$: Cyclical component of the churning rate with constant employment shares, $CHR(E)$: Cyclical component of the churning rate at expanding plants, $CHR(Z)$: Cyclical component of the churning rate at constant plants, $CHR(S)$: Cyclical component of the churning rate at shrinking plants.

Figure V *Panel A* displays $CHR^{D-fix}(k)_t$. As expected, all three series show very similar patterns over the business cycle. The contribution of plants without employment change is somewhat smaller, because less firms are in this category compared to the other two. *Panel B* allows $ec(k)_t$ to vary over the cycle[25]. The procyclicality of the aggregate churning rate is almost entirely driven by the procyclicality of churning at expanding plants. Recall from Figure III that cyclical changes in the employment distribution are mainly concentrated at the right side of the distribution. Hence, the share of employment and thus the amount of churning varies more strongly at expanding plants. Put differently, cyclical changes in the employment growth distribution have little effects on cyclical dynamics of worker flows because all plant types expand worker flows during booms. However, the dynamics change the composition of worker flows among different plants.

7 Conclusion

Worker flows exceed job flows by a factor of around two in Germany and the US. We introduce a new dataset that allows us to study the relationship between German job and worker flows at the plant level for four full business cycles and show systematic differences in cyclical behavior of these flows.

We decompose the accession and separation rate into cyclical movements resulting from changes in the distribution of plants' employment growth and into cyclical changes of worker flows conditional on pants' employment growth. The employment growth distribution shifts in a non-monotonic fashion over the cycle with few changes at shrinking plants. Worker flows increase during a boom conditional on plants' employment changes. Consequently, most of the procyclical worker flows can be explained by changes in worker flows conditional on plants' employment growth. Mapping our data into the frequency domain suggests that shifts in the distribution of employment growth explain mostly high frequency changes of worker flow rates. While these results suggests that tracking cyclical changes in the employment growth distribution carries little additional insights for understanding cyclical worker flows, we show that such a conclusion is not warranted. The non-monotonic shift in the distribution with cyclical changes taking place mostly in the right part of the distri-

[25] We apply the HP-filter to the rates in levels (as opposed to logs) to insure that the subcomponents aggregate almost to the aggregate series.

bution leads to the fact that expanding plants are quantitatively the main driver of cyclical dynamics in worker flows.

We argue that on the job search models are able to capture non monotonic shifts in the employment growth distribution and procyclical conditional worker flows for a range of the growth distribution. They fail to rationalize procyclical accession rates for low productive plants and procyclical separation rates for the most productive plants.

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A Structural Break Adjustment

This section describes how we perform structural break adjustment. Call any seasonal adjusted series Y. For each Y we detect the number of structural breaks and assign a dummy variable to each D_{it} that takes the value 1 during the break. We have the following model for the DGP in mind:

$$Y_t = \beta_0 + \beta_1 D_{1t} + ... + \beta_n D_{nt} + f_t + \epsilon_t$$

where n is the number of structural breaks, ϵ_t is some short time fluctuation and f_t is a smooth time trend that is estimated semi-parametrically. To be more specific, we employ a local linear Gaussian kernel regression of the original series where points in the structural break receive zero weight. We then compute the residual

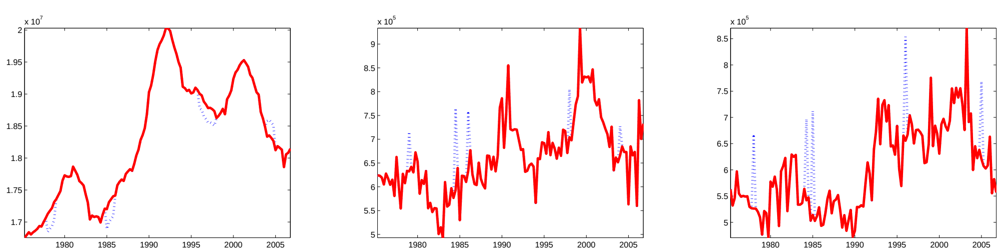
$$Y_t - f_t = \beta_0 + \beta_1 D_{1t} + ... + \beta_n D_{nt}$$

We regress this residual on the defined set of dummy variables to obtain their predicted effects $\hat{\beta}_i$. The structural break adjusted series is then computed by

$$Y_t^{sb} = Y_t - \hat{\beta}_1 D_{1t} - ... - \hat{\beta}_n D_{nt}$$

Figure VI: Structural Break Adjustment

(A) Employment (B) Job Creation (C) Job Destruction



Notes: The figure displays our structural break adjusted series. The red solid line is the adjusted series, the blue dashed line the original series.

Figure VI provides the original series and the structural break adjusted series.

The first structural break is from 1978 Q1 until 1978 Q4. The year was characterized by a series of major strikes in the metal industry. Workers demanded a 35 hour week and employers reacted by locking out workers, leading to 4281284 lost working days.

A similar even occurred in 1984, leading to our second structural break. Workers from the metal and printing industry demanded the 35 hour week, resulting again in lockouts and 5617595 lost working days. The strike was located in the second and third quarter, leading to an initial spike in job destruction and a subsequent spike in job creation.

We make three further break adjustments, of which the source is unknown unfortunately. First, the BLH drops a large amount of workers with university degree during the years 96 and 97. Second, in 1985 Q1 a large amount of jobs are destroyed, that are created again in 1986 Q1. Third, a large amount of jobs are created in 2004 Q1, but vanish again in 2005 Q1.

B Comparing German and US Plant Structure

This section compares the micro structure of German and US plants with respect to size and sector composition. The Business Dynamics Statistics (*BDS*) provides yearly measures for the number of plants, total employment, job creation and job destruction for different industry and size classes in the US from 1977-2010. To obtain comparable measures, we aggregate the *ELFLOP* data to the yearly level[26]. The *BDS* covers the entire manufacturing sector, the primary sector and private services. It misses information on private households and governmental employees. To insure consistency, we drop these sectors from *ELFLOP* in this section. Similarly, we aggregate the plants in *ELFLOP* to six size classes that correspond to those reported in the *BDS*.

Table 11 shows the share of plants, the share of employment, the share of job creation and the share of job destruction that is attributed to the primary sector, the

[26] This assumes that the concepts of job creation and destruction are the same on the quarterly and yearly level. Given that some employment decisions may be reversed, our yearly aggregate is an upper bound for a yearly measure of flow rates.

Table 11: Sector Structure

	EMP	JC	JD	N	$J\hat{C}R$	$J\hat{D}R$
			Germany			
Primary	0.07	0.05	0.05	0.03	0.11	0.11
Manufactuaring	0.53	0.45	0.48	0.35	0.13	0.13
Services	0.41	0.51	0.46	0.62	0.19	0.16
			US			
Primary	0.01	0.02	0.02	0.02	0.22	0.21
Manufactuaring	0.25	0.21	0.24	0.15	0.14	0.15
Services	0.74	0.78	0.74	0.83	0.18	0.15

Notes: Germany: *ELFLOP* 1977-2006, US: *BDS* 1977-2006, N: Share of plants, EMP: Share of employment, JC: Share of job creation, JD: Share of job destruction, $J\hat{C}R$: Yearly job creation rate using as denominator march employment, $J\hat{D}R$: Yearly job destruction rate using as denominator march employment.

manufacturing sector and the service sector in Germany and the US. The primary sector is somewhat larger in Germany, but the share in the total economy is almost negligible in both cases. The major difference between the two countries is that the service sector is larger and the manufacturing sector is smaller in the US compared to Germany. Job destruction exceeded job creation in manufacturing in both countries implying a decreasing importance over the sample period. The opposite is true for the service sector. The table also suggests that the share of job creation and destruction relative to the employment share is lower in manufacturing than in services. Put differently, part of the lower job flows in Germany can be explained by differences in sectoral composition. The last two columns make this point more explicit and compute flow rates for the two countries[27]. With the exception of the primary sector, both job creation and job destruction rates turn out to be similar among the two countries.

Table 12 compares the two economies with respect to their plant size structure. Using the size structure implies that we have to take into account plant entry. For the US, we compute employment for all size categories net of job creation from entering plants assuming that plants enter at a constant rate over the year. Employment at entering plants is the amount of yearly job creation done by these plants. For Germany, we aggregate jobs created by entering plants to a yearly basis. Note that these measures are not directly comparable, and we overstate the importance of plant entry in the the US relative to Germany. Germany has a larger employment shares at the largest plant category and somewhat less at intermediate plant sizes. Plants with $1 - 4$ employees are the only plants which job creation share exceeds their destruction share. In the US, no size category has a larger job creation than destruction share representing the larger amount of newly entering plants. Plants have higher job creation rates in the US than in Germany at all size categories. For the job destruction rate; however, the cross-country difference is only substantial for

[27]The *BDS* does not provide beginning and end of period employment for each series, but only employment in the middle of March. To make the German data comparable, we aggregate the *ELFLOP* data to yearly frequency and compute flow rates ($\hat{JCR}$,$\hat{JDR}$) using employment at the beginning of second quarter as denominator. Note, this yields two comparable series for each country; however, these series are not directly comparable to those reported in Section 3.

Table 12: Size Structure

	EMP	JC	JD	N	$J\hat{C}R$	$J\hat{D}R$
		Germany				
$1-4$	0.09	0.19	0.18	0.59	0.33	0.29
$5-9$	0.08	0.11	0.14	0.16	0.21	0.25
$10-19$	0.10	0.12	0.16	0.11	0.17	0.21
$20-49$	0.13	0.12	0.15	0.06	0.14	0.16
$50-99$	0.10	0.07	0.10	0.02	0.11	0.13
100+	0.47	0.18	0.27	0.02	0.06	0.08
Entry	0.03	0.21	0.00	0.04	1.00	0.00
		US				
$1-4$	0.05	0.10	0.14	0.44	0.46	0.40
$5-9$	0.08	0.09	0.12	0.20	0.26	0.23
$10-19$	0.10	0.09	0.13	0.12	0.22	0.19
$20-49$	0.15	0.13	0.17	0.08	0.20	0.17
$50-99$	0.12	0.09	0.12	0.03	0.18	0.15
100+	0.43	0.23	0.33	0.02	0.13	0.12
Entry	0.06	0.27	0.00	0.11	1.00	0.00

Notes: Germany: *ELFLOP* 1977-2006, US: *BDS* 1977-2006, N: Share of plants, EMP: Share of employment, JC: Share of job creation, JD: Share of job destruction, $J\hat{C}R$: Yearly job creation rate using as denominator march employment, $J\hat{D}R$: Yearly job destruction rate using as denominator march employment. Data excludes the primary sector, as data on size-industry cells is too thin there, the public service sector and households.

plants with $1-4$ and with more than 100 employees.

B.1 German Labor Market Flows with US Plant Composition

The difference in size and sector decomposition suggests that differences in labor market flows may be partially explained by these differences. We investigate this question by creating synthetic flow rates in Germany with US plant weights. We compute for the manufacturing and private service sector flow rates and ec_t as before. We compute for both countries the mean employment share of each individual sector/size category and take the ratio of these means

$$\overline{R} = \frac{\overline{ec}^{US}_{march}}{\overline{ec}^{G}_{march}}.$$

We now create synthetic flow rates for Germany, e.g., for the accession rate

$$ACCR_t = accr_t ec_t \overline{R},$$

where we scale the sum of $ec_t\overline{R}$ to one in each period. We report the results of this exercise in Table 4.

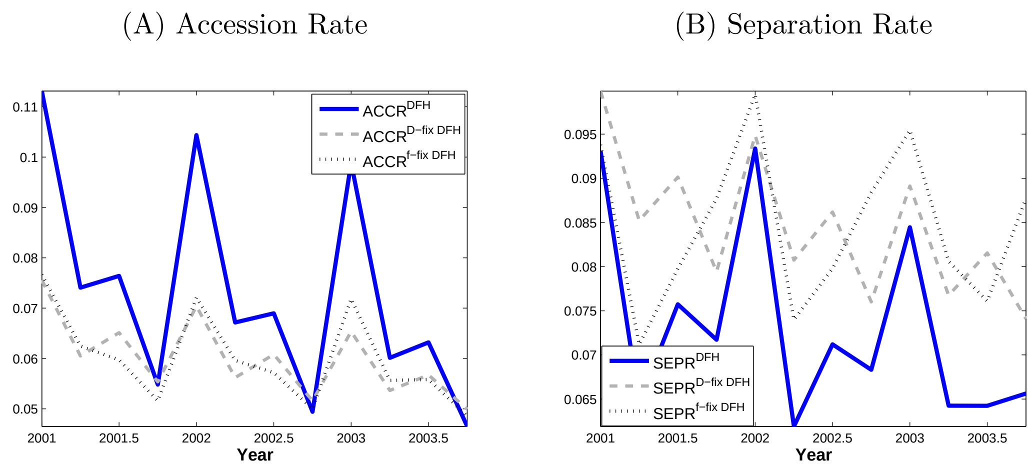
C Allowing for Seasonal Movements

Davis et al. (2006) use monthly seasonally non-adjusted data to establish the importance for explaining cyclical changes in worker flows by changes in the employment growth distribution. In this section, we investigate whether we also find a more important role for variations in the employment growth distribution when we use seasonally non-adjusted data. We investigate this question using their approach with our quarterly seasonally non-adjusted data for the same time horizon[28]. Figure

[28] If seasonality played a major role, monthly data would extrapolate the effect even beyond our quarterly data.

VII displays that changes in the employment growth distribution and changes in the plant behavior conditional on plant growth explain both significant parts of the variance in worker flows. The share explained by each is very similar and larger for separations than for accessions. This finding supports our earlier notion that changes in the employment growth distribution are the main driver behind higher frequency spikes in worker flows.

Figure VII: Components of the Accession and Separation Rate Seasonally Non-adjusted



Notes: The figure decomposes seasonally non-adjusted worker flows as in Davis et al. (2006). $ACCR^{D-fixDFH}$: Accession rate computed with constant employment distribution, $ACCR^{f-fixDFH}$: Accession rate computed with constant conditional worker flows, $SEPR^{D-fixDFH}$: Separation rate computed with constant employment distribution, $SEPR^{f-fixDFH}$: Separation rate computed with constant conditional worker flows.