Labour Market Dynamics in Germany: Hirings, Separations, and Job-to-Job Transitions over the Business Cycle

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Abstract

This paper analyses the cyclical properties of gross worker flows, accessions, and separations in western Germany in 1975-2001 based on a dataset that contains daily information on 2% of the German workforce covered by social security legislation. Separations are found to be relatively flat over the cycle, while accessions are markedly procyclical. The increased flow into unemployment in a recession is therefore due to reduced hirings, and lower job-to-job transitions, rather than increased match separations. I argue that this finding can be explained by differences in the cyclical characteristics of the worker flows underlying accessions and separations. This important feature of labour market dynamics is ignored by the standard two-state search and matching model. Furthermore, this finding implies that the focus of economists and policy makers on firing restrictions might have been exaggerated. Instead, more attention should be directed to studying firms’ hiring behaviour. These findings thus have important implications both for the way labour market dynamics should be modelled and for the way we evaluate labour market policies.

JEL codes: J63, J64, J21, E24

Keywords: worker flows, accessions, separations, business cycle, job-to-job, employer-to-employer.

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1 Introduction

There used to be a consensus among macroeconomists about the reason for increased unemployment inflows during a recession: a negative productivity shock leads to a burst in match break-ups, which in turn results in previously employed workers becoming unemployed. This seemed to be a natural conclusion emanating from the stylised facts about job creation and destruction. Most prominently, Davis, Haltiwanger, and Schuh (1996) found job destruction to be much more volatile than job creation in the manufacturing sector of the US. Furthermore, this mechanism features prominently in the standard search and matching model of the labour market as epitomised in Mortensen and Pissarides (1994). This view has however been challenged by recent empirical research on the US labour market.1

In this paper, I analyse the cyclical properties of accessions, separations, and job-to-job transitions on the West German labour market. This is done using a very large micro data set which derives from registry data, the IAB employment sample, which covers the years 1975-2001. As described in detail below, these data make it possible to observe a very large number of employees on a daily basis over a time span of 26 years. This enables me to record worker transitions on the labour market, including job-to-job flows, on a daily basis for two full business cycle swings. I am therefore able to exactly quantify worker flows, and to provide a comprehensive analysis of their cross-sectional and time-series properties. Furthermore, the data set makes it possible control for unobserved heterogeneity in the econometric analysis. As opposed to the US studies relying on monthly survey data, this data source is very accurate as it provides daily employment and unemployment records, it covers a much longer time span, and it follows the same workers over a long period of time.2

In terms of results, the contributions of the paper are as follows. First, while I do confirm many of the findings by the authors cited above, I am able to give a more detailed picture of the cyclical response of labour market flows. Looking at the West German economy, I corroborate the findings for the US that the decline of job-to-job transitions contributes at least as much to worker flows into unemployment during a recession as do increased lay-offs. This points to the importance of the hiring activity of firms for the cyclical features of labour market flows. I also show that one should not only look at gross hirings, separations, and job-to-job transitions. One of the key points of this paper is that it is important to look at the flows underlying hirings and separations. Such an analysis shows that two facts lead to the observed cyclicality of hirings and separations: on the one hand, flows underlying separations are more strongly, and negatively, correlated, which in the aggregate leads to relatively flat separations; on the other hand, some of the flows making up separations are less volatile themselves. These findings have

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1 Blanchard and Diamond (1990) were among the first to provide direct evidence on gross worker flows in the US. Fallick and Fleischman (2004), Nagypál (2004), Hall (2005b), and Shimer (2005a) extend this analysis by including job-to-job transitions in the US for the time period 1994-2003. This literature is discussed in more detail in the next section.

2 As described below, direct evidence on job-to-job transitions in the US is only available in the Current Population Survey from 1994.
important implications for the way we think about labour market dynamics. In particular, empirical work stressing the flatness of separations has lead many theorists (e.g. Hagedorn and Manovskii 2005) to use business cycle models featuring an exogenous match separation process. As will be discussed in more detail below, in the light of the empirical evidence presented in this paper, this is not warranted.

The plan of the paper is as follows. In the next section, I give a brief overview of the literature on the cyclical features of worker flows in the labour market, and job-to-job transitions in particular. In section 3, I describe the data set used and the theoretical concepts underlying the empirical analysis. Furthermore, I discuss measurement issues. Section 4 presents the empirical evidence in the following way: In Section 4.1, I give an overview of gross worker flows in western Germany. In particular, I study the relative importance of the different flows. Section 4.2 analyses which impact worker heterogeneity has on the cross-sectional properties of gross labour market flows. Finally, Section 4.3 investigates the cyclical properties of gross worker flows, as well as the question whether it is increased match separations or a reduced hiring activity which lead to increased worker flows into unemployment in a recession. Section 6 summarises the main findings and concludes.

2 Hirings, Separations, and Job-to-Job Transitions in the Literature

Nagypál (2004) and Fallick and Fleischman (2004) provide direct evidence on gross worker flows, including job-to-job transitions, in the US for the time period 1994-2003. Both papers exploit the "dependent interviewing" techniques introduced in the Current Population Survey (CPS) in 1994. Nagypál (2004) finds that, while separations are relatively flat over the business cycle, accessions are much more volatile, and puts this down to a decline in job-to-job transitions during recessions. Fallick and Fleischman (2004) provide similar evidence by pointing out that job-to-job transitions are large, that they are procyclical, and that they are centered around the recession. For France, related evidence was presented by Abowd, Corbel, and Kramarz (1999). Using a representative sample of French establishments they find that employment adjustment occurs primarily through changes in entry rates and not through exit rates (excluding quits). However, it should be pointed out that their analysis only covers the time period 1987 to 1990, which means that they focus on idiosyncratic, rather than cyclical, variation in employment.

These empirical findings have been formalised by Shimer (2005a). He shows that in a search model where unemployed workers accept any job and employed workers move to better jobs, the cyclicality of the job-to-job transition rate depends on the nature of the shock. While fluctuations in the separation rate lead to a countercyclical transition rate, fluctuations in the job finding rate lead to a procyclical

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3It should, however, be pointed out that the pro-cyclicality of quits was already recognized by Akerlof, Rose, and Yellen (1988). Furthermore, Mortensen and Pissarides, despite being the starting point of the described conventional wisdom, are well aware of the fact that "flows into employment are strongly pro-cyclical and separations mildly pro-cyclical or neutral" (cf. Mortensen and Pissarides 1999).
job-to-job transition rate. As it is the latter that we observe, fluctuations in the job finding rate play a more prominent role over the cycle. Nagypál (2005) shows that this has important implications for the propagation of shocks. Because workers who have been previously employed are less likely to continue to search after moving to a new job, firms prefer to hire them instead of hiring the unemployed in order to save on future search costs. During booms, a large fraction of job seekers is employed, which raises expected profits. Therefore, firms create more vacancies thus enhancing the effects of a positive productivity shock. Krause and Lubik (2006) develop a similar mechanism in a model with two types of jobs and highly elastic on-the-job search. In a boom, there is more on-the-job search, which leads to more creation of good jobs, and vice versa. This mechanism is self-reinforcing, which leads to increased persistence of productivity shocks. These studies thus stress the importance of direct job-to-job transitions for the role of the labour market as a propagation mechanism of productivity shocks. Hall (2005a) shows that the observed importance of hirings relative to separations emerges in a model with rigid wages where employment governance is efficient, i.e. where there are no inefficient separations. Finally, Mortensen and Nágy (2005) develop a search and matching model with job-destruction shocks and job-to-job worker flows. Given that the opportunity cost of continuing a job-worker match is high enough (where the opportunity cost includes both a worker’s opportunity cost of employment and turnover costs), their model can explain U.S. labour market data with respect to both the volatility of vacancies and of unemployment, as well as the quantitative properties of the Beveridge curve.

Direct job-to-job transitions also have an important impact on the way we view recessions. The traditional view is the Schumpeterian one which postulates that bad matches are weeded out during recessions. This conclusion follows also from the standard search and matching model of the labour market. There, a negative aggregate shock leads to the destruction of matches featuring low idiosyncratic productivity. This cleansing effect of recessions has however been challenged by Barlevy (2002). He argues that on-the-job search usually leads to better matches, as otherwise workers would not search while employed. If recessions hamper job-to-job transitions, then matches created during recessions are likely to be of lower quality. In this case, recessions could exert a sullying, rather than a cleansing, effect by worsening the quality of newly created matches.

Despite the perceived importance of accessions, separations, and direct job-to-job transitions for labour market dynamics, empirical evidence for Germany remains relatively scarce. Erlinghagen (2005) uses a representative German household survey, the German Socio-economic Panel (SOEP), in order to analyse the evolution of lay-offs and job security for the time period 1985-2001. He finds that the business cycle is the most important determinant for the observed evolution, and that there is no discernible long-run trend. Schmidt (2000) also uses the SOEP, stressing the heterogeneous experience of different demographic groups, especially with respect to their sensitivity to cyclical factors. Finally, Fitzenberger
and Garloff (2005) use the same data source and calculate labour market transitions. They do not, however, specifically look at accessions and separations. Furthermore, they only consider year-on-year changes, which, as I show below, means that a lot of the actual dynamics are not recorded in their study.

The present analysis differs from the above studies in the following ways. First, as opposed to the existing German studies, I emphasise the role of accessions and separations in order to account for the evolution of labour market flows and unemployment. Second, as opposed to the US studies and as opposed to the German studies using the SOEP (Erlinghagen 2005, and Schmidt 2000), I use a very large data set which derives from registry data, the IAB employment sample. As described below, these data make it possible to observe a very large number of employees on a daily basis over a time span of 26 years. This enables me to record worker transitions on the labour market, including job-to-job flows, on a daily basis for two full business cycle swings. I am therefore able to exactly quantify worker flows, and to provide a comprehensive analysis of their cross-sectional and time-series properties. The time span analysed is thus much longer than in the US studies which use the CPS.5 Furthermore, I can control for unobserved heterogeneity in the econometric analysis, which is impossible in the CPS studies.

3 The Data, Concepts, Measurement

3.1 The Data Set

The data set used is the IAB Regional File 1975-2001 (IABS-R01), which is provided by the Institute for Employment Research (IAB) of the German Federal Employment Agency. The data base covers 2% of all the persons who, between the 1st January 1975 (for western German employees) or the 1st January 1992 (for eastern German employees) and the 31st December 2001, worked in an employment covered by social security. The data source consists of notifications made by employers to the social security agencies, which include health insurances, statutory pension schemes, and the unemployment insurance agencies.6 These notifications are made on the behalf of workers, employees and trainees who pay contributions to the social insurance system. This means that, for example, civil servants and the self-employed are not included. Overall, the subsample includes over 1.29 million people, of which 1.1 million are from western Germany. For 1995, the employment statistics, from which the IAB Regional File is drawn, cover nearly 79.4% of the employed persons in western Germany, and 86.2% of all employed persons in eastern Germany. As for the unemployed, only those entitled to unemployment benefits are covered. This means that the unemployment stock is about one third lower compared to official labour statistics.7 It should also be mentioned that the unemployment records are incomplete until 1979. I therefore only use information on unemployment from 1980.

5Direct evidence on job-to-job transitions is only recorded directly in the CPS from 1994.
6For a complete description of the data set, see Bender, Haas, and Klose (2000).
7See Bender, Haas, and Klose (1999).
The notification procedure is important for the measurement issues discussed below. For employment spells, notifications are made for the year when the spell begins, for every completed year of the spell, and for the year when the spell ends. To take an example, if an employment spell lasts from May 15, 1975 until the May 15, 1977, then there will be three notifications: one for the time period 15/5/1975-31/12/1975, one for the time period 1/1/1976-31/12/1976, and one for the time period 1/1/1977-15/5/1975. For unemployment spells, there is just one single record. The information provided for each spell is the following: sex, year of birth, and degree of education/training. Also, information on the occupation and the gross earnings of workers, an establishment number, and the economic sector is available on a daily basis. Two states of the labour market can be directly derived from the data set: employment covered by social security, and unemployment, if the worker is receiving some form of unemployment compensation. The third state considered, “non-participation”, is not directly recorded but can be inferred. It is defined as: not paying social security contributions while full-time employed, and not receiving unemployment benefits. This means that non-participation can coincide with the state “out-of-the-labour-force”. However, it can also mean self-employment, civil service employment\(^8\), retirement, or marginal employment. Thus, for those ever registered with the social security system, “non-participation” provides an upper bound for “out-of-the-labour force”.\(^9\)

The advantages of the data set are thus as follows: first, it does not suffer from the problems inherent in most panel data sets, e.g. there is no sample attrition, and it follows workers over a long period of time because there is no need for rotation as in the CPS. Given the length of our times series, the evidence here is likely to be more conclusive than the US studies cited above, which observe only one episode of labour market tightening (1994-2000) and loosening (2000-2003). The data set used here covers two decades and two full business cycle swings. Second, it offers observations at a very high frequency, which means that every actual transition is observed. Again, this is a distinct advantage over survey data like the CPS or the SOEP, which does not record multiple transitions that take place between two interview dates and, in the case of the SOEP, uses retrospective data. There are two disadvantages to the data set. On the one hand, it is representative for the working population covered by social security legislation, and not the entire working population. It should be pointed out here that the share of workers covered by social security relative to total employment is large and relatively stable, at around 80 %. On the other hand, it only covers the unemployed who receive unemployment benefits. Therefore, this special structure of the data set has to be taken into account when interpreting the different flows however, especially the ones going to and from non-participation.

\(^8\)This applies to “Beamte”, public sector employees under a special, life-time form of civil service employment. Other workers in the public sector are included in the data set.

3.2 Theoretical Concepts

Given the data on the employment state of workers, it is possible to calculate worker flows. There are two basic options. First, one can use point-in-time comparisons. This implies checking the labour force state of each individual at two given dates (e.g. at the beginning of two consecutive months), and infer the ensuing flow from this comparison. Second, one can calculate flows cumulatively, i.e. take into account every change of state that takes place, even if there are several flows within a certain time period (e.g. a month). As the data record every single move with daily accuracy, I opt for the latter approach.

Abstracting from labour force growth, this concept yields the following stock-flow identities:

\[ e_{t+\tau} = e_t + u_{t+\tau} + n_{t+\tau} - (e_{t+\tau} + e_{t+\tau}) \]  
\[ u_{t+\tau} = u_t + e_{t+\tau} + n_{t+\tau} - (u_{t+\tau} + n_{t+\tau}) \]  

Here, \( e_t \) and \( u_t \) denote the stocks of employment and unemployment at the end of a given time period. Importantly, \( x_{t+\tau} \) indicates the sum of all transitions from state \( x \) to state \( y \) during time period \([t, t+\tau]\].

Equation 1 shows that the employment stock at date \( t + \tau \) is given by employment at date \( t \) plus any inflows during the time period \([t, t+\tau]\] that originated from unemployment (measured by \( u_{t+\tau} \)) and from non-participation (measured by \( n_{t+\tau} \)), minus outflows from employment to unemployment (\( e_{t+\tau} \)) and to non-participation (\( e_{t+\tau} \)). The unemployment stock follows a similar calculation in equation 2. Note that job-to-job transitions do not feature in these stock-flow identities, as they do not change the stocks.

Furthermore, it is worth emphasising that the IAB data set makes it possible to use this cumulative calculation, thus taking into account very short spells as well, which are usually not recorded in other data sets.

There are also two basic choices for normalising the worker flows. First, one can normalise the flows by the labour force. This makes it possible to abstract from labour force growth, which facilitates international comparisons. However, the data set does not record the stock of non-registered workers. I therefore restrict the definition of the labour force, \( l_t \), to the sum of the stocks of the employed and of the unemployed, i.e. \( l_t = e_t + u_t \). Using the notation above, the normalised flows are then given by \( x_{t+\tau}/l_t \). This also approximately yields the probability of a worker in the labour force making one such transition during a certain time interval. The other option is to calculate transition probabilities conditional on the state of origin, i.e. the probability of a worker to make a specific transition, given the worker’s state. For example, the average probability of an unemployed worker to make a transition to employment is given by \( u_{t+\tau}/u_t \), and the inverse of this ratio is the duration of unemployment. Both concepts are used in the subsequent analysis.
3.3 Measurement

As it is possible to track the employment and unemployment history of every person in the data set, it is possible to construct worker flows for the aggregate economy. I compute the flows between the three mentioned states and within the employment state in the cumulative way described above. It should be noted here that the notion of a job is establishment (not firm) based. This means that a change of establishment within the same firm will also be recorded as a job change.

It has to be taken into account that there might be measurement error in the data because of the way the data are collected. In particular, workers’ notifications of becoming unemployed or leaving the state of unemployment might not always correspond exactly to the actual change of labour market state. For example, this can arise when a worker gets laid off and does not report to the unemployment office immediately. I correct for this latter potential measurement error in the following way: If the time interval between two records (employment or unemployment) is smaller than 30 days, then this is counted as a direct transition between the two states recorded.\textsuperscript{10} If the gap between two notifications is larger than 30 days, then this is counted as an intervening spell of non-participation. As for job-to-job flows, records that are from the same person and the same establishment are counted as one single spell as long as the time between two consecutive employment notifications does not exceed 7 days. The latter issue arises in the case of annual notifications (see Section 3.1).

As I am interested in consistent time series that go back as far as possible, the empirical analysis only considers workers from western Germany. As there is no information on the place of residence in the data set, I discard observations on employees that at some point have worked in eastern Germany. I also discard some worker groups, such as artists, who feature an implausibly high number of spells. As these observations are due to administrative rules, they are not interesting from an economic point of view. I therefore drop these observations from the data set by eliminating all observations for any person who features more than 200 employment spells over the time period considered.

Unfortunately, the records on unemployment benefit recipients are incomplete during the time period 1975-79. Therefore, the stock of those people, as well as the flows to and from that state, cannot be used for the analysis before 1980. As employment is correctly measured, I nevertheless obtain reliable estimates for direct job-to-job transitions, and for separations and accessions. However, it is not possible to decompose the latter two time series into their constituent parts before 1980. Therefore, one cannot tell neither the destination of a worker who leaves the state of employment, nor the origin of a worker who enters employment before 1980. It is however possible to do so from 1980 onwards. The empirical results are in the next section.

\textsuperscript{10}I did the calculation for smaller intervals as well. This does not change the results significantly.
4 Gross Worker Flows in Western Germany

4.1 The Overall Picture

In the following, seven different flows are considered: six flows between the three labour market states, and job-to-job flows. As the data are right-censored, I only consider the time period up to 2000:12. Otherwise, one would obtain too many exits into non-registration which are only observed because there are no observations beyond the year 2001. Averages for the time period 1980:1 - 2000:12 for the flows normalised by the labour force are depicted in Figure 1. “U” denotes unemployment, “N” non-participation as defined above, and “E” employment.

Figure 1: Worker flows in Germany 1980-2000

Source: IABS-R01 and author’s calculations.
Notes: E, U, and N stand for the labour market states of employment, unemployment, and non-participation (see text for further details). The flows are monthly averages normalized by the labour force, and are expressed in per cent.

The figure gives an indication of the respective magnitudes and of the relative importance of the different flows. Note that one can interpret the numbers in the figure as the probabilities of a worker in the labour force (i.e. employed or unemployed) of making a certain transition within a given month. As one can see, flows between employment and non-participation are the most important quantitatively. Very close in order of magnitude are direct job-to-job transitions. Flows between employment and unemployment, on which most of the theoretical search and matching literature focuses, only come third. Finally, flows between unemployment and non-participation are relatively small. These figures are roughly in line with the ones reported in Burda and Wyplosz (1994). The main difference is that I find slightly higher flows between employment and non-participation. This is mainly due to the fact that the third state I consider, non-participation, differs from the usual definition of “out of the labour force” (OLF).

Table 1 gives the probabilities, or hazards, of making a certain transition within a given month for

\[ \text{Inflows not equalling outflows for a given state are due to the fact that the stocks are not constant over time.} \]
the time period 1980-2000. The results show that 97.7% of those employed full-time at the beginning of

Table 1: Monthly transition probabilities across labour market states for 1980-2000

<table>
<thead>
<tr>
<th>Destination</th>
<th>Same employer</th>
<th>New employer</th>
<th>Unemployed</th>
<th>Not registered</th>
</tr>
</thead>
<tbody>
<tr>
<td>Origin</td>
<td>Employed</td>
<td>97.7</td>
<td>0.8</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>Unemployed</td>
<td>-</td>
<td>7.1</td>
<td>88.5</td>
</tr>
</tbody>
</table>

Source: IABS-R01 and author’s calculations.

a given month stay with their old employer within that month. 0.8% of the employed switch directly to
a new job, 0.6% become unemployed, and 0.8% leave the system of social security within a given month.
As for the unemployed, 7.1% find a job, 88.5% remain unemployed, and 4.4% leave to non-registration
within a month. These hazard rates reveal large differences to the US labour market, especially for
the unemployed. According to Fallick and Fleischman (2004), 93.4% of US employees stay with their
employer in a given month, and 1.3% become unemployed. As for the unemployed, however, 28.3% of
the unemployed find a new job within a given month, and only 48.4% remain unemployed. Clearly, the
latter figure is much lower than the German one. While this is partly due to different definitions of who
qualifies as unemployed, the lower dynamics of the German labour market are to be held responsible as
well.

4.2 Cross-sectional features of hirings, separations, and gross worker flows

Consider first the cross-sectional features of separations and of the flows making up separations, namely
the flows from one job to another (EE flows), from employment to unemployment (EU flows), and from
employment to non-participation (EN flows). Monthly averages of separations and its underlying flows
for the time period 1980-2000 and for different worker categories are reported in Table 4.12 The categories
considered are age and sex, as well as the industry, the educational background, and the working time
(part time or full time) of a worker. For all categories except the age category, I concentrate on the prime
age labour force (25-55). For every category, separations are computed as share of the employment stock,
and the flows are computed both as share of the employment stock and as share of the total number of
separations. Several features are worth noting. First, there is a general tendency of separations to decline
with age. This can be justified by the accumulation of job-specific human capital on the one hand (cf.
Pissarides 1994), and learning about match quality on the other hand (cf. Jovanovic 1984). The only
exception is the oldest age group, where separations rise again. As this is mainly due to an increase in
flows into non-participation, this is clearly linked to retirement decisions. Also, note that the increased
flow into unemployment in the older age group can be seen as a form of (hidden) early retirement. The
youngest age cohort features important inflows into non-participation as well. This is in all likelihood

12The figures for accessions (not reported here) are very similar. This means that the results are not driven by a long-term
rise or decline of a specific worker group.
due to workers returning to the education sector. As the analysis here is not concerned with life-cycle choices linked to education and retirement, I restrict the following analysis to prime-age workers, defined as workers aged between 25 and 55.

The sex of a worker also has an impact on the likelihood of separation. A male worker is less likely to separate from his employer in a given month. This is mainly due to the fact that women experience less direct job-to-job movements, but instead transit more often from employment to non-participation. I put this down to the fact that women more often leave the labour market in order to raise children. Working in a specific industrial sector also influences the likelihood of separation. As one can see from the table, separations are highest in the construction sector, with the flows between employment and unemployment being of particular importance. The most likely reason for this is that workers in this sector are laid off during seasonal downturns, receive unemployment benefits during their spell of unemployment, and are re-employed again thereafter. Unsurprisingly, turnover is particularly low for government employees.

The type of degree a worker holds also plays an important role for the kind of separation she is likely to experience. Workers with relatively low skills, namely those without vocational training (with or without a high-school degree) have a high risk of experiencing a separation, in which case they face a high probability of unemployment or non-participation. Workers who have accumulated more specific human capital through, e.g., a vocational training or a degree at a polytechnical university, are more likely to have a new job lined up upon separation. Comparing these results with the ones reported by Nagypál (2004) for the United States reveals that the differences in separation probabilities between education cohorts are generally less pronounced in Germany than in the United States.\(^\text{13}\)

Finally, separations are also affected by the type of contractual working time arrangement. Full-time employees have a much lower probability of separating from their employer than part-timers. This means that full-time jobs are more stable than part-time jobs. The type of separation a worker is likely to experience is also very different. Employees working full time are much more likely to experience a direct job-to-job transition than to drop out of the social security labour force. For part-time employees, the opposite is the case. Thus, part-time employees are more likely to leave social security employment than to move to a new job covered by social security legislation.

Summarising the above results, it is evident that worker characteristics play an important role in determining aggregate flows in the economy. As the composition of the workforce might change over the business cycle, these heterogeneities have to be taken into account when analysing the cyclical features of worker flows. This is explicitly done in section 5. First, however, I compute the stylised business cycle facts of worker flows in Western Germany. This is done by implicitly assuming that all workers are homogeneous.

\(^\text{13}\)See Fitzenberger and Kohn (2006) for a related result. They find that the substitution elasticities between employees in different skill groups are lower in Germany than the elasticities in the US reported by Katz and Murphy (1992) and Card and Lemieux (2001).
4.3 Hirings, Separations, and Gross Worker Flows Over the Cycle

I now use the spell information on individual workers to construct time series for the different flows. As I show later, there is no clear trend in the data. The following analysis therefore focuses on the cyclical features of the flow series. I start by examining the evolution of separations, accessions, and employer-to-employer movements over the cycle. The evolution of these flows for the time period 1975-2000 is depicted in Figure 2. Separations are calculated as the sum of all matches that split up during a given year, i.e.

Figure 2: Separations, accessions, and job-to-job transitions

Source: IABS-R01 and author’s calculations.
Notes: ACC are accessions, SEP separations, and EE direct job-to-job transitions; L is the labour force as defined in the text. All flows are cumulatively calculated and expressed per annum. Shaded areas are times of recession.

The flows going from one job to another (EE flow), into unemployment (EU), or into non-registration (EN). Accessions are calculated as the sum of the flows going to employment from any possible state of origin, i.e. from employment (EE), from unemployment (UE), and from non-participation (NE). Again, I normalise all the flows by the labour force. The shaded areas in the graph mark the dates of the beginning (business cycle peak) and the end (business cycle trough) of a recession. The peaks of the German business cycle are in 80/I and 92/I, and the troughs are in 82/IV and 93/IV. As one can see, separations are much flatter than accessions over the cycle. As expected, accessions decline during recessions. This is partly a consequence of the drop in direct job-to-job transitions shown in the graph. Surprisingly, however, separations decline during recessions as well, i.e. there is clearly no increase in match break-ups. The evolution of the three flows is thus consistent with a shift of job-to-job transitions to employment-to-unemployment transitions in a recession. This evidence therefore provides support for
the hypothesis that recessions go along with a decline in hiring activity, rather than a burst in match separations. I investigate this hypothesis further by looking at the flows that make up hirings and separations.

The worker flows for the time period 1980-2000 are depicted in Figure 6.\textsuperscript{14} First of all, it is worth noting that there is no clear trend in the data, i.e. worker turnover in the economy does not seem to have changed much during the time period considered.\textsuperscript{15} In terms of volatility, however, there are marked differences between the flows. Table 5 contains the means, standard deviations, and the relative standard deviations of the different flows. Job-to-job flows turn out to be by far the most volatile ones, followed by the flows from non-participation to employment and the flows between employment and unemployment. Table 6 depicts the contemporaneous correlations of the different worker flows with the GDP growth rate. As one can see, job-to-job flows are clearly procyclical, as are flows from non-participation to employment, and the flows between unemployment and non-participation. The flow from employment to non-participation, as well as the flows between employment and unemployment are countercyclical.

These results are in line with other research (cf. Mortensen and Pissarides 1999).

I now turn to the flows making up accessions and separations. The latter are depicted separately in Figure 3. From this figure, the cyclical features discussed become apparent again: the flow from employment to unemployment is strongly countercyclical, the flow from employment to non-registration is procyclical, as is the flow from employment to employment. Summing over these flows (EU+EE+EN), one gets a relatively acyclical time series, i.e. total separations. These various flows are caused by very different mechanisms. It seems fair to say that the majority of workers that transit from employment to unemployment do so involuntarily - if this is true, then one can associate the EU flow more or less accurately with layoffs.\textsuperscript{16} On the other hand, EE flows are to a great extent caused by workers engaging in job-shopping - these flows are therefore in large part voluntary, and one can associate them with quits.\textsuperscript{17} The picture one gets about separations and the underlying worker flows is thus consistent with the explanation that during a recession, the number of layoffs rises while the number of quits falls, leaving overall separations relatively unaffected. Davis, Faberman, and Haltiwanger (2006) present direct evidence that this is the case on the US labour market, as does Erlinghagen (2005) for western Germany using the SOEP data. The indirect evidence in the present paper confirms this statement for the German labour market. It is also underlined by the fact that the contemporaneous correlation between the EU and the EE flows is negative and strong (see Table 7).

The above analysis shows that the level of separations is relatively flat over time. However, its

\textsuperscript{14}As noted above, the records on the origin and destination of workers entering or leaving the state of employment before 1980 are incomplete and are therefore discarded.
\textsuperscript{15}However, gross flows seem to be rising from the mid-1990s. Whether this is a long-run trend will only become clear once more data are made available.
\textsuperscript{16}Note that some workers might voluntarily quit into unemployment.
\textsuperscript{17}Dismissals with advance notice might lead to direct job-to-job transitions. Given the strong procyclicality of EE flows, this factor only seems to have a limited influence here.
Figure 3: The evolution of the worker flows making up separations, 1980-2000

Source: IABS-R01 and author’s calculations.
Notes: EE are direct job-to-job transitions; EU and EN are transitions from employment to unemployment and to non-participation, respectively. L is the labour force as defined in the text. All flows are calculated on a cumulative basis and expressed per annum. Shaded areas are times of recession.

composition is subject to important variations. This in turn has important implications for labour market dynamics and outcomes. As described in the introduction, this is for example the case because of the role job-to-job transitions play for the evolution of match quality over the cycle (cf. Barlevy 2002). Thus, this composition effect should be taken into account in the modelling of the dynamics of worker flows over the business cycle. Furthermore, this effect is likely to be important in other contexts as well. It is, e.g., conceivable that changes in labour market institutions do not have a level effect on flows, although they have a composition effect. This could be the case for changes in firing costs. To take a specific example, Bauer, Bender, and Bonin (2007) scrutinize the effects of changes in dismissal protection in small establishments on worker turnover. Interestingly, they find that such changes did not have significant effects on the hiring and firing behaviour of the affected firms. However, they only look at separation rates, hiring rates, and job flow rates, and do not analyse the underlying worker flows separately. Therefore, a fall in quits and an increase in firings which leaves overall separations unchanged might go unnoticed. The present analysis suggests that this might well be the case.

The different flows that make up accessions are depicted in Figure 4. Both from this figure and from Tables 6 and 7 two important differences between the flows making up accession and the flows making up separations become apparent. First, the flow from non-participation to employment is more strongly influenced by the business cycle than the flow in the opposite direction. Second, the contemporaneous
Figure 4: The evolution of the worker flows making up accessions, 1980-2000

$\begin{array}{c}
\text{EE/L} \\
\text{UE/L} \\
\text{NE/L}
\end{array}$

**Source:** IABS-R01 and author’s calculations.

**Notes:** EE are direct job-to-job transitions; UE and NE are transitions from unemployment and from non-registration to employment, respectively. All flows are cumulatively calculated and expressed per annum. Shaded areas are times of recession.

The correlation between the EE flow and the UE flow (which are part of accessions) is much weaker than the contemporaneous correlation between the EE flow and the EU flow (which are part of separations), i.e. the UE flow is less responsive to the business cycle than the EU flow. One explanation for this is the time-consuming nature of the matching process in the labour market.\(^{18}\)

It is worth noting that the stylised facts computed above for worker flows that are normalised by the labour force are consistent with some well-known facts about different hazard rates - i.e. worker flows divided by the state of origin (cf. for example Machin and Manning 1999). I depict the hazards of flowing from employment to unemployment and vice-versa in Figures 8 and 9, respectively. Two observations are in order. First, the hazard of transiting from employment to unemployment is strongly influenced by the business cycle and does not show a trend. Second, the hazard of transiting from unemployment to employment is mainly dominated by the evolution of the unemployment rate. This can be seen from the fact that the hazard declines in recessions, while the normalised flow from unemployment to employment rises. The reason for this is as follows. In a recession, the *absolute* number of transitions from unemployment to employment rises, because many workers who lose their job in a recession quickly find a new one. At the same time, the stock of unemployment rises, and does so more quickly than the

\[^{18}\text{See Fahr and Sunde (2006) for a recent analysis of the matching process in Germany.}\]
the absolute number of UE transitions. Therefore, the hazard rate of exiting unemployment \((ue_{t+\tau}/u_t)\) falls in a recession. The normalisation by the labour force \((ue_{t+\tau}/(e_t + u_t))\) yields a different result because the labour force does not change significantly during a recession. Therefore, the evolution in UE transitions thus normalised is dominated by the evolution of the absolute number of UE transitions. The UE flow normalised by the labour force thus rises in a recession. The stock of unemployment dominating the hazard of exiting unemployment also plays a role for its long-term evolution: over the time period considered, this hazard features a strong level effect. Unemployment increases in a stepwise fashion after each of the two recessions in the time span considered, while the absolute number of transitions from unemployment to employment is relatively stable (compared to the stock of unemployment). This implies a reduction in the probability of making such a transition, and a concomitant increase in the overall duration of unemployment.

Finally, it is worth pointing out the importance of calculating the transitions cumulatively, i.e. of not doing a points-in-time comparison in order to calculate flows. To do so, I decompose the flow from unemployment to employment into different duration classes. This means that I calculate the number of workers who have been unemployed for a certain period of time and transit to employment, and divide this number by the total number of workers flowing from unemployment to employment. The result of this exercise is depicted in Figure 7. As one can see, those workers who have been unemployed for less than 7 days and who become employed in a given year account for only a small fraction of all unemployment to employment flows (5%). The unemployment duration class of less than 30 days makes up nearly 20% of all unemployment-employment transitions. And for the less than 90 days duration class, the corresponding figure is already higher than 40%. This shows that relatively short unemployment spells play an important role in the dynamics of the German labour market. Therefore, length-biased sampling is likely to be an important problem if points-in-time comparisons are used.\(^{19}\) The reason for this is that a large number of transitions going to or originating from spells characterised by short durations will be missed. This is especially true when the reference dates are far apart from each other.

5 Worker Heterogeneity, Flows, and the Cycle

5.0.1 Descriptive Evidence

While the above discussion implicitly assumed that workers are homogeneous, I now explicitly take into account worker heterogeneity. This is important because, given the cross-sectional features of separations and of the underlying worker flows, the above results could derive from composition effects which are due to the business cycle. For example, young workers might be more likely to lose their job during a downturn than older workers, which would influence the aggregate results. As I want to concentrate on

\(^{19}\)Cf. Kiefer (1988) for a discussion of this issue.
the core labour force, the following analysis only considers workers who are between 25 and 55 of age, and who work in a full-time job.

I follow Nagypál (2004) and decompose the process of becoming unemployed in the following way: denote the labour market state by \( s \), let subscripts \( i \) and \( t \) denote a person and point in time, respectively, and let \( P_{it+\tau}^j \) be the probability of event \( j \) happening to person \( i \) during time period \([t, t+\tau]\). Furthermore, let \( S \) be the event of a separation, \( LF \) the event of staying in the labour force conditional on having been employed, but having separated from the employer. Finally, let superscript \( U \) denote the event of becoming unemployed conditional on having been employed, having separated from the employer, and having stayed in the labour force upon separation. Then the probability of a transition from employment to unemployment, \( EU \), can be decomposed as follows:\(^{20}\)

\[
P_{it+\tau}^{EU} = P_{it+\tau}^S P_{it+\tau}^{LF} P_{it+\tau}^U
\]

with

\[
P_{it+\tau}^{EU} = P(s_{it+\tau} = U | s_{it} = E) \\
P_{it+\tau}^S = P(\text{separate from employer during period } [t, t+\tau] | s_{it} = E) \\
P_{it+\tau}^{LF} = P(\text{stay in LF} | \text{separate from employer in period } [t, t+\tau], s_{it} = E) \\
P_{it+\tau}^U = P(s_{it+\tau} = U | \text{stay in LF, separate from employer in period } [t, t+\tau], s_{it} = E),
\]

with \( \tau \in [0, 1] \). Note that these formulae respect the fact that transitions are recorded cumulatively. Also, it is important to realise that this decomposition does not imply a sequential timing of events. Instead, it simply calculates the different conditional probabilities involved in the process of becoming unemployed during a certain time period.

I start by applying this decomposition to explicitly calculate from the data the three probabilities involved. In doing so, I use the fact that with the large number of observations at hand, the sample means equal the respective probabilities. For example, the probability that an employed person who is randomly drawn from the sample will separate from his employer during a given month is given by the size of the separation flow divided by the number of people employed. I thus get a time series from 1980-2000 for each of the three probabilities. Table 2 provides some descriptive statistics of these time series, namely the mean, the variance, and the relative variance, i.e. the variance divided by the mean. For the purpose at hand, the latter statistic is the most important one. It shows that the relative variability of the conditional probability of becoming unemployed is about 17.5 times larger than the conditional probability of staying in the labour force, and about 35 times larger than the relative variability of the conditional probability of separating from one’s employer. This shows that the conditional probability

\(^{20}\)A graphical representation of this decomposition can be found in Figure 10 in the appendix.
Table 2: Descriptive statistics for the conditional probabilities.

|        | P(S|E) | P(LF|S) | P(UE|LF) |
|--------|-------|--------|----------|
| $\bar{x}$ | 26.5  | 58.3   | 44.8     |
| $SD(x)$ | 1.8   | 1.4    | 7.5      |
| $\bar{SD}(x)$ | 6.8   | 2.4    | 16.7     |

Source: IABS-R01 and author’s calculations.

Notes: P(S|E), P(LF|S), P(UE|LF) are the conditional probabilities of separation given employment, of staying in the labour force upon separation, and of becoming unemployed upon staying in the labour force, respectively. $\bar{x}$ is the mean, SD the standard deviation of a probability. All figures in per cent per annum.

of separating is much less variable that the conditional probability of becoming unemployed. This also becomes evident in Figure 5, where the three different time series are depicted. Clearly, the conditional Figure 5: The conditional probabilities of separation, of staying in the labour force, and of becoming unemployed.

![Figure 5](image.png)

Source: IABS-R01 and author’s calculations.

Notes: P(S|E), P(LF|S), P(UE|LF) are the conditional probabilities of separation given employment, of staying in the labour force upon separation, and of becoming unemployed upon staying in the labour force, respectively.

probabilities of separation given employment and of staying in the labour force upon separation are quite stable. This stands in stark contrast to the probability of becoming unemployed, conditional on having stayed in the labour force upon separation. The latter probability is extremely volatile over the sample period considered. Here, the business cycle influence appears much more important than for the other two probabilities, with the probability reaching lows at the time of business cycle peaks in 1980 and 1991,
and hitting highs at the time of business cycle troughs in 1982/3 and 1993. The probability of becoming unemployed upon staying in the labour force jumps by nearly 50% in both recessions. This is a large effect, especially when compared with the business cycle responses of the other probabilities.

One can also look at different worker groups when calculating the probabilities. I do this for the conditional probability of separation.\textsuperscript{21} Figure 11 depicts the results for employees with different education levels, and Figure 12 shows the results for employees working in different industrial sectors. For very few of the sub-groups considered is there a burst in separations. Thus, the results obtained from the aggregate evidence about separations do not appear to be driven by composition effects.

5.0.2 Econometric Analysis

Up to now, the results have been purely descriptive, in that I have calculated the different probabilities by looking at their sample means. I now estimate the decomposition stated in Equation 3 in a panel data model which will allow me to explicitly take into account the influence on the probabilities both of the business cycle and of individual worker characteristics. To do so, I use a logit specification of the form

\[
Pr[y_{it} = 1|x_{it}, \beta, \alpha_i] = \Lambda(\alpha_i + x'_{it}\beta), \quad \Lambda(z) = e^z/(1 + e^z),
\]

where \(y\) is the binary outcome variable which only takes on the values 0 and 1, \(x\) includes the explanatory variables, \(\beta\) and \(\alpha\) are coefficients, \(i = 1, ..., N\) and \(t = 1, ..., T\) indicate individuals and time periods, respectively, and \(\Lambda(z)\) is the logistic cumulative distribution function. This formulation is very general in that it allows for the presence of time-invariant individual-specific effects, as well as for possible correlations between these effects and the error terms. Unfortunately, this model is subject to the incidental parameters problem, which means that it is not possible to estimate the \(\alpha_i\) consistently with \(T\) fixed and \(N \to \infty\).\textsuperscript{22} Given the number of cross-sectional observations in the data set, this clearly is an issue here. There are several ways around this problem. First, if fixed effects are not present, then one can obtain consistent estimates by simply using a pooled binary model with \(Pr[y_{it} = 1|x_{it}] = F(x'_{it}\beta)\), where \(F\) is a cumulative distribution function. If fixed effects are present, however, this will lead to inconsistent results. Second, one can assume that the individual-specific component of the error term is normally distributed with mean zero, i.e. \(\alpha_i \sim N(0, \sigma^2_\alpha)\). This yields the random effects model with likelihood function

\[
f(y_i|X_i, \beta, \sigma^2_\alpha) = \int f(y_i|X_i, \alpha_i, \beta) \frac{1}{\sqrt{2\pi}\sigma_\alpha} \exp \left(\frac{-\alpha_i}{2\sigma_\alpha^2}\right) d\alpha_i,
\]

where \(f(y_i|X_i, \alpha_i, \beta)\) is the conditional density of the \(i\)th observation. This log-likelihood can be maximised in order to estimate the model.

\textsuperscript{21}I did this for the other conditional probabilities and worker groups as well, which yields similar results. The latter are obtainable from the author upon request.

\textsuperscript{22}The following discussion draws on Baltagi (2005), ch. 11, Cameron and Trivedi (2005), ch. 23, and Wooldridge (2002), ch. 15.
Third, one can use the conditional maximum likelihood estimator in order to estimate the fixed effects model. As shown by Chamberlain (1980), it is possible to eliminate the $\alpha_i$ from the likelihood function by conditioning on $\sum_t y_{it}$. The drawback of this approach is that it is not possible to condition on $\sum_t y_{it} = 0$ or $\sum_t y_{it} = T$, which means that one cannot use individuals for which $y_{it} = 0$ or $y_{it} = 1$, $\forall t$. In other words, only individuals for which both outcomes are observed can be considered. This can imply considerable loss of information, and induce a selection problem. Furthermore, time-invariant variables have to be dropped from the estimation. The ensuing conditional density is that of a conditional logit model, with invariant parameters, and regressors varying over alternatives:

$$f\left(y_i \mid \sum_t y_{it} = c, x_i, \beta\right) = \frac{\exp\left(\sum_t y_{it} x'_it \beta\right)}{\sum_{d \in B_c} \exp\left(\sum_t d_{it} x'_it \beta\right)},$$

where the set $B_c = \{d_i \mid \sum_t d_{it} = \sum_t y_{it} = c\}$ is the set of all possible sequences of 0s and 1s for which the sum of $T$ binary outcomes $\sum_t y_{it} = c$. Calculating the marginal effects emanating from this model is not straightforward. The problem is that the marginal effects of the explanatory variables depend on the fixed effect as well. As the latter can not be estimated directly, one has to make an assumption about the value of the fixed effect in order to be able to calculate the marginal effect.

It is possible to test for unobserved heterogeneity in two different ways. First, one can use a simple likelihood-ratio test in order to assess whether the pooled model or the random effects model is more appropriate. Second, one can test whether the fixed effects model is preferred to the pooled model. In the latter test, under the null hypothesis of homogeneity, both estimators are consistent, but the maximum likelihood estimator from the pooled model is more efficient. Under the alternative hypothesis of fixed individual effects, the former estimator is inconsistent, while the latter is consistent and efficient. It is therefore possible to conduct a Hausman-type test. This test is based on the difference between the conditional maximum likelihood from the Chamberlain estimator and the pooled logit maximum likelihood estimator. The test statistic is asymptotically $\chi^2$ distributed with $k$ degrees of freedom and is given by

$$H = (\hat{\beta}_{CML} - \hat{\beta}_{PML})'(\hat{V}_{CML} - \hat{V}_{PML})^{-1}(\hat{\beta}_{CML} - \hat{\beta}_{PML}),$$

and $k = \text{rank}(\hat{V}_{CML} - \hat{V}_{PML})$. For the present logit specification, it is however not possible to test whether the random or the fixed effects model is appropriate. The reason is that the two econometric models are estimated using two different populations which is due to the fact that the Chamberlain estimator only uses a subset of the data. Therefore, the likelihood functions are not comparable, and neither a likelihood ratio test nor a Hausman-type set-up can be used to discriminate between the two specifications.

I now run three different regressions for each of the transition probabilities. As explanatory variables,
I include quarterly indicators, as well as indicator variables for education, age cohorts, industries, sex, duration cohorts (quarters on the job before separation), and the aggregate GDP growth rate. Furthermore, in order to be able to run a panel data regression, I transform the spells in the data set to quarterly observations. I do this by attributing the state of employment (unemployment) to a person in quarter I/II/III/IV if she is employed (unemployed) on the 15th of February/May/August/November. Unfortunately, due to limited computational capacity, I can only run the regressions for 25% of the original sample, which I choose at random. I then calculate the different transitions from changes in state from one quarter to the other.

The regression results are in tables 8, 9, and 10. Each table contains the results from the three specifications, the pooled model, the random effects model, and the fixed effects model. The first point to note is that the results from the descriptive evidence are confirmed by the regression results. For all three specifications, the coefficients on the GDP growth rate feature a positive sign for the probability of separating, and of staying in the labour force. This is in line with the descriptive evidence and with the expectation that a business cycle upswing leads to an increase in separations, and to a higher probability of leaving the labour force. However, as for the probability of leaving the labour force upon separation, the coefficient on the GDP growth rate is statistically not significantly different from zero even at the 10% level of significance in either of the three econometric specifications. This means that business cycle swings do not play a significant role for the conditional probability of moving out of the labour force.

Looking at the influence of the business cycle on the conditional probability of separation, one can see that the coefficient of the GDP growth rate is significant only at the 10% level in the pooled model and in the random effects model, and it is significant at the 5% level in the fixed effects model. Given the sample size of the data set, this is no very strong evidence for business cycle swings to affect either match break-ups or the decision of a worker to stay in the labour force after a match break-up. By contrast, the coefficients on the GDP growth rate in the regressions featuring the conditional probability of becoming unemployed are statistically significant at the 1% level of significance. The negative sign of the coefficient, implies that a business cycle upswing leads to a significant reduction in the probability of becoming unemployed, and that a downturn leads to a corresponding significant increase in this probability. One can rationalise this finding by the line of argument made earlier: the driving force behind the increase in the flow from employment to unemployment is not the increase in separations, but the reduction in vacancies available to workers who have separated from their employer. The results from the logit regression models show that this evolution is clearly related to the influence of the business cycle.

Another point to note is that for the three regressions, all three specifications yield qualitatively similar (although not identical) results. The different coefficients in the three regression models are nearly always the same in the random effects and the fixed effects model. Therefore, it does not seem to play a role for the direction of the effects of the different variables whether one takes correlation between regressors and
error terms into account or not. However, it is indeed important to consider unobserved heterogeneity, which is borne out by the fact that the signs of the coefficients in the pooled regressions sometimes differs from the sign of the coefficients of the random effects and the fixed effects regression. This is confirmed by the two specification tests described above. The likelihood ratio test between the pooled model and the random effects model yields a $\chi^2$ value of 1173, which means that the null hypothesis of homogeneity is very strongly rejected. To conduct the Hausman test between the pooled model and the fixed effects model, I run a new regression excluding the time-invariant gender dummy variable and drop the constant in order to calculate the required test statistic. This test very strongly rejects homogeneity as well, with a test statistic of 1957. Thus, both the random effects model and the fixed effects model are clearly preferred to the pooled model. As pointed out above, it is unfortunately impossible to test whether the random effects or the fixed effects model is more appropriate in this set-up.

I next investigate the magnitude of the different effects. As discussed above, one has to make assumptions on the individual error terms in order to calculate marginal effects for the random effects and for the fixed effects logit models. I do so by setting the individual error term equal to zero. The results are reported in Table 3. As one can see, the probability of staying in the labour force does not depend upon the influence of the business cycle at all. In all three specifications, the impact of the GDP growth rate is insignificant even at the 10% level of significance. The other two probabilities, however, are significantly affected. For the conditional probability of separation, this is the case at the 5% level of significance. The conditional probability of becoming unemployed is even significant at the 1% level. Furthermore, the latter probability is an order of magnitude more important than the former, namely by a factor of 58.5 in the pooled model, a factor of 139 in the random effects models, and a factor of 60 in the fixed effects model. Thus, the business cycle has an impact that is 58.5-139 times stronger for the conditional probability of becoming unemployed than for the conditional probability of separating. This confirms and quantifies the previous results. The magnitude of the marginal effect of GDP growth on the conditional probability of becoming unemployed can be interpreted as follows: a 1% reduction of the GDP growth rate increases the probability of becoming unemployed given one has separated from one’s employer by

<table>
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<th>Pooled</th>
<th>Random effects</th>
<th>Fixed effects</th>
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<tbody>
<tr>
<td>$P(S \mid .)$</td>
<td>-0.0002**</td>
<td>-0.0001***</td>
<td>-0.0008**</td>
</tr>
<tr>
<td>$P(LF \mid .)$</td>
<td>0.0006</td>
<td>0.0007</td>
<td>0.0013</td>
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<tr>
<td>$P(U \mid .)$</td>
<td>-0.0117***</td>
<td>-0.0139***</td>
<td>-0.0120***</td>
</tr>
</tbody>
</table>

Source: IABS-R01 and Statistisches Bundesamt.

Notes: $P(S|E)$, $P(LF|S)$, $P(U|LF)$ are the conditional probabilities of separation given employment, of staying in the labour force upon separation, and of becoming unemployed upon staying in the labour force, respectively. $\overline{X}$ is the mean, SD the standard deviation of a probability. See Tables 8, 9, and 10 for number of observations. Significance levels: *: 10%, **: 5%, ***: 1%.
1.1% in the pooled model, by 1.39% in the random effects model, and by 1.2% in the fixed effects model.

6 Conclusion

In this paper, I have analysed the dynamics of the German labour market by investigating worker flows along various dimensions. First, I provided both time-series and cross-sectional evidence on these flows. This showed that the flows between employment and non-participation, as well as job-to-job flows, are much more important quantitatively than the flows between employment and unemployment. As pointed out by Burgess (1993), this also has implications for the outflow rate from unemployment, as employed job searchers crowd out unemployed job searchers. Furthermore, worker characteristics play an important role for worker flows. In the main part of the paper, I analysed match separations and accessions, and their underlying flows. I found that, in the aggregate, accessions are more volatile over the cycle than separations. While the latter are relatively flat, the former are clearly pro-cyclical. Therefore, hirings seem to play a more important role for labour market dynamics than separations. This issue was further investigated by decomposing the process of becoming unemployed using a method proposed by Nagypál (2004). This analysis showed that separations are relatively flat over the business cycle also for different worker groups. Therefore, the aggregate results do not seem to be caused by composition effects. Finally, I corroborated the above results by running a panel data logit regression for the three conditional probabilities involved in the probability of making a transition from employment to unemployment. I was thus able to directly show that business cycle swings most strongly affect the probability of flowing into unemployment conditional on having separated from the previous match. The probability of a worker separating from his employer itself seems to be only mildly affected by the business cycle. I concluded that the increased inflow into unemployment in a recession is mainly due to the decline in direct job-to-job transitions, and not to increased match break-ups. The second important point made in this paper is that the changing composition of separation flows plays an important role for the dynamics of the labour market over the business cycle. In a recession, direct job-to-job transitions fall while transitions from employment to unemployment rise. This leaves separations relatively unchanged.

The empirical evidence on the relative importance of hirings and separations over the cycle has important implications for the way labour market dynamics should be modelled. As Shimer (2005b) emphasises, the “conventional wisdom” posits that worker flow dynamics are driven by swings in match separations. This understanding of labour market dynamics emanates from the search and matching-type model as epitomised in Mortensen and Pissarides (1994). However, as pointed out above, Mortensen and Pissarides (1999) acknowledge the fact that separations are relatively flat over the cycle. I would therefore rather describe the Mortensen and Pissarides (1994) model as a good tool for thinking about involuntary separations. The latter are however only one determinant of labour market dynamics, the influence of
which seems to be very limited. The evidence found both in this paper and in studies for the US labour market point to hirings, rather than to separations, as the central force underlying worker flow dynamics. More attention to models that adequately stress the role of hirings therefore seems to be called for.

The changing composition of hirings and separations over the cycle leads me to another general point: separations (and turnover) can remain constant even though the composition changes. This fact is not taken into account by many empirical studies looking at the effect of changes in firing costs. This omission stems from the conventional wisdom which implies that the level of separations will be affected by such changes. However, it is possible that new labour market regulations of dismissal protection do not have an impact on the level of separations, but nevertheless have important consequences for the composition of the underlying flows - which would lead to very different worker flow dynamics. This implies that studies that look at the effect of dismissal protection by examining overall separations might yield the wrong conclusions. The (policy) conclusions emanating from the “conventional wisdom” might therefore have to be rethought to an extent.

In sum, the results in this paper provide evidence that recessions do not lead to a burst in match separations. The most important influence on labour market dynamics during recessions seems to be the reduction in the hiring activity of firms. This leads both to reduced job-to-job transitions, and to increased inflows into unemployment. This is a challenge to the conventional wisdom about the link between unemployment and recessions. The results of this paper should therefore be of interest to labour economists and macroeconomists alike.
References


### Table 4: Cross-sectional properties of separation flows

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<tr>
<th></th>
<th>As share of employment</th>
<th>As share of sep.</th>
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<tr>
<td></td>
<td>Sep.</td>
<td>EE</td>
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<tr>
<td><strong>All obs.</strong></td>
<td></td>
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<tr>
<td><strong>By age</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16-24</td>
<td>2.21</td>
<td>0.71</td>
</tr>
<tr>
<td>25-29</td>
<td>4.82</td>
<td>1.44</td>
</tr>
<tr>
<td>30-34</td>
<td>2.85</td>
<td>1.03</td>
</tr>
<tr>
<td>35-39</td>
<td>2.19</td>
<td>0.82</td>
</tr>
<tr>
<td>40-44</td>
<td>1.70</td>
<td>0.67</td>
</tr>
<tr>
<td>45-49</td>
<td>1.42</td>
<td>0.57</td>
</tr>
<tr>
<td>50-54</td>
<td>1.26</td>
<td>0.47</td>
</tr>
<tr>
<td>55+</td>
<td>1.23</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>2.16</td>
<td>0.30</td>
</tr>
<tr>
<td><strong>By sex, age 25-55</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>1.72</td>
<td>0.71</td>
</tr>
<tr>
<td>Female</td>
<td>1.95</td>
<td>0.61</td>
</tr>
<tr>
<td><strong>By industry, age 25-55</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Agr., Energy, Mining</td>
<td>1.61</td>
<td>0.50</td>
</tr>
<tr>
<td>Production</td>
<td>1.29</td>
<td>0.52</td>
</tr>
<tr>
<td>Construction</td>
<td>2.98</td>
<td>0.79</td>
</tr>
<tr>
<td>Trade, transport</td>
<td>2.19</td>
<td>0.90</td>
</tr>
<tr>
<td>Services</td>
<td>2.13</td>
<td>0.75</td>
</tr>
<tr>
<td>State</td>
<td>1.25</td>
<td>0.45</td>
</tr>
<tr>
<td><strong>By education, age 25-55</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>no vt, no Abi</td>
<td>2.04</td>
<td>0.55</td>
</tr>
<tr>
<td>vt, no Abi</td>
<td>1.61</td>
<td>0.64</td>
</tr>
<tr>
<td>no vt, Abi</td>
<td>2.82</td>
<td>0.84</td>
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<tr>
<td>vt, Abi</td>
<td>1.94</td>
<td>0.86</td>
</tr>
<tr>
<td>polytec</td>
<td>1.35</td>
<td>0.75</td>
</tr>
<tr>
<td>university</td>
<td>2.09</td>
<td>0.88</td>
</tr>
<tr>
<td><strong>By working time</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Part-time, with UI</td>
<td>1.97</td>
<td>0.53</td>
</tr>
<tr>
<td>Full time</td>
<td>1.79</td>
<td>0.69</td>
</tr>
</tbody>
</table>

Source: IABS-R01 and author’s calculations.

Notes: Underlying flows calculated cumulatively for 1980-2000 and expressed as monthly averages. vt denotes vocational training, Abi Abitur (high-school degree), and polytec and university stand for a degree from a technical and a regular university, respectively. UI denotes unemployment insurance.
Table 5: Mean and standard deviation of monthly worker flows

<table>
<thead>
<tr>
<th></th>
<th>EE</th>
<th>EU</th>
<th>EN</th>
<th>UE</th>
<th>NE</th>
<th>NU</th>
<th>UN</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{x}$</td>
<td>0.66</td>
<td>0.53</td>
<td>0.85</td>
<td>0.44</td>
<td>0.95</td>
<td>0.26</td>
<td>0.34</td>
</tr>
<tr>
<td>SD</td>
<td>0.58</td>
<td>0.26</td>
<td>0.34</td>
<td>0.19</td>
<td>0.64</td>
<td>0.06</td>
<td>0.08</td>
</tr>
<tr>
<td>SD/$\bar{x}$</td>
<td>0.88</td>
<td>0.49</td>
<td>0.40</td>
<td>0.43</td>
<td>0.67</td>
<td>0.23</td>
<td>0.24</td>
</tr>
</tbody>
</table>

Source: IABS-R01 and author’s calculations.

Notes: Flows normalized by the labour force. $\bar{x}$ is the mean, SD the standard deviation of a flow. All flows calculated on a cumulative basis for 1980-2000 and expressed in per cent.

Table 6: Correlations between labour market flows and GDP growth

<table>
<thead>
<tr>
<th></th>
<th>EE</th>
<th>EU</th>
<th>EN</th>
<th>UE</th>
<th>NE</th>
<th>UN</th>
<th>NU</th>
</tr>
</thead>
<tbody>
<tr>
<td>EE</td>
<td>0.120</td>
<td>-0.152</td>
<td>-0.035</td>
<td>-0.223</td>
<td>0.071</td>
<td>0.395</td>
<td>0.138</td>
</tr>
</tbody>
</table>

Source: Mönch and Uhlig (2005), IABS-R01, and author’s calculations.


Table 7: Cross-correlations of the flows making up accessions and separations

<table>
<thead>
<tr>
<th>Accession flows</th>
<th>Separation flows</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EE</td>
</tr>
<tr>
<td>EE</td>
<td>1.00</td>
</tr>
<tr>
<td>UE</td>
<td>-0.62</td>
</tr>
<tr>
<td>NE</td>
<td>-0.80</td>
</tr>
</tbody>
</table>

Source: IABS-R01 and author’s calculations.

Table 8: Logit regression results for $P(S_i)$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled Coeff. (SE)</th>
<th>Random Effects Coeff. (SE)</th>
<th>Fixed Effects Coeff. (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>q2</td>
<td>0.063*** (0.007)</td>
<td>0.034*** (0.007)</td>
<td>-0.004 (0.007)</td>
</tr>
<tr>
<td>q3</td>
<td>0.211*** (0.007)</td>
<td>0.181*** (0.007)</td>
<td>0.110*** (0.007)</td>
</tr>
<tr>
<td>q4</td>
<td>0.802*** (0.006)</td>
<td>0.790*** (0.006)</td>
<td>0.759*** (0.006)</td>
</tr>
<tr>
<td>vt, no Abi</td>
<td>-0.363*** (0.005)</td>
<td>-0.394*** (0.005)</td>
<td>-0.206*** (0.009)</td>
</tr>
<tr>
<td>no vt, Abi</td>
<td>0.142*** (0.019)</td>
<td>0.269*** (0.023)</td>
<td>0.387*** (0.038)</td>
</tr>
<tr>
<td>vt, Abi</td>
<td>-0.445*** (0.012)</td>
<td>-0.471*** (0.014)</td>
<td>-0.450*** (0.023)</td>
</tr>
<tr>
<td>polytec</td>
<td>-0.549*** (0.013)</td>
<td>-0.621*** (0.015)</td>
<td>-0.860*** (0.028)</td>
</tr>
<tr>
<td>university</td>
<td>-0.415*** (0.011)</td>
<td>-0.442*** (0.013)</td>
<td>-0.789*** (0.029)</td>
</tr>
<tr>
<td>Age 30-35</td>
<td>-0.187*** (0.006)</td>
<td>-0.222*** (0.006)</td>
<td>-0.331*** (0.008)</td>
</tr>
<tr>
<td>Age 35-40</td>
<td>-0.355*** (0.007)</td>
<td>-0.419*** (0.007)</td>
<td>-0.601*** (0.009)</td>
</tr>
<tr>
<td>Age 40-45</td>
<td>-0.479*** (0.007)</td>
<td>-0.578*** (0.008)</td>
<td>-0.812*** (0.011)</td>
</tr>
<tr>
<td>Age 45-50</td>
<td>-0.535*** (0.008)</td>
<td>-0.671*** (0.009)</td>
<td>-0.967*** (0.012)</td>
</tr>
<tr>
<td>Age 50-55</td>
<td>-0.479*** (0.008)</td>
<td>-0.644*** (0.009)</td>
<td>-0.960*** (0.012)</td>
</tr>
<tr>
<td>Production</td>
<td>-0.246*** (0.012)</td>
<td>-0.264*** (0.014)</td>
<td>-0.316*** (0.028)</td>
</tr>
<tr>
<td>Construction</td>
<td>0.246*** (0.013)</td>
<td>0.267*** (0.015)</td>
<td>0.234*** (0.030)</td>
</tr>
<tr>
<td>Trade, Transport</td>
<td>0.047 (0.012)</td>
<td>0.011 (0.014)</td>
<td>-0.117*** (0.028)</td>
</tr>
<tr>
<td>Services</td>
<td>-0.010 (0.012)</td>
<td>-0.002 (0.014)</td>
<td>-0.139*** (0.028)</td>
</tr>
<tr>
<td>State</td>
<td>-0.250*** (0.014)</td>
<td>-0.285*** (0.017)</td>
<td>-0.443*** (0.033)</td>
</tr>
<tr>
<td>Man</td>
<td>-0.041*** (0.006)</td>
<td>-0.078*** (0.005)</td>
<td>-</td>
</tr>
<tr>
<td>duration 2q-5q</td>
<td>-0.448*** (0.006)</td>
<td>-0.349*** (0.010)</td>
<td>0.083*** (0.007)</td>
</tr>
<tr>
<td>duration 6q-10q</td>
<td>-1.045*** (0.007)</td>
<td>-0.843*** (0.010)</td>
<td>-0.790*** (0.008)</td>
</tr>
<tr>
<td>duration 11q-20q</td>
<td>-1.385*** (0.007)</td>
<td>-1.107*** (0.010)</td>
<td>-0.070*** (0.008)</td>
</tr>
<tr>
<td>duration 21q-30q</td>
<td>-1.763*** (0.008)</td>
<td>-1.455*** (0.011)</td>
<td>-0.140*** (0.010)</td>
</tr>
<tr>
<td>duration 31q-50q</td>
<td>-1.852*** (0.008)</td>
<td>-1.465*** (0.009)</td>
<td>0.488*** (0.012)</td>
</tr>
<tr>
<td>duration 50q+</td>
<td>-1.777*** (0.009)</td>
<td>-1.259*** (0.011)</td>
<td>1.867*** (0.015)</td>
</tr>
<tr>
<td>GDP growth</td>
<td>-0.003* (0.001)</td>
<td>-0.003*** (0.001)</td>
<td>-0.003*** (0.001)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-1.355*** (0.013)</td>
<td>-1.491*** (0.016)</td>
<td>-</td>
</tr>
</tbody>
</table>

Log-likelihood: -999661 -999661 -719528

No. of observations: 4,831,513 (pooled and r.e.); 4,174,223 (f.e.)
Base categories: Quarter: quartal1; Education: no vt, no Abi; Industry: Agr., Energy, Mining;
Age: Alter 25-30; Duration: 1q
Significance levels: *: 10%, **: 5%, ***: 1%
Data: IABS-R01 and author's calculations.
Table 9: Logit regression results for $P(\text{LF}_j)$.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pooled</th>
<th>Random Effects</th>
<th>Fixed Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
<td>Coeff. (SE)</td>
</tr>
<tr>
<td>q2</td>
<td>-0.307***</td>
<td>-0.357***</td>
<td>-0.396***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.017)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>q3</td>
<td>-0.309***</td>
<td>-0.367***</td>
<td>-0.404***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.016)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>q4</td>
<td>-0.087***</td>
<td>-0.136***</td>
<td>-0.166***</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.015)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>vt, no Abi</td>
<td>0.304***</td>
<td>0.341***</td>
<td>0.140***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.011)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>no vt, Abi</td>
<td>-0.780***</td>
<td>-0.817***</td>
<td>-0.364***</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.046)</td>
<td>(0.068)</td>
</tr>
<tr>
<td>vt, Abi</td>
<td>0.185***</td>
<td>0.255***</td>
<td>0.258***</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.029)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>polytec</td>
<td>0.422***</td>
<td>0.568***</td>
<td>0.827***</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.035)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>university</td>
<td>0.011</td>
<td>0.074***</td>
<td>0.698***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.028)</td>
<td>(0.060)</td>
</tr>
<tr>
<td>Age 3035</td>
<td>0.366***</td>
<td>0.405***</td>
<td>0.091</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.015)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Age 3540</td>
<td>0.528***</td>
<td>0.592***</td>
<td>0.215***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.017)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Age 4045</td>
<td>0.630***</td>
<td>0.740***</td>
<td>0.516***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.017)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>Age 4550</td>
<td>0.578***</td>
<td>0.695***</td>
<td>0.624***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Age 5055</td>
<td>0.289***</td>
<td>0.353***</td>
<td>0.437***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Production</td>
<td>0.182***</td>
<td>0.303***</td>
<td>0.095*</td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.030)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Construction</td>
<td>0.470***</td>
<td>0.555***</td>
<td>0.166***</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.033)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>Trade, transport</td>
<td>0.191***</td>
<td>0.311***</td>
<td>0.118*</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.031)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Services</td>
<td>-0.006</td>
<td>0.110***</td>
<td>0.088**</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.030)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>State</td>
<td>-0.104***</td>
<td>-0.060</td>
<td>-0.084</td>
</tr>
<tr>
<td></td>
<td>(0.029)</td>
<td>(0.036)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Man</td>
<td>0.364***</td>
<td>0.420***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.012)</td>
<td>-</td>
</tr>
<tr>
<td>duration 2q-5q</td>
<td>0.410***</td>
<td>0.405***</td>
<td>0.237**</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.014)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>duration 6q-10q</td>
<td>0.250***</td>
<td>0.244***</td>
<td>0.013</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.017)</td>
<td>(0.020)</td>
</tr>
<tr>
<td>duration 11q-20q</td>
<td>0.095***</td>
<td>0.083***</td>
<td>-0.103***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.017)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>duration 21q-30q</td>
<td>-0.220***</td>
<td>-0.209***</td>
<td>-0.012***</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.020)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>duration 31q-50q</td>
<td>-0.602**</td>
<td>-0.618***</td>
<td>-0.063***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.020)</td>
<td>(0.030)</td>
</tr>
<tr>
<td>duration 50q+</td>
<td>-0.935***</td>
<td>-0.958***</td>
<td>0.302***</td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.022)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>GDP growth</td>
<td>0.002</td>
<td>0.003</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.209***</td>
<td>-0.454***</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.027)</td>
<td>(0.034)</td>
<td>-</td>
</tr>
</tbody>
</table>

Log-likelihood: -181648, -182426, -54074

No. of observations: 290,405 (pooled and r.e.); 148,824 (f.e.).
Base categories and significance levels as in Table 8.
Data: IABS-R01 and author’s calculations.
Table 10: Logit regression results for $P(U|.)$

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coeff. (SE)</th>
<th>Coeff. (SE)</th>
<th>Coeff. (SE)</th>
</tr>
</thead>
<tbody>
<tr>
<td>quartal2</td>
<td>0.079*** (0.024)</td>
<td>0.085*** (0.023)</td>
<td>0.040 (0.028)</td>
</tr>
<tr>
<td>quartal3</td>
<td>0.223*** (0.018)</td>
<td>0.223*** (0.023)</td>
<td>0.208*** (0.027)</td>
</tr>
<tr>
<td>quartal4</td>
<td>0.186*** (0.016)</td>
<td>0.192*** (0.020)</td>
<td>0.424*** (0.025)</td>
</tr>
<tr>
<td>vt, no Abi</td>
<td>-0.502*** (0.012)</td>
<td>-0.521*** (0.016)</td>
<td>-0.016 (0.023)</td>
</tr>
<tr>
<td>no vt, Abi</td>
<td>-0.743*** (0.063)</td>
<td>-0.751*** (0.085)</td>
<td>0.130 (0.134)</td>
</tr>
<tr>
<td>vt, Abi</td>
<td>-1.165*** (0.035)</td>
<td>-1.233*** (0.046)</td>
<td>-0.142** (0.067)</td>
</tr>
<tr>
<td>polytec</td>
<td>-1.322*** (0.039)</td>
<td>-1.423*** (0.053)</td>
<td>-0.156** (0.085)</td>
</tr>
<tr>
<td>university</td>
<td>-1.200*** (0.033)</td>
<td>-1.330*** (0.046)</td>
<td>-0.095 (0.096)</td>
</tr>
<tr>
<td>Alter30-35</td>
<td>-0.094*** (0.015)</td>
<td>-0.167*** (0.021)</td>
<td>-0.168** (0.028)</td>
</tr>
<tr>
<td>Alter35-40</td>
<td>-0.094*** (0.018)</td>
<td>-0.196*** (0.023)</td>
<td>-0.281*** (0.034)</td>
</tr>
<tr>
<td>Alter40-45</td>
<td>-0.053*** (0.019)</td>
<td>-0.190*** (0.026)</td>
<td>-0.392*** (0.041)</td>
</tr>
<tr>
<td>Alter45-50</td>
<td>0.041** (0.021)</td>
<td>-0.010* (0.029)</td>
<td>-0.425*** (0.049)</td>
</tr>
<tr>
<td>Alter50-55</td>
<td>0.177*** (0.021)</td>
<td>0.072*** (0.031)</td>
<td>-0.355*** (0.055)</td>
</tr>
<tr>
<td>Production</td>
<td>-0.296*** (0.031)</td>
<td>-0.153*** (0.046)</td>
<td>-0.080 (0.073)</td>
</tr>
<tr>
<td>Construction</td>
<td>0.466*** (0.033)</td>
<td>0.620*** (0.050)</td>
<td>0.266*** (0.077)</td>
</tr>
<tr>
<td>Trade, Transport</td>
<td>-0.735*** (0.031)</td>
<td>-0.618*** (0.047)</td>
<td>-0.284*** (0.073)</td>
</tr>
<tr>
<td>Services</td>
<td>-0.650*** (0.031)</td>
<td>-0.618*** (0.047)</td>
<td>-0.393*** (0.074)</td>
</tr>
<tr>
<td>State</td>
<td>-0.501*** (0.038)</td>
<td>-0.510*** (0.057)</td>
<td>-0.460*** (0.088)</td>
</tr>
<tr>
<td>Man</td>
<td>-0.260*** (0.011)</td>
<td>-0.403*** (0.018)</td>
<td>- -</td>
</tr>
<tr>
<td>duration 2q-5q</td>
<td>0.050*** (0.015)</td>
<td>0.035*** (0.019)</td>
<td>0.057*** (0.022)</td>
</tr>
<tr>
<td>duration 6q-10q</td>
<td>-0.460*** (0.018)</td>
<td>-0.434*** (0.023)</td>
<td>-0.218*** (0.027)</td>
</tr>
<tr>
<td>duration 11q-20q</td>
<td>-0.719*** (0.019)</td>
<td>-0.712*** (0.023)</td>
<td>-0.378*** (0.030)</td>
</tr>
<tr>
<td>duration 21q-30q</td>
<td>-0.717*** (0.023)</td>
<td>-0.722*** (0.030)</td>
<td>-0.564*** (0.040)</td>
</tr>
<tr>
<td>duration 31q-50q</td>
<td>-0.781*** (0.024)</td>
<td>-0.803*** (0.032)</td>
<td>-0.698*** (0.047)</td>
</tr>
<tr>
<td>duration 50q+</td>
<td>-0.996*** (0.030)</td>
<td>-1.082*** (0.039)</td>
<td>-1.011*** (0.072)</td>
</tr>
<tr>
<td>GDP growth</td>
<td>-0.047*** (0.003)</td>
<td>-0.048*** (0.004)</td>
<td>-0.049*** (0.005)</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.946*** (0.036)</td>
<td>0.906*** (0.052)</td>
<td>- -</td>
</tr>
</tbody>
</table>

Log-likelihood: -110962 / -105563 / -29055

No. of observations: 174,242 (pooled and r.e.); 77,817 (l.e.).
Base categories and significance levels as in Table 8.
Data: IABS-R01 and author’s calculations.

Table 11: Tests for heterogeneity

|           | $P(S|.)$ | $P(LF|.)$ | $P(U|.)$ |
|-----------|---------|---------|---------|
| LR        | 9179    | 7194    | 10797   |
| Hausman   | 130733  | 4201    | 2028    |

Notes:
The likelihood ratio test (LR) compares the random effects model to the pooled model; the Hausman test compares the fixed effects model to the pooled model. The null hypothesis is homogeneity.
B Figures

Figure 6: The evolution of worker flows, 1980-2000

![Graph showing the evolution of worker flows from 1980 to 2000 with shaded areas indicating times of recession.](image)

Source: IABS-R01 and author’s calculations.

Notes: A flow XY indicates a transition from labour market state X to labour market state Y. The labour market states considered are dependent-status employment (E), unemployment (U), and non-participation (N). See the text for the precise definitions. All flows are cumulatively calculated, normalized by the labour force and expressed per annum. Shaded areas are times of recession.

Figure 7: The share of different unemployment duration classes in total transitions from unemployment to employment, 1980-2000

![Graph showing the share of different unemployment duration classes from 1980 to 2000 with shaded areas indicating times of recession.](image)

Source: IABS-R01 and author’s calculations.

Notes: Transitions calculated cumulatively. Shaded areas are times of recession.
Figure 8: The transition rate from employment to unemployment within a given year, 1980-2000

Source: IABS-R01 and author’s calculations.
Notes: EU, the flow from employment to unemployment, is calculated cumulatively. E is dependent-status employment. Shaded areas are times of recession.

Figure 9: The transition rate from unemployment to employment within a given year, 1980-2000.

Source: IABS-R01 and author’s calculations.
Notes: UE, the flow from unemployment to employment, is calculated cumulatively. U is the state of unemployment as defined in the text. Shaded areas are times of recession.
Figure 10: The Nagypal (2004) decomposition of becoming unemployed and ensuing worker flows

- Work at employer
  - Separate
    - Yes → 1
    - No
  - Stay in LF
    - Yes → 2
    - No → Remain with employer
  - Become UE'd
    - Yes → 3
    - No → EN flow
- EU flow
- EE flow

1. \( P(S|\cdot) \)
2. \( P(LF|\cdot) \)
3. \( P(U|\cdot) \)
Figure 11: Conditional probability of separation for workers with different education

Source: IABS-R01 and author’s calculations.
Notes: vt denotes vocational training, Abi is Abitur; polytec, and uni indicate a degree from a polytechnical university and from a university, respectively. Shaded areas are times of recession.

Figure 12: Conditional probability of separation for workers in different industrial sectors

Source: IABS-R01 and author’s calculations.
Notes: Shaded areas denote times of recession.