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The Ins and Outs of German Unemployment

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The Ins and Outs of German Unemployment

(very preliminary)

Carsten Ochsen*

January 29, 2015

Abstract

This paper analyzes the contribution of flow rates and flow probabilities for unemployment dynamics of different age groups using administrative panel data for Germany. I consider a three-state model and allow for flows from/to inactivity (out of the labor force) to/from unemployment. The dynamics that arise from the inactivity and activity flows account for about 40% of unemployment dynamics (inactivity is more important), while the contribution of separation and job finding is roughly 40% and 20% respectively. Across five age cohorts I find remarkable differences in flow contributions. In the steady state approach the overall contribution of inflow and outflow rates is roughly 50%:50%, but for the non-steady state approach I find a slightly stronger contribution of the outflow rates. I also point out the possibility of a regional aggregation bias that can be of similar importance as the time aggregation bias.

Keywords: separation rate, job finding rate, unemployment dynamics, demographic change

JEL classification: J63, J64, E24, J10

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1 Introduction

In this paper I study the contribution of unemployment inflows and outflows to the dynamics of the unemployment rate for different age groups in Germany. While in recent studies the focus is more on the relative contribution of in- and outflows, I will additionally show that younger, prime age, and older workers differ significantly in their labor market flow rates using administrative data from the German Federal Employment Agency. I also provide an alternative solution to consider the flows from/to the non-labor market to/from unemployment that allows a measurement of their relative contribution.

With respect to the literature on the relative importance of separation and job finding rates for the dynamics of the unemployment rate, Hall (2005) and Shimer (2005, 2012) conclude for the US labor market that the job finding rate is more relevant, while Darby et al. (1986), Fujita and Ramey (2009), and Elsby et al. (2009) come to the opposite conclusion and find evidence for a relative larger contribution of job separation. Smith (2011) find evidence for UK that increases in the unemployment rate come along with rising separations. Petrongolo and Pissarides (2008) conclude that both flow rates are of similar importance for the UK labor market, while job finding rates contribute relative more to the French and Spanish unemployment fluctuations.

When older and younger workers are perfect substitutes, the findings in the literature are relevant for both age groups similarly. This is important because labor markets in developed countries face an increasing challenge because of demographic change, particularly from population aging. The end of the baby boom and persistently low fertility rates fundamentally changed the age composition of the working age population and, hence, of the labor force in many developed countries.

The literature on the effects of differences in population age cohorts on

unemployment originates in a study by Perry (1970), who developed the hypothesis of cohort crowding based on the assumption that young and prime age workers are perfect substitutes. That is, they do not differ in employment relevant attributes, and hence, age-related changes in labor demand are inconsistent with this theory.¹ Shimer (2001) argues that a high proportion of young workers provides an incentive for firms to create new jobs because younger workers undertake more search activities, which reduce the firms' recruitment costs. Burgess (1993) and Pissarides and Wadsworth (1994) find evidence in Great Britain that rates of job separation are higher for young workers because a higher proportion of such workers engage in on-the-job search activities.

A higher probability of job separation and lower job finding rates for older workers can result from age discrimination (Johnson and Neumark, 1997, Charness and Villeval, 2007, Langot and Moreno-Galbis 2008) and assumed or actual productivity differentials (Haltiwanger et al., 1999, Hellerrstein et al., 1999, Daniel and Heywood, 2007). Productivity may increase with age if job experience is important (Autor et al., 2003, Nordström Skans 2008) or decline if human capital depreciates over time, particularly due to technological change or a loss of manual abilities (Bartel and Sicherman 1993, Börsch-Supan 2003, Autor and Dorn 2009). Concerning cognitive abilities, the age effect is more complex. The ability to engage in information processing is lower among senior workers (Baltes and Lindenberger, 1997), which makes it difficult to employ older workers in challenging jobs, such as flight control. Employment effects may also stem from differences between the age-earning profile and the age-productivity profile, for which Lazear (1979) and Hutchens (1987, 1989) provide empirical evidence.

Considering these findings, I argue that it is not evident which implications the increasing relative appearance of older job seekers and job can-

¹See Shimer (2001) for a detailed discussion of methodical and theoretical issues.

didates may have relative to job-worker matching in the labor market and, ultimately, for unemployment dynamics. This study adds to the literature as follows. First, I provide an alternative solution for both the theoretical and empirical analyses of flow contributions on unemployment dynamics in a three-state model (flows between employment, unemployment, and inactivity). Second, this is the first contribution, that analyze age related flow contributions to unemployment fluctuations. Third, this is the first study that considers panel data with regional flow rates in the empirical analysis. Fourth, I consider the time aggregation bias (Shimer (2012)) and show that there is also a regional aggregation bias, that can be of similar importance.

Main findings are: The dynamics that arise from the inactivity and activity flows account on average for about 40% of unemployment dynamics. In the steady state approach the inactivity contribution is twice as large as that of the activity flow, while in the non-steady state case the ratio is 5:1. The remaining roughly 60% of unemployment fluctuations are explained by the separation rate and job finding rate respectively. The contribution of the separation rate is about one and a half times larger than the unemployment dynamics due to the job finding rate. Across five age cohorts I find remarkable differences in flow contributions. For example, the contribution of separation rates is larger for older workers, while the activity flow has a larger contribution for younger workers. Also, the non-activity flow is more important for the explanation of unemployment fluctuations than the job finding rate. The overall contribution of inflow and outflow rates is roughly 50%:50%, but in the dynamic approach I find a slightly stronger contribution of the outflow rates. I consider the time aggregation bias and find that it is useful to show the differences to the standard results related to arrival rates. However, I also point out that it is possible to have a regional aggregation bias. As an example, I aggregate my data across regions and compare the results with the standard results. The differences are at least as large, as

for the time aggregation bias.

The remainder of the paper is organized as follows. In section 2, I provide a theoretical model for the analysis of relative contributions of flow rates to the dynamics of unemployment. Section 3 provides an analysis of administrative data for the German labor market using the approach from section 2. Finally, I summarize the main findings in section 4.

2 The Dynamics of Unemployment

Following Elsby et al. (2009) for the US, Smith (2011) for UK, and Petrongolo and Pissarides (2008) for different European countries, I describe the transition rates relating to unemployment inflows and outflows to unemployment dynamics in Germany. I provide an alternative three-state model and use monthly administrative data from the German Federal Employment Agency to calculate the unemployment inflow and outflow variables to measure their relative contribution to unemployment fluctuations.

In a two-state model only the flows between unemployment U and employment E are considered and workers neither enter nor exit the labor force. The three-state model considers flows out of and into the labor force from/to the the stock inactivity I . I consider flows from unemployment to employment UE , flows from employment to unemployment EU , flows from unemployment to inactivity UI , and flows from inactivity to unemployment IU . During period t the following transition rates according to a Poisson process are considered: job finding rate $f_t = UE_t/U_{t-1}$, non-activity rate $n_t = UI_t/U_{t-1}$, separation rate $s_t = EU_t/E_{t-1}$, and activity rate $a_t = IU_t/E_{t-1}$. The latter arrival rate should be in fact related to I . However, the stock of inactive people is difficult to measure. In addition, using the stock of the employed has the advantage to be more compatible with the equilibrium unemployment rate calculated below. For all transition rates we have $0 \leq f_t, n_t, s_t, a_t \leq 1$.

The official unemployment rate $u_t = U_t / (U_t + E_t)$ will be approximated using the equilibrium unemployment rate u_t^* . In this case, the stock of the unemployed is $U_t = U_{t-1} + s_t E_t - f_t U_t$. Adding the flows from and to inactivity, $a_t E_t$ and $n_t U_t$, and dividing by the labour force yield:

$$u_t = u_{t-1} + s_t (1 - u_t) - f_t u_t + a_t (1 - u_t) - n_t u_t \quad (1)$$

In steady state, inflow equals outflow, $\dot{u}_t = 0$. Rearranging this steady state unemployment rate lead to

$$u_t^* = \frac{s_t + a_t}{s_t + a_t + f_t + n_t}. \quad (2)$$

In contrast to Petrongolo and Pissarides (2008) and Smith (2011) I uses a_t instead of using the outflow rate from employment to inactivity weighted by the proportion of the outflow from inactivity to unemployment to all outflows from I . Similarly, Smith (2011) uses instead n_t the outflow rate from unemployment to inactivity weighted by the proportion of the outflow from inactivity to employment to all outflows from I . Both weights sum up to 1. The flow rates s_t and a_t can be added to the inflow rate $i_t = s_t + a_t$ and the rates f_t and n_t add up to the exit rate $e_t = f_t + n_t$, with $0 \leq s_t, i_t \leq 1$.

Taking first differences of i_t and e_t allows us to measure the contribution of s_t, a_t, f_t ; and n_t :

$$\frac{\Delta i_t}{i_{t-1}} = \frac{\Delta s_t}{i_{t-1}} + \frac{\Delta a_t}{i_{t-1}} \quad (3)$$

$$\frac{\Delta e_t}{e_{t-1}} = \frac{\Delta f_t}{e_{t-1}} + \frac{\Delta n_t}{e_{t-1}} \quad (4)$$

Equation (2) can then be written as

$$u_t^* = \frac{i_t}{i_t + e_t}. \quad (5)$$

Following Petrongolo and Pissarides (2008) and Smith (2011) I now show the relative contribution to unemployment fluctuations if unemployment inflows and outflows in a three-state model resulting from changes in i_t and e_t . This relative contribution is, however, related to the equilibrium unemployment rate u_t^* . We therefore have to consider also the relative contribution of u_t^* to u_t . Differencing (2) yields:

$$\Delta u_t^* = \frac{i_t}{i_t + e_t} - \frac{i_{t-1}}{i_{t-1} + e_{t-1}} = (1 - u_t^*) u_{t-1}^* \frac{\Delta i_t}{i_{t-1}} - u_t^* (1 - u_{t-1}^*) \frac{\Delta e_t}{e_{t-1}}. \quad (6)$$

Assuming that $u_t^* = u_{t-1}^*$ we can approximate the percentage change in u_t^* by

$$\frac{\Delta u_t^*}{u_{t-1}^*} \approx \underbrace{(1 - u_{t-1}^*) \frac{\Delta i_t}{i_{t-1}}}_{u_t^{*i}} - \underbrace{(1 - u_{t-1}^*) \frac{\Delta e_t}{e_{t-1}}}_{u_t^{*e}}. \quad (7)$$

u_t^{*i} measures the contribution of changes in the inflow rate i_t to changes in u_t^* while u_t^{*e} measures the amount of variation of the exit rate e_t . An alternative way to calculate the relative contributions of s_t, a_t, f_t ; and n_t is given by

$$\begin{aligned}
u_t^{*s} &= (1 - u_{t-1}^*) \frac{\Delta s_t}{i_{t-1}}, u_t^{*a} = (1 - u_{t-1}^*) \frac{\Delta a_t}{i_{t-1}}, \\
u_t^{*f} &= (1 - u_{t-1}^*) \frac{\Delta f_t}{e_{t-1}}, u_t^{*n} = (1 - u_{t-1}^*) \frac{\Delta n_t}{e_{t-1}}.
\end{aligned} \tag{8}$$

Finally, the individual flow related variance contribution to the dynamics in u_t^* is equivalent to the concept of beta in finance. For example, for the inflow rate i_t and exit rate e_t we get

$$\beta^i = \frac{\text{cov}(\Delta u_{t-1}^*, u_t^{*i})}{\text{var}(\Delta u_{t-1}^*)} \text{ and } \beta^e = \frac{\text{cov}(\Delta u_{t-1}^*, u_t^{*e})}{\text{var}(\Delta u_{t-1}^*)}, \tag{9}$$

with $\beta^i + \beta^e = 1$. From this we can calculate the contributions $\beta^s + \beta^a + \beta^f + \beta^n = 1$, the percentage contributions of the unemployment inflows and outflows in a three-state model.

2.1 Non-Steady State

With respect to a non-steady state decomposition I follow Smith (2011) and calculate the contribution of the flow rates of changes in the official unemployment rate u_t . Using (1) and (5)

$$u_t = \frac{i_t}{i_t + e_t} - \frac{\dot{u}_t}{i_t + e_t} = \frac{i_t}{i_t + e_t} - \frac{du_t}{dt} \frac{1}{i_t + e_t}. \tag{10}$$

This equation allows to calculate the relative contribution of s_t, a_t, f_t , and n_t on u_t . Differencing (10) with respect to time, we get the following second-order differential equation:

$$\frac{d^2 u_t}{dt^2} = \frac{du_t^*}{dt} (i_{t-1} + e_{t-1}) + \frac{du_t}{dt} \left[\frac{1}{i_t + e_t} \frac{d(i_t + e_t)}{dt} - (i_t + e_t) \right]. \quad (11)$$

We get the following recursive expression for the dynamics of the official unemployment rate, if we treat (11) as first order differential equation in du/dt and discretise and rearrange:

$$\Delta u_t = \frac{(i_t + e_t) i_{t-1}}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}} \frac{\Delta u_t^*}{u_{t-1}^*} + \frac{i_t + e_t}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}} \Delta u_{t-1} \quad (12)$$

Equation (12) shows that high transition rates will lead to closer movements of the official unemployment rate and the equilibrium rate. Low transition rates, however, lead to a larger relative effect of past changes in both transition rates and equilibrium unemployment. The term $\Delta u_t^*/u_{t-1}^*$ can be interpreted as the rate of convergence to the steady state unemployment rate. The contribution of inflow and exit rates to changes in the official unemployment rate can be calculated using (12) and the relationship in (7):

$$u_t^i = u_t^{*i} \frac{(i_t + e_t) i_{t-1}}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}} + u_{t-1}^i \frac{i_t + e_t}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}}, \quad (13)$$

with $u_0^i = 0$, and

$$u_t^e = u_t^{*e} \frac{(i_t + e_t) i_{t-1}}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}} + u_{t-1}^e \frac{i_t + e_t}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}}, \quad (14)$$

with $u_0^e = 0$.

The relative contributions of s_t , a_t , f_t ; and n_t can be calculated analogue following equations (7) and (8). The difference to equation (7), however, is that we have here an additional contribution to the variation in official

unemployment from the initial conditional time $t = 0$

$$u_t^0 = u_{t-1}^0 \frac{i_t + e_t}{(i_t + e_t)^2 + i_{t-1} + e_{t-1}},$$

with $u_0^0 \equiv u_0 - u_0^*$.

Finally, the individual flow related variance contribution to the dynamics in u_t can be measured with the concept of beta in finance, again. For example, for the inflow rate i_t and exit rate e_t we get

$$\beta^i = \frac{\text{cov}(\Delta u_t, u_t^i)}{\text{var}(\Delta u_t)} \text{ and } \beta^e = \frac{\text{cov}(\Delta u_t, u_t^e)}{\text{var}(\Delta u_t)}. \quad (15)$$

From this we can calculate again the contributions $\beta^i + \beta^e = \beta^s + \beta^a + \beta^f + \beta^n$.

2.2 Time Aggregation Bias

To take the time aggregation bias into account (Shimer 2012) I will use the arrival rate to calculate their corresponding probabilities. Although the time aggregation bias is "a logical extreme"², I substitute in the empirical section the flow rates above for probabilities to account for continuous time transitions and to compare the two approaches. This is necessary when an individual will lose and find (or find and lose) a job within the considered time period. Using discrete data and corresponding arrival rates will yield biased measures of the instantaneous transitions. According to the literature, however, this measurement bias appears to be small.³

I follow Shimer (2012) and calculate the probability $X_t \in [0, 1]$ as function of the corresponding arrival rate x_t using $X_t = 1 - e^{-x_t}$. However,

²Shimer (2012), p. 131.

³See, for example, Shimer (2012), Elsby et al. (2009), Fujita and Ramey (2009), and Petrongolo and Pissarides (2008).

while in case of the arrival rates $i_t = s_t + a_t$ and $e_t = f_t + n_t$ is true, $I_t = 1 - e^{-i_t} > S_t + A_t$ (with $S_t = 1 - e^{-s_t}$ and $A_t = 1 - e^{-a_t}$). The same holds for E_t, F_t , and N_t . I use in the empirical section the definitions $S_t + A_t \equiv I_t$ and $F_t + N_t \equiv E_t$. This is relevant for the equations (5), (7), (13), and (14) when they are applied in the empirical section.

3 Data and Empirical Analysis

The following analysis will point out the relative contribution of inflow and outflow rates to the fluctuations of unemployment in Germany. I use monthly data with exact information on the stocks of employment E and unemployment U as well as on flows between these two stocks and between unemployment and inactivity I (three-state model), e.g., between period $t - 1$ and t .

I use the flows from unemployment to employment UE , from employment to unemployment EU , from unemployment to inactivity UI , and from inactivity to unemployment IU to calculate the arrival rates: job finding rate $f_t = UE_t/U_{t-1}$, non-activity rate $n_t = UI_t/U_{t-1}$, separation rate $s_t = EU_t/E_{t-1}$, and activity rate $a_t = IU_t/E_{t-1}$. Using in the latter case the stock of the employed has the advantage to be more compatible with the equilibrium unemployment rate calculated next. The inflow rate is $i_t = s_t + a_t$ and the exit rate is $e_t = f_t + n_t$. For all transition rates we have $0 \leq i_t, e_t, f_t, n_t, s_t, a_t \leq 1$. The causes for the transition rates a_t and n_t are discouragement, apprenticeship, training, and medical leave.

I use administrative official data from the German Federal Employment Agency from January 2007 to December 2013. In contrast to the existing literature I use panel data and five age groups, for which I have all stock and flow data.

The data are available for overall 473 regions (Kreise) in Germany. To show that regional aggregation can have significant effects on the measured

flow rates, the complete panel data is used first and subsequent in section 3.1 I aggregate over regions. In the latter case I have one (regional average) observation per month. Before 2007 the regional disaggregated data are not available.

With regional index r , equation (5) is equal to

$$u_{rt}^* = \frac{i_{rt}}{i_{rt} + e_{rt}}, \quad (16)$$

and equations (7) and (13) are equal to (equation (14) is equivalent to (13))

$$\frac{\Delta u_{rt}^*}{u_{rt-1}^*} \approx \underbrace{(1 - u_{rt-1}^*)}_{u_{rt}^{*i}} \frac{\Delta i_{rt}}{i_{rt-1}} - \underbrace{(1 - u_{rt-1}^*)}_{u_{rt}^{*e}} \frac{\Delta e_{rt}}{e_{rt-1}}, \quad (17)$$

$$u_{rt}^i = u_{rt}^{*i} \frac{(i_{rt} + e_{rt}) i_{rt-1}}{(i_{rt} + e_{rt})^2 + i_{rt-1} + e_{rt-1}} + u_{rt-1}^i \frac{i_{rt} + e_{rt}}{(i_{rt} + e_{rt})^2 + i_{rt-1} + e_{rt-1}}. \quad (18)$$

In addition, the data are available for the age cohorts 15-24 years, 25-34 years, 35-44 years, 45-54 years, and 55-64 years old. As we will see below, age cohorts differ markedly in their labor market flows and due to the ongoing aging of the German labor force, it is important to know what differences are existing for younger and older workers.

To illustrate the direct relationship between age group related unemployment rates and the overall unemployment rate, we rearrange the equilibrium unemployment rate (16) using age-specific rates weighted at the relevant population share p_j , with $j = 1, 2, 3, \dots, J$,

$$u_{rt}^* = \sum_{j=1}^J p_j u_{jrt}^* = \sum_{j=1}^J p_j \frac{i_{jrt}}{i_{jrt} + e_{jrt}}. \quad (19)$$

From equation (19) it follows, that equal inflow and exit rates across age groups would make weighting by population shares unnecessary. However, since age specific equilibrium rates are different, their flow rates will be different too.

Table 1 shows average values for the arrival rates, the equilibrium unemployment rate using the inflow and exit rates, and the official unemployment rate for each age group and for all workers for the period January 2007 to December 2013 and 473 regions in Germany.

Table 1: Average Values on Arrival Rates and Unemployment Rates

age groups	f_{rt}	n_{rt}	s_{rt}	a_{rt}	e_{rt}	i_{rt}	u_{rt}^*	u_{rt}
share 15-24	0.182	0.307	0.011	0.022	0.489	0.033	7.03	6.63
share 25-34	0.116	0.161	0.011	0.014	0.277	0.025	8.99	8.91
share 35-44	0.096	0.144	0.007	0.008	0.240	0.015	6.55	6.56
share 45-54	0.081	0.138	0.007	0.008	0.219	0.015	7.21	7.26
share 55-64	0.043	0.124	0.006	0.008	0.167	0.014	7.91	8.28
all	0.095	0.158	0.008	0.010	0.253	0.018	7.27	7.25

Notes: The average arrival rates are calculated as described in the previous section. The equilibrium rate is calculated according to equation (16). All average values are unweighted. Period: January 2007 - December 2013. Number of regions: 473. Number of observations: 32,709.

Several findings are striking.⁴ With respect to the exit rate the non-activity rate is always larger than the job finding rate. In addition, all three measures for exiting unemployment are declining, the older the worker are. For the inflow rate, I also find that the activity rates are always larger than the separation rates. As well as the exit flows the inflow rates decline with increasing age of the labor force. From this it follows, that a) the consideration of age groups seems to be important and b) the consideration of a three-state model is necessary for a better understanding of labor market dynamics.

⁴For the arrival rates we have the relationships $i_t = s_t + a_t$ and $e_t = f_t + n_t$.

The last two columns show average values for the equilibrium unemployment rate and the official unemployment rate. In most cases, the equilibrium rate is very near to the official one. This is a further indication of age group related significant differences in flow rates.

Before we continue with the relative contribution of the arrival rates, we take a look at the distribution of unemployment by duration shown in Table 2. Each row sum up to 1 and shows the percentage distribution by duration for each of the considered age group. Long-term unemployment is by definition a duration of 12 month or more. For the age cohort 55-64 years this applies to almost 50%, and within three month only 20% of the stock will leave unemployment. In contrast, almost 57% of the age cohort 15-24 years leave unemployment within the first three month and only 8,3% of them are on average long-term unemployed. A closer look to the other cohorts point out, that the shares in the different duration categories first fall and then rise with age almost continuously. This finding is in line with the pattern in Table 1.

Table 2: Basic Statistics on Unemployment Duration by Age Groups

age groups	shares by unemployment duration (in months)					
	<1	≥1...<3	≥3...<6	≥6...<12	≥12...<24	≥24
share 15-24	26.1	31.0	21.4	14.2	6.0	2.3
share 25-34	14.2	21.1	19.4	19.5	14.5	11.3
share 35-44	11.5	17.6	17.1	18.7	16.0	19.1
share 45-54	10.3	15.8	15.8	18.1	16.7	23.3
share 55-64	7.7	12.4	13.9	18.8	21.0	26.2
all	12.6	18.4	17.1	18.3	15.8	17.8

Table 3 shows the relative contribution of the arrival rates for the different age groups. As pointed out in the former section, the parameters $\beta^i = \beta^s + \beta^a$ and $\beta^e = \beta^f + \beta^n$ (with $\beta^i + \beta^e = \beta^s + \beta^a + \beta^f + \beta^n = 1$) measure the percentage contributions of the unemployment inflows and outflows

in a three-state model. The overall relative contribution for all workers of inflow and outflow is almost 50%:50%. This applies not, however, to the overall comparison of the separation rate and the job finding rate. Also noticeable is that $\beta^n > \beta^f$. More generally, inflow rates are more important for unemployment of younger workers, while exit rates are more important for older workers. While separation rates are rising with age, job finding rates are larger for prime age workers.⁵ It should be mentioned that β^n includes besides discouraged workers also those who leave unemployment for an apprenticeship, for training, and for medical leave. The latter is more important for older workers, while apprenticeship is a frequent reason for the youth. The difference between a two-state and a three state model, the flows from and to inactivity, explains on average more than 40%. For the old it is almost 50% and for the youth even 75%. Finally, about one third of the youth unemployment rate variation is explained by flows from activity to unemployment. These are the young people born into unemployment.

Table 3: Contribution from the Transition Rates

age groups	β^i	β^e	β^s	β^a	β^f	β^n	$cor(u, u^*)$
share 15-24	0.454	0.546	0.105	0.349	0.144	0.402	0.887
share 25-34	0.472	0.528	0.311	0.161	0.233	0.295	0.910
share 35-44	0.495	0.505	0.350	0.145	0.234	0.271	0.868
share 45-54	0.527	0.473	0.362	0.165	0.218	0.255	0.859
share 55-64	0.559	0.441	0.357	0.202	0.131	0.310	0.820
all	0.502	0.498	0.377	0.125	0.213	0.285	0.893

Notes: The average arrival rate contributions are calculated as described in the previous section. using equation (10). $cor(u, u^*)$ is the coefficient of correlation for the equilibrium unemployment rate and the actual unemployment rate. All average values are unweighted. Period: January 2007 - December 2013. Number of regions: 473. Number of observations: 32,709.

⁵Elsby et al. (2008) do also find that separation is more important than job finding for the unemployment dynamics in Germany. However, Nordmeier (2014) comes to the opposite conclusion. Kluge et al. (2009) also find that re-employment rates are lowest for older workers.

Petrongolo and Pissarides (2008) find for UK also an almost fifty-fifty ratio for β^i and β^e related to all workers. They also find similar values for β^s and β^a , but their values for β^f and β^n differ from those in Table 3 ($\beta^f = 0.364$ and $\beta^n = 0.151$). They also calculate relative contributions from data for the US and get results that are different from the values in Table 3. The probably most important different is that the flows from and to inactivity in the US account for only 8.8% of the unemployment dynamics.

The finance beta's in Table 4 are the continuous time transition probabilities, calculated using the values in Table 3 and equation (9). In some cases the relative contributions in Table 4 are similar to their counterparts in Table 3 - which is in line with the recent literature. In other cases, however, I find significant differences and even different conclusions. The most striking difference is that the inflow rates have a larger contribution for all age groups - "the ins win"⁶. Also, the separation probability plays a more important role while the job finding probabilities are lower than the job finding rates in Table 3. Other findings like, for example, $\beta^N > \beta^F$, the relative contribution of flows from and to inactivity in general and in particular for the youth and older workers, and the transition probability β^N persist.

The next two Tables 5 and 6 are the counterparts for Table 3 and 4 using the non-steady state solution. The difference between the transition rates in the Tables 5 and 3 is that the results in the following Table are calculated using the non-steady state approach in section 2.1. The overall relative contribution for all workers of inflow and outflow is now 43%:57%. The inflow rates have a larger contribution for all age groups but the age cohort 55-64 years. This applies not, however, to the overall comparison of the separation rates and the job finding rates, except for the youth. Also noticeable is that $\beta^n > \beta^f$. While separation rates are rising with age, job finding rates are larger for prime age workers. Also in this dynamic

⁶Darby et al. (1986).

Table 4: Contribution from the Transition Probabilities

age groups	β^I	β^E	β^S	β^A	β^F	β^N	$cor(u, u^*)$
share 15-24	0.536	0.464	0.136	0.400	0.141	0.323	0.898
share 25-34	0.506	0.496	0.395	0.111	0.206	0.288	0.914
share 35-44	0.527	0.473	0.437	0.090	0.193	0.280	0.872
share 45-54	0.558	0.442	0.440	0.118	0.172	0.270	0.863
share 55-64	0.590	0.410	0.416	0.174	0.112	0.298	0.822
all	0.533	0.467	0.406	0.127	0.168	0.299	0.897

Notes: The average transition probability contributions are calculated as described in the previous section using equation (10). $cor(u, u^*)$ is the coefficient of correlation for the equilibrium unemployment rate and the actual unemployment rate. All average values are unweighted. Period: January 2007 - December 2013. Number of regions: 473. Number of observations: 32,709.

framework, the difference between a two-state and a three state model, the flows from and to inactivity, explains on average more than 40%. For the old, however, it is almost one third and for the youth even almost 80%. Finally, about one third of the youth unemployment rate variation is explained by flows from activity to unemployment. The most remarkable difference to Table 3 is the small contribution of the flow from inactivity to unemployment for prime age and older workers.

Table 6 provides the results for the transition probabilities using the non-steady state approach. Overall the results are very similar to those in Table 5 and all conclusion remain the same. In this case, the time aggregation bias is relatively small. Therefore the results in Table 6 differ from the calculations for the transition probabilities in Table 4.

3.1 Comparison of regional aggregation levels

In this section I provide results for aggregated data. I now aggregate the regional arrival rates and unemployment rates and calculate only one average value for time t . That is to say, I aggregate the variables to single

Table 5: Contribution from the Transition Rates in Non-Steady State

age groups	β^i	β^e	β^s	β^a	β^f	β^n
share 15-24	0.435	0.565	0.069	0.366	0.141	0.424
share 25-34	0.408	0.592	0.360	0.048	0.263	0.329
share 35-44	0.450	0.550	0.426	0.024	0.254	0.296
share 45-54	0.476	0.524	0.438	0.038	0.262	0.262
share 55-64	0.513	0.487	0.444	0.069	0.218	0.269
all	0.434	0.567	0.370	0.063	0.245	0.322

Notes: The average arrival rate contributions are calculated as described in the previous section using equation (15). All average values are unweighted. Period: January 2007 - December 2013. Number of regions: 473. Number of observations: 32,709.

time series averaged over the regions for each month, without weighting for regional labor market size. The average arrival rates remain unchanged by this approach and are exactly the same as provided in Table 1. However, the variance of the variables change since the cross section observations are lost.

Table 7 provides the calculated relative contributions for both the arrival rates and the continuous time transition probabilities using the same approach as for the results in Table 3 and Table 4. When aggregation across regions would not affect the finance beta's, the results in Table 7 must conform to the results in Tables 3 and 4.

TABLE 7 ABOUT HERE

The results differ in some cases remarkably. With respect to the transition rate based calculations I find that the contributions for all workers differ from Table 3 up to 6.6%. Most striking is the difference for β^i and β^e for the age cohort 55-64 years. This is driven by a separation rate contribution of almost 60% and a very low job finding rate contribution of only 5.2%. In general, β^s is larger in all cases in Table 7, while β^a is smaller in all cases,

Table 6: Contribution from the Transition Probabilities in Non-Steady State

age groups	β^I	β^E	β^S	β^A	β^F	β^N
share 15-24	0.481	0.519	0.080	0.401	0.147	0.372
share 25-34	0.415	0.585	0.364	0.051	0.265	0.320
share 35-44	0.465	0.535	0.440	0.025	0.251	0.284
share 45-54	0.488	0.512	0.449	0.039	0.256	0.256
share 55-64	0.528	0.472	0.456	0.072	0.214	0.258
all	0.446	0.554	0.384	0.062	0.243	0.311

Notes: The average transition probability contributions are calculated as described in the previous section using equation (15).

All average values are unweighted. Number of observations: 32,709

except for the youth. Also, β^f is smaller in all cases in Table 7, while β^n is larger in all cases, except for the youth. The difference between a two-state and a three state model, the flows from and to inactivity, still explains on average more than 40%. For the old it is now only 34% and for the youth 74%.

For the second part of Table 7, the contributions of the transition probabilities using aggregated data and equation (9), we find generally similar results compared to the first part of Table 7. Compared to Table 4, however, there are differences concerning β^S , β^A , and β^F , except for the youth. Also for the age cohort 55-64 years I come to the same conclusion as for the transition rate contributions.

Hence, as we have seen above, the time aggregation bias has in some cases significant differences. Table 7 shows, however, that there is also an "region aggregation bias", that seems in Table 7 to be larger or even as large as the time aggregation bias. The conclusions for older workers are significantly different for the two data.

3.2 Policy Implications

My empirical analysis shows that differences in the relative contributions of flow rates on unemployment dynamics across age groups exist. A first policy concern should be the low job find rate and the corresponding small contribution to the unemployment fluctuation for older workers. The most important reason for this is that the regional and occupational mobility of older workers is low and aging reduces the average mobility. This makes the hiring process more costly for firms. As a consequence, governments should provide incentives and support for a higher mobility of those aged 50 and older. Certainly, age discrimination (against older workers), as found in the studies by Johnson and Neumark (1997) for the US and by Charness and Villevall (2007) for France, is counterproductive especially in a labor force which grows old. Another cause can be age-biased directed technological change, which is presumably positively correlated with the separation rate contribution rate of older workers.⁷ The way policy can mitigate these adverse effects is setting incentives for retaining and training old workers. Langot and Moreno-Galbis (2008) have demonstrated the benefits of such measures.

The relative low labor turnover (measured as separation rate plus job finding rate) could also be associated with the impact of the institutional design of the German labor market. The replacement rate and employment protection especially for experienced workers are examples. Using international data, the share of older unemployed is positively correlated with the replacement rate, while it is negatively related to employment protection. Also, the age-earning profile could be important. Again, training can improve the productivity of older workers and help reduce a productivity-wage

⁷According to Acemoglu (1998) "new technologies are not complementary to skills by nature, but by design." It is possible that this implies an advantage for younger workers when new technologies will be implemented. In fact, Langot and Moreno-Galbis (2008) provide a framework that yields this result.

gap.

Since the job finding rate and their contribution is much lower for older than for younger workers, one has to pay more attention to early retirement schemes. In this case, firms presumably dismiss unproductive old workers and keep only the highly productive ones. The early retired workers are removed from the group of job candidates. This raises the search productivity, and firms are willing to create more jobs. But job creation benefits only artificially from aging, and the positive effect (if existent) will disappear as soon as early retirement programs phase out, as it is now the case in most of the European countries. Hence, it is necessary to analyze the importance of this policy change for unemployment dynamics of older workers in the future.

4 Conclusions

In this paper, I examined the contribution of flow rates and flow probabilities for unemployment dynamics of different age groups using administrative panel data for Germany. I consider a three-state model and allow for flows from/to inactivity (out of the labor force) to/from unemployment. The dynamics that arise from the inactivity and activity flows account for about 40% of unemployment dynamics. The remaining roughly 60% of unemployment fluctuation are explained by the separation rate and job finding rate respectively. Across five age cohorts I find remarkable differences in flow contributions. For example, the contribution of separation rates is larger for older workers, while the activity flow has a larger contribution for younger workers. Also, the non-activity flow is more important for the explanation of unemployment fluctuations than the job finding rate. The overall contribution of inflow and outflow rates is roughly fifty-fifty, but for the dynamic approach I find a slightly stronger contribution for the exit rates.

I consider the time aggregation bias and find that it is useful to show

the differences to the standard results related to arrival rates. However, I also point out that it is possible to have a regional aggregation bias. As an example, I aggregate my data across regions and compare the results with the standard results. The differences are at least as large, as for the time aggregation bias.

5 References

- Acemoglu, D., 1998, Why do new Technologies Complement Skills? Directed Technical Change and Wage Inequality, *Quarterly Journal of Economics* 113, 1055-1089.
- Autor, D.H.; Dorn, D., 2009, This Job is "Getting Old": Measuring Changes in Job Opportunities Using Occupational Age Structure, NBER Working Paper Series, No. 14652.
- Autor, D.H.; Levy, F.; Murnane, J.R., 2003, The Skill Content of Recent Technological Change: An Empirical Exploration, *Quarterly Journal of Economics* 118(4), 1279-1334.
- Baltes, P.B.; Lindenberger, U., 1997, Emergence of a Powerful Connection Between Sensory and Cognitive Functions Across the Adult Life Span: A new Window to the Study of Cognitive Aging?, *Psychology and Aging* 12(1), 12-21.
- Bartel, A.; Sicherman, N., 1993, Technological Change and Retirement Decisions of Older Workers, *Journal of Labor Economics* 11, 162-183.
- Börsch-Supan, A., 2003, Labor Market Effects of Population Aging, *Labour* 17, 5-44.
- Burgess, S. 1993, A Model of Competition between Unemployed and Employed Searchers: An Application to the Unemployment Outflows in

- Britain, *Economic Journal* 103, 1190-1204.
- Charness, G.; Villeval, M.-C., 2007, Cooperation, Competition, and Risk Attitudes: An Intergenerational Field and Laboratory Experiment, IZA Discussion Paper No. 2574.
- Daniel, K.; Heywood, J. S., 2007, The Determinants of Hiring Older Workers: UK Evidence, *Labour Economics* 14, 35-51.
- Darby, M.R.; Haltiwanger, J.C.; Plant, M.W., 1986, The Ins and Outs of Unemployment: The Ins Win, National Bureau of Economic Research Working Paper 1997.
- Elsby, M.W.L.; Hobijn, B.; Sahin, A., 2008, Unemployment Dynamics in the OECD, NBER Working Paper Series, Working Paper 14617.
- Elsby, M.W.L.; Michaels, R.; Solon, G., 2009, The Ins and Outs of Cyclical Unemployment, *American Economic Journal: Macroeconomics* 1 (1), 84-110.
- Fujita, S.; Ramey, G., 2009, The Cyclicalities of Separation and Job Finding Rates, *International Economic Review* 50 (2), 415-430.
- Hall, R.E., 2005, Employment Efficiency and Sticky Wages: Evidence from Flows in the Labor Market, *Review of Economics and Statistics* 87 (3), 397-407.
- Haltiwanger, J.C.; Lane, J.I.; Spletzer, J.R., 1999, Productivity Differences Across Employers: The Roles of Employer Size, Age, and Human Capital, *American Economic Review* 89(2), 94-98.
- Hellerstein, J.K.; Neumark, D.; Troske, K.R., 1999, Wages, Productivity and Workers Characteristics: Evidence From Plant Level Production Function and Wage Equations, *Journal of Labor Economics* 17, 409-446.

- Hutchens, R.M., 1987, A Test of Lazear's Theory of Delayed Payment Contracts, *Journal of Labor Economics* 5, 153-170
- Hutchens, R.M., 1989, Seniority, Wages and Productivity: A Turbulent Decade, *Journal of Economic Perspectives* 3(4), 49-64.
- Johnson, R.W.; Neumark, D., 1997, Age Discrimination, Job Separations and Employment Status of Older Workers: Evidence from Self-Reports, *Journal of Human Resources* 32, 779-811.
- Kluge, J.; Schaffner, S.; Schmidt, C.M., 2009, Labor Force Status Dynamics in the German Labor Market, *RUHR Economic Papers* #139,
- Langot, F.; Moreno-Galbis, E., 2008, Does the Growth Process Discriminate Against Older Workers, IZA Discussion Paper Series, No. 3841
- Lazear, E.P., 1979, Why is there Mandatory Retirement?, *Journal of Political Economy* 87 (6), 1261-1284.
- Nordmeier, D., 2014, Worker flow in Germany: Inspecting the time aggregation bias, *Labour Economics* 28, 70-83.
- Nordström Skans, O., 2008, How does the Age Structure Affect Regional Productivity?, *Applied Economics Letters* 15, 787-790.
- Petrongolo, B.; Pissarides, C.A., 2008, The Ins and Outs of European Unemployment, *American Economic Review*, 98 (2), 256-262.
- Perry, G., 1970, Changing Labor Markets and Inflation, *Brookings Papers on Economic Activity*, 411-441.
- Pissarides, C.A. and J. Wadsworth, 1994, On-the-Job Search: Some Empirical Evidence from Britain, *European Economic Review* 38, 385-401.
- Shimer, R., 2001, The Impact of Young Workers on the Aggregate Labor market, *Quarterly Journal of Economics* 116 (3), 969-1007.

Shimer, R., 2005, The Cyclical Behavior of Equilibrium Unemployment and Vacancies, *American Economic Review* 95 (1), 25-49.

Shimer, R., 2012, Reassessing the Ins and Outs of Unemployment, *Review of Economic Dynamics* 15, 127-148.

Smith, J.C., 2011, The Ins and Outs of UK Unemployment, *Economic Journal* 121 (May), 402-444.

Table 7: Contribution from Transition Rates and Transition Probabilities using aggregated data

age groups	transition rate contributions					transition probabilities contributions						
	β^i	β^e	β^s	β^a	β^f	β^n	β^I	β^E	β^S	β^A	β^F	β^N
share 15-24	0.499	0.501	0.119	0.380	0.141	0.360	0.559	0.441	0.135	0.424	0.141	0.300
share 25-34	0.478	0.522	0.466	0.012	0.178	0.344	0.502	0.498	0.485	0.017	0.173	0.325
share 35-44	0.525	0.475	0.514	0.011	0.154	0.321	0.545	0.455	0.531	0.014	0.150	0.305
share 45-54	0.577	0.423	0.514	0.063	0.122	0.301	0.595	0.405	0.527	0.068	0.120	0.285
share 55-64	0.714	0.286	0.605	0.109	0.052	0.234	0.726	0.274	0.613	0.113	0.055	0.219
all	0.516	0.484	0.443	0.073	0.147	0.337	0.539	0.461	0.460	0.079	0.145	0.316

Notes: The average flows (arrival rates and transition probabilities) and contributions are calculated as described in the previous section, using equation (10). All average values are unweighted. Period: January 2007 - December 2013. Number of regions: 473. Number of observations: 32,709.