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The Cyclicality of Worker Flows: Evidence from Germany

Daniela Nordmeier

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Preface

This book is a slightly revised version of my dissertation, which was accepted by the University of Erlangen-Nuremberg in July 2013.

It would not have been possible to accomplish this thesis without the support of many people. I would like to express my appreciation to all those who contributed to complete my dissertation project:

Foremost, I would like to thank Christian Merkl for supervising my dissertation project. In particular, I am grateful for his helpful suggestions and for the valuable discussions through our joint work. I also thank my second supervisor Enzo Weber for his advice and for the cooperative and uncomplicated collaboration. Moreover, I owe special thanks to Hermann Gartner, who was an outstanding mentor for me. He supported my dissertation project from the very beginning and never hesitated to share his experience of research with me.

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Finally, I thank my family and Fedor-Immanuel for their unconditional support and for believing in my accomplishment.

1 Introduction

Work is an essential part of daily life. The individual work performance depends on various factors, such as a worker's experience and job match quality. In case of unemployment, the individual job search intensity is basically determined by a worker's income expectations and opportunity costs. Hence, individual job finding and separation probabilities may differ substantially.

From a macroeconomic perspective, worker flows and the underlying transition rates are strongly influenced by the economic situation. In booms, firms post more vacancies and the job finding probability rises. In recessions, firms reduce their labor demand and workers are more likely to lose their job. From a political point of view, these fluctuations are challenging. They are desirable as they ensure a flexible adjustment of firms to new circumstances, but they are also undesirable as they cause uncertainty for workers.

In practice, labor market fluctuations appear to be large. The empirical evidence on unemployment dynamics has also led to some caveats on the search and matching model – the workhorse in modern macroeconomic labor market research. Shimer (2005) shows that the baseline version of the search and matching model fails to replicate the observed fluctuations in the U.S. labor market. The so-called Shimer puzzle has triggered a rich discussion on the standard model, from both a theoretical and an empirical point of view. The attempts to overcome the quantitative shortcoming have subsided nowadays, but a reconsideration of the model setup remains.

This dissertation addresses different issues on the cyclicality of worker flows in three self-contained essays. The issues include (i) the cyclical behavior of the job finding and separation rates, (ii) the role of productivity shocks in explaining labor market fluctuations and (iii) the matching function as modeling device for labor market frictions. These issues are crucial for macroeconomic outcomes and are interesting topics by themselves. For example, the argument of a cyclical time aggregation bias in the measurement of worker flows has initiated a new assessment of variations in the separation rate. In addition, recent evidence on the Schumpeterian paradigm has challenged the traditional view of decreasing unemployment after a positive productivity shock. Finally, the matching function has obtained a novel role in evaluating the aggregate effects of labor market reforms, though it still lacks on a microfoundation.

The following essays analyze the aforementioned issues for the German economy. They take advantage of process-generated data from the Federal Employment Agency (*Bundesagentur für Arbeit*) and shed new light on recent discussions on worker flows. They contribute to the literature on labor market fluctuations and derive interesting questions for future research.

The dissertation is structured as follows. The introduction chapter proceeds with a review of background topics and provides an overview of the three essays. The essays follow in Chapters 2, 3 and 4. Chapter 5 concludes with final remarks.

1.1 Background

1.1.1 The Search and Matching Model

The search and matching model has become the standard approach to represent the dynamics in the labor market. Based on the seminal contributions of Peter Diamond, Dale Mortensen and Christopher Pissarides, the model considers that the search and matching process is costly and time-consuming. Therefore, it is able to explain the coexistence of vacancies and (involuntary) unemployment as an equilibrium phenomenon (see, e.g., Pissarides, 2000).

A central building block of the search and matching model is the matching function. The matching function summarizes labor market frictions in a single relation and gives the number of job matches (M) as a function of the stocks of unemployment (U) and vacancies (V):

$$M = \mathrm{M}(U, V), \tag{1.1}$$

where $\mathrm{M}(\cdot)$ is increasing and concave in both its arguments and satisfies $\mathrm{M}(0, V) = \mathrm{M}(U, 0) = 0$ as well as $\mathrm{M}(U, V) = \min(U, V)$. The standard assumption is that the matching function has constant returns to scale, which implies that each unemployed worker finds a job with probability $\mathrm{M}(U, V)/U$ and each vacancy is filled with probability $\mathrm{M}(U, V)/V$.

The search and matching model provides an useful approach to integrate labor market frictions into a more general macroeconomic framework. In its baseline version, the search and matching model assumes the following steps after an aggregate productivity shock:

- Firms reassess the expected profits from a job.
- Vacancies are posted according to a free entry condition.
- Unemployed workers apply for vacant positions.
- Firms and applicants meet via the matching function.
- Firm-worker pairs negotiate about the wage.
- Employed workers produce an output, while unemployed workers receive an unemployment income.
- Some of the existing jobs are destroyed and affected workers separate into unemployment.

The changes in unemployment then feed back through the matching function and, subsequently, the labor market returns to equilibrium.

Moreover, the brief outline shows that the search and matching model is an attractive starting point for many applications. In particular, the analysis of labor market policies has received much attention, because specific institutions, such as employment protection or the unemployment insurance system, can be directly linked to the model's components.

1.1.2 The Shimer Puzzle

Shimer (2005) argues that the standard search and matching model cannot explain the cyclical behavior of unemployment and vacancies. The author analyzes the fluctuations in the U.S. labor market and compares them with the prediction of the search and matching model by simulating a productivity shock that fits the data on productivity. The separation rate is assumed to be exogenous as in the standard textbook model (see Pissarides, 2000, Chapter 1). Table 1.1 presents the summary statistics of the empirical and simulated data.

Table 1.1: Summary statistics for U.S. data

		U	*V*	*V/U*	*f*	*s*	*a*
Standard deviation		0.190	0.202	0.382	0.118	0.075	0.020
		[0.009]	[0.027]	[0.035]	[0.010]	[–]	[0.020]
Autocorrelation		0.936	0.940	0.941	0.908	0.733	0.878
		[0.939]	[0.835]	[0.878]	[0.878]	[–]	[0.878]
Correlation	*U*	1	–0.894	–0.971	–0.949	0.709	–0.408
matrix		[1]	[-0.927]	[-0.958]	[-0.958]	[–]	[-0.958]
	V		1	0.975	0.897	-0.684	0.364
			[1]	[0.996]	[0.996]	[–]	[0.995]
	V/U			1	0.948	-0.715	0.396
				[1]	[1.000]	[–]	[0.999]
	f				1	-0.574	0.396
					[1]	[–]	[0.999]
	s					1	-0.524
						[1]	[–]
	a						1
							[1]

Source: Shimer (2005), Tables 1 and 3. Quarterly U.S. data from 1951 to 2003. Data on unemployment (*U*), vacancies (*V*), the job finding rate (*f*) and the separation rate (*s*) are quarterly averages of monthly series. Values in brackets are obtained from a simulation with a productivity (*a*) shock. Cyclical components are computed as log deviations from an Hodrick-Prescott trend with smoothing parameter $\lambda = 10^5$.

The comparison of the standard deviations shows that the cyclical components of the labor market data are much larger than the corresponding fluctuations generated by the model simulation. Unemployment and vacancies deviate from their trend by approximately 20% in the data, while the search and matching model predicts a volatility of only 1% and 3%, respectively. Due to an opposite cyclicality of unemployment and vacancies the observed volatility of labor market tightness, i.e. the ratio of vacancies to unemployment, even amounts to 38%; however, the model suggests a standard deviation of 4%. The job finding rate fluctuates by 12% in the data, whereas the model simulation yields a volatility of only 1%. The observed business cycle component of the separation rate varies by 8%; thus, it is less volatile than the business cycle component of the job finding rate.

The autocorrelation coefficients demonstrate a high persistence of labor market fluctuations, though the separation rate appears to adjust less gradually than the other variables. The search and matching model can generate the persistent features of the variables, but it seems to be unsatisfying with respect to vacancies. Moreover, the model is able to replicate the sign of the correlations between the different variables, most importantly the negative relationship between unemployment and vacancies (i.e. the Beveridge curve). However, the magnitude of the correlations is mostly overestimated. Particularly the predictions of the relations with productivity appear to be too large. This observation indeed points out that the standard model lacks on a mechanism that propagates the aggregate productivity shock and amplifies the labor market responses.

Cardullo (2010) surveys the literature that aims to solve the Shimer puzzle. The author distinguishes three avenues, namely changes in wage formation, changes in the calibration and changes in the model specification. Cardullo (2010) concludes that extensions of the baseline model, such as an endogenization of the separation rate or the incorporation of turnover costs, seem to achieve the most effective results.

1.1.3 Ongoing Debates on Worker Flows

The role of the job finding and separation margins in understanding labor market fluctuations has been widely discussed over years. Early studies relate recessions to large waves of job separations along with job destruction, because job destruction is observed to respond more sensitively to business cycle shocks than job creation (see, e.g., Davis and Haltiwanger, 1992; Blanchard and Diamond, 1990). Accordingly, Mortensen and Pissarides (1994) consider countercyclical variations of job destruction in the search and matching model by allowing for idiosyncratic productivity shocks.

The conventional view of a separation-driven labor adjustment has been challenged by two studies. Hall (2005) demonstrates that the U.S. separation rate is nearly constant over the past 50 years, while the job finding rate exhibits a high volatility on business cycle frequency. Shimer (2005; 2012) advocates a dominant role of the job finding rate by accounting for a procyclical time aggregation bias in the separation rate. Hence, the new evidence on labor market dynamics appears to result from churning effects (i.e. the difference between job and worker flows at the firm level) as well as a careful measurement of worker flows.

However, there are several arguments that counter a focus on the job finding margin (see, e.g. Davis, 2005; Kennan, 2005; Fujita and Ramey, 2006). In particular, more recent studies apply a variance decomposition of unemployment fluctuations and demonstrate a substantial impact of the separation rate (see Fujita and Ramey, 2009; Elsby et al., 2009b). In European countries the contributions of the job finding and separation rates even tend to be closer (see Elsby et al., 2009a).

Moreover, emphasizing either adjustment margin has important implications for the theoretical paradigm underlying a productivity shock. The separation-driven view has motivated Schumpeterian arguments of creative destruction (see, e.g. Caballero and Hammour, 1994), while the job finding-driven view has been underpinned by the Real Business Cycle (RBC) theory (see, e.g., Merz, 1995; Andolfatto, 1996). After a positive impulse, RBC models feature a fall in unemployment due to higher labor demand. In contrast to that, the Schumpeterian paradigm implies a (temporary) rise in unemployment following a positive productivity shock. This mechanism is actually revived by recent research that is based on structural vectorautoregressive (SVAR) estimations (see Canova et al., forthcoming). At the same time, there is some evidence that productivity shocks have ambiguous effects on the job finding margin, which can be explained by skill-biased technological change (see Balleer, 2012).

In the standard search and matching model, the job finding margin is formalized by a matching function. The matching function captures the impact of labor market frictions without modeling them explicitly. Frictions in the labor market may derive from different reasons: imperfect information, heterogeneities, mobility costs, congestion or other factors (see Petrongolo and Pissarides, 2001). The matching function accounts for those frictions in a single relation with a small number of variables. However, the success of the matching function rather relies on its simple specification than on a convincing microfoundation.

So far, the literature provides some models that represent special types of labor market frictions. For example, the prominent urn-ball model derived from the study of Butters (1977) focuses on coordination failures of unemployed workers ("balls") when applying for jobs ("urns"). Due to information deficits about other workers' behavior some workers may apply for the same job and some jobs may end up with no applications. Ranking models, like that of Blanchard and Diamond (1994), assume that firms have preferences over job applicants in terms of their skills or unemployment duration and thus offer their jobs to the workers ranked first. Another approach is given by stock-flow matching (see Coles and Smith, 1998), where job seekers can remain unmatched because of unsuitable jobs among the existing vacancies and vice versa. The unmatched job seekers and vacancies then have to wait for new entries to find a suitable match.

The existing approaches of specific labor market frictions give some intuition about the underlying mechanisms of the aggregate matching function, but they are not seen to make the reduced-form specification obsolete (see Pissarides, 2008). In contrast, the empirical support in favor of an aggregate matching function still convinces many economists to rely on its simple form.

1.1.4 Definition of Unemployment

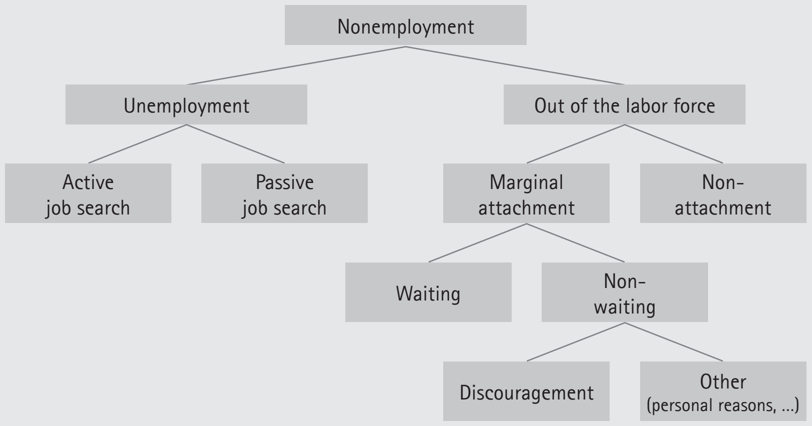
The definition of labor market states plays a crucial role for the measurement of worker flows. In particular, the definition of unemployment is a challenging issue across countries. Given the heterogeneity of nonemployed people, most OECD countries use information on job search activities to distinguish between unemployment and the out of labor force (see Jones and Riddell, 1999).

Figure 1.1 illustrates the classification of nonemployment along the conventional "job search" criterion. Thereby, the unemployment status comprises people using both active and passive job search methods. Active job search includes, for example, the registration at public employment agencies, contacting of employers or placing job advertisements. In contrast, looking at advertisements is regarded as passive job search.

The out of labor force is typically divided in terms of labor market attachment. Non-attachment may refer to students, retirees or non-employable persons. Marginally attached workers desire work and can be further distinguished with respect to their availability for a job. Workers characterized by the waiting status do not search because of awaiting a recall to a former job, waiting for replies from employers or waiting for a new job starting in the near future. Workers referred to as non-waiting do not search because of being discouraged, i.e. they believe that no suitable job is available, or due to personal reasons.

The diversity of the out of labor force has given rise to questions on the adequacy of the conventional "job search" criterion to measure unemployment, because it affects not only the level of unemployment but also the duration of unemployment periods. Jones and Riddell (1999) merge two Canadian survey data sets and analyze the different subcategories of nonemployment. The results indicate that the "desire for work" criterion provides important information about future employment and therefore should supplement the conventional "job search" criterion. Moreover, the authors identify the waiting group to be misclassified as a part of the out of labor force, because it behaves more closely to unemployment or even employment.

Figure 1.1: Heterogeneity of nonemployment



Note: Classification of nonemployment according to the "job search" criterion (see Jones and Riddell, 1999).

The following essays take an alternative stand of the definition of unemployment. They rely on administrative data of actual labor market processes and use information on unemployment benefit receipt to approximate *the* unemployment pool. Thereby, the applied unemployment definition is assumed to combine the aforementioned criteria, because it considers both unemployment periods with benefit receipt and unemployment periods without benefit receipt.

1.2 Overview of the Essays

1.2.1 The Time Aggregation Bias in Worker Flows

The first essay analyzes the effects of time aggregation in the measurement of worker flows. Time aggregation, i.e. the observation of data processes at a lower frequency than they actually evolve, causes an underestimation of flow variables, because it neglects transitions that are reversed within two measurement points.

In the context of worker flows, Shimer (2005) argues that time aggregation primarily affects the separation rate, because unemployment periods are on average shorter than employment periods. The essay addresses Shimer's argument by exploiting daily information from German administrative data on individual labor market biographies. For this purpose, it introduces an unemployment measure that overcomes missing unemployment periods in the administrative database (so-called nonemployment proxy).

The study derives a monthly measure of the time aggregation bias in the job finding and separation rates. It examines the bias in terms of its level and cyclicality and compares it with the prediction of a theoretical approach that aims to correct for time aggregation. Moreover, the study investigates the cyclicality of the job finding and separation rates by considering the dynamics of the time aggregation bias. In this context, the study gives particular attention to the low transition rates in the German labor market, because it suggests an unconventional variance decomposition of unemployment fluctuations.

An earlier version of this study is available as IAB Discussion Paper (see Nordmeier, 2012).

1.2.2 Unemployment Dynamics Conditional on Shocks

The second essay studies the dynamics of unemployment in response to different structural shocks. Thereby, a structural shock represents an unexpected change in a specific variable and is based on assumptions about its dynamic interaction with other variables.

The study employs a vectorautoregressive (VAR) model that captures the job finding and separation rates as well as productivity, interest rate and government spending. The latter variables are necessary to identify the structural shocks of interest, i.e. a technology shock, a monetary policy shock and a fiscal policy shock. Accordingly, the study identifies both supply- and demand-side shocks. This approach implies a combination of short- and long-run restrictions and thus requires a numeric estimation procedure. Given the conditional movements of the job finding and separation rates, the study then derives the resulting unemployment response based on its law of motion.

A particular objective of the study is to evaluate whether the unemployment adjustment process varies with the identified shocks or whether it is similar across shocks. The study discusses the responses to the different shocks and assesses their relative importance for the transition rates. In addition, the study analyzes the persistence of shocks to get a better understanding of the results.

This study is joint work with Enzo Weber and available as IAB Discussion Paper (see Nordmeier and Weber, 2013).

1.2.3 A Selection-Based Interpretation of the Matching Function

The third essay investigates the matching function. In its simplest and prevalent specification, the matching function determines the number of matches according to a Cobb-Douglas form:

$$M = AU^{a}V^{b}, \tag{1.2}$$

where the scale parameter A is referred to as the matching efficiency and a and b denote the matching elasticities of unemployment and vacancies, respectively.

The study examines the common practice of applying a Cobb-Douglas matching function from both an empirical and a theoretical point of view. In a first step, the study performs several matching function estimations based on a precise measurement of the key variables. The study particularly proves the standard assumption of constant returns to scale, i.e. $a + b = 1$. Then, it turns to restricted matching elasticities and extends the baseline specification by a large set of control variables, which account for composition effects of the unemployment pool as well as institutional aspects.

In a second step, the study explores the empirical matching function by using a labor selection model. The model provides a more in-depth formulation of the firms' hiring process and thus obviates the matching function. A simulated version of the model, however, allows to imitate the empirical analysis of the aggregate matching function. The study compares the simulation-based results with the empirical evidence and explains the underlying mechanism analytically.

This study is joint work with Britta Kohlbrecher and Christian Merkl and available as LASER Discussion Paper (see Kohlbrecher et al., 2013).

2 Worker Flows in Germany: Inspecting the Time Aggregation Bias

This paper analyzes the effects of time aggregation in the measurement of worker flows by exploiting daily information from German administrative data. Time aggregation caused by comparing monthly labor market states leads to an underestimation of total worker flows by around 10%, which is larger than the prediction of a theoretical correction approach. Multiple labor market transitions within a month induce a procyclical bias in the job finding rate, but not in the separation rate. This observation may reveal some facts about quits. The reconsideration of the total transition rates shows a strong cyclicality of German worker flows, where the job finding rate appears to play a larger role in explaining unemployment fluctuations.

2.1 Introduction

Worker flows play a crucial role for understanding labor market dynamics. Modern labor market theory explicitly accounts for the continuous process of job findings and separations, and thereby intends to match stylized facts of labor market data. Data on worker flows are typically observed by comparing individual labor market states at a monthly or quarterly frequency. This procedure, however, induces a downward bias if individuals face multiple labor market transitions within two measurement points.

The objective of this paper is to analyze the so-called time aggregation bias by using German administrative labor market data. In addition to the absence of sample rotation and sample attrition,[1] German administrative data have the advantage of daily information. As every daily change of the individuals' labor market status can be taken into account, worker flows based on this information do not face a time aggregation bias. Nevertheless, German administrative data allow to derive one by additionally computing labor market transitions at a lower frequency.[2]

Being aware of a time aggregation bias in his monthly measured worker flows, Shimer (2005) points out that the U.S. job separation rate is nearly acyclic. Shimer (2012) reinforces a procyclical time aggregation bias in the separation rate by

1 In a survey data set, sample rotation and sample attrition involve a margin error as workers fail to be matched. See Fujita and Ramey (2006) for a more detailed description.

2 This procedure abstracts from workers who find and lose a job within a day and vice versa. However, losing a job and finding another job within a day is rather referred to direct job-to-job transitions which are beyond the scope of this paper.

formulating a correction approach for neglected worker flows. Since a draft of his paper was circulated, Shimer's correction approach has evolved to a standard approach to adjust for time aggregation (see, e.g., Fujita and Ramey, 2006; 2009; Petrongolo and Pissarides, 2008; Gomes, 2012). Moreover, Shimer's conclusion of a nearly acyclical separation rate has led many studies to assume an exogenous separation rate when employing the search and matching model. This development has given rise to a reconsideration of the cyclicality of the job finding and separation rates. In particular, Fujita and Ramey (2009) and Elsby et al. (2009b) caution against the assumption of an exogenous separation rate by demonstrating that the U.S. separation rate is strongly countercyclical and contributes substantially to unemployment fluctuations.[3]

Following a comprehensive literature dealing with U.S. labor market dynamics, similar studies for European countries have emerged. For example, Petrongolo and Pissarides (2008) focus on France, Spain and the U.K. and find deviating contributions of the job finding and separation rates to unemployment variations, which are explained by different institutional settings. Elsby et al. (2009a) investigate unemployment dynamics in the OECD. For Nordic and Continental European countries, the authors conclude that each transition rate explains half of unemployment fluctuations. Smith (2011) and Elsby et al. (2011) provide more detailed analyses for unemployment flows in the U.K. These authors demonstrate that the separation rate drives unemployment rises in recessions, while the job finding rate dominates unemployment variations in times of moderation. For Germany, however, the evidence on the driving forces of unemployment dynamics is rather scarce and has not reached a consensus yet.

While studies examining worker flows in the U.S. or other countries use survey data, studies on German labor market transitions are mostly based on administrative data (see, e.g., Bachmann, 2005; Jung and Kuhn, 2011; Gartner et al., 2012). Bachmann and Schaffner (2009) address this issue and compare worker flows computed from German administrative data with those computed from a German household survey. However, the authors do not find any substantial differences in the transition rates. Nevertheless, there is no study that exploits the daily information from German administrative data and investigates the time aggregation bias.[4]

This study derives a monthly measure of the time aggregation bias as suggested by related studies on U.S. labor market transitions. For this purpose, I use a new administrative data set on German labor market processes, which has two advantages over its precursor data set used by previous studies. First, the new data

3 Yashiv (2007) provides a survey of further questions that concern the search and matching model.

4 To my knowledge, only Bachmann (2005) computes worker flows on a daily basis, but he does not compare them with labor market transitions computed at a lower frequency.

set is representative for both employment subject to social security[5] and benefit receipt. Second, the new data set covers a longer time period and thus provides first insights into the development of worker flows after the Hartz reforms.[6]

Moreover, I apply an unemployment definition that corrects for unemployment periods without benefit receipt. Those periods are most likely to result from an expiration of entitlements and lead to information gaps in the administrative data set. However, the information gaps may be relevant for measuring the time aggregation bias. Accordingly, the adjustment procedure addresses the fact that not all unemployed workers are successful in finding a job during benefit receipt (see Fitzenberger and Wilke, 2010).

Finally, the more comprehensive measurement of worker flows suggests a reconsideration of German labor market dynamics. Therefore, I complement the analysis of the time aggregation bias by examining the job finding and separation rates on business cycle frequency. In light of recent research, I investigate the volatility and the cyclical behavior of the transition rates and evaluate their contributions to unemployment fluctuations.

The results indicate that monthly point-in-time comparisons of labor market states lead to an underestimation of total worker flows by around 10%. The correction approach of Shimer (2012), however, predicts an underestimation of only 3%. The time aggregation bias in the job finding rate, i.e. the probability of finding and losing a job within a month, shows a procyclical behavior. In contrast, the time aggregation bias in the separation rate, i.e. the monthly reemployment probability of a separated worker, appears to be less affected by the business cycle. I argue that the different effects may reveal an opposite cyclicality of job-to-job transitions and the take up of unemployment benefits. The reconsideration of the total job finding and separation rates indicates a strong cyclicality of German worker flows. The job finding rate turns out to play a dominant role for explaining unemployment fluctuations, though the contributions of the separation rate are considerable as well.

The paper is structured as follows. Section 2.2 describes the data set and the measurement of worker flows. The time aggregation bias is investigated in Section 2.3. After obtaining a measure of the actual time aggregation bias and assessing the correction approach of Shimer (2012), the effects of time aggregation are evaluated on business cycle frequency. Section 2.4 reconsiders cyclical facts on the job finding and separation rates by considering the additional dynamics of the time aggregation bias. Section 2.5 concludes.

5 Employment subject to social security excludes, for example, so-called *Minijobs*.

6 The Hartz reforms were implemented subsequently from 2003 to 2005 and have led to major changes of German labor market institutions. See Jacobi and Kluve (2007) for a comprehensive description.

2.2 Data Description

I use the Sample of Integrated Labor Market Biographies (SIAB) provided by the Institute for Employment Research (*Institut für Arbeitsmarkt- und Berufsforschung, IAB*). The SIAB is a 2% random sample of the Integrated Employment Biographies (IEB), which consists of all German residents who are characterized by at least one of the following labor market states during the time period 1975–2008: employment subject to the social security system, receipt of unemployment benefits, participation in active labor market policies (since 2000) and registered job search (since 2000). With the exception of participation in active labor market policies, the SIAB is representative for all included labor market states (see Dorner et al., 2010).

The main advantage of the administrative data set is the availability of daily information. Regardless of the data source, however, most studies rely on monthly point-in-time comparisons. I follow those studies and calculate the number of monthly worker flows, but I rely on a daily measurement. The continuous procedure avoids an underestimation of labor market transitions and a possible bias on business cycle frequency.[7]

According to the standard search and matching model, I focus on transitions between employment (E) and unemployment (U). To obtain time series that are as long as possible, the definition of unemployment is based on unemployment benefit receipt.[8] In Germany, unemployment benefits include benefits from the unemployment insurance system (*Arbeitslosengeld*), means-tested benefits (*Arbeitslosenhilfe/Arbeitslosengeld II*) as well as income maintenance during training (*Unterhaltsgeld*).[9] Even though the administrative data comprises actual labor market processes, it can become difficult to reconstruct a worker's labor market biography if he or she loses the entitlement to unemployment benefits. This may result from a regular exhaustion of unemployment benefits or an irregular break along with a sanction.

To correct for unemployment periods without benefit receipt, I apply the nonemployment proxy introduced by Fitzenberger and Wilke (2010). The adjustment for missing unemployment periods, in particular, ensures that the continuous measurement of worker flows does not fail to capture relevant

7 Strictly speaking, a daily measurement is still discrete, but this study considers it as a continuous framework.

8 See Appendix 2.A for further information on data selection.

9 Along with the Hartz IV reform the means-tested benefit system has changed. Until 2004, an unemployed worker could have been entitled to unemployment assistance *(Arbeitslosenhilfe)* after the expiration of an entitlement to unemployment insurance benefits *(Arbeitslosengeld)*. In 2005, unemployment assistance was replaced by unemployment benefits II *(Arbeitslosengeld II)*, which also covers the former social assistance *(Sozialhilfe)*. The receipt of unemployment benefits II does not require a foregoing entitlement to unemployment insurance benefits, but it can be a supplement to insurance-based benefits if the latter do not ensure the subsistence level.

labor market transitions.[10] Table 2.1 presents the implications of the adjustment procedure for unemployment durations. The first column indicates that nearly 30% of all benefit receipt spells have been contracted. As a consequence, the mean unemployment duration increases from nearly 8 months (228 days) to over 1 year (371 days). The standard deviation of both measures indicates that the distribution of unemployment durations is highly right-skewed. Moreover, the second last column demonstrates that unemployment benefits are even taken up for only 1 day. In contrast, the maximum unemployment duration increases from 17.5 to approximately 33 years. Accordingly, there is at least one worker who is detected to be unemployed for more than half of his or her working life.

Table 2.1: Unemployment durations

	Observations	Mean	Std. dev.	Min.	Max.
Benefit receipt	2,961,581	228	316	1	6,406
Nonemployment proxy	2,101,799	371	537	1	11,992
Note: Durations in days.					

Given the two-state environment, a worker may leave the unemployment pool and enter the employment state (*UE* flow or job finding) or leave the employment state and enter the unemployment pool (*EU* flow or separation). The worker flows are defined by their underlying transition rates, i.e. all transitions during month t are referred to the initial labor market state in month $t-1$. Hence, the job finding rate (f) and the separation rate (s) satisfy

$$f_t = \frac{\left(\sum_{s=1}^{S} UE_s\right)_t}{U_{t-1}} \quad \text{and} \quad s_t = \frac{\left(\sum_{s=1}^{S} EU_s\right)_t}{E_{t-1}}, \tag{2.1}$$

where t denotes the 10th day of a month and S denotes the number of days since the 10th day of the previous month.

The generated time series of the transition rates are then adjusted as follows. First, I account for a structural break along with the German reunification in 1990. Eastern German workers have been captured stepwise by the labor market registers and the data set is complete for the whole economy only since 1993. Therefore, I use time series for Western Germany until 1992 and link them to those for whole

10 The unemployment measure is referred to as *non*employment proxy because it cannot ruled out that it includes persons out of the labor force, such as temporarily discouraged workers. More details on the unemployment definition are given in Appendix 2.B.

Germany.[11] Second, I smooth out seasonal effects with the Census X12 procedure. Third, I transform the monthly transition rates into quarterly averages to obtain measures at the same frequency as standard business cycle indicators.[12]

Figure 2.1: Transition rates

Notes: Solid lines show quarterly averages of monthly transition rates. Dotted lines display the HP trend with a smoothing parameter of $\lambda = 1{,}600$. Shaded areas are times of recessions.

11 It is worth noting that the extraction of time series for Western Germany turns out vague in the early 1990s because the information about the place of residence is not available before 1999. For employment spells, however, the place of work is known throughout the sample and to acquire an entitlement to unemployment benefits a worker usually has to have a foregoing employment period.

12 Using quarterly averages of monthly data is in line with the literature. In particular, Shimer (2012) explains this adjustment by smoothing out high-frequency fluctuations that are likely to result from survey-based measurement errors. Even though my measures do not face such measurement errors, this adjustment may smooth out elusive labor market transitions of individuals that have not been captured by data selection. Otherwise, an extrapolation of the worker flows would have been likely to overestimate quarterly labor market transitions. See Gomes (2012) for a discussion of the extrapolation error.

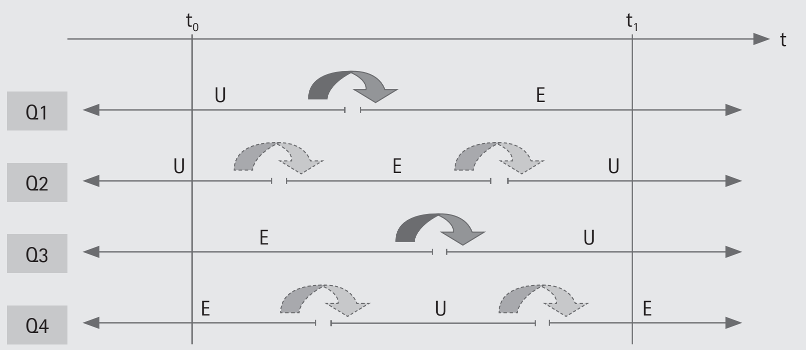
Figure 2.1 plots the time series of the aggregate transition rates from 1981 to 2007. The job finding rate declines from over 10% in 1981 to around 5% after the reunification. Thus, the expected search duration for jobs subject to the German social security system has increased. The separation rate amounts to around 1% throughout the sample period. Accordingly, the average tenure of jobs subject to social security has been relatively constant. However, the deviations of both transition rates from their trend seem to follow a cyclical pattern.

The main question of this paper is what difference it would have made for the development of the transition rates if the daily information had not been considered. Therefore, the next section turns to measures computed at a lower frequency and inspects the resulting time aggregation bias.

2.3 Time Aggregation Bias

The time aggregation bias captures all transitions that are reversed within two measurement points. Figure 2.2 illustrates the time aggregation problem by presenting four different spell sequences *Q*. The measurement points are given by t_0 and t_1. In t_0, one observes two unemployment spells and two employment spells. The spells are followed by transitions into the other labor market state at different dates and with different durations. The new labor market states in *Q1* and *Q3* persist until the next measurement point, and thus each labor market transition is taken into account by the discrete measurement. However, the new labor market states in *Q2* and *Q4* do not persist until the next measurement point because there is a preceding labor market transition in the opposite direction. Hence, in t_1, one observes the same labor market state as in t_0. As a consequence, the discrete measurement neglects the transitions in *Q2* and *Q4*, and the resulting number of worker flows is underestimated.

Figure 2.2: Point-in-time measurement



To address recent conclusions on the time aggregation bias, this section proceeds closely to the related literature on U.S. labor market dynamics. After briefly outlining the related studies, I extract a measure from monthly point-in-time comparisons and compare it with the prediction of the correction approach suggested by Shimer (2012). I then present cyclical properties of the monthly time aggregation bias and explore the effects on unemployment decomposition.

2.3.1 Related Literature

The recent discussion on the effects of time aggregation in the measurement of worker flows is triggered by Shimer (2005). The author assumes a procyclical time aggregation bias in the separation rate and concludes that the U.S. separation rate is nearly acyclic. Shimer (2012) complements this conclusion by deriving a correction approach for time aggregation. He relates discretely measured transition rates to a continuous-time framework by assuming that during a given time period all unemployed workers face the same job finding probability and all employed workers face the same separation probability.

More specific, Shimer argues that "ignoring time aggregation will bias a researcher towards finding a countercyclical employment exit probability, because when the job finding probability falls, a worker who loses her job is more likely to experience a measured spell of unemployment" (Shimer, 2012, p. 129). With respect to Figure 2.2, Shimer's argument implies that in economic upswings there is a significantly higher share of spell sequences *Q4* compared to *Q3*, meaning that the time aggregation bias in the separation rate is procyclical. Accordingly, Shimer claims that the share of observed unemployment spells varies with the business cycle.

Obviously, the discrete measurement of spell sequence *Q4* also neglects a job finding as well as in *Q2*. However, Shimer argues that "because the probability of losing a job during the month is comparatively small, time aggregation causes relatively little bias in the job finding rate" (Shimer, 2012, p. 131). Hence, short employment spells should be less relevant when measuring the job finding rate.

A prominent reply to Shimer's argument of a procyclical time aggregation bias in the separation rate is given by Fujita and Ramey (2006). The authors apply the correction approach of Shimer (2012) for monthly U.S. data and show that although the level of the time aggregation bias is considerable, the cyclical fluctuations of the adjusted and unadjusted transition rates display a very similar pattern. Thus, Fujita and Ramey (2006) conclude that the effect of time aggregation on the cyclical behavior of the transition rates is negligible.

Nekarda (2009) provides a more comprehensive analysis of the time aggregation bias in U.S. worker flows. The author compares monthly point-in-time measures from the commonly used Current Population Survey (CPS) with weekly information from the Survey of Income and Program Participation (SIPP) and detects that the *true* number of monthly transitions is underestimated by 15–24%. In addition, Nekarda (2009) shows that the time aggregation bias in both job findings and separations is procyclical. As these effects nearly offset each other, the author concludes that time aggregation induces a cyclical bias neither in discretely measured gross flows nor in their underlying transition rates. Nevertheless, when he adjusts the worker flows according to the correction approach of Shimer (2012), Nekarda (2009) finds a lower contribution of the separation rate to steady state unemployment fluctuations.

2.3.2 A Monthly Measure

In contrast to U.S. studies, I extract a measure of the time aggregation bias that is based on daily information and stems from a single data source. Therefore, I compute worker flows from monthly point-in-time comparisons and confront them with the continuous measures presented in the previous section.

The discretely measured job finding and separation rates are given by

$$\overline{f}_t = \frac{UE_t}{U_{t-1}} \text{ and } \overline{s}_t = \frac{EU_t}{E_{t-1}}, \tag{2.2}$$

where t again denotes the 10th day of a month. As a first piece of evidence, Figure 2.C.1 in the Appendix contrasts the discretely measured transition rates with their continuous counterparts. It can be seen that the discrete measures are significantly lower than the continuous ones, but they seem to develop in a similar manner.

The resulting time aggregation bias (δ) is defined by the difference between the continuously measured transition rates from Equation 2.1 and the discretely measured transition rates from Equation 2.2, i.e.

$$\delta_t^i = i_t - \overline{i}_t, \tag{2.3}$$

where $i = f, s$. Hence, the time aggregation bias denotes the aggregate probability that a transition will be reversed within one month.

Table 2.2: Descriptive statistics of time aggregation bias

	Job finding rate		Separation rate	
	Actual (1981–2007)	Estimated (1981–2007)	Actual (1981–2007)	Estimated (1981–2007)
Mean	0.006	0.002	0.001	0.000
Relative to total measures	0.101	0.031	0.094	0.031
Standard deviation	0.103	0.146	0.070	0.067
Relative to total measures	1.296	1.827	1.092	1.040
Autocorrelation	0.621	0.573	0.428	0.465
Relative to total measures	1.002	0.924	0.750	0.814

Notes: Mean refers to the level. Standard deviations and autocorrelations account for log deviations from the HP trend with $\lambda = 1{,}600$. Total measures are the continuously measured transition rates.

Table 2.2 reports descriptive statistics of the monthly time aggregation bias, where the first and third columns refer to Equation 2.3 (i.e. the actual bias). Admittedly, the probabilities of reversing a job finding or a separation within one month are quite low with means of 0.6% and 0.1%, respectively. In relation to the continuously measured transition rates, however, the time aggregation bias appears to be important. The comparison of monthly labor market states leads to an underestimation of total worker flows by around 10%. This number is fairly the half of what Nekarda (2009) reports for U.S. worker flows; however, it seems to be considerable as the German labor market is known to be less flexible.

Figures 2.C.2 and 2.C.3 show the development of the time aggregation bias over the sample period, where the solid lines refer to the actual bias. In fact, the bias shows significant fluctuations. The probability of reversing a job finding within one month fluctuates by around 0.8% in the 1980s, falls to around 0.4% in the 1990s, and then increases gradually to 0.6%. Thus, the probability of quickly returning to unemployment from a new job that is subject to social security decreases after the reunification, but in the late 1990s those new jobs again turn out to be less stable in the one-month horizon. The probability of a monthly reversed separation, i.e. the probability of finding a new job within one month after becoming unemployed, fluctuates by around 0.1%, but it also shows an upward trend since the late 1990s. This development holds in relation to the total transition rates. The relative time aggregation bias increases up to 14% in the second part of the sample period.

The recent rise of the time aggregation bias may reveal some effects of labor market reforms that have been implemented to increase labor market flexibility. For example, tightened job acceptance regulations are intended to stimulate returns to employment, while facilitation of temporary work and a weaker dismissal protection are supposed to boost job findings in general. In fact, the interpretation of an increased flexibility can be reconciled with the result of Fahr and Sunde (2009) who find an accelerated matching process along with the Hartz reforms.

2.3.3 The Shimer (2012) Correction Approach

The correction approach of Shimer (2012) intends to account for worker flows that are neglected by discrete measurements. Fujita and Ramey (2006) apply the three-state approach of Shimer (2012) for a two-state model and derive estimates for continuous-time transition rates, i.e. job finding and separation rates that are adjusted for time aggregation.[13] The adjusted transition rates result as:

$$\hat{f}_t = -\frac{\log(1-\bar{s}_t-\bar{f}_t)\bar{f}_t}{\bar{s}_t+\bar{f}_t} \quad \text{and} \quad \hat{s}_t = -\frac{\log(1-\bar{s}_t-\bar{f}_t)\bar{s}_t}{\bar{s}_t+\bar{f}_t}, \tag{2.4}$$

where t again denotes the 10th day of a month. As can be seen from Figure 2.C.1, the adjusted transition rates evolve above the discrete measures, but they do not reach the level of the continuously measured transition rates.

To evaluate how well the theoretical correction approach accounts for the actual time aggregation bias, I also extract the time aggregation bias that results from the correction approach. Therefore, I take the difference between the adjusted transition rates from Equation 2.4 and the unadjusted measures from Equation 2.2, i.e. the estimated time aggregation bias $(\hat{\delta})$ satisfies

$$\hat{\delta}_t^i = \hat{i}_t - \bar{i}_t, \tag{2.5}$$

where $i = f, s$.

Figures 2.C.2 and 2.C.3 show that the estimated bias is significantly lower than the actual time aggregation bias. On average, the correction approach predicts that monthly point-in-time comparisons underestimate total worker flows by only 3% (see also the second and forth columns in Table 2.2). Moreover, Figure 2.C.4 displays the coverage of the correction approach over the sample period. The estimated time aggregation bias accounts for a declining fraction of the actual bias. The coverage amounts to more than 50% at the beginning of the sample period and then decreases to around 20%.

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13 For a two-state labor market model, Shimer (2012) provides an alternative correction approach, which uses a measure of short-term unemployment to obtain the job finding rate. For an application of this approach see Elsby et al. (2009).

The low coverage may result from the key assumption underlying the correction approach. Recall that the correction approach assumes constant transition rates during a time period, i.e. all unemployed workers have the same probability of finding a job and all employed workers have the same probability of losing their job. In other words, the correction approach abstracts from worker heterogeneity arising from duration dependence or individual characteristics. However, Kluve et al. (2009) analyze individual transition rates for Germany and find significant differences between specific demographic groups. Accordingly, the correction approach may be more practical for adjusting disaggregate worker flows.

2.3.4 Cyclical Properties

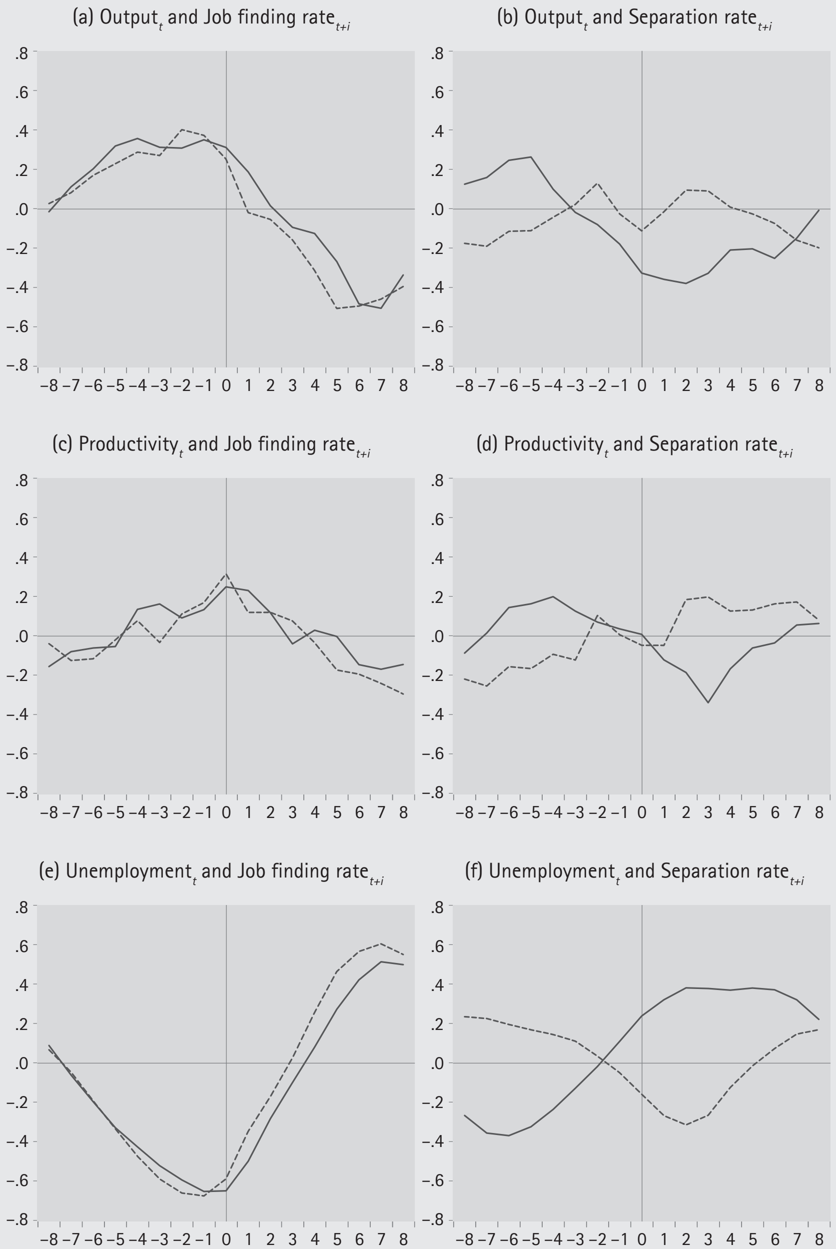
A central question is whether time aggregation involves a cyclical bias in discretely measured worker flows. To address the arguments of Shimer (2005; 2012), I extract the cyclical components of the time aggregation bias by computing the log deviations from the underlying Hodrick-Prescott (HP) trend.[14]

Table 2.2 presents standard deviations and autocorrelation coefficients of the cyclical components. The time aggregation bias in the job finding rate appears to be more volatile than in the separation rate. Interestingly, the bias in both transition rates is more volatile than the transition rates themselves, i.e. the probabilities of reversing a transition within one month react more sensitively to business cycle shocks than the total transition rates. In addition, the cyclical bias in the job finding rate is more persistent than in the separation rate, where the latter is even less persistent than the total separation rate.

To examine the cyclical behavior of the time aggregation bias, I use output, labor productivity and unemployment as business cycle indicators. Figure 2.3 shows cross correlations of the cyclical components. With respect to all three business cycle indicators, the time aggregation bias in the job finding rate displays a procyclical behavior. Even though the contemporaneous correlations with output and productivity are less striking (approximately 0.3), they are relatively strong with unemployment (-0.6). In addition, the time aggregation bias in the job finding rate tends to lead the cycle, because it reaches its peak correlation with output at a lag of four and with unemployment at a lag of one. The procyclical behavior of the time aggregation bias in the job finding rate indicates that economic upswings are associated with a significantly higher share of workers who leave and return to unemployment within one month.

14 I use the standard smoothing parameter of $\lambda = 1{,}600$ for quarterly data.

Figure 2.3: Cross correlations of time aggregation bias with business cycle indicators



Notes: Log deviations from HP trend with $\lambda = 1{,}600$. Solid lines show the actual time aggregation bias and dashed lines the estimated time aggregation bias. Measure *i* along the abscissa accounts for leads (positive values) and lags (negative values) at a quarterly frequency. Output measures gross domestic product (GDP). Labor productivity is the ratio of GDP to total hours worked.

In contrast, the cyclical behavior of the time aggregation bias in the separation rate is less distinctive. One may argue that there is also a procyclical pattern at higher lags, but the peak correlations are lower than for the job finding rate. In addition, the contemporaneous correlations show opposite signs and the correlation with productivity is even close to zero. A rather acyclical behavior is also indicated by the estimated time aggregation bias in the separation rate, though it reflects the actual bias worse than for the job finding rate. Consequently, the time aggregation bias in the separation rate does not reveal that monthly time aggregation neglects a significantly higher share of unemployment spells in economic upswings as emphasized by Shimer (2005; 2012).

However, Shimer argues that using the HP filter with the standard smoothing parameter "seems to remove much of the cyclical volatility in the variable of interest" (Shimer, 2012, footnote 10) and therefore suggests a smoothing parameter of $\lambda = 10^5$. I check the robustness of the preceding results by using the higher smoothing parameter. Indeed, the time aggregation bias in the separation rate becomes more volatile and more persistent in relation to the total separation rate (see Table 2.D.1), but there is still no indication for a procyclical behavior (see Figure 2.D.1). Instead, using the HP filter with a smoothing parameter of $\lambda = 10^5$ turns out to be less suitable for German business cycle fluctuations, because the positive correlations of the bias in the job finding rate with both output and productivity disappear.[15] Accordingly, I focus on the standard smoothing parameter.

The procyclical time aggregation bias in the job finding rate may be reconciled with a procyclical behavior of quits. A higher relevance of short employment periods in economic upswings may indicate that workers are more willing to quit a new job in good times, while they keep their jobs longer in bad times. Hence, the prospect of a better job even seems to make a worker to accept a further unemployment period in upswings. As labor demand is high, the expected unemployment duration is relatively short. This can be also underpinned by a procyclical behavior of the job finding rate.

On the one hand, the acyclical time aggregation bias in the separation rate appears to challenge a procyclical behavior of the job finding rate, because it implies that the share of monthly unemployment periods is constant over the business cycle. On the other hand, the acyclical bias in the separation rate may also indicate a procyclical behavior of job-to-job transitions. This interpretation, in turn, would strengthen the argument of a higher quit rate in good times. Hence, unemployment periods are not only shorter in economic upswings, but they are

15 This may challenge the view that the choice of the smoothing parameter has only little effects on relative terms (see, e.g., Hornstein et al., 2005).

also less likely to occur. The latter can have two reasons. Either workers are more likely to change to new employers within a day (*direct* job-to-job transition) or workers are less likely to take up unemployment benefits in case of a short transition period (*indirect* job-to-job transition). Recall that the nonemployment proxy solely corrects for unemployment periods before and after benefit receipt but not between two employment spells, because the latter case is considered to be a deliberated employment interruption.

2.3.5 Effects on Unemployment Decomposition

Given the cyclicality of the time aggregation bias, a further question concerns the extent to which monthly time aggregation affects the variance decomposition of labor market states. Therefore, I apply a conventional variance decomposition of unemployment fluctuations and compare the contributions of the different measures of the transition rates.

The conventional variance decomposition of unemployment assumes that the actual unemployment rate moves closely to the steady state unemployment rate. Thus, the actual unemployment rate u_t is approximated by

$$u_t \approx u_t^* \equiv \frac{s_t}{s_t + f_t}, \tag{2.6}$$

where * indicates the steady state value.

Fujita and Ramey (2009) demonstrate that the variance of the detrended steady state unemployment rate can be decomposed into the detrended transition rates. The relative contributions of the transition rate are summarized by

$$\beta_i^* = \frac{cov(du_t^*, di_t)}{var(du_t^*)}, \tag{2.7}$$

where d indicates a detrending method and $i = f, s$. Note that there also arises a residual term ε, which constitutes the approximation error and contributes to unemployment variations with $\beta_\varepsilon^* = 1 - \beta_f^* - \beta_s^*$.

Table 2.3 shows the contributions of the transition rates, where the first row refers to the continuous measures. The job finding rate turns out to play a larger role for German unemployment variations. Fluctuations in the job finding rate account for 55% and fluctuations in the separation rate contribute 42%. These numbers can be reconciled with the conclusion of Elsby et al. (2009a) that the job finding and separation rates are equally important for unemployment fluctuations in Continental European countries. Focusing on the post-reunification period even reinforces a 50:50 split.

Table 2.3: Contributions to steady state unemployment fluctuations

	Job finding rate		Separation rate	
	Full sample (1981–2007)	Reunified Germany (1993–2007)	Full sample (1981–2007)	Reunified Germany (1993–2007)
Continuous measures	0.550	0.534	0.424	0.471
Discrete measures	0.534	0.524	0.444	0.481
Adjusted measures	0.546	0.534	0.431	0.471

Note: Log deviations from HP trend with $\lambda = 1{,}600$.

The second row displays the variance decomposition using the discretely measured transition rates. Due to the time aggregation bias the contribution of the job finding rate is underestimated and the contribution of the separation rate is overestimated. However, the deviation does not exceed 2 percentage points. In the subsample, the deviation accounts for only 1 percentage point.

The unemployment decomposition based on the adjusted transition rates is shown in the third row of Table 2.3. It can be seen that the correction approach of Shimer (2012) is able to counter the deviation and actually removes it in the post-reunification period. Hence, the observation of Nekarda (2009) that the theoretical correction approach leads to a distorted contribution of the separation rate cannot be confirmed.

Applying Shimer's smoothing parameter of $\lambda = 10^5$ verifies the preceding results (see Table 2.D.2). Interestingly, the continuously measured transition rates show the same contributions as with the standard smoothing parameter. The adjusted measures again correct the biased contributions in the right direction. However, in the subsample the bias becomes larger and the contributions of the job finding and separation rates diverge more. The same holds for the approximation error of the variance decomposition. Thus, doubts on the suitability of the higher smoothing parameter arise once more.

Moreover, I follow Fujita and Ramey (2009) and check the robustness of the variance decomposition by using first differences as an alternative detrending method. Table 2.D.3 shows the results. The contributions of the continuously measured job finding and separation rates are of the same magnitude as before and appear to be robust. However, using first differences the time aggregation bias works in the opposite direction. It increases the contribution of the job finding rate and lowers the contribution of the separation rate. In addition, adjusting the discretely measured transition rates with the correction approach of Shimer (2012) boosts the time aggregation bias. Accordingly, using first differences, I can confirm the finding of Nekarda (2009) that applying the theoretical correction approach can distort the role of the separation rate. This observation, in turn, may indicate a sensitivity of the correction approach with respect to detrending methods.

2.4 Stylized Facts of German Worker Flows

The preceding section has shown that the additional dynamics of the time aggregation bias affect both the level and the cyclicality of worker flows. Moreover, the acyclical behavior of the bias in the separation rate suggests a relevance of unemployment periods without benefit receipt. Previous studies on German labor market fluctuations do not apply the nonemployment proxy to measure unemployment periods, but focus on benefit receipt instead. Thereby, Jung and Kuhn (2011) find a larger volatility of the separation rate along with a larger contribution to unemployment fluctuations. Gartner et al. (2012), however, use a broader definition of worker flows and observe similar volatilities of the job finding and separation rates.

This section investigates the cyclicality of German worker flows by using the continuously measured transition rates defined in Section 2.2. In particular, I reconsider the stylized facts about the cyclical components of the transition rates and discuss their contributions to unemployment fluctuations. I also apply an alternative variance decomposition that has been suggested for countries with low labor turnover.

2.4.1 Cyclical Components

Table 2.4 presents descriptive statistics of the cyclical components of the job finding and separation rates.[16] It can be seen that the job finding rate is more volatile than the separation rate. The standard deviation of the job finding rate amounts to 8% and the standard deviation of the separation rate is 6%. The volatility of both transition rates declines after the reunification. In relation to the business cycle indicators, however, the transition rates become more volatile in the post-reunification period. The relative rise implies that the standard deviations of output, productivity and unemployment have decreased more strongly than that of the transition rates.

In particular, the volatility ratios with respect to productivity are striking. With factors of 12–15 and 10–13, respectively, German job finding and separation rates

16 As before, the cyclical components are computed as log deviations from the underlying HP trend with the standard smoothing parameter of $\lambda = 1{,}600$.

even appear to be more volatile than U.S. transition rates.[17] In terms of the Shimer puzzle, productivity shocks thus seem to have a remarkably strong amplification effect in Germany. However, the relatively large volatility ratio with respect to productivity can also imply that productivity shocks are not the actual source of German labor market fluctuations and thus play a minor role (e.g., compared to output shocks).[18]

The autocorrelation coefficients indicate that the cyclical component of the job finding rate is slightly more persistent than that of the separation rate. Moreover, the fluctuations of the transition rates are similar persistent as those of output and productivity, but they are less persistent than the fluctuations of unemployment. The latter relation can be reconciled with the hysteresis problem of German unemployment.

Table 2.4: Descriptive statistics of transition rates

	Job finding rate		Separation rate	
	Full Sample (1981–2007)	Reunified Germany (1993–2007)	Full Sample (1981–2007)	Reunified Germany (1993–2007)
Standard deviation	0.080	0.069	0.064	0.062
Relative to output	6.975	8.379	5.632	7.519
Relative to productivity	12.213	14.560	9.861	13.065
Relative to unemployment	1.085	1.136	0.876	1.019
Autocorrelation	0.620	0.595	0.571	0.580
Relative to output	1.225	1.181	1.128	1.151
Relative to productivity	1.419	0.982	1.307	0.957
Relative to unemployment	0.697	0.663	0.642	0.649

Notes: Log deviations from HP trend with $\lambda = 1{,}600$. Output measures gross domestic product (GDP). Productivity is the ratio of GDP to total hours worked.

Figure 2.4 shows the cyclical behavior of the transition rates. It can be seen that the job finding rate is procyclical and the separation rate is countercyclical. The peak correlations of the job finding and separation rates with output are 0.4 and -0.4, respectively, and turn out to be stronger after the reunification (0.6 and -0.6, respectively). In addition, the peak correlations with output indicate a rather leading behavior of the transition rates, whereas the peak correlations with productivity show a rather lagging behavior. The cross correlations with productivity are lower

17 Most prominently, Shimer (2005) finds for the U.S. that the volatility of the job finding rate is 6 and that of the separation rate is 4 times as large as the volatility of labor productivity (so-called Shimer puzzle).

18 See also Balleer (2012), who studies the Shimer puzzle for U.S. labor market fluctuations.

than with output, which again raises the question on the importance of productivity shocks for German labor market fluctuations.

Moreover, both transition rates show high and well-shaped cross correlations with unemployment. The correlation between the job finding rate and unemployment reaches nearly -0.8, while the correlation between the separation rate and unemployment is up to 0.6. The peak correlations with unemployment arise at lags of 1-2 quarters, meaning that the transition rates precede unemployment. This might reinforce that the transition rates are referred to as the driving forces of unemployment fluctuations (see Fujita and Ramey, 2006).

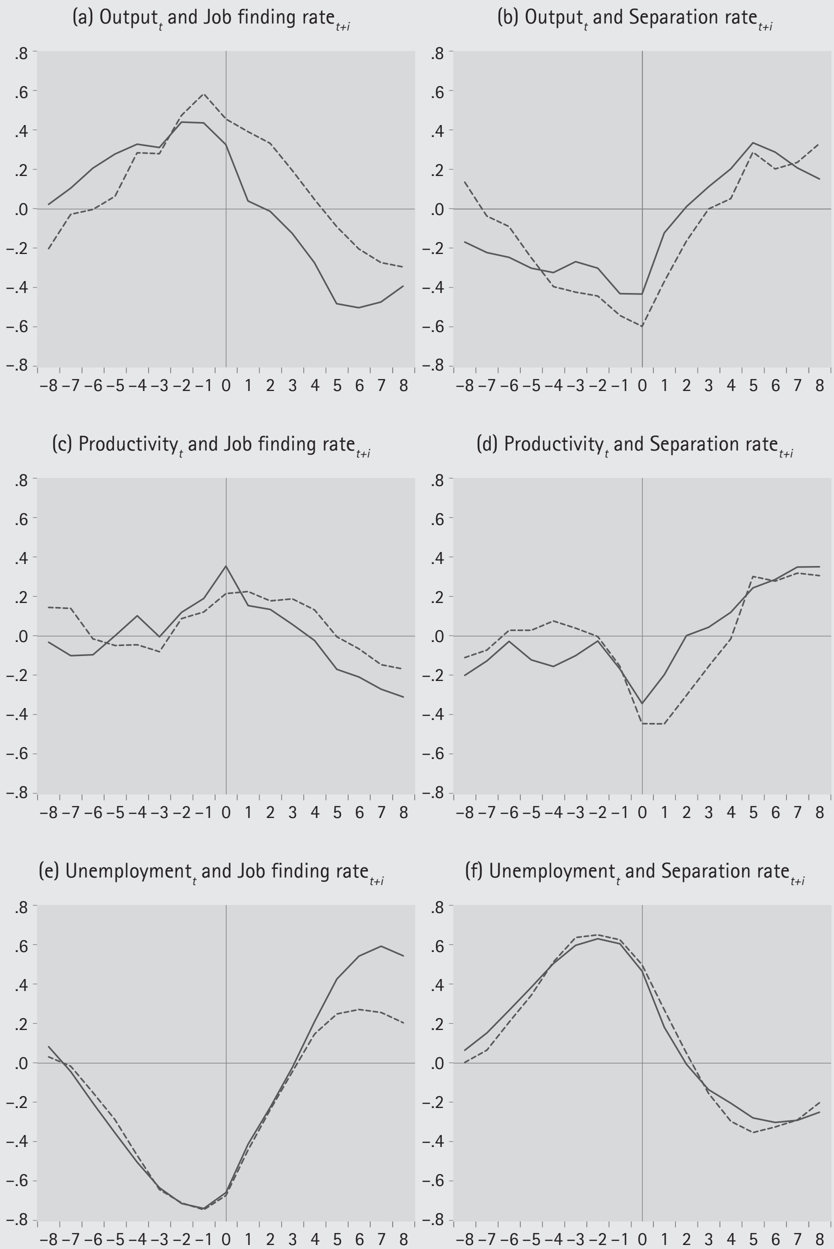
2.4.2 Contributions to Unemployment Fluctuations

The contributions of worker flows to unemployment fluctuations have become a major topic because they have important policy implications. In Section 2.3.5, the variance decomposition of the steady state unemployment rate has shown that the job finding rate plays a slightly dominant role for explaining unemployment fluctuations. For France, Petrongolo and Pissarides (2008) also find a larger role of the unemployment outflow rate, which they explain by a strict employment protection. Germany is also known for a strict employment protection; thus, the result of a larger role of the German job finding rate appears to be plausible.

However, Elsby et al. (2009a) argue that the steady state unemployment rate is a weak approximation for the actual unemployment rate if labor turnover is low. On average, the sum of the monthly job finding and separation rates amounts to only 7% in Germany (see Figure 2.1). Figure 2.5 demonstrates the resulting divergence of the actual and steady state unemployment rates. The steady state unemployment rate mainly overestimates the actual unemployment rate, where the deviations become more relevant in times of recessions. After the reunification, the deviations even range up to 5 percentage points. Moreover, the actual unemployment rate moves quite gradually, while the steady state unemployment rate exhibits rapid changes.

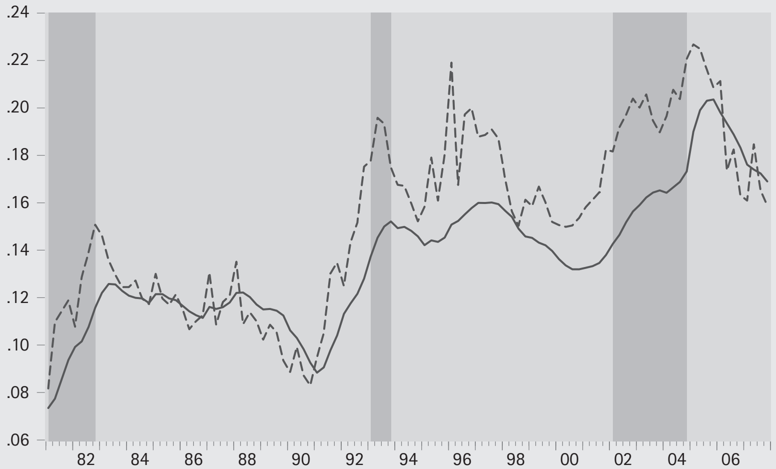
Therefore, Elsby et al. (2009a) conclude that the steady state variance decomposition is inappropriate for unemployment rates in Continental European countries. The authors propose a procedure that decomposes the variance of actual unemployment. The so-called non-steady state variance decomposition allows actual unemployment to deviate from its steady state and captures the influence of both contemporaneous and lagged fluctuations of the transition rates. In addition, Smith (2011) demonstrates that the lower the job finding and separation rates, the larger is the relative impact of past variations.

Figure 2.4: Cross correlations of transition rates with business cycle indicators



Notes: Log deviations from HP trend with $\lambda = 1{,}600$. Solid lines refer to the full sample period (1981–2007) and dashed lines to the post-reunification period (1993–2007). Measure *i* along the abscissa accounts for leads (positive values) and lags (negative values) at a quarterly frequency. Output measures gross domestic product (GDP). Labor productivity is the ratio of GDP to total hours worked.

Figure 2.5: Unemployment rates



Notes: The solid line shows the actual unemployment rate and the dashed line the steady state unemployment rate. Time series show quarterly averages of monthly measures. Shaded areas are times of recessions.

The approach of Elsby et al. (2009a) considers unemployment fluctuations as first differences of the log unemployment rate. Then, the relative contributions are given by

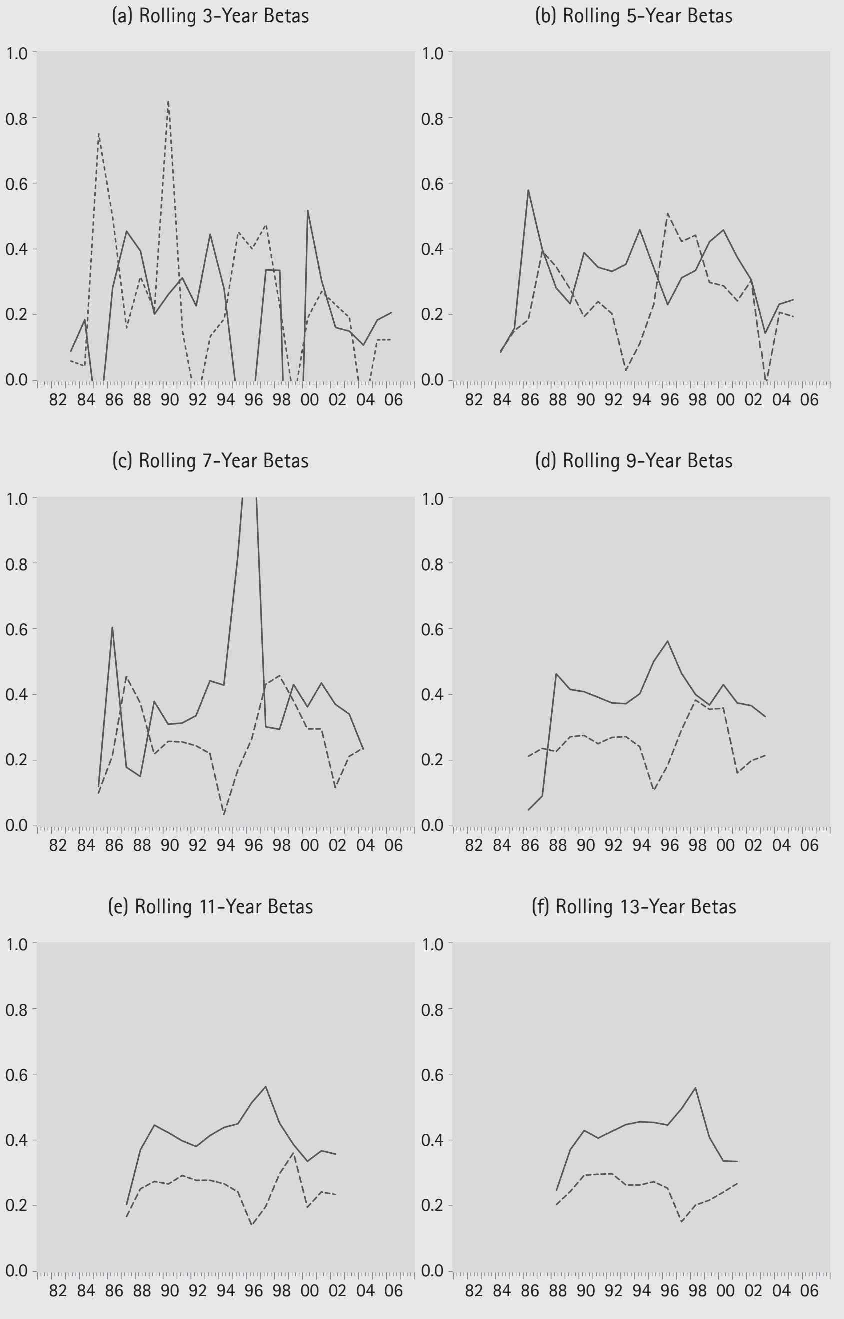
$$\beta_i = \frac{cov(\Delta \log u_t, C_t^i)}{var(\Delta \log u_t)}, \qquad (2.8)$$

where $i = f, s, 0$. C_t^f and C_t^s denote the cumulative contributions of current and past variations in the job finding and separation rates. C_t^0 describes the contribution of the deviation of actual unemployment from its steady state at the beginning of the sample period, where $C_0^0 = \Delta \log u_0$ measures the value of the initial deviation. The share of the residual component ε now satisfies $\beta_\varepsilon = 1 - \beta_f - \beta_s - \beta_0$.[19]

To allow for time variation in the relative contributions, I follow Smith (2011) and compute rolling β_i's. Moreover, I convert the monthly job finding and separation rates into annual averages and investigate their contributions in different time horizons. Figure 2.6 presents the results. The relative contributions of the transition rates indeed vary considerably over time. In the 3-year periods, the contributions of the transition rates display an alternating pattern. Nevertheless, it is worth noting that the separation rate contributes about 80% to unemployment changes in the periods 1984–1986 and 1989–1991.

19 For a more detailed description of the non-steady state decomposition see Elsby et al. (2009a, p. 18f).

Figure 2.6: Contribution to actual unemployment fluctuations



Notes: First differences of log variables. Solid lines refer to the job finding rate and dashed lines to the separation rate. Variables are annual averages of monthly measures.

Turning to 5-year periods, the high contributions of the separation rate disappear and fluctuations in the job finding rate seem to be at least as important as those in the separation rate. The contributions of the job finding rate amount to 20–60%, while the contributions of the separation rate even shrink to nearly 0% in the early 1990s and 2000s. Apart from the outlier of the job finding rate in the 7-year periods, the contributions become smoother with longer time frames and the relative importance of the transition rates turns out more clearly. In the longer time horizons, the two transition rates explain about 60% of actual unemployment variations, where the job finding rate accounts for 40% and the separation rate contributes 20%.

To sum up, the non-steady state variance decomposition reveals a relevance of both the job finding rate and the separation rate for understanding unemployment fluctuations in Germany; however, the job finding rate appears to be the dominant force in longer time frames. Hence, the result of the non-steady state variance decomposition does not depart from the conclusion of the conventional steady state variance decomposition, but the decomposition of the actual unemployment rate provides a more realistic picture of labor market dynamics.

2.5 Conclusion

This paper has analyzed the effects of time aggregation in the measurement of worker flows, which has stimulated recent research on U.S. labor market dynamics. Therefore, I have exploited daily information from German administrative data and computed monthly job finding and separation rates.

In particular, I have compared three measures of worker flows: one that considers every daily change of the individuals' labor market status, one that compares the individuals' labor market status at a specific day per month and one that applies the correction approach of Shimer (2012), which intends to account for neglected worker flows in discrete measurements.

The comparison of discretely and continuously measured worker flows reveals that monthly point-in-time measurements underestimate total worker flows by around 10% in Germany. Applying the correction approach of Shimer (2012), however, predicts an underestimation of only 3%. Hence, the homogeneity assumption underlying the theoretical correction approach appears to be too strong for German worker flows and thus may be more practical for disaggregate labor market transitions.

Moreover, this paper has analyzed the cyclical properties of the time aggregation bias by using different business cycle indicators. The time aggregation bias in the job finding rate shows a procyclical behavior, which implies more short employment periods in economic upswings. In contrast, the time aggregation bias in the separation rate is relatively unaffected by the business cycle, which may challenge the claim of Shimer (2005; 2012) that a monthly point-in-time measurement neglects more unemployment spells in booms.

However, the results are more likely to reveal some facts about quits. Better job opportunities in upswings appear to induce a higher willingness of workers to quit a (new) job. If a quitting worker has not found a more suitable job yet, it is likely that he or she registers at an employment agency and applies for unemployment benefits. However, if a quitting worker faces only a short transition period to another job, it seems to be more likely that he or she refuses to register at an employment agency. Accordingly, the incidence of indirect job-to-job transitions may influence the take up of unemployment benefits and vice versa.

Finally, this paper has analyzed the cyclicality of the job finding and separation rates by considering the additional dynamics of the time aggregation bias. Both transition rates reinforce a high volatility and a strong cyclical behavior of German worker flows. Fluctuations in the job finding rate turn out to play a dominant role in explaining unemployment fluctuations; however, this result seems to be less influenced by the time aggregation bias.

2.A Data Selection

In contrast to theoretical labor market models, where workers are assumed to be either employed or unemployed, the SIAB may include parallel employment and unemployment spells due to the merging of different registers. Parallel notifications can occur when a recipient of unemployment benefits has a spare-time work (so-called *Hinzuverdiener*) or an employed worker loses his or her second job and becomes part-time unemployed. However, the data set suffers also from inconsistent spells, which make it difficult to identify the main labor market status. Jaenichen et al. (2005) inspect overlapping spells in German administrative data and detect employment spells to be more reliable than unemployment spells. Therefore, employment spells have priority in determining the actual labor market status.

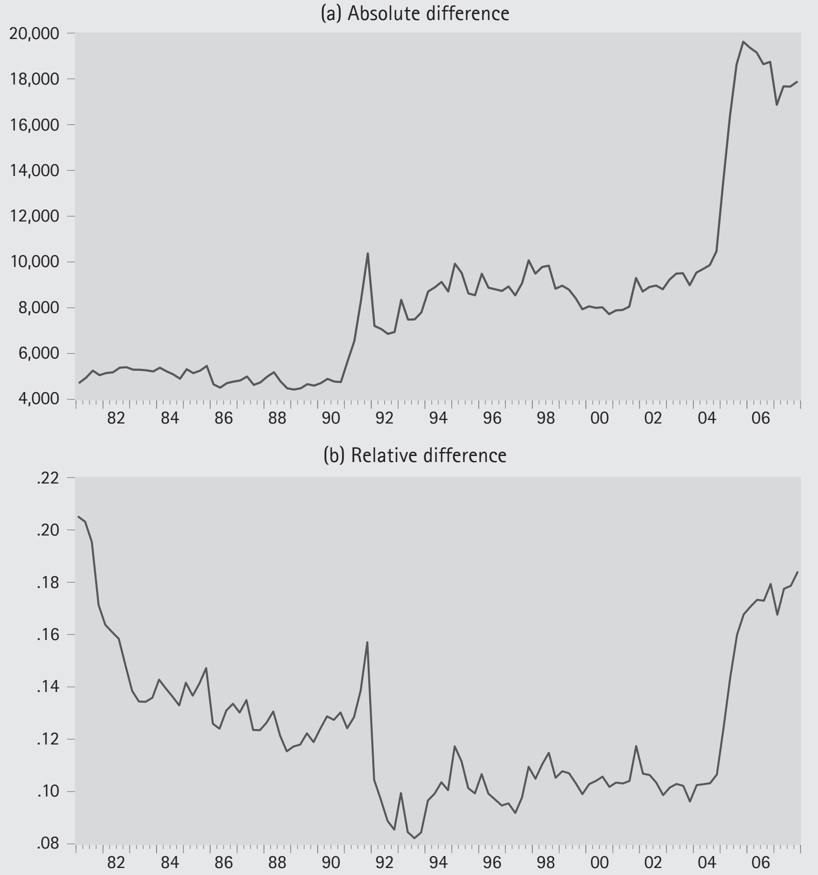
Moreover, I refine the data set as follows. From the employment pool, I exclude apprentices, trainees, family assistants as well as recipients of early retirement pension or compensations allowance. I also drop marginal employment (*geringfügige Beschäftigung*), which is covered by the social security system only since 1999. Omitting marginal employment avoids that unemployed persons with a spare-time work are counted as employed. In addition, I drop workers with more than 50 employment spells per year, which may occur with artists or other freelancers. Besides, the data set does not cover self-employment and civil services.

From benefit receipt, I drop persons who are not attached to the labor force. These include, for example, non-employable persons who live with a recipient of unemployment benefits II in a so-called community of needs (*Bedarfsgemeinschaft*). Due to administrative reasons all persons of a community of needs have to be registered by the employment agencies. However, the data set does not include all notifications of unemployment benefits II in 2005/2006 along with the change in the benefit system. Therefore, I consider job search spells of unemployed workers in these years if a corresponding notification of benefit receipt is missing. In addition, reports of benefit receipt are incomplete in the late 1970s, but they cannot be adjusted. Consequently, the analysis starts in 1980.

The resulting sample consists of 1,418,952 persons and 27,267,428 spells.

2.B A Nonemployment Proxy according to Fitzenberger and Wilke (2010)

Figure 2.B.1: Filled information gaps



Notes: Absolute numbers are the difference between the nonemployment proxy and benefit receipt. Relative numbers show the difference in relation to the nonemployment proxy.

This study applies the nonemployment proxy introduced by Fitzenberger and Wilke (2010) for German administrative labor market data. The nonemployment proxy is an useful measure to approximate unemployment by relying on notifications of unemployment benefit receipt. It consists of all nonemployment periods after an employment spell if at least one benefit receipt notification is available. Thus, the nonemployment proxy includes both unemployment periods with benefit receipt and unemployment periods without benefit receipt. If the last notification of benefit receipt is not followed by any further notification, the nonemployment proxy is treated as right censored.

Figure 2.B.2: Unemployment measures

Notes: The solid line presents the projected nonemployment proxy (quarterly averages of monthly data). The dashed line is the ILO unemployment measure (interpolation of yearly data provided by the National Accounts). The time period 1990-1992 exhibits the stepwise inclusion of Eastern Germany in labor market registers.

I consider information gaps before and after unemployment benefit receipt. The information gaps may also cover periods of marginal employment, because it has been dropped before. A marginal employment, however, is likely to be a temporary arrangement, which might justify that a marginally employed worker is assumed to search for a regular job anymore. The same may apply for an intervening period of self-employment as it has become an instrument of active labor market policy.

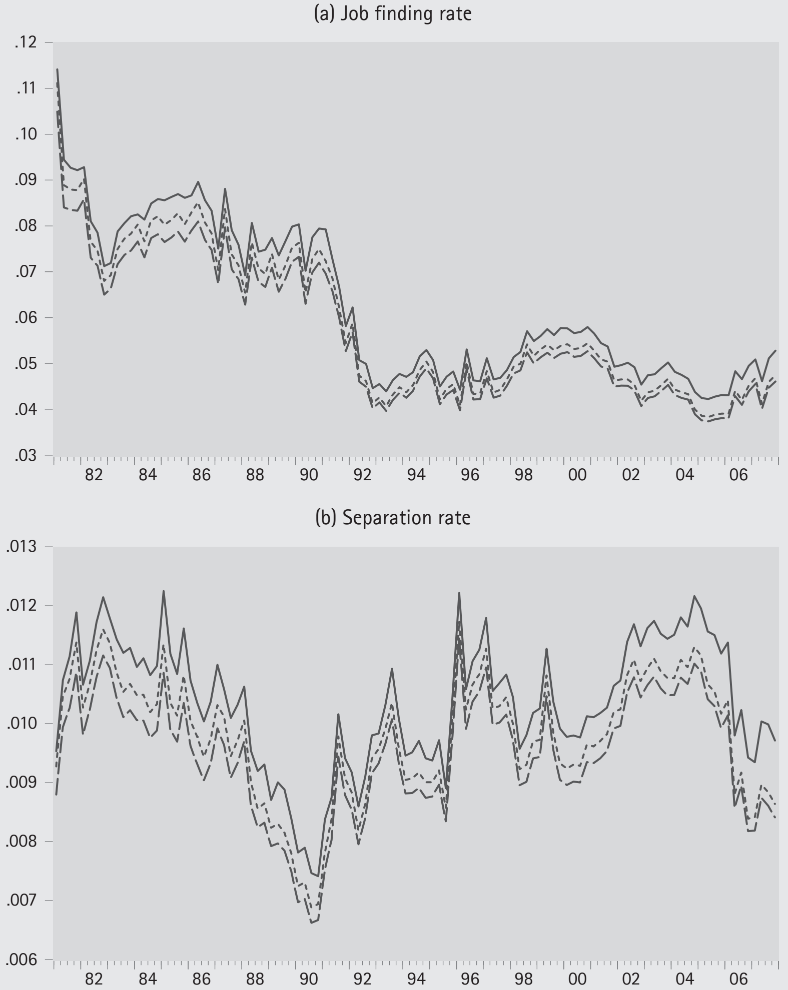
I fill only nonemployment periods by up to one year, which captures over 80% of all relevant information gaps. The restriction to one year particularly avoids a too extensive measure of unemployment. The observation period then reduces to 1981–2007 to ensure a high filling degree over the whole sample period.

Figure 2.B.1 illustrates the number of filled information gaps. The difference between benefit receipt and the nonemployment proxy amounts to around 5,000 workers in the 1980s and nearly 10,000 persons in the 1990s. Following the consolidation of the means-tested benefit systems in 2005, information gaps occur with over 18,000 persons afterwards. In relative terms, the adjustment of benefit receipt accounts for 20% of the unemployment pool in 1981. The significance of the adjustment procedure then declines to around 10% in the 1990s/early 2000s. Since 2005 the filling of information gaps again becomes more relevant and amounts to 18% of the unemployment pool. The latter rise is likely to result from shortened entitlement periods of unemployment benefits as well as tightened sanctions, which have been implemented in the course of the Hartz reforms.

Moreover, Figure 2.B.2 confronts the nonemployment proxy with a survey-based unemployment measure according to the definition of the International Labor Organization (ILO). It can be seen that the two unemployment measures fluctuate in a similar manner. However, the nonemployment proxy tends to be higher than the survey-based measure. The difference is likely to indicate a significance of marginal employment. The Federal Employment Agency allows unemployed workers to have a spare-time work of less than 15 hours per week, while the ILO counts workers with a job of at least 1 hour per week as employed.

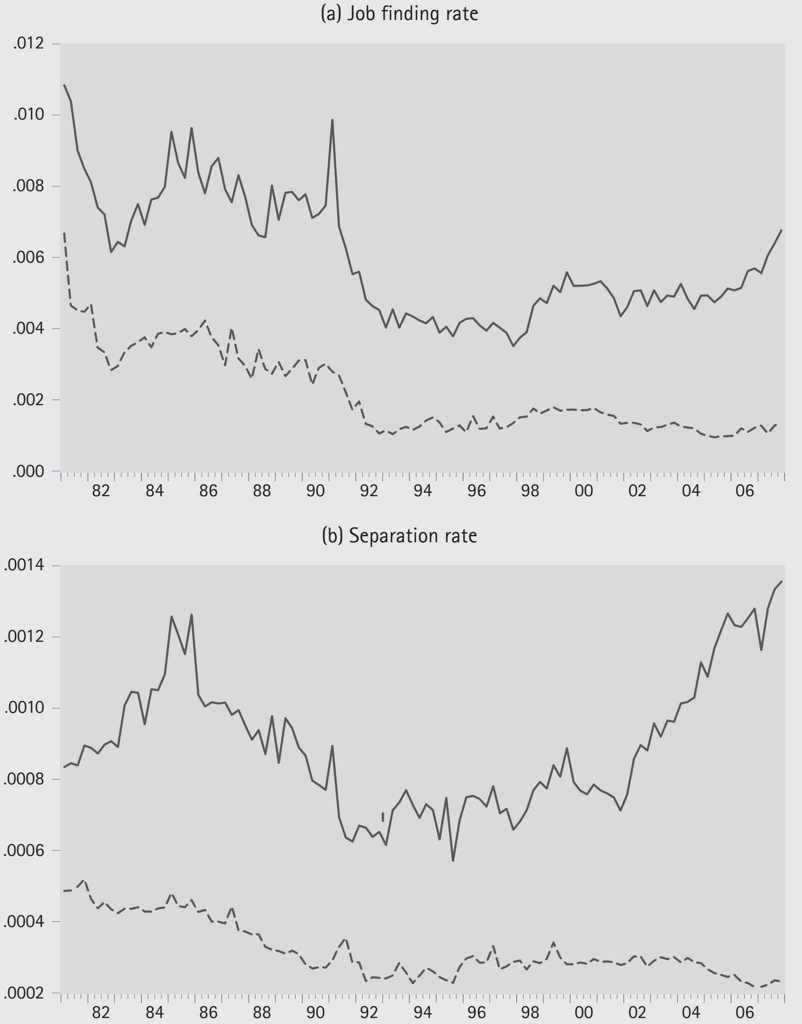
2.C Figures of the Time Aggregation Bias

Figure 2.C.1: Measures of transition rates



Notes: Solid lines present the continuous measures, dashed lines the monthly point-in-time measures and dotted lines the adjusted monthly point-in-time measures. Time series show quarterly averages of monthly data.

Figure 2.C.2: Absolute time aggregation bias



Note: Solid lines show the actual time aggregation bias and dashed lines the estimated time aggregation bias.

Figure 2.C.3: Relative time aggregation bias

Notes: Time aggregation bias over continuously measured transition rate. Solid lines show the actual time aggregation bias and dashed lines the estimated time aggregation bias.

Figure 2.C.4: Coverage of correction approach

Note: Estimated time aggregation bias over actual time aggregation bias.

2.D Robustness Checks

Table 2.D.1: Descriptive statistics of time aggregation bias applying Shimer's smoothing parameter

	Job finding rate		Separation rate	
	Actual (1981–2007)	Estimated (1981–2007)	Actual (1981–2007)	Estimated (1981–2007)
Standard deviation	0.158	0.226	0.122	0.106
Relative to total measures	1.317	1.883	1.341	1.165
Autocorrelation	0.821	0.809	0.789	0.784
Relative to total measures	1.002	0.988	1.021	1.014

Notes: Log deviations from HP trend with $\lambda = 10^5$. Total measures are the continuously measured transition rates.

Table 2.D.2: Contributions to steady state unemployment fluctuations applying Shimer's smoothing parameter

	Job finding rate		Separation rate	
	Full sample (1981–2007)	Reunified Germany (1993–2007)	Full sample (1981–2007)	Reunified Germany (1993–2007)
Continuous measures	0.547	0.677	0.423	0.385
Discrete measures	0.519	0.641	0.460	0.425
Adjusted measures	0.530	0.657	0.447	0.412

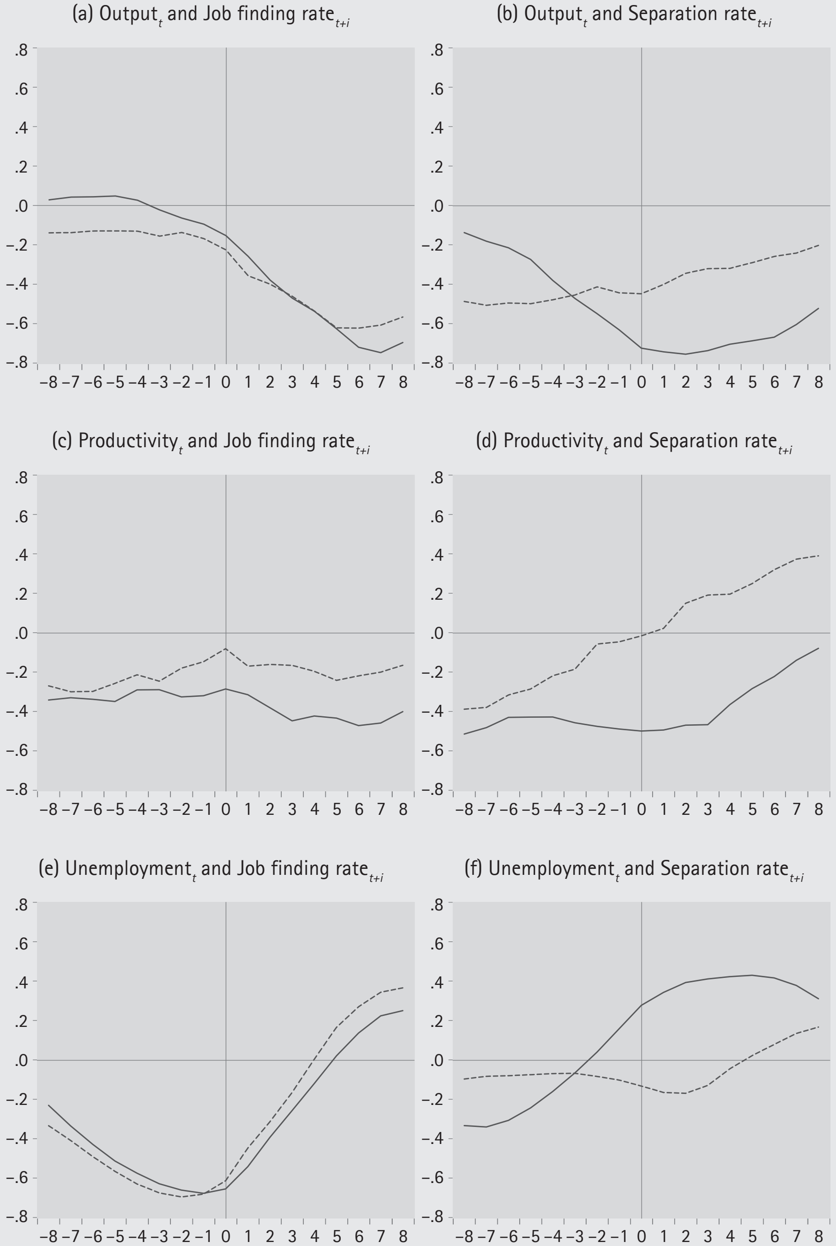
Note: Log deviations from HP trend with $\lambda = 10^5$.

Table 2.D.3: Contributions to steady state unemployment fluctuations using first differences

	Job finding rate		Separation rate	
	Full sample (1981–2007)	Reunified Germany (1993–2007)	Full sample (1981–2007)	Reunified Germany (1993–2007)
Continuous measures	0.556	0.485	0.430	0.467
Discrete measures	0.574	0.500	0.405	0.439
Adjusted measures	0.586	0.510	0.390	0.428

Note: First differences of log variables.

Figure 2.D.1: Cross correlations of time aggregation bias with business cycle indicators applying Shimer's smoothing parameter



Notes: Log deviations from HP trend with $\lambda = 10^5$. Solid lines show the actual time aggregation bias and ashed lines the estimated time aggregation bias. Measure *i* along the abscissa accounts for leads (positive values) and lags (negative values) at a quarterly frequency. Output measures gross domestic product (GDP). Labor productivity is the ratio of GDP to total hours worked.

3 Patterns of Unemployment Dynamics in Germany

(with Enzo Weber)

This paper provides a deeper insight into unemployment dynamics in Germany. Using a structural vectorautoregressive (SVAR) model, we identify the effects of a technology shock as well as two policy shocks. We find that the worker reallocation process varies substantially with the identified shocks. The job finding rate plays a larger role after a technology shock and a monetary policy shock, whereas the separation rate appears to be the dominant margin after a fiscal policy shock. Technology shocks turn out to be relatively important for variations in the transition rates, though they do not seem to trigger the high volatilities of German labor market variables. Considering policy shocks, our results point toward fiscal interventions as a promising instrument, but with several limitations.

3.1 Introduction

Unemployment dynamics receive substantial attention in business cycle research. Their net changes shape the adjustment of unemployment and are an important indicator of the economic situation. A high magnitude of unemployment dynamics, on the one hand, implies labor market flexibility but, on the other hand, creates considerable uncertainty.

The objective of this paper is to investigate the patterns of unemployment dynamics in Germany. The German case is attractive due to the availability of high-quality data and its labor market development, which is significantly different from that of the U.S. The primary aim is to provide a deeper insight into the worker reallocation process, i.e. the flows in and out of unemployment. For this purpose, we employ a structural vectorautoregressive (SVAR) model and specify different shocks that are considered to play an important role for labor market fluctuations. These shocks include a technology shock, a monetary policy shock and a fiscal policy shock.[1]

In Germany, the number of unemployed workers fluctuates by approximately 30,000 each month.[2] The underlying worker flows are about 20 times larger and challenge both policymakers and theoretical approaches. Labeled as the Shimer (2005) puzzle, it is well-known that the empirical evidence on labor market fluctuations cannot be replicated by the canonical search and matching model.

1 The choice of structural shocks is in line with Ravn and Simonelli (2008), who analyze the effects on labor market stock variables in the U.S. In contrast to Ravn and Simonelli (2008), however, we do not distinguish between neutral and investment-specific technology shocks because we focus on the extensive margin of labor adjustment. Investment-specific technology shocks have proven to explain a major part of the dynamics of the intensive margin, i.e. hours worked (see also Fisher, 2006).

2 Average change after seasonal adjustment from 1991 to 2012.

Consequently, a number of studies have stated shortcomings of the standard model, most prominently the assumption of an exogenous separation rate.

Several studies demonstrate the relevance of both the job finding rate and the separation rate to account for country-specific unemployment fluctuations. However, those studies are mainly based on unconditional analyses that provide only an overall picture of the prevalent margin of unemployment changes. Therefore, more recent studies emphasize the importance of switching to conditional analyses on shocks (see, e.g., Canova et al., forthcoming; Balleer, 2012).

We disentangle different structural shocks to inspect whether the worker reallocation process depends on the underlying shock or whether it is constant across shocks. In addition, some studies criticize the focus on productivity shocks in the search and matching literature (see, e.g., Barnichon, 2007). Accordingly, we overcome the single-shock assumption and enrich the discussion on the sources of unemployment dynamics by specifying demand-side impulses. However, we do not model the whole demand side of the economy but evaluate the role of technology shocks under the consideration of two specific demand shocks, i.e. a monetary policy shock and a fiscal policy shock.

The analysis of a technology shock corresponds to the standard search and matching model where changes in productivity are seen as the central source of unemployment dynamics. The empirical evidence on unemployment responses, however, is ambiguous. For example, Canova et al. (forthcoming) find Schumpeterian features of neutral technology shocks in the U.S., i.e. unemployment increases after a positive technology shock. This observation clearly counters the traditional view in the search and matching literature in which positive technology shocks are assumed to reduce unemployment.

The analysis of policy shocks addresses the question of the usefulness of discretionary policy interventions for controlling unemployment dynamics. While the focus has often been on the effects of monetary policy, the interest in fiscal policy shocks has revived. The recent financial crisis has shown that using monetary policy measures is limited when interest rates are low. Despite wide skepticism about the effects of fiscal policy, it is argued that governments would have been better able to fight the crisis if they had been able to adopt a more expansionary fiscal stance (see Blanchard et al., 2010). In addition, for Germany as a member state of the European Economic and Monetary Union (EMU), decisions on monetary policy are made on a supra-national level. Because those decisions may not necessarily reflect the domestic situation, fiscal policy may be more relevant for stabilizing national unemployment fluctuations.

Considering two specific demand shocks, our paper extends the study of Bachmann and Balleer (2011), who compare the effects of technology shocks for the U.S. and Germany. Interestingly, the authors find significant cross-country differences in the responses to a positive technology shock. In Germany, unemployment increases due to a rise in the separation rate, and in the U.S., unemployment increases due to a fall in the job finding rate. Accordingly, Bachmann and Balleer (2011) conclude that non-technology shocks, such as demand shocks, are necessary to understand the overall dynamics of unemployment.

Moreover, our analysis is related to several studies on the worker reallocation process in the U.S. For example, Braun et al. (2009) analyze the responses of labor market variables to different types of shocks. The authors find qualitatively similar results across shocks, where the responses of the job finding rate determine unemployment changes. Demand shocks induce less persistent effects compared to supply shocks, but the demand shocks appear to be more important. When directly comparing technology and monetary policy shocks, Braun et al. (2009) identify a higher contribution of monetary policy shocks. Also related to our study is that of Fujita (2011), who shows that a fast response of the separation rate and a hump-shaped behavior of the job finding rate are robust features with respect to several specifications.

While the worker reallocation process in the U.S. seems to be independent of the underlying type of shock, our results show interesting differences for Germany. Most notably, the job finding rate is the prevalent margin after a technology shock and a monetary policy shock, while the separation rate appears to be the driving force after a fiscal policy shock. In addition, technology shocks are relatively important for variations in the transition rates, though they cannot explain the high volatilities in the German labor market. The consideration of policy shocks points toward fiscal interventions as a promising instrument for controlling unemployment dynamics. However, our analysis identifies also several limitations, such as a short-lived influence of government spending shocks. We argue that the persistence of shocks may be relevant when accounting for unemployment dynamics.

The paper is structured as follows: Section 3.2 describes our data on German worker flows. Section 3.3 outlines the empirical approach, including the model specification and the estimation procedure. The benchmark results are presented in Section 3.4. Section 3.5 provides several robustness checks regarding data issues and model assumptions. In Section 3.6, we investigate the subsample stability. The conclusion follows in Section 3.7.

3.2 Data Description

While we use official data to obtain the structural shocks of interest, we generate worker flows from the Sample of Integrated Labor Market Biographies (SIAB). The

SIAB is a 2% random sample of all German residents who are registered by the Federal Employment Agency for the administration of the unemployment insurance and benefit systems. In contrast to survey data, the administrative data face neither sample attrition nor sample rotation problems and provide the individuals' labor market status on a daily basis, which is important to measure worker flows without a time aggregation bias.[3] This information yields a considerable advantage over the commonly used U.S. data.

Worker flows are calculated as the number of transitions between employment and unemployment within a month. Employment is measured as employment subject to social security and thus excludes, e.g., self-employment, apprenticeships or marginal jobs. Unemployment is measured by benefit receipt. Following Fitzenberger and Wilke (2010), we also correct for specific periods without benefit receipt that are likely to result from the expiration of entitlements or that may constitute times of sanctions.[4]

The worker flows are defined by their underlying transition hazard rates because these rates are interpreted as the driving forces of unemployment dynamics. Accordingly, the monthly job finding rate (f) and separation rate (s) satisfy

$$f_t = \frac{\left(\sum_{s=1}^{S} UE_s\right)_t}{U_{t-1}} \quad \text{and} \quad s_t = \frac{\left(\sum_{s=1}^{S} EU_s\right)_t}{E_{t-1}}, \tag{3.1}$$

where t denotes the 10th day of a month and S denotes the number of days since the 10th day of the previous month. To account for a structural break due to the German reunification, the time series are backward adjusted in 1993. The transition rates are then adjusted for seasonality and represented by their quarterly averages. The latter is necessary to obtain data at the same frequency as the official data that we use to specify the structural shocks.

Figure 3.1 shows the transition rates from 1981 to 2007. The job finding rate declines from over 10% to approximately 5%. Thus, the average unemployment duration between two socially secured jobs has increased from under 1 year to almost 2 years. This development, in turn, implies a substantial increase in long-term unemployment. According to our definition, the share of long-term unemployment accounts for around 50% after the reunification.[5] The separation rate fluctuates around 1% throughout the sample period. Hence, a job that is subject to social

3 Nordmeier (2012) analyzes monthly reversed worker flows in Germany and finds that point-in-time measurements underestimate both the level of worker flows and the flows' cyclical movements.

4 More details on data selection and measurement are given by Nordmeier (2012).

5 Obviously, this number is higher than the official numbers on long-term unemployment because our unemployment definition also includes workers who are marginally attached to the labor force.

security lasts, on average, approximately 8 years. In addition, the transition rates display different movements on business cycle frequency. While the job finding rate adjusts quite gradually, the separation rate depicts relatively sharp variations. The latter holds, for example, for the drop in the late 1980s (which does not result from the statistical break at the German reunification).

Figure 3.1: Transition rates

Note: Quarterly averages of monthly data in %.

3.3 Empirical Model

We employ a SVAR model to analyze macroeconomic fluctuations in a framework that requires a minimum of theoretical assumptions. Hence, this tool enables us to address several ongoing discussions concerning the sources and patterns of unemployment dynamics.

Our empirical approach proceeds as follows. First, we specify the VAR model and identify different structural shocks that are considered to play an important role for labor market dynamics. These shocks include a technology shock, a monetary policy shock and a fiscal policy shock. Then, we describe our estimation procedure and derive the conditional unemployment response.

3.3.1 VAR Specification

We consider the following reduced-form VAR model:

$$y_t = \mu + A(L)y_{t-1} + \nu_t, \tag{3.2}$$

where y_t is a vector of the endogenous variables, μ denotes a vector of constants, $A(L)$ is a lag polynomial of order p and ν_t captures the residuals. In our benchmark specification, the included variables are changes in government spending (Δg_t), changes in labor productivity (Δa_t), the separation rate (s_t), the job finding rate (f_t) and the interest rate (r_t) (see Table 3.A.1 for exact definitions of the variables). The ordering of the variables may support the identifying restrictions toward a nearly triangular identification scheme.

The use of first differences follows from unit root tests that are presented in Table 3.A.2. The augmented Dickey-Fuller (ADF) test indicates a nonstationary behavior of government spending and productivity. However, we do not impose the nonstationarity assumption on the job finding and separation rates but leave it to the system estimation to identify a unit root or not. This approach has the advantage of allowing a flexible decision. In case of nonstationarity, the VAR model would still be consistently estimated (see, e.g., Sims et al., 1990).

3.3.2 Identification of Shocks

Because the innovations ν_t from a reduced-form VAR are typically correlated, interpreting them as structural shocks would be misleading. Therefore, we need to impose identifying restrictions on the reduced-form residuals, which allow us to disentangle structural shocks in the variables. To that end, we include a matrix B that relates the structural shocks to the reduced-form innovations

$$v_t = B\varepsilon_t, \tag{3.3}$$

where $\varepsilon_t \sim (0, \Sigma_\varepsilon)$ summarizes the structural shocks and B describes the immediate effects of the shocks on the variables y_t. The structural shocks are assumed to be orthogonal with unit variance, i.e. $\Sigma_\varepsilon = E(\varepsilon_t, \varepsilon_t') = I$, following the convention in the literature.

Our aim is to provide evidence on unemployment dynamics in response to economically well-founded shocks. Therefore, we base our analysis on standard identifying restrictions. In doing so, we distinguish between long-run restrictions for the technology shock and short-run restrictions for the two policy shocks. Short-run restrictions contain assumptions about contemporaneous relations between shocks and variables and are thus imposed on matrix B. In contrast, long-run restrictions are imposed on the impulse responses (see Appendix 3.B).

The technology shock ε^a is identified as a neutral technology shock. According to Gali (1999), we allow only technology shocks to have a permanent impact on productivity. Thus, we assume that the unit root in productivity exclusively results from technology shocks and that the long-run effects of all other shocks are zero. However, other shocks can affect productivity temporarily through its interdependency with policy and labor market variables. Such transitory impacts can be quite substantial.

The identification of the monetary shock ε^r follows Christiano et al. (1996). Accordingly, the monetary authority can react to other structural shocks immediately; however, the intervention works only with a one-period time lag. Hence, the monetary shock cannot influence other variables within the same period. We further assume that the monetary authority has a direct influence on the interbank money market rate.

The fiscal policy shock describes a shock in government spending. Following Blanchard and Perotti (2002), we identify the government spending shock ε^g by assuming that the government reacts to other shocks only with a one-quarter implementation lag. Hence, government spending depends on its own history and on lagged values of other variables but not on unexpected movements in any other variable. Put differently, government spending is predetermined.

3.3.3 Estimation

The combination of short- and long-run restrictions leads to a non-recursive structure in our SVAR model and thus prevents an ordinary least square estimation. Therefore, we estimate our model with the maximum likelihood (ML) method using the Newton algorithm.

After we obtain the results of the ML estimation, we apply a residual-based bootstrap procedure and run 1,000 replications to compute confidence intervals for the impulse response functions. We also adopt the median from the empirical bootstrap distribution because the point estimates may be biased in small samples (compare also Canova et al., forthcoming).

Given the bootstrapped impulse responses of the transition rates, we follow Fujita (2011) and trace the unemployment response based on the law of motion. In general, a change in unemployment is given by the sum of its in- and outflows. In our two-state environment, the unemployment response satisfies

$$\Delta u_t = -\tilde{f}_t u_{t-1} + \tilde{s}_t e_{t-1}, \tag{3.4}$$

where $\tilde{f}_t$, $\tilde{s}_t$ denote the conditional transition rates and $e_t = (1 - u_t)$.

The starting point of the law of motion is the steady state unemployment rate:

$$u_0 = u^* = \frac{\bar{s}}{\bar{f} + \bar{s}}, \tag{3.5}$$

where $\bar{f}$, $\bar{s}$ indicate the sample average of the transition rates.

The conditional developments of the job finding and separation rates are received by transforming their impulse responses into levels:

$$\tilde{f}_t = \bar{f} + \psi^f_{e,t} \; and \; \tilde{s}_t = \bar{s} + \psi^s_{e,t}, \tag{3.6}$$

where the sample averages $\bar{f}$, $\bar{s}$ again represent the baseline value and $e \in [\varepsilon^a, \varepsilon^r, \varepsilon^g]$ describes the structural shock of interest.

This procedure neglects any flows in and out of the labor force and thus provides the *pure* response of the unemployment rate that arises from the worker reallocation process within the labor force.

3.4 Results

Our benchmark results are based on a lag order of $p = 2$. The choice of the lag order follows different selection criteria (see Table 3.A.3). Considering the variation along with the maximum number of lags, the chosen lag structure satisfies most criteria.

In what follows, we present the conditional worker reallocation process and the corresponding unemployment adjustment as obtained by the impulse responses. Subsequently, we decompose the variance of the forecast errors and discuss the importance of the different shocks for the transition rates.

3.4.1 Impulse Responses

Impulse responses illustrate the dynamic reaction of a variable to a structural shock. The impulses are normalized to a unit increase in the underlying variable. The responses of the labor market variables are presented in percentage points; Table 3.A.4 gives the steady state values.

Technology shock. Figure 3.2 shows the dynamic responses to a technology shock. A positive technology shock leads to an increase in the job finding rate and a decline in the separation rate. Accordingly, the unemployment rate goes down. The response of the job finding rate is significant for 4 quarters, while the response of the separation rate is borderline significant. Hence, the technology shock appears to work primarily along the job finding margin. This observation corresponds to the standard setup of the search and matching model, where the transmission mechanism of a productivity change is modeled by a matching function.[6] Nevertheless, the separation rate does demonstrate a reaction that supports the postulation of an endogenous separation margin in theoretical approaches.

The reduction in the unemployment rate is in line with the traditional view of the Real Business Cycle (RBC) theory, which has strongly influenced the search and matching model.[7] A positive productivity shock raises the expected profits from a match such that firms will post more vacancies. Because unemployment is predetermined, the rise in vacancies leads to a higher market tightness and, according to the matching function, a higher job finding rate. The higher job finding rate, in turn, reduces unemployment. The fall in unemployment then counters the increased job finding rate via the matching function in subsequent periods. In general, the variables adjust gradually to the steady state after a one-off increase in productivity.

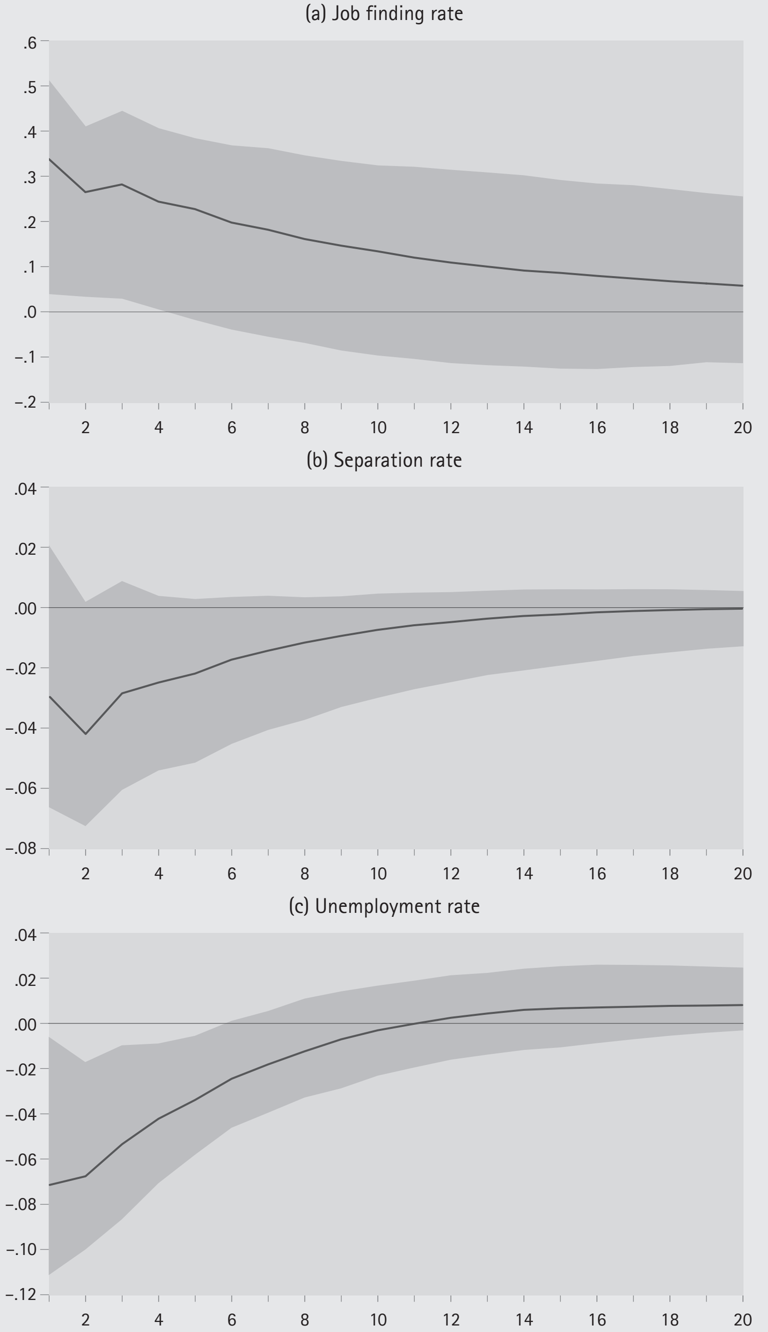
In terms of magnitude, the unemployment rate shows a relatively resilient response. A one percent increase in productivity leads to a 0.07 percentage point reduction of unemployment, which is 0.5% of the baseline value. In contrast, the transition rates react more sensitively to a technology shock. The impact effects amount to 5.4% in case of the job finding rate and to 2.8% in case of the separation rate.[8] Considering that a one percent increase in productivity is of

6 Under standard assumptions, the job finding rate is a function of labor market tightness.

7 See, e.g., Merz (1995) for an integration of the search and matching approach in an RBC model.

8 Gartner et al. (2012) explain the high volatility of German worker flows by large hiring costs and low quit rates. Using a labor selection model with worker-firm specific productivity shocks, the authors demonstrate that those factors depress the level of the transition rates and thereby increase their sensitivity to aggregate shocks.

Figure 3.2: Responses to a technology shock



Notes: Impulse responses to a one-off increase in productivity. The abscissa accounts for the quarters after an impulse. The black line shows the median from bootstrapping, and the grey area demonstrates the 90% confidence interval. Benchmark sample: 1981–2007.

plausible magnitude,[9] the technology shock fails to account for the unconditional volatilities on the German labor market. This observation, in turn, reinforces the critique on the single-shock assumption when analyzing unemployment dynamics.

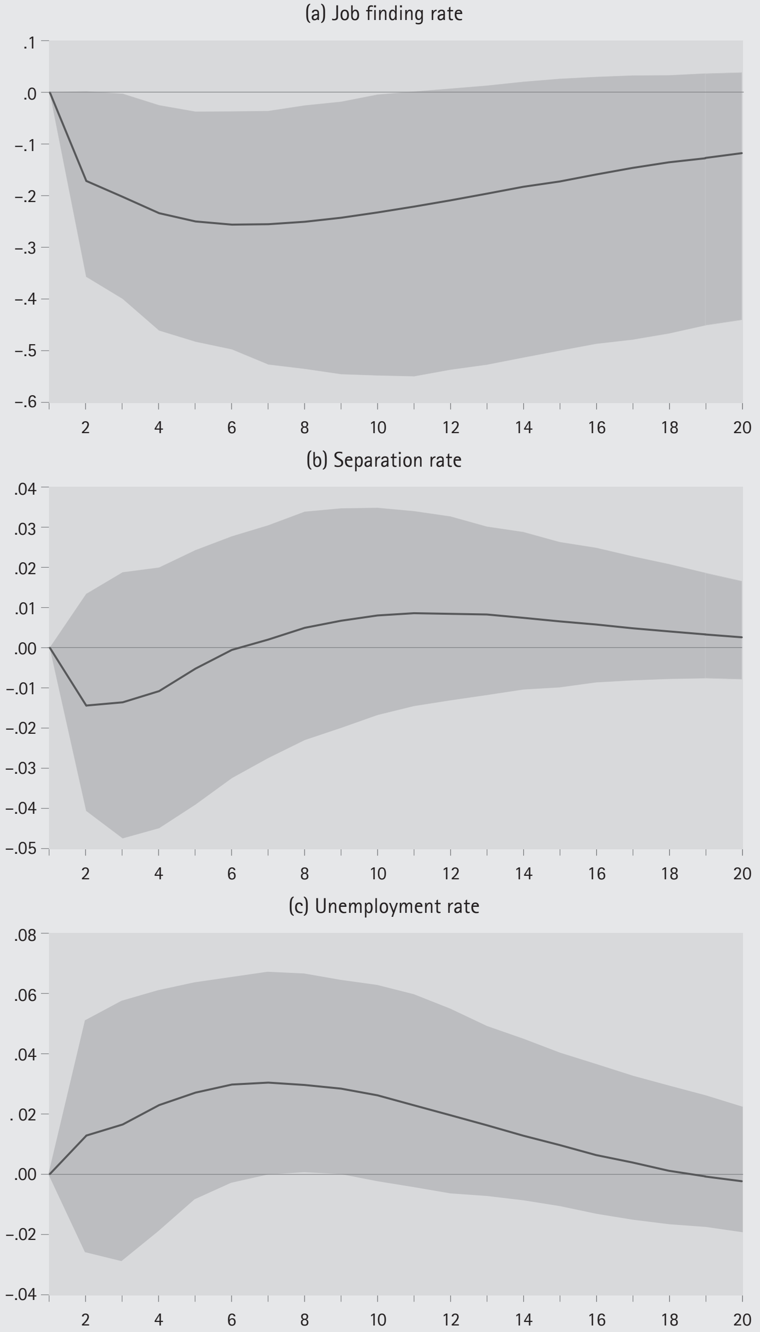
Monetary policy shock. Figure 3.3 presents the dynamic adjustment process after a contractionary monetary policy shock. The monetary impulse triggers hump-shaped responses in the job finding rate and the unemployment rate. The job finding rate decreases significantly after 4 to 9 quarters in response to a rise in the interest rate, and it then adjusts gradually to the steady state. The behavior of the unemployment rate mirrors the response of the job finding rate, though it is slightly smoothed by the reaction of the separation rate. The separation rate responds with a temporary drop and increases after 6 quarters, according to the contractionary impulse. The influence on the separation rate, however, is low and insignificant. Consequently, a monetary policy shock appears to be transmitted to unemployment through its impact on the job finding rate.

A hump-shaped pattern after a monetary policy shock has been documented in several studies. Interestingly, the velocity of the adjustment process appears to depend on the underlying labor market structure. For example, Islas-Camargo and Cortez (2011) observe a maximum effect of monetary policy shocks on Mexican unemployment after only 3 quarters. The authors explain this result by the existence of a large informal sector and schemes that have led to more employment flexibility. In contrast, Ravn and Simonelli (2008) find a peak effect on U.S. unemployment after 6 quarters, and Alexius and Holmlund (2008) report a maximum increase in Swedish unemployment after 9 quarters. Our results for Germany show a peak effect on unemployment after 7 quarters. Accordingly, the degree of labor market regulation tends to increase the persistence of responses to monetary policy shocks.

The effects of a monetary policy shock are smaller than those of a productivity shock. A unit increase in the interest rate leads to a maximum reduction in the job finding rate by around 0.26 percentage points, which corresponds to 4.2% of its baseline value. The maximum increase in the unemployment rate amounts to 0.03 percentage points, which is half the impact effect of the technology shock. Considering that the changes in key interest rates are about 0.25–0.5 percentage points, the effects appear even smaller.

9 A one percent increase in productivity resembles the standard deviation of its cyclical component. For example, Gartner et al. (2012) report a standard deviation of 1.3% by computing the log deviation from the HP trend with $\lambda = 10^5$. Using the standard smoothing parameter of $\lambda = 1{,}600$, we observe a standard deviation of 0.7%.

Figure 3.3: Responses to a monetary policy shock



Notes: Impulse responses to a one-off increase in the interest rate. The abscissa accounts for the quarters after an impulse. The black line shows the median from bootstrapping, and the grey area demonstrates the 90% confidence interval. Benchmark sample: 1981–2007.

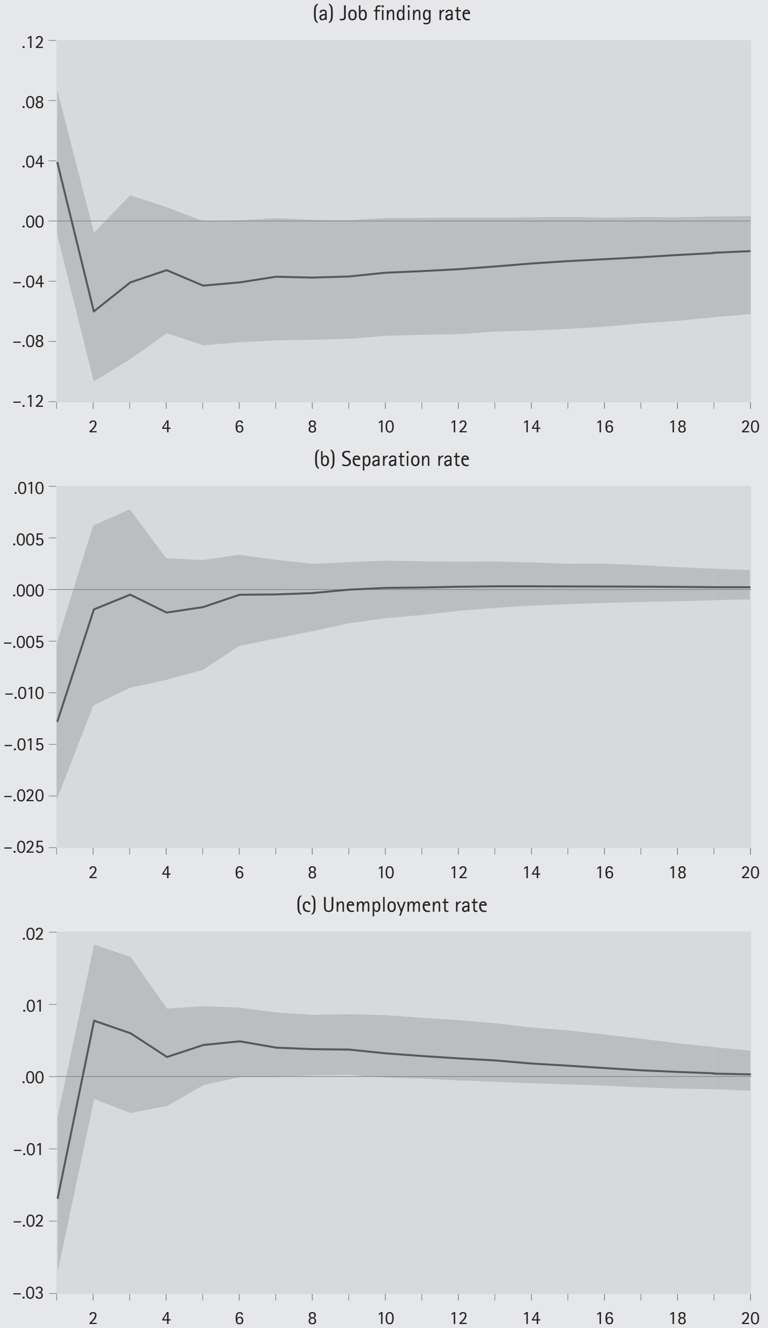
Fiscal policy shock. The effects of a fiscal policy shock are plotted in Figure 3.4. In the impact period, the variables show the expected reactions to a rise in government spending. The job finding rate goes up, the separation rate goes down and, as a result, the unemployment rate shrinks. Interestingly, the job finding rate decreases after the positive impact effect, and then returns sluggishly to its baseline value. At first glance, the negative side effect might indicate a Ricardian behavior; thus, the general skepticism about the effects of fiscal policy. Based on Ricardian equivalence arguments, the increase in government spending is likely to lead to a future rise in distorting taxes and thereby to lower profits. In turn, firms will reduce their labor demand, and the job finding rate will decrease. However, the negative effect on the job finding rate is rather borderline insignificant and should not be overstated.

Except for the negative side effect on the job finding rate, the government spending shock tends to have a short-lived influence only. Nevertheless, a rapid adjustment process after a fiscal policy shock appears to be characteristic for Germany. For example, Bode et al. (2006), Tenhofen et al. (2010) and Baum and Koester (2001) show short-run effects of both government spending and revenue shocks on German GDP. Instead, Ravn and Simonelli (2008) document rather hump-shaped effects of a fiscal policy shock on U.S. output and labor market variables, with peak effects observed after 3 years.

Because the positive impact effect on the job finding rate is insignificant, the fall in the unemployment rate can be mainly ascribed to the separation margin. This observation, however, challenges the conclusion of Turrini (2012). For highly regulated labor markets in OECD countries, Turrini (2012) reports a dominant role of the job finding rate after a fiscal policy shock.[10] Thus, the result of Turrini (2012) implies that a fiscal policy shock tends to influence the average unemployment duration. Our result implies an impact on job stability, though Germany has a relatively strict employment protection. However, when firms are aware of the vanishing character of fiscal stimulus, search frictions may hinder a temporarily capacity extension along the job finding margin and fixed-term contracts may help to overcome employment protection after a negative impulse.

10 Turrini (2012) uses an action-based variable on fiscal consolidation. Because this measure does not include cyclical movements, it can be considered as exogenous.

Figure 3.4: Responses to a fiscal policy shock



Notes: Impulse responses to a one-off increase in government spending. The abscissa accounts for the quarters after an impulse. The black line shows the median from bootstrapping, and the grey area demonstrates the 90% confidence interval. Benchmark sample: 1981-2007.

The size of the responses underpins the dominant role of the separation rate. On impact, a one percent increase in government spending reduces the separation rate by 0.013 percentage points and 1.2% of its baseline value. In contrast, the government spending shock raises the job finding rate by 0.4 percentage points, which corresponds to 0.6% of the sample average. The government spending shock, thus, can generate a small amplification effect on the separation rate but not on the job finding rate. The impact multiplier with respect to unemployment is only 0.1.[11]

To sum up, the transmission channel to unemployment responses varies significantly with the identified shocks. The job finding rate turns out to be the driving force of unemployment responses after a technology shock and a monetary policy shock, whereas the separation rate appears to be the dominant margin in case of a fiscal policy shock. Differences occur also in the timing and the velocity of the adjustment process. The effects of the technology shock emerge on impact and remain significant for over 1 year. In contrast, the monetary policy shock reaches its peak effect after 1.5 years, while the influence of a fiscal policy shock vanishes rapidly. These patterns indeed can be reconciled with the stylized fact that fluctuations of the job finding rate are more persistent than those of the separation rate.

3.4.2 Forecast Error Variance Decomposition

The variance decomposition of the forecast errors reveals the relevance of the shocks for movements in the different variables. This composition provides information over and above impulse responses, which display dynamic reactions to hypothetical shocks. The interpretation of the variance decomposition, however, is restricted to the *relative* importance of the identified shocks because the forecast errors depend substantially on the underlying VAR system.

Table 3.1 gives the proportions of variations in the transition rates due to the different structural shocks. It can be seen that the three shocks account for approximately 40% of the forecast error variance in the job finding rate and approximately 30% of the forecast error variance in the separation rate.[12] Thereby, the technology shock plays a prevailing role. However, the relative contribution of the technology shock compared to the two policy shocks diverges over time.

For the job finding rate, the technology shock shows a maximum contribution of 41% after 4 periods and then decreases to 32% over the 5-year forecast horizon.

11 The returned interest in fiscal policy has also revived the debate on fiscal multipliers. Monacelli et al. (2010) analyze fiscal multipliers with respect to labor market variables and demonstrate that wage rigidity may dampen the size of unemployment multipliers.

12 The difference to unity captures the contributions of exogenous disturbances in the transition rates themselves.

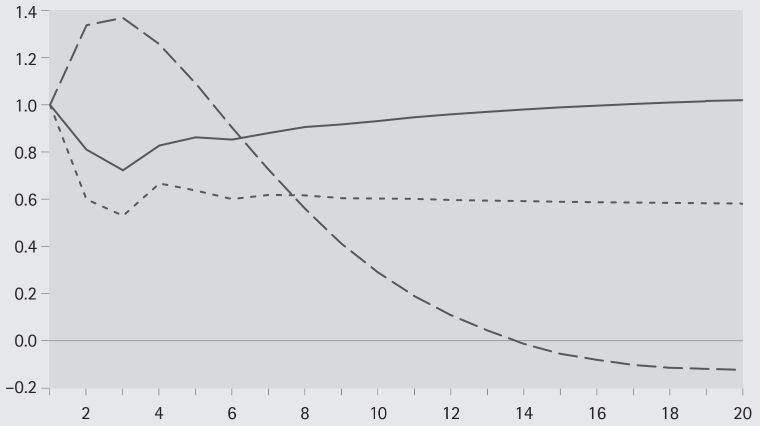
At the same time, the contributions of both policy shocks increase. In particular, the monetary policy shock explains up to 8%. The different developments can be related to the different shapes of the impulse responses. While the technology shock has its maximum effect on impact, the monetary policy shock reaches its peak effect on the job finding rate only after around 1.5 years. Accordingly, the cumulative effect of the monetary policy shock arises in longer forecast horizons. The fiscal policy shock accounts for about 6% in the long run.

Table 3.1: Forecast error variance decomposition

	Job finding rate			Separation rate		
Forecast horizon	Technology shock	Monetary shock	Fiscal shock	Technology shock	Monetary shock	Fiscal shock
1	0.365	0.000	0.022	0.120	0.000	0.103
2	0.388	0.012	0.048	0.227	0.003	0.065
3	0.403	0.020	0.047	0.239	0.005	0.052
4	0.406	0.030	0.044	0.251	0.006	0.048
5	0.402	0.038	0.047	0.260	0.006	0.045
6	0.394	0.046	0.048	0.266	0.006	0.043
7	0.386	0.053	0.049	0.269	0.006	0.042
8	0.377	0.058	0.051	0.271	0.006	0.041
9	0.369	0.063	0.052	0.273	0.006	0.041
10	0.361	0.066	0.053	0.274	0.007	0.041
11	0.354	0.070	0.054	0.275	0.007	0.040
12	0.347	0.072	0.054	0.275	0.008	0.040
13	0.342	0.074	0.055	0.275	0.009	0.040
14	0.336	0.076	0.055	0.275	0.009	0.040
15	0.332	0.077	0.056	0.275	0.010	0.040
16	0.328	0.078	0.056	0.275	0.010	0.040
17	0.324	0.079	0.056	0.275	0.010	0.040
18	0.321	0.079	0.057	0.275	0.010	0.040
19	0.319	0.080	0.057	0.275	0.010	0.040
20	0.316	0.080	0.057	0.275	0.010	0.040

Note: Based on medians from bootstrapping.

Figure 3.5: Adjustment mechanisms



Note: The solid line shows the adjustment of productivity, the dashed line the adjustment of the interest rate and the dotted line the adjustment of government spending.

In contrast, the importance of the technology shock for movements in the separation rate increases steadily in shorter forecast horizons and then remains nearly unchanged. The monetary policy shock hardly contributes to fluctuations in the separation rate, while the fiscal policy shock matters in the short run due to its sharp impact effect. In the first forecast period, the fiscal policy shock is nearly as important as the technology shock.

3.4.3 Discussion

Our results show that the worker reallocation process in Germany does not proceed independently from the underlying type of shock. In particular, the impulse responses indicate that the significance of the transition rates varies with the identified innovations. The forecast error variance decomposition exhibits the different adjustment processes through a changing relevance of the structural shocks over time. This observation might suggest a role for the persistence of shocks to understand the conditional patterns of unemployment dynamics.

Figure 3.5 shows the impulse responses of productivity, interest rate and government spending to their own shocks. The impulse responses are equivalent to the movements of the variables conditional on the individual shocks. Indeed, these movements differ substantially in the degree of persistence.[13] The adjustment process is finished rather quickly for government spending. Compared to that, productivity adjusts with moderate persistence, and the adjustment of the interest

13 We call a process persistent if it takes a long time to reach a new steady state.

rate takes the most time. The impression of a differing persistence in the adjustment mechanisms is supported by the coefficients for the first-order autocorrelation of the conditional movements (see Table 3.A.5).

Moreover, Table 3.A.5 provides the correlations between those variables and the transition rates based on the different shocks. Interestingly, the separation rate shows constantly higher cross-correlations in absolute values than the job finding rate, indicating that the separation margin is more sensitive to contemporaneous changes. Nevertheless, those contemporaneous relations are less significant in the cases of a technology shock and of a monetary policy shock, which induce more persistent patterns.

In fact, several authors emphasize the role of persistence for the dynamic responses of labor market variables. For example, Mayer et al. (2010) and Kato and Miyamoto (2013) demonstrate that the degree of persistence of government spending shocks strongly influences the response of unemployment. Mayer et al. (2010) find that the sign of the unemployment response changes when they assume a serially uncorrelated shock. Kato and Miyamoto (2013) explicitly incorporate an endogenous role of the separation margin and show higher impact multipliers than by assuming an exogenous separation rate; however, the authors also find that the magnitude of labor market responses decreases the less persistent government spending shocks are. Moreover, a lower persistence of government spending shocks accelerates a negative side effect on the job finding rate.

Recall that the worker reallocation process in the U.S. has been found to be similar across shocks. Here, the hump-shaped behavior of the job finding rate dominates the sharp responses of the separation rate, which, in turn, explains the conditional patterns of labor market stock variables (see Braun et al., 2009; Fujita, 2011; Ravn and Simonelli, 2008). Accordingly, our results may suggest that shocks in the U.S. tend to trigger more persistent adjustment mechanisms than in Germany and that differences in the reactions to specific shocks are less pronounced.

3.5 Robustness Analysis

This section reconsiders the foregoing results along the following dimensions. First, we address some data issues, such as the indicated nonstationarity of the transition rates and their trending behavior. Then, we proceed by modifying the lag length and inspect the identifying assumptions. Afterwards, we examine technology shocks in a small VAR model, as was performed in previous studies.

Unit Roots. When variables appear to be integrated, it is not necessary to impose the unit root because the estimation of a nonstationary VAR model yields consistent parameters. For an incorrect restriction, the model would be misspecified, and the estimation results are likely to be biased. However, if the restriction is correct, the estimation would gain more efficient parameters.

Because the ADF test cannot reject the null hypothesis of nonstationarity for the job finding rate, we check our results by including the job finding rate in first differences. We also assume a unit root in the separation rate, though the null hypothesis can be rejected at the 5% significance level. Nevertheless, redoing the unit root test by allowing for a higher lag structure, as assumed in the VAR model, points more to an integrated separation rate.[14]

The results show only slight changes. After a technology shock, the responses of the job finding rate and unemployment rate are less significant. The response of the separation rate to a contractionary monetary policy shock turns out strictly positive, though still insignificant. Accordingly, the unemployment response becomes more significant after the monetary policy shock. These changes, however, do not affect the implications of our benchmark estimation.

Structural Break. Although the transition rates have been adjusted for the German reunification, the striking movement in the early 1990s requires investigating their trend behavior. A closer look at the development of the German Beveridge curve reveals a substantial right shift in 1991 because many workers became unemployed when Eastern Germany was transformed toward a market economy (see Klinger and Weber, 2012). If a significant number of those workers moved to the Western part to enhance their reemployment probability, the registration at Western German employment agencies would indeed trigger a downward shift in the Western German job finding rate.

A Chow test indicates a structural break in the job finding rate in 1991Q3. Once we include a shift dummy for the job finding rate, we obtain lower and less persistent impulse responses. However, the signs and shapes of the benchmark results appear to be robust. In addition, the changes are countered if we also consider a shift dummy for the separation rate, as suggested by the Chow test.

Cyclical Components. An alternative procedure to treat low-frequency movements is to use a detrending method. In particular, Fernald (2007) demonstrates that VARs with long-run restrictions are sensitive to low frequencies. Even if low-frequency movements do not reflect a unit root, they can be problematic. Therefore, Fernald (2007) recommends verifying the results using alternative detrending methods.

Particularly the job finding rate displays a notable trend behavior. In the first part of our sample period, the job finding rate exhibits a reduction of more than one half of its initial value in 1981. In general, labor market dynamics may decline

14 Further evidence comes from Klinger and Weber (2012).

for several reasons. For example, changes in the composition of the labor force, such as aging, are a prominent explanation.[15] Other explanations include a fall in outside wage offers or a rise in mobility costs.

Against the background of the debate initiated by Shimer (2005), we use the Hodrick-Prescott (HP) filter to remove the trending behavior in the transition rates.[16] This specification of the transition rates may be interpreted as the underlying business cycle component.[17] The general pattern of our benchmark results is unchanged. Interestingly, the responses to a technology shock become insignificant, whereas the positive impact effect of the government spending shock on the job finding rate turns out to be significant. This result might indicate that technology shocks are more important for low-frequency movements and that government spending shocks rather affect high-frequency variations, which could be a valuable path for future research. Moreover, the negative side effect of the fiscal policy shock on the job finding rate nearly disappears.

Lag Length. We also reestimate our benchmark model with a higher lag length of $p = 4$, as suggested by three selection criteria.

Allowing for a more complex adjustment process leads to more persistent responses with slightly lower impact effects. In general, the responses are less significant (which is not surprising in view of the higher number of parameters), and the negative response of the job finding rate to a government spending shock again turns out less pronounced. Nevertheless, the key results remain unchanged.

Identifying Assumptions. So far, we have assumed that government spending does not react contemporaneously to unexpected changes in any other variable. This assumption is convincing as long as the government spending measure does not include transfer payments, such as unemployment benefits. Nevertheless, the government spending measure may capture other unemployment-related subsidies that are counted as public consumption.

In 2011, for example, the unemployment-related government consumption amounted to 4.39 billion euro, i.e. approximately 0.9% of overall government consumption.[18] Therefore, we relax our assumption and allow for non-zero effects of exogenous disturbances in the transition rates. Accordingly, innovations in government spending result as

$$v_t^g = b_{11}\varepsilon_t^g + b_{13}\varepsilon_t^s + b_{14}\varepsilon_t^f, \tag{3.7}$$

15 However, Fujita (2012) shows for the U.S. separation rate that aging cannot account for the whole decline that has been observed for over three decades.

16 We use the standard smoothing parameter of $\lambda = 1{,}600$ for quarterly data.

17 See Cogley and Nason (1995) for a critical view on the HP filter. These authors argue that the HP filter can generate a spurious cycle if a time series is integrated.

18 See Statistisches Bundesamt (2012).

where b_{13} and b_{14} denote the automatic responses to shocks in the transition rates. At the same time, this modification leads to an exact identification of our VAR model and thus reconsiders the overidentification issue in our benchmark specification. However, the responses of our benchmark estimation are unchanged because the modified assumption primarily affects the shocks in the transition rates.

Small VAR. To relate our results to previous evidence, we also reestimate our VAR model by identifying a productivity shock only, i.e. $y_t = [a_t, s_t, f_t]'$. Accordingly, we must impose two long-run restrictions to identify the technology shock and one short-run restriction to disentangle the innovations in the transition rates. Hence, this specification also satisfies an exact identification.

The results show that our benchmark estimation is robust with respect to the technology shock. In particular, the signs and magnitude of the impulse responses do not change once we exclude other variables. However, the full specification gives a more comprehensive picture of the sources of unemployment dynamics.

3.6 Subsample Analysis

In this section, we investigate the subsample stability of the preceding results. We follow the natural break along with the German reunification. Our data are complete for all of Germany since 1993; thus, we consider the time period from 1993 to 2007. The impulse responses are plotted in Figures 3.A.1–3.A.3.

It can be seen that the responses change notably. In particular, the responses to a technology shock change their sign. The job finding rate shows a negative response to a positive technology shock. Interestingly, this effect has also been found for the U.S. labor market. Balleer (2012) explains the "job finding puzzle" by skill-biased technological change. Because a positive technology shock may increase the relative productivity of high-skilled to low-skilled workers, low-skilled workers will be substituted out of employment. Accordingly, the job finding rate of low-skilled workers decreases, while the job finding rate of high-skilled workers may increase. Then, if the negative effect outweighs the positive effect, the aggregate job finding rate will decrease.

Indeed, the argumentation along with a substitution of low-skilled workers can be reconciled with the initial rise in the separation rate. In terms of the Schumpeterian paradigm, new technologies can cause a wave of creative destruction when existing jobs do not satisfy the new standards. The positive impact effect on the separation rate is also in line with recent evidence for the U.S. In particular, Canova et al. (forthcoming) discuss the Schumpeterian creative destruction hypothesis for neutral technology shocks and argue that search frictions can trigger a temporary rise in unemployment. This explanation appears to match our results. After the impact period, however, the responses of the transition rates offset each other and the unemployment rate adjusts to the steady state.[19]

The insignificance of the responses may result not only from fewer observations but also from different features of a technology shock; i.e. traditional and Schumpeterian responses offset each other. In addition, the forecast error variance decomposition indicates that technology shocks per se have become less important after the reunification (see Table 3.A.6). Compared to our benchmark period, the relative importance of the technology shock shrinks for fluctuations in both transition rates. In short forecast horizons, the relative contribution accounts for up to 30% for the job finding rate and 19% for the separation rate. In longer forecast horizons, the contributions decrease to 26% and 16%, respectively. In relation to the policy shocks, however, the technology shock still plays a prevailing role, particularly for the job finding rate.

The monetary policy shock contributes only around 1% to the variation in the transition rates. Moreover, the responses to a monetary policy shock are low and insignificant. Particularly the impact on the unemployment rate is close to zero as both transition rates respond negatively. The disappearing relevance of monetary policy shocks for German unemployment dynamics might be traced back to the implementation of the EMU. It seems that the national labor market has become more resilient to monetary policy shocks. At the same time, monetary policy shocks have become less important to control unemployment dynamics.

In turn, the fiscal policy shock gains in importance. The contributions to the forecast errors increase by a factor of about 2–3. The shock again shows a significant impact effect on the unemployment rate through the separation margin. The response of the job finding rate, however, turns out strictly positive, indicating that the negative side effect of preceding results is not stable. In addition, the impact multipliers with respect to both transition rates increase. Considering the baseline values for the subsample, a one percent increase in government spending raises the job finding rate by 1.1% and reduces the separation rate by 1.8%. The fiscal multiplier with respect to unemployment is again around 0.1%.

3.7 Conclusion

Using a structural VAR approach, this paper has analyzed the conditional patterns of unemployment dynamics in Germany. For this purpose, we have specified a technology shock, a monetary policy shock and a fiscal policy shock.

19 These patterns seem to mirror the economic development in the 1990s. See also Smolny (2012) who describes the macroeconomic adjustment after the reunification.

Our analysis reveals various patterns of unemployment dynamics; i.e. the worker reallocation process is not constant across the identified shocks. In particular, the significance of the transition rates varies with the different types of shocks. The impulse responses indicate a larger role of the job finding rate after a technology shock and a monetary policy shock, while the separation rate appears to be the dominant margin after a fiscal policy shock. In line with the unconditional movements of the transition rates, the transmission mechanism through the job finding margin is relatively persistent, while the effects along the separation margin are sharp and short-lived. Several robustness checks reinforce this clear-cut pattern.

The forecast error variance decomposition demonstrates that the identified shocks account for 40% of the variations in the job finding rate and 30% of the variations in the separation rate. Thereby, the technology shock plays a substantial role. In our benchmark sample, the technology shock shows traditional features, i.e. an increase in productivity reduces unemployment. When we restrict our time period to reunified Germany, we also observe Schumpeterian features, i.e. an increase in productivity leads to higher separations. In addition, the relative importance of technology shocks shrinks over time.

Monetary policy shocks seem to have become less important for unemployment dynamics in Germany. Particularly after the reunification, changes in the interest rate account for only 1% of the variations in the transition rates. The loss of importance can be reconciled with the implementation of the EMU. Nevertheless, it should be noted that those results do not concern the functioning of rule-based monetary interventions. Accordingly, the results may also indicate that the monetary authority does rarely deviate from its policy rule or that discretionary policy interventions are anticipated due to a transparent strategy.

Instead, fiscal policy shocks may be a more promising instrument to account for unemployment dynamics. The effects of the government spending shock are significant for different specifications, and the fiscal multipliers of the transition rates have increased over time. However, our analysis also indicates several limitations. First, the effects of a government spending shock turn out to be very short-lived. Second, there are indications of a Ricardian equivalence behavior, though this observation is not stable. Third, the fiscal multipliers are of a moderate magnitude, which might fuel concerns about fiscal debt levels. Forth, the transmission of a government spending shock works primarily through the separation rate; thus, fiscal policy may be less suitable to control rises in long-term unemployment triggered by other factors.

Hence, further evidence on the sources and mechanisms of labor market dynamics seems to be crucial for determining an optimal policy instrument. A key result from our study is that those analyses should not neglect the separation margin, particularly when shocks tend to be less persistent.

3.A Further Tables and Figures

Table 3.A.1: Sources and definitions of data

Time series	Definition	Source
Government spending	Sum of government consumption and government gross fixed capital formation divided by output deflator (2000 = 100), logged	National accounts
Labor productivity	Real gross domestic product (GDP) divided by total hours worked (2000 = 100), logged	National accounts
Job finding rate	Transition rate from unemployment to employment (average of monthly rates based on daily transitions)	SIAB
Separation rate	Transition rate from employment to unemployment (average of monthly rates based on daily transitions)	SIAB
Interest rate	Nominal interbank money market rate (average of daily rates)	Deutsche Bundesbank

Notes: All series are seasonally adjusted using quarterly data. Western German data are linked to reunified German data in 1993.

Table 3.A.2: Augmented Dickey-Fuller tests

	Level		First difference	
	Model specification	Test statistic	Model specification	Test statistic
Government spending	t, c, $L=4$	-1.707	c, $L=3$	-4.201***
Productivity	t, c, $L=4$	-2.293	c, $L=3$	-4.452***
Separation rate	c, $L=0$	-3.031**	$L=0$	-12.062***
Job finding rate	c, $L=1$	-2.157	$L=0$	-13.688***
Interest rate	c, $L=1$	-3.771***	$L=0$	-5.277***

Notes: The ADF regressions cover a number of lags (L) according to the Schwarz and Hannan-Quinn information criteria. Regressions may include a trend (t) and/or a constant (c). ***, ** and * indicate significance at the 1%, 5% and 10% levels.

Table 3.A.3: VAR lag order selection

	Selection criteria				
Maximum lag length	LR	FPE	AIC	SIC	HQ
2	2	2	2	1	1
4	4	4	4	1	1
6	4	2	4	1	2
8	4	2	2	1	1
10	4	2	2	1	1
12	4	2	12	1	1

Note: LR = Likelihood ratio test statistic, FPE = Final prediction error, AIC = Akaike information criterion, SIC = Schwarz information criterion, HQ = Hannan-Quinn information criterion.

Table 3.A.4: Steady state values

	Benchmark sample	Subsample
	(1981–2007)	(1993–2007)
Job finding rate	6.247	4.960
Separation rate	1.036	1.056
Unemployment rate	14.225	17.553

Note: Values are based on the sample averages of the transition rates.

Table 3.A.5: Conditional correlations

		Productivity	Interest rate	Gov. spending
Autocorrelation		0.718	0.917	-0.005
Correlation	f	-0.705	-0.291	0.823
matrix	s	0.796	-0.862	-0.966

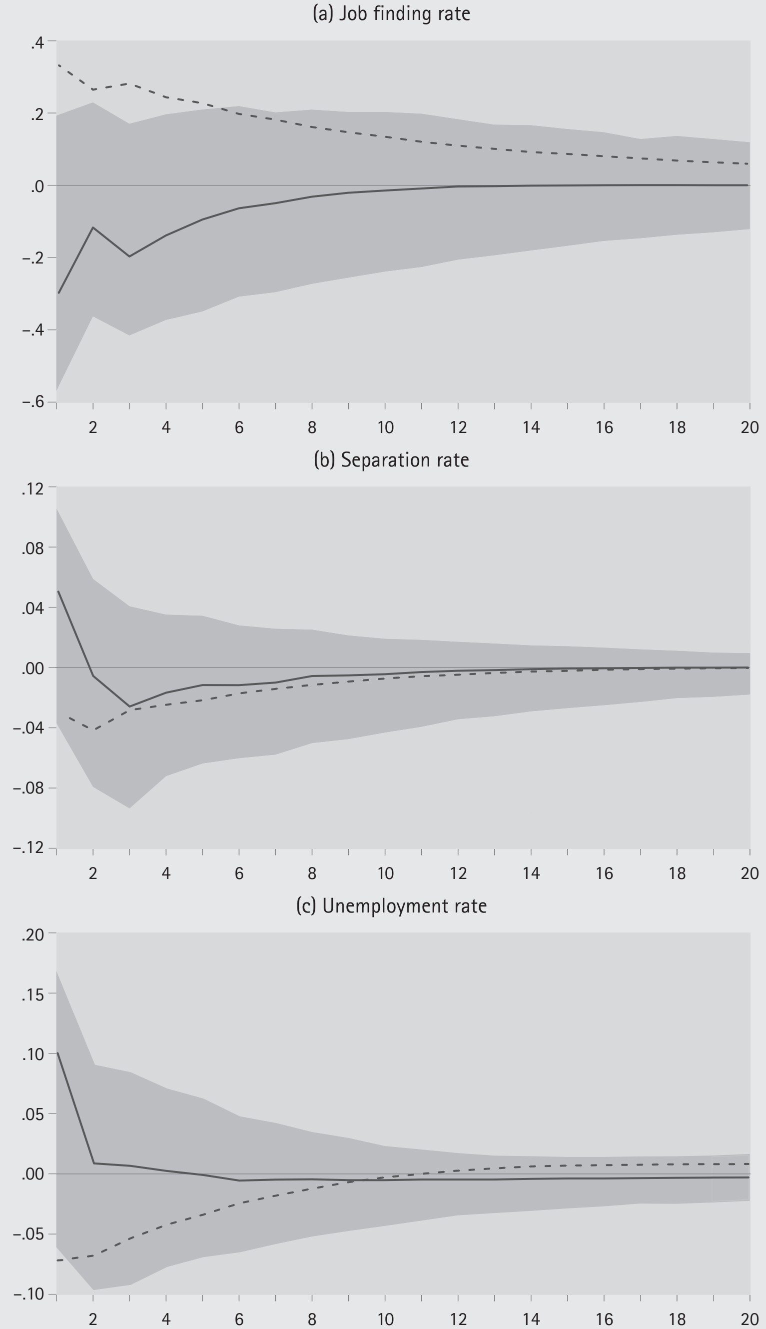
Notes: Based on medians from bootstrapping. The first column refers to the technology shock, the second column to the monetary policy shock and the last column to the fiscal policy shock.

Table 3.A.6: Forecast error variance decomposition in the subsample (1993–2007)

	Job finding rate			Separation rate		
Forecast horizon	Technology shock	Monetary shock	Fiscal shock	Technology shock	Monetary shock	Fiscal shock
1	0.300	0.000	0.076	0.192	0.000	0.210
2	0.265	0.004	0.071	0.142	0.001	0.171
3	0.294	0.005	0.087	0.147	0.004	0.143
4	0.294	0.007	0.099	0.149	0.009	0.142
5	0.289	0.007	0.100	0.149	0.011	0.141
6	0.281	0.007	0.103	0.152	0.012	0.138
7	0.276	0.007	0.106	0.154	0.013	0.137
8	0.272	0.007	0.106	0.154	0.014	0.137
9	0.269	0.007	0.107	0.155	0.014	0.136
10	0.267	0.007	0.107	0.156	0.014	0.136
11	0.265	0.007	0.107	0.156	0.014	0.136
12	0.264	0.007	0.107	0.156	0.014	0.136
13	0.263	0.007	0.107	0.156	0.014	0.136
14	0.263	0.007	0.107	0.156	0.014	0.136
15	0.262	0.007	0.107	0.156	0.014	0.136
16	0.262	0.007	0.107	0.156	0.014	0.136
17	0.262	0.007	0.107	0.156	0.014	0.136
18	0.262	0.007	0.107	0.156	0.014	0.136
19	0.262	0.007	0.107	0.156	0.014	0.136
20	0.262	0.007	0.107	0.156	0.014	0.136

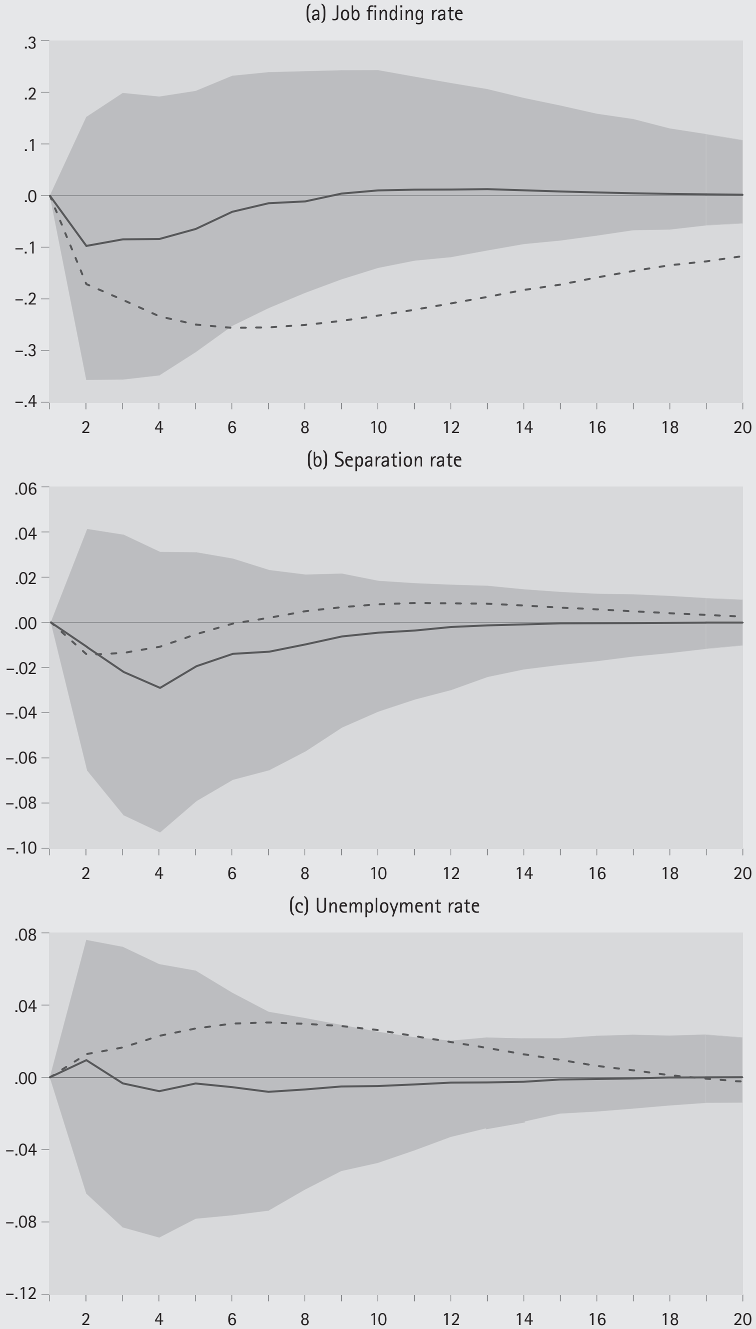
Note: Based on medians from bootstrapping.

Figure 3.A.1: Responses to a technology shock in the subsample (1993–2007)



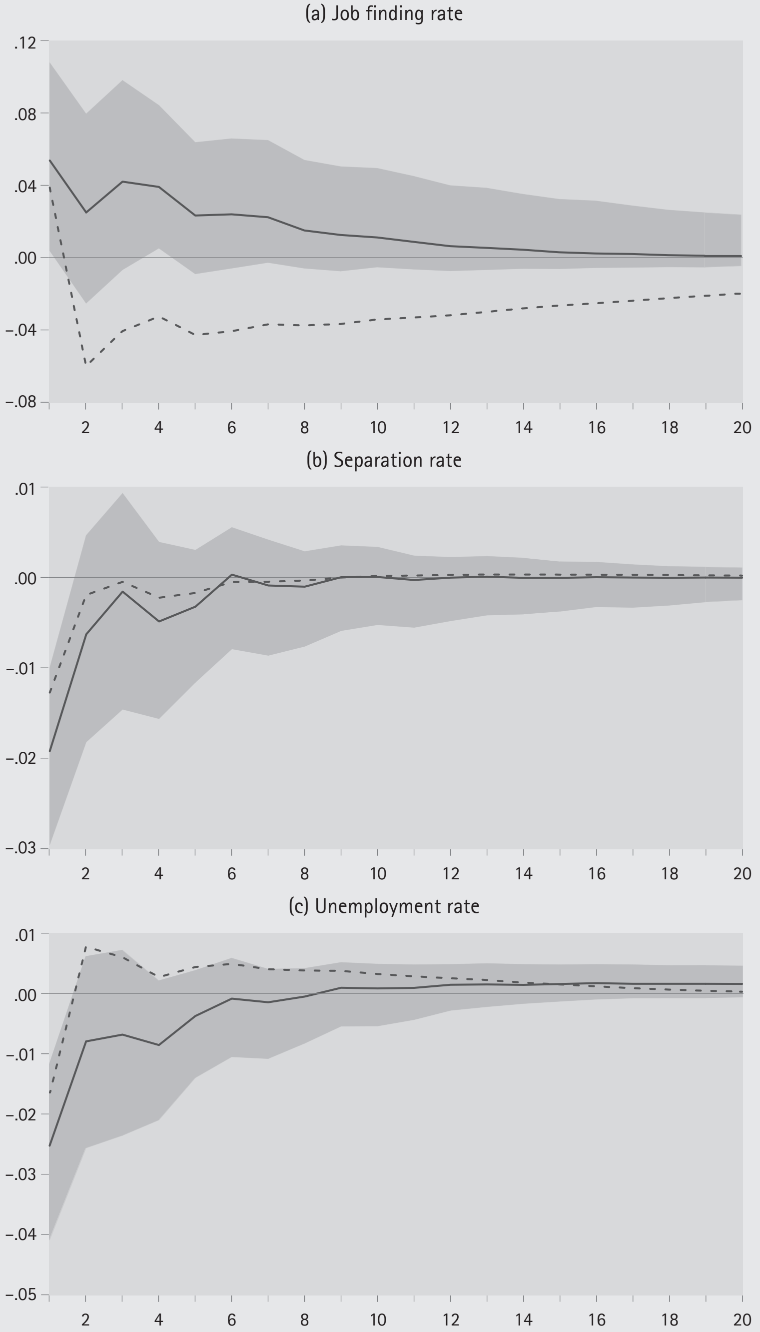
Notes: Impulse responses to a one-off increase in productivity. Dotted lines refer to the benchmark period (1981–2007).

Figure 3.A.2: Responses to a monetary policy shock in the subsample (1993–2007)



Notes: Impulse responses to a one-off increase in the interest rate. Dotted lines refer to the benchmark period (1981–2007).

Figure 3.A.3: Responses to a fiscal policy shock in the subsample (1993–2007)



Notes: Impulse responses to a one-off increase in government spending. Dotted lines refer to the benchmark period (1981–2007).

3.B Imposing Identifying Restrictions

One way to demonstrate the relation between the endogenous variables y_t and the residuals v_t is using the Wold moving average (WMA) representation

$$y_t = \sum_{i=0}^{p} \Psi_i v_{t-i}, \tag{3.8}$$

where the Ψ_i capture the responses to an impulse i periods ago. Substituting Equation 3.3 gives the link to the structural shocks ε_t

$$y_t = \sum_{i=0}^{p} \Psi_i B \varepsilon_{t-i}. \tag{3.9}$$

The sum of the impulse responses Ψ_i derives as follows:

$$\sum_{i=0}^{\infty} \Psi_i = (I_K - A_1 - A_2 - \dots - A_p)^{-1} = (I_K - \sum_{i=1}^{p} A_i)^{-1}. \tag{3.10}$$

Then, the accumulated long-run effect of a structural shock is equal to

$$\Phi = (I_K - \sum_{i=1}^{p} A_i)^{-1} B. \tag{3.11}$$

The latter expression demonstrates the interdependence of the matrices B and Φ and thus the link of short- and long-run restrictions.

Given our identifying assumptions, the matrices B and Φ take the form

$$B = \begin{pmatrix} b_g^g & 0 & 0 & 0 & 0 \\ b_g^a & b_a^a & b_s^a & b_f^a & 0 \\ b_g^s & b_a^s & b_s^s & 0 & 0 \\ b_g^f & b_a^f & b_s^f & b_f^f & 0 \\ b_g^r & b_a^r & b_s^r & b_f^r & b_r^r \end{pmatrix} \tag{3.12}$$

and

$$\Phi = \begin{pmatrix} \varphi_g^g & \varphi_a^g & \varphi_s^g & \varphi_f^g & \varphi_r^g \\ 0 & \varphi_a^a & 0 & 0 & 0 \\ \varphi_g^s & \varphi_a^s & \varphi_s^s & \varphi_f^s & \varphi_r^s \\ \varphi_g^f & \varphi_a^f & \varphi_s^f & \varphi_f^f & \varphi_r^f \\ \varphi_g^r & \varphi_a^r & \varphi_s^r & \varphi_f^r & \varphi_r^r \end{pmatrix}. \tag{3.13}$$

4 The Matching Function: A Selection-Based Interpretation *(with Britta Kohlbrecher and Christian Merkl)*

This paper reconsiders the matching function. In a first step, we estimate an aggregate matching function with German administrative data. Our results provide renewed evidence for a Cobb-Douglas matching function with constant returns to scale. Relying on restricted matching elasticities, we further show that it is important to control for heterogeneity in the aggregate job finding rate. In a second step, we derive a simple labor selection model where vacancies do not have any aggregate effects, but appear as a worker attraction device. When we simulate this model for the German economy and estimate a matching function from the generated data, we also obtain evidence for a Cobb-Douglas function with constant returns to scale. In this fictional matching function, the elasticity of matches with respect to vacancies is a function of the exogenous contact probability. Thus, our paper suggests that the empirical evidence of the matching function may have a completely different interpretation.

4.1 Introduction

The matching function has become a very popular tool in labor market economics (see, e.g., Pissarides, 2000; Mortensen and Pissarides, 1994) because it allows to model labor market frictions (i.e. the costly and time-consuming search and matching process) in a tractable way. The matching function is not only theoretically helpful but also empirically relevant (see Blanchard and Diamond, 1991). In particular for U.S. data, there is widespread evidence for an aggregate matching function where the Cobb-Douglas form has been found to be a convincing specification (see Petrongolo and Pissarides, 2001, for a survey).

But how strong is the evidence for the existence of an aggregate Cobb-Douglas matching function? And how informative are the matching elasticities with respect to unemployment and vacancies? We reconsider these issues from two perspectives. First, we estimate an aggregate matching function based on administrative labor market data for Germany (compare, e.g., Schmieder et al., 2012; Dustmann et al., 2009), which enable us to overcome various shortcomings other databases suffer from. In particular, German administrative data provide actual labor market transitions, a consistent vacancy measure and several control variables for the composition of the unemployment pool.[1] Our results lend renewed support for

1 It is well-known that there is duration dependence of individual job finding rates. Recent research by Hornstein (2012) and Barnichon and Figura (2011) suggests that this may be due to composition effects of the unemployment pool.

the existence of a Cobb Douglas matching function, where constant returns to scale cannot be rejected. Relying on restricted matching elasticities, we further demonstrate that it is relevant to account for heterogeneity in the aggregate job finding rate.

Second, we set up a simple labor selection model to approach a frictional labor market from a theoretical perspective. In this model, each job seeker has a fixed contact probability with a firm. The individual job finding probability is driven by an idiosyncratic draw from a training cost distribution (see, e.g., Brown et al., 2009; Lechthaler et al., 2010, for richer selection models). Thereby, firms post vacancies to attract workers, but they do not generate additional jobs in the aggregate, i.e. the selection model does not contain a traditional matching function. Nevertheless, when we parameterize and simulate our model for Germany, we can investigate whether it is consistent with the aggregate matching function that we find in the data.[2] Our matching function estimations from the simulated data indeed replicate the empirical evidence. Thus, our exercise sounds a cautionary note on interpreting reduced-form estimations.

Moreover, our exercise has two virtues. On the one hand, it allows testing for the validity of the labor selection model. On the other hand, it enables us to gain insights into the underlying mechanisms that lead to the empirical observation of an aggregate matching function. The latter seems to be desirable as the aggregate matching function may shift due to policy changes (see, e.g., Lagos, 2000).

For the theoretical exercise, we use a labor selection model as in Brown et al. (2009) and Lechthaler et al. (2010) and simplify it to its core mechanism, i.e. a partial equilibrium with exogenous separations.[3] We assume that there is an exogenous contact rate.[4] Upon contact, an idiosyncratic training cost realization is decisive for whether a searching worker gets a job or not. Firms have to pay for vacancy posting to be recognized by workers. However, labor market dynamics are exclusively driven by the cutoff point of idiosyncratic training costs. Thus, although there is vacancy posting in this labor market, the role of vacancies is very different than in a standard search and matching model. If one more firm enters the market, it obtains a certain fraction of all workers who make a contact with firms. This additional vacancy does not generate any new jobs because this certain fraction of searching workers would have made a contact in any case and the training cost realization is unaffected by the number of vacancies.

2 Note that this is a natural benchmark for simulated versions of any labor market model.

3 Brown et al. (2009) and Lechthaler et al. (2009) apply a labor selection model to investigate whether it can generate strong labor market reactions to aggregate shocks.

4 We do not claim that this assumption is necessarily very realistic. However, we want to analyze how close such an economy can bring us to the conventional matching function relationship.

What is the underlying intuition for a fictional matching function in the selection model? Job findings are procyclical because a positive aggregate productivity shock provides an incentive to firms to hire workers with a larger idiosyncratic training cost realization.[5] This leads to a countercyclical unemployment rate. Vacancies are procyclical because when productivity rises, this raises aggregate profits and more firms enter the market to get a share of the increased surpluses. When we test whether this cyclical pattern of the variables can generate a matching function, we obtain three results. First, we reveal strong evidence for a matching function of the prominent Cobb-Douglas form. Second, the coefficients of the matching function can be reconciled with constant returns to scale. Third, the matching elasticity with respect to unemployment depends on the exogenous contact rate. With a low contact rate, we observe a matching function close to the empirical estimations. Interestingly, these results are robust with respect to many model modifications. In a simplified version of the selection model, we show analytically that the driving force behind the estimated elasticity is the first derivative of the expected training costs at the cutoff point.

The rest of the paper proceeds as follows. Section 4.2 outlines the German administrative database and examines the empirical evidence on the aggregate matching function. Section 4.3 derives the simple labor selection model. Section 4.4 describes our model parametrization and provides the estimation results based on simulated data. Section 4.5 strips down the selection model to a version that allows us to illustrate the underlying mechanisms analytically. Section 4.6 concludes.

4.2 Estimations from Empirical Data

We use German administrative data for our matching function estimations because it offers a coherent definition of matches, unemployment and vacancies. The administrative database is provided by the Federal Employment Agency, which is responsible for the unemployment insurance system and active labor market policies in Germany. Although the administrative information is not fully comparable to U.S. data, it offers several advantages. First, we have real vacancies instead of a job advertising index for longer time series. Second, it provides actual labor market transitions, i.e. we do not have to construct labor market flows from unemployment, employment and duration data (see, e.g., Shimer, 2005; 2012). Third, the information is not survey-based and we do not have to deal with measurement

5 Merkl and van Rens (2012) show that the job finding rate and its dynamics are isomorphic in a model with idiosyncratic training costs (under a Pareto distribution) and in the search and matching model. However, their model does not contain any vacancies and is thus silent on the shape of the matching function.

errors due to sample rotation or sample attrition. Fourth, we can observe several control variables that are likely to influence the search and matching process.

Similar to the evidence for the U.S., there are a number of matching function estimations for Germany. Therefore, the next subsection gives a short overview of related studies for Germany and points out to what extent our model specification differs from the existing literature. Then, we describe our data and estimation strategy. Afterwards, we present the estimation results.

4.2.1 Literature Review

The estimation of a matching function may be motivated by various objectives. Early studies focus on the matching function itself and investigate its functional form, whereas more recent studies tend to deal with specific data issues, such as the definition of the matching function variables. Appendix 4.A summarizes several papers that estimate a matching function for Germany (see Table 4.A.1).

Burda and Wyplosz (1994) provide an exemplary study for early approaches. The authors accept the Cobb-Douglas form against a more general specification and cannot reject the hypothesis of constant returns to scale (CRS). The weights on unemployment and vacancies display a 2 : 1 split, which is supported by most of subsequent studies. In contrast, Sunde (2007) relies on segmented labor markets and discusses different definitions of matches. The matching elasticities of unemployment and vacancies turn out much closer and do hardly sum up to unity. Fahr and Sunde (2009) and Klinger and Rothe (2012) estimate an aggregate matching function to assess the macroeconomic performance of the Hartz reforms. For this purpose, the authors consider "treatment" dummies that indicate whether a particular reform was in place or not. The inclusion of the reform dummies, however, does not seem to affect the matching elasticities.

Moreover, it can be seen that previous studies mainly rely on official data, though the availability of consistent data for longer time periods is limited. However, the Federal Employment Agency also provides information on the individual level, which comprise labor market biographies over a long time period. Some of the existing studies use the micro data to obtain time series on matches, but they do not measure unemployment from the same data source. This may lead to a potential bias as the micro data is based on notifications on unemployment benefit receipt, whereas the official unemployment series accounts for more specific criteria, such as search effort.

We overcome this shortcoming and measure both matches and unemployment from the same micro data set. This procedure enables us to obtain long and coherent time series. In addition, the micro data include a number of control variables and are available on a daily basis, which allows for a precise and flexible handling of the time structure.

4.2.2 Data Description

We use monthly data for reunified Germany from 1993 to 2007. The restriction on this time period results from the Sample of Integrated Labor Market Biographies (SIAB) where we extract our time series for matches and unemployment from.

The SIAB presents a 2% random sample of all German residents who are registered by the Federal Employment Agency because of paying social security contributions or receiving unemployment benefits (see Dorner et al., 2010). The data set includes information on the individuals' labor market status, their wage and unemployment income as well as several socio-demographic characteristics. This has the advantage of controlling for the composition of the unemployment pool and for different search intensities that might emerge from unemployment benefit receipt.[6]

Matches are defined as transitions from unemployment to employment subject to social security. Even though marginal employment has become subject to social security since 1999, we do not consider this kind of employment because it is often regarded as a stepping stone into regular jobs. The transitions are calculated continuously, i.e. we take into account every daily transition. Hence, we do not neglect any job findings that are reversed within a month.

Unemployment is obtained by an adjusted measure of unemployment benefit receipt. As the benefit system has been reformed in course of the Hartz reforms, the unemployment benefit measure faces a level shift in 2005. This holds for the adjustment procedure according to Fitzenberger and Wilke (2010), which corrects for unemployment periods without benefit receipt.[7]

Vacancies are taken from the official statistics and cover open positions that are reported to the Federal Employment Agency.[8] According to the IAB Job Vacancy Survey, the reported vacancies account for about 30–40% of overall vacancies in Germany. As this survey is available at least on a yearly basis, it enables us to adjust the vacancy series in some way. However, it remains unclear to what extent the reporting rate is representative for socially secured jobs. Consequently, we leave the adjustment of vacancies to the robustness analysis.[9]

6 See, e.g., Katz and Meyer (1990), who find evidence for an influence of unemployment benefit receipt on the workers' job acceptance behavior.

7 For a comprehensive description of the unemployment definition see Nordmeier (2012).

8 In line with our measurement of matches, we exclude vacancies for marginal employment as job opportunity.

9 Appendix 4.B illustrates the reporting rate of vacancies.

Figure 4.1 shows the time series of matches, unemployment and vacancies. One striking feature of matches is their high volatility. While the matches amount to around 220,000 per month, monthly unemployment changes are much lower implying that there is a high labor turnover. Along with the redefinition of unemployment and the larger pool of captured job seekers, matches display a level shift in 2005 and average around 260,000 job findings per month afterwards. Note that the upward shift in the number of unemployed is also driven by the adjustment of unemployment periods before and after benefit receipt. The adjustment procedure accounts for about 10% of the unemployment pool before 2005 and goes up to nearly 20% after the Hartz reforms have been implemented. Nevertheless, unemployment decreases remarkably in subsequent years, which is ascribed to both the labor market reforms and the upswing in those years. The reported vacancies move from nearly 300,000 to around 600,000 positions over the sample period, where the development after the Hartz IV reform is considerable as well. Moreover, the adjustment of registered vacancies with the reporting rate causes primarily a level shift and does not appear to affect the fluctuations of vacancies.

4.2.3 Estimation Strategy

We rely on the following estimation procedure. First, we estimate a Cobb-Douglas function with unrestricted matching elasticities

$$\log M_t = \beta_0 + \beta_1 \log U_{t-1} + \beta_2 \log V_{t-1} + \beta_3 trend + \beta_4 d_{2005} + \psi_t, \tag{4.1}$$

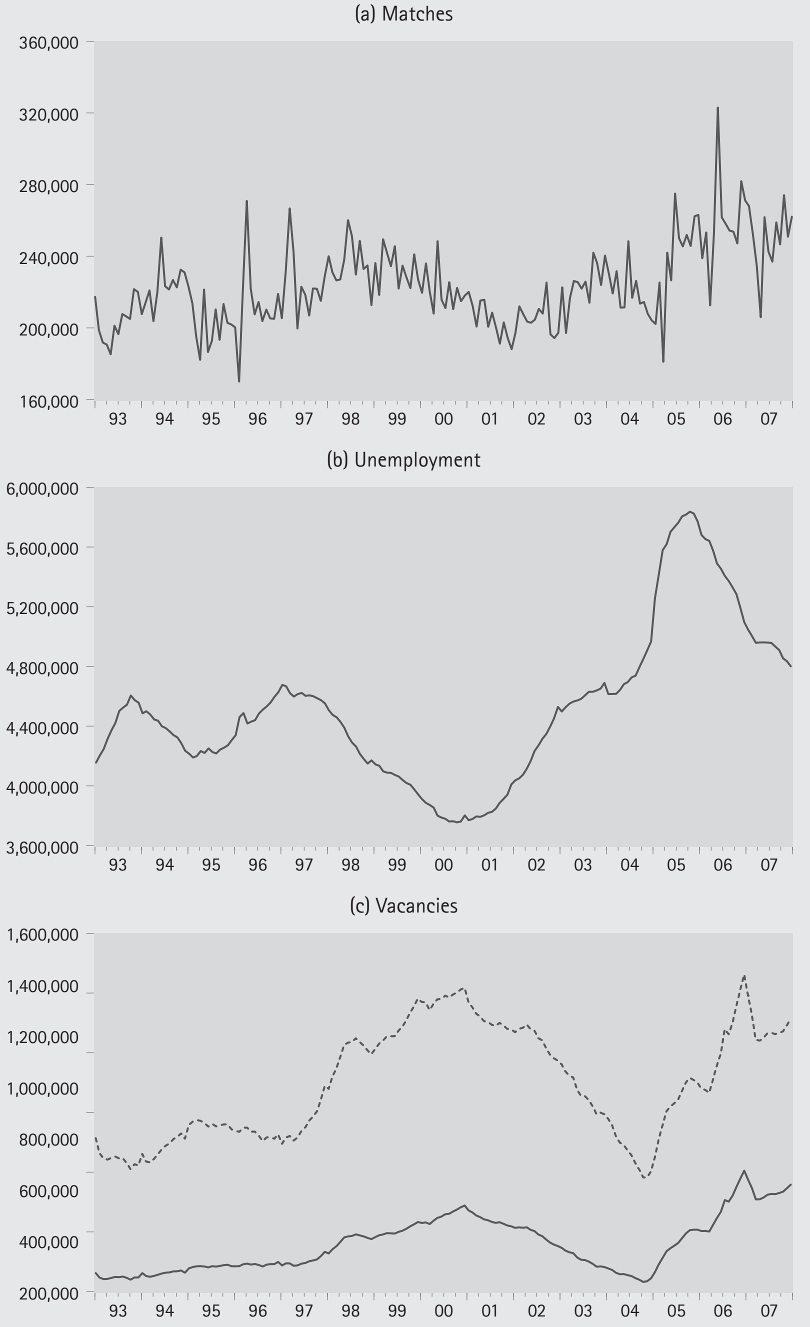
where M are matches, U is unemployment, V are vacancies, *trend* is a linear time trend, d_{2005} is a shift dummy that takes the value of one from 2005 onwards and ψ is the error term. Unemployment and vacancies are measured at the end of month $t-1$ and thus display the beginning-of-month-t stocks. Accordingly, our measures of unemployment and vacancies are not depleted by the endogenous variable.

Equation 4.1 allows us to test the hypothesis of constant returns to scale $(\beta_1 + \beta_2 = 1)$. Once we cannot reject the constant returns to scale assumption, we proceed by estimating a Cobb-Douglas function with restricted matching elasticities. Then, our second specification equals

$$\log f_t = \beta_0 + \beta_2 \log \theta_{t-1} + \beta_3 trend + \beta_4 d_{2005} + \psi_t, \tag{4.2}$$

where $f = M/U$ is the job finding rate and $\theta = V/U$ denotes the labor market tightness.

Figure 4.1: Matches, unemployment and vacancies



Notes: (a) Matches per month, (b) Unemployment, (c) Reported vacancies (solid line) and adjusted vacancies (dashed line). Sample measures are projected by multiplication with 50.

To account for the effects of a changing unemployment pool on the aggregate job finding rate, we finally extend Equation 4.2 by observable control variables

$$\log f_t = \beta_0 + \beta_2 \log\theta_{t-1} + \beta_3 trend + \beta_4 d_{2005} + \beta_5 controls + \psi_t, \tag{4.3}$$

where *controls* capture both individual characteristics and factors that are assumed to influence the individuals' search effort.[10] This specification implies different matching efficiencies for heterogeneous workers and thus different job finding rates within the unemployment pool.[11]

4.2.4 Results

Table 4.1 presents the results from matching function estimations with unrestricted parameters. The first regression displays a standard ordinary least squares (OLS) estimation. Because the Durbin-Watson (DW) statistic indicates positive autocorrelation in the residuals, the second regression explicitly allows for a first-order autocorrelated error term. The third estimation shows an instrumented variable (IV) regression using lagged unemployment and vacancies in order to address a potential bias in case of endogeneity.[12]

Table 4.1: Unrestricted matching function estimations

	(i)	(ii)	(iii)
constant	-4.8237*	-5.4194*	-5.4180**
log U_{-1}	0.8860***	0.9166***	0.9246***
log V_{-1}	0.2827***	0.2930***	0.2831***
trend	-0.0004**	-0.0004*	-0.0004
d_{2005}	-0.1131***	-0.1159**	-0.1218**
adjusted R^2	0.4495	0.4983	0.4448
DW statistic	1.3619	2.0757	–
CRS t-statistic	1.0074	0.9533	1.1184

Notes: (i) OLS estimation, (ii) OLS estimation with AR(1) disturbance term, (iii) IV estimation with Newey-West standard errors. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

10 See Appendix 4.D for a detailed description of generated control variables.

11 Obviously, a further extension could be a decomposition of the matching elasticity, but our methodological exercise solely asks for aggregate parameters.

12 Even though our matching function specification does not face a simultaneity problem due to a precise timing of stocks and flows, we are precautionary with respect to an omitted variable bias.

The results are similar across the different estimation approaches and show a fairly good fit in terms of the adjusted R^2. The coefficients of unemployment and vacancies are significant at the 1% level and seem to be robust. The matching elasticity with respect to unemployment is about 0.9, while the matching elasticity with respect to vacancies is nearly 0.3. Although the matching elasticities sum up to above unity, the hypothesis of constant returns to scale cannot be rejected in any case. Appendix 4.C demonstrates that this holds for several robustness checks. In particular, the adjustment of vacancies with the reporting rate and the consideration of labor market rates do hardly alter our benchmark results. The sum of the matching elasticities from quarterly data points closer to unity, whereas the coefficients from the subsample before the Hartz IV reform and from detrended data deviate somewhat more. From a statistical point of view, however, the results cannot be discriminated from constant returns to scale. Therefore, we rely on the homogeneity of the matching function and proceed by imposing the constant returns to scale assumption on the matching elasticities.

Table 4.2 shows the results from estimating the matching function with restricted coefficients. Thereby, the coefficient of the labor market tightness θ represents the matching elasticity with respect to vacancies. Compared to the unrestricted estimations, the weight on vacancies decreases slightly to 0.25. The Durbin-Watson statistic again indicates a positively autocorrelated error term, but the stepwise inclusion of control variables eliminates the serial correlation. Accordingly, it seems that we achieve efficient estimates by solely accounting for heterogeneity on the workers' side. Nevertheless, it is worth stressing that we are able to overcome the serial correlation definitely when we consider benefit-related control variables in addition to sociodemographic characteristics. This might indicate that the unemployment insurance system indeed influences the search and matching process.[13] Moreover, controlling for observable heterogeneity in the unemployment pool strengthens the role of vacancies as the matching elasticity of vacancies in relation to unemployment increases to 0.35.

To sum up, our data estimations provide renewed evidence in favor of a Cobb-Douglas matching function with constant returns to scale. Hence, from an empirical point of view the formulation of the search and matching process via a matching function seems to be a reliable concept. However, in the next sections we will question the standard interpretation of the matching function by confronting the empirical evidence with a labor selection model that does not contain a matching function.

13 Note that aggregate studies often have failed to find an influence of the unemployment insurance system, which may result from the difficulty of measuring institutional aspects in a time series (see Petrongolo and Pissarides, 2001).

Table 4.2: Restricted matching function estimations

	(iv)	(v)	(vi)	(vii)
constant	-2.3498***	-7.3804***	-4.3403**	-4.8473**
log θ_{-1}	0.2458***	0.3116***	0.3463***	0.3507***
trend	-0.0003**	-0.0043*	-0.0054**	-0.0038
d_{2005}	-0.0798***	-0.0472	-0.0766	-0.1290**
young		yes	yes	yes
old		yes	yes	yes
low-skilled		yes	yes	yes
high-skilled		yes	yes	yes
foreign		yes	yes	yes
female		yes	yes	yes
married		yes	yes	yes
child		yes	yes	yes
long-term		yes	yes	yes
UB I receipt			yes	yes
x replacement ratio				yes
x rest entitlement				yes
adjusted R^2	0.5134	0.5805	0.6162	0.6284
DW statistic	1.3664	1.6935	1.8407	1.8477

Notes: OLS estimations. Control variables denote shares of the unemployment pool. In specification (vii), the share of unemployment benefit (UB) I recipients is interacted with the replacement ratio and rest entitlement, respectively. ***, ** and * indicate significance at the 1%, 5% and 10% levels.

4.3 A Simple Selection Model

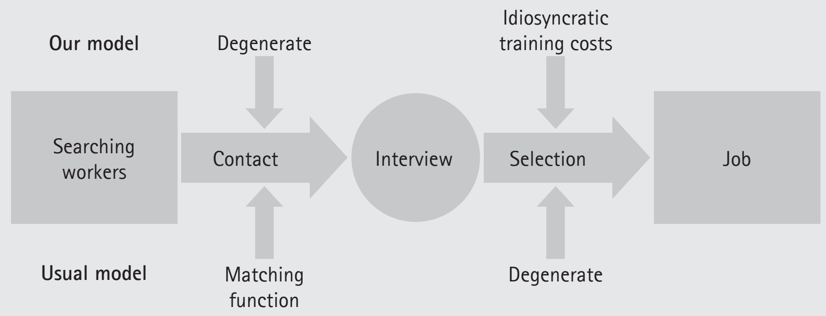
4.3.1 Model Environment

Our economy is populated with a continuum of workers who can either be employed or unemployed. Employed workers are separated with an exogenous probability φ.[14] Unemployed workers look for a job. It is standard practice in the search and matching literature to assume that workers' contact probability is endogenous and driven by a matching function, while the selection probability (i.e. the probability of being selected after an interview) is usually assumed to be exogenous/degenerate. In our baseline specification, we assume the opposite case, namely an exogenous contact probability, $c \leq 1$. Thus, the dynamics of the job finding rate is completely driven by the selection rate. When workers obtain an interview, they draw an idiosyncratic training cost realization ε_{it}. Firms will only hire workers with training costs $\varepsilon_{it} \leq \widetilde{\varepsilon}_t$,

14 In Appendix 4.E we report numerical results for a version of the model with endogenous separations. As our core results are unaffected by this modification, we restrict our attention to the simpler case of exogenous separations.

where $\widetilde{\varepsilon}_t$ is the cutoff point that makes a firm indifferent between hiring and not hiring. The sequence in our selection model and in standard search and matching models is illustrated in Figure 4.2.

Figure 4.2: Contact and selection



We assume that firms have to post vacancies to obtain a share of the economy wide applicants (namely, the firm's vacancy divided by the overall number of vacancies, which is determined by a free-entry condition). Since the contact probability is exogenous in our baseline specification, more vacancies do not create more jobs, but just lead to a different allocation of workers.

4.3.2 The Selection Decision

Once worker-firm pairs have been formed, firms decide whether to hire a particular worker or not. There is a random worker-firm pair specific idiosyncratic training cost shock, ε_{it}, which is *iid* across workers and time[15], with density function $f(\varepsilon_t)$ and the cumulative distribution $F(\varepsilon_t)$. ε_t is observed by the worker and the firm. Thus, the expected discounted profit, $\pi_t^E(\varepsilon_t)$, of hiring an unemployed worker is equal to the current productivity minus the current wage (which may be dependent on ε), $w_t(\varepsilon_t)$, minus the idiosyncratic random training cost shock, ε_t, and a fixed training cost component, h, plus the expected discounted future profits:

$$\pi_t^E(\varepsilon_t) = a_t - w_t(\varepsilon_t) - \varepsilon_t - h + \delta(1-\varphi)E_t(\pi_{t+1}), \tag{4.4}$$

with

$$\pi_t = a_t - w_t + \delta(1-\varphi)E_t(\pi_{t+1}). \tag{4.5}$$

15 Due to the *iid* assumption, we abstract from the worker-firm pair specific index i from here onwards.

δ is the discount factor. Incumbent worker-firm pairs are not subject to further training costs.[16] Thus, an incumbent workers' wage does not depend on ε_t.

The firm hires an unemployed worker whenever there is an expected positive surplus. Thus, the selection rate is given by:

$$\eta_t = P\left(\tilde{\varepsilon}_t < a_t - w_t\left(\varepsilon_t\right) - h + \delta\left(1-\varphi\right)E_t\left(\pi_{t+1}\right)\right). \tag{4.6}$$

4.3.3 Firms' Free-Entry Decision

We assume that each vacancy corresponds to one firm. Entrepreneurs who want to enter the market have to pay a fixed vacancy posting cost κ. They know that the vacancy will be filled with a certain probability, namely the number of searching workers at the beginning of the period, s_t, multiplied with the contact and selection rates divided by the number of aggregate vacancies. Thus, entrepreneurs will enter the market up to the point where the expected costs of finding a worker equals the expected return of finding a worker.

Thus, new firms will post vacancies as long as

$$\frac{\kappa}{c\eta_t s_t / V_t} \leq \frac{\int_{-\infty}^{\tilde{\varepsilon}_t}\left(a_t - w_t\left(\varepsilon_t\right) - \varepsilon_t - h\right)f\left(\varepsilon_t\right)d\varepsilon_t}{\eta_t} + \delta\left(1-\varphi\right)E_t\left(\pi_{t+1}\right), \tag{4.7}$$

where the left-hand side is the average cost of posting a vacancy (vacancy posting cost divided by the probability of finding a worker). The right-hand side is the expected return from hiring a worker, namely the expected return in the contemporaneous period (since vacancies are posted before the interview, the expected training cost realization conditional on being hired is taken into account) and the expected return in future periods. Thus, in equilibrium

$$V_t = \frac{c\eta_t s_t}{\kappa}\left(\frac{\int_{-\infty}^{\tilde{\varepsilon}_t}\left(a_t - w_t\left(\varepsilon_t\right) - \varepsilon_t - h\right)f\left(\varepsilon_t\right)d\varepsilon_t}{\eta_t} + \delta\left(1-\varphi\right)E_t\left(\pi_{t+1}\right)\right). \tag{4.8}$$

Importantly, in our baseline specification more vacancies do not lead to more jobs in the aggregate since we have fixed the contact probability exogenously. However, it is perfectly rational for individual firms to enter the market. Under a positive aggregate productivity shock, the expected returns of hiring a worker increase. Thus, more firms will enter the market to compete for these profits until the free-entry condition holds again. This will make vacancies procyclical, although they do not have any effects on the number of newly created jobs in our baseline specification.

16 We relax this assumption in Appendix 4.E.

4.3.4 Wages

As in standard search and matching models, worker-firm pairs are associated with rents. Workers are worse off quitting the job because this would require searching for a new job and drawing a new training cost realization (with a probability smaller than 1 to find a job). If a firm loses the worker, it will have to post a new vacancy and try to find a new worker. Thus, once workers and firms are matched, there is a bilateral monopoly. We assume that rents will be shared by Nash bargaining between each worker-firm pair.

The flow value of a job for a newly employed worker is

$$V_t^E(\varepsilon_t) = w_t^E(\varepsilon_t) + \delta E_t\left((1-\varphi)V_{t+1}^I - \varphi V_{t+1}^U\right), \tag{4.9}$$

and the flow value of a job for an incumbent worker is

$$V_t^I = w_t^I + \delta E_t\left((1-\varphi)V_{t+1}^I - \varphi V_{t+1}^U\right). \tag{4.10}$$

The fallback option for all workers is the value of unemployment:

$$V_t^U = b + \delta E_t\left(c\eta_{t+1}V_{t+1}^E + (1-c\eta_{t+1})V_{t+1}^U\right), \tag{4.11}$$

where b denotes unemployment compensation.

The firm's value of a newly filled vacancy and the value of a continuing match are given by Equations 4.4 and 4.5, respectively. We assume that the fixed training cost component is sunk (i.e. has to be payed before bargaining).[17]

Under disagreement, the firm's fallback position is equal to 0, i.e. the firm can break the interview at zero cost and can post a new vacancy, which has a zero value in equilibrium.

The wages are thus determined by the following maximization problem:

$$w_t^E(\varepsilon_t) \in \operatorname{argmax}\left(V_t^E(\varepsilon_t) - V_t^U\right)^{\alpha}\left(\pi_t^E(\varepsilon_t) + h\right)^{1-\alpha}, \tag{4.12}$$

and

$$w_t^I \in \operatorname{argmax}\left(V_t^I - V_t^U\right)^{\alpha}\left(\pi_t\right)^{1-\alpha}. \tag{4.13}$$

17 This assumption is without loss of generality for our matching function estimations in the theoretical model. It prevents that some of the entrants' wages are negative. The latter would prevent calculating a meaningful mean-min ratio and thus limit the possibilities for comparisons to the data.

The solution to this problem is:

$$w_t^E(\varepsilon_t) = \alpha\left(a_t - \varepsilon_t + \delta c E_t(\eta_{t+1}\pi_{t+1})\right) + (1-\alpha)\left(b + \delta c E_t(\eta_{t+1}(V_{t+1}^E - V_{t+1}^I))\right), \tag{4.14}$$

and

$$w_t^I = \alpha\left(a_t + \delta c E_t(\eta_{t+1}\pi_{t+1})\right) + (1-\alpha)\left(b + \delta c E_t(\eta_{t+1}(V_{t+1}^E - V_{t+1}^I))\right). \tag{4.15}$$

Note that our bargaining corresponds to the standard bargaining under search and matching. Wages look somewhat more cumbersome because entrants are assumed to be subject to training costs, while incumbent workers are not.

4.3.5 Employment

We assume an economy with a fixed labor force L, which is normalized to 1. Thus, the employment stock is equal to the employment rate, n. The unemployment rate is denoted with u. Thus, the employment dynamics in this economy is determined by

$$n_t = \left(1 - \varphi - c\eta_t\right) n_{t-1} + c\eta_t. \tag{4.16}$$

The number of searching workers, s_t, is thus equal to the number of unemployed workers at the end of period $t-1$.

4.3.6 Labor Market Equilibrium

The labor market equilibrium consists of Equations 4.5, 4.8, 4.14, 4.15, 4.6 and 4.16. In the dynamic version of the model, we will assume that aggregate productivity is governed by a first-order autocorrelation process.

4.4 Estimations from Simulated Data

4.4.1 Parametrization of Model

We parameterize the model on a quarterly basis.[18] In line with our data, we set the separation rate to 0.03 and the target of the steady state job finding rate to 0.15.

18 Calibrating the model on a monthly basis does not change our results. However, due to the small German labor market flows, a monthly calibration may generate numerical problems. Since we simulate the model as a system of log-linearized first-order difference equations, the smaller the labor market flows are, the larger is the likelihood of obtaining a job finding rate below zero due to a larger negative shock. A simulation in the full nonlinear setting of equations would prevent this problem.

The discount factor is 0.99, the bargaining power of workers is 0.5 and vacancy posting costs are set to 0.1.

The steady state productivity is normalized to 1. We simulate the model with productivity shocks that have an autocorrelation of 0.95 and a standard deviation of 1%. Unemployment compensation is 0.8.

We vary the contact rate from 0.2 to 1. In order to close our model, we adjust the mean of our training costs to get the desired steady state selection rate. Depending on our specification, the mean training cost varies between 40% and 90% of quarterly productivity. The distribution of training costs is assumed to be Gaussian. To our knowledge, there is no empirical evidence for the distribution of training costs in Germany. Therefore, we vary the standard deviation of the training cost shock, σ, between 0.25 and 1. In light of evidence on U.S. training costs (see, e.g., Barron et al., 1989; Dolfin, 2006) these appear to be plausible parameters. However, as we show, our core results are unaffected by variations in this parameter.

4.4.2 Simulation

We simulate the model 1,000 times. Each time we use 60 periods corresponding to the 60 quarters in our data to estimate the matching function from above:[19]

$$\log M_t = \beta_0 + \beta_1 \log U_{t-1} + \beta_2 \log V_{t-1} + \psi_t. \tag{4.17}$$

We approach the simulated data as an applied econometrician who is unaware of the true data generating process in the economy and conjectures that there is a Cobb-Douglas matching function.

Table 4.3 shows the estimation results for different contact rates. Several observations are worthwhile pointing out. First, the estimations indeed suggest the existence of a Cobb-Douglas matching function. The coefficients are highly significant in any of the 1,000 simulations.[20] This is astonishing as our theoretical model does not originally contain the matching function that we estimated. Not only do we find evidence in favor of a Cobb-Douglas matching function, the sum of coefficients is also remarkably close to unity. The acceptance rate of

19 We omit the linear time trend conventionally used in empirical estimations as we only consider mean-reverting shocks.

20 We do not report test-statistics as means over simulations would not have a meaningful interpretation in this context. Instead, we have checked in every single estimation if the coefficients are significant at the 5% level, if constant returns are rejected or if the coefficients lie within the confidence interval of the empirical counterpart.

constant returns is always above 60%[21] in any of the combinations of c and σ. In most cases, acceptance rates are between 70 and 80%. We therefore do not report results for the reduced form specification, as the coefficients are hardly changed.

Second, the estimated coefficients on unemployment and vacancies are hardly changed by variations in the standard deviation of the idiosyncratic training cost shock. We are therefore confident that our results are not driven by arbitrary assumptions about the distribution of the training costs.

Table 4.3: Matching functions for different contact rates

	c = 1	c = 0.75	c = 0.5	c = 0.25	c = 0.2
			$\sigma = 0.25$		
constant	-0.05	-0.17	-0.38	-0.96	-1.28
log U_{-1}	0.19	0.22	0.26	0.41	0.51
log V_{-1}	0.80	0.77	0.72	0.56	0.44
CRS rate	70%	71%	68%	66%	63%
			$\sigma = 0.5$		
constant	-0.60	-0.69	-0.87	-1.31	-1.53
log U_{-1}	0.20	0.22	0.26	0.42	0.53
log V_{-1}	0.80	0.78	0.73	0.57	0.45
CRS rate	75%	75%	72%	70%	72%
			$\sigma = 1$		
constant	-1.14	-1.23	-1.36	-1.68	-1.82
log U_{-1}	0.20	0.22	0.26	0.42	0.53
log V_{-1}	0.80	0.78	0.73	0.57	0.46
CRS rate	78%	76%	78%	76%	77%

Notes: Coefficients are means over 1,000 simulations. *CRS* rate reports in how many percent the constant returns to scale assumption could not be rejected.

Finally, the weight on unemployment increases with a lower exogenous contact rate. The estimation results for an economy with low exogenous contact rates (e.g., 0.2 or 0.25) resemble very much the estimation results for the German economy in Section 4.2.4. In regression (vii), the confidence interval for the coefficient on market tightness (vacancies) ranges from 0.20 to 0.50. The coefficient on vacancies for the lowest contact rate clearly lies within these bands. Indeed, the confidence intervals from our simulation exercise and the empirical confidence interval always overlap for a contact rate of 0.2. Extending

21 60% in this context means that in 60 out of 100 simulations constant returns could not be rejected.

the model to include endogenous separations does not alter our results as can be seen in Appendix 4.E.

Thus, our exercise implies that our simple selection model can generate an aggregate matching function of the form that is usually found in the data.

4.4.3 Further Statistics

Table 4.4 reports some further interesting features of the selection model. The model consistently generates a negative correlation between unemployment and vacancies, although somewhat smaller than in the real data. In addition, although the relative volatility of unemployment with respect to productivity shocks is low compared to the data, the model's performance in this respect is much better than a comparably simplistic search and matching model as in Shimer (2005). Amplification is especially high for a relatively tight distribution of training costs and high contact rates. Note that these results hinge neither on wage stickiness as in Hall (2005) nor on a small surplus calibration as in Hagedorn and Manovskii (2008). Furthermore, for low contact rates and a wider distribution of training costs, the model generates a substantial wage dispersion, as measured by the mean-min ratio. Thus, our model faces a similar tradeoff between amplification and wage dispersion as other search models (see Hornstein et al., 2011).

Table 4.4: Further statistics from simulated model

	c = 1	c = 0.75	c = 0.5	c = 0.25	c = 0.2	data
			$\sigma = 0.25$			
corr (U, V)	-0.27	-0.28	-0.32	-0.43	-0.50	0.04 (-0.83)
SD(u)/SD(a)	3.82	3.79	3.68	3.24	2.76	12.92
wage ratio	1.04	1.04	1.05	1.08	1.11	1.78
			$\sigma = 0.5$			
corr (U, V)	-0.26	-0.27	-0.32	-0.43	-0.50	0.04 (-0.83)
SD(u)/SD(a)	3.22	3.18	3.05	2.53	2.01	12.92
wage ratio	1.07	1.08	1.09	1.17	1.23	1.78
			$\sigma = 1$			
corr (U, V)	-0.26	-0.29	-0.31	-0.41	-0.49	0.04 (-0.83)
SD(u)/SD(a)	2.46	2.42	2.29	1.72	1.27	12.92
wage ratio	1.11	1.13	1.17	1.34	1.53	1.78

Notes: The reported figures are means over 1,000 simulations. U and V are beginning-of-period stocks. Standard deviations (SD) have been calculated from HP filtered series with smoothing parameter $\lambda = 10^5$. The wage ratio corresponds to the mean-min ratio, defined as the 50 to 10 percentiles ratio of the wage distribution. The empirical data refer to the time period 1993–2007 (1993–2004).

4.5 Fictional Matching Function Analytics

4.5.1 Static Toy Model Mechanics

In the previous numerical section, we have simulated the full dynamic model and estimated whether we find evidence for an aggregate matching function. We have indeed found numerical evidence for a Cobb-Douglas constant returns to scale specification. This section simplifies the underlying model to a static version in order to make analytical statements.

We assume that all workers are exogenously separated after having produced for one period, i.e. all workers are unemployed/searching at the beginning of the period. Thus, the employment level after matching corresponds to the job finding rate which is the product of the exogenous contact rate and the endogenous selection rate

$$n = c\eta. \tag{4.18}$$

A firm hires all workers that generate a profit, i.e.

$$\varepsilon < a - w(\varepsilon). \tag{4.19}$$

Let us assume for simplicity that the wage is a constant share of aggregate productivity and the idiosyncratic training cost realization[22]

$$w = \alpha\,(a - \varepsilon). \tag{4.20}$$

Thus, workers are hired up to the point

$$\tilde{\varepsilon} = a. \tag{4.21}$$

The selection rate in the economy is

$$\eta = \int_{-\infty}^{\tilde{\varepsilon}} f\left(\varepsilon\right) d\varepsilon. \tag{4.22}$$

Although more vacancies do not lead to more jobs in the aggregate, firms compete for the applicants and post vacancies until the expected return is equal to the expected cost. Since vacancies are posted before contacts take place, the free-entry condition is based on ex-ante expected profits, i.e.

22 We can show that our results hold for more general wage settings.

$$V=\frac{c\eta}{\kappa}\left(a(1-\alpha)-\frac{(1-\alpha)\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta}\right). \tag{4.23}$$

What would an empirical researcher do who looks for a matching function? In the standard constant returns specification he or she would estimate $\ln f=\ln c\eta=\beta_o+\beta_1\ln\theta$. In the static version of the model, the beginning of the period unemployment stock was assumed to be 1. Thus, the empirical researcher would implicitly estimate $\ln f=\beta_o+\beta_1\ln V$. In a simple OLS estimation, he or she would estimate how strongly the job finding rate and vacancies co-move in percentage terms.

We can calculate this connection analytically, namely $\frac{\partial\ln(c\eta)}{\partial\ln V}$, by deriving the elasticity of the job finding rate with respect to productivity and by deriving the elasticity of vacancies with respect to productivity:

$$\frac{\partial\ln(c\eta)}{\partial\ln a}=\frac{af(\tilde{\varepsilon})}{\eta}, \tag{4.24}$$

$$\frac{\partial\ln V}{\partial\ln a}=\frac{a}{a-\frac{\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta}}. \tag{4.25}$$

Thus, the empirical "matching function" correlation is:

$$\frac{\partial\ln(c\eta)}{\partial\ln V}=\frac{f(\tilde{\varepsilon})}{\eta}\left(\tilde{\varepsilon}-\frac{\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta}\right). \tag{4.26}$$

Interestingly, this expression corresponds exactly to the first derivative of the expected training costs conditional on being selected. Proof:

$$\left(\frac{\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta}\right)'=\left(\frac{\eta\,\tilde{\varepsilon}\,f(\tilde{\varepsilon})-f(\tilde{\varepsilon})\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta^2}\right)=\frac{f(\tilde{\varepsilon})}{\eta}\left(\tilde{\varepsilon}-\frac{\int_{-\infty}^{\tilde{\varepsilon}}\varepsilon f(\varepsilon)d\varepsilon}{\eta}\right). \tag{4.27}$$

Important: In the dynamic simulations, we obtain the same result. The estimated elasticity of the matching function with respect to vacancies is driven by the first derivative of the expected idiosyncratic training cost realization conditional on being selected.

4.5.2 Intuition

In our framework, the estimated matching function relationship is a "fictional relationship", i.e. more vacancies do not lead to more jobs, but there is a positive correlation between the job finding rate and market tightness. What is the underlying economic mechanism?

When productivity rises, firms have an incentive to hire workers with larger idiosyncratic training costs. Thus, hiring/selection is clearly procyclical. When productivity rises, this also increases the returns from posting a vacancy. Thus, firms compete for the larger pie of profits and more of them enter the market. These two mechanisms combined lead to a positive comovement between the job finding rate and vacancies.

What is the intuitive reason that vacancies rise less than proportionally compared to the job finding rate (or put differently: why is there a concave relationship with respect to vacancies in the fictional matching function)? With larger productivity, the increase of the job finding rate is driven by the density at a given point in a distribution. Assume for illustration purposes that the underlying distribution is uniform. Then a one percent rise in productivity would lead to the same absolute deviation of the job finding rate independently of the point of the distribution, i.e. the level of the job finding rate.

The dynamics of the job finding rate is driven by the ex-post realization of training costs. By contrast, the dynamics of the vacancy posting process is driven by the ex-ante expectations of profits. Entrepreneurs anticipate that larger aggregate productivity means that they will hire more workers with larger idiosyncratic training costs. Thus, the realization of the conditional distribution of training costs becomes relevant. To be more precise: the first derivative tells us how fast the average training costs of hired workers rise if more workers are selected. Due to this countervailing effect, vacancies rise less than proportionally compared to the job finding rate.

Why does a smaller exogenous contact rate lead to a smaller elasticity of the job finding rate with respect to vacancies? Technically speaking, in a calibration that targets the steady state job finding rate, an exogenous reduction of the contact probability automatically raises the selection rate. For a given absolute deviation, this leads to a smaller log deviation (see denominator of Equation 4.24). In addition, the numerator of Equation 4.24 may change (sign unclear). For an underlying normal distribution and large selection rates (> 0.5), smaller contact/larger selection rates lead to an unambiguous reduction of the log deviation.

By contrast, the log deviation of vacancies increases with smaller exogenous contact rates. Why? For a given job finding rate, a smaller contact rate leads to a larger selection rate. This increases the conditional expectations term in Equation 4.25 (i.e. the denominator falls) and the log deviation increases.

Combining these two effects, a smaller contact rate and a larger selection rate lead to a smaller log deviation of the job finding rate and a larger log deviation of vacancies with respect to productivity. Thus, as shown in Equation 4.26, with a smaller contact rate, an empirical researcher would estimate a smaller elasticity of the job finding rate with respect to vacancies, i.e. the coefficient on vacancies in the matching function would fall. This is exactly what we find in our numerical estimations.

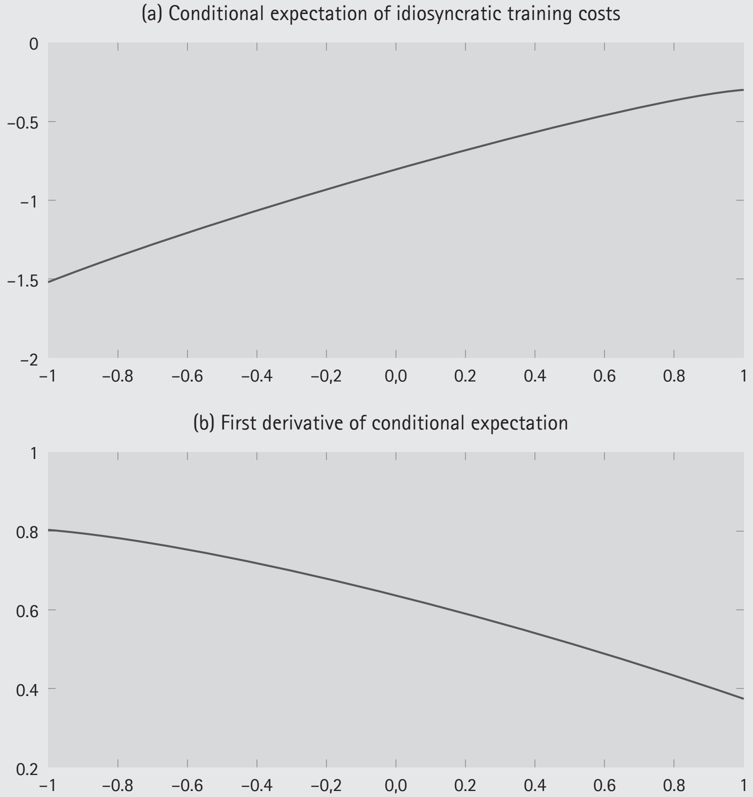
4.5.3 Connection to Simulation

In our numerical section, there was a clear trade-off in the calibration. A smaller contact rate leads to a larger steady state selection rate. Assuming a normal distribution for the idiosyncratic training costs, a larger selection rate moves the steady state cutoff point to the right (i.e. to a point in the distribution where the first derivative of the conditional expectation of the idiosyncratic training costs with respect to productivity is smaller).

Figure 4.3 illustrates this connection. The first panel shows the conditional expectation of idiosyncratic training costs, namely $\int_{-\infty}^{\tilde{\varepsilon}} \varepsilon f\left(\varepsilon\right) d\varepsilon / \eta$. The second panel shows the first derivative of this expression, corresponding to Equation 4.26. In our estimations, the estimated elasticity of matches with respect to vacancies corresponds almost exactly to the first derivative of the expected training cost at the cutoff point, just as our analytical exercise above would predict.

Thus, our calibrated model can only match the coefficients of the empirical matching function when we assume a relatively small exogenous contact rate and a relatively larger selection rate (moving the steady state cutoff point to the right). Very small contact rates may seem unrealistic from the perspective of an Anglo-Saxon labor market. Three comments are in order. First, German labor market flows are a lot smaller than, for example, American labor market flows. Second, this fact is even reinforced by the administrative data we use because it provides a fairly broad definition of unemployment (leading to a data consistent unemployment rate of more than 10%). Third, we have some preliminary evidence from a survey data set that the contact rate in Germany is indeed very small. The labor market survey PASS shows that only around 30% of all searching workers get an interview in a given month (see Appendix 4.F for details).

Figure 4.3: Conditional expectation for normal distribution ($\sigma = 1$)



Note: The abscissa denotes the cutoff point of the selection process ($\tilde{\varepsilon}_t$).

4.6 Conclusion

This paper has reconsidered the matching function, which has become a popular tool to model labor market frictions in a tractable way. Therefore, we have derived the conventional Cobb-Douglas specification from two different perspectives.

In a first step, we have estimated an aggregate matching function from German administrative data. Despite empirical support by previous studies, the existing matching function estimations may suffer from biases due to incoherent measures of matches, unemployment and vacancies. We have used detailed information on individual labor market biographies to overcome this shortcoming. Our empirical results provide renewed evidence in favor of a constant returns Cobb-Douglas matching function. Relying on restricted matching elasticities, we further show that it is important to control for the composition of the unemployment pool as well as for different search incentives resulting from the unemployment insurance system.

In a second step, we have set up a simple model of labor selection. In this model, more vacancies do not lead to more matches in the aggregate but appear as a worker attraction device. Upon an exogenous contact rate, the individual job finding rate solely depends on an idiosyncratic draw from a training cost distribution. Even though the selection model does not contain a matching function, we have been able to estimate one by simulating the model with an aggregate productivity shock. Interestingly, our simulation results provide evidence in favor of a standard Cobb-Douglas matching function. Moreover, simulations with low contact rates are successful in replicating the empirical results.

We have explained the underlying mechanism in an analytically tractable version of the selection model, where we show that the matching elasticity with respect to vacancies is determined by the first derivative of expected training costs at the cutoff point. Thus, our paper suggests that the empirical evidence of the matching function may have a completely different interpretation.

4.A Previous Matching Function Studies

Table 4.A.1: Aggregate matching function estimations for Germany

Author(s)	Coverage and segmentation	Period and frequency	Dependent variable	Job seekers	Job vacancies	Other variables
Buttler and Cramer (1991)	West Germany	1983–1990, monthly	placements of unemployed	registered unemployed	reported vacancies	linear time trend
Burda (1983)	West Germany, local employment agencies East Germany, local employment agencies	1990–1992, monthly 1990–1992, monthly	unemployment outflows	registered unemployed	reported vacancies	linear time trend – linear time trend –
Burda and Wyplosz (1994)	West Germany	1968–1991, monthly	unemployment outflows	registered unemployed	reported vacancies	linear time trend
Gross (1997)	West Germany	1972–1983, quarterly 1984–1994, quarterly	all new hires	registered unemployed	reported vacancies	real wages, real energy price
Entorf (1998)	West Germany, occupational groups	1971–1992, yearly averages of monthly data	hirings	registered unemployed	reported vacancies corrected vacancies	linear time trend
Kosfeld (2006)	Germany, local employment agencies	1998-2004, monthly	flows from unemployment to employment	registered unemployed	adjusted vacancies	– demographical, educational and labor market variable
Sunde (2007)	West Germany, occupational groups	1980–1995, yearly	all hirings hirings from unemployed hirings from nonemployment hirings from reg. vacancies	registered unemployed	reported vacancies	occupational and time dummies
Fahr and Sunde (2009)	Germany, occupational groups	2000–2003, monthly 2003–2004, monthly	flows from unemployment to employment	registered unemployed	reported vacancies	stock inflows, Hartz I/II dummy stock inflows, Hartz III dummy
Klinger and Rothe (2012)	Germany, federal states	1998–2008, monthly	flows from unemployment to employment	registered unemployed	corrected vacancies	linear time trend, stock inflows + Hartz dummies, share of long-term unemployed, GDP growth + interaction terms
Poeschel (2012)	Germany	2004–2009, monthly	outflow rate from unemployment to employment	registered unemployed	Job index of the Federal Employment Agency	linear time trend

Table 4.A.1: Aggregate matching function estimations for Germany (continued)

Author(s)	Model specification	Estimation approach	Coef. [ln U] (elasticity)	Coef. [ln V] (elasticity)	CRS hypothesis	(adjusted) R^2
Buttler and Cramer (1991)	Cobb-Douglas	–	0.54	0.45	–	0.84
Burda (1983)	Cobb-Douglas	pooled	0.62	0.20	rejected	0.79
		fixed effects	0.88	0.11	not rejected	0.93
		pooled	0.99	0.17	not rejected	0.77
		fixed effects	1.75	0.09	rejected	0.83
Burda and Wyplosz (1994)	Cobb-Douglas (accepted against CES)	White's robust std. errors	0.68	0.27	not rejected	0.97
			0.71	0.29	constrained	0.98
Gross (1997)	Cobb-Douglas	error correction model	0.55	1.27	rejected	–
			0.89/0.37	0.40/0.19	(not) rejected	–
Entorf (1998)	Cobb-Douglas	pooled	0.07 (insign.)	0.32	–	0.74
			0.41	0.59	constrained	0.61
			-0.22 (insign.)	0.08 (insign.)	–	0.56
			0.35	0.65	constrained	0.13
Kosfeld (2006)	Cobb-Douglas	pooled	0.77	0.13	rejected	0.95
			0.86	0.09	rejected	0.97
Sunde (2007)	Cobb-Douglas	–	0.31	0.23	–	0.98
			0.44	0.14	–	0.96
			0.35	0.25	–	0.97
			0.50	0.42	–	0.97
Fahr and Sunde (2009)	Cobb-Douglas	occupation and time fixed effects	1.01	-0.28 (insign.)	–	0.48
			2.27	0.04	–	0.57
Klinger and Rothe (2012)	Cobb-Douglas	two-stage least squares with regional fixed effects	0.58	0.06	–	0.98
			0.56	0.08	–	0.98
			0.57	0.08	–	0.98
Poeschel (2012)	Cobb-Douglas	generalized method of moments (GMM)	0.77	0.23	constrained	0.89

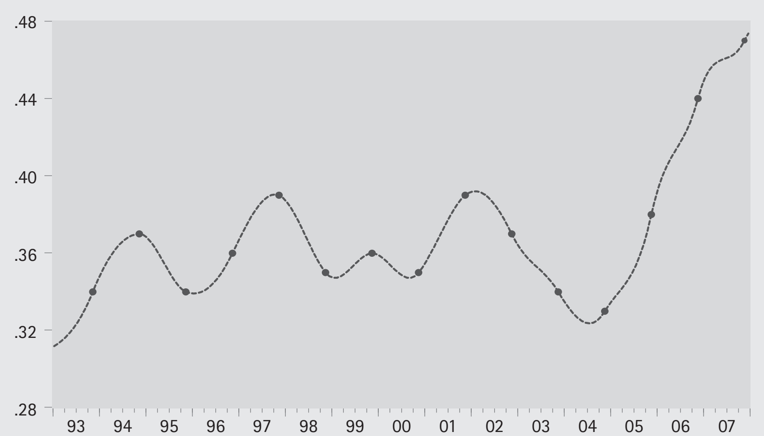
Note: CES = constant elasticity of substitution.

4.B Reporting Rate of Vacancies

The IAB Job Vacancy Survey (*Erhebung des gesamtwirtschaftlichen Stellenangebots, EgS*) aims to gain information on the structure of open positions in Germany. The survey enquires the number of vacancies as well as the related search process from a representative sample of firms and administrations, which are randomly drawn from the register of the Federal Employment Agency. The questionnaire started in 1989 for Western Germany and was extended to Eastern Germany in 1992. It takes place each fourth quarter a year and has a response rate of about 20%. See Kettner and Vogeler-Ludwig (2010) for details on the implementation of the survey.

The questions include a firm's number of vacancies and the number of vacancies that a firm has reported to an employment agency. The aggregate share of reported vacancies is deduced by using an iterative projection method, which accounts for different sectors and firm sizes. The dots in Figure 4.B.1 illustrate the official reporting rates over our observation period. It can be seen that the reporting rate first amounts to 30–40% and then increases to nearly 48%. Interestingly, the reporting behavior does not appear to be affected by the business cycle nor the emergence of online job markets in the early 2000s. However, the incentive of reporting vacancies to an employment agency seems to be influenced by the Hartz reforms, which have also induced new forms of subsidized employment.

Figure 4.B.1: Reporting rate



Notes: Interpolated reporting rate of vacancies. Dots show the official values for the fourth quarter each year.

We interpolate the yearly reporting rates to a monthly time series by applying the Catmull-Rom spline. Therefore, we assume that the official reporting rate is representative for the middle of each survey period. The Catmull-Rom spline then leads to a continuous curve that passes through all given reporting rates (so-called control points).

4.C Robustness Checks of the CRS Assumption

Table 4.C.1: Matching function estimations with adjusted vacancies

	(i)	(ii)	(iii)
constant	-5.2998*	-6.2945*	-6.4749**
log U_{-1}	0.8644***	0.9127***	0.9331***
log V_{-1}	0.3199***	0.3390***	0.3293***
trend	-0.0004**	-0.0005*	-0.0004**
d_{2005}	-0.0784**	-0.0835*	-0.0931**
adjusted R^2	0.4284	0.4897	0.4242
DW statistic	1.3070	2.0924	–
C RS t-statistic	1.0044	1.0284	1.3611
Note: Adjustment of vacancies with reporting rate.			

Table 4.C.2: Matching function estimations with labor market rates

	(i)	(ii)	(iii)
constant	-1.7464***	-1.6616*	-1.6643***
log u_{-1}	0.9425***	0.9662***	0.9820***
log v_{-1}	0.2964***	0.3045***	0.2976***
trend	-0.0005**	-0.0006**	-0.0005**
d_{2005}	-0.1200***	-0.1200***	-0.1200***
adjusted R^2	0.5305	0.5683	0.5235
DW statistic	1.3683	2.0734	–
C RS t-statistic	1.5460	1.3071	1.5602
Note: Unemployment and vacancies are divided by the corresponding labor force, i.e. the sum of employment subject to social security and unemployment.			

Table 4.C.3: Matching function estimations on quarterly frequency

	(i)	(ii)	(iii)
constant	-2.0567	-1.9551	-3.4188
log U_{-1}	0.8170***	0.8169***	0.9035***
log V_{-1}	0.2353***	0.2281***	0.2389***
trend	-0.0012*	-0.0004	-0.0013*
d_{2005}	-0.0813*	-0.1159	-0.0983**
adjusted R^2	0.6139	0.6710	0.5951
DW statistic	1.0985	2.1052	–
C RS t-statistic	0.2942	0.2168	0.7480
Note: *U* and *V* are end-of-quarter stocks.			

Table 4.C.4: Matching function estimations in subsample 1993–2004

	(i)	(ii)	(iii)
constant	-6.1390*	-11.7852**	-7.6186**
log U_{-1}	0.9634***	1.2577***	1.0477***
log V_{-1}	0.2934***	0.3847***	0.3086***
trend	-0.0004**	-0.0006*	-0.0005**
adjusted R^2	0.1772	0.3304	0.1680
DW statistic	1.1189	2.1403	–
C RS t-statistic	1.1431	1.6144	1.5173
Note: Exclusion of post-reform period			

Table 4.C.5: Matching function estimations with detrended variables

	(i)	(ii)	(iii)
log U_{-1}	0.5785***	0.6298***	0.7092***
log V_{-1}	0.1316*	0.1456*	0.0911
d_{2005}	-0.0749***	-0.0581***	-0.0816***
adjusted R^2	0.1036	0.1305	0.0980
DW statistic	1.5950	2.0105	–
C RS t-statistic	-1.7329*	-1.0891	-1.1127
Notes: *U* and *V* are detrended by using the HP filter with $\lambda = 14{,}400$. In this case, d_{2005} denotes an impulse dummy in 2005M1.			

4.D Control Variables

Table 4.D.1: Description of control variables

Data	Variable	Definition
Age	*young*	Share of unemployed with age ≤ 25 years
	old	Share of unemployed with age ≥ 55 years
Education	*low-skilled*	Share of unemployed without vocational training (see Fitzenberger et al., 2005)
	high-skilled	Share of unemployed with university degree (see Fitzenberger et al., 2005)
Nationality	*foreign*	Share of unemployed with immigration background (see Wichert and Wilke, 2012)
Gender	*female*	Share of female unemployed
Family status	*married*	Share of married unemployed
	child	Share of unemployed with at least one child
Unemployment duration	*long-term*	Share of long-term unemployed (unemployment duration ≥ 1 year)
Benefit receipt	*UB I receipt*	Share of unemployment benefit (UB) I recipients
Income	*replacement ratio*	Median of UB I payments over median of wages
Rest entitlement	*rest entitlement*	Median of UB I rest entitlements in days

Figure 4.D.1: Control variables (I)

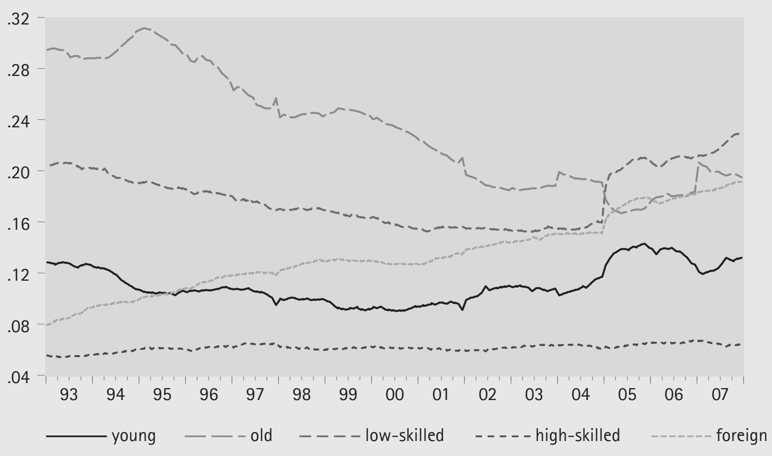


Figure 4.D.2: Control variables (II)

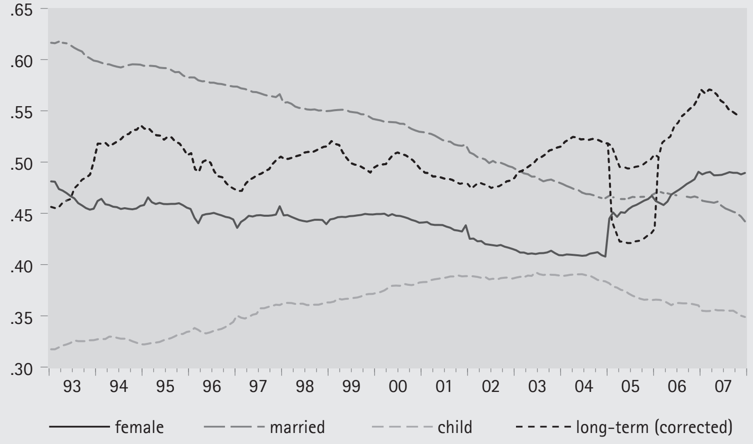


Figure 4.D.3: Control variables (III)

4.E Endogenous Separations

The "fictional" matching function estimated from the simulated data can also be obtained if we relax our assumption of exogenous separations. Table 4.E.1 reports the results for a version of the selection model where both entrants and incumbents are subject to the idiosyncratic shock and where firing is endogenous.[23] Compared to the model with exogenous separations, the results are hardly changed.

Table 4.E.1: Matching functions for model with endogenous separations

	c = 1	c = 0.75	c = 0.5	c = 0.25	c = 0.2
			$\sigma = 0.25$		
constant	–0.59	–0.69	–0.86	–1.29	–1.51
log U_{-1}	0.19	0.22	0.26	0.41	0.52
log V_{-1}	0.80	0.78	0.73	0.58	0.47
CRS rate	69%	69%	68%	67%	63%
			$\sigma = 0.5$		
constant	–1.14	–1.23	–1.36	–1.68	–1.81
log U_{-1}	0.19	0.22	0.26	0.42	0.53
log V_{-1}	0.80	0.78	0.73	0.57	0.47
CRS rate	74%	74%	75%	74%	74%
			$\sigma = 1$		
constant	–1.70	–1.76	–1.87	–2.07	–2.13
log U_{-1}	0.19	0.22	0.26	0.42	0.53
log V_{-1}	0.80	0.78	0.73	0.58	0.47
CRS rate	77%	76%	76%	79%	76%

Notes: Coefficients are means over 1,000 simulations. *CRS* rate reports in how many percent the constant returns to scale assumption could not be rejected.

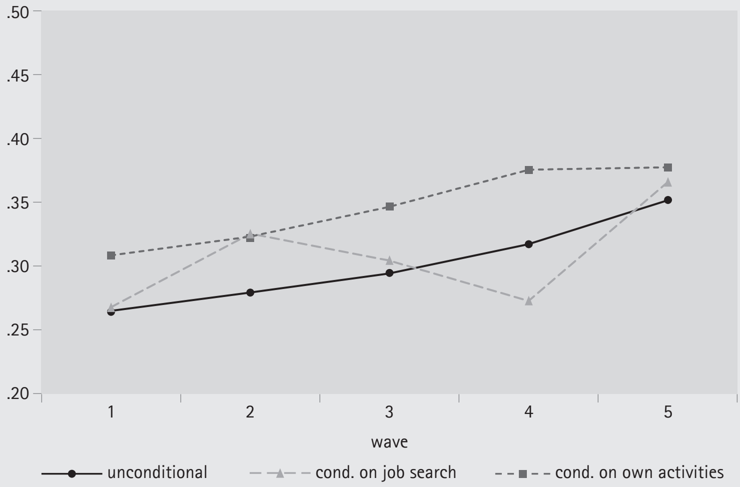
4.F Contact Rate

The household panel study "The Labor Market and Social Security" (*Panel Arbeitsmarkt und soziale Sicherung, PASS*) conducted by the IAB is designed to evaluate the Hartz reforms, but it also allows to address broader questions on unemployment and poverty in Germany. Therefore, PASS draws a sample of unemployment benefit II recipients as well as a sample of the general population. The survey started in 2006/2007 (inquiry period from December to July) with around 12,000 households and is repeated annually. The response rate of the first wave was 27%. See Trappmann et al. (2010) for more information on the survey design.

23 We assume 60% exogenous quits and 40% endogenous firing. This assumption is without consequence for our matching function results but ensures that the separation rate is not unrealistically volatile.

The main advantage compared to administrative data is that PASS collects information on job search activities of unemployed workers. The questions include a general statement on whether a person looks for a job or not as well as details on own search activities, such as sending unsolicited applications or placing job advertisements. Moreover, the survey contains information on job interviews within the last four weeks. This information enables us to compute an aggregate contact rate of unemployed workers.

Figure 4.F.1: Contact rates



Notes: Shares of unemployed workers with at least one job interview in the last four weeks. Denominators: All unemployed workers who are asked about interviews (solid line), who state to search for a job (dashed line) and who declare to undertake own search activities (dotted line). Sampling weights are considered.

Figure 4.F.1 shows different definitions of the contact rate over the available waves. Roughly speaking, the contact rate increases from 25% to 35%. The slight upward trend might indicate an increased pressure on unemployed workers to look for a job, which is likely to result from tightened sanction schemes. The contact rate conditional on own search activities is steadily higher than the contact rate conditional on general job search or than the unconditional contact rate. Obviously, the higher the search intensity of an unemployed worker, the more likely he or she gets a job interview. However, the deviations of the different definitions are quite low and one can conclude an aggregate contact rate of approximately 30%.

5 Conclusion

This dissertation has presented three essays on the cyclicality of worker flows. The transitions in the labor market are substantial components of modern labor market theory. They play a crucial role for macroeconomic outcomes and policy implications. Therefore, a clear understanding of their cyclical behavior appears to be indispensable.

In the first essay, I have analyzed the effects of time aggregation in the measurement of worker flows. Therefore, I have exploited daily information from German administrative data and derived a monthly measure of the time aggregation bias in the job finding and separation rates. The monthly bias accounts for a considerable fraction of worker flows, but it does not indicate a procyclical behavior in the separation rate as recently stated in the literature. I have argued that this observation may reveal some facts about job-to-job transitions. The reconsideration of the job finding and separation rates shows a conventional behavior on business cycle frequency, where the job finding rate has turned out to play a dominant role in explaining unemployment fluctuations.

In the second essay, I have studied the cyclical behavior of unemployment dynamics in more detail. Therefore, I have employed a SVAR model and explored the worker reallocation process in response to a set of economically well-founded shocks. The adjustment process of unemployment indeed varies with the identified innovations. Further, the differences in the prevalent transmission channel can be related to differences in the persistence of shocks. Accordingly, the more persistent shocks are, the more likely is an unemployment adjustment along the job finding margin. Productivity shocks contribute relatively strong to variations in the transition rates; however, their importance shrinks after the German reunification in favor of fiscal policy shocks.

In the third essay, I have examined the empirical evidence of a Cobb-Douglas matching function. Thereby, I have updated previous matching function estimations by using consistent measures of stock and flow variables. The results provide strong evidence in favor of the standard constant returns to scale assumption. Turning to restricted matching elasticities, I have extended the baseline specification by several control variables that refer to the underlying unemployment pool. The control variables are important to eliminate the autocorrelation issue in the error term and strengthen the role of vacancies in explaining the aggregate job finding rate. However, the empirical evidence can be replicated by a labor selection model that obviates a matching function. In particular, the model does not contain a direct link between the job finding rate and vacancies, which implies a cautionary note on interpreting the aggregate matching function.

To sum up, the contributions of this dissertation reinforce a more precise consideration of worker flows in the search and matching model. This concerns, in particular, the cyclical behavior of the separation rate, the different effects of aggregate shocks and the interpretation of the matching function. Although the literature provides a lot of promising extensions of the standard model, their convenience is typically confronted with several criteria, such as the replication of stylized facts. For example, the endogenization of the separation rate is often prejudged to fail the relationship of the Beveridge curve. Therefore, further insight from the micro level seems to be necessary to overcome those drawbacks.

Throughout my dissertation, I have emphasized the usefulness of administrative micro data. The high-frequency information of German labor market processes has enabled me to compute a monthly time aggregation bias and to capture additional unemployment dynamics one would neglect by applying survey data. However, the contributions of this dissertation have also indicated some limitations of process-generated data. For example, the administrative database is silent about individual attitudes concerning the take-up of unemployment benefits. The same holds for the incentives of firms to report their vacancies to an employment agency. Therefore, I have complemented the estimation of the matching function with survey information on job vacancies. In addition, I have used a household survey to shed light on the probability of job interviews. Accordingly, the merging of administrative and survey data may be a promising step to address a lot of additional questions.

Moreover, the essays of this dissertation suggest a number of interesting issues for future research. First, the investigation of the time aggregation bias raises the hypothesis of a cyclicality in the take-up of unemployment benefits. If the take-up of unemployment benefits and thus the registration of job seekers at an employment agency depends on the expected unemployment duration, this may have important implications for the public placement service. Second, the conditional patterns of unemployment dynamics point to fiscal interventions as a promising tool for controlling labor market fluctuations. An investigation of specific fiscal stimuli, as used in course of the financial crisis, is likely to provide more insight into the functioning of the labor market. In addition, Germany has a large export sector and an analysis of trade shocks may help to explain the large volatilities in the labor market. Finally, the analysis of the matching function gives rise to further research on the worker selection process. Empirical evidence on training costs of newly hired workers would not only help to verify the selection model, but it would also help to shed light on the quality of job matches. In this context, the impact of the Hartz reforms and their long-run effects are still an open question. Hence, the German labor market will continue to be an interesting example to address ongoing debates on worker flows.

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Abstract

The development of unemployment and employment is strongly determined by labor market flows. This dissertation analyzes worker flows, i.e. job findings and separations, over the business cycle. The analysis uses process-generated micro data provided by the Institute for Employment Research (IAB), which allow gaining comprehensive insights into labor market dynamics in Germany.

The first essay investigates the effects of time aggregation, which is of particular importance in the context of flow data. If labor market states are measured on larger intervals, it is likely to neglect transitions that are reversed within two measurement points. The daily data base for Germany allows quantifying this bias by comparing labor market transitions that are calculated on different frequencies. The main result is that a monthly measurement of labor market states underestimates total worker flows by 10%. In contrast, a theoretical correction approach implies an underestimation of only 3%. The time aggregation bias in the job finding rate shows a procyclical behavior, while the time aggregation bias in the separation rate appears to be relatively unaffected by the economic situation.

The second essay studies German worker flows in response to structural shocks. The results show various patterns of how the labor market adjusts to the steady state. In particular, the transmission channel varies with the different impulses. After a technology shock, unemployment adjusts gradually via the job finding margin. A monetary policy shock triggers a hump-shaped reaction, which is also determined by the job finding rate. In contrast, a fiscal policy shock leads to a short-lived variation in unemployment, where the separation rate plays a larger role.

The third essay deals with the modeling of the job finding margin. Job findings are typically represented by a matching function, where the number of matches depends on the stocks of unemployment and vacancies. There is evidence that this approach is empirically relevant – both in standard form and in extended form. The estimation results are then replicated by simulations of a theoretical model, which describes a firm's hiring process. This model implies an alternative interpretation of the matching function because it assumes that vacancies merely appear as a worker attraction device, while the number of matches is determined by the idiosyncratic productivity of the applicants.

Kurzfassung

Die Entwicklung von Arbeitslosigkeit und Beschäftigung wird maßgeblich von den Übergängen auf dem Arbeitsmarkt beeinflusst. Die vorliegende Dissertation analysiert die Übergänge von Arbeitskräften, also Einstellungen und Entlassungen, im konjunkturellen Zusammenhang. Dabei werden prozessgenerierte Personendaten des Instituts für Arbeitsmarkt- und Berufsforschung (IAB) verwendet, welche einen umfassenden Einblick in die Dynamik am deutschen Arbeitsmarkt ermöglichen.

Die erste Studie beschäftigt sich mit den Effekten der Zeitaggregation, die bei Stromgrößen von besonderer Bedeutung sind. Sind die Erwerbszustände von Personen nur über größere Zeitabstände beobachtbar, so werden möglicherweise Übergänge vernachlässigt, die zwischen zwei Beobachtungszeitpunkten wieder rückgängig gemacht werden. Die tagesgenaue Datenbasis für Deutschland ermöglicht eine Quantifizierung dieser Verzerrung, indem die Arbeitsmarktübergänge auf unterschiedlichen Frequenzen ausgewertet werden. Das zentrale Ergebnis ist, dass die Übergänge am deutschen Arbeitsmarkt durch eine monatliche Messung der Erwerbszustände um 10% unterschätzt werden. Ein theoretischer Korrekturansatz impliziert dagegen nur eine Unterschätzung von 3%. Weiterhin weist die Verzerrung in der Einstellungsrate ein prozyklisches Verhalten auf, während die Verzerrung in der Entlassungsrate nahezu unabhängig von der wirtschaftlichen Entwicklung ist.

Die zweite Studie untersucht die Übergänge am deutschen Arbeitsmarkt in Abhängigkeit von strukturellen Schocks. Hierbei ergeben sich ganz unterschiedliche Muster, wie sich der Arbeitsmarkt zurück zum Gleichgewicht bewegt. Insbesondere variiert der Transmissionskanal mit den verschiedenen konjunkturellen Impulsen. So ist nach einem Technologieschock eine sukzessive Anpassung der Arbeitslosigkeit zu beobachten, die primär von Schwankungen in der Einstellungsrate bestimmt wird. Nach einem geldpolitischen Impuls zeigt sich eine buckelförmige Reaktion, die ebenfalls von der Einstellungsrate determiniert wird. Ein fiskalpolitischer Impuls bewirkt hingegen eine kurzfristige Veränderung in der Arbeitslosigkeit, wobei die Entlassungsrate eine größere Rolle spielt.

Die dritte Studie befasst sich mit der Modellierung von Einstellungen. Typischerweise werden Einstellungen mithilfe einer Matchingfunktion dargestellt, welche die Zahl der Einstellungen in Abhängigkeit der Bestände von Arbeitslosigkeit und offenen Stellen bestimmt. Es wird gezeigt, dass dieser Ansatz empirisch relevant ist – sowohl in der Standard-Form als auch in erweiterter Form. Die Schätzergebnisse werden anschließend durch Simulationen eines theoretischen Modells zum betrieblichen Such- und Einstellungsprozess repliziert. Dieses Modell geht mit

einer alternativen Interpretation der Matchingfunktion einher, denn es wird angenommen, dass Stellenausschreibungen lediglich eine Signalfunktion für Bewerber aufweisen, während die Zahl der Einstellungen von der individuellen Produktivität der Bewerber abhängt.