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Worker flows in Germany: Inspecting the time aggregation bias

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Inspecting the Time Aggregation Bias

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Contents

Abstract

This paper analyzes the importance 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%. Contrary to the claim of Shimer (2005, 2012), the time aggregation bias in the separation rate is relatively unaffected by business cycle fluctuations, whereas the time aggregation bias in the job finding rate is procyclical. Nevertheless, monthly time aggregation does not have notable effects on the relative contributions to steady-state unemployment dynamics. The reconsideration of German worker flows reveals that both the job finding rate and the separation rate play an important role for German unemployment dynamics, but the job finding rate dominates in the long run.

Zusammenfassung

In diesem Papier wird die Bedeutung der Zeitaggregation bei der Messung von Arbeitnehmerfluktuationen untersucht, wobei tagesgenaue Informationen eines administrativen Datensatzes aus Deutschland verwendet werden. Es zeigt sich, dass ein monatlicher Stichtagsvergleich von Erwerbszuständen die Übergänge am Arbeitsmarkt um etwa 10% unterschätzt. Entgegen der Behauptung von Shimer (2005, 2012) weist die Verzerrung in der Übergangsrate in Arbeitslosigkeit keine konjunkturelle Abhängigkeit auf, während sich die Verzerrung in der Übergangsrate in Beschäftigung prozyklisch verhält. Die relativen Beiträge der Übergangsraten zu den Schwankungen um die gleichgewichtige Arbeitslosigkeit werden jedoch kaum von der Zeitaggregation beeinflusst. Die Analyse der Arbeitsmarktübergänge zeigt, dass in Deutschland sowohl die Übergangsrate in Beschäftigung als auch die Übergangsrate in Arbeitslosigkeit wesentliche Determinanten der Schwankungen der Arbeitslosigkeit darstellen, wobei die Übergangsrate in Beschäftigung langfristig dominiert.

JEL classification: J64, J63, E32

Keywords: Time aggregation, worker flows, job finding rate, separation rate, unemployment decomposition

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1 Introduction

Worker flows play a crucial role for understanding unemployment dynamics. In particular, the so-called Shimer (2005) puzzle[1] has triggered a growing literature studying the ins and outs of unemployment in more detail. Focusing on the underlying transition hazard rates as used in the search and matching model, a major objective is to investigate the relative importance of the job finding and separation rates for unemployment dynamics.[2] From recent research on U.S. labor market dynamics, however, it is well known that the measurement is substantial for the impact of the transition rates (see, e.g., Yashiv, 2006).

A central issue in the debate on the measurement of U.S. worker flows is a time aggregation error resulting from point-in-time inquiries. As worker flows that are reversed within two measurement points cannot be captured, discretely measured labor market transitions underestimate total worker flows. Hence, the time aggregation bias captures all worker flows that are neglected due to the availability of labor market data.

The main objective of this paper is to analyze the importance of the time aggregation bias by using German administrative labor market data. In addition to the absence of sample rotation and sample attrition,[3] 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 these information do not face a time aggregation bias. Nevertheless, German administrative data enable to derive one by additionally computing labor market transitions at a lower frequency.[4]

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.[5] Shimer (2012) reinforces a procyclical time aggregation bias in the separation rate by formulating a correction approach for neglected worker flows. Since a draft of his paper was circulated, Shimer's approach has evolved to a standard procedure to adjust for time aggregation (see, e.g., Fujita/Ramey, 2006, 2009; Petrongolo/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.[6] However, more recent studies, such as Fujita/Ramey (2009) and Elsby/Michaels/Solon (2009), caution against this procedure by demonstrating that the separation rate is strongly countercyclical and contributes substantially to unemployment fluctuations.

[1] Shimer (2005) observes that the standard search and matching model cannot generate empirical volatilities of U.S. labor market variables.

[2] Note that previous studies analyze labor market transitions mainly through gross worker flows (see, e.g., Blanchard/Diamond, 1990; Burda/Wyplosz, 1994: for the U.S. and Europe, respectively). However, Fujita/Ramey (2006: p. 11) point out that sharp adjustments in gross worker flows must be triggered by changes in the underlying hazard rates as labor market stocks adjust only gradually.

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

[4] 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 job-to-job transitions which are beyond the scope of this paper.

[5] The conclusion of an acyclical separation rate is also drawn by Hall (2005).

[6] For an overview of theoretical papers addressing the study of Shimer (2005) see Cardullo (2010).

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

In contrast to studies examining worker flows in the U.S. or other countries, studies on German worker flows are mostly based on administrative data (see, e.g., Bachmann, 2005; Jung/Kuhn, 2011; Gartner/Merkl/Rothe, 2012). Comparing worker flows computed from German administrative data with those computed from a German household survey, Bachmann/Schaffner (2009), however, do not find any substantial differences in the transition rates. Nevertheless, there is no study that exploits daily information from administrative data and investigates the time aggregation bias.[7] In addition, previous studies do not deal carefully with certain measurement problems which may have contributed to some discrepancies in the existing evidence. For example, the out of labor force status is not recorded in administrative data and thus the measurement of a third labor market state becomes very vague.

Therefore, a second objective of this paper is to reconsider the existing evidence on German worker flows. In particular, I rely on a reasonable unemployment definition that considers information gaps between certain labor market notifications which are likely to constitute times of sanctions or other policy measures that obscure unemployment. Moreover, I do not restrict the sample on Western Germany but consider the whole economy after the reunification as unemployment is not less a concern in the Eastern part.

In doing so, I use a new administrative data set which has two advantages over its precursor data set used by previous studies. First, it is not only representative for employment subject to social security but also for benefit receipt. Second, it covers a longer time period and can provide first insights into the development of worker flows after the comprehensive labor market reforms in 2003-2005 (so-called Hartz reforms).[8]

The paper is structured as follows. Section 2 describes the data set and the measurement of worker flows. The time aggregation bias is investigated in Section 3. After deriving a measure of the actual time aggregation bias and assessing the correction approach of Shimer (2012), the importance of time aggregation is evaluated on business cycle fre-

[7] To my knowledge, only Bachmann (2005) computes worker flows on a daily basis, but he does not compare them with data computed at a lower frequency.

[8] The Hartz reforms consist of four parts and were implemented subsequently from 2003 to 2005. See Jacobi/Kluve (2007) for an extensive description.

quency. Section 4 reconsiders stylized facts of German worker flows and Section 5 concludes.

2 Data Description

I use the Sample of Integrated Labor Market Biographies (SIAB) provided by the Institute for Employment Research. The SIAB presents 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 which cause a time aggregation bias. I follow those studies and calculate monthly worker flows but exploit daily information during a month. The continuous measures avoid worker flows to be underestimated and possibly biased on business cycle frequency.[9]

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, unemployment is measured by benefit receipt.[10] In Germany, benefit payments for unemployed workers include unemployment benefits (*Arbeitslosengeld*), unemployment assistance (*Arbeitslosenhilfe*) until 2004 and unemployment benefits II (*Arbeitslosengeld II*) since 2005 as well as income maintenance (*Unterhaltsgeld*) during training.[11] However, this procedure makes it difficult to reconstruct a worker's employment history if he or she faces unemployment periods without benefit receipt. Therefore, I make use of the nonemployment proxy introduced by Fitzenberger/Wilke (2010) to approximate search unemployment. In general, the nonemployment proxy consists of all nonemployment periods after an employment spell that contain at least one report of benefit receipt. Hence, this measure can account for unemployment periods that are not recorded in the data set.[12]

Given the two-state environment, a worker may leave the unemployment pool and enter the employment status (UE flow or job finding) or leave the employment status and enter the unemployment pool (EU flow or separation).[13] Then, the worker flows are defined by

9 Strictly speaking, a daily measurement is still discrete, but this study considers it as a continuous framework.
10 See Appendix A for more details on data selection.
11 Until 2004, an unemployed worker may have been entitled to unemployment assistance after termination of the entitlement to unemployment benefits. Unemployment assistance was means tested and paid for an unlimited time period. As a result of the Hartz IV reform in 2005, unemployment assistance has been replaced by unemployment benefits II. Unemployment benefits II is also means tested and paid for an unlimited time period but also includes benefits for former recipients of social assistance. Besides, the receipt of unemployment benefits II does not require a foregoing receipt of unemployment benefits but can be paid since the first day of unemployment.
12 Further information on the unemployment definition are given in Appendix B.
13 Although the unemployment measure is likely to capture a share of the out of labor force, such as temporarily

referring all transitions during month *t* to the initial labor market state in month *t-1*. More precisely, the job finding rate (f) and the separation rate (s) satisfy

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

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

Finally, the time series of the transition rates are adjusted as follows. First, 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 Germany.[14] Second, seasonal effects are smoothed out with the Census X12 procedure. Third, the monthly transition rates are represented by their quarterly averages to obtain measures at the same frequency as business cycle indicators.[15]

Figure 1 plots time series of the aggregate transition rates during the sample period 1981-2007. The job finding rate declines from over 10% in 1981 to around 5% after the reunification. Put differently, the average search duration for jobs subject to the German social security system has increased from under 1 year to nearly 2 years. The separation rate fluctuates around 1% throughout the sample period. Hence, a job that is subject to social security lasts on average about 8 years. In addition, Figure 1 indicates that the deviations of both transition rates from their trend 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 available. Therefore, the next section turns to measures computed at a lower frequency and inspects the resulting time aggregation bias.

3 Time Aggregation Bias

The time aggregation bias captures all worker flows that are reversed within two measurement points. As labor market data are typically available at a monthly frequency, I focus on a monthly measurement of the time aggregation bias, which is also suggested by related studies on U.S. worker flows.

discouraged workers, it should be noted that job findings exclude labor market entries at the beginning of an employment history and separations exclude labor market exits at the end of an employment history.

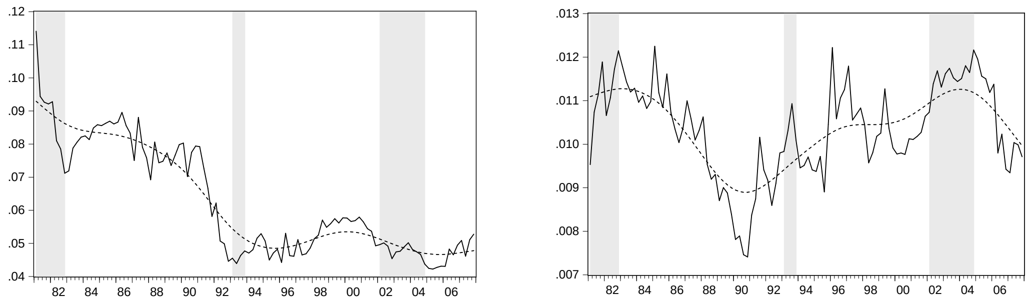
[14] It is worth noting that the extraction of Western German time series turns out somewhat vague as the information about the place of residence is not available before 1999. For employment spells, however, the place of work is known throughout the sample and to acquire an entitlement to unemployment benefits a worker usually has to have a foregoing employment period.

[15] 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 would have been likely to overestimate quarterly labor market transitions. See Gomes (2012) for a discussion of the extrapolation error.

Figure 1: Transition rates

(a) Job finding rate

(b) Separation rate



Notes: Solid lines show quarterly averages of monthly transition rates. Dotted lines display the HP-trend with a smoothing parameter of $\lambda = 1600$. Shaded areas are times of recessions.

Figure 2 depicts the issue of time aggregation graphically 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 tenures. The new labor market status in $Q1$ and $Q3$ persists until the next measurement point and each labor market transition is taken into account by the discrete measurement. However, the new labor market status in $Q2$ and $Q4$ does not persist until the next measurement point due to a preceding labor market transition in 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.

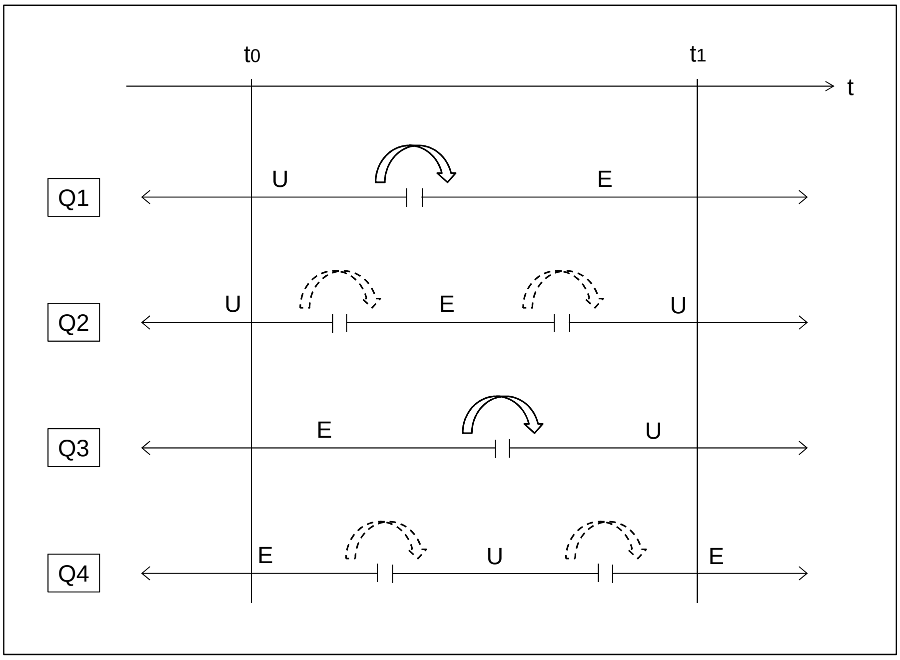
To address several claims on the time aggregation bias, this section proceeds closely to the related literature on U.S. labor market dynamics. After briefly outlining the related studies, I extract a measure from monthly point-in-time comparisons and confront it with the correction approach of Shimer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

3.1 Related Literature

The recent discussion on the time aggregation bias in discretely measured worker flows is triggered by Shimer (2005) who concludes that the U.S. separation rate is nearly acyclic. Shimer (2012) reinforces this conclusion by deriving a correction approach for time aggregation. 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, he relates discretely measured transition rates to a continuous-time framework.

In particular, Shimer (2012: p. 129) 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." Hence, Shimer claims that the probability of separating from

Figure 2: Point-in-time measurement



a job does not depend on the economic situation but rather the length of unemployment spells. With respect to Figure 2, this argument implies that in economic upswings there is a significant higher share of spell sequences $Q4$ compared to $Q3$, meaning that the time aggregation bias in the separation rate is procyclical.

Obviously, the discrete measurement of spell sequence $Q4$ also neglects a job finding such as in $Q2$. Nevertheless, Shimer (2012: p. 131) claims 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." Hence, neglecting the transitions in spell sequence $Q2$ should not matter when measuring the job finding rate.

A prominent reply to Shimer's conclusion of a nearly acyclical separation rate is given by Fujita/Ramey (2006, 2009). Applying the correction approach of Shimer (2012) for monthly U.S. data, these studies indicate that the separation rate is strongly countercyclical. Moreover, Fujita/Ramey (2006) demonstrate that the level of the time aggregation bias is considerable, whereas the adjusted and unadjusted transition rates fluctuate in a very similar pattern. Hence, they 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. Comparing monthly point-in-time measures from the commonly applied Current Population Survey (CPS) with weekly information from the Survey of Income and Program Participation (SIPP), he detects that the "true" number of monthly transitions is underestimated by 15-24%. In addition, he shows that the time aggregation bias in both job

Table 1: 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 HP-trend with $\lambda = 1600$. Total measures are continuously measured transition rates.

findings and separations is procyclical. As these effects nearly offset each other, Nekarda (2009) concludes that time aggregation does not induce a cyclical bias neither in discretely measured gross flows nor in their underlying transition hazard rates. However, he states that adjusting worker flows according to the correction approach of Shimer (2012) biases the separation rate towards a lower contribution in accounting for steady state unemployment dynamics.

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 additionally 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

$$\bar{f}_t = \frac{UE_t}{U_{t-1}} \quad \text{and} \quad \bar{s}_t = \frac{EU_t}{E_{t-1}} \tag{2}$$

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

To obtain more insights, the time aggregation bias (δ) is defined by the difference between the continuously measured transition rates from Equation 1 and the discretely measured transition rates from Equation 2, i.e.

$$\delta_t^i = i_t - \bar{i}_t, \tag{3}$$

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

Table 1 reports descriptive statistics of the monthly time aggregation bias, where the second and forth columns refer to Equation 3, i.e., the actual one. Admittedly, the probabilities of reversing a job finding or separation within a 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 important. Comparing monthly labor market states leads to an underestimation of total worker flows by around 10%. Even though this number is fairly the half of what Nekarda (2009) reports for the U.S. economy, it seems to be considerable as Germany faces relatively strict employment regulations.

Figures C.2 and C.3 show the development of the time aggregation bias in absolute and relative terms over the sample period, where the solid lines refer to the actual one. In each case, the bias shows significant fluctuations. The probability of reversing a job finding within one month fluctuates around 0.8% in the 1980s, falls to around 0.4% in the 1990s and then increases slightly to 0.6%. Put differently, the hazard of quickly returning to unemployment from a new job that is subject to social security decreases after the reunification, but since the late 1990s those new jobs become again somewhat less stable in the short run. The probability of a monthly reversed separation, i.e., the probability of finding a new job within one month after becoming unemployed, fluctuates around 0.1% but shows an upward trend since the late 1990s as well. This development holds in relation to the total transition rates. The relative time aggregation bias in both transition rates 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 intend to increase labor market flexibility. For example, tightened job acceptance regulations are imposed to stimulate returns to employment, while facilitations in temporary work and a weaker dismissal protection are supposed to boost job findings. In particular, the interpretation of an accelerated matching process along with the Hartz reforms is in line with the results of Fahr/Sunde (2009).

3.3 The Shimer (2012) Correction Approach

The correction approach of Shimer (2012) intends to address worker flows that are neglected by discrete measurements. Fujita/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.[16] For the adjusted transition rates it follows

$$\widehat{f}_t = -\frac{\log(1-\bar{s}_t-\bar{f}_t)\bar{f}_t}{\bar{s}_t+\bar{f}_t} \quad \text{and} \quad \widehat{s}_t = -\frac{\log(1-\bar{s}_t-\bar{f}_t)\bar{s}_t}{\bar{s}_t+\bar{f}_t} \tag{4}$$

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

[16] For a two-state labor market model, Shimer (2012) provides an alternative correction approach that applies a measure of short-term unemployment to obtain the job finding rate. For an application of this approach see Elsby/Michaels/Solon (2009).

To evaluate how well the correction approach of Shimer (2012) can account for the actual time aggregation bias, I extract the time aggregation bias underlying the correction approach. Therefore, I confront the adjusted transition rates from Equation 4 with the unadjusted measures from Equation 2. Taking again the difference, the estimated time aggregation bias ($\widehat{\delta}$) satisfies

$$\widehat{\delta}_t^i = \widehat{i}_t - \bar{i}_t, \tag{5}$$

where $i = f, s$. Obviously, the estimated time aggregation bias is significantly lower than the actual one (see Figures C.2-C.3). In particular, the estimated measure identifies monthly point-in-time comparisons to underestimate total worker flows by only 3% (see second row in Table 1).

Figure C.4 displays the performance of the estimated time aggregation bias during the sample period, i.e., the share of the actual time aggregation bias that is captured by the correction approach of Shimer (2012). It turns out that the estimated time aggregation bias accounts for a declining fraction of the actual bias. While the adjusted measures can capture more than 50% in the early 1980s, the share decreases to around 20% at the second part of the sample period.

A reasonable explanation for the shrinking outcome may come from the key assumption underlying the correction approach. The 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. The approach thus abstracts from worker heterogeneity resulting from duration dependence or individual characteristics. Kluve/Schaffner/Schmidt (2009) analyze individual transition rates for Germany and find significant differences between certain demographic groups. Hence, the correction approach of Shimer (2012) may be more practical for disaggregate studies, especially in recent years.

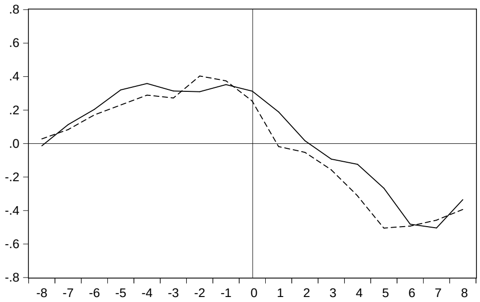
3.4 Cyclical Properties

A crucial question is whether time aggregation involves a cyclical bias in discretely measured worker flows as emphasized by Shimer (2005, 2012). Therefore, I compute the cyclical components of the time aggregation bias by extracting the log deviations from the underlying Hodrick/Prescott (1997) (HP) trend with the standard smoothing parameter of $\lambda = 1600$ for quarterly data. Before I turn to the cyclical behavior, I first discuss the cyclical volatility and persistence of the bias.

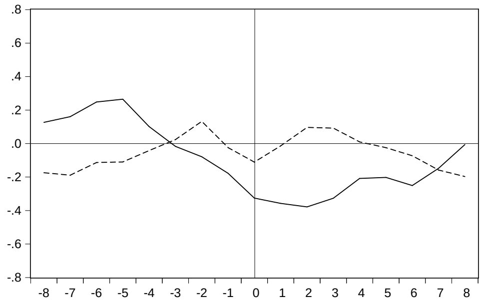
Table 1 presents standard deviations and autocorrelation coefficients of the cyclical components. The time aggregation bias in the job finding rate appears to be more volatile than in the separation rate. Interestingly, the time aggregation bias in both transition rates is more volatile than the transition rates themselves, i.e., the hazards of reversing a transition within one month react more sensitive 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 and the latter is even less persistent than the total separation rate.

Figure 3: Cross correlations of time aggregation bias with business cycle indicators

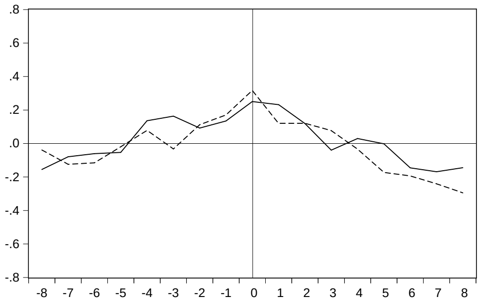
(a) Output$_t$ and Job finding rate$_{t+i}$



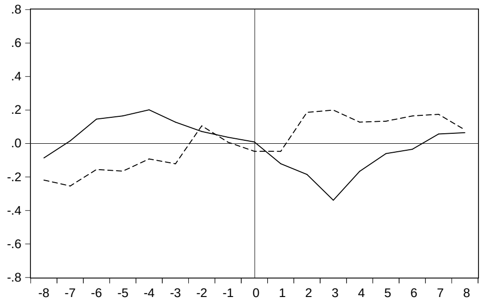
(b) Output$_t$ and Separation rate$_{t+i}$



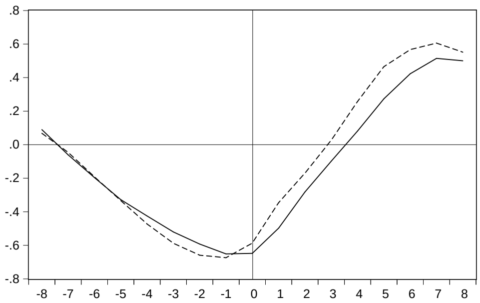
(c) Productivity$_t$ and Job finding rate$_{t+i}$



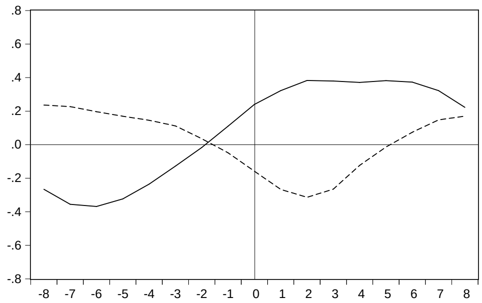
(d) Productivity$_t$ and Separation rate$_{t+i}$



(e) Unemployment$_t$ and Job finding rate$_{t+i}$



(f) Unemployment$_t$ and Separation rate$_{t+i}$



Notes: Log deviations from HP-trend with $\lambda = 1600$. 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.

To examine the cyclical behavior of the time aggregation bias in the transition rates, I use output, labor productivity and unemployment as business cycle indicators. Figure 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 outstanding (around 0.3), it is relatively strong with unemployment (-0.6). In addition, the time aggregation bias in the job finding rate tends to lead the cycle as it reaches its peak correlation with output at a lag of four and with unemployment at a lag of one.

The procyclicality of the time aggregation bias in the job finding rate implies that in economic upswings there is a significant higher share of workers who leave and return to unemployment within a month. Hence, it is more likely to measure short employment periods in times of high labor demand. Obviously, workers retain their jobs longer in bad times, while they seem to be more willing to quit new jobs in good times. Contrary to the claim of Shimer (2012), the spell sequence $Q2$ in Figure 2 thus matters when measuring the job finding rate.

In contrast, the cyclical behavior of the time aggregation bias in the separation rate is less pronounced. One may argue that there is also a procyclical pattern at higher lags, but the peak correlations are lower than in the case of the job finding rate. In addition, the contemporaneous correlations show opposite signs and the correlation with productivity is even close to zero. A rather acyclic behavior is also indicated by the estimated bias in the separation rate, even though it reflects the actual one worse than in the case of the job finding rate.

Rejecting Shimer's claim of a procyclical time aggregation bias in the separation rate means that I do not identify a significant higher share of short unemployment spells in economic upswings. Obviously, workers are more likely to change to new employers directly in good times but can also be less likely to take up unemployment benefits in case of short unemployment periods. Consequently, the short unemployment notification of spell sequence $Q4$ in Figure 2 is not more relevant in upswings than in recessions.

However, Shimer (2012: footnote 10) argues that the use of the HP-filter with the standard smoothing parameter of $\lambda = 1600$ "seems to remove much of the cyclical volatility in the variable of interest." Therefore, I check the robustness of the preceding results using a higher smoothing parameter as recommended by Shimer (2012), i.e., $\lambda = 10^5$. Indeed, the time aggregation bias in the separation rate becomes more volatile and persistent in relation to the total separation rate (see Table D.1), but there is still no indication for a procyclical behavior (see Figure D.1). Instead, the use of the HP-filter with a smoothing parameter of $\lambda = 10^5$ turns out to be less suitable for German business cycle fluctuations as the positive correlations of the time aggregation bias in the job finding rate with both output and productivity disappear.

Table 2: Variance decomposition of steady state unemployment dynamics

	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

Notes: Log deviations from HP-trend with λ=1600.

3.5 Effects on Unemployment Decomposition

Given the cyclicality of the time aggregation bias in the transition rates, the resulting question is whether monthly time aggregation affects the variance decomposition of labor market states. Therefore, I apply a conventional variance decomposition and analyze the contributions of the continuously and discretely measured transition rates to German unemployment dynamics. In addition, I investigate the claim of Nekarda (2009) that adjusting the discretely measured transition rates according to Shimer (2012) leads to an underestimation of the role of the separation rate.

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

$$u_t \approx u_t^* \equiv \frac{s_t}{s_t + f_t} \tag{6}$$

where * indicates the steady state value.

Fujita/Ramey (2009) demonstrate that the variance of the detrended steady state unemployment rate can be decomposed into the detrended transition rates. The relative contribution of each transition rate is then summarized by

$$\beta_i^* = \frac{cov(du_t^*, di_t)}{var(du_t^*)} \tag{7}$$

where d denotes detrending and $i = f, s$. In addition, there arises a residual term ϵ that constitutes the approximation error and contributes to unemployment dynamics with $\beta_\epsilon^* = 1 - \beta_f^* - \beta_s^*$.

Table 2 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 somewhat larger role for German unemployment dynamics. Fluctuations in the job finding rate account for 55%, while fluctuations in the separation rate contribute 42%. However, the general conclusion of Elsby/Hobijn/Sahin (2009) that each transition rate explains half of unemployment fluctuations in Continental European countries cannot be rejected. Focusing on the post-reunification period even reinforces a 50:50 split.

The second row displays the steady state variance decomposition with respect to the discretely measured transition rates. Due to time aggregation the contribution of the job finding rate is underestimated and the contribution of the separation rate is overestimated, but the difference is not larger than 2 percentage points. In the subsample, the bias accounts for just 1 percentage point.

The unemployment decomposition based on the adjusted transition rates according to Shimer (2012) is shown in the third row. Indeed, the correction approach is able to counter the bias and even removes it in the post-reunification period. Hence, the claim of Nekarda (2009) that the correction approach of Shimer (2012) introduces a bias towards separations in explaining unemployment fluctuations cannot be confirmed for Germany.

Applying Shimer's smoothing parameter of $\lambda = 10^5$ verifies the preceding results (see Table D.2). Interestingly, the continuously measured transition rates show the same contributions as with the lower smoothing parameter to unemployment dynamics and the adjusted measures correct the biased contributions in the right direction. On the other hand, the bias becomes larger in the subsample and the contributions of the job finding and separation rates diverge more. In addition, the approximation error of the variance decomposition becomes larger as well and doubts on the suitability of the higher smoothing parameter arise once more.

Therefore, I follow Fujita/Ramey (2009) and check the robustness of the variance decomposition by using first differences as an alternative detrending method. Table D.3 shows the results. Interestingly, the contributions of the continuously measured job finding and separation rates are of the same magnitude as before and seem to be robust for steady state unemployment dynamics. On the other hand, time aggregation now works in 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 according to Shimer (2012) boosts the effects of time aggregation. Hence, using first differences, I find evidence for Nekarda's observation on the U.S. labor market that the role of the separation rate is underestimated, especially when applying Shimer's correction approach. Nevertheless, the bias accounts for just 4 percentage points and does not affect the relative importance of the transition rates notably.

To sum up, the steady state variance decomposition demonstrates that both the job finding rate and the separation rate contribute substantially to unemployment fluctuations in Germany, where the contributions become closer after the reunification. Nevertheless, it is worth stressing that the job finding rate plays a slightly dominant role. For France, Petrongolo/Pissarides (2008) also find a larger role of the unemployment outflow rate for steady state unemployment fluctuations, which they explain by a strict employment protection. As Germany is known for a strict employment protection as well, the result of a larger role of the German job finding rate appears plausible.

However, Elsby/Hobijn/Sahin (2009) argue that the steady state variance decomposition is inappropriate for unemployment dynamics in Continental European countries. Accordingly, I turn to a more appropriate variance decomposition in the next section.

4 Stylized Facts of German Worker Flows

The discussion on U.S. worker flows has demonstrated that the cyclical behavior of transition rates is not only important for explaining empirical unemployment fluctuations but also for modeling the search and matching approach. Along with this literature, Jung/Kuhn (2011) and Gartner/Merkl/Rothe (2012) discuss labor market flows in Western Germany.

In particular, these studies indicate that although the average German transition rates are relatively low, their volatility is considerable (e.g., compared to the U.S.). However, the relative importance of the cyclical components of the job finding and separation rates is unclear. While Gartner/Merkl/Rothe (2012) find nearly the same volatilities of both transition rates, Jung/Kuhn (2011) find a larger volatility of the separation rate. In addition, Jung/Kuhn (2011) demonstrate a dominant role of the separation rate by applying a steady state variance decomposition of unemployment dynamics. Obviously, the discrepancies result from differences in the measurement.

This study intends to overcome certain shortcomings of previous studies. In particular, I rely on a reasonable unemployment measure and use worker flows computed on a daily basis. The next two subsections reconsider the existing evidence, where I take into account the whole economy after the German reunification and apply a more appropriate variance decomposition of unemployment dynamics as suggested by Elsby/Hobijn/Sahin (2009).

4.1 Cyclical Components

Table 3 presents descriptive statistics of the cyclical components of the continuously measured transition rates.[17] It can be seen that the job finding rate is more volatile than the separation rate. The standard deviation of the job finding rate measures 8.0% and the standard deviation of the separation rate is 6.4%. After the reunification, the volatilities become lower. In relation to the business cycle indicators, however, the transition rates become more volatile in the post-reunification period as the standard deviations of output, productivity and unemployment decrease more strongly after the reunification.

In particular, the volatility ratios with respect to productivity are outstanding. With factors of 12-15 and 10-13, respectively, German job finding and separation rates are more volatile than U.S. transition rates. Compared with Shimer (2005), the German labor market even appears to be twice as volatile as the U.S. one.[18] Against the background of the search and matching model, there seems to be a remarkably strong amplification effect of productivity shocks in Germany. However, the relatively large volatility ratio with respect to productivity can also indicate that productivity shocks are not the actual source of German labor market fluctuations and play a minor role (e.g., compared to output shocks).

[17] As before, the cyclical components are computed as log deviations from the underlying HP-trend with the standard smoothing parameter of $\lambda = 1600$.

[18] 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. Despite different smoothing parameters, the comparability may be ensured by Hornstein/Krusell/Violante (2005) who show that the choice of the smoothing parameter has virtually no effect on the volatility ratios.

Table 3: 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 λ=1600. Output measures gross domestic product (GDP). Productivity is the ratio of GDP to total hours worked.

The autocorrelation coefficients in Table 3 confirm the consistent observation that the cyclical component of the job finding rate is more persistent than that of the separation rate. In addition, the transition rates are more or similar persistent as output and productivity but less persistent than unemployment, which indicates the hysteresis problem of German unemployment fluctuations.

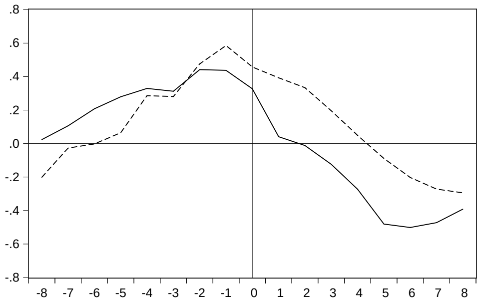
Figure 4 shows the cyclical behavior of the job finding and separation rates. It can be seen that the job finding rate is procyclical and the separation rate is countercyclical. The peak correlations of the transition rates with output are 0.4 and -0.4, respectively, and turn out to be stronger after 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 indicate a rather lagging behavior. The cross correlations with productivity are lower than with output, which again raises the question on the relevance of productivity shocks for German labor market fluctuations. Moreover, both transition rates show high and well-shaped cross correlations with unemployment. The correlations between the job finding rate and unemployment reach nearly -0.8, while the correlations between the separation rate and unemployment are up to 0.6. The peak correlations arise at lags of 1-2 quarters. Hence, the transition rates precede unemployment, which emphasizes their role as driving forces of unemployment dynamics.

4.2 Contributions to Unemployment Dynamics

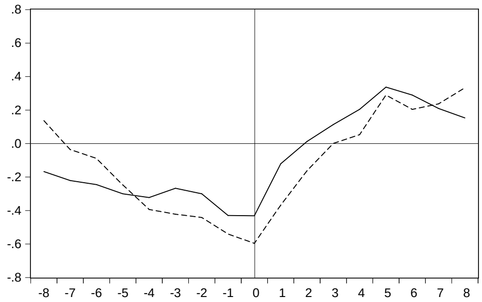
Several recent studies investigate the relative influence of worker flows to unemployment dynamics as it has important policy implications. In the previous section, the variance decomposition of the steady state unemployment rate suggested a slightly dominant role of the job finding rate. However, Elsby/Hobijn/Sahin (2009) argue that the steady state unemployment rate is a weak approximation for the actual unemployment rate if labor turnover is low. In fact, the sum of the monthly job finding and separation rates averages just 7% in Germany (see Figure 1).

Figure 4: Cross correlation of transition rates with business cycle indicators

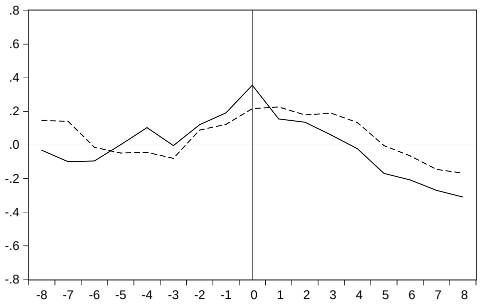
(a) Output$_t$ and Job finding rate$_{t+i}$



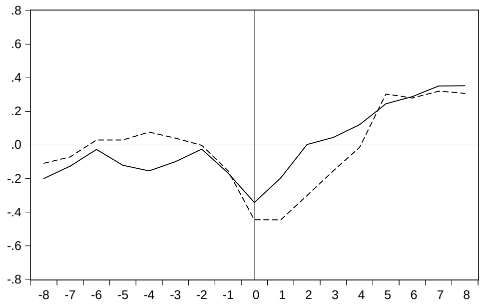
(b) Output$_t$ and Separation rate$_{t+i}$



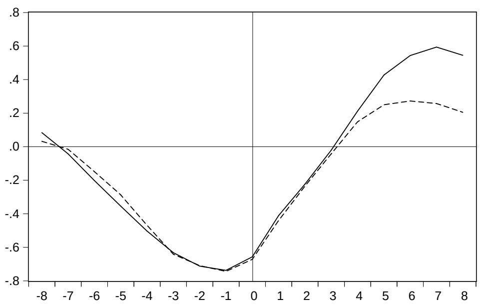
(c) Productivity$_t$ and Job finding rate$_{t+i}$



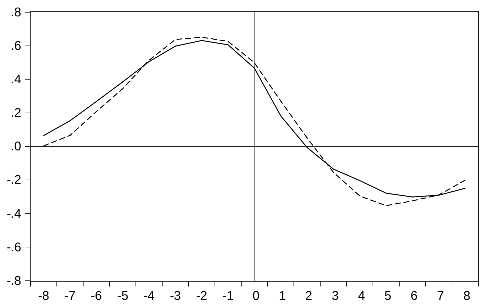
(d) Productivity$_t$ and Separation rate$_{t+i}$



(e) Unemployment$_t$ and Job finding rate$_{t+i}$

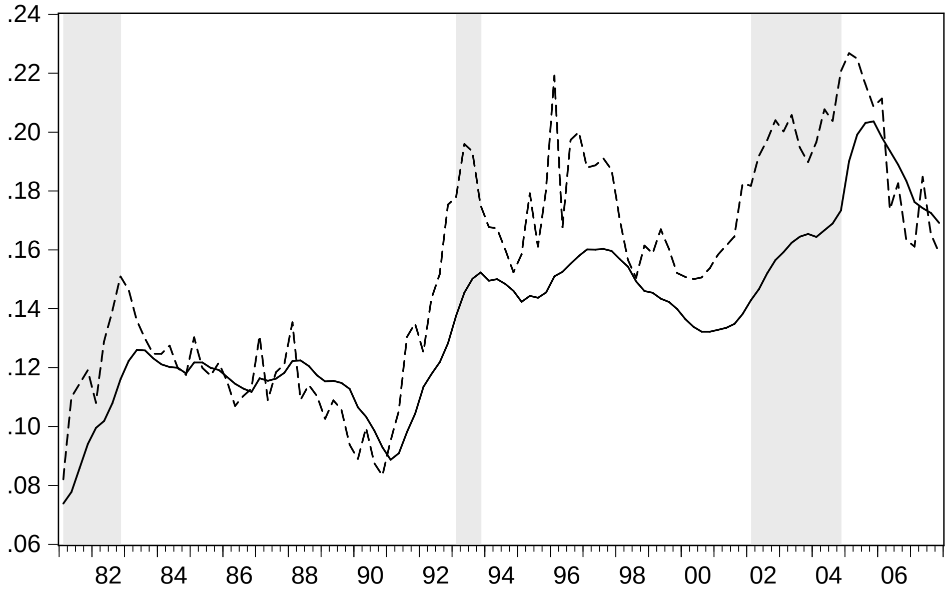


(f) Unemployment$_t$ and Separation rate$_{t+i}$



Notes: Log deviations from HP-trend with $\lambda = 1600$. 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 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.

Figure 5 demonstrates the resulting divergence of the actual and steady state unemployment rates. The steady state unemployment rate mainly overestimates the actual unemployment rate and 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/Hobijn/Sahin (2009) state that the steady state variance decomposition is inappropriate for unemployment rates in Continental European countries. They propose a procedure which decomposes the variance of actual unemployment. The so-called non-steady state variance decomposition allows actual unemployment to deviate from its steady state and considers the influence of both contemporaneous and lagged dynamics of transition hazard rates to actual unemployment fluctuations. In addition, Smith (2011) demonstrates that the lower the job finding and separation rates, the larger is the relative impact of past variations.

The approach of Elsby/Hobijn/Sahin (2009) considers unemployment dynamics as first differences of the log unemployment rate. Then, the relative contributions are given by

$$\beta_i = \frac{cov(\triangle \log u_t, C_t^i)}{var(\triangle \log u_t)} \tag{8}$$

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 $C_0^0 = \triangle \log u_0$ measures the value of the initial deviation. The share of the residual component ϵ now satisfies $\beta_\epsilon = 1 - \beta_f - \beta_s - \beta_0$.[19]

To allow for time variation in the relative contributions, I follow Smith (2011) and compute rolling β_i's. In addition, I convert the monthly job finding and separation rates into annual averages and investigate their contributions at different time horizons. Figure 6 presents the results. Indeed, the relative contributions of the transition rates vary considerably over time. Especially with respect to 3-year periods, the contributions jump up and down and show even negative covariations. Nevertheless, it is worth noting that the separation rate contributes about 80% to unemployment dynamics in the periods 1984-1986 and 1989-1991.

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 in the separation rate. The contributions of the job finding rate vary in the range of 20-60%, whereas the contributions of the separation rate also deviate to nearly 0% in the early 1990s and 2000s. Except for the outlier of the job finding rate in the 7-year variance decomposition, the contributions become smoother with longer time periods. In particular, the relative importance of the transition rates turns out more clearly and the job finding rate appears to play a dominant role on the German labor market. For longer periods, the two transition rates explain about 60% of actual unemployment dynamics, where the job finding rate accounts for 40% and the separation rate contributes 20%.

To sum up, the non-steady state variance decomposition reveals the importance of both the job finding rate and the separation rate for unemployment dynamics in Germany, but the job finding rate dominates in the long run. In this respect, the non-steady state variance decomposition does not depart from the results of the conventional steady state variance decomposition.

5 Conclusion

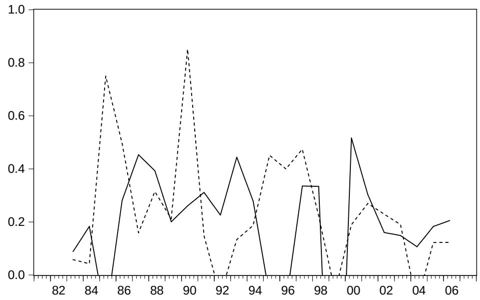
Exploiting daily information from German administrative data, this paper has analyzed the importance of time aggregation in the measurement of monthly worker flows, which has stimulated recent research on U.S. labor market dynamics.

In particular, I have compared three measures of worker flows: one that takes into account every daily change of the individuals' labor market status, one that compares the labor market status of individuals at a specific day of a month and one that applies the prominent correction approach of Shimer (2012) which intends to address neglected worker flows in monthly point-in-time comparisons. The measures are based on transitions between employment subject to social security and a reasonable unemployment pool during the time period 1981-2007.

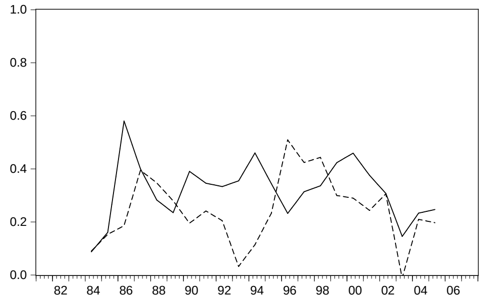
[19] For a more detailed description of the non-steady state decomposition see Elsby/Hobijn/Sahin (2009: p. 18f).

Figure 6: Variance decomposition of actual unemployment dynamics

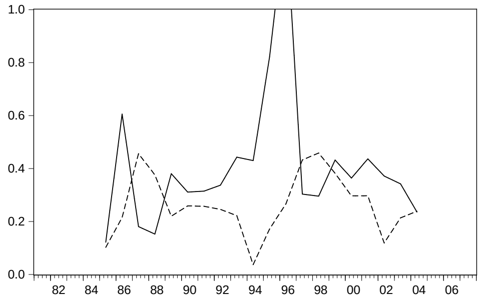
(a) Rolling 3-Year Betas



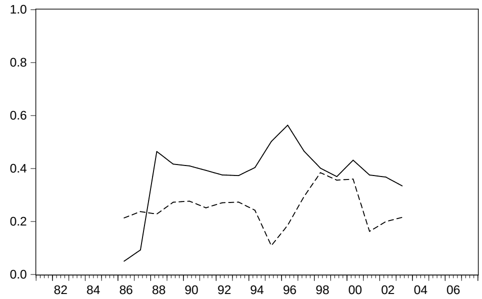
(b) Rolling 5-Year Betas



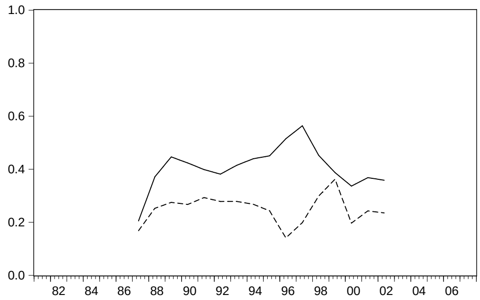
(c) Rolling 7-Year Betas



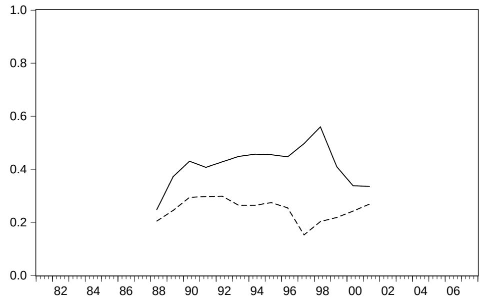
(d) Rolling 9-Year Betas



(e) Rolling 11-Year Betas



(f) Rolling 13-Year Betas



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.

Confronting discretely measured worker flows with continuously measured worker flows demonstrates that monthly point-in-time comparisons underestimate total worker flows by around 10% in Germany. The time aggregation bias, defined as the hazard rate of reversing a transition within one month, shows significant fluctuations in the sample period. In particular, if the time aggregation bias is interpreted as a measure for labor market flexibility, it seems to reveal some effects of recent labor market reforms. Applying the correction approach of Shimer (2012), however, accounts only partially for the actual time aggregation bias. Therefore, the correction approach may be more practical for disaggregate studies as it does not account for heterogeneity.

In light of related U.S. studies, the cyclical behavior of the time aggregation bias appears more relevant as it has influenced the setup of theoretical approaches. Using different business cycle indicators, the time aggregation bias in the job finding rate shows a procyclical behavior, while the time aggregation bias in the separation rate seems to be relatively unaffected by business cycle fluctuations. Hence, the far-reaching claim of Shimer (2005, 2012) that time aggregation biases the separation rate towards countercyclicality cannot be confirmed for Germany. In contrast, time aggregation is no reliable argument for assuming an exogenous separation rate.

Obviously, the (non-)cyclicality in the underlying (un)employment durations indicates a cyclical behavior of quits. Shorter employment periods in economic upswings are likely to result from a higher willingness of workers to quit their jobs, while they retain their jobs longer in recessions. The absence of shorter unemployment periods in upswings may reveal a higher share of direct job-to-job transitions, i.e., workers who change to new employers within a day. Nevertheless, the (non-)cyclicality of monthly reversed transitions can also point to some cyclicality in the take-up of unemployment benefits. Hence, the absence of shorter unemployment spells in upswings can also result from a higher share of workers who do not have an entitlement to unemployment benefits or who refuse to register as unemployed because they expect only short unemployment periods due to high labor demand.

Besides, monthly time aggregation does not have notable effects on the decomposition of steady-state unemployment dynamics. With respect to all three measures of worker flows, the contributions of the job finding and separation rates are of a similar magnitude, which holds for different detrending methods.

Finally, this paper has reconsidered stylized facts of German worker flows. As pointed out by previous studies, the probabilities of finding and separating from a job are more volatile than those on the U.S. labor market, i.e., German worker flows deviate much stronger from their trend in response to exogenous shocks. Cross correlations demonstrate that the job finding rate is procyclical and the separation rate is countercyclical, but raise the question on the relevance of productivity shocks for German labor market fluctuations. Moreover, the decomposition of actual unemployment dynamics reveals that both transition rates play an important role on the German labor market, but the job finding rate dominates in the long run. Therefore, future research will provide a more in-depth analysis of the German job finding rate by inspecting the matching function as modeling device.

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A Data Selection

In contrast to theoretical labor market models, which assume workers to be either employed or unemployed, the SIAB suffers from parallel notifications due to the merging of different registers. In particular, a recipient of unemployment benefits may have a spare-time work (so-called *Hinzuverdiener*) or an employed worker may lose his or her second job and becomes part-time unemployed. However, there are also inconsistent notifications 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 notifications have priority.

Moreover, I refine the data set to obtain rather homogeneous labor market states. From employment subject to social security, I exclude apprentices, trainees, family assistants as well as recipients of early retirement pension and recipients of compensations allowance. I likewise drop marginal employed workers (*geringfügig Beschäftigte*) to avoid a structural break as marginal employment is covered only since 1999. Besides, omitting marginal employed workers also avoids unemployed persons having a spare-time work to be counted as employed. In addition, I drop workers with more than 50 employment notifications in a year which may reveal artists or other freelancers. Self-employed workers and civil servants are absent from the data set anyway.

From benefit recipients, I drop persons who are not searching for a job. This group includes, for instance, non-employable persons who are registered by the employment agency because they live with a recipient of unemployment benefits in a community of needs (so-called *Bedarfsgemeinschaft*). Due to administrative reasons all persons of a community of needs have to be registered.

However, the data set does not include all unemployment benefits II spells in 2005/2006 after the Hartz IV reform has been implemented. Therefore, I add job search notifications of unemployed workers to the benefit measure in these years if a corresponding benefit notification is missing. In addition, reports of benefit receipt are incomplete in the late 1970s but cannot be adjusted as respective job search notifications are not available. Therefore, the analysis starts in 1980.

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

B A Nonemployment Proxy according to Fitzenberger/Wilke (2010)

This study relies on the nonemployment proxy introduced by Fitzenberger/Wilke (2010) for German administrative labor market data. The nonemployment proxy consists of all nonemployment periods after an employment spell that contain at least one report of benefit receipt and is treated as right censored if the last benefit receipt is not followed by any notification. I also consider gaps after benefit receipt being the first notification of a labor market biography. For example, this case occurs when a person becomes unemployed after apprenticeship during which he or she has acquired an entitlement to unemployment benefits. To avoid a too extensive unemployment measure, I only fill gaps by up to one year. Accordingly, the sample period reduces to 1981-2007 to ensure a high filling degree at the sample margins.

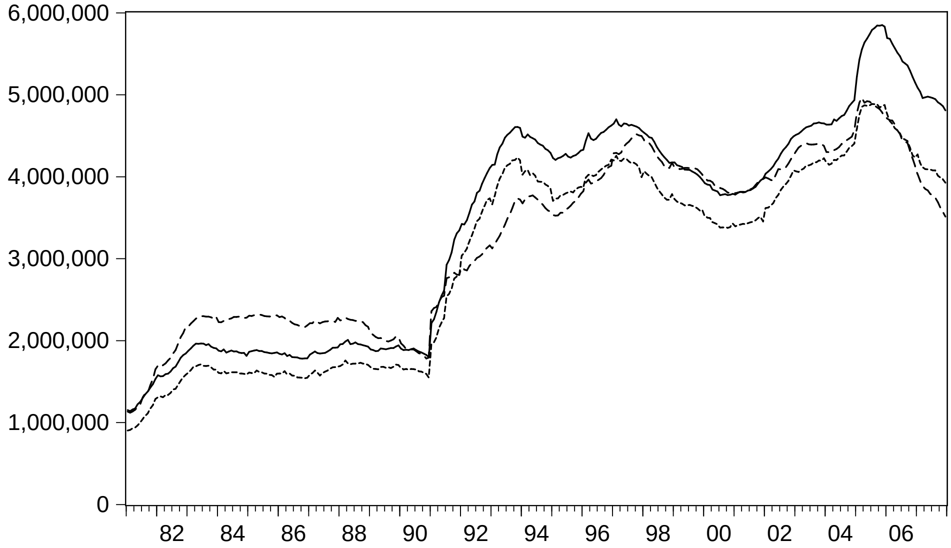
With this definition, unemployment periods that are not recorded in the data set are covered as well. It should be noted that an unemployment period may also cover marginal employment because it has been dropped before. As a marginal part-time work between benefit receipt and regular employment is likely to be a temporary arrangement, the marginal part-time worker is assumed to search for a regular job anymore. The same may apply for a short self-employment period after benefit receipt since supporting self-employment is a measure of active labor market policy. However, it should be also noted that information gaps between two employment spells are not considered as they are likely to constitute deliberated interruptions such as sabbaticals or maternity leaves.

Figure B.1 shows the nonemployment proxy together with benefit receipt and the official unemployment series. Even though all series display a similar development over time, there are varying differences in the level. In particular, the difference between official unemployment and benefit receipt seems striking. Official unemployment may be expected to exceed benefit receipt since some unemployed workers that do not have an entitlement to benefits register voluntarily at the employment agency to take advantage of the placement service. However, after the German reunification this expectation does not hold. In 2005/2006, the benefit receipt measure corresponds to official unemployment due to the data adjustment described in Appendix A, where slight differences may occur due to data selection. Moreover, official unemployment exceeds the nonemployment proxy in the time period 1982-1989 even though latter is constructed to capture certain information gaps.

To shed more light on the relevance of the adjustment procedure of the benefit measure, Figure B.2 exhibits the difference between benefit receipt and the nonemployment proxy, i.e., the extent of filled gaps. In absolute values, gaps occur with nearly 300,000 workers in the pre-reunification period and with 500,000 persons after the reunification. Since the Hartz IV reform in 2005, which redefines former social assistance recipients as unemployed, the difference between benefit receipt and nonemployment accounts for nearly 1,000,000 persons. In relative terms, information gaps account for over 20% in the early 1980s and shrink around 14% in the late 1980s. After the reunification, the relative difference fluctuates around 10% until 2004. Since 2005 information gaps again become more relevant and occur with nearly 20% of captured unemployment. The latter jump is likely to result from extended and tightened sanctions and from shortened entitlement periods of unemployment benefits, which have been implemented in the course of the Hartz reforms.

Obviously, the adjustment procedure has also an effect on unemployment durations. Table B.1 presents descriptive statistics for unemployment durations based on benefit receipt and based on the nonemployment proxy. The first column indicates that nearly 30% of all benefit receipt spells have been contracted. Therefore, the mean unemployment duration increases from 228 days to over 1 year (371 days). In consideration of the mean duration, the standard deviation of both measures indicates that the distribution of unemployment durations is highly right-skewed. Moreover, the second last column demonstrates that even entitlements of only 1 day are taken up. Due to the contraction of unemployment spells the maximum unemployment duration finally increases from 17.5 to nearly 33 years. Hence, there is at least one worker who is detected as unemployed for more than half of his or her working life.

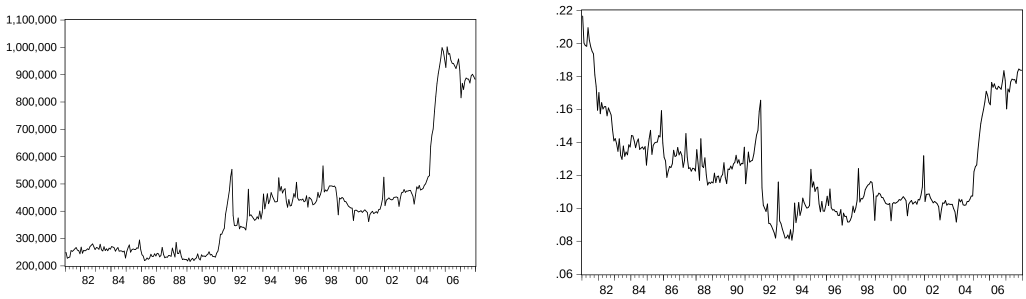
Figure B.1: Unemployment measures



Notes: The solid line presents the nonemployment proxy and the dotted line the receipt of unemployment benefits. Both measures are multiplied by 50 due to the 2% sampling. The time period 1990-1992 exhibits the stepwise capturing of Eastern Germany in labor market registers. The dashed line denotes official unemployment. Time series show quarterly averages of monthly data.

Figure B.2: Amount of filled gaps

(a) Absolute difference (b) Relative difference



Notes: Difference between nonemployment proxy and benefit receipt. Absolute difference displays the projected difference. Relative difference is the absolute difference over the nonemployment proxy.

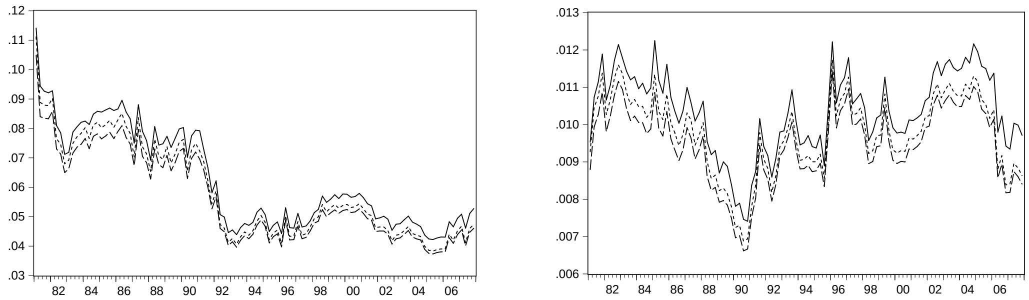
Table B.1: Unemployment durations

	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

C Figures of the Time Aggregation Bias

Figure C.1: Measures of transition rates

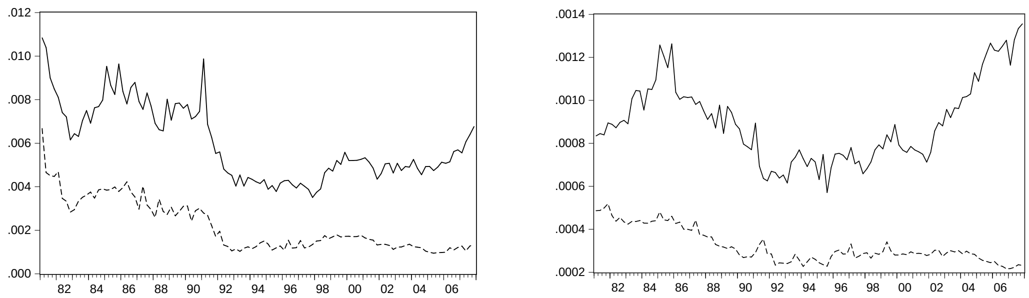
(a) Job finding rate (b) Separation rate



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 C.2: Absolute time aggregation bias

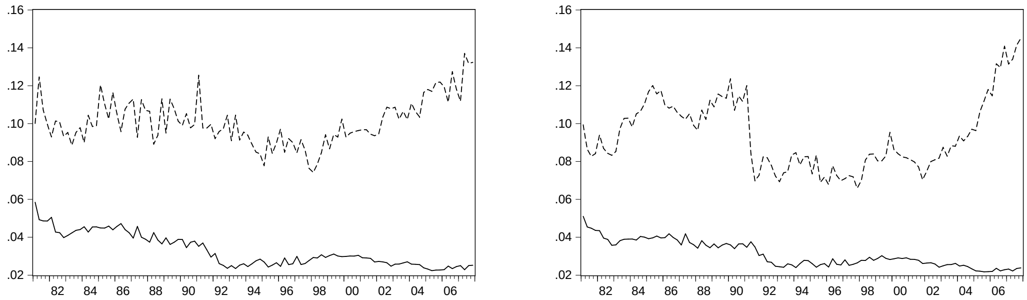
(a) Job finding rate (b) Separation rate



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

Figure C.3: Relative time aggregation bias

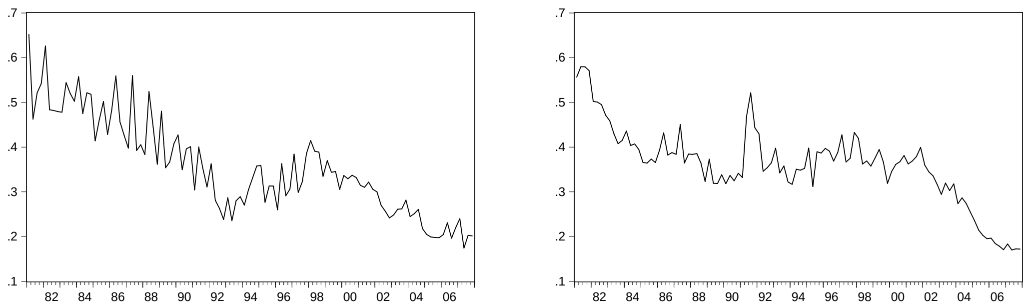
(a) Job finding rate (b) Separation rate



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 C.4: Corrected share of actual time aggregation bias

(a) Job finding rate (b) Separation rate



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

D Robustness Checks

Table D.1: Descriptive statistics of cyclical 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 continuously measured transition rates.

Table D.2: Variance decomposition of steady state unemployment dynamics 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

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

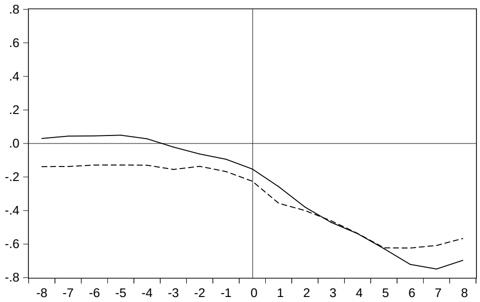
Table D.3: Variance decomposition of steady state unemployment dynamics using first differences

	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

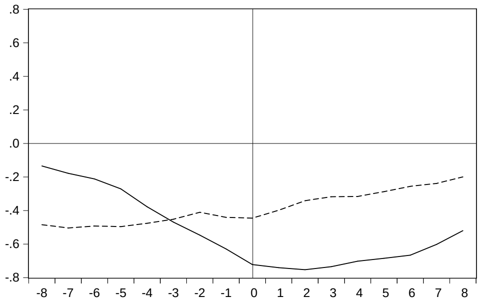
Notes: First differences of log variables.

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

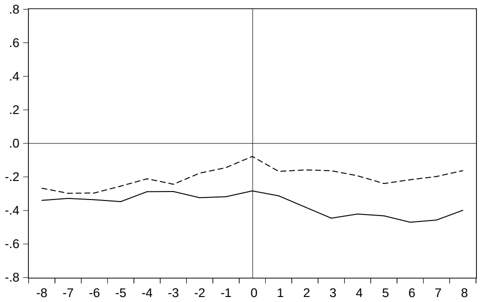
(a) Output$_t$ and Job finding rate$_{t+i}$



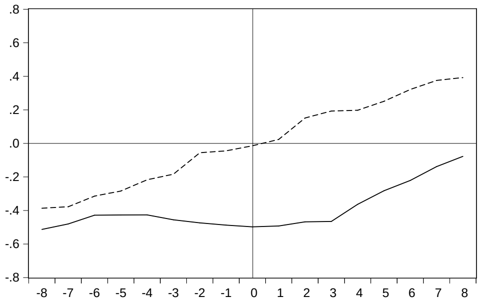
(b) Output$_t$ and Separation rate$_{t+i}$



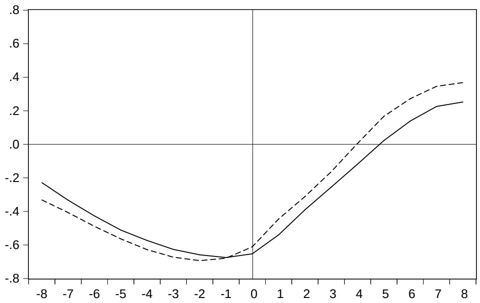
(c) Productivity$_t$ and Job finding rate$_{t+i}$



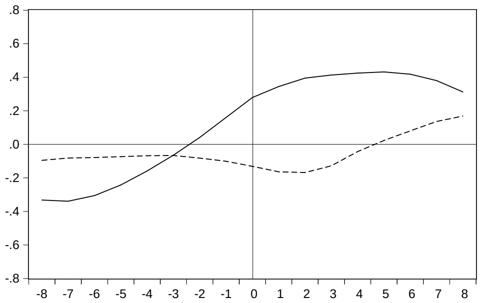
(d) Productivity$_t$ and Separation rate$_{t+i}$



(e) Unemployment$_t$ and Job finding rate$_{t+i}$



(f) Unemployment$_t$ and Separation rate$_{t+i}$



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

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