The importance of frequency in estimating labour market transition rates[*]

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Abstract

Labour markets transition rates are typically estimated using survey data, which are mainly carried at monthly or quarterly frequency. I argue that rates from surveys at different frequencies are not comparable, even if corrected for time aggregation. I estimate labour market transition rates using monthly and quarterly frequency CPS data. I apply time-aggregation correction to make them comparable. I find notable differences in terms of levels and volatilities. While the continuous time-aggregation correction does not alter the unemployment decomposition using the monthly survey, it does so when using the quarterly survey.

JEL Classification: E24; J60.

Keywords: job-finding rate; job-separation rate; transition rates; time-aggregation correction; unemployment decomposition.

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1 Introduction

The macroeconomic analysis of the US labour market is commonly done using the *Current Population Survey* (CPS). The CPS is a monthly survey that allows the estimation the transition rates between employment, unemployment, and inactivity since 1976. Amongst others, it has been used by Blanchard and Diamond (1990), Shimer (2005), Elsby *et al.* (2009) or Fujita and Ramey (2009).

For several other countries, the comparable labour force survey is only carried at a quarterly frequency. Gomes (2012), Elsby *et al.* (2011) and Elsby and Smith (2010) have examined quarterly survey data from the United Kingdom; Silva and Vázquez-Grenno (2013) from Spain; and Hairault *et al.* (2012) from France.[1] Particularly standing out is Petrongolo and Pissarides (2008), who compare the relative importance of job-finding and job-separation rates across countries using administrative data (France and United Kingdom), data from quarterly surveys (Spain and United Kingdom) and from monthly surveys (United States).

The different frequency of surveys poses the question of how comparable the transition flows between employment, unemployment and inactivity are. Shimer (2005) and, more specifically, Shimer (2012) propose a methodology to correct for time aggregation. This correction is made defining the length of the time unit (say a week), making a partition of the frequency period in the time units (a month is formed by 4 weeks), assuming a constant transition rate between every two states for each time unit and adding up the product of the transition rates for all the possible paths that link the initial state with the final state. To investigate the comparability of the data flows from datasets at different frequencies, it suffices to estimate the counterparts of the transition rates to the same time unit and verify whether they coincide.

Shimer (2012) argues that the time aggregation affects the cyclicality of transition rates and creates a bias when measuring the relative importance of job-finding and job-separation rate for unemployment fluctuations. He defends the use of a continuous time-aggregation correction that became a standard practice in the literature. Elsby *et al.* (2009) prefer the use

[1] The later paper also computes the monthly transitions based on administrative data. Also worth mentioning is Hertweck and Sigrist (2015) that compute the monthly transitions for Germany.

of a discrete weekly time-aggregation correction. Although they acknowledge Shimer's point, they find that the effect of the correction on the cyclicality of flows is quantitatively small. Nekarda (2009) further investigates the performance of the time-aggregation correction. Using weekly data from the Survey of Income and Program Participation, he is able to compute both the weekly and monthly transitions and check their consistency. He find that the monthly data understates the true transitions by 15 to 24 percent. However, as in Elsby *et al.* (2009), he concludes that using the monthly data does not create a significant cyclical bias. This result was subsequently used by Smith (2011) to disregard the correction.

The objective of this paper, similar to Nekarda (2009), is to investigate how the frequency of a survey matters for measuring labour market flows, and evaluate the performance of the time-aggregation correction. I calculate transition rates, at monthly and quarterly frequency, from the CPS between 1976 and 2011. I apply both the discrete and continuous time-aggregation corrections. As in Nekarda (2009), I find significant differences in the transition rates obtained at different frequencies, across all state pairs, both in terms of levels and volatilities. Using a quarterly survey understates the measured monthly transitions rates by 30 to 50 percent.

I also evaluate whether the frequency of the survey affects the unemployment decomposition. Applying the continuous time-aggregation correction on the monthly survey data, does not alter the relative importance of job-finding and job-separation rates, which is 50-50 in my sample. This result confirms the findings of Nekarda (2009) and Elsby *et al.* (2009). However, the data from the quarterly survey shows a different picture. Without correcting the data, the job-separation rate is measured to be more important (60-40). While the continuous time aggregation correction over-states the importance of the job-finding rate (40-60).

To understand these differences, the key insight is that the time-aggregation correction crucially imposes a within-period invariant transition rate as if transiting from one state to another were a memoryless stochastic process. Using the monthly survey, I calculate conditional transition probabilities that differ substantially depending on the previous labour market state. In the last section, I briefly discuss possible causes for history-dependent transition rates that have been identified in the labour literature.

2 Theory of time aggregation

This section follows closely the notation of Shimer (2012). Consider a labour market with three states: employment (E), unemployment (U) and inactivity (I). Each period $t \in \{0, 1, 2, 3, ..\}$ corresponds to a month. A monthly survey observes the transitions between t and $t+1$ recorded in a 3×3 discrete time Markov transition matrix n_m, with columns summing to 1. A quarterly survey observes the transitions between t and $t+3$ recorded in an equivalent transition matrix n_q. It is possible to extrapolate (and correct for the time-aggregation) the monthly transition matrix from the quarterly discrete transition matrix (and call it $\hat{n}_m$) as well as the quarterly transition matrix from the monthly discrete transition matrix (and call it $\hat{n}_q$). Let μ_i denote a diagonal matrix of eigenvalues and p_i the matrix with corresponding eigenvectors of the discrete transition matrix at frequency $i \in \{m, q\}$. Then,

$$\hat{n}_q = n_m \times n_m \times n_m = p_m \mu_m^3 p_m^{-1}, \tag{1}$$

$$\hat{n}_m = p_q \mu_q^{1/3} p_q^{-1}. \tag{2}$$

Suppose now that the transitions occur in a continuous time environment. Let λ be the 3×3 continuous time Markov transition matrix that records in the off-diagonal the Poisson continuous arrival rate, λ^{AB} from state $A \in \{E, U, I\}$ to state $B \neq A$. We can retrieve the continuous time transition matrix from the limit of either the monthly transition matrix (and call it $\hat{\lambda}_m$) or the quarterly transition matrix (and call it $\hat{\lambda}_q$).

$$\hat{\lambda}_m = \lim_{\Delta \to 0} \frac{p_m \mu_m^{\Delta} p_m^{-1} - I}{\Delta}, \tag{3}$$

$$\hat{\lambda}_q = \frac{1}{3} \lim_{\Delta \to 0} \frac{p_q \mu_q^{\Delta} p_q^{-1} - I}{\Delta}. \tag{4}$$

The reason I divide by 3 in the latter expression is to make the two instantaneous rates comparable (total transitions per month). In the following section, I test using CPS data whether the discrete time extrapolated transition matrices are equal to the observed ones, $\hat{n}_q = n_q$ and $\hat{n}_m = n_m$, and whether the instantaneous rates also coincide, $\hat{\lambda}_q = \hat{\lambda}_m$.

3 Transition rates at different frequencies

I use CPS monthly data between 1976 and 2011 to compute the transition rates. The CPS surveys households for four consecutive months, leaves them out for 8 months and interviews them again for four other months. Taking advantage of the CPS structure, we can compute the transition probabilities in the labour market by comparing the status of a worker in two different periods and then aggregating across individuals. I compare two consecutive waves to obtain monthly transition rates. The quarterly transition rates are derived by comparing the first and the forth waves and the fifth and eight waves.[2] Throughout the paper, I refer to the quarterly survey to classify the frequency of the interviews (t and $t + 3$) and not the frequency of the survey itself, which is monthly in both cases.

3.1 Levels and volatilities

Table 1 shows the off-diagonal elements of the matrices n_m, $\hat{n}_m$, n_q, and $\hat{n}_q$. The numbers of the extrapolated transitions are far from the directly observable ones. The extrapolated monthly rates have a downward bias that ranges from 30 to 50 percent. Job-finding and job-separation rates are understated by one third, while the transitions in and out of inactivity have an even larger bias. From the extrapolated data we would calculate an expected tenure of 40 months, compared to only 22 months using the original data.[3] The expected unemployment

[2]I extend Shimer's code, publicly available in his webpage. There are fives breaks in the survey: 1978m1, 1985m7, 1985m10, 1994m1 and 1995m6 to 1995m9. The missing values are extrapolated by doing the average of the same month of the previous and following year. All the series were then seasonally adjusted using US Census Bureau X12. All the original and treated series used in the paper, as well as the MATLAB codes for time-aggregation bias correction, are available at the author's website.

[3]If we consider only the outflow of employment to unemployment, the calculated job tenure would be of 8.3 years, using extrapolated data and 5.5 years using the original series.

Table 1: Level and Volatility of Transition Probabilities

	Monthly		Quarterly		Continuous	
	Original	Extrapolated	Original	Extrapolated	Corrected	Corrected
	n_m	$\hat{n}_m$	n_q	$\hat{n}_q$	$\hat{\lambda}_m$	$\hat{\lambda}_q$
Mean						
E → U	0.015	0.010	0.023	0.027	0.020	0.012
E → I	0.029	0.015	0.046	0.086	0.358	0.213
U → E	0.260	0.178	0.383	0.460	0.028	0.015
U → I	0.221	0.120	0.259	0.376	0.312	0.145
I → E	0.046	0.023	0.070	0.139	0.044	0.022
I → U	0.026	0.013	0.027	0.044	0.036	0.015
Volatility						
E → U	0.0025	0.0018	0.0046	0.0058	0.0029	0.0020
E → I	0.0026	0.0014	0.0039	0.0070	0.0728	0.0408
U → E	0.0405	0.0295	0.0486	0.0456	0.0028	0.0014
U → I	0.0240	0.0158	0.0248	0.0230	0.0481	0.0223
I → E	0.0040	0.0020	0.0059	0.0110	0.0039	0.0020
I → U	0.0035	0.0016	0.0045	0.0085	0.0037	0.0017

Note: Average transition rates and standard deviation from 1976:2 to 2011:6. n_m and n_q are the matrices calculated directly from CPS. $\hat{n}_m$ and $\hat{n}_q$ are calculated using equations (1) and (2). $\hat{\lambda}_m$ and $\hat{\lambda}_q$ are the continuous transition rates calculated using equations (3) and (4).

duration would be 5.6 months compared to 3.8 using the original data. The reverse side of the coin is the extrapolation of the quarterly rates (based on the monthly survey) that largely overestimate the actual rates. The upward bias ranges from 20 to 100 percent. The same bias is observed in the standard deviation of the series.

Table 1 also shows the instantaneous transition rates $\hat{\lambda}_m$ and $\hat{\lambda}_q$, as defined by expressions (3) and (4), as well as their volatilities. The differences between them are even larger than for the discrete rates. The average transition rates from and into inactivity calculated from the monthly survey are roughly twice as large as their quarterly-based counterparts. For the job-finding and job-separation rates the difference is around 60 percent. The standard deviations are also substantially higher for the transitions obtained from the monthly survey. However the ratio of standard deviation to the mean is roughly proportional across the two sets.

3.2 Unemployment decomposition

As found by Nekarda (2009), the fact the mean and volatility of transition rates are different, does not imply a different cyclical pattern. To measure it, I perform an unemployment decomposition based on Shimer (2012). I first compute the three-states equilibrium unemployment rate, calculated from both sets of continuous transition rates:

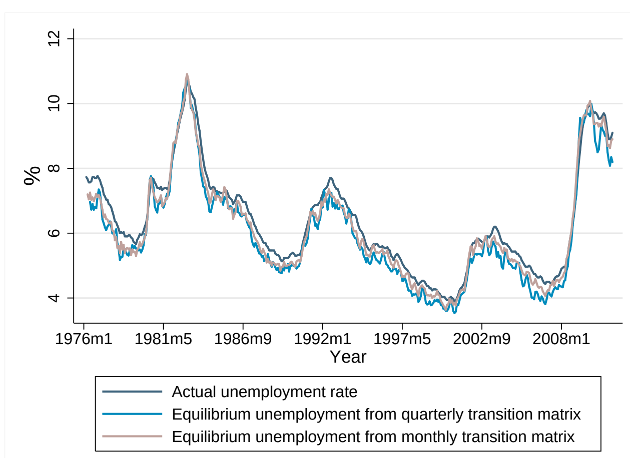
$$\tilde{u}_{t,i} = \frac{\hat{\lambda}^{EI}_{t,i}\hat{\lambda}^{IU}_{t,i} + \hat{\lambda}^{IE}_{t,i}\hat{\lambda}^{EU}_{t,i} + \hat{\lambda}^{IU}_{t,i}\hat{\lambda}^{EU}_{t,i}}{(\hat{\lambda}^{EI}_{t,i}\hat{\lambda}^{IU}_{t,i} + \hat{\lambda}^{IE}_{t,i}\hat{\lambda}^{EU}_{t,i} + \hat{\lambda}^{IU}_{t,i}\hat{\lambda}^{EU}_{t,i}) + (\hat{\lambda}^{UI}_{t,i}\hat{\lambda}^{IE}_{t,i} + \hat{\lambda}^{IU}_{t,i}\hat{\lambda}^{UE}_{t,i} + \hat{\lambda}^{IE}_{t,i}\hat{\lambda}^{UE}_{t,i})}, \quad i \in \{m, q\}. \tag{5}$$

Somehow surprisingly, even with such distinct transition rates, the equilibrium unemployment based on the quarterly survey is basically indistinguishable from its monthly-based counterpart. They both track closely the actual unemployment rate, as shown in Figure 1.

The decomposition is based on a calculation of counterfactual unemployment rates, where all probabilities are kept constant at the sample mean, except one that is allowed to float. For instance, for the job-separation rate we construct a counterfactual unemployment $\tilde{u}^{EU}_{t,i} = u(\hat{\lambda}^{EU}_{t,i}, \bar{\lambda}^{EI}_{i}, \bar{\lambda}^{UE}_{i}, \bar{\lambda}^{UI}_{i}, \bar{\lambda}^{IE}_{i}, \bar{\lambda}^{IU}_{i})$, and measure its contribution by $\frac{Cov(\tilde{u}_{t,i}, \tilde{u}^{EU}_{t,i})}{Var(\tilde{u}_{t,i})}$.

The results are reported in Table 2. When using monthly survey data, the time-aggregation correction does not seem to matter for the decomposition. Both the original and corrected

Figure 1: Unemployment Rate



Note: All the series are a 3-month moving average.

Table 2: Unemployment Decomposition

	Monthly Survey		Quarterly Survey			
	Original	Corrected	Original	Corrected		
		Continuous		Monthly	Weekly	Continuous
	n_m	$\hat{\lambda}_m$	n_q	$\hat{n}_m$	$\hat{n}_w^*$	$\hat{\lambda}_q$
E $\rightarrow$ U	0.312	0.301	0.412	0.332	0.293	0.247
E $\rightarrow$ I	-0.001	-0.001	-0.002	-0.004	-0.004	0.001
U $\rightarrow$ E	0.335	0.340	0.277	0.387	0.442	0.392
U $\rightarrow$ I	0.105	0.107	0.073	0.109	0.125	0.106
I $\rightarrow$ E	0.086	0.087	0.062	0.059	0.055	0.097
I $\rightarrow$ U	0.164	0.166	0.177	0.117	0.090	0.158

*Note: n_m and n_q are calculated directly from CPS from 1976:2 to 2011:6. $\hat{\lambda}_m$ and $\hat{\lambda}_q$ are calculated using equations (3) and (4). *Discrete weekly correction calculated $\hat{n}_w = p_q \mu_q^{1/12} p_q^{-1}$. The unemployment decomposition is based on Shimer (2012). I report the $\frac{Cov(\tilde{u}_{t,i}, \tilde{u}_{t,i}^{AB})}{Var(\tilde{u}_{t,i})}$, normalized to add up to 1.*

series have similar decompositions, with the job-finding rate only marginally more important than the job-separation rate, confirming the findings of Nekarda (2009) and Elsby *et al.* (2009).

The quarterly survey provides another conclusion. Using the original data, the job-separation rate is more important with, roughly, a 60-40 split. However, the continuous time-aggregation correction over-compensates, giving a 40-60 split in favour of the job-finding rate. I investigate two alternative discrete corrections: a monthly and a weekly (based on Elsby *et al.*, 2009). Out of the two, the monthly discrete correction provides results that are more consistent with the monthly survey.

4 Understanding the differences

One key assumption of the time-aggregation correction is that the transition rates remain constant within the period. I now check whether the discrepancies found in the previous section result from the failure of this assumption. Using the transition matrices in discrete time, assume that the transition rates in the second and third month $\hat{n}_{m2}$ are potentially different from the ones in the first month:

$$n_m \times \hat{n}_{m2} \times \hat{n}_{m2} = n_q \Rightarrow \hat{n}_{m2}^2 = (n_m)^{-1} n_q. \tag{6}$$

I retrieve the matrix $\hat{n}_{m2}$ in two steps. First, I write its canonical form and multiply it by itself. Then I do the spectral decomposition of the matrix $(n_m)^{-1}n_q$. Because of expression (6) and the uniqueness of the spectral decomposition, I derive the eigenvalues and eigenvectors of the matrix, $\hat{n}_{m2}$. I report its off-diagonal numbers in the first column of Table 3. For comparability, the second column shows the numbers of matrix n_m. For n_m and n_q to be consistent, the transition rates in the second and third month have to be substantially lower. The job-separation rate has to be roughly half and the job-finding rate less than one half.

To have a deeper sense of these insights, I compute the monthly transition rates conditional on the labour market status in the previous period as in Gomes (2012). I calculate three transition matrices from time t to $t+1$, each one conditional on a different state at time $t-1$. There are substantial differences in conditional rates. For instance, the employment-to-unemployment rate is 1.2% if the person was employed in the previous month, 13% if she was previously unemployed and 4% if inactive. The job-finding rate is 43% if the job seeker was employed in the previous period but around 20% if unemployed or inactive. These differences are consistent with the gaps between the first two columns of Table 3. The bottom line is that transition flows cannot be treated as driven by a memoryless stochastic process. On the contrary, there are substantial history-dependent effects.

These findings are in line with Elsby *et al.* (2013). They estimate the monthly job-finding rates for OECD countries building upon the methodology of Shimer (2012) using data on the unemployed by different duration spells. They find that the calculated rates are statistically

Table 3: Understanding the Differences

	$2nd, 3rd$ Month	Unconditional	Conditional on:		
	$\hat{n}_{m2}$	n_m	E_{t-1}	U_{t-1}	I_{t-1}
E $\rightarrow$ U	0.008	0.015	0.012	0.132	0.038
E $\rightarrow$ I	0.008	0.029	0.019	0.076	0.277
U $\rightarrow$ E	0.119	0.260	0.439	0.207	0.194
U $\rightarrow$ I	0.062	0.221	0.133	0.166	0.403
I $\rightarrow$ E	0.013	0.046	0.340	0.126	0.026
I $\rightarrow$ U	0.001	0.026	0.066	0.261	0.016

Note: averages between 1976:2 and 2011:6, calculated from CPS. $\hat{n}_{m2}$ calculated using equation (6).

different depending on which unemployment length was used. In a companion paper, Hobijn and Sahin (2009) report that the US monthly job-finding rate is 42% for unemployment spells shorter than 1 month, whereas it falls to 31% when considering spells between 1 to 3 months and 13% with spells between 3 to 6 months.

There are a several reasons for why the aggregate conditional probabilities are so different. Here, I briefly comment on four of them: ex-ante heterogeneity, ex-post heterogeneity, country specific characteristics and response-error bias.

Ex-ante heterogeneity

Workers are heterogeneous in many observable and unobservable characteristics that are time-invariant to a large extent such as education, sex and ability. If the transition rates differ across such dimensions, the aggregate rate might vary because of composition variation of the pool of workers. Suppose that there are only two states A and B and two groups of workers, type 1 and type 2. These workers only differ in their transition rates from state A to state B, with continuous time rates satisfying $\lambda_1^{AB} > \lambda_2^{AB}$. Then, the observed average rate would decrease over time because the pool of workers in state A would be increasingly formed by type 2 workers, who have a lower outflow rate. The empirical labour literature refers to this mechanism that explains falling job-finding rates as spurious negative duration dependence.

Ex-post heterogeneity

Even in the absence of ex-ante heterogeneity, ex-post heterogeneity may result from a number of history-dependent causes and make the aggregate transition rates differ across histories. For instance, if general and job-specific human capital accumulates (depreciates) when employed (unemployed), the probability of becoming unemployed (employed) may vary with tenure (unemployment duration) [Laureys (2013)]. Stigma and search discouragement are alternative mechanisms the empirical literature has identified as causes of state-dependent negative duration. See e.g. Gonzalez and Shi (2010) and Fernandez-Blanco and Preugschat (2012).

Country specific characteristics

In the United States, on average since 1990, 13 percent of the unemployed are on temporary layoff. They expect to be called back by their former employer. Fujita and Moscarini (2013) document that nearly 40 percent of all job-seekers are rehired by the same employer, whereas this percentage rises to 85 percent for temporary laid-offs. Although this is neither an inherent characteristic of the worker nor duration-dependent, it is certainly the case that temporary laid-off workers experience different transition patterns. Calculations from the CPS show that the probability of finding a job within a month is 45 percent for the temporary laid-offs, and 23 percent for the other unemployed. Also, the probability of going to inactivity is roughly half compared to the regular unemployed. Temporary layoffs are more likely to be captured in monthly surveys than in quarterly ones since many Employment–Unemployment–Employment transitions take place in weeks when temporary layoffs are involved.

While temporary layoffs are less relevant outside the United States, features of the institutional environment in Europe might also create duration dependence. Suppose that, as in many European countries, there are two types of contracts, permanent and temporary, with different separation rates (as analysed in Silva and Vázquez-Grenno (2013)). The longer the employment spell the lower would be the job-separation rate because the pool of employment would be increasingly formed by permanent contracts.

Response error bias

When using survey data to estimate worker flows there is the additional problem of response-error bias. The response-error bias may be severe because the errors are cumulative in longitudinal data and lead to an overestimation of flows. This bias is present irrespective of the frequency and should have the same magnitude. However, the bias should be larger *relative* to actual transitions in a monthly survey, because there are few recorded transitions there. This bias might be particularly relevant for the transitions between unemployment and inactivity, which are more prone to be misreported. But, as the time-aggregation correction is computed with all the elements of the transition matrix, all the continuous rates are affected.

5 Conclusion

I show that, even correcting for time aggregation, transition rates calculated from the CPS at monthly and quarterly frequencies are different in terms of levels and volatility. While the time-aggregation correction does not affect the unemployment decomposition using monthly survey data, it does so when using the quarterly survey. Several elements can contribute to these differences: ex-ante and ex-post heterogeneity, country specific characteristics and response-error bias in surveys.

The main result is important in three dimensions. First, we should be aware of it when comparing labour market facts obtained from data sources with different frequencies. This is particularly relevant for cross-country comparisons, particularly between European countries and the United States, as in Petrongolo and Pissarides (2008), Elsby *et al.* (2011), Silva and Vázquez-Grenno (2013) or Hairault *et al.* (2012). Whenever a quarterly survey is used, the size of the transition rates should be compared to the quarterly CPS numbers provided here.

Second, while the time-aggregation correction might be disregarded for unemployment decomposition in a monthly survey, it is important when using a quarterly survey. It seems however, that a continuous correction somehow overstates the importance of the job finding rate. In the particular case studied, a discrete monthly correction provides more consistent results.

The result has also implications for labour market models and their calibration. While the two sets of numbers at monthly and quarterly frequency are inconsistent between them, they are both valid and it is not clear which one should be preferred. If the inconsistency is only due to the presence of heterogeneity, ideally, we should model the heterogeneity and match the labour market at several frequencies.[4] When the heterogeneity is not modeled, the quarterly numbers put a larger weight on people with lower transition rates, so perhaps the monthly number are more suited. However, if a significant fraction of the discrepancy is

[4]One interesting attempt is Morchio (2015). He documents that 10 percent of individuals account for two thirds of all unemployment spells in the United States. He then sets up a model feature worker unobserved heterogeneity and match quality heterogeneity. He identifies the heterogeneity by looking at inequality in unemployment over the lifetime.

due to temporary layoffs and response-error bias, the monthly transitions might overstate the actual labour market flexibility. Disentangling the potential causes was not the objective of this paper. It is a difficult task, but worthwhile pursuing.

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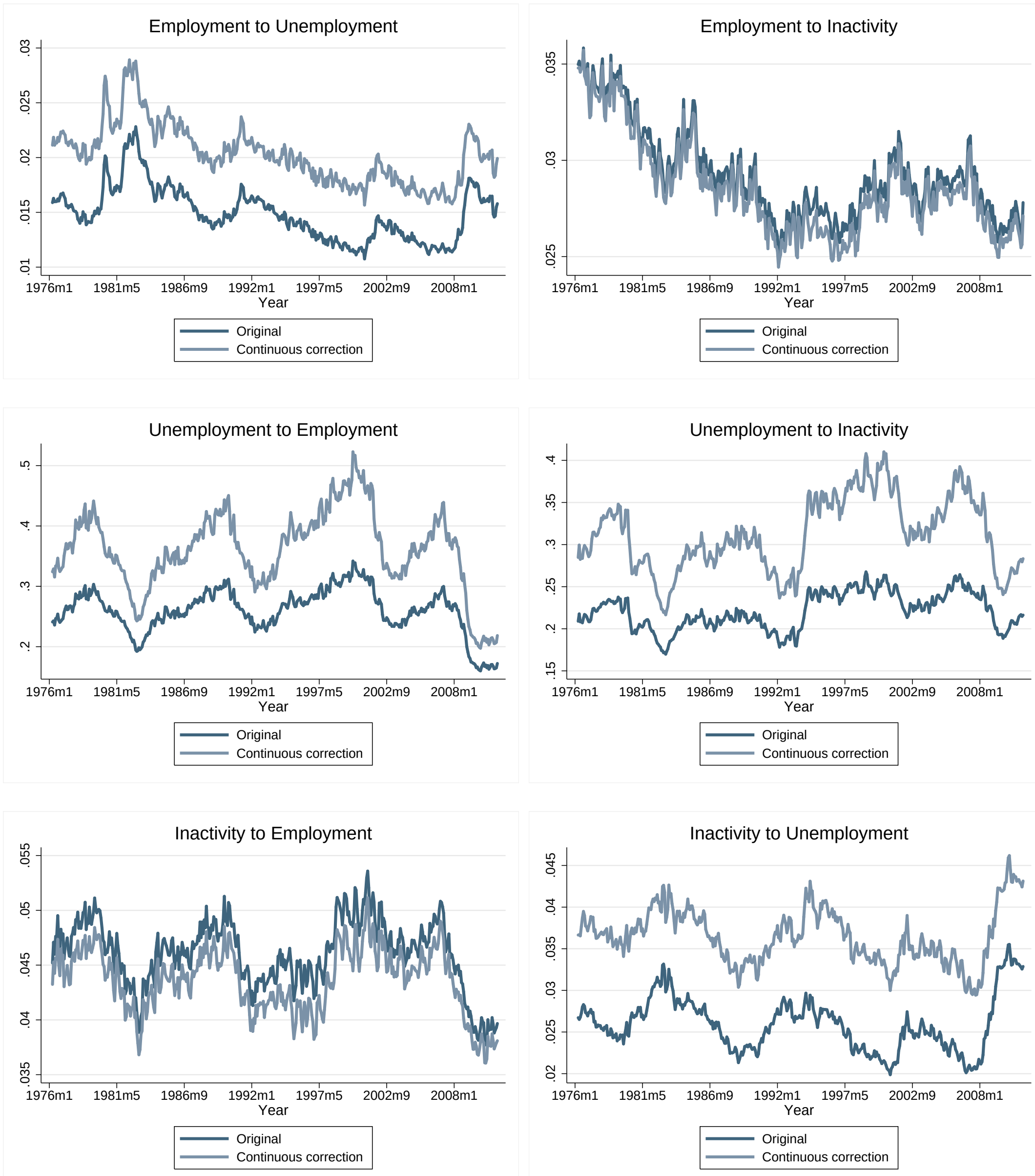
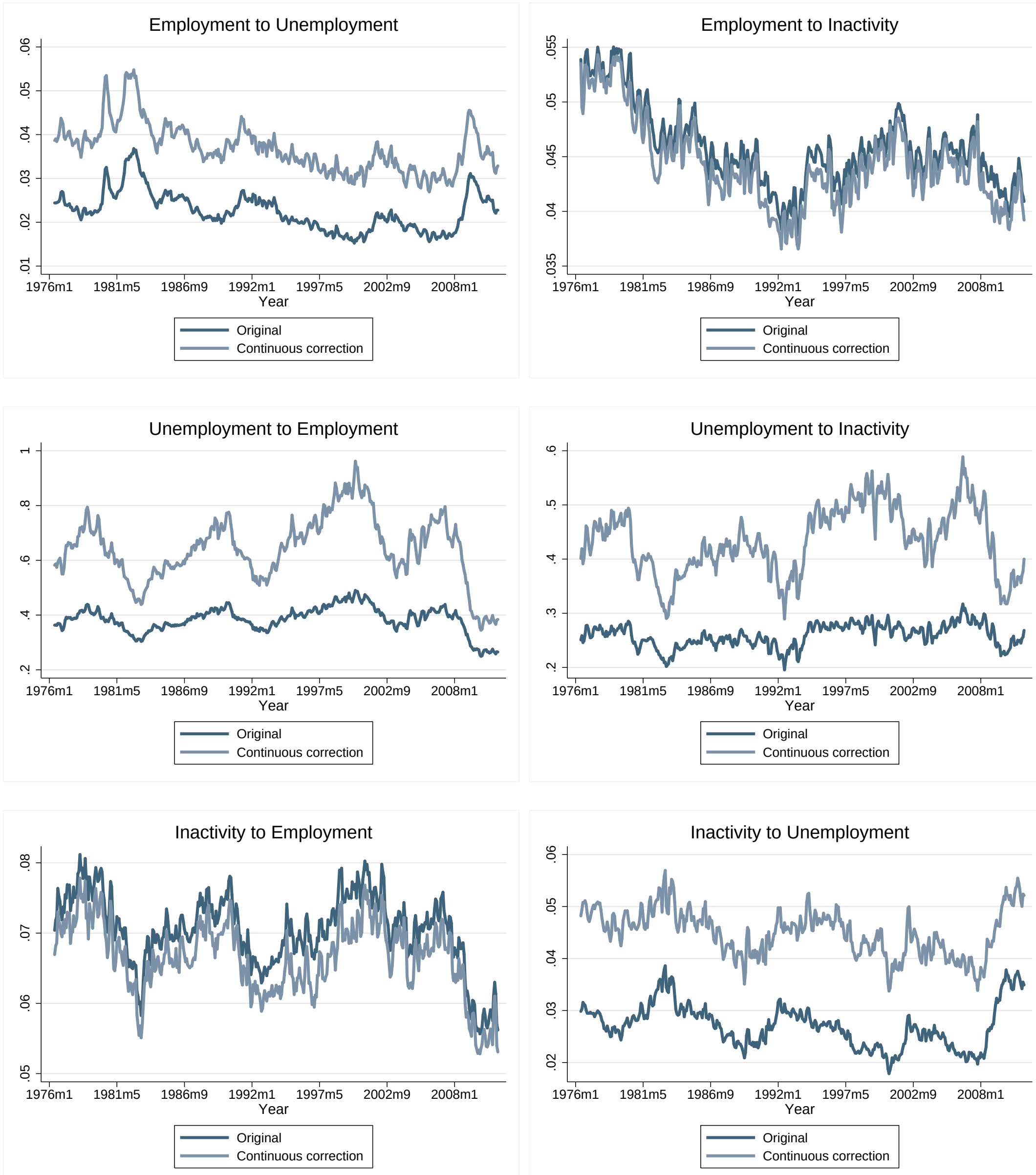
6 Appendix - NOT FOR PUBLICATION

Figure A1: Comparison of monthly transition rates (original vs. continuous correction)



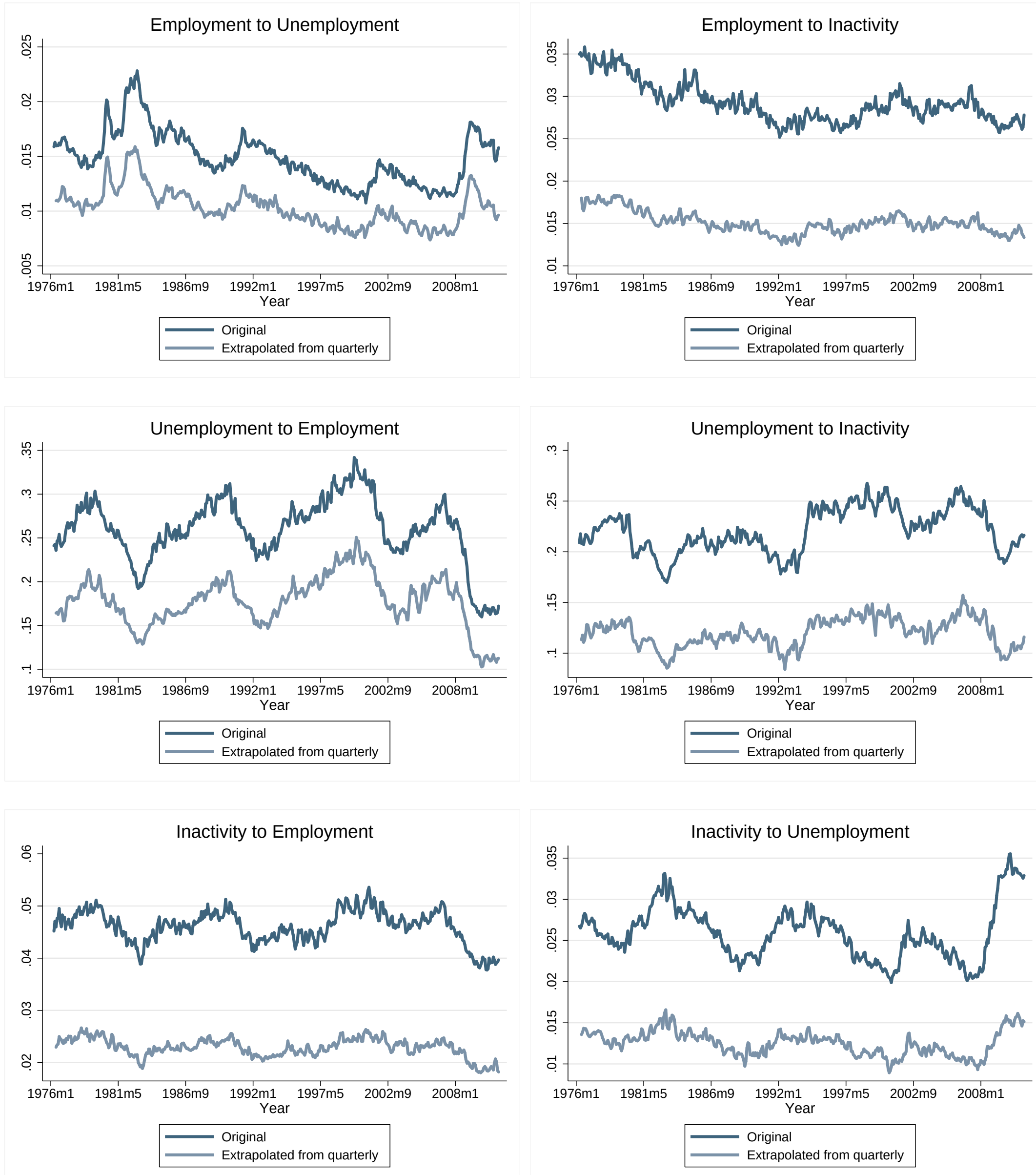
Notes: n_m are the transition rates calculated directly from CPS. $\hat{\lambda}_m$ are the continuous transition rates calculated using equation (3). All the series are a 3-month moving average.

Figure A2: Comparison of quarterly transition rates (original vs. continuous correction)



Notes: n_q are the transition rates calculated directly from CPS. $3 \times \hat{\lambda}_q$ are the continuous transition rates calculated using equation (4). All the series are a 3-month moving average.

Figure A3: Comparison of monthly transition rates (original vs. extrapolated)



Notes: n_m *are the transition rates calculated directly from CPS.* $\hat{n}_m$ *are the extrapolated rates calculated using equation (2). All the series are a 3-month moving average.*

Figure A4: Comparison of quarterly transition rates (original vs. extrapolated)

Notes: n_q are the transition rates calculated directly from CPS. $\hat{n}_q$ are the extrapolated rates calculated using equation (1). All the series are a 3-month moving average.