Online Appendix: Misclassification Errors and the Underestimation of the U.S. Unemployment Rate

Shuaizhang Feng* Yingyao Hu†

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Abstract

This online appendix accompanies the paper "Misclassification Errors and the Underestimation of the U.S. Unemployment Rate" by Shuaizhang Feng and Yingyao Hu. Section 1 of the appendix lists summary statistics of the CPS sample used in the paper. Section 2 of the appendix provides a detailed proof of theorem 1 in the paper. Section 3 evaluates assumptions 1 and 2 in the paper through detailed monte carlo simulations. Section 4 tests assumptions 3 and 4 in the paper directly using CPS data. Additional empirical results including robustness checks are presented in sections 5, 6 and 7.

*School of Economics, Shanghai University of Finance and Economics, 715 Econ Building, 111 Wuchuan Road, Shanghai 200433, China and IZA. E-mail: shuaizhang.feng@gmail.com

†Corresponding author. Department of Economics, Johns Hopkins University, 440 Mergenthaler Hall, 3400 N. Charles Street, Baltimore, MD 21218, USA and IZA. E-mail: yhu@jhu.edu

Outline

1 Summary statistics

We use monthly basic CPS data from January 1996 to August 2011. The whole study period is divided into three sub-periods based on the US business cycles.[1] The first sub-period goes from the beginning of our study period to October 2001, which is roughly the end of the 2001 recession. The second sub-period goes from November 2001 to November 2007, corresponding to the expansion period between two recessions (the 2001 recession and the most recent 2007-09 recession). The third sub-period goes from December 2007 to the end of our study period (Aug 2011), which includes the 2007-2009 recession and its aftermath.

Table A1 presents simple summary statistics. Because all variables are 0/1 dummies, we only report sample means. The sample includes all persons aged 16 years and over in CPS monthly files. The first three rows show labor force statuses. For the whole study period, around 63% are employed, and 4% are unemployed and the rest are not in the labor force. Compared with the first two sub-periods, sub-period 3 is characterized by much higher levels of unemployment and presumably reflecting considerably weaker labor market conditions.

The next three rows summarize some demographic characteristics in the sample which we use to divide the whole sample into different demographic groups. The percentages of females, nonwhites and those aged below 40 are 53%, 16% and 43%, respectively. The last row shows sample sizes. For the whole period we have a sample size of over 19 million.

[1]See http://www.nber.org/cycles.html.

Table A1: Summary statistics: sample means

	Sub-period 1 (1996/01-2001/10)	Sub-period 2 (2001/11-2007/11)	Sub-period 3 (2007/12-2011/8)	All Periods (1996/01-2011/08)
Employed	0.64	0.63	0.60	0.63
Unemployed	0.03	0.03	0.05	0.04
Not in labor force	0.33	0.33	0.35	0.34
Female	0.53	0.53	0.52	0.53
Nonwhite	0.15	0.16	0.17	0.16
40 or younger	0.46	0.42	0.41	0.43
Sample size	6,540,589	7,790,199	4,736,019	19,066,807

Note: Sample restricted to those aged 16 and above. Standard deviations are not reported as all variables are 0/1 dummies.

2 Proof of Theorem 1

This section provides a formal proof of Theorem 1, which states that Under Assumptions 1, 2, 3, 4, and 5, the misclassification probability of the labor force status, i.e., $\Pr\left(U_t|U_t^*, X\right)$, is uniquely determined by the observed joint probability of the self-reported labor force status in three periods, i.e., $\Pr\left(U_{t+1}, U_t, U_{t-9}|X\right)$, through a unique eigenvalue-eigenvector decomposition.

Assumptions 1 implies that the observed joint probability of the self-reported labor force status equals

$$\begin{aligned} & \Pr\left(U_{t+1}, U_t, U_{t-9}|X\right) \\ = & \sum_{U_{t+1}^*}\sum_{U_t^*}\sum_{U_{t-9}^*} \Pr\left(U_{t+1}, U_t, U_{t-9}, U_{t+1}^*, U_t^*, U_{t-9}^*|X\right) \\ = & \sum_{U_{t+1}^*}\sum_{U_t^*}\sum_{U_{t-9}^*} \Pr\left(U_{t+1}|U_{t+1}^*, U_t^*, U_{t-9}^*, U_t, U_{t-9}, X\right) \Pr\left(U_t|U_{t+1}^*, U_t^*, U_{t-9}^*, U_{t-9}, X\right) \\ & \times \Pr\left(U_{t-9}|U_{t+1}^*, U_t^*, U_{t-9}^*, X\right) \Pr\left(U_{t+1}^*, U_t^*, U_{t-9}^*|X\right) \\ = & \sum_{U_{t+1}^*}\sum_{U_t^*}\sum_{U_{t-9}^*} \Pr\left(U_{t+1}|U_{t+1}^*, X\right) \Pr\left(U_t|U_t^*, X\right) \Pr\left(U_{t-9}|U_{t-9}^*, X\right) \Pr\left(U_{t+1}^*, U_t^*, U_{t-9}^*|X\right). \end{aligned} \tag{1}$$

Furthermroe, Assumption 2 implies that

$$\begin{aligned} & \Pr\left(U_{t+1}, U_t, U_{t-9}|X\right) \\ = & \sum_{U_{t+1}^*}\sum_{U_t^*}\sum_{U_{t-9}^*} \Pr\left(U_{t+1}|U_{t+1}^*, X\right) \Pr\left(U_t|U_t^*, X\right) \Pr\left(U_{t-9}|U_{t-9}^*, X\right) \\ & \times \Pr\left(U_{t+1}^*|U_t^*, X\right) \Pr\left(U_t^*, U_{t-9}^*|X\right) \\ = & \sum_{U_t^*} \left(\sum_{U_{t+1}^*} \Pr\left(U_{t+1}|U_{t+1}^*, X\right) \Pr\left(U_{t+1}^*|U_t^*, X\right)\right) \Pr\left(U_t|U_t^*, X\right) \\ & \times \left(\sum_{U_{t-9}^*} \Pr\left(U_{t-9}|U_{t-9}^*, X\right) \Pr\left(U_t^*, U_{t-9}^*|X\right)\right) \\ = & \sum_{U_t^*} \Pr\left(U_{t+1}|U_t^*, X\right) \Pr\left(U_t|U_t^*, X\right) \Pr\left(U_t^*, U_{t-9}|X\right). \end{aligned} \tag{2}$$

Integrating out U_{t+1} leads to

$$\Pr(U_t, U_{t-9}|X) = \sum_{U_t^*} \Pr(U_t|U_t^*, X) \Pr(U_t^*, U_{t-9}|X). \tag{3}$$

We then define

$$\begin{aligned} M_{U_t|U_t^*,x} &= [\Pr(U_t = i|U_t^* = k, X = x)]_{i,k} \\ M_{U_t,U_{t-9}|x} &= [\Pr(U_t = i, U_{t-9} = k|X = x)]_{i,k}, \\ M_{U_t^*,U_{t-9}|x} &= [\Pr(U_t^* = i, U_{t-9} = k|X = x)]_{i,k}, \\ M_{1,U_t,U_{t-9}|x} &= [\Pr(U_{t+1} = 1, U_t = i, U_{t-9} = k|X = x)]_{i,k} \end{aligned}$$

and a diagonal matrix

$$D_{1|U_t^*,x} = diag\,[\Pr(U_{t+1} = 1|U_t^* = k, X = x)]_k.$$

As shown in Hu (2008), Equations (2) and (3) are equvalent to the following two matrix equations

$$M_{1,U_t,U_{t-9}|x} = M_{U_t|U_t^*,x} D_{1|U_t^*,x} M_{U_t^*,U_{t-9}|x} \tag{4}$$

and

$$M_{U_t,U_{t-9}|x} = M_{U_t|U_t^*,x} M_{U_t^*,U_{t-9}|x}. \tag{5}$$

Assumption 3 implies that the matrix $M_{U_t,U_{t-9}|x}$ is invertible. We may then consider

$$\begin{aligned} M_{1,U_t,U_{t-9}|x} M^{-1}_{U_t,U_{t-9}|x} &= M_{U_t|U_t^*,x} D_{1|U_t^*,x} M_{U_t^*,U_{t-9}|x} \left(M_{U_t|U_t^*,x} M_{U_t^*,U_{t-9}|x}\right)^{-1} \\ &= M_{U_t|U_t^*,x} D_{1|U_t^*,x} \left(M_{U_t^*,U_{t-9}|x} M^{-1}_{U_t^*,U_{t-9}|x}\right) M^{-1}_{U_t|U_t^*,x} \\ &= M_{U_t|U_t^*,x} D_{1|U_t^*,x} M^{-1}_{U_t|U_t^*,x}. \end{aligned} \tag{6}$$

This equation implies that the observed matrix on the left-hand-side (LHS) has an eigenvalue-eigenvector decomposition on the RHS. The three eigenvalues are the three diagonal entries in $D_{1|U_t^*,x}$ and the three eigenvectors are the three columns in $M_{U_t|U_t^*,x}$. Note that each column of $M_{U_t|U_t^*,x}$ is a distribution so that the column sum is 1, which implies that the eigenvectors are normalized. Assumption 4 implies that the eigenvalues are distinctive, and therefore, the three eigenvectors are linearly independent.

Assumption 5 implies that the true labor force status is the mode of the conditional distribution of the self-reported labor force status in each column of the eigenvector matrix. After diagonalizing the directly-estimable matrix $M_{1,U_t,U_{t-9}|x} M^{-1}_{U_t,U_{t-9}|x}$, we rearrange the order of the eigenvectors such that the largest element of each column or each eigenvector, i.e, the mode of the corresponding distribution, is on the diagonal of the eigenvector matrix. Therefore, the ordering of the eigenvectors is fixed and the the eigenvector matrix $M_{U_t|U_t^*,x}$ is uniquely determined from the eigenvalue-eigenvector decomposition of the observed matrix $M_{1,U_t,U_{t-9}|x} M^{-1}_{U_t,U_{t-9}|x}$. *QED.*

3 Evaluation of Assumptions 1 &2 by Monte Carlo simulations

In this section, we use simulated data to show the robustness of the estimator in Feng and Hu (2011). First, we present a baseline data generating process (DGP) which satisfies all the maintained assumptions, and show the consistency of our estimator. Second, we let the DGP deviate from the baseline case to check the robustness of our estimator when each of the assumptions is violated.

3.1 Simulation setups

We start with the definition of notations. Let U_t^* and U_t denote the true and self-reported labor force status (LFS) in period t, respectively. The marginal distribution of the true LFS is denoted as:

$$\Pr(U_t^*) = \left[\Pr(U_t^* = 1), \Pr(U_t^* = 2), \Pr(U_t^* = 3)\right]^T,$$

where $\Pr(U_t^* = k)$ is the probability that the true LFS is k (1:employed, 2:unemployed, 3:not-in-labor-force). Given the marginal distribution, we may generate the true LFS for each observation in our simulated sample. We let the underlying true LFS follow a first-order Markov process, defined by the following Markovian transition matrix:

$$M_{U_t^*|U_{t-1}^*} = \left[\Pr(U_t^* = i|U_{t-1}^* = j)\right]_{i,j},$$

where $\Pr(U_t^* = i|U_{t-1}^* = j)$ is the conditional probability $\Pr(U_t^* = i|U_{t-1}^* = j)$. We assume the Markov kernal is time-invariant. Therefore, the two-period Markov transition matrix is

$$M_{U_t^*|U_{t-2}^*} = M_{U_t^*|U_{t-1}^*} M_{U_{t-1}^*|U_{t-2}^*} = M_{U_t^*|U_{t-1}^*}^2.$$

In general, a k-period transition matrix is $M_{U_t^*|U_{t-k}^*} = M_{U_t^*|U_{t-1}^*}^k$. We generate the series of LFS according to these conditional probabilities. The self-reported LFS U_t is generated according to the true LFS U_t^* and the misclassification probability

$$M_{U_t|U_t^*} = \left[\Pr(U_t = i|U_t^* = j)\right]_{i,j}.$$

3.1.1 Setup #1: consistency under maintained assumptions

First, we present the baseline DGP which satisfies all the maintained assumptions to show the consistency of our estimator.

We start by choosing the marginal distribution of the true LFS at period $t-10$, $\Pr(U^*_{t-10})$ and the Markov transition matrix $M_{U^*_t|U^*_{t-1}}$, where parameter values are chosen to mimic real CPS data. Each observation contains U^*_t and U_t in several periods, which are genreated as follows:

Step 1: draw the true LFS U^*_{t-10} at period $t-10$ according to the distribution $\Pr(U^*_{t-10})$;

Step 2: draw U^*_{t-9} according to the Markovian transition matrix $M_{U^*_t|U^*_{t-1}}$ and U^*_{t-10}. That means if U^*_{t-10} in step 1 equals 1, we use the distribution in the first column of $M_{U^*_t|U^*_{t-1}}$ to generate U^*_{t-9}; if U^*_{t-10} in step 1 equals 2, we use the second column of $M_{U^*_t|U^*_{t-1}}$; if U^*_{t-10} in step 1 equals 3, we use the third column of $M_{U^*_t|U^*_{t-1}}$;

Step 3, draw U^*_{t-8} using U^*_{t-9} in step 2 and $M_{U^*_t|U^*_{t-1}}$;

Step 4, draw U^*_{t-1} using U^*_{t-8} in step 3 and $M_{U^*_t|U^*_{t-7}} = M^7_{U^*_t|U^*_{t-1}}$;

Step 5, draw U^*_t using U^*_{t-1} in step 4 and $M_{U^*_t|U^*_{t-1}}$;

Step 6, draw U^*_{t+1} using U^*_t in step 5 and $M_{U^*_t|U^*_{t-1}}$;

After we have generated the true LFS in six periods $\left(U^*_{t+1}, U^*_t, U^*_{t-1}, U^*_{t-8}, U^*_{t-9}, U^*_{t-10}\right)$. we then generate the observed (misreported) LFS.

Step 7, draw U_s using U^*_s and $M_{U_t|U^*_t}$, respectively for $s = t+1, t, t-1, t-8, t-9, t-10$. The observed LFS $U_{t+1}, U_t, U_{t-1}, U_{t-8}, U_{t-9}, U_{t-10}$ are generated independently one by one.

In order to show consistency, we only need (U_{t+1}, U_t, U_{t-9}) in each observation. We then repeat the steps 1-7 N times to obtain an i.i.d. sample containing $\{U_{i,t+1}, U_{i,t}, U_{i,t-9}\}$ for $i = 1, 2, ..., N$.

We choose the following parameter values to mimic the observed CPS data:

$$M_{U_t|U^*_t} = \begin{bmatrix} 0.98 & 0.2 & 0.01 \\ 0.01 & 0.6 & 0.01 \\ 0.01 & 0.2 & 0.98 \end{bmatrix}, \Pr(U^*_{t-10}) = \begin{bmatrix} 0.6256 \\ 0.0544 \\ 0.32 \end{bmatrix}$$

$$M_{U^*_t|U^*_{t-1}} = \begin{bmatrix} 0.98 & 0.1 & 0.015 \\ 0.01 & 0.85 & 0.005 \\ 0.01 & 0.05 & 0.98 \end{bmatrix}.$$

Note that all simulation results are qualitatively robust to perturbations of parameter values within reasonable ranges. For brevity, we only report results for the parameter values as chosen.

We then apply our estimator to this simulated sample of $\{U_{i,t+1}, U_{i,t}, U_{i,t-9}\}$ to estimate $M_{U_t|U_t^*}$ as well as U_t^* to check the consistency of our estimator.

3.1.2 Setup #2: checking robustness of assumption 1

In this subsection, we relax assumption 1 in the DGP by allowing the misclassification probability matrix $M_{U_t|U_t^*}$ to vary with the self-reported LFS U_{t-1} or the true LFS U_{t-1}^*.

Case 1: reported LFS depends on last period true LFS In this case, We relax our assumption 1 to allow the misreporting probability to depend on the true labor force status in the previous period. That is,

$$\begin{aligned} \Pr(U_t|U_t^*, U_{<t}, U_{<t}^*) &= \Pr(U_t|U_t^*, U_{t-1}^*) \\ &\neq \Pr(U_t|U_t^*). \end{aligned}$$

Under this relaxed version, we only need to change step 7 in the baseline setup #1 as follows:

Step 7, draw U_s using U_s^*, U_{s-1}^* and $\Pr(U_t|U_t^*, U_{t-1}^*)$ respectively for $s = t+1, t, t-9$.

The conditional probability $\Pr(U_t|U_t^*, U_{t-1}^*)$ may be expressed as three misclassification probabilities: $\Pr(U_t|U_t^*, U_{t-1}^* = 1)$, $\Pr(U_t|U_t^*, U_{t-1}^* = 2)$, and $\Pr(U_t|U_t^*, U_{t-1}^* = 3)$. In matrix notation, we may have

$$M_{U_t|U_t^*,U_{t-1}^*} \equiv \left[\begin{array}{ccc} M_{U_t|U_t^*,U_{t-1}^*=1} & M_{U_t|U_t^*,U_{t-1}^*=2} & M_{U_t|U_t^*,U_{t-1}^*=3} \end{array} \right].$$

We may allow $M_{U_t|U_t^*,U_{t-1}^*=k}$ for $k = 1, 2, 3$ to deviate from the baseline misclassification probability $M_{U_t|U_t^*}$. Obviously, there are many ways to deviate from $M_{U_t|U_t^*}$ or $\Pr(U_t|U_t^*)$ to $M_{U_t|U_t^*,U_{t-1}^*=k}$ or $\Pr(U_t|U_t^*, U_{t-1}^* = k)$. In our simulation, the matrices $M_{U_t|U_t^*,U_{t-1}^*=k}$ are generated by letting the entries in $M_{U_t|U_t^*}$ to deviate according to the confidence intervals in the baseline case.

Let the original

$$M_{U_t|U_t^*} = \left[\begin{array}{ccc} m_{1|1} & m_{1|2} & m_{1|3} \\ m_{2|1} & m_{2|2} & m_{2|3} \\ m_{3|1} & m_{3|2} & m_{3|3} \end{array} \right].$$

Under assumption 1, we have $M_{U_t|U_t^*,U_{t-1}^*} = \left[\begin{array}{ccc} M_{U_t|U_t^*} & M_{U_t|U_t^*} & M_{U_t|U_t^*} \end{array} \right]$. This misclassification matrix transforms joint distribution of true LFS in periods t and $t-1$ into observed LFS at period t, i.e., $\Pr(U_t) = M_{U_t|U_t^*,U_{t-1}^*} \Pr(U_t^*, U_{t-1}^*)$, where

$$\Pr(U_t) = \left[\begin{array}{c} p(U_t = 1) \\ p(U_t = 2) \\ p(U_t = 3) \end{array} \right]$$

and

$$\Pr(U_t^*, U_{t-1}^*) = \left[\begin{array}{c} p(U_t^* = 1, U_{t-1}^* = 1) \\ p(U_t^* = 2, U_{t-1}^* = 1) \\ p(U_t^* = 3, U_{t-1}^* = 1) \\ p(U_t^* = 1, U_{t-1}^* = 2) \\ p(U_t^* = 2, U_{t-1}^* = 2) \\ p(U_t^* = 3, U_{t-1}^* = 2) \\ p(U_t^* = 1, U_{t-1}^* = 3) \\ p(U_t^* = 2, U_{t-1}^* = 3) \\ p(U_t^* = 3, U_{t-1}^* = 3) \end{array} \right].$$

In order to relax assumption 1, we allow the misclassification probabilities $m_{i|j} = \Pr(U_t = i|U_t^* = j)$ to vary according to their confidence intervals. Let the estimated standard error of $m_{i|j}$ be $s_{i|j}$, then obtain the 95% confidence interval (CI) $\left[\underline{m}_{i|j}, \overline{m}_{i|j}\right]$. Define:

$$\underline{M_{U_t|U_t^*}} = \left[\begin{array}{lll} 1 - \underline{m}_{2|1} - \underline{m}_{3|1} & \underline{m}_{1|2} & \underline{m}_{1|3} \\ \underline{m}_{2|1} & 1 - \underline{m}_{1|2} - \underline{m}_{3|2} & \underline{m}_{2|3} \\ \underline{m}_{3|1} & \underline{m}_{3|2} & 1 - \underline{m}_{1|3} - \underline{m}_{2|3} \end{array} \right],$$

$$\overline{M_{U_t|U_t^*}} = \left[\begin{array}{lll} 1 - \overline{m}_{2|1} - \overline{m}_{3|1} & \overline{m}_{1|2} & \overline{m}_{1|3} \\ \overline{m}_{2|1} & 1 - \overline{m}_{1|2} - \overline{m}_{3|2} & \overline{m}_{2|3} \\ \overline{m}_{3|1} & \overline{m}_{3|2} & 1 - \overline{m}_{1|3} - \overline{m}_{2|3} \end{array} \right],$$

which are the deviated misclassification probability matrices generated by allowing the off-diagonal entries to deviate to the upper or lower bounds of their confidence intervals. Note that the off-diagonal elements are misclassification error probabilities while the diagonal elements are probabilities that the LFS is corrected reported.

In general, we can consider the following deviations:

$$M_{U_t|U_t^*,U_{t-1}^*} = \left[\begin{array}{ccc} M_{U_t|U_t^*,U_{t-1}^*=1} & M_{U_t|U_t^*,U_{t-1}^*=2} & M_{U_t|U_t^*,U_{t-1}^*=3} \end{array} \right],$$

where

$$M_{U_t|U_t^*,U_{t-1}^*=k} = (1-\lambda_k)\,\underline{M_{U_t|U_t^*}} + \lambda_k \overline{M_{U_t|U_t^*}}$$

with different combinations of the constants $(\lambda_1, \lambda_2, \lambda_3)$. Note that there are large numbers of possible combinations. For example, when we consider three possible values, $0, 0.5$,and 1, for λ_k, which corresponds to the 95% lower bound, the baseline value (no deviation), and the 95% upper bound of the misclassification errors, there are $3^3 - 3 = 24$ cases in which the $\lambda_1, \lambda_2, \lambda_3$ are not the same. (if $\lambda_1 = \lambda_2 = \lambda_3$ then assumption 1 holds).

We choose the parameters to mimic the observed CPS sample as follows:

$$M_{U_t|U_t^*} = \begin{bmatrix} 0.98 & 0.2 & 0.01 \\ 0.01 & 0.6 & 0.01 \\ 0.01 & 0.2 & 0.98 \end{bmatrix}, M_{U_t^*|U_{t-1}^*} = \begin{bmatrix} 0.98 & 0.1 & 0.015 \\ 0.01 & 0.85 & 0.005 \\ 0.01 & 0.05 & 0.98 \end{bmatrix}$$

$$\underline{M_{U_t|U_t^*}} = \begin{bmatrix} 0.984 & 0.16 & 0.008 \\ 0.008 & 0.68 & 0.008 \\ 0.008 & 0.16 & 0.984 \end{bmatrix}, \overline{M_{U_t|U_t^*}} = \begin{bmatrix} 0.976 & 0.24 & 0.012 \\ 0.012 & 0.52 & 0.012 \\ 0.012 & 0.24 & 0.976 \end{bmatrix} \text{ and } \Pr(U_{t-10}^*) = \begin{bmatrix} 0.6256 \\ 0.0544 \\ 0.32 \end{bmatrix}.$$

Case 2: reported LFS depends on last period reported LFS In case 2, we relax Assumption 1 to

$$\begin{aligned} \Pr(U_t|U_t^*, U_{<t}, U_{<t}^*) &= \Pr(U_t|U_t^*, U_{t-1}) \\ &\neq \Pr(U_t|U_t^*), \end{aligned}$$

where the misclassification probabilities may be different for different self-reported LFS U_{t-1} in the previous period. Under this relaxed version, we only need to change step 7 in the baseline setup #1 as follows:

Step 7, draw U_s using U_s^*, U_{s-1} and $\Pr(U_t|U_t^*, U_{t-1})$ respectively for $s = t+1, t, t-9$.

Similar to Case 1, the conditional probability $\Pr(U_t|U_t^*, U_{t-1})$ may be considered as the joint of three distinct misclassification probabilities, i.e., $\Pr(U_t|U_t^*, U_{t-1} = 1)$, $\Pr(U_t|U_t^*, U_{t-1} = 2)$, and $\Pr(U_t|U_t^*, U_{t-1} = 3)$. In matrix notation, we have

$$M_{U_t|U_t^*,U_{t-1}} \equiv \left[\begin{array}{ccc} M_{U_t|U_t^*,U_{t-1}=1} & M_{U_t|U_t^*,U_{t-1}=2} & M_{U_t|U_t^*,U_{t-1}=3} \end{array}\right],$$

with

$$M_{U_t|U_t^*,U_{t-1}=k} = (1-\lambda_k)\,\underline{M_{U_t|U_t^*}} + \lambda_k \overline{M_{U_t|U_t^*}}.$$

The rest of the simulation setup and the parameters chosen are the same as in Case 1.

Case 3: reported LFS depends on both last period true LFS and last period reported LFS In case 3, we consider the more general relaxation of Assumption 1 to

$$\begin{aligned} \Pr(U_t|U_t^*,U_{<t},U_{<t}^*) &= \Pr(U_t|U_t^*,U_{t-1}^*,U_{t-1}) \\ &\neq \Pr(U_t|U_t^*), \end{aligned}$$

where the misclassification probabilities may be different for different self-reported LFS U_{t-1} as well as true LFS U_{t-1}^* in the previous period. Because possible deviations are too large to be tractable, following a suggestion by a referee, we consider a special case in which:

$$\Pr(U_t|U_t^*,U_{<t},U_{<t}^*) = \begin{cases} p \times I\left(U_t = U_{t-1}\right) + (1-p)\Pr(U_t|U_t^*) & \text{if } U_t^* = U_{t-1}^* \\ \Pr(U_t|U_t^*) & \text{otherwise} \end{cases},$$

where $I(\cdot)$ is a 0-1 indicator function.

This case allows us to directly evaluate how correlated reporting behavior affects our results. The idea is that people who misreport in one period and have the same true LFS in the next period are likely to report the same way as in the previous period.

Under this relaxed version, we only need to add one step to the baseline setup #1 as follows:

Step 8, replace U_t as U_{t-1} with probability p if $U_t^* = U_{t-1}^*$.

All parameters are the same as in the baseline setup #1, except p, which is allowed to vary from 0 to 1 to assess the robustness of our estimator.

3.1.3 Setup #3: checking robustness of Assumption 2

In this section, we relax Assumption 2 to

$$\Pr(U_{t+1}^*|U_t^*,U_{t-9}^*) \neq \Pr(U_{t+1}^*|U_t^*).$$

Under this relaxed assumption, we only need to change steps 5 and 6 for simplicity in setup #1 as follows:

Step 5, draw U_t^* using U_{t-1}^*, U_{t-10}^* and $\Pr(U_{t+1}^*|U_t^*, U_{t-9}^*)$.

Step 6, draw U_{t+1}^* using U_t^*, U_{t-9}^* and $\Pr(U_{t+1}^*|U_t^*, U_{t-9}^*)$.

We start with the original Markovian transition kernel $M_{U_{t+1}^*|U_t^*} = M_{U_t^*|U_{t-1}^*} = \begin{bmatrix} m_{1|1} & m_{1|2} & m_{1|3} \\ m_{2|1} & m_{2|2} & m_{2|3} \\ m_{3|1} & m_{3|2} & m_{3|3} \end{bmatrix}$. Under assumption 2, we have $M_{U_{t+1}^*|U_t^*,U_{t-9}^*} = \begin{bmatrix} M_{U_t^*|U_{t-1}^*} & M_{U_t^*|U_{t-1}^*} & M_{U_t^*|U_{t-1}^*} \end{bmatrix}$. We may consider $M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k}$ for $k = 1, 2, 3$ as deviations from the baseline Markovian transition probability $M_{U_{t+1}^*|U_t^*}$. Similar to what was discussed in the previous subsection, there are many ways to deviate from $M_{U_{t+1}^*|U_t^*}$ or $\Pr(U_{t+1}^*|U_t^*)$ to $M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k}$ or $\Pr(U_{t+1}^*|U_t^*, U_{t-9}^* = k)$. In our simulation, the matrices $M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k}$ are generated by letting the entries in $M_{U_{t+1}^*|U_t^*}$ to deviate according to their confidence intervals in the baseline case.

In order to relax assumption 2, we allow the Markov transition probabilities $m_{i|j} = \Pr(U_{t+1}^* = i|U_t^* = j)$ to vary according to their confidence intervals. Let the estimated standard error of $m_{i|j}$ be $s_{i|j}$, then obtain the 95% confidence interval (CI) $\left[\underline{m}_{i|j}, \overline{m}_{i|j}\right]$. We define

$$\underline{M_{U_t^*|U_{t-1}^*}} = \begin{bmatrix} 1 - \underline{m}_{2|1} - \underline{m}_{3|1} & \underline{m}_{1|2} & \underline{m}_{1|3} \\ \underline{m}_{2|1} & 1 - \underline{m}_{1|2} - \underline{m}_{3|2} & \underline{m}_{2|3} \\ \underline{m}_{3|1} & \underline{m}_{3|2} & 1 - \underline{m}_{1|3} - \underline{m}_{2|3} \end{bmatrix}$$

$$\overline{M_{U_t^*|U_{t-1}^*}} = \begin{bmatrix} 1 - \overline{m}_{2|1} - \overline{m}_{3|1} & \overline{m}_{1|2} & \overline{m}_{1|3} \\ \overline{m}_{2|1} & 1 - \overline{m}_{1|2} - \overline{m}_{3|2} & \overline{m}_{2|3} \\ \overline{m}_{3|1} & \overline{m}_{3|2} & 1 - \overline{m}_{1|3} - \overline{m}_{2|3} \end{bmatrix},$$

which are the deviated Markov transition matrices generated by allowing the off-diagonal entries (error probabilities) to deviate to the upper or lower bounds of their confidence intervals.

In general, we can consider the following deviations:

$$M_{U_{t+1}^*|U_t^*,U_{t-9}^*} \equiv \begin{bmatrix} M_{U_{t+1}^*|U_t^*,U_{t-9}^*=1} & M_{U_{t+1}^*|U_t^*,U_{t-9}^*=2} & M_{U_{t+1}^*|U_t^*,U_{t-9}^*=3} \end{bmatrix},$$

with

$$M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k} = (1 - \lambda_k)\, \underline{M_{U_t^*|U_{t-1}^*}} + \lambda_k \overline{M_{U_t^*|U_{t-1}^*}}.$$

with different combinations of the constants $(\lambda_1, \lambda_2, \lambda_3)$. Again, there are large numbers of possible combinations. For example, when we consider three possible values, $0, 0.5$,and 1, for λ_k, which corresponds to the 95% lower bound, the baseline value (no deviation), and the 95% upper bound of the misclassification errors, there are $3^3 - 3 = 24$ cases in which the $\lambda_1, \lambda_2, \lambda_3$ are not the same. (if $\lambda_1 = \lambda_2 = \lambda_3$ then assumption 2 holds).

We choose the following parameter values:

$$\underline{M_{U_t^*|U_{t-1}^*}} = \begin{bmatrix} 0.984 & 0.08 & 0.013 \\ 0.008 & 0.89 & 0.003 \\ 0.008 & 0.03 & 0.984 \end{bmatrix}, \overline{M_{U_t^*|U_{t-1}^*}} = \begin{bmatrix} 0.976 & 0.12 & 0.017 \\ 0.012 & 0.81 & 0.007 \\ 0.012 & 0.07 & 0.976 \end{bmatrix}.$$

Other parameter values are the same as in the baseline setup #1.

3.2 Simulation results

This section reports all simulation results. Based on the generated data, we produce the following estimates:

Unemp_C: corrected unemployment rate, which was estimated from observed data using the proposed estimator.

Unemp_R: reported unemployment rate, which are uncorrected and subject to misclassification error.

Unemp_T: true unemployment rate implied by the generated sample.

LFP_C: corrected labor force participation rate.

LFP_R: reported labor force participation rate.

LFP_T: true labor force participation rate.

In all cases we report both the mean value of the statistic as well as the 95% confidence lower and upper bounds from 500 repetitions. In all tables we set samples size to be 100,000 in order to match the width of confidence intervals of the estimates based on the observed CPS data. The only exception is Table 1 where we vary sample size to show consistency.

3.2.1 Setup #1: consistency of our estimator

Table A2 shows the results when we maintain all assumptions in the paper. One can see that as sample size increases, the estimated *Unemp_C* become closer to the true underlying unemployment rate $Unemp\_T$, which is 7.98%. Even with sample size at 10,000, the mean of our estimates from 500 repetitions are quite close to the true value and the 95% confidence intervals always cover the true value. When sample size is increased to 100,000, mean estimate of $Unemp\_C$ is 8.02%, which is very close to $Unemp\_T$ and the width of the confidence interval become relatively small (2.4%). In contrast, the reported $Unemp\_R$ has a mean value of 6.32% which severely under-estimate the true level of unemployment. In addition, its 95% confidence intervals do not cover $Unemp\_T$ in all cases.

Results for Labor Force Participation (LFP) rate are quite similar. With sample size of 10,000, the corrected mean of LFP_C is 65.8%, which is exactly the true LFP. On the other hand, reported LFP has a relatively large and statistically significant bias.

We have also reported $\Pr(U_t = U_{t-1}|U_t^* = U_{t-1}^*)$, which measures whether people tend to report the same LFS if their true LFS does not change. Note that although we only condition U_t on U_t^*, because the misclassification probabilities are the same for all time periods and because the rate of transition among different underlying true LFS is relatively slow, (mis)reporting behaviors across time are correlated. In the generated data, for those who has the same true LFS in periods t-1 and t, about 94% would report the same LFS in both periods. Thus our model setup is able to capture the observed correlations in (mis)reporting across time.

3.2.2 Setup #2 case 1: relaxing Assumption 1 to allow observed LFS to depend on last period true LFS

We then report simulation results when we relax assumption 1 to allow observed LFS to also depends on last period true LFS. As described in the previous section, the degree of deviation is controlled by λ. In Table A3.1, we consider the 24 combination where λ can take values of 0, 0.5 and 1. Note that in this case we have:

$$
\begin{aligned}
& M_{U_t|U_t^*,U_{t-1}^*=k} = (1-\lambda_k)\,\underline{M_{U_t|U_t^*}} + \lambda_k \overline{M_{U_t|U_t^*}} \\
& = \underline{M_{U_t|U_t^*}} = \begin{bmatrix} 0.984 & 0.16 & 0.008 \\ 0.008 & 0.68 & 0.008 \\ 0.008 & 0.16 & 0.984 \end{bmatrix} if\ \lambda_k = 0 \\
& = M_{U_t|U_t^*} = \begin{bmatrix} 0.98 & 0.2 & 0.01 \\ 0.01 & 0.6 & 0.01 \\ 0.01 & 0.2 & 0.98 \end{bmatrix} if\ \lambda_k = 0.5 \\
& = \overline{M_{U_t|U_t^*}} = \begin{bmatrix} 0.976 & 0.24 & 0.012 \\ 0.012 & 0.52 & 0.012 \\ 0.012 & 0.24 & 0.976 \end{bmatrix} if\ \lambda_k = 1
\end{aligned}
$$

The corrected unemployment rate using our proposed method ($Unemp\_C$) are relatively close to the true unemployment rate ($Unemp\_T$) and the 95% confidence interval for $Unemp\_C$ always cover the true value of unemployment, which is 7.98%. Also, the width of the 95% confidence interval is relatively small and close to the case with no deviations (see column 3 of Table A2). On the other hand, the reported unemployment rate ($Unemp\_R$) consistently underestimate the true level of unemployment rate, and its 95% upper intervals are always lower than $Unemp\_T$. Thus our proposed estimator consistently outperforms the reported (uncorrected) even when assumption 1 is violated to some extent.

Table A3.2 consider the case with slightly more deviations, and presents results for the 24 possible combinations of λ taking values of -0.5, 0.5 and 1.5. In this case, we have:

$$M_{U_t|U_t^*,U_{t-1}^*=k} = (1-\lambda_k)\underline{M_{U_t|U_t^*}} + \lambda_k \overline{M_{U_t|U_t^*}}$$
$$= \begin{bmatrix} 0.988 & 0.12 & 0.006 \\ 0.006 & 0.76 & 0.006 \\ 0.006 & 0.12 & 0.988 \end{bmatrix} if\ \lambda_k = -0.5$$
$$= M_{U_t|U_t^*} = \begin{bmatrix} 0.98 & 0.2 & 0.01 \\ 0.01 & 0.6 & 0.01 \\ 0.01 & 0.2 & 0.98 \end{bmatrix} if\ \lambda_k = 0.5$$
$$= \begin{bmatrix} 0.972 & 0.28 & 0.014 \\ 0.014 & 0.44 & 0.014 \\ 0.014 & 0.28 & 0.972 \end{bmatrix} if\ \lambda_k = 1.5$$

As expected, results shown in Table A3.2 are somewhat worse than those in Table A3.1. For example, when $\{\lambda_1, \lambda_2, \lambda_3\} = \{0.5, -0.5, 0.5\}$, the mean of $Unemp\_C$ is 9.19%, implying a upward bias of 1.21%, and also with the width of the confidence interval being 3.4%. Nevertheless, to some extent results in Table A3.2 are still acceptable because in all cases the 95% confidence intervals contain the ture value of unemployment, which is 7.98%. In contrast, none of the confidence intervals for $Unemp\_R$ cover the true value of unemployment rate.

It is tempting to test whether our estimator could "fail" if there are "too much" deviations in the misclassification probabilities. In Table A3.3 we allow λ to take values between -3 and 4. When λ are too far away out of the [0,1] range, the implied misclassification matrix may contain elements smaller than 0 or larger than 1. To deal with this case, we apply a normalization procedure, which first transfer any elements greater than 1 to 1, and transfer any elements smaller than 0 to 0, and then divide each elements by its column sum to make sure each column sum to 1. After the normalization, we have:

$$M_{U_t|U_t^*,U_{t-1}^*=k} =$$
$$= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} if\ \lambda_k = -3$$
$$= \begin{bmatrix} 0.952 & 0.48 & 0.024 \\ 0.024 & 0.04 & 0.024 \\ 0.024 & 0.48 & 0.952 \end{bmatrix} if\ \lambda_k = 4$$

Table A3.3 reports the results. In general the biases are quite large and the confidence intervals are too wide to be informative. For example, in the last row we have the mean value of corrected unemployment rate of 28.5% while the true value is 7.98%. The 95% confidence lower bound is 0.65% and the upper bound is 81%. Thus it is possible for the estimator to "fail" if the deviations from assumption 1 are too large.

Corresponding results for labor force participation rates (LFP) are presented in Tables A4.1-4.3. Table A4.1 and A4.2 report results when λs are relatively small. The corrected LFP has mean values close to the true LFP, which is 65.8%, and the 95% confidence interval is relatively tight. Table A4.3 report results when λs are relatively large. Even in this case the biases are not big compared to results reported in Table A3.3 for unemployment rates. But again in the last row, the mean of corrected LFP is 73.7%, representing an upward bias of around 8%.

3.2.3 Setup #2 case 2: relaxing Assumption 1 to allow observed LFS to depend on last period observed LFS

We then consider a different type of deviation to assumption 1, and allow observed LFS U_t to depend on both U_t^* and last period observed LFS U_{t-1}. The setup and parameters chosen are otherwise similar to the previous case.

In Table A5.1, we consider the 24 combination where λ can take values of 0, 0.5 and 1. Similar to Table A3.1, the corrected unemployment rate using our proposed method (*Unemp_C*) are relatively close to the true unemployment rate (*Unemp_T*) and the 95% confidence interval for *Unemp_C* always cover the true value of unemployment, which is 7.98%. Also, the width of the 95% confidence interval is relatively small and close to the case with no deviations (see column 3 of Table A2). On the other hand, the reported unemployment rate (*Unemp_R*) consistently underestimate the true level of unemployment rate, and its 95% upper intervals are always lower than *Unemp_T*.

Table A5.2 consider the case with slightly more deviations, and presents results for the 24 possible combinations of λ taking values of -0.5, 0.5 and 1.5. As expected, results shown in Table A5.2 are somewhat worse than those in Table A5.1 but still acceptable.

Table A5.3 presents results when λs are allowed to vary between -3 and 4. Note here we have rather large biases and wide confidence bounds. For example, in the last row of table A5.3, mean value of $Unemp\_C$ is as large as 71.9%.

Table A6.1-6.3 display results for labor force participation rates (LFP). Once again, the corrected LFP using our proposed method (LFP_C) are very close to the true LFP (LFP_T) and the 95% confidence interval for LFP_C always cover the true value of LFP, which is 65.8%. This is even the case when λs are relatively large as in Table A6.3. On the other hand, the reported LFP (LFP_R) consistently underestimate the true level of LFP and its 95% confidence intervals do not cover the true values of LFP.

3.2.4 Setup #2 case 3: reported LFS depends on both last period true LFS and last period reported LFS

We then report results for setup #2 case 3, allowing U_t to depends on U_t^* as well as U_{t-1}^* and U_{t-1}. But we only focus on a very special case in which people consistently (mis)report. When $U_t^* = U_{t-1}^*$, we replace the value of U_t to be equal to U_{t-1} with probability p, which ranges from 0 to 1 at the interval of 0.1.

Table A7 reports results for unemployment rates and Table A8 reports results for LFP rates. The results are very similar to the no deviation case and our corrected estimator works very well. The results are kind of expected because in the baseline case $\Pr(U_t = U_{t-1} | U_t^* = U_{t-1}^*)$ is already around 94%. But the results here more formally show that our estimator is robust to consistent (mis)reporting behavior.

3.2.5 Setup #3: relaxing Assumption 2

Lastly, we report simulation results when we relax assumption 2 to allow U_{t+1}^* depends on both U_t^* and U_{t-9}^*. As described in the previous section, the degree of deviation is controlled by λ. In Table A9.1, we consider the 24 combination where λ can take values of 0, 0.5 and 1. Note that in this case we have:

$$
\begin{aligned}
&M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k} = (1-\lambda_k)\,\underline{M_{U_{t+1}^*|U_t^*}} + \lambda_k\overline{M_{U_{t+1}^*|U_t^*}}\\
&= \underline{M_{U_{t+1}^*|U_t^*}} = \begin{bmatrix} 0.984 & 0.08 & 0.013 \\ 0.008 & 0.89 & 0.003 \\ 0.008 & 0.03 & 0.984 \end{bmatrix} \; if\ \lambda_k = 0\\
&= M_{U_{t+1}^*|U_t^*} = \begin{bmatrix} 0.98 & 0.1 & 0.015 \\ 0.01 & 0.85 & 0.005 \\ 0.01 & 0.05 & 0.98 \end{bmatrix} \; if\ \lambda_k = 0.5\\
&= \overline{M_{U_{t+1}^*|U_t^*}} = \begin{bmatrix} 0.976 & 0.12 & 0.017 \\ 0.012 & 0.81 & 0.007 \\ 0.012 & 0.07 & 0.976 \end{bmatrix} \; if\ \lambda_k = 1
\end{aligned}
$$

The corrected unemployment rate using our proposed method (*Unemp_C*) are relatively close to the true unemployment rate (*Unemp_T*) and the 95% confidence interval for *Unemp_C* always cover the true value of unemployment. Also, the width of the 95% confidence interval is relatively small and close to the case with no deviations (see column 3 of Table A2). On the other hand, the reported unemployment rate (*Unemp_R*) consistently underestimate the true level of unemployment rate, and its 95% upper intervals are always lower than *Unemp_T*. Thus our proposed estimator consistently outperforms the reported (uncorrected) even when assumption 2 is violated to some extent.

Table A9.2 considers the case with slightly more deviations, and presents results for the 24 possible combinations of λ taking values of -0.5, 0.5 and 1.5. In this case, we have:

$$
\begin{aligned}
&M_{U_{t+1}^*|U_t^*,U_{t-9}^*=k} = (1-\lambda_k)\,\underline{M_{U_{t+1}^*|U_t^*}} + \lambda_k\overline{M_{U_{t+1}^*|U_t^*}}\\
&= \begin{bmatrix} 0.988 & 0.06 & 0.011 \\ 0.006 & 0.93 & 0.001 \\ 0.006 & 0.01 & 0.988 \end{bmatrix} \; if\ \lambda_k = -0.5\\
&= M_{U_{t+1}^*|U_t^*} = \begin{bmatrix} 0.98 & 0.1 & 0.015 \\ 0.01 & 0.85 & 0.005 \\ 0.01 & 0.05 & 0.98 \end{bmatrix} \; if\ \lambda_k = 0.5\\
&= \begin{bmatrix} 0.972 & 0.14 & 0.019 \\ 0.014 & 0.77 & 0.009 \\ 0.014 & 0.09 & 0.972 \end{bmatrix} \; if\ \lambda_k = 1.5
\end{aligned}
$$

As expected, results shown in Table A9.2 are somewhat worse than those in Table A9.1. For example, when $\{\lambda_1, \lambda_2, \lambda_3\} = \{1.5, -0.5, -0.5\}$, the mean of *Unemp_C* is 8.82%, implying a upward bias of about 1%. Nevertheless, to some extent results in Table A9.2 are still acceptable because in all cases the 95% confidence intervals contain the true value of unemployment, which varies by the combinations of λs.

In contrast, none of the confidence intervals for $Unemp\_R$ cover the true value of unemployment rate.

We also test whether our estimator could "fail" if there are "too much" deviations in the Markovian assumption. In Table A9.3 we allow λ to take values between -3 and 4. When λ are too far away out of the [0,1] range, the implied transition matrix may contain elements smaller than 0 or larger than 1. To deal with this case, we apply a normalization procedure, which first transfer any elements greater than 1 to 1, and transfer any elements smaller than 0 to 0, and then divide each elements by its column sum to make sure each column sum to 1. After the normalization, we have:

$$M_{U^*_{t+1}|U^*_t,U^*_{t-9}=k} =$$
$$= \begin{bmatrix} 1 & 0 & 0.001 \\ 0 & 1 & 0 \\ 0 & 0 & 0.999 \end{bmatrix} if\ \lambda_k = -3$$
$$= \begin{bmatrix} 0.952 & 0.24 & 0.029 \\ 0.024 & 0.57 & 0.019 \\ 0.024 & 0.19 & 0.952 \end{bmatrix} if\ \lambda_k = 4$$

Table A9.3 reports the results. In some cases the biases are large and the 95% confidence intervals do not cover the true unemployment rate. For example, in the first row of Table A9.3 we see a statistically significant downward bias, while the last row shows a statistically significant upward bias.

Corresponding results for labor force participation rates (LFP) are presented in Tables A10.1-10.3. Table A10.1 and A10.2 report results when λs are relatively small. The corrected LFP has mean values close to the true LFP, and the 95% confidence interval is relatively tight. Table A10.3 report results when λs are relatively large. Results are better than reported in Table A9.3 because the 95% confidence intervals always cover true LFP. Thus violation of assumption 2 is a more severe issue for unemployment rates than for LFP.

Table A2: Simulation results under maintained assumptions

Sample size	10,000	100,000	1,000,000
Unemp_C (%)	8.60 (5.27, 14.38)	8.02 (6.86, 9.28)	7.98 (7.60, 8.36)
Unemp_R (%)	6.32 (5.68, 6.97)	6.32 (6.13, 6.50)	6.32 (6.27, 6.38)
Unemp_T (%)	7.98 (7.30, 8.62)	7.98 (7.76, 8.18)	7.98 (7.91, 8.04)
LFP_C (%)	66.1 (64.1, 70.1)	65.8 (65.1, 66.8)	65.8 (65.5, 66.0)
LFP_R (%)	64.8 (63.9, 65.8)	64.8 (64.5, 65.1)	64.8 (64.7, 64.9)
LFP_T (%)	65.8 (64.9, 66.8)	65.8 (65.5, 66.1)	65.8 (65.7, 65.9)
$\Pr(U_t = U_{t-1} \mid U_t^* = U_{t-1}^*)$	0.937 (0.932, 0.941)	0.937 (0.935, 0.938)	0.937 (0.936, 0.937)

Note: number of repetitions is 500 for each column. For each statistic listed we report mean as well as 95% lower and confidence bounds (in parentheses) based on the generated data.

Table A3.1: Simulation results for setup #2 case 1 (results for unemployment rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.0	1.0	0.5	7.94 (6.98, 9.03)	6.72 (6.52, 6.90)	7.98
1.0	1.0	0.0	7.98 (6.99, 9.14)	6.79 (6.59, 7.00)	7.98
1.0	0.5	1.0	8.26 (7.12, 9.56)	6.12 (5.95, 6.32)	7.98
1.0	0.5	0.5	8.13 (7.07, 9.24)	6.19 (6.01, 6.38)	7.98
1.0	0.5	0.0	8.13 (6.97, 9.47)	6.27 (6.08, 6.47)	7.98
1.0	0.0	1.0	8.38 (7.18, 9.72)	5.59 (5.41, 5.76)	7.98
1.0	0.0	0.5	8.37 (7.08, 9.67)	5.66 (5.49, 5.86)	7.98
1.0	0.0	0.0	8.35 (7.27, 9.61)	5.74 (5.56, 5.91)	7.98
0.5	1.0	1.0	7.92 (6.88, 8.98)	6.78 (6.59, 6.98)	7.98
0.5	1.0	0.5	7.86 (6.86, 8.91)	6.85 (6.66, 7.04)	7.98
0.5	1.0	0.0	7.82 (6.73, 8.97)	6.92 (6.73, 7.11)	7.98
0.5	0.5	1.0	8.04 (6.91, 9.16)	6.25 (6.08, 6.44)	7.98
0.5	0.5	0.0	7.98 (7.02, 9.25)	6.39 (6.22, 6.57)	7.98
0.5	0.0	1.0	8.31 (7.09, 9.53)	5.71 (5.53, 5.89)	7.98
0.5	0.0	0.5	8.21 (6.88, 9.61)	5.78 (5.58, 5.96)	7.98
0.5	0.0	0.0	8.20 (7.01, 9.57)	5.87 (5.68, 6.05)	7.98
0.0	1.0	1.0	7.75 (6.76, 8.89)	6.90 (6.70, 7.12)	7.98
0.0	1.0	0.5	7.75 (6.67, 8.98)	6.98 (6.79, 7.18)	7.98
0.0	1.0	0.0	7.70 (6.57, 8.87)	7.04 (6.84, 7.23)	7.98
0.0	0.5	1.0	7.90 (6.86, 9.03)	6.37 (6.19, 6.59)	7.98
0.0	0.5	0.5	7.83 (6.83, 9.06)	6.44 (6.25, 6.62)	7.98
0.0	0.5	0.0	7.91 (6.83, 9.20)	6.52 (6.33, 6.71)	7.98
0.0	0.0	1.0	8.18 (6.95, 9.71)	5.84 (5.67, 6.02)	7.98
0.0	0.0	0.5	8.09 (6.88, 9.44)	5.91 (5.75, 6.09)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A3.2: Simulation results for setup #2 case 1 (results for unemployment rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.5	1.5	0.5	7.96 (7.04, 9.04)	7.13 (6.93, 7.33)	7.98
1.5	1.5	−0.5	7.93 (6.97, 9.03)	7.26 (7.06, 7.46)	7.98
1.5	0.5	1.5	8.33 (7.36, 9.50)	5.93 (5.76, 6.11)	7.98
1.5	0.5	0.5	8.31 (7.32, 9.39)	6.08 (5.91, 6.26)	7.98
1.5	0.5	−0.5	8.22 (7.22, 9.51)	6.21 (6.03, 6.39)	7.98
1.5	−0.5	1.5	9.14 (7.60, 10.41)	4.85 (4.67, 5.02)	7.98
1.5	−0.5	0.5	8.86 (7.57, 10.48)	5.00 (4.84, 5.17)	7.98
1.5	−0.5	−0.5	8.99 (7.43, 10.23)	5.15 (4.99, 5.31)	7.98
0.5	1.5	1.5	7.79 (6.76, 8.88)	7.24 (7.04, 7.47)	7.98
0.5	1.5	0.5	7.76 (6.81, 8.91)	7.37 (7.19, 7.57)	7.98
0.5	1.5	−0.5	7.71 (6.59, 8.96)	7.51 (7.30, 7.72)	7.98
0.5	0.5	1.5	8.12 (7.16, 9.18)	6.18 (6.00, 6.34)	7.98
0.5	0.5	−0.5	7.96 (6.91, 9.19)	6.46 (6.26, 6.65)	7.98
0.5	−0.5	1.5	8.97 (7.27, 10.28)	5.10 (4.93, 5.27)	7.98
0.5	−0.5	0.5	9.19 (7.06, 10.46)	5.25 (5.09, 5.43)	7.98
0.5	−0.5	−0.5	8.81 (7.04, 10.18)	5.40 (5.23, 5.57)	7.98
−0.5	1.5	1.5	7.51 (6.54, 8.53)	7.48 (7.27, 7.70)	7.98
−0.5	1.5	0.5	7.49 (6.49, 8.66)	7.64 (7.44, 7.85)	7.98
−0.5	1.5	−0.5	7.46 (6.39, 8.80)	7.76 (7.55, 7.97)	7.98
−0.5	0.5	1.5	7.80 (6.74, 8.92)	6.43 (6.25, 6.61)	7.98
−0.5	0.5	0.5	7.77 (6.65, 9.00)	6.57 (6.39, 6.76)	7.98
−0.5	0.5	−0.5	7.73 (6.46, 9.10)	6.71 (6.52, 6.91)	7.98
−0.5	−0.5	1.5	8.59 (6.73, 9.82)	5.36 (5.18, 5.54)	7.98
−0.5	−0.5	0.5	8.32 (6.67, 9.78)	5.50 (5.32, 5.67)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A3.3: Simulation results for setup #2 case 1 (results for unemployment rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
−1.5	4.0	1.0	7.41 (6.64, 8.86)	9.39 (9.17, 9.62)	7.98
4.0	0.5	−3.0	8.42 (7.23, 9.83)	6.20 (6.00, 6.41)	7.98
−0.5	0.5	2.0	7.81 (6.73, 8.93)	6.35 (6.18, 6.54)	7.98
−0.5	−2.0	−2.5	47.30 (6.12, 93.44)	4.33 (4.15, 4.48)	7.98
−0.5	−2.5	0.0	46.16 (6.91, 92.39)	3.39 (3.25, 3.53)	7.98
3.0	3.5	−3.0	8.38 (7.35, 10.22)	8.76 (8.55, 8.95)	7.98
2.5	2.0	1.0	8.08 (7.21, 9.03)	7.33 (7.13, 7.55)	7.98
3.0	−3.0	−2.5	28.49 (0.65, 81.23)	2.41 (2.30, 2.52)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A4.1: Simulation results for setup #2 case 1 (results for LFP rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.0	1.0	0.5	65.78 (65.03, 66.56)	65.15 (64.83, 65.45)	65.78
1.0	1.0	0.0	65.78 (65.13, 66.64)	65.25 (64.94, 65.54)	65.78
1.0	0.5	1.0	65.93 (65.24, 66.77)	64.84 (64.57, 65.15)	65.78
1.0	0.5	0.5	65.83 (65.20, 66.65)	64.96 (64.69, 65.26)	65.78
1.0	0.5	0.0	65.81 (65.18, 66.68)	65.07 (64.76, 65.38)	65.78
1.0	0.0	1.0	65.94 (65.15, 66.81)	64.65 (64.33, 64.93)	65.78
1.0	0.0	0.5	65.91 (65.17, 66.93)	64.77 (64.50, 65.06)	65.78
1.0	0.0	0.0	65.90 (65.23, 66.80)	64.89 (64.64, 65.15)	65.78
0.5	1.0	1.0	65.80 (65.14, 66.62)	64.86 (64.57, 65.21)	65.78
0.5	1.0	0.5	65.77 (65.10, 66.52)	65.00 (64.71, 65.28)	65.78
0.5	1.0	0.0	65.72 (65.03, 66.58)	65.11 (64.83, 65.39)	65.78
0.5	0.5	1.0	65.81 (65.09, 66.60)	64.68 (64.39, 64.97)	65.78
0.5	0.5	0.0	65.79 (65.11, 66.72)	64.94 (64.62, 65.22)	65.78
0.5	0.0	1.0	65.91 (65.15, 66.81)	64.51 (64.22, 64.78)	65.78
0.5	0.0	0.5	65.89 (65.16, 66.94)	64.64 (64.35, 64.96)	65.78
0.5	0.0	0.0	65.84 (65.04, 66.80)	64.75 (64.46, 65.05)	65.78
0.0	1.0	1.0	65.73 (65.04, 66.55)	64.73 (64.44, 65.04)	65.78
0.0	1.0	0.5	65.71 (65.00, 66.54)	64.85 (64.51, 65.15)	65.78
0.0	1.0	0.0	65.69 (65.03, 66.59)	64.97 (64.65, 65.30)	65.78
0.0	0.5	1.0	65.78 (65.12, 66.52)	64.54 (64.22, 64.87)	65.78
0.0	0.5	0.5	65.74 (65.03, 66.51)	64.66 (64.35, 64.97)	65.78
0.0	0.5	0.0	65.78 (65.10, 66.77)	64.80 (64.50, 65.09)	65.78
0.0	0.0	1.0	65.91 (65.17, 67.02)	64.37 (64.08, 64.69)	65.78
0.0	0.0	0.5	65.84 (65.06, 66.85)	64.49 (64.18, 64.81)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A4.2: Simulation results for setup #2 case 1 (results for LFP rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.5	1.5	0.5	65.77 (65.17, 66.56)	65.46 (65.16, 65.74)	65.78
1.5	1.5	−0.5	65.75 (65.14, 66.57)	65.70 (65.43, 65.96)	65.78
1.5	0.5	1.5	65.92 (65.29, 66.66)	64.85 (64.54, 65.17)	65.78
1.5	0.5	0.5	65.88 (65.22, 66.71)	65.09 (64.80, 65.39)	65.78
1.5	0.5	−0.5	65.84 (65.17, 66.73)	65.34 (65.04, 65.63)	65.78
1.5	−0.5	1.5	66.12 (65.36, 67.04)	64.49 (64.20, 64.78)	65.78
1.5	−0.5	0.5	66.04 (65.29, 67.12)	64.74 (64.46, 65.05)	65.78
1.5	−0.5	−0.5	66.00 (65.15, 67.17)	64.98 (64.69, 65.26)	65.78
0.5	1.5	1.5	65.73 (65.12, 66.42)	64.91 (64.61, 65.21)	65.78
0.5	1.5	0.5	65.71 (65.03, 66.50)	65.16 (64.86, 65.47)	65.78
0.5	1.5	−0.5	65.68 (65.01, 66.53)	65.42 (65.13, 65.71)	65.78
0.5	0.5	1.5	65.86 (65.23, 66.67)	64.56 (64.27, 64.84)	65.78
0.5	0.5	−0.5	65.77 (65.05, 66.70)	65.06 (64.76, 65.36)	65.78
0.5	−0.5	1.5	66.05 (65.30, 67.16)	64.22 (63.94, 64.53)	65.78
0.5	−0.5	0.5	65.98 (65.17, 67.10)	64.45 (64.13, 64.75)	65.78
0.5	−0.5	−0.5	65.94 (65.15, 67.13)	64.71 (64.40, 64.98)	65.78
−0.5	1.5	1.5	65.67 (64.98, 66.44)	64.64 (64.34, 64.94)	65.78
−0.5	1.5	0.5	65.62 (64.94, 66.38)	64.89 (64.60, 65.22)	65.78
−0.5	1.5	−0.5	65.61 (64.87, 66.47)	65.15 (64.84, 65.45)	65.78
−0.5	0.5	1.5	65.77 (65.11, 66.67)	64.28 (63.99, 64.59)	65.78
−0.5	0.5	0.5	65.73 (65.09, 66.52)	64.52 (64.20, 64.83)	65.78
−0.5	0.5	−0.5	65.73 (64.96, 66.72)	64.79 (64.51, 65.10)	65.78
−0.5	−0.5	1.5	65.93 (65.01, 66.95)	63.92 (63.64, 64.22)	65.78
−0.5	−0.5	0.5	65.89 (65.14, 66.92)	64.18 (63.89, 64.47)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A4.3: Simulation results for setup #2 case 1 (results for LFP rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
−1.5	4.0	1.0	65.68 (65.03, 66.70)	65.03 (64.69, 65.31)	65.78
4.0	0.5	−3.0	65.91 (65.09, 66.88)	66.40 (66.10, 66.68)	65.78
−0.5	0.5	2.0	65.80 (65.13, 66.54)	64.16 (63.87, 64.46)	65.78
−0.5	−2.0	−2.5	66.58 (64.58, 72.15)	64.39 (64.09, 64.72)	65.78
−0.5	−2.5	0.0	69.33 (64.71, 90.91)	63.58 (63.28, 63.89)	65.78
3.0	3.5	−3.0	66.05 (65.26, 67.35)	67.29 (66.99, 67.58)	65.78
2.5	2.0	1.0	65.81 (65.17, 66.57)	65.79 (65.47, 66.05)	65.78
3.0	−3.0	−2.5	73.67 (65.39, 96.76)	65.02 (64.73, 65.33)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}^*. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A5.1: Simulation results for setup #2 case 2 (results for unemployment rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.0	1.0	0.5	8.25 (7.12, 9.51)	6.64 (6.46, 6.82)	7.98
1.0	1.0	0.0	8.43 (7.21, 9.70)	6.61 (6.43, 6.80)	7.98
1.0	0.5	1.0	8.00 (7.02, 9.04)	6.32 (6.12, 6.50)	7.98
1.0	0.5	0.5	8.22 (7.14, 9.33)	6.30 (6.10, 6.50)	7.98
1.0	0.5	0.0	8.45 (7.38, 9.77)	6.27 (6.09, 6.45)	7.98
1.0	0.0	1.0	8.01 (7.14, 9.13)	6.03 (5.85, 6.22)	7.98
1.0	0.0	0.5	8.24 (7.18, 9.42)	6.00 (5.83, 6.17)	7.98
1.0	0.0	0.0	8.44 (7.25, 9.74)	5.97 (5.80, 6.17)	7.98
0.5	1.0	1.0	7.81 (6.84, 8.95)	6.68 (6.49, 6.89)	7.98
0.5	1.0	0.5	8.05 (7.02, 9.26)	6.66 (6.45, 6.83)	7.98
0.5	1.0	0.0	8.27 (7.11, 9.58)	6.63 (6.44, 6.84)	7.98
0.5	0.5	1.0	7.80 (6.88, 8.98)	6.35 (6.16, 6.53)	7.98
0.5	0.5	0.0	8.24 (6.98, 9.44)	6.28 (6.10, 6.47)	7.98
0.5	0.0	1.0	7.79 (6.73, 8.94)	6.06 (5.87, 6.26)	7.98
0.5	0.0	0.5	8.06 (6.91, 9.31)	6.02 (5.83, 6.21)	7.98
0.5	0.0	0.0	8.22 (6.98, 9.73)	5.98 (5.80, 6.17)	7.98
0.0	1.0	1.0	7.67 (6.61, 9.00)	6.72 (6.54, 6.90)	7.98
0.0	1.0	0.5	7.88 (6.72, 9.34)	6.67 (6.48, 6.84)	7.98
0.0	1.0	0.0	8.10 (6.73, 9.59)	6.62 (6.43, 6.82)	7.98
0.0	0.5	1.0	7.61 (6.57, 8.75)	6.37 (6.18, 6.57)	7.98
0.0	0.5	0.5	7.85 (6.70, 9.12)	6.32 (6.14, 6.52)	7.98
0.0	0.5	0.0	8.10 (6.74, 9.70)	6.28 (6.10, 6.48)	7.98
0.0	0.0	1.0	7.60 (6.47, 8.86)	6.07 (5.90, 6.26)	7.98
0.0	0.0	0.5	7.87 (6.78, 9.23)	6.04 (5.85, 6.22)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A5.2: Simulation results for setup #2 case 2 (results for unemployment rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.5	1.5	0.5	8.35 (7.29, 9.50)	6.99 (6.79, 7.19)	7.98
1.5	1.5	−0.5	8.82 (7.63, 10.35)	6.96 (6.76, 7.15)	7.98
1.5	0.5	1.5	7.96 (7.18, 8.87)	6.29 (6.10, 6.47)	7.98
1.5	0.5	0.5	8.39 (7.47, 9.42)	6.26 (6.09, 6.44)	7.98
1.5	0.5	−0.5	8.82 (7.65, 10.06)	6.21 (6.02, 6.41)	7.98
1.5	−0.5	1.5	8.04 (7.09, 9.01)	5.72 (5.56, 5.90)	7.98
1.5	−0.5	0.5	8.45 (7.30, 9.72)	5.71 (5.52, 5.88)	7.98
1.5	−0.5	−0.5	8.89 (7.79, 10.06)	5.65 (5.47, 5.80)	7.98
0.5	1.5	1.5	7.66 (6.57, 8.79)	7.09 (6.90, 7.29)	7.98
0.5	1.5	0.5	8.09 (6.84, 9.50)	7.05 (6.87, 7.25)	7.98
0.5	1.5	−0.5	8.50 (7.16, 9.95)	6.98 (6.78, 7.19)	7.98
0.5	0.5	1.5	7.63 (6.61, 8.71)	6.38 (6.19, 6.57)	7.98
0.5	0.5	−0.5	8.53 (7.28, 10.03)	6.23 (6.04, 6.41)	7.98
0.5	−0.5	1.5	7.66 (6.64, 8.73)	5.81 (5.64, 5.98)	7.98
0.5	−0.5	0.5	8.07 (6.91, 9.32)	5.76 (5.57, 5.93)	7.98
0.5	−0.5	−0.5	8.45 (7.21, 9.93)	5.67 (5.50, 5.84)	7.98
−0.5	1.5	1.5	7.35 (6.28, 8.54)	7.14 (6.95, 7.34)	7.98
−0.5	1.5	0.5	7.71 (6.49, 9.22)	7.06 (6.84, 7.27)	7.98
−0.5	1.5	−0.5	8.19 (6.49, 10.05)	6.93 (6.72, 7.12)	7.98
−0.5	0.5	1.5	7.22 (6.26, 8.36)	6.41 (6.23, 6.61)	7.98
−0.5	0.5	0.5	7.63 (6.44, 8.90)	6.33 (6.15, 6.51)	7.98
−0.5	0.5	−0.5	8.10 (6.62, 9.86)	6.19 (6.01, 6.37)	7.98
−0.5	−0.5	1.5	7.25 (6.08, 8.65)	5.87 (5.68, 6.04)	7.98
−0.5	−0.5	0.5	7.65 (6.45, 8.98)	5.78 (5.60, 5.96)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A5.3: Simulation results for setup #2 case 2 (results for unemployment rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
−1.5	4.0	1.0	6.75 (5.83, 8.13)	8.80 (8.61, 9.01)	7.98
4.0	0.5	−3.0	10.77 (9.13, 12.65)	5.96 (5.78, 6.14)	7.98
−0.5	0.5	2.0	7.05 (6.03, 7.99)	6.45 (6.27, 6.63)	7.98
−0.5	−2.0	−2.5	53.20 (6.92, 92.75)	4.72 (4.54, 4.88)	7.98
−0.5	−2.5	0.0	66.78 (6.16, 93.02)	4.96 (4.81, 5.13)	7.98
3.0	3.5	−3.0	7.75 (6.77, 9.72)	8.57 (8.37, 8.78)	7.98
2.5	2.0	1.0	8.38 (7.40, 9.37)	7.29 (7.11, 7.49)	7.98
3.0	−3.0	−2.5	71.94 (9.71, 91.14)	4.44 (4.31, 4.60)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A6.1: Simulation results for setup #2 case 2 (results for LFP rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.0	1.0	0.5	65.97 (65.21, 66.86)	65.10 (64.81, 65.42)	65.78
1.0	1.0	0.0	66.07 (65.26, 67.05)	65.18 (64.89, 65.50)	65.78
1.0	0.5	1.0	65.71 (65.13, 66.47)	64.89 (64.59, 65.18)	65.78
1.0	0.5	0.5	65.84 (65.21, 66.67)	64.98 (64.68, 65.27)	65.78
1.0	0.5	0.0	65.99 (65.29, 66.87)	65.08 (64.81, 65.37)	65.78
1.0	0.0	1.0	65.60 (64.98, 66.33)	64.79 (64.49, 65.11)	65.78
1.0	0.0	0.5	65.74 (65.07, 66.47)	64.88 (64.60, 65.19)	65.78
1.0	0.0	0.0	65.83 (65.14, 66.79)	64.97 (64.67, 65.27)	65.78
0.5	1.0	1.0	65.78 (65.03, 66.56)	64.84 (64.57, 65.15)	65.78
0.5	1.0	0.5	65.92 (65.12, 66.79)	64.92 (64.62, 65.24)	65.78
0.5	1.0	0.0	66.06 (65.27, 67.02)	65.01 (64.73, 65.29)	65.78
0.5	0.5	1.0	65.67 (65.06, 66.40)	64.73 (64.42, 65.02)	65.78
0.5	0.5	0.0	65.94 (65.21, 66.83)	64.90 (64.62, 65.18)	65.78
0.5	0.0	1.0	65.56 (64.94, 66.32)	64.62 (64.33, 64.92)	65.78
0.5	0.0	0.5	65.70 (65.06, 66.50)	64.70 (64.40, 64.99)	65.78
0.5	0.0	0.0	65.83 (65.12, 66.82)	64.79 (64.51, 65.06)	65.78
0.0	1.0	1.0	65.75 (64.98, 66.70)	64.66 (64.37, 64.99)	65.78
0.0	1.0	0.5	65.92 (65.17, 66.89)	64.76 (64.45, 65.05)	65.78
0.0	1.0	0.0	66.06 (65.24, 67.11)	64.84 (64.52, 65.11)	65.78
0.0	0.5	1.0	65.65 (65.00, 66.52)	64.55 (64.28, 64.82)	65.78
0.0	0.5	0.5	65.81 (65.07, 66.80)	64.63 (64.30, 64.94)	65.78
0.0	0.5	0.0	65.96 (65.12, 67.02)	64.71 (64.39, 65.02)	65.78
0.0	0.0	1.0	65.56 (64.92, 66.26)	64.46 (64.17, 64.73)	65.78
0.0	0.0	0.5	65.68 (64.99, 66.60)	64.54 (64.24, 64.83)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A6.2: Simulation results for setup #2 case 2 (results for LFP rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.5	1.5	0.5	66.02 (65.27, 66.89)	65.40 (65.09, 65.70)	65.78
1.5	1.5	−0.5	66.32 (65.44, 67.47)	65.57 (65.26, 65.89)	65.78
1.5	0.5	1.5	65.60 (65.03, 66.20)	64.96 (64.68, 65.23)	65.78
1.5	0.5	0.5	65.84 (65.20, 66.61)	65.15 (64.83, 65.43)	65.78
1.5	0.5	−0.5	66.12 (65.39, 66.93)	65.34 (65.06, 65.62)	65.78
1.5	−0.5	1.5	65.43 (64.87, 66.02)	64.77 (64.49, 65.10)	65.78
1.5	−0.5	0.5	65.65 (65.00, 66.39)	64.97 (64.67, 65.27)	65.78
1.5	−0.5	−0.5	65.87 (65.16, 66.79)	65.13 (64.83, 65.44)	65.78
0.5	1.5	1.5	65.73 (65.02, 66.55)	64.87 (64.55, 65.18)	65.78
0.5	1.5	0.5	66.02 (65.09, 67.04)	65.06 (64.77, 65.34)	65.78
0.5	1.5	−0.5	66.32 (65.41, 67.32)	65.24 (64.94, 65.54)	65.78
0.5	0.5	1.5	65.56 (64.93, 66.31)	64.63 (64.34, 64.93)	65.78
0.5	0.5	−0.5	66.12 (65.28, 67.18)	64.98 (64.68, 65.28)	65.78
0.5	−0.5	1.5	65.38 (64.77, 65.99)	64.45 (64.08, 64.72)	65.78
0.5	−0.5	0.5	65.58 (64.97, 66.28)	64.63 (64.33, 64.90)	65.78
0.5	−0.5	−0.5	65.83 (65.03, 66.75)	64.79 (64.50, 65.07)	65.78
−0.5	1.5	1.5	65.71 (64.97, 66.55)	64.54 (64.23, 64.82)	65.78
−0.5	1.5	0.5	65.99 (65.17, 66.98)	64.72 (64.41, 65.01)	65.78
−0.5	1.5	−0.5	66.33 (65.27, 67.72)	64.84 (64.55, 65.12)	65.78
−0.5	0.5	1.5	65.49 (64.85, 66.26)	64.29 (63.98, 64.58)	65.78
−0.5	0.5	0.5	65.75 (65.02, 66.76)	64.44 (64.17, 64.74)	65.78
−0.5	0.5	−0.5	66.12 (65.19, 67.41)	64.60 (64.31, 64.92)	65.78
−0.5	−0.5	1.5	65.31 (64.74, 65.97)	64.11 (63.82, 64.39)	65.78
−0.5	−0.5	0.5	65.57 (64.85, 66.44)	64.27 (63.97, 64.56)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A6.3: Simulation results for setup #2 case 2 (results for LFP rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
−1.5	4.0	1.0	65.52 (64.84, 66.46)	64.86 (64.54, 65.15)	65.78
4.0	0.5	−3.0	67.22 (66.05, 68.69)	66.26 (65.98, 66.57)	65.78
−0.5	0.5	2.0	65.39 (64.78, 66.10)	64.21 (63.93, 64.48)	65.78
−0.5	−2.0	−2.5	66.30 (64.74, 69.48)	64.50 (64.21, 64.77)	65.78
−0.5	−2.5	0.0	65.33 (64.53, 66.49)	64.09 (63.80, 64.40)	65.78
3.0	3.5	−3.0	65.58 (64.81, 66.89)	67.17 (66.85, 67.47)	65.78
2.5	2.0	1.0	66.01 (65.33, 66.76)	65.77 (65.47, 66.08)	65.78
3.0	−3.0	−2.5	65.97 (65.05, 67.25)	65.68 (65.39, 65.98)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that U_t depends on both U_t^* and U_{t-1}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A7: Simulation results for setup #2 case 3 (results for unemployment rates).

p	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
0.0	7.96 (6.90, 9.13)	6.33 (6.14, 6.50)	7.98
0.1	8.04 (6.97, 9.29)	6.32 (6.12, 6.52)	7.98
0.2	8.02 (6.93, 9.27)	6.33 (6.16, 6.52)	7.98
0.3	7.99 (6.88, 9.33)	6.33 (6.15, 6.50)	7.98
0.4	8.04 (6.76, 9.32)	6.32 (6.11, 6.51)	7.98
0.5	8.02 (7.03, 9.24)	6.31 (6.13, 6.51)	7.98
0.6	8.01 (6.92, 9.21)	6.32 (6.16, 6.49)	7.98
0.7	8.03 (6.97, 9.22)	6.32 (6.13, 6.50)	7.98
0.8	7.99 (6.93, 9.23)	6.32 (6.12, 6.51)	7.98
0.9	8.02 (6.80, 9.26)	6.32 (6.14, 6.50)	7.98
1.0	8.02 (6.87, 9.33)	6.31 (6.15, 6.51)	7.98

Note: Results showing unemployment rates when assumption 1 is relaxed such that when $U^*_{t-1} = U^*_t$ we replace the value of U_t with U_{t-1} with probability p. Sample size is 100,000. The last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A8: Simulation results for setup #2 case 3 (results for LFP rates).

p	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
0.0	65.75 (65.06, 66.58)	64.80 (64.50, 65.10)	65.78
0.1	65.82 (65.14, 66.75)	64.81 (64.53, 65.11)	65.78
0.2	65.81 (65.12, 66.61)	64.81 (64.50, 65.11)	65.78
0.3	65.78 (65.07, 66.75)	64.80 (64.50, 65.11)	65.78
0.4	65.83 (65.08, 66.79)	64.82 (64.53, 65.15)	65.78
0.5	65.80 (65.13, 66.67)	64.81 (64.53, 65.13)	65.78
0.6	65.82 (65.18, 66.61)	64.82 (64.53, 65.09)	65.78
0.7	65.83 (65.16, 66.67)	64.81 (64.49, 65.09)	65.78
0.8	65.77 (65.08, 66.72)	64.81 (64.53, 65.08)	65.78
0.9	65.79 (65.06, 66.59)	64.80 (64.47, 65.13)	65.78
1.0	65.80 (65.11, 66.67)	64.81 (64.53, 65.07)	65.78

Note: Results showing LFP rates when assumption 1 is relaxed such that when $U^*_{t-1} = U^*_t$ we replace the value of U_t with U_{t-1} with probability p. Sample size is 100,000. The last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A9.1: Simulation results for setup #3 (results for unemployment rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.0	1.0	0.5	8.02 (6.92, 9.26)	6.35 (6.18, 6.53)	8.04
1.0	1.0	0.0	8.09 (6.83, 9.43)	6.37 (6.18, 6.55)	8.06
1.0	0.5	1.0	8.15 (7.03, 9.30)	6.29 (6.12, 6.47)	7.93
1.0	0.5	0.5	8.27 (7.21, 9.50)	6.31 (6.13, 6.49)	7.96
1.0	0.5	0.0	8.30 (7.16, 9.53)	6.33 (6.14, 6.51)	8.00
1.0	0.0	1.0	8.33 (7.22, 9.46)	6.25 (6.06, 6.43)	7.87
1.0	0.0	0.5	8.36 (7.20, 9.53)	6.26 (6.08, 6.44)	7.89
1.0	0.0	0.0	8.39 (7.28, 9.71)	6.28 (6.10, 6.47)	7.93
0.5	1.0	1.0	7.82 (6.75, 9.17)	6.34 (6.15, 6.51)	8.01
0.5	1.0	0.5	7.92 (6.83, 9.18)	6.36 (6.18, 6.55)	8.05
0.5	1.0	0.0	7.94 (6.83, 9.33)	6.39 (6.20, 6.57)	8.08
0.5	0.5	1.0	7.99 (6.88, 9.22)	6.30 (6.10, 6.48)	7.95
0.5	0.5	0.0	8.05 (6.90, 9.31)	6.33 (6.15, 6.51)	8.00
0.5	0.0	1.0	8.13 (7.05, 9.31)	6.26 (6.08, 6.45)	7.87
0.5	0.0	0.5	8.18 (7.03, 9.32)	6.28 (6.09, 6.47)	7.91
0.5	0.0	0.0	8.22 (7.21, 9.39)	6.29 (6.09, 6.48)	7.94
0.0	1.0	1.0	7.67 (6.60, 8.94)	6.36 (6.16, 6.55)	8.02
0.0	1.0	0.5	7.69 (6.60, 8.91)	6.37 (6.19, 6.56)	8.06
0.0	1.0	0.0	7.76 (6.55, 9.09)	6.40 (6.22, 6.59)	8.10
0.0	0.5	1.0	7.77 (6.70, 8.89)	6.31 (6.12, 6.50)	7.96
0.0	0.5	0.5	7.80 (6.71, 9.09)	6.34 (6.15, 6.55)	7.99
0.0	0.5	0.0	7.94 (6.74, 9.14)	6.36 (6.17, 6.55)	8.04
0.0	0.0	1.0	7.94 (6.81, 9.14)	6.27 (6.07, 6.46)	7.89
0.0	0.0	0.5	7.96 (6.82, 9.18)	6.29 (6.11, 6.47)	7.92

Note: Results showing unemployment rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A9.2: Simulation results for setup #3 (results for unemployment rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
1.5	1.5	0.5	8.19 (7.16, 9.48)	6.38 (6.20, 6.56)	8.09
1.5	1.5	−0.5	8.30 (7.25, 9.61)	6.41 (6.22, 6.63)	8.15
1.5	0.5	1.5	8.36 (7.38, 9.49)	6.26 (6.06, 6.45)	7.89
1.5	0.5	0.5	8.43 (7.33, 9.62)	6.30 (6.13, 6.47)	7.95
1.5	0.5	−0.5	8.53 (7.26, 9.82)	6.33 (6.15, 6.51)	8.01
1.5	−0.5	1.5	8.74 (7.66, 9.87)	6.18 (6.01, 6.36)	7.76
1.5	−0.5	0.5	8.77 (7.54, 10.13)	6.21 (6.02, 6.40)	7.81
1.5	−0.5	−0.5	8.82 (7.54, 10.07)	6.25 (6.06, 6.43)	7.88
0.5	1.5	1.5	7.69 (6.69, 8.81)	6.36 (6.17, 6.56)	8.05
0.5	1.5	0.5	7.75 (6.68, 8.92)	6.40 (6.21, 6.59)	8.11
0.5	1.5	−0.5	7.94 (6.70, 9.27)	6.44 (6.24, 6.63)	8.19
0.5	0.5	1.5	7.93 (6.88, 9.14)	6.28 (6.11, 6.48)	7.91
0.5	0.5	−0.5	8.14 (7.05, 9.36)	6.36 (6.17, 6.54)	8.04
0.5	−0.5	1.5	8.31 (7.32, 9.46)	6.20 (6.03, 6.40)	7.78
0.5	−0.5	0.5	8.30 (7.14, 9.55)	6.23 (6.04, 6.41)	7.83
0.5	−0.5	−0.5	8.40 (7.09, 9.71)	6.27 (6.08, 6.46)	7.90
−0.5	1.5	1.5	7.31 (6.26, 8.44)	6.39 (6.21, 6.57)	8.08
−0.5	1.5	0.5	7.35 (6.17, 8.64)	6.42 (6.24, 6.60)	8.14
−0.5	1.5	−0.5	7.49 (6.36, 8.83)	6.47 (6.29, 6.66)	8.21
−0.5	0.5	1.5	7.58 (6.51, 8.69)	6.31 (6.13, 6.50)	7.94
−0.5	0.5	0.5	7.62 (6.57, 8.81)	6.35 (6.17, 6.55)	8.02
−0.5	0.5	−0.5	7.65 (6.56, 8.82)	6.37 (6.18, 6.56)	8.07
−0.5	−0.5	1.5	7.85 (6.76, 9.06)	6.23 (6.02, 6.42)	7.81
−0.5	−0.5	0.5	7.93 (6.76, 9.17)	6.27 (6.11, 6.44)	7.88

Note: Results showing unemployment rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A9.3: Simulation results for setup #3 (results for unemployment rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$Unemp\_C(\%)$	$Unemp\_R(\%)$	$Unemp\_T(\%)$
−1.5	4.0	1.0	6.45 (5.36, 7.84)	6.51 (6.31, 6.68)	8.26
4.0	0.5	−3.0	9.12 (7.88, 10.36)	6.29 (6.09, 6.48)	7.97
−0.5	0.5	2.0	7.53 (6.47, 8.65)	6.31 (6.13, 6.49)	7.93
−0.5	−2.0	−2.5	8.79 (7.46, 10.17)	6.25 (6.05, 6.45)	7.86
−0.5	−2.5	0.0	8.88 (7.55, 10.32)	6.12 (5.94, 6.31)	7.64
3.0	3.5	−3.0	7.71 (6.82, 8.90)	6.44 (6.27, 6.61)	8.21
2.5	2.0	1.0	8.28 (7.23, 9.44)	6.29 (6.11, 6.49)	7.96
3.0	−3.0	−2.5	11.03 (9.51, 12.62)	5.99 (5.80, 6.15)	7.46

Note: Results showing unemployment rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A10.1: Simulation results for setup #3 (results for LFP rates with $\lambda \in \{0, 0.5, 1\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.0	1.0	0.5	65.92 (65.18, 66.76)	64.98 (64.67, 65.26)	65.96
1.0	1.0	0.0	66.04 (65.29, 66.85)	65.05 (64.74, 65.36)	66.04
1.0	0.5	1.0	65.88 (65.16, 66.70)	64.87 (64.55, 65.16)	65.84
1.0	0.5	0.5	65.96 (65.30, 66.96)	64.95 (64.66, 65.26)	65.93
1.0	0.5	0.0	66.03 (65.31, 66.99)	65.02 (64.71, 65.31)	66.00
1.0	0.0	1.0	65.87 (65.19, 66.68)	64.87 (64.57, 65.15)	65.82
1.0	0.0	0.5	65.91 (65.23, 66.76)	64.94 (64.67, 65.27)	65.90
1.0	0.0	0.0	66.00 (65.19, 66.88)	65.01 (64.70, 65.28)	65.98
0.5	1.0	1.0	65.75 (65.06, 66.57)	64.76 (64.47, 65.06)	65.73
0.5	1.0	0.5	65.85 (65.18, 66.74)	64.83 (64.53, 65.15)	65.81
0.5	1.0	0.0	65.88 (65.19, 66.76)	64.90 (64.61, 65.22)	65.89
0.5	0.5	1.0	65.77 (65.10, 66.67)	64.74 (64.44, 65.03)	65.70
0.5	0.5	0.0	65.87 (65.14, 66.75)	64.89 (64.60, 65.20)	65.86
0.5	0.0	1.0	65.76 (65.13, 66.63)	64.73 (64.43, 65.04)	65.68
0.5	0.0	0.5	65.81 (65.12, 66.65)	64.79 (64.52, 65.08)	65.75
0.5	0.0	0.0	65.87 (65.20, 66.65)	64.88 (64.56, 65.16)	65.85
0.0	1.0	1.0	65.63 (64.94, 66.43)	64.61 (64.31, 64.89)	65.58
0.0	1.0	0.5	65.69 (64.93, 66.56)	64.69 (64.40, 64.98)	65.67
0.0	1.0	0.0	65.74 (64.92, 66.65)	64.76 (64.44, 65.05)	65.74
0.0	0.5	1.0	65.60 (64.92, 66.45)	64.60 (64.28, 64.90)	65.55
0.0	0.5	0.5	65.68 (65.01, 66.46)	64.67 (64.41, 64.94)	65.64
0.0	0.5	0.0	65.76 (64.98, 66.70)	64.74 (64.48, 65.07)	65.72
0.0	0.0	1.0	65.61 (64.92, 66.46)	64.57 (64.26, 64.87)	65.52
0.0	0.0	0.5	65.66 (64.97, 66.44)	64.67 (64.40, 64.99)	65.62

Note: Results showing LFP rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A10.2: Simulation results for setup #3 (results for LFP rates with $\lambda \in \{-0.5, 0.5, 1.5\}$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
1.5	1.5	0.5	66.15 (65.43, 67.03)	65.14 (64.83, 65.44)	66.14
1.5	1.5	−0.5	66.30 (65.55, 67.20)	65.28 (64.97, 65.60)	66.30
1.5	0.5	1.5	65.97 (65.33, 66.76)	64.94 (64.63, 65.24)	65.91
1.5	0.5	0.5	66.11 (65.44, 66.94)	65.10 (64.82, 65.39)	66.08
1.5	0.5	−0.5	66.21 (65.46, 67.13)	65.24 (64.94, 65.55)	66.23
1.5	−0.5	1.5	65.95 (65.33, 66.69)	64.91 (64.61, 65.20)	65.86
1.5	−0.5	0.5	66.06 (65.38, 66.91)	65.06 (64.76, 65.34)	66.02
1.5	−0.5	−0.5	66.15 (65.43, 67.04)	65.20 (64.91, 65.49)	66.17
0.5	1.5	1.5	65.70 (65.08, 66.55)	64.68 (64.39, 65.00)	65.66
0.5	1.5	0.5	65.83 (65.11, 66.69)	64.85 (64.54, 65.14)	65.84
0.5	1.5	−0.5	65.99 (65.20, 66.91)	64.99 (64.68, 65.29)	66.00
0.5	0.5	1.5	65.69 (65.03, 66.64)	64.66 (64.38, 64.95)	65.62
0.5	0.5	−0.5	65.95 (65.19, 66.93)	64.96 (64.67, 65.25)	65.95
0.5	−0.5	1.5	65.67 (65.01, 66.47)	64.63 (64.31, 64.93)	65.56
0.5	−0.5	0.5	65.76 (65.12, 66.61)	64.78 (64.47, 65.07)	65.72
0.5	−0.5	−0.5	65.90 (65.21, 66.76)	64.93 (64.62, 65.19)	65.90
−0.5	1.5	1.5	65.43 (64.75, 66.23)	64.41 (64.13, 64.70)	65.38
−0.5	1.5	0.5	65.54 (64.81, 66.42)	64.56 (64.27, 64.84)	65.54
−0.5	1.5	−0.5	65.69 (64.96, 66.63)	64.72 (64.40, 65.01)	65.71
−0.5	0.5	1.5	65.45 (64.82, 66.26)	64.38 (64.07, 64.69)	65.33
−0.5	0.5	0.5	65.52 (64.85, 66.34)	64.53 (64.25, 64.83)	65.49
−0.5	0.5	−0.5	65.66 (64.95, 66.44)	64.70 (64.41, 65.00)	65.68
−0.5	−0.5	1.5	65.39 (64.75, 66.13)	64.35 (64.07, 64.63)	65.28
−0.5	−0.5	0.5	65.51 (64.83, 66.26)	64.49 (64.21, 64.80)	65.43

Note: Results showing LFP rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

Table A10.3: Simulation results for setup #3 (results for LFP rates with $\lambda \in [-3, 4]$).

λ_1	λ_2	λ_3	$LFP\_C(\%)$	$LFP\_R(\%)$	$LFP\_T(\%)$
−1.5	4.0	1.0	65.13 (64.39, 66.09)	64.21 (63.90, 64.51)	65.19
4.0	0.5	−3.0	66.72 (65.90, 67.60)	65.92 (65.62, 66.18)	66.94
−0.5	0.5	2.0	65.36 (64.72, 66.19)	64.29 (64.00, 64.58)	65.23
−0.5	−2.0	−2.5	65.86 (65.12, 66.83)	64.89 (64.62, 65.20)	65.85
−0.5	−2.5	0.0	65.53 (64.87, 66.31)	64.50 (64.20, 64.81)	65.42
3.0	3.5	−3.0	66.46 (65.89, 67.30)	65.96 (65.66, 66.27)	67.01
2.5	2.0	1.0	66.25 (65.50, 67.16)	65.27 (64.97, 65.59)	66.26
3.0	−3.0	−2.5	66.55 (65.76, 67.55)	65.72 (65.43, 65.99)	66.66

Note: Results showing LFP rates when assumption 2 is relaxed such that U^*_{t+1} depends on both U^*_t and U^*_{t-9}. Sample size is 100,000. For each combination of λ_1, λ_2 and λ_3, the last three columns report mean values from 500 repetitions and 95% lower and upper bounds (in parentheses).

4 Evaluation of Assumptions 3 & 4 using CPS data

Assumption 3 requires the observed matrix $M_{U_t,U_{t-9}|x}$ to be invertible. We therefore test the assumption using CPS data directly. Based on the pooled matched CPS sample, we calculate the determinants directly and using bootstrap to derive standard errors. Table A11 present the results. For each demographic group, we can always reject the null that the determinant is zero at the 1% significance level. Therefore, it seems that assumption 3 holds with CPS data.

Under Assumptions 1, 2, and 3, Assumption 4 requires the eigenvalues of $M_{1,U_t,U_{t-9}|x}M^{-1}_{U_t,U_{t-9}|x}$, which is also an observed matrix to be distinctive. Therefore we may similar test this assumption using CPS data. We first derive the three eigenvalues of $M_{1,U_t,U_{t-9}|x}M^{-1}_{U_t,U_{t-9}|x}$ and then rank them in ascending order, such that Eig1≤Eig2≤Eig3. We then calculate the two differences Eig2-Eig1 and Eig3-Eig2 and derive standard errors via bootstrapping. The results are shown in Table A12. Once again, for all demographic groups, the t-values are large and we reject the null that at least two eigenvalues are the same at the 1% level.

Table A11: Testing assumption 3

Demographic group	Determinant	S.E.	t-value
(1) Male/White/Age≤40	6.5e-004	(1.4e-005)	45.8
(2) Male/White/Age > 40	8.5e-004	(2.1e-005)	41.1
(3) Male/Nonwhite/Age≤40	2.3e-003	(6.7e-005)	33.8
(4) Male/Nonwhite/Age > 40	1.6e-003	(6.6e-005)	24.0
(5) Female/White/Age≤40	6.2e-004	(1.5e-005)	40.7
(6) Female/White/Age > 40	5.2e-004	(1.3e-005)	38.9
(7) Female/Nonwhite/Age≤40	1.6e-003	(5.5e-005)	28.7
(8) Female/Nonwhite/Age > 40	9.8e-004	(4.6e-005)	21.1

Note: S.E. are standard errors based on 500 bootstrap repetitions.

Table A12: Testing assumption 4

Demographic group	Eig2-Eig1	Eig3-Eig2
(1) Male/White/Age≤40	0.14	0.78
	(0.01)	(0.01)
	[16.5]	[93.0]
(2) Male/White/Age > 40	0.15	0.83
	(0.01)	(0.01)
	[18.2]	[100.6]
(3) Male/Nonwhite/Age≤40	0.11	0.82
	(0.01)	(0.01)
	[11.1]	[82.9]
(4) Male/Nonwhite/Age > 40	0.12	0.85
	(0.01)	(0.01)
	[8.3]	[60.9]
(5) Female/White/Age≤40	0.16	0.77
	(0.01)	(0.01)
	[15.5]	[76.8]
(6) Female/White/Age > 40	0.15	0.82
	(0.01)	(0.01)
	[14.3]	[76.9]
(7) Female/Nonwhite/Age≤40	0.07	0.86
	(0.01)	(0.01)
	[6.3]	[81.2]
(8) Female/Nonwhite/Age > 40	0.14	0.82
	(0.02)	(0.02)
	[7.6]	[44.9]

Note: Numbers reported in parentheses are standard errors based on 500 bootstrap repetitions. Numbers reported in square brackets are associated t-values.

5 Additional results on misclassification probabilities

This section provides some additional results and robustness checks on the estimated misclassification probabilities.

5.1 Testing differences in misclassification probabilities between demographic groups

First, we formally test for differences in the misclassification probabilities between demographic groups. Table A13 reports the results with all statistically significant differences listed. The first panel compares males vs. females, controlling for the race and age categories. When employed, males are more likely to misreport as unemployed but less likely to misreport as not-in-labor-force. The differences are always statistically significant at the 5% significance level except for the comparison between young nonwhite males and young nonwhite females. When unemployed, the differences are mostly insignificant, with the only exception being that old white males are less likely to (mis)report as being not-in-labor-force compared to old white females. In addition, when not-in-labor-force, males are more likely to be misclassified as employed.

Panel 2 of Table A13 compares whites with nonwhites. When employed, whites are less likely to be misclassified, either to unemployed or to not-in-labor-force. However, unemployed young whites are more likely to misreport as employed. We also found that young white females are much less likely to misreport as not-in-labor-force compared to young nonwhite females, with the difference in probabilities being 18.6% and statistically significant.

The last panel in Table A13 compares young people (aged 40 and less) with older people (aged over 40). In general, young people are more likely to misreport when they are employed or not-in-labor-force, as the first and last two columns show. Compared with older white females, young white females are less likely to misreport as being not-in-labor-force when they are actually unemployed.

Some previous studies have made strong assumptions regarding between-group misclassification errors. For example, in order to achieve identification, Sinclair and Gastwirth (1998) assume that males and females have the same misclassification error probabilities (see also Sinclair and Gastwirth 1996). Our results suggest that the equality assumptions of misclassification probabilities across different subgroups, which are essential for identification in the H-W models, are unlikely to hold in reality.

5.2 Comparing with existing estimates

Our results are broadly consistent with those in the existing literature. Table A14 compares our weighed average estimates of misclassification probabilities with some of those obtained in the previous literature. Note that all the estimates share the same general pattern: the biggest misclassification probabilities happen when unemployed individuals misreport their labor force status as either not-in-labor-force ($\Pr(U_t = 3|U_t^* = 2)$) or employed ($\Pr(U_t = 1|U_t^* = 2)$), while the other misclassification probabilities are all below 3%. Our point estimates of $\Pr(U_t = 3|U_t^* = 2)$ and $\Pr(U_t = 1|U_t^* = 2)$ are somewhat higher than many of the existing estimates. However, several previous estimates of $\Pr(U_t = 3|U_t^* = 2)$ and $\Pr(U_t = 1|U_t^* = 2)$ in Table A14 have large standard errors so that our point estimates are well within their 95% confidence intervals. Due to our methodological advantage and the large sample size, we are able to produce much more precise estimates.

Table A13: Comparing misclassification probabilities (%) across demographic groups

	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
Male vs. Female						
(1)-(5)	0.3*	-0.8*	1.5	6.4	1.6*	0.0
	(0.07)	(0.12)	(2.03)	(4.86)	(0.50)	(0.41)
(2)-(6)	0.1*	-0.5*	-1.5	-9.4*	0.3*	0.1
	(0.04)	(0.08)	(1.88)	(4.07)	(0.09)	(0.08)
(3)-(7)	0.1	-0.3	1.5	-11.3	2.8*	4.3*
	(0.13)	(0.21)	(1.98)	(9.42)	(0.84)	(1.26)
(4)-(8)	0.2*	-0.3*	1.6	-3.1	-0.0	-0.7*
	(0.10)	(0.15)	(2.66)	(8.07)	(0.18)	(0.19)
White vs. Nonwhite						
(1)-(3)	-0.2	-0.9*	6.7*	-0.9	0.9	-4.3*
	(0.11)	(0.15)	(1.78)	(4.85)	(0.56)	(1.32)
(2)-(4)	-0.2*	-0.6*	1.0	-3.1	0.1	0.1
	(0.08)	(0.11)	(2.15)	(5.91)	(0.17)	(0.14)
(5)-(7)	-0.5*	-0.5*	6.7*	-18.6*	2.2*	0.0
	(0.10)	(0.19)	(2.21)	(9.42)	(0.79)	(0.08)
(6)-(8)	-0.1	-0.3*	4.0	3.2	-0.2*	-0.7*
	(0.07)	(0.13)	(2.45)	(6.83)	(0.11)	(0.15)
Young vs. Old						
(1)-(2)	0.5*	0.4*	3.6*	-1.7	4.6*	-0.1
	(0.06)	(0.08)	(1.71)	(3.46)	(0.43)	(0.41)
(3)-(4)	0.4*	0.7*	-2.1	-3.9	3.8*	4.3*
	(0.13)	(0.17)	(2.20)	(6.82)	(0.40)	(1.27)
(5)-(6)	0.3*	0.7*	0.6	-17.4*	3.4*	0.0
	(0.05)	(0.12)	(2.18)	(5.31)	(0.27)	(0.08)
(7)-(8)	0.6*	0.8*	-2.0	4.4	1.0	-0.7*
	(0.11)	(0.19)	(2.48)	(10.35)	(0.75)	(0.15)

Note: $\Pr(i|j)$ stands for $\Pr(U_t = i|U_t^* = j)$. The numbers in parentheses in the first column refer to demographic groups defined as follows: (1) Male/White/Age$\leq$40; (2) Male/White/Age $>$ 40; (3) Male/Nonwhite/Age$\leq$40; (4) Male/Nonwhite/Age $>$ 40 ; (5) Female/White/Age$\leq$40; (6) Female/White/Age $>$ 40; (7) Female/Nonwhite/Age$\leq$40 ; (8) Female/Nonwhite/Age $>$ 40. Numbers in parentheses are standard errors, and '*' signifies statistical significance at the 5% level.

Table A14: Comparing misclassification probabilities (%) with those in previous studies

	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
PS	0.54	1.72	3.78	11.46	1.16	0.64
	(0.07)	(0.18)	(0.70)	(1.09)	(0.13)	(0.09)
BB1	0.40	0.00	4.60	27.90	2.60	0.00
	(0.10)	(n.a.)	(15.20)	(5.30)	(1.50)	(n.a.)
BB2	0.40	0.80	8.60	17.00	1.10	0.90
	(0.10)	(0.10)	(1.00)	(1.20)	(0.10)	(0.10)
SG1	0.00	0.80	6.35	16.80	1.87	0.96
	(0.47)	(0.38)	(10.61)	(5.38)	(0.65)	(0.40)
SG2	0.00	0.96	11.13	10.00	2.02	1.09
	(0.98)	(0.25)	(12.58)	(2.46)	(0.34)	(0.24)
SG3	0.00	0.96	9.74	10.84	2.27	1.03
	(0.69)	(0.31)	(7.17)	(2.21)	(0.44)	(0.29)
This paper	0.6	1.5	17.3	20.2	2.9	0.2
	(0.02)	(0.03)	(0.59)	(1.39)	(0.10)	(0.09)

Note: $\Pr(i|j)$ stands for $\Pr(U_t = i|U_t^* = j)$. 'PS' refers to estimates by Poterba and Summers (1986) (from their Table III); 'BB1' refers to the estimates of Biemer and Bushery (2000) using H-W model for year 1996 (from their Table 5); 'BB2' refers to the estimates of Biemer and Bushery (2000) using MLCA model for year 1996 (from their Table 5); 'SG1' refers to estimates in Sinclair and Gastwirth (1998) for years with low levels of unemployment (1988-1990) (from their Table 5); 'SG2' refers to estimates in Sinclair and Gastwirth (1998) for years with moderate levels of unemployment (1981, 1984-1986) (from their Table 5); 'SG3' refers to estimates in Sinclair and Gastwirth (1998) for years with high levels of unemployment (1982-1983) (from their Table 5); 'This paper' refers to our weighted estimates, which are copied from the last two rows of Table 1.

5.3 Robustness check: pooling different periods of data

We then do several robustness checks for the estimated misclassification probabilities. First, in this version of the paper we have updated the sample period from Jan 1996-Dec 2009 to Jan 1996- Aug 2011, representing an increase of 20 sample months. Nevertheless, we still keep the estimated misclassification matrix in the previous version using data up to Dec 2009. The implicit assumption is that misclassification behaviors are relatively stable over time. Therefore, it is not necessary to update misclassification probabilities as new monthly data come out. And readers interested can just update the corrected unemployment series using the misclassification probabilities reported in this paper, without having to be involved in the more complicated procedure of estimating the misclassification probabilities again. Therefore, it is important to test whether updating the joint distributions to August 2011 would make any difference.

Table A15 report the results. For each demographic group, the first row lists misclassification probabilities when we pool data up to Aug 2011. The second row is the differences between the first row and our baseline case (which are reported in Table 1 of the paper when we pool data up to Dec 2009). The third row lists standard errors of the difference. Overall the differences are small and only in a few cases we see statistically significant differences.

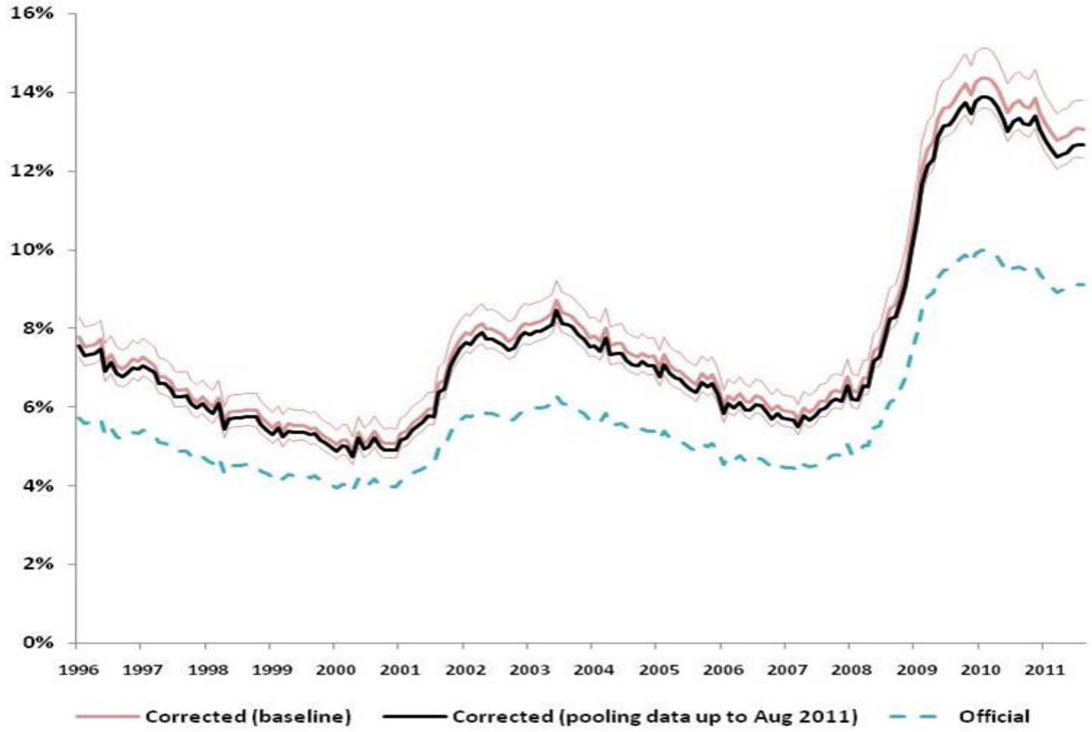
It is perhaps even more important to examine whether levels and trends of the corrected unemployment rates are sensitive to choices made when estimating the misclassification matrices. Figure A1 depicts corrected unemployment rates based on the misclassification matrices reported in Table A15 as well as the baseline case. Note that the two corrected unemployment series are very close to each other and not statistically significantly different based on the confidence intervals for the whole period.

Table A15: Check whether Misclassification probabilities (%) change if pool data from different time periods

Demographic group	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
(1) Male/White/Age≤40	1.0	1.3	17.6	17.0	5.5	0.0
	-0.1	0.0	2.5*	0.2	0.4	0.0
	(0.0)	(0.0)	(1.2)	(3.7)	(0.4)	(0.4)
(2) Male/White/Age > 40	0.5	0.9	14.3	17.2	1.4	0.1
	-0.1	-0.0	2.2*	1.6	0.0	0.0
	(0.0)	(0.0)	(1.1)	(2.7)	(0.1)	(0.1)
(3) Male/Nonwhite/Age≤40	1.1	2.2	11.8	15.1	5.0	4.3
	-0.0	0.0	1.5	3.0	0.1	0.0
	(0.1)	(0.1)	(1.4)	(6.1)	(0.4)	(1.9)
(4) Male/Nonwhite/Age > 40	0.7	1.4	13.9	18.0	1.3	0.0
	0.0	0.0	1.6	4.0	-0.0	0.0
	(0.1)	(0.1)	(2.1)	(6.7)	(0.2)	(0.2)
(5) Female/White/Age≤40	0.6	2.1	15.6	13.9	4.4	0.0
	-0.0	0.0	2.9	-3.2	0.1	0.0
	(0.1)	(0.1)	(1.7)	(5.4)	(0.2)	(0.1)
(6) Female/White/Age > 40	0.4	1.4	14.3	29.0	1.1	0.0
	-0.0	-0.0	3.7*	-0.8	-0.0	0.0
	(0.0)	(0.0)	(1.5)	(3.9)	(0.0)	(0.0)
(7) Female/Nonwhite/Age≤40	1.1	2.5	9.9	36.4	1.5	0.0
	-0.0	0.1	1.9	-7.0	0.7	0.0
	(0.1)	(0.1)	(1.7)	(10.3)	(1.0)	(0.1)
(8) Female/Nonwhite/Age > 40	0.5	1.8	10.9	27.1	1.2	0.4
	-0.0	-0.0	2.9	-2.0	0.0	0.3
	(0.1)	(0.1)	(2.3)	(8.1)	(0.1)	(0.3)

Note: for each subgroup, the first row lists misclassification probabilities when we pool data up to Aug 2011. the second row is difference between the first row and numbers reported in table 1 (where we pool data up to Dec 2009). the standard errors of the differences are reported in the third row. * signifies the difference is statistically significant at the 5% level.

Figure A1: Corrected unemployment rates using estimated misclassification probabilities when pool data up to Aug 2011



Note: Figure showing seasonally-adjusted corrected unemployment rate series when we pool data up to August 2011 in estimating the misclassification matrix, in addition to the baseline corrected unemployment rate series and official unemployment rate series showing in Figure 1. The thin lines signify 95% upper and lower confidence bounds for the baseline corrected series.

5.4 Robustness check: misclassification probabilities dependent on labor market conditions

Next, we divide our sample into three sub-periods based on the US business cycles and allow misclassification probabilities to be different for each sub-period. The first sub-period goes from the beginning of our study period (January 1996) to October 2001, which is roughly the end of the 2001 recession. The second sub-period goes from November 2001 to November 2007, corresponding to the expansion period between two recessions (the 2001 recession and the most recent 2007-09 recession). The third sub-period goes from December 2007 to the end of our study period (Aug 2011), which includes the 2007-2009 recession and its aftermath. Compared with the first two sub-periods, sub-period 3 is characterized by much higher levels of unemployment and presumably reflecting considerably weaker labor market conditions. Therefore we are able to test directly whether misclassification probabilities are affected by labor market conditions.

Table A16 reports the misclassification probabilities for each sub-period. There does seem to be differences in misclassification behaviors among different sub-periods characterized by different labor market conditions. For example, column (3) shows the probability of reporting employed while the true status is unemployed. Note that for all the demographic sub-groups, the probabilities of misreporting in sub-period 3 is considerably lower than in sub-periods 1 and 2. This shows that when labor market are weak and the pool of unemployed people includes a larger share of job losers and others whose status is unambiguous, then misreporting of unemployment tend to be less prevalent. In Table A17 we test the statistical significance of the differences between misclassification probabilities in different sub-periods. It has been that shown that there do exist some significant differences.

Nevertheless, we are able to show that such differences in the misclassification probabilities do not lead to estimated corrected unemployment rates to significantly differ from our baseline series. Figure A2 show corrected unemployment rate series constructed by using different misclassification matrices for each sub-period as reported in Table A16, in addition to our baseline corrected unemployment rate series and the official unemployment rate series. The two corrected series are very close to each other, and the one constructed using three different misclassification matrices are within the 95% confidence bounds of the baseline series. In addition, the two corrected series are quite different from the official series in terms of levels and cyclical patterns. Thus we can conclude that the cyclical pattern of differences between the official and corrected unemployment rates shown in Figure 1 is not an artifact of not allowing the prevalence of reporting errors to vary with labor market conditions.

In summary, the misclassification probabilities may be statistically significantly different, but they is economically insignificant because the corrected unemployment rates are not statistically different from our baseline estimates.

Table A16: misclassification probabilities (%) for the three different subperiods

Demographic group	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
(1) Male/White/Age≤40	0.8	1.3	29.2	7.5	6.7	2.9
	0.9	1.4	19.5	15.5	6.1	0.0
	1.2	1.1	11.6	27.6	3.8	0.0
(2) Male/White/Age > 40	0.4	0.9	17.4	21.6	1.5	0.1
	0.4	0.9	16.0	20.6	1.3	0.2
	0.6	0.9	12.3	11.0	1.2	0.1
(3) Male/Nonwhite/Age≤40	1.4	2.1	16.9	8.9	4.9	3.0
	0.9	2.3	12.8	19.0	5.3	5.9
	1.2	2.1	8.1	8.8	4.2	3.1
(4) Male/Nonwhite/Age > 40	0.7	1.5	18.6	21.5	1.6	0.3
	0.6	1.5	16.3	20.3	1.2	0.0
	0.6	1.2	11.1	11.4	1.0	0.0
(5) Female/White/Age≤40	0.7	2.0	20.6	16.6	4.1	0.0
	0.5	2.2	18.3	9.3	4.7	0.3
	0.7	1.9	10.2	19.1	3.8	0.0
(6) Female/White/Age > 40	0.3	1.4	22.8	28.1	1.1	0.0
	0.3	1.4	17.2	30.9	1.0	0.0
	0.4	1.4	10.2	25.6	1.1	0.0
(7) Female/Nonwhite/Age≤40	1.2	2.4	11.9	43.8	0.0	0.0
	1.0	2.8	11.7	19.4	3.4	0.0
	0.9	2.1	6.2	51.9	0.0	0.0
(8) Female/Nonwhite/Age > 40	0.2	1.7	18.2	14.3	1.3	0.9
	0.5	1.9	12.4	26.6	1.2	0.2
	0.6	1.7	6.8	40.8	1.2	0.0

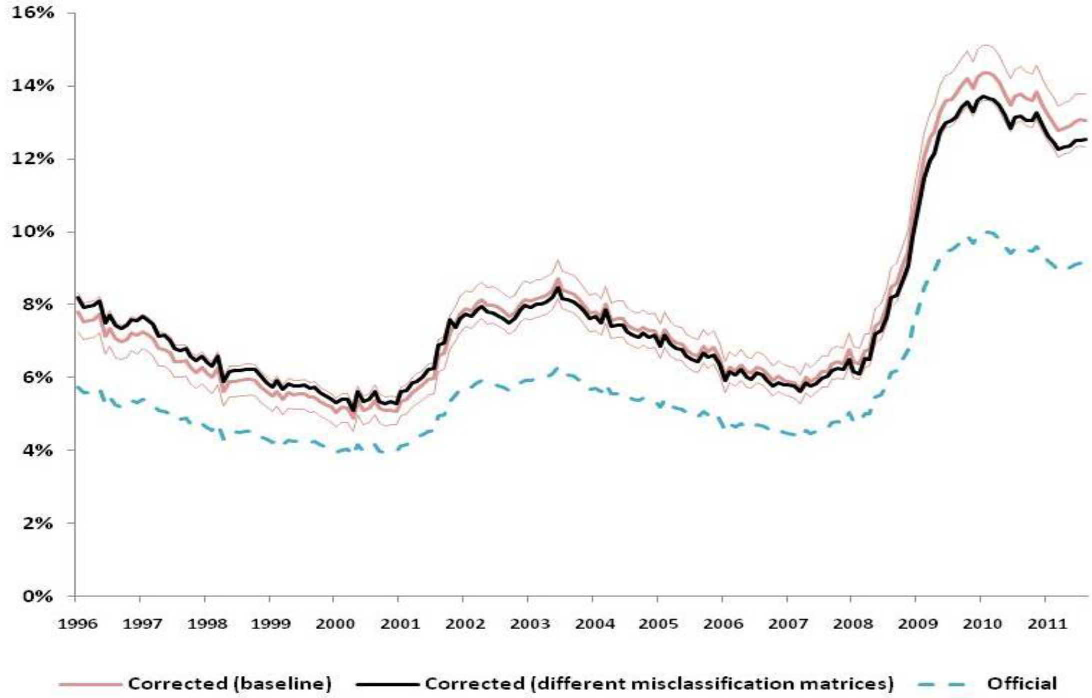
Note: $\Pr(i|j)$ stands for $\Pr(U_t = i|U_t^* = j)$. Each panel represents a demographic group as defined. Within each panel, the three rows represent misclassification probabilities for sub-period 1, 2, and 3, respectively.

Table A17: Testing whether misclassification probabilties are the same for the three different subperiods

Demographic group	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
(1) Male/White/Age≤40	-0.1	-0.1	9.7*	-7.9	0.6	2.9*
	-0.3*	0.3*	7.9*	-12.1	2.3*	0.0
	0.4*	-0.1	-17.6*	20.1*	-3.0*	-2.9*
(2) Male/White/Age > 40	-0.1	-0.0	1.4	0.9	0.1	-0.1
	-0.2*	-0.0	3.7*	9.6	0.1	0.1*
	0.3*	0.0	-5.1	-10.6	-0.2	-0.0
(3) Male/Nonwhite/Age≤40	0.5*	-0.2*	4.1	-10.1*	-0.4	-2.8*
	-0.2*	0.2	4.7*	10.2	1.1	2.8*
	-0.3*	-0.0	-8.8*	-0.1	-0.7	0.1
(4) Male/Nonwhite/Age > 40	0.0	-0.1	2.3	1.2	0.5	0.3
	0.0	0.3*	5.2*	8.9	0.2	0.0
	-0.0	-0.3*	-7.5*	-10.1	-0.7	-0.3
(5) Female/White/Age≤40	0.2*	-0.3*	2.3	7.3	-0.6	-0.3
	-0.2*	0.4*	8.0*	-9.8*	1.0	0.3*
	-0.0	-0.1*	-10.4*	2.5	-0.4	0.0
(6) Female/White/Age > 40	0.0	-0.1	5.6*	-2.8	0.1	0.0
	-0.1	0.1*	7.1*	5.3	-0.1	0.0
	0.1	0.0	-12.7*	-2.5	0.1	-0.0
(7) Female/Nonwhite/Age≤40	0.2	-0.4*	0.3	24.4*	-3.4*	0.0
	0.1	0.8*	5.5*	-32.5*	3.4*	0.0
	-0.4*	-0.3*	-5.8*	8.0*	0.0	0.0
(8) Female/Nonwhite/Age > 40	-0.4*	-0.1*	5.8*	-12.3	0.1	0.7
	-0.0	0.1*	5.6*	-14.1*	0.0	0.2*
	0.4*	0.0	-11.5*	26.5*	-0.1	-0.9

Note: Pr($i|j$) stands for Pr($U_t = i|U_t^* = j$). within each panel, the first line is the difference between subperiod 1 and subperiod 2, the second row is the difference between subperiod 2 and subperiod 3, and the third row is the difference between subperiod 3 and subperiod 1. signifies statistical difference at the 5% level.

Figure A2: Corrected unemployment rates when using three different misclassification matrices for each subperiod



Note: Figure showing seasonally-adjusted corrected unemployment rate series when misclassification probabilities are allowed to vary in different sub-periods, in addition to the baseline corrected unemployment rate series and official unemployment rate series showing in Figure 1. The thin lines signify 95% upper and lower confidence bounds for the baseline corrected series.

5.5 Robustness check: using different matching weights

Lastly, we check the role played by matching weights when we derive joint LFS distributions from matching CPS monthly data. It is well known that attrition is a serious issue in matched CPS samples and the matched sample may not be representative of the US population along important dimensions (see for example: Paracchi and Welch, 1995). Therefore we calculate and use matching weights when matching three CPS monthly data sets. We first run a Logit model to estimate the probability of attrition, then use the predicted probability to construct matching weights. Under the assumption that the probability of attrition is determined by the variables we included, our method is consistent.

Nevertheless, there might be attrition based on unobservables which we are not able to incorporate when calculating the matching weights. To examine the robustness of our method, we have tried not using the matching weights, i.e., not accounting for attrition, when matching CPS monthly data sets. Table A18 presents the results, where for each demographic group, the first row list misclassification probabilities when we do not use matching weights (i.e., assuming there's no attrition in matching). The second row show differences between the first row and the baseline probabilities as shown in Table 1. Standard errors are shown in the third row. Overall, the differences in misclassification probabilities are very small and there are only a few statistically significant differences.

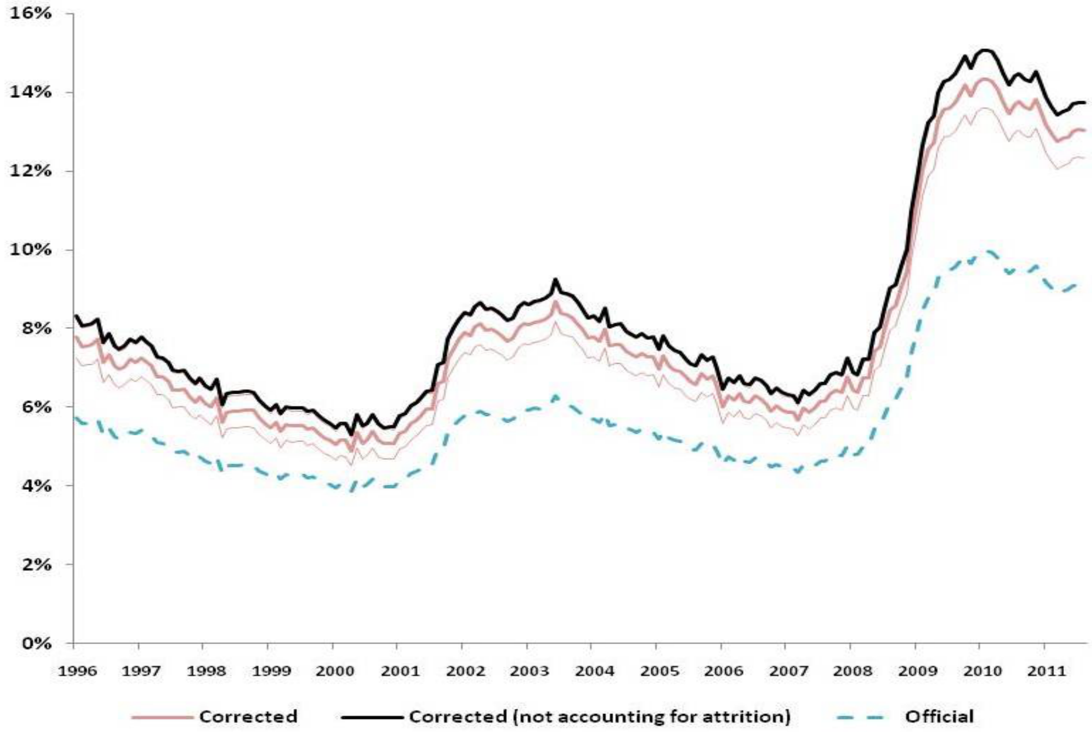
Figure A3 compares the corrected unemployment rate series using different weights. Note that the corrected unemployment rates only change very modestly when we do not account for attrition and are with the 95% confidence bounds of the baseline series. Both corrected unemployment rates are far from the official unemployment rate series. Therefore, our results are robust to the procedure to correct the weights for attrition.

Table A18: Check whether it matters or not to use matching weight to account for attrition

Demographic group	Pr(2|1)	Pr(3|1)	Pr(1|2)	Pr(3|2)	Pr(1|3)	Pr(2|3)
(1) Male/White/Age≤40	0.7	1.1	22.5	17.6	6.2	0.0
	0.2*	0.2*	-2.5	-0.4	-0.2	0.0
	(0.1)	(0.1)	(1.6)	(4.7)	(0.5)	(0.6)
(2) Male/White/Age > 40	0.4	0.9	17.5	19.3	1.4	0.1
	0.0	0.0	-1.0	-0.5	-0.0	0.0
	(0.0)	(0.0)	(1.4)	(3.6)	(0.1)	(0.1)
(3) Male/Nonwhite/Age≤40	0.9	1.9	15.5	20.2	5.4	3.2
	0.2	0.3	-2.1	-2.1	-0.4	1.1
	(0.1)	(0.1)	(1.9)	(7.5)	(0.6)	(2.1)
(4) Male/Nonwhite/Age > 40	0.6	1.4	16.8	22.1	1.3	0.0
	0.1	0.1	-1.3	-0.2	-0.1	0.0
	(0.1)	(0.1)	(2.8)	(8.7)	(0.2)	(0.2)
(5) Female/White/Age≤40	0.5	1.9	20.9	12.4	4.4	0.0
	0.1	0.2*	-2.3	-1.6	-0.0	0.0
	(0.1)	(0.1)	(2.3)	(6.8)	(0.3)	(0.1)
(6) Female/White/Age > 40	0.3	1.4	18.7	28.7	1.1	0.0
	0.0	0.0	-0.8	-0.5	-0.0	0.0
	(0.0)	(0.0)	(1.8)	(4.7)	(0.1)	(0.0)
(7) Female/Nonwhite/Age≤40	0.9	2.3	13.1	31.1	2.7	0.0
	0.2	0.2	-1.2	-1.7	-0.5	0.0
	(0.1)	(0.1)	(2.5)	(12.7)	(1.2)	(0.1)
(8) Female/Nonwhite/Age > 40	0.4	1.7	15.1	24.4	1.3	0.6
	0.1	0.0	-1.2	0.7	-0.1	0.0
	(0.1)	(0.1)	(3.0)	(8.8)	(0.1)	(0.2)

Note: $\Pr(i|j)$ stands for $\Pr(U_t = i|U_t^* = j)$. for each subgroup, the first row lists misclassification probabilities when we do not account for attrition when matching CPS monthly data sets. the second row is difference between the first row and numbers reported in table 1 (where we do account for attrition). the standard errors of the differences are reported in the third row. * signifies the difference is statistically significant at the 5% level.

Figure A3: Corrected unemployment rates using estimated misclassification probabilities not accounting for attrition



Note: Figure showing corrected unemployment rate series when we do not account for attrition in estimating the misclassification matrix, in addition to the baseline corrected unemployment rate series and official unemployment rate series showing in Figure 1. The thin lines signify 95% upper and lower confidence bounds for the baseline corrected series. The corrected series not accounting for attrition is indistinguishable on the graph from the 95% upper bounds of the baseline corrected series, although numbers are not identical.

6 Additional results on unemployment rates

First, we report monthly corrected unemployment rates from January 1996 to August 2011 in Table A19. Note that researchers can update the series when new data come in using our estimated misclassification probabilities. The numbers reported in Table A19 are not seasonally adjusted. Standard errors are also reported using bootstrapping.

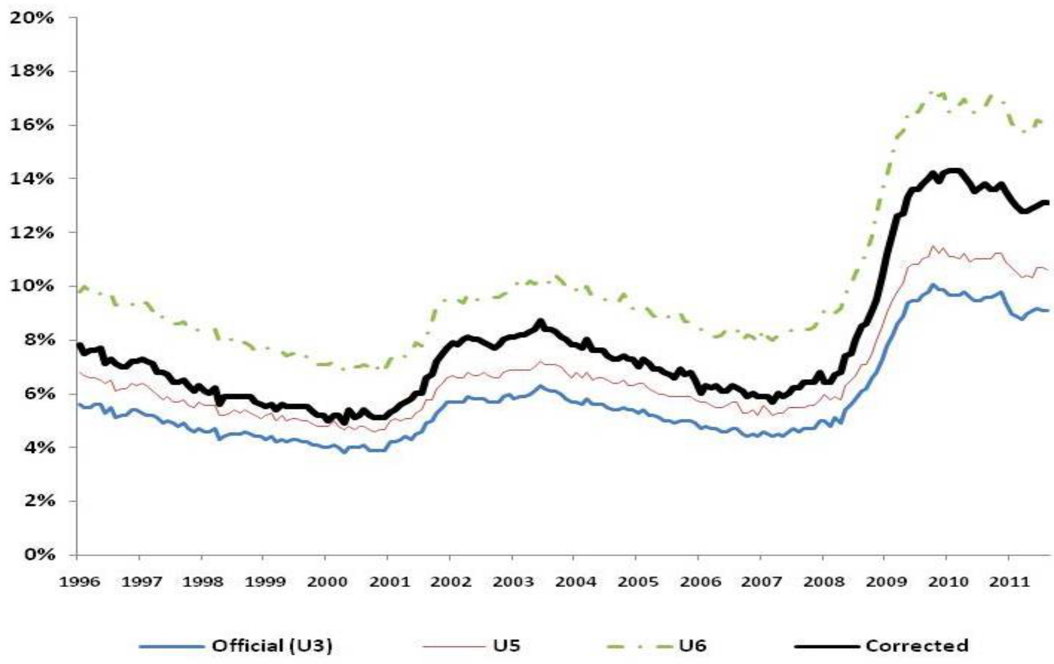
Next we compare our corrected unemployment rates with several alternative unemployment measures announced by BLS. in Figure A4 Note that our corrected series are somewhat in between two broad measures of unemployment rates that BLS report: U5 and U6. U5 basically includes all marginally attached workers (such as discouraged workers) as unemployed, while U6 includes both marginally attached workers and part-time workers for economic reasons as unemployed. Thus our corrected series at least partly correct for the LFS of the two groups of people which are difficult to classify conceptually. This can also be seen by the relatively large estimates of $\Pr(U_t = 3|U_t^* = 2)$ and $\Pr(U_t = 1|U_t^* = 2)$ using our procedure.

Table A19: Monthly corrected unemployment rates (%)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	8.7	8.2	7.9	7.3	7.2	7.4	7.7	6.9	6.7	6.6	6.8	6.7
	(0.28)	(0.26)	(0.26)	(0.25)	(0.24)	(0.25)	(0.25)	(0.24)	(0.24)	(0.23)	(0.23)	(0.23)
1997	8.2	7.8	7.4	6.5	6.3	6.9	6.8	6.3	6.2	5.8	5.7	5.8
	(0.27)	(0.26)	(0.25)	(0.22)	(0.22)	(0.24)	(0.23)	(0.23)	(0.22)	(0.21)	(0.21)	(0.21)
1998	6.9	6.7	6.6	5.3	5.4	6.2	6.2	5.8	5.7	5.4	5.3	5.1
	(0.24)	(0.23)	(0.23)	(0.20)	(0.20)	(0.22)	(0.22)	(0.22)	(0.21)	(0.20)	(0.20)	(0.19)
1999	6.3	6.3	5.8	5.3	5.0	5.8	5.8	5.4	5.2	4.9	4.9	4.7
	(0.22)	(0.22)	(0.21)	(0.20)	(0.19)	(0.21)	(0.21)	(0.20)	(0.20)	(0.19)	(0.19)	(0.18)
2000	5.9	5.8	5.5	4.6	4.9	5.4	5.5	5.3	4.8	4.6	4.7	4.6
	(0.21)	(0.21)	(0.20)	(0.18)	(0.19)	(0.20)	(0.20)	(0.20)	(0.19)	(0.18)	(0.19)	(0.18)
2001	6.2	6.0	6.0	5.4	5.3	6.2	6.3	6.5	6.3	6.7	7.2	7.3
	(0.22)	(0.21)	(0.21)	(0.20)	(0.20)	(0.22)	(0.22)	(0.22)	(0.22)	(0.23)	(0.24)	(0.23)
2002	8.7	8.4	8.4	7.9	7.5	8.3	8.2	7.8	7.3	7.2	7.7	7.7
	(0.27)	(0.26)	(0.26)	(0.26)	(0.25)	(0.26)	(0.26)	(0.25)	(0.24)	(0.24)	(0.25)	(0.25)
2003	8.9	8.8	8.5	8.0	7.9	9.0	8.7	8.3	7.9	7.6	7.7	7.4
	(0.27)	(0.27)	(0.26)	(0.25)	(0.25)	(0.27)	(0.27)	(0.26)	(0.25)	(0.25)	(0.25)	(0.24)
2004	8.6	8.3	8.3	7.3	7.2	7.9	7.8	7.2	6.9	6.8	7.0	6.9
	(0.27)	(0.27)	(0.27)	(0.24)	(0.25)	(0.26)	(0.25)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)
2005	7.8	7.9	7.3	6.6	6.5	7.1	7.0	6.5	6.5	6.1	6.5	6.1
	(0.25)	(0.25)	(0.24)	(0.23)	(0.23)	(0.23)	(0.24)	(0.23)	(0.22)	(0.22)	(0.22)	(0.21)
2006	6.9	6.9	6.4	6.0	5.8	6.4	6.7	6.2	5.7	5.3	5.6	5.6
	(0.23)	(0.23)	(0.22)	(0.21)	(0.21)	(0.22)	(0.23)	(0.21)	(0.21)	(0.20)	(0.20)	(0.20)
2007	6.7	6.5	6.0	5.6	5.5	6.3	6.5	6.1	6.0	5.8	5.9	6.4
	(0.23)	(0.22)	(0.21)	(0.20)	(0.20)	(0.21)	(0.23)	(0.22)	(0.21)	(0.21)	(0.21)	(0.22)
2008	7.3	7.1	7.1	6.3	7.1	7.8	8.3	8.4	8.2	8.4	9.0	10.0
	(0.24)	(0.23)	(0.23)	(0.21)	(0.23)	(0.25)	(0.26)	(0.27)	(0.26)	(0.26)	(0.28)	(0.29)
2009	12.1	12.7	12.9	12.3	12.9	13.9	14.0	13.7	13.6	13.6	13.4	13.9
	(0.34)	(0.35)	(0.36)	(0.34)	(0.36)	(0.38)	(0.37)	(0.38)	(0.38)	(0.37)	(0.37)	(0.38)
2010	15.2	15.1	14.7	13.6	13.4	13.8	14.0	13.7	13.2	13.0	13.4	13.1
	(0.40)	(0.40)	(0.39)	(0.38)	(0.37)	(0.38)	(0.39)	(0.38)	(0.38)	(0.36)	(0.37)	(0.37)
2011	14.1	13.7	13.2	12.4	12.5	13.4	13.4	13.0				
	(0.38)	(0.38)	(0.37)	(0.35)	(0.35)	(0.37)	(0.38)	(0.37)				

Note: Not seasonally adjusted. Numbers reported in parentheses are bootstrapped standard errors.

Figure A4: Comparing our corrected unemployment rates with alternative measures announced by BLS



Note: Figure showing corrected unemployment rate series, official unemployment rate series as well as two alternative measures of unemployment that BLS uses. U5 classify marginally attached people as unemployed while U6 classify both marginally attached and part-time workers for economic reasons as unemployed. All series are seasonally adjusted. Sources: U5, U6 and Official unemployment rate series (U3) are from http://www.bls.gov/webapps/legacy/cpsatab15.htm.

7 Results on labor force participation rates

This section reports the results on the labor force participation rates. Table A20 presents results for each demographic group for the three sub-periods: January 1996 to October 2001, November 2001 to November 2007, and December 2007 to August 2011. For each demographic group and each sub-period, the corrected labor force participation rates are always higher than the reported ones, but the differences are small and not statistically significant. For example, for young white males, in the first sub-period (January 1996 to October 2001), the corrected labor force participation rate is 87.8%, which is higher than the reported rate by 1.3 percentage points. In the second sub-period, the corrected labor force participation rate is 84.9%, again higher than the reported rate of 83.6% by 1.3 percentage points. In the latest recession period, the difference between corrected and reported labor force participation rates is 1.9 percentage points. By contrast, the standard errors are close to 4%.

The last two rows of Table A20 reports LFP for the whole US population. The corrected participation rate is always slightly higher than the reported one, but the average difference is less than 2%, and not statistically significant. For the three sub-periods, the corrected labor force participation rate is 68.1%, 67.3% and 66.8%, respectively. The reported rates are only slightly lower, at 67.1%, 66.2% and 65.2%, respectively.

Table A21 reports all monthly seasonally unadjusted labor force participation rates as well as bootstrapped standard errors. Figure A5 graphically depicts both the corrected and the official seasonally adjusted series, with both somewhat flat during the period under study.

Table A20: Labor force participation rates (%) averaged over three sub-periods for different demographic groups

Demographic group	Sub-period 1 (1996/01-2001/10)		Sub-period 2 (2001/11-2007/11)		Sub-period 3 (2007/12-2011/8)	
	reported	corrected	reported	corrected	reported	corrected
(1) Male/White/Age≤40	86.5	87.8	83.6	84.9	80.8	82.7
	(3.9)	(3.9)	(3.7)	(3.8)	(3.6)	(3.7)
(2) Male/White/Age > 40	65.5	66.0	66.6	67.3	66.4	67.6
	(2.9)	(3.0)	(3.0)	(3.0)	(3.0)	(3.0)
(3) Male/Nonwhite/Age≤40	75.6	76.5	74.1	74.8	71.8	73.1
	(3.4)	(3.5)	(3.3)	(3.4)	(3.2)	(3.4)
(4) Male/Nonwhite/Age > 40	63.6	65.0	64.9	66.6	64.2	66.7
	(2.8)	(2.9)	(2.9)	(3.0)	(2.9)	(3.0)
(5) Female/White/Age≤40	72.4	73.2	69.6	70.2	68.3	69.0
	(3.2)	(3.3)	(3.1)	(3.1)	(3.1)	(3.1)
(6) Female/White/Age > 40	49.0	49.8	51.6	52.6	52.4	54.0
	(2.2)	(2.2)	(2.3)	(2.4)	(2.3)	(2.4)
(7) Female/Nonwhite/Age≤40	68.9	73.0	66.7	70.7	64.9	69.7
	(3.1)	(3.5)	(3.0)	(3.4)	(2.9)	(3.5)
(8) Female/Nonwhite/Age > 40	52.6	53.3	54.5	55.6	54.4	55.8
	(2.4)	(2.4)	(2.4)	(2.5)	(2.4)	(2.5)
Total	67.1	68.1	66.2	67.3	65.2	66.8
	(1.3)	(1.3)	(1.3)	(1.3)	(1.2)	(1.3)

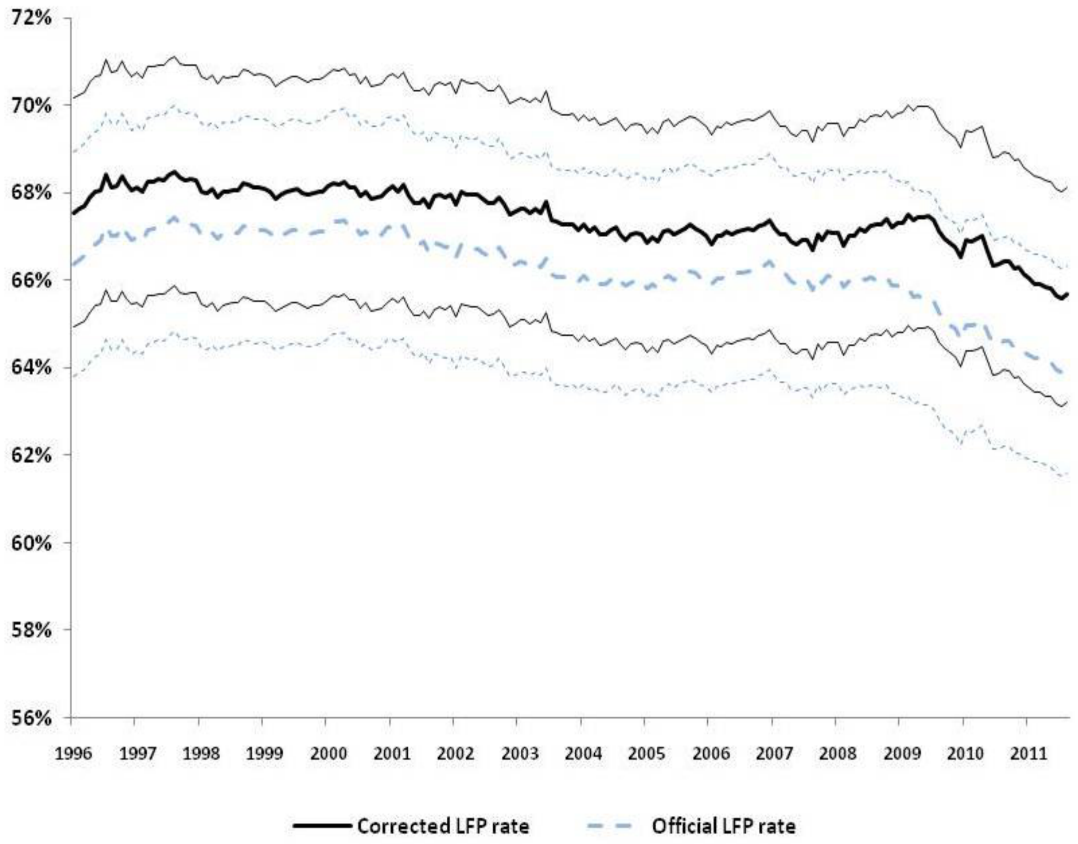
Note: Numbers reported in parentheses are bootstrapped standard errors based on 500 repetitions.

Table A21: Monthly corrected labor force participation rates (%)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1996	67.1	67.3	67.6	67.5	67.9	68.8	69.4	68.4	67.9	68.3	68.1	67.8
	(1.33)	(1.33)	(1.33)	(1.33)	(1.34)	(1.36)	(1.37)	(1.34)	(1.33)	(1.34)	(1.34)	(1.33)
1997	67.7	67.7	68.2	67.8	68.2	69.0	69.4	68.8	68.1	68.2	68.2	68.1
	(1.33)	(1.33)	(1.34)	(1.33)	(1.34)	(1.35)	(1.36)	(1.34)	(1.33)	(1.33)	(1.33)	(1.33)
1998	67.6	67.7	68.0	67.5	67.9	68.7	69.0	68.4	68.0	68.1	68.0	67.9
	(1.32)	(1.32)	(1.32)	(1.31)	(1.32)	(1.34)	(1.34)	(1.33)	(1.32)	(1.32)	(1.32)	(1.32)
1999	67.7	67.8	67.8	67.6	67.8	68.8	69.0	68.3	67.7	67.9	67.9	67.8
	(1.31)	(1.32)	(1.32)	(1.31)	(1.32)	(1.34)	(1.34)	(1.32)	(1.31)	(1.31)	(1.31)	(1.31)
2000	67.8	68.1	68.1	67.9	67.9	68.8	68.8	68.3	67.6	67.8	67.8	67.9
	(1.31)	(1.32)	(1.32)	(1.31)	(1.31)	(1.33)	(1.33)	(1.32)	(1.31)	(1.31)	(1.31)	(1.31)
2001	67.9	67.9	68.1	67.6	67.5	68.4	68.6	67.9	67.7	67.9	67.8	67.8
	(1.31)	(1.31)	(1.31)	(1.30)	(1.30)	(1.32)	(1.32)	(1.31)	(1.30)	(1.31)	(1.31)	(1.30)
2002	67.5	67.9	67.9	67.6	67.7	68.5	68.5	68.0	67.7	67.7	67.4	67.3
	(1.30)	(1.31)	(1.31)	(1.30)	(1.30)	(1.32)	(1.32)	(1.31)	(1.30)	(1.30)	(1.30)	(1.29)
2003	67.4	67.5	67.4	67.3	67.3	68.4	68.2	67.6	67.0	67.2	67.3	66.9
	(1.29)	(1.29)	(1.29)	(1.29)	(1.29)	(1.31)	(1.30)	(1.29)	(1.28)	(1.28)	(1.28)	(1.28)
2004	67.0	66.9	67.0	66.7	66.8	67.7	68.0	67.3	66.7	67.0	67.1	66.9
	(1.28)	(1.28)	(1.28)	(1.27)	(1.28)	(1.29)	(1.30)	(1.28)	(1.27)	(1.28)	(1.28)	(1.27)
2005	66.5	66.7	66.6	66.7	66.9	67.7	68.0	67.5	67.1	67.2	67.1	66.8
	(1.27)	(1.27)	(1.27)	(1.27)	(1.28)	(1.29)	(1.29)	(1.28)	(1.28)	(1.28)	(1.28)	(1.27)
2006	66.5	66.7	66.8	66.7	66.8	67.7	68.0	67.5	67.0	67.2	67.3	67.2
	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)	(1.29)	(1.29)	(1.28)	(1.27)	(1.28)	(1.28)	(1.28)
2007	66.8	66.7	66.8	66.5	66.6	67.6	67.8	67.0	66.9	66.9	67.0	66.9
	(1.27)	(1.27)	(1.27)	(1.26)	(1.27)	(1.28)	(1.29)	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)
2008	66.7	66.5	66.7	66.6	67.0	67.8	68.1	67.7	67.1	67.3	67.1	67.1
	(1.27)	(1.26)	(1.27)	(1.26)	(1.27)	(1.29)	(1.29)	(1.28)	(1.27)	(1.28)	(1.28)	(1.27)
2009	67.0	67.2	67.1	67.1	67.3	68.1	68.2	67.5	66.8	66.7	66.6	66.3
	(1.28)	(1.28)	(1.28)	(1.28)	(1.28)	(1.30)	(1.30)	(1.29)	(1.28)	(1.28)	(1.27)	(1.26)
2010	66.6	66.6	66.7	66.7	66.6	67.0	67.2	66.8	66.3	66.1	66.1	65.8
	(1.27)	(1.27)	(1.27)	(1.27)	(1.27)	(1.28)	(1.28)	(1.27)	(1.27)	(1.26)	(1.26)	(1.25)
2011	65.7	65.6	65.7	65.5	65.7	66.3	66.4	66.1				
	(1.25)	(1.25)	(1.25)	(1.25)	(1.25)	(1.26)	(1.26)	(1.26)				

Note: Not seasonally adjusted. Numbers reported in parentheses are bootstrapped standard errors.

Figure A5: Corrected and Official (Reported) Labor Force Participation Rates



Note: Figure displays corrected and official (reported) Labor Force Participation (LFP) rates for the whole population (seasonally adjusted) from January 1996 to August 2011. The thin lines signify 95% upper and lower confidence bounds.

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