Misclassification Errors and the Underestimation of U.S. Unemployment Rates *

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Abstract

Using recent results in the measurement error literature, we show that the official U.S. unemployment rates substantially underestimate the true levels of unemployment, due to misclassification errors in labor force status in Current Population Surveys. Our closed-form identification of the misclassification probabilities relies on the key assumptions that the misreporting behaviors only depend on the true values and that the true labor force status dynamics satisfy a Markov-type property. During the period of 1996 to 2009, the corrected monthly unemployment rates are 1 to 4.6 percentage points (25% to 45%) higher than the official rates, and are more sensitive to changes in business cycles. Labor force participation rates, however, are not affected by this correction. We also provide results for various subgroups of the U.S. population defined by gender, race and age.

Keywords: Unemployment Rate, Labor Force Participation Rate, Misclassification, Measurement Error, Current Population Survey.

JEL Classification: J21, J64, C14.

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1 Introduction

Unemployment rate is among the few most important economic indicators in modern society. In the United States, the official unemployment rate, announced by the Bureau of Labor Statistics (BLS) each month, is based on the Current Population Survey (CPS) conducted by the Census Bureau. Due to misclassification among different labor force statuses, the official unemployment rate and its trend are potentially subject to error. Using recent results in the measurement error literature, we show that the official U.S. unemployment rates substantially underestimate the true levels of unemployment. During the period from January 1996 to December 2009, average corrected unemployment rate is higher than the corresponding official figure by 1.9 percentage points. In terms of monthly differences, corrected rates are between 25% to 45% (1 to 4.6) higher than the official rates, and are more sensitive to changes in business cycles.

CPS interviews around 60,000 households each month to collect basic demographic and labor force status information. Based on answers to survey questions on job-related activities, CPS assigns each individual to either employed, unemployed or not-in-labor-force. Classification errors among the three labor force statuses have been a substantial issue in the CPS. The incidence of errors due to response and coding mistakes is well demonstrated by the Reinterview Surveys, during which a small subsample of the households included in each month's CPS are recontacted and asked the same questions.[1] Treating CPS reconciled Reinterview Surveys sample as reflecting true labor force status, there exists considerable errors in the original CPS. Actual errors in labor force status are likely to be substantially larger than suggested in reconciled CPS reinterviews, as argued by Porterba and Summers (1995), Biemer

[1]The CPS reinterview sample consists two components, one is "nonreconciled", in which case no attempt is made to determine which answers are correct, the other is "reconciled", in which case the second interviewer would compare the responses from the first survey with the reinterview answers and try to resolve any conflicts (Poterba and Summers, 1984).

and Forsman (1992) and Sinclair and Gastwirth (1996).

The problem of misclassification of labor force statuses in CPS and other similar surveys has received considerable attention in the literature. To identify the classification error probabilities, early studies typically rely on some exogenous source of "truth", such as the reconciled CPS reinterview surveys (see e.g. Abowd and Zellner 1985, Porterba and Summers 1986, and Magnac and Visser 1999). But subsequent research using other methods show that reconciled CPS reinterviews are not the "truth" and may contain even more errors than the original CPS sample (Sinclair and Gastwirth, 1996). Other studies rely on two repeated measures of the labor force status of the same individuals at the same time (as with unreconciled CPS reinterview data), and assume that error probabilities are the same for different subsamples.[2] More recent studies, such as Biemer and Bushery (2000) and Bassi and Trivellato (2008), explore the panel nature of the surveys and treat the underlying true labor force status as a latent process, to be jointly modeled with the misclassification process.

Almost all existing studies focus on adjusting flows, i.e., gross labor flows between two consecutive months, not stocks, such as unemployment rate and labor market participation rate. While those studies acknowledge that classification errors cause serious problems for flows, they assume that such errors tend to cancel out for stocks (e.g. Singh and Rao 1995). The only study that has tried to correct for unemployment rate is Sinclair and Gastwirth (1998). However, they rely on the key identification assumption that males and females have the same misclassification error probabilities, which we reject in this paper.

In this paper, we use recent results in the measurement error literature to identify the misclassification probabilities (Hu, 2008). Our method relies only on short panels formed by matching CPS monthly data sets, thus avoids using auxiliary information such as reinterview surveys.[3] The approach is close to the Markov Latent Class Analysis (MLCA) method proposed by Biemer and Bushery (2000), but we use an

[2]see Sinclair and Gastwirth (1996, 1998), which use the H-W model first proposed by Hui and Walter (1980).

[3]Reinterview surveys are not available for many labor force surveys. When available, they typically have small sample sizes and are themselves contaminated with errors.

eigenvalue-eigenvector decomposition to establish a closed-form global identification, while they took a maximum likelihood approach with local identifiablity. Our assumption regarding the underlying true labor force status dynamics is also weaker than their first-order Markov chain assumption. In addition, Biemer and Bushery (2000) use group level data, which are subject to potential biases from within-group heterogeneities. Our identification results enable us to take advantage of the large sample size in CPS, and therefore, to achieve more efficient estimates.

To control for heterogeneities among people with different characteristics, we separately estimate labor force status misclassification probabilities for each demographic group, defined by individual's gender, race and age. Based on those misclassification probabilities, we then estimate corrected monthly unemployment rates and labor force participation rates for all demographic groups, and for the whole US population. For the period of January 1996 to December 2009, our corrected unemployment rates are higher than official ones by 25%-45% and on average by 35%, and the differences are always statistically significant. The results are intuitive as the most substantial misclassification errors occur when unemployed people misreport as either not-in-labor-force or employed. On the other hand, corrected labor force participation rates and official ones are rather close and never statistically significantly different, primarily due to the large base of people in the labor force.

The structure of the rest of the paper is as follows. Section 2 provides a closed-form identification of the misclassification probabilities and the underlying labor force status distribution. Section 3 presents results, including estimated misclassification probabilities, corrected unemployment rates and labor force participation rates, along with reported (official) ones. The last section concludes.

2 Closed-form Identification

This section presents a closed-form identification procedure, which maps the observed distribution of the self-reported labor force status uniquely to the misclassification probabilities and the underlying true labor force status distribution. Let U_t denote the self-reported labor force status in month t. Let X be a vector of covariates, defined by demographic variables such as gender, race and age. We begin with an i.i.d sample of $\{U_{t+s}, U_t, U_{t-v}, X\}_i$ with $s > 0$ and $t > v$ for individual i ($i = 1, 2, ..., N$). In our empirical work, we will let $s = 1$ and $v = 9$. For example, if U_t stands for the labor force status of an individual in January 2008, then U_{t+s} and U_{t-v} denote her labor force statuses in February 2008 and in April 2007, respectively. The self-reported labor force status U_t is defined as follows:

$$U_t = \begin{cases} 1 & \text{employed} \\ 2 & \text{unemployed} \\ 3 & \text{not-in-labor-force} \end{cases}.$$

We also assume the latent true labor force status U_t^* has the same support as U_t. Let $f(\cdot)$ stand for probability density functions or probability mass functions of its arguments, we outline our identification assumptions as follows.

Assumption 1. *Conditional independence of the misclassification process.*

$$f\left(U_t | U_t^*, X, \mathcal{U}_{\neq t}\right) = f\left(U_t | U_t^*, X\right) \text{ for all } t,$$

with $\mathcal{U}_{\neq t} = \{(U_\tau, U_\tau^*), \text{ for } \tau = 1, ..., T \text{ and } \tau \neq t\}$.

Assumption 1 says that misreporting behaviors are independent of everything else conditional on the current period true labor force status and the covariate X.[4] This is a standard assumption in the literature and allows the misclassification behavior to be summarized by a simple misclassification matrix.[5] Assumption 1 implies that the observed probability $f(U_{t+s}, U_t, U_{t-v}|X)$ is associated with unobserved ones as

[4]Note that Assumption 1 still allows the misclassification errors to be correlated with the true labor force status U_t^* and variables in other periods through U_t^*. This is weaker than the classical measurement error assumption, where the error is independent of everything else, including the true values.

[5]Assumption 1 also implies the independence of classification errors (ICE) between two time periods, which has been used by many previous studies. Meyer (1988) examines the ICE assumption and finds it to be valid for CPS data.

follows:

$$\begin{aligned} & f\left(U_{t+s}, U_t, U_{t-v}|X\right) && (1) \\ = & \sum_{U_{t+s}^*}\sum_{U_t^*}\sum_{U_{t-v}^*}\left[f\left(U_{t+s}|U_{t+s}^*, X\right)f\left(U_t|U_t^*, X\right)f\left(U_{t-v}|U_{t-v}^*, X\right)f\left(U_{t+s}^*, U_t^*, U_{t-v}^*|X\right)\right]. \end{aligned}$$

Having established the conditional independence of the misclassification process, our next assumption deals with the dynamics of the latent true labor force status.

Assumption 2. *Markovian transition of the true labor force status.*

$$f\left(U_{t+s}^*|U_t^*, U_{t-v}^*, X\right) = f\left(U_{t+s}^*|U_t^*, X\right)$$

for all t.

This assumption implies that the true labor force status in period $t-v$ has no predictive power over the labor force status in period $t+s$ given that in period t, conditional on X. Biemer and Bushery (2000) assume a first-order Markov property for the latent labor force status variable, which states $f\left(U_{t+1}^*|U_t^*, U_{t-1}^*, ..., U_1^*\right) = f\left(U_{t+1}^*|U_t^*\right)$. Their assumption is likely to be too strong due to the presence of state dependency, serial correlation among idiosyncratic shocks and unobserved heterogeneity (see e.g. Hyslop 1999). Our assumption 2 is considerably weaker as we choose U_{t-v}^* to be the true labor force status nine month ago, i.e., $v = 9$, when using CPS data. Under Assumption 2, equation (1) becomes

$$\begin{aligned} & f\left(U_{t+s}, U_t, U_{t-v}|X\right) \\ = & \sum_{U_{t+s}^*}\sum_{U_t^*}\sum_{U_{t-v}^*} f\left(U_{t+s}|U_{t+s}^*, X\right)f\left(U_t|U_t^*, X\right)f\left(U_{t-v}|U_{t-v}^*, X\right)f\left(U_{t+s}^*|U_t^*, X\right)f\left(U_t^*, U_{t-v}^*|X\right) \\ = & \sum_{U_t^*}\left(\sum_{U_{t+s}^*} f\left(U_{t+s}|U_{t+s}^*, X\right)f\left(U_{t+s}^*|U_t^*, X\right)\right)f\left(U_t|U_t^*, X\right)\left(\sum_{U_{t-v}^*} f\left(U_{t-v}|U_{t-v}^*, X\right)f\left(U_t^*, U_{t-v}^*|X\right)\right) \\ = & \sum_{U_t^*}\left[f\left(U_{t+s}|U_t^*, X\right)f\left(U_t|U_t^*, X\right)f\left(U_t^*, U_{t-v}|X\right)\right]. && (2) \end{aligned}$$

Following the identification results in Hu (2008), we show that all the unobservables on the right-hand-side (RHS) of Equation (2) may be identified under reasonable assumptions. Integrating out U_{t+s} in Equation (2) leads to

$$f\left(U_t, U_{t-v}|X\right) = \sum_{U_t^*} [f\left(U_t|U_t^*, X\right) f\left(U_t^*, U_{t-v}|X\right)]. \tag{3}$$

We then introduce our matrix notation. For any given covariate x, we define

$$\begin{aligned} M_{U_t|U_t^*,x} &= \begin{bmatrix} f_{U_t|U_t^*,X}\left(1|1,x\right) & f_{U_t|U_t^*,X}\left(1|2,x\right) & f_{U_t|U_t^*,X}\left(1|3,x\right) \\ f_{U_t|U_t^*,X}\left(2|1,x\right) & f_{U_t|U_t^*,X}\left(2|2,x\right) & f_{U_t|U_t^*,X}\left(2|3,x\right) \\ f_{U_t|U_t^*,X}\left(3|1,x\right) & f_{U_t|U_t^*,X}\left(3|2,x\right) & f_{U_t|U_t^*,X}\left(3|3,x\right) \end{bmatrix} \\ &\equiv \left[f_{U_t|U_t^*,X}\left(i|k,x\right)\right]_{i,k}. \end{aligned}$$

The matrix $M_{U_t|U_t^*,x}$ contains the same information as the conditional probability function $f_{U_t|U_t^*,X=x}$. That means the identification of $M_{U_t|U_t^*,x}$ implies that of $f_{U_t|U_t^*,X=x}$. Each column of matrix $M_{U_t|U_t^*,x}$ is a distribution of the self-reported labor force status conditional on a given true labor force status.

Similarly, we have $M_{U_t,U_{t-v}|x} = \left[f_{U_t,U_{t-v}|X}\left(i,k|x\right)\right]_{i,k}$, $M_{U_t^*,U_{t-v}|x} = \left[f_{U_t^*,U_{t-v}|X}\left(i,k|x\right)\right]_{i,k}$ and $M_{1,U_t,U_{t-v}|x} = \left[f_{U_{t+s},U_t,U_{t-v}|X}\left(1,i,k|x\right)\right]_{i,k}$. We also define a diagonal matrix as follows

$$\begin{aligned} D_{1|U_t^*,x} &= \begin{bmatrix} f_{U_{t+s}|U_t^*,X}\left(1|1,x\right) & 0 & 0 \\ 0 & f_{U_{t+s}|U_t^*,X}\left(1|2,x\right) & 0 \\ 0 & 0 & f_{U_{t+s}|U_t^*,X}\left(1|3,x\right) \end{bmatrix} \\ &\equiv diag\left[f_{U_{t+s}|U_t^*,X}\left(1|k,x\right)\right]_k. \end{aligned}$$

A useful observation is that Equations (2) and (3) imply the following two matrix equations

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

and

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

In order to solve for the unknown matrix $M_{U_t|U_t^*,x}$, we need a technical assumption as follows:

Assumption 3. *for all x, matrix $M_{U_t,U_{t-v}|x}$ is invertible.*

This assumption is imposed directly on the observed probabilities so that it is testable. It requires the self-reported labor force status to be correlated in the two periods t and $t-v$, conditional on covariates. Under Assumption 3, Equation (5) implies that both $M_{U_t|U_t^*,x}$ and $M_{U_t^*,U_{t-v}|x}$ are invertible. Eliminating matrix $M_{U_t^*,U_{t-v}|x}$ in Equations (4) and (5) leads to

$$M_{1,U_t,U_{t-v}|x} M_{U_t,U_{t-v}|x}^{-1} = M_{U_t|U_t^*,x} D_{1|U_t^*,x} M_{U_t|U_t^*,x}^{-1}. \tag{6}$$

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.

Since we do not observe U_t^* in the sample, we have to reveal its value in the matrix of eigenvectors. In other words, the ordering of the eigenvalues or the eigenvectors is still arbitrary. In order to eliminate this ambiguity in Equation (6), we make the following assumption:

Assumption 4. *for all x, $f_{U_{t+s}|U_t^*,X}(1|k,x)$ are different for different $k \in \{1,2,3\}$.*

This assumption is also testable from Equation (6). This is because $f_{U_{t+s}|U_t^*,X}(1|k,x)$ for $k \in \{1,2,3\}$ are eigenvalues of the observed matrix $M_{1,U_t,U_{t-v}|x} M_{U_t,U_{t-v}|x}^{-1}$. Therefore, Assumption 4 holds if and only if all the eigenvalues of $M_{1,U_t,U_{t-v}|x} M_{U_t,U_{t-v}|x}^{-1}$ in

Equation (6) are distinctive. Intuitively, this assumption implies that the true labor force status at period t has an impact on the probability of reporting to be employed s periods later.

The distinctiveness of the eigenvalues guarantees the linear independence of the eigenvectors. The next assumption provides the ordering of the eigenvectors.

Assumption 5. *for all x, $f_{U_t|U_t^*,X}(k|k,x) > f_{U_t|U_t^*,X}(j|k,x)$ for $j \neq k$.*

It says that people are more likely to report the true value than any other possible values. Assumption 5 is consistent with results from CPS reinterviews (see e.g.: Poterba and Summers, 1984) and other validation studies discussed in Bound et al. (2001).

Technically, 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. 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 $M_{1,U_t,U_{t-v}|x}M^{-1}_{U_t,U_{t-v}|x}$. Practically, after diagonalizing the directly-estimable matrix $M_{1,U_t,U_{t-v}|x}M^{-1}_{U_t,U_{t-v}|x}$, 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. Consequently, the misclassification probability $f_{U_t|U_t^*,X}$ may be expressed as a closed-form function of the observed probability $f_{U_{t+s},U_t,U_{t-v}|X}$.

We summarize the results so far as follows.

Theorem 1. *Under Assumptions 1-5, there exists a known function Ψ such that for all x,*

$$f_{U_t|U_t^*,X}(i|k,x) = \Psi\left(i, k, f_{U_{t+s},U_t,U_{t-v}|X}(i',j',k'|x)\big|_{i',j',k'\in\{1,2,3\}}\right).$$

for all $i,k \in \{1,2,3\}$.

Notice that the known function Ψ stands for the closed-form identification procedure we present above, which maps from the observed $f_{U_{t+s},U_t,U_{t-v}|X}$ to the unobserved misclassification probabilities $f_{U_t|U_t^*,X}$.

Finally, in order to identify the distribution of the latent true labor force status $f_{U_t^*|X}$, we define $\overrightarrow{f_{U_t|x}} = \left[f_{U_t|X}(1|x), f_{U_t|X}(2|x), f_{U_t|X}(3|x)\right]^T$ and similarly $\overrightarrow{f_{U_t^*|x}} = \left[f_{U_t^*|X}(1|x), f_{U_t^*|X}(2|x), f_{U_t^*|X}(3|x)\right]^T$. It is straightforward to show that equation $f_{U_t|X} = \sum_{U_t^*} f_{U_t|U_t^*,X} f_{U_t^*|X}$ is equivalent to $\overrightarrow{f_{U_t|x}} = M_{U_t|U_t^*,x}\overrightarrow{f_{U_t^*|x}}$. Therefore, the distribution of the latent true labor force status for given x is identified as follows:

$$\overrightarrow{f_{U_t^*|x}} = M_{U_t|U_t^*,x}^{-1}\overrightarrow{f_{U_t|x}}. \tag{7}$$

That means we have identified the conditional distribution $f_{U_t^*|X}$. Given the marginal distribution of X, f_X, we may identify the marginal distribution of the latent true labor force status $f_{U_t^*}$,

$$f_{U_t^*} = \sum_X f_{U_t^*|X} f_X.$$

This gives the unemployment rate

$$\mu_t^* \equiv \frac{f_{U_t^*}(2)}{f_{U_t^*}(1) + f_{U_t^*}(2)},$$

and the labor force participation rate

$$\rho_t^* \equiv f_{U_t^*}(1) + f_{U_t^*}(2).$$

Our identification procedure is constructive as it leads directly to an estimator. A nice property of our approach is that if there is no misclassification error in the data, our estimator would produce the same unemployment rate and participation rate based on the raw data, under the assumptions above.

Moreover, our method establishes a global identification of the misclassification probabilities and the labor force status distribution. In contrast, parametric GMM or MLE methods typically rely on a local identification argument that the number of unknowns does not exceed that of the restrictions. Given the observed distribution, our identification and estimation procedure directly leads to the unique true values of the unknowns without using the regular optimization algorithms. Therefore, we do not need to be concerned about choosing initial values and obtaining a local maximum in the estimation procedure. In that sense, our estimates are more reliable than those based on local identification (e.g., Biemer and Bushery 2000).

3 Empirical Results

3.1 Matching of CPS data

We use public-use micro CPS data to estimate unemployment rates and labor force participation rates.[6] Each CPS monthly file contains 8 rotation groups that differ in month-in-sample. Households in each rotation group are interviewed for 4 consecutive months after they enter, withdraw temporarily for 8 months, then reenter for another 4 months of interview before exiting CPS permanently. Because of the rotational group structure, CPS can be matched to form longitudinal panels, allowing us to derive joint probabilities of the labor force status. To match individuals from different monthly files, we first use household and individual identifiers to derive crude matches, then validate those matches based on information on age, sex and race. For details of the matching algorithm, please refer to Madrian and Lefgren (2000) and Feng (2001).

We illustrate our empirical procedure using January 2008 as month t. Then, $t-9$ is April 2007 and $t+1$ is February 2008. In order to obtain the joint probabilities of self-reported labor force status for a given demographic group, i.e., $f_{U_{t+1},U_t,U_{t-9}|x}$, we first match the same individuals in corresponding rotation groups, i.e, we match rotation group 4 in April 2007, rotation group 5 in January 2008, and rotation group 6 in February 2008. As previous literature (e.g.: Paracchi and Welch 1995 and Feng 2008) has documented, due to attritions in matching, the matched sample, denoted by S_t, is not representative of the cross-sectional sample in period t. To correct for attrition, we first run a logit model for period t cross-sectional sample, where the dependent variable is either 1 (the observation is matched) or 0 (the observation is not matched), and the independent variables are sex, race, age, schooling and labor

[6] All data are downloaded from www.bls.census.gov/cps_ftp.html.

force status in period t. We next calculate the predicted probability of being matched for all the observations in the matched sample. The final matched sample S_t is then weighted using the inverse of the predicted matching probabilities. This adjustment procedure ensures the cross-sectional sample and the matched sample have the same marginal distributions on key individual characteristics for period t.

3.2 Misclassification probabilities

For each demographic group, we pool matched samples in all periods (1996-2009) to estimate a misclassification matrix. Table 1 reports results for all eight groups, including (1) White males aged 40 and less (M/W/Y); (2) White males aged over 40 (M/W/O); (3) Nonwhite males aged 40 and less (M/NW/Y); (4) Nonwhite males aged over 40 (M/NW/O); (5) White females aged 40 and less (F/W/Y); (6) White females aged over 40 (F/W/O); (7) Nonwhite females aged 40 and less (F/NW/Y); (8) Nonwhite females aged over 40 (F/NW/O). There exist some consistent patterns across all groups. When the actual labor force status is either employed or not-in-labor-force, the probabilities of being misreported to a different labor force status are never above 5%. The biggest errors are from the unemployed people being misclassified as either not-in-labor-force or employed. Only around 50-70% of unemployed people correctly report their true labor force status. For example, for white males aged 40 and less, 20% of the unemployed report to be employed, while another 17% of them report as not-in-labor-force. On the other hand, there are considerable heterogeneities among different demographic groups. For example, young white females have a value of 10.5% for $f_{U_t|U_t^*}(3|2)$, while all other groups have much higher probabilities of reporting to be not-in-labor-force while unemployed.

We next test formally for differences in misclassification errors between groups. Table 2 reports the results, with all statistically significant differences listed. The first panel compares males vs. females, controlling for race and age category. 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% level except for the comparison between old nonwhite males and old 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 2 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 probability being 18.6% and statistically significant.

The last panel in Table 2 compares young people (aged 16-40) with old 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 to old 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 assumptions of equality of misclassification error probabilities for different subgroups, which are essential for identification in the H-W models, are unlikely to hold in reality.

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

3.3 Unemployment rates

3.3.1 Unemployment rates for individual demographic groups

Given the estimated misclassification matrices for each month, we then calculate latent labor force status for each demographic group based on Equation (7). To estimate $\overrightarrow{f_{U_t|x}}$, we use all 8 rotation groups in any given CPS monthly file, which subsequently give us the self-reported unemployment rate and the labor force participation rate. Once we have $\overrightarrow{f_{U_t^*|x}}$, we can calculate the corrected unemployment rate and the corrected labor force participation rate. In order to be consistent with officially-announced statistics, all numbers are weighted using final weights provided by CPS and seasonally adjusted.[7]

Table 4 presents results for each demographic group. We break the study period of January 1996 to December 2009 into three sub-periods and calculate average reported and corrected unemployment rates for each sub-period. The first period ends in October 2001, which corresponds to the end of the 2001 recession. The second period runs from November 2001 to November 2007, which corresponds to a period of economic expansion. The last period goes from December 2007 to December 2009, which is the latest recession period. Average standard errors are also reported.

For each demographic group and for each sub-period, corrected unemployment rates are always higher than reported ones, which suggests that self-reported data underestimate true unemployment rates. Note also that for all demographic groups, sub-period 3 posts the highest levels of unemployment, followed by sub-period 2, and then by the first sub-period. This relationship is unchanged using either reported or corrected rates. In addition, the degree of underestimation is larger when the

[7]Final weights in CPS micro data have been adjusted for a composite estimation procedure that BLS uses to produce official labor force statistics (Appendix I in BLS, 2000). For seasonally adjustment, we use Census Bureau's WinX12 software, such that our reported series correspond to the officially announced statistics.

level of unemployment is higher. For example, for young white males, in the first sub-period (January 1996 to October 2001), corrected unemployment rate is 6.4%, which is higher than reported unemployment rate by 1.5 percentage points (or 29% in terms of percentages). In the second sub-period, corrected unemployment rate is 8.2%, which is higher than reported unemployment rate by 2.1% (or 35% in terms of percentages). The largest differential appears in the latest recession period, corrected unemployment rate is 13.3%, which is higher than reported unemployment rate by 3.9% (or 42% in terms of percentages).

More detailed information is presented in Appendix Figure A1, which depicts monthly time series of corrected and reported unemployment rates for all eight demographic groups. Confidence intervals are also shown based on standard errors bootstrapped using 1000 repetitions. In all figures in the paper, the corrected series is shown by the thick solid line, with the two thin solid lines showing 95% confidence intervals. The reported series is shown by the thick dashed line, with the two thin dashed lines showing 95% confidence intervals.

3.3.2 Unemployment rates for the whole US population

We then derive unemployment rates and corresponding standard errors for the whole US population, based on results for all demographic groups. Figure 1 reports the results for both the corrected and reported values. For the whole period, the corrected unemployment rate is always higher than the reported one and the difference is between 1% and 4.6%. Average corrected unemployment rate is 7.2%, which is higher than the reported rate by 1.9% (or 35% in terms of percentage). The substantial degree of underestimation of unemployment rate may not be very surprising because most of the misclassification errors are from unemployed people misreporting their labor force status as either employed or not-in-labor-force.

Next, we compare levels and linear trends of the two series of unemployment rates for each sub-period, using regression techniques. Table 5 presents the results, including regression coefficients and robust standard errors.[8] In terms of levels, average reported

[8]Note that in the regression, the dependent variable, which include both corrected

(official) unemployment rates are 4.63%, 5.28% and 7.45% for the three sub-periods, respectively. The corrected rates are significantly higher, by 1.44%, 1.85%, and 3.03%, respectively. In terms of linear tends, for the first period (1996/01-2001/10), the reported unemployment rate decreases at 0.02% per month, while the corrected series suggest an additional 0.01% decline, although the difference is not significant at the 1% level. For the second period, with economic expansion, the reported series decreases also by 0.02% per month, but the rate of decrease implied by the corrected series is higher by 0.01% with the difference statistically significant. Finally, for the last sub-period which corresponds to the latest recession, reported unemployment rate increases at 0.26% per month, while the corrected series increases at an even higher rate of 0.4% per month. The difference between the two series is 0.14% and highly statistically significant. In all sub-periods, unemployment rate volatilities suggested by the corrected series are substantially larger than the reported series.

Last, we decompose the underestimation of unemployment rate in Table 6. For the period of 1996 to 2009, on average the official statistics underestimate the unemployment rate by 1.9 percentage points. The degree of underestimation vary, however, by demographic group. On one hand, the young nonwhite female group posts the largest level of underestimation, at 4.6 percentage points. On the other hand, the official statistics only underestimate by a meager 1.1 percentage points for old white males. In terms of contributions to the total degree of underestimation, old white females declare the largest share of the total (27%), followed by young white males (21%). Nonwhite groups contributed relatively little as they account for smaller percentages of the US total population.

3.4 Labor force participation rates

This subsection reports results on labor force participation rates. Table 7 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 December 2009. For

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and reported unemployment rates, is based on estimates, although the standard errors are small compared to estimates. Lewis and Linzer (2005) recommend using OLS with heteroscedastic robust standard errors.

each demographic group and for each sub-period, corrected labor force participation rates are always higher than 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), corrected labor force participation rate is 87.8%, which is higher than reported rate by 1.3 percentage points (or 1.5% in terms of percentages). In the second sub-period, corrected labor force participation rate is 84.9%, again higher than the reported rate of 83.6% by 1.3 percentage points (or 1.6% in terms of percentages). In the latest recession period, the difference between corrected and reported labor force participation rates is 1.8 percentage points (or 2.2% in terms of percentages). By contrast, average standard errors are between 2.6%-2.8%. Appendix Figure A2 depicts monthly time series of both corrected and reported labor force participation rates for all eight demographic groups, together with confidence intervals.

Figure 2 presents results for the whole US population. Both the corrected and reported series are somewhat flat during the period under study. 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, corrected labor force participation rate is 68.1%, 67.3% and 67.1%, respectively. The reported rates are only slightly lower, at 67.1%, 66.2% and 65.7%, respectively.

The finding that misclassification errors cause little change to labor force participation rate is not very surprising. Compared to number of unemployed people, total number of people who are in labor force is much larger. Hence any corrections due to misclassification errors will have a relatively small effect.

4 Conclusion

In this paper, we show that due to misclassification errors in the self-reported labor force status, the official U.S. unemployment rates are significantly underestimated. In addition, our estimates suggest that unemployment might be much more sensitive to business cycles than previously thought. Given unemployment rate is such an important economic indicator, revising unemployment numbers should have a broad impact on research regarding labor market and macro economy, as well as policymaking.

Our empirical findings can be summarized as follows. In terms of the misclassification probabilities, we find that i) when the actual labor force status is either employed or not-in-labor-force, the probabilities of being misreported to a different labor force status are never above 5%; ii) The biggest errors are from the unemployed people being misclassified as either not-in-labor-force or employed. And only around 50-70% of unemployed people correctly report their true labor force status; iii) There exist considerable heterogeneities among different demographic groups.

As for the unemployment rate, our empirical results suggest that i) for each demographic group and for each sub-period, corrected unemployment rates are always larger than officially reported ones. In addition, the degree of underestimation is larger when the level of unemployment is higher; ii) for the whole US population, the corrected unemployment rate is always higher than the reported one and the difference is between 1% and 4.6%. Average corrected unemployment rate is 7.2% during the studied period, which is higher than the reported rate by 1.9% (or 35% in terms of percentage); iii) in all sub-periods, unemployment rate volatilities suggested by the corrected series are substantially larger than the reported series. iv) the composition of the total degree of underestimation suggests that old white females declare the largest share of the total (27%), followed by young white males (21%).

For the labor force participation rates, we find that i) for each demographic group and for each sub-period, corrected labor force participation rates are always higher than reported ones, but the differences are small and not statistically significant; ii) for the whole sample, both the corrected and reported series are somewhat flat during the period under study. The corrected participation rate is always slightly higher than the reported one, but the average difference is less than 2%, and not statistically significant.

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Table 1: Misclassification probabilities for different demographic groups

	$f_{U_t\|U_t^*}(2\|1)$	$f_{U_t\|U_t^*}(3\|1)$	$f_{U_t\|U_t^*}(1\|2)$	$f_{U_t\|U_t^*}(3\|2)$	$f_{U_t\|U_t^*}(1\|3)$	$f_{U_t\|U_t^*}(2\|3)$
(1) M/W/Y	0.9%	1.3%	20.1%	17.2%	6.0%	0.0%
	(0.05%)	(0.05%)	(1.12%)	(2.71%)	(0.37%)	(0.39%)
(2) M/W/O	0.4%	0.9%	16.5%	18.8%	1.4%	0.1%
	(0.03%)	(0.04%)	(1.03%)	(2.29%)	(0.06%)	(0.08%)
(3) M/NW/Y	1.1%	2.2%	13.4%	18.1%	5.0%	4.3%
	(0.10%)	(0.12%)	(1.16%)	(4.32%)	(0.34%)	(1.29%)
(4) M/NW/O	0.7%	1.5%	15.5%	22.0%	1.2%	0.0%
	(0.07%)	(0.09%)	(1.78%)	(5.30%)	(0.15%)	(0.13%)
(5) F/W/Y	0.6%	2.1%	18.6%	10.5%	4.4%	0.0%
	(0.04%)	(0.08%)	(1.47%)	(4.10%)	(0.23%)	(0.08%)
(6) F/W/O	0.3%	1.4%	17.9%	28.2%	1.0%	0.0%
	(0.03%)	(0.05%)	(1.33%)	(3.13%)	(0.05%)	(0.01%)
(7) F/NW/Y	1.1%	2.6%	11.9%	29.1%	2.2%	0.0%
	(0.08%)	(0.13%)	(1.48%)	(8.21%)	(0.75%)	(0.04%)
(8) F/NW/O	0.4%	1.8%	13.9%	25.0%	1.2%	0.7%
	(0.07%)	(0.10%)	(1.97%)	(5.86%)	(0.08%)	(0.16%)

Note: M - Male; F - Female; W - White; NW - Nonwhite; Y - Young people (age less than or equal to 40); O - Older people (age greater than 40). Bootstrapped standard errors based on 1000 repetitions are in parentheses.

Table 2: Comparing misclassification probabilities across demographic groups

	$f_{U_t\|U_t^*}(2\|1)$	$f_{U_t\|U_t^*}(3\|1)$	$f_{U_t\|U_t^*}(1\|2)$	$f_{U_t\|U_t^*}(3\|2)$	$f_{U_t\|U_t^*}(1\|3)$	$f_{U_t\|U_t^*}(2\|3)$
Males vs. Females						
(1)-(5)	0.3%	-0.8%	ns	ns	1.6%	ns
	(0.06%)	(0.09%)			(0.44%)	
(2)-(6)	0.1%	-0.5%	ns	-9.4%	0.3%	ns
	(0.04%)	(0.07%)		(3.88%)	(0.08%)	
(3)-(7)	ns	-0.3%	ns	ns	2.8%	4.3%
		(0.17%)			(0.82%)	(1.29%)
(4)-(8)	0.2%	-0.3%	ns	ns	ns	-0.7%
	(0.10%)	(0.13%)				(0.20%)
Whites vs. Nonwhites						
(1)-(3)	ns	-0.9%	6.7%	ns	ns	-4.3%
		(0.13%)	(1.61%)			(1.34%)
(2)-(4)	-0.2%	-0.6%	ns	ns	ns	ns
	(0.08%)	(0.10%)				
(5)-(7)	-0.5%	-0.5%	6.7%	-18.6%	2.2%	ns
	(0.09%)	(0.15%)	(2.09%)	(9.18%)	(0.78%)	
(6)-(8)	ns	-0.3%	ns	ns	-0.2%	-0.7%
		(0.11%)			(0.09%)	(0.16%)
Young vs. Old						
(1)-(2)	0.5%	0.4%	3.6%	ns	4.6%	ns
	(0.06%)	(0.06%)	(1.52%)		(0.38%)	
(3)-(4)	0.4%	0.7%	ns	ns	3.8%	4.3%
	(0.12%)	(0.15%)			(0.37%)	(1.29%)
(5)-(6)	0.3%	0.7%	ns	-17.7%	3.4%	ns
	(0.05%)	(0.10%)		(5.15%)	(0.23%)	
(7)-(8)	0.6%	0.8%	ns	ns	ns	-0.7%
	(0.11%)	(0.16%)				(0.16%)

Note: The numbers in parentheses in the first column refer to demographic groups defined the same way as in table 1. For example, (1) means young white males and (5) means young white females. For the rest of the columns, 'ns' signifies not being statistically significant at the 5% level and numbers in parentheses are standard errors.

Table 3: Comparing misclassification probabilities with those in previous studies

	$f_{U_t\|U_t^*}(2\|1)$	$f_{U_t\|U_t^*}(3\|1)$	$f_{U_t\|U_t^*}(1\|2)$	$f_{U_t\|U_t^*}(3\|2)$	$f_{U_t\|U_t^*}(1\|3)$	$f_{U_t\|U_t^*}(2\|3)$
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%)	(0.54%)	(1.39%)	(0.09%)	(0.10%)

Note: 'PS' refers to estimates by Porterba 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, based on results reported in Table 1 and weighted using CPS sample from 1996-2009.

Table 4: Unemployment rates averaged over three sub-periods for different demographic groups

	Sub-period 1 (1996/01-2001/10)		Sub-period 2 (2001/11-2007/11)		Sub-period 3 (2007/12-2009/12)	
	reported	corrected	reported	corrected	reported	corrected
(1) M/W/Y	5.0%	6.4%	6.1%	8.2%	9.4%	13.3%
	(0.2%)	(0.4%)	(0.2%)	(0.4%)	(0.3%)	(0.6%)
(2) M/W/O	2.7%	3.4%	3.4%	4.5%	5.6%	7.8%
	(0.1%)	(0.2%)	(0.1%)	(0.3%)	(0.2%)	(0.4%)
(3) M/NW/Y	10.0%	11.1%	10.8%	12.0%	14.5%	17.2%
	(0.5%)	(1.1%)	(0.5%)	(1.1%)	(0.6%)	(1.4%)
(4) M/NW/O	4.8%	6.5%	5.8%	8.0%	8.2%	11.7%
	(0.4%)	(0.7%)	(0.4%)	(0.8%)	(0.4%)	(1.0%)
(5) F/W/Y	5.1%	6.4%	5.8%	7.3%	7.5%	9.8%
	(0.2%)	(0.4%)	(0.2%)	(0.5%)	(0.3%)	(0.6%)
(6) F/W/O	2.7%	4.4%	3.2%	5.3%	4.7%	7.9%
	(0.1%)	(0.3%)	(0.1%)	(0.3%)	(0.2%)	(0.5%)
(7) F/NW/Y	10.0%	14.4%	10.3%	14.9%	11.8%	17.0%
	(0.5%)	(1.6%)	(0.5%)	(1.6%)	(0.5%)	(1.8%)
(8) F/NW/O	4.2%	5.1%	5.2%	6.8%	6.3%	8.5%
	(0.3%)	(0.7%)	(0.3%)	(0.8%)	(0.4%)	(0.9%)

Note: Demographic groups are defined the same way as in table 1. Numbers reported in parentheses are standard errors average over the corresponding sub-period.

Table 5: Comparing levels and trends of the reported and corrected unemployment rate series for the whole sample

	coefficient	standard error
level of the reported series		
sub-period 1	4.63%*	(0.04%)
sub-period 2	5.28%*	(0.03%)
sub-period 3	7.45%*	(0.07%)
difference in levels: corrected vs. reported series		
sub-period 1	1.44%*	(0.08%)
sub-period 2	1.85%*	(0.05%)
sub-period 3	3.03%*	(0.13%)
linear trend of the reported series		
sub-period 1	-0.02%*	(0.003%)
sub-period 2	-0.02%*	(0.002%)
sub-period 3	0.26%*	(0.01%)
difference in linear trends: corrected vs. reported series		
sub-period 1	-0.01%	(0.005%)
sub-period 2	-0.01%*	(0.003%)
sub-period 3	0.14%*	(0.02%)

Note: * signifies statistical significance at the 1% level. Numbers in parentheses are robust standard errors.

Table 6: Decomposing underestimation in unemployment rate (μ) by demographic groups (averaged over 1996-2009).

	Underestimation in μ	% of US population	Contribution to US population total	
			value	percentage
(1) M/W/Y	2.1%	18.4%	0.39%	21%
(2) M/W/O	1.1%	21.7%	0.24%	13%
(3) M/NW/Y	1.4%	4.4%	0.06%	3%
(4) M/NW/O	2.2%	3.7%	0.08%	4%
(5) F/W/Y	1.5%	18.1%	0.27%	15%
(6) F/W/O	2.1%	24.1%	0.50%	27%
(7) F/NW/Y	4.6%	5.0%	0.23%	12%
(8) F/NW/O	1.6%	4.6%	0.07%	4%
US population total	1.9%	100%	1.9%	100%

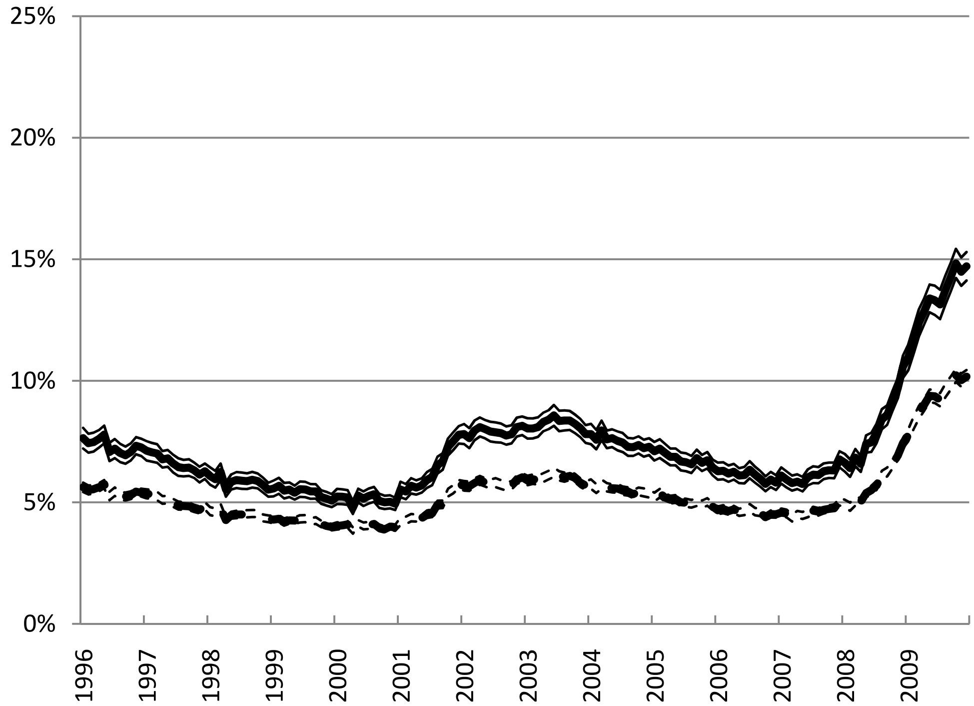
Note: Demographic groups are defined the same way as in table 1.

Table 7: Labor force participation rates averaged over three sub-periods for different demographic groups

	Sub-period 1 (1996/01-2001/10)		Sub-period 2 (2001/11-2007/11)		Sub-period 3 (2007/12-2009/12)	
	reported	corrected	reported	corrected	reported	corrected
(1) M/W/Y	86.5%	87.8%	83.6%	84.9%	81.6%	83.5%
	(2.7%)	(2.8%)	(2.7%)	(2.7%)	(2.6%)	(2.7%)
(2) M/W/O	65.5%	66.0%	66.6%	67.3%	66.9%	68.0%
	(2.1%)	(2.1%)	(2.1%)	(2.1%)	(2.1%)	(2.2%)
(3) M/NW/Y	75.6%	76.5%	74.1%	74.8%	72.8%	74.0%
	(2.4%)	(2.6%)	(2.4%)	(2.5%)	(2.3%)	(2.6%)
(4) M/NW/O	63.6%	65.0%	64.9%	66.6%	64.4%	66.6%
	(2.1%)	(2.2%)	(2.1%)	(2.2%)	(2.1%)	(2.2%)
(5) F/W/Y	72.4%	73.2%	69.6%	70.1%	68.9%	69.6%
	(2.3%)	(2.3%)	(2.2%)	(2.2%)	(2.2%)	(2.2%)
(6) F/W/O	49.0%	49.8%	51.6%	52.6%	52.5%	53.9%
	(1.6%)	(1.6%)	(1.6%)	(1.7%)	(1.7%)	(1.7%)
(7) F/NW/Y	68.9%	73.0%	66.7%	70.7%	65.6%	69.9%
	(2.2%)	(2.7%)	(2.2%)	(2.6%)	(2.1%)	(2.7%)
(8) F/NW/O	52.6%	53.3%	54.5%	55.5%	54.9%	56.2%
	(1.8%)	(1.8%)	(1.8%)	(1.9%)	(1.8%)	(1.9%)

Note: Demographic groups are defined the same way as in table 1. Numbers reported in parentheses are standard errors average over the corresponding sub-period.

Figure 1: Reported and Corrected Unemployment Rates



Note: Solid lines stand for corrected values and 95% confidence bounds, dashed lines stand for reported values and 95% confidence bounds. The same applies to all other figures.

Figure 2: Reported and Corrected Labor Force Participation Rates

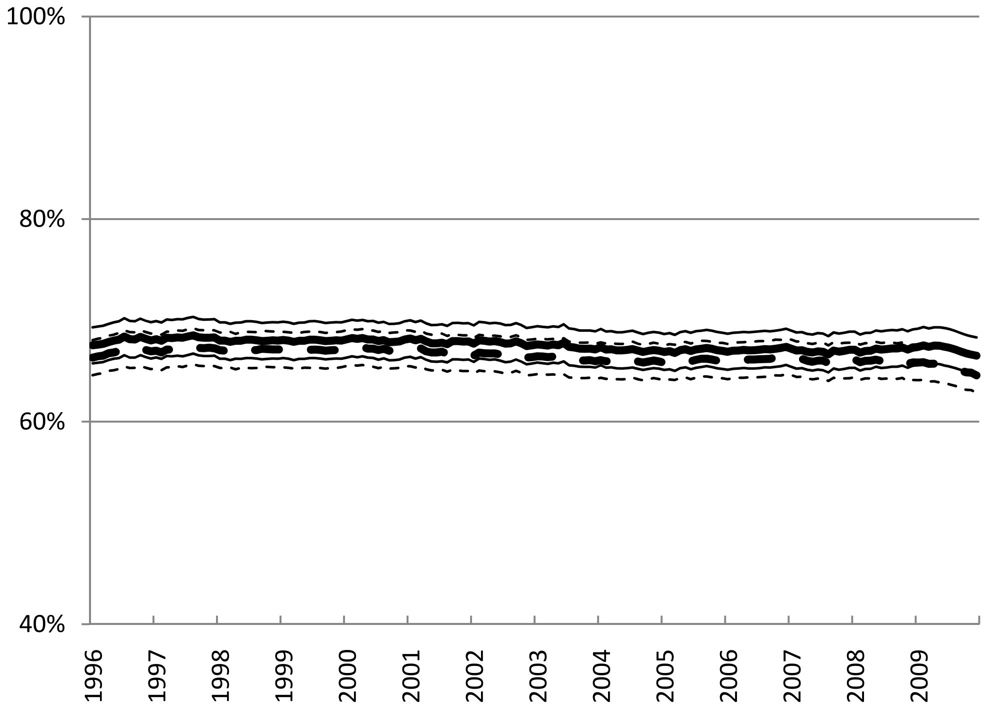
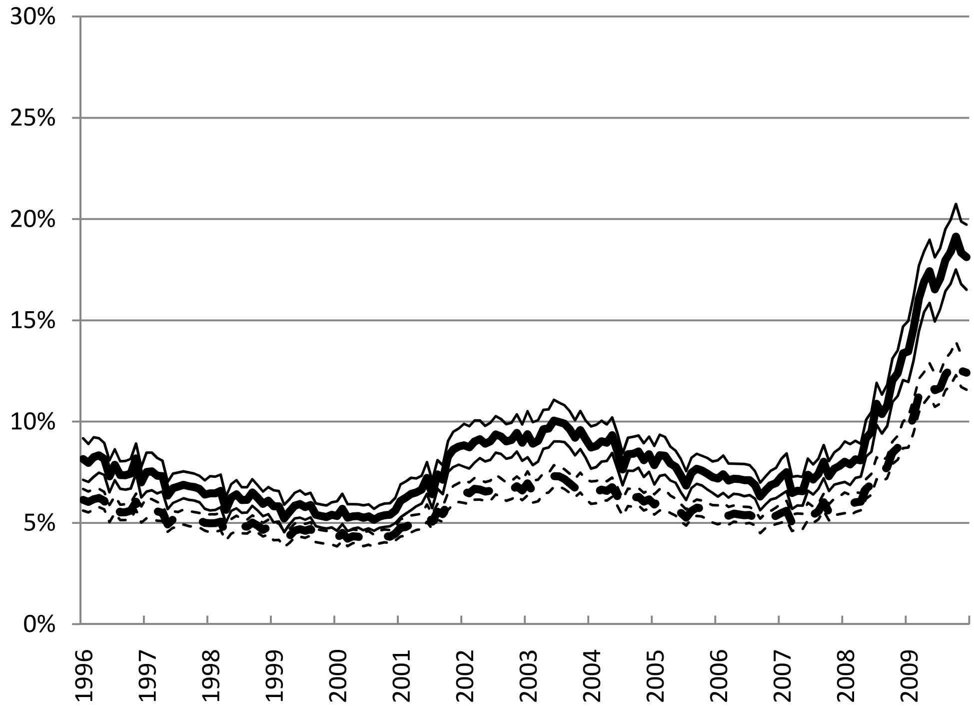
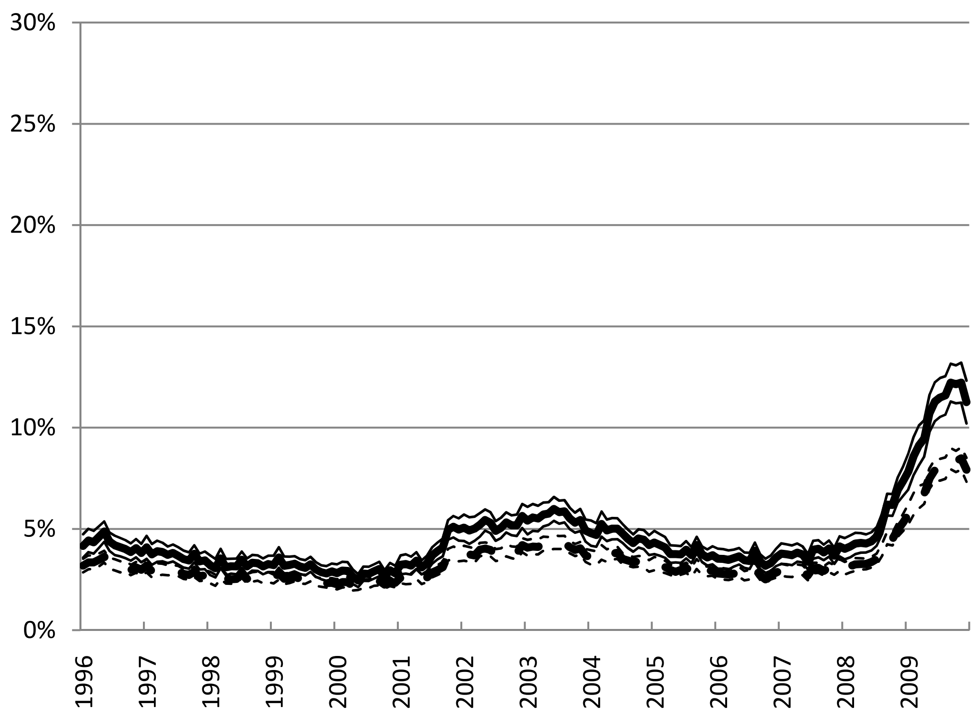


Figure A1: Reported and Corrected Unemployment Rates for demographic groups

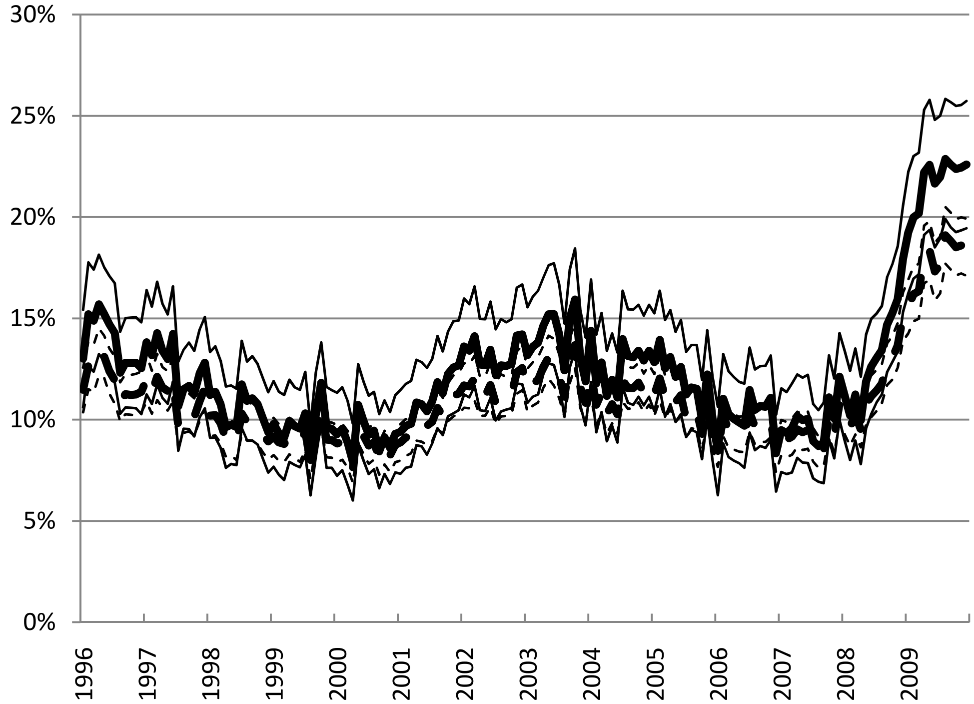
A: Young White Males



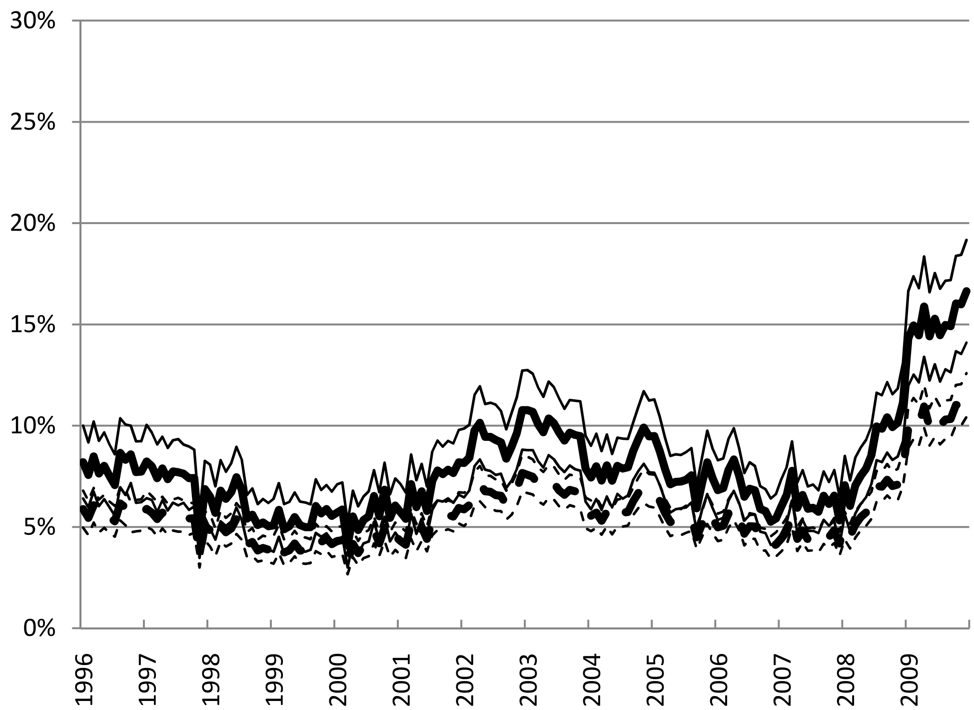
B: Old White Males



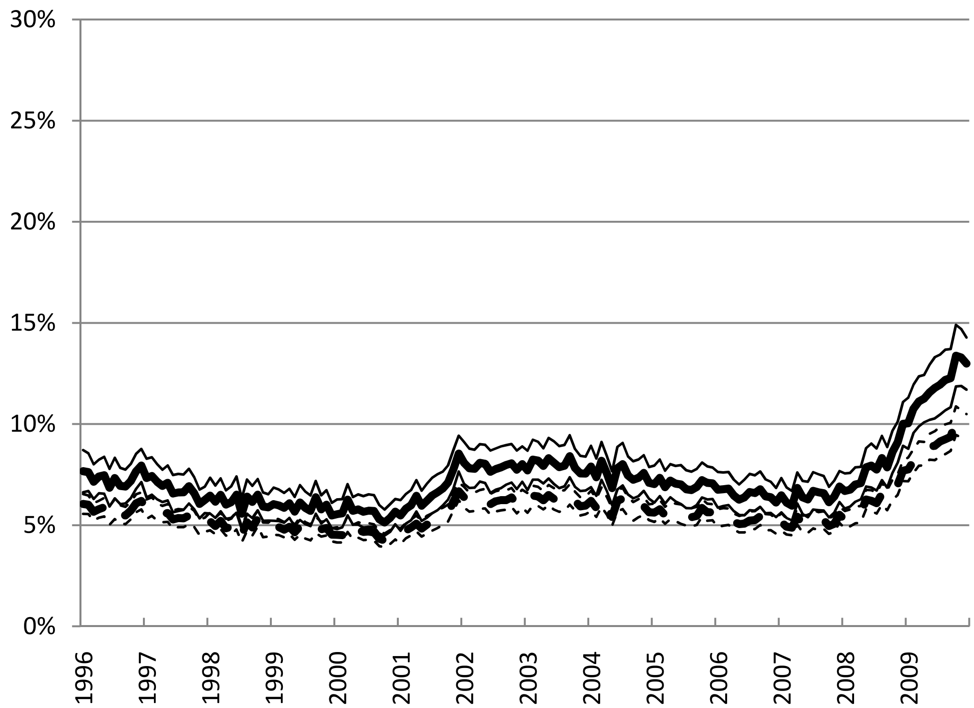
C: Young Nonwhite Males



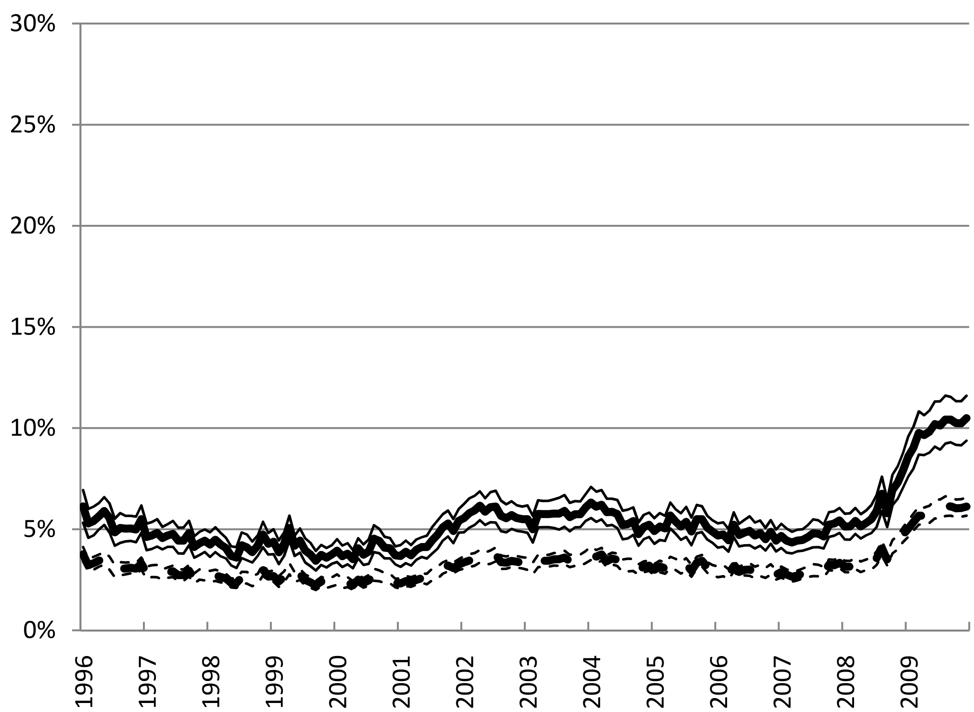
D: Old Nonwhite Males



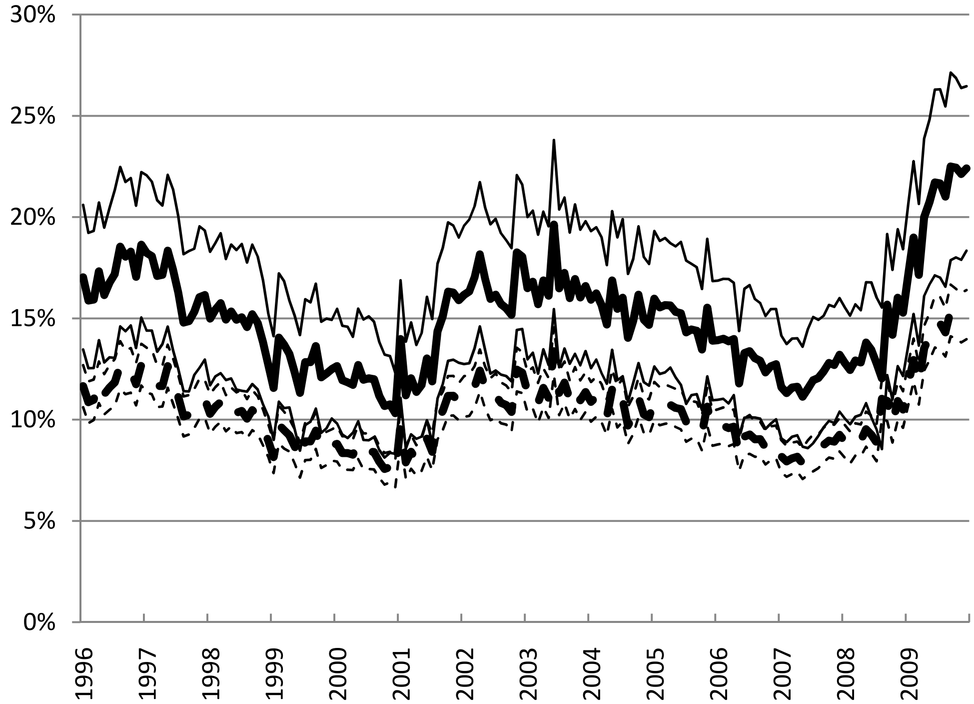
E: Young White Females



F: Old White Females



G: Young Nonwhite Females



H: Old Nonwhite Females

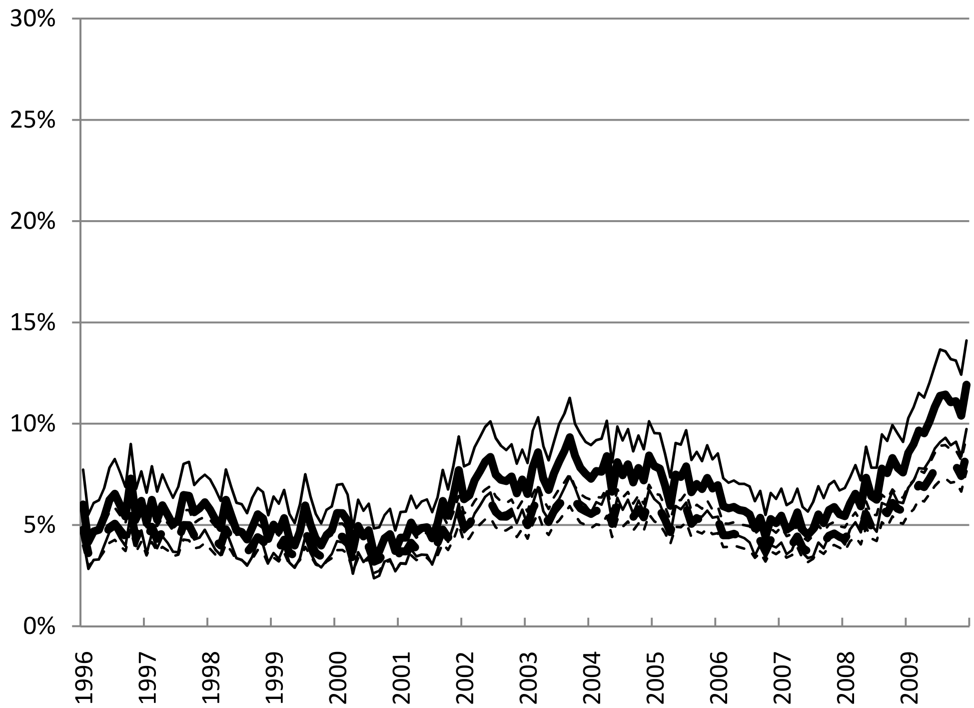
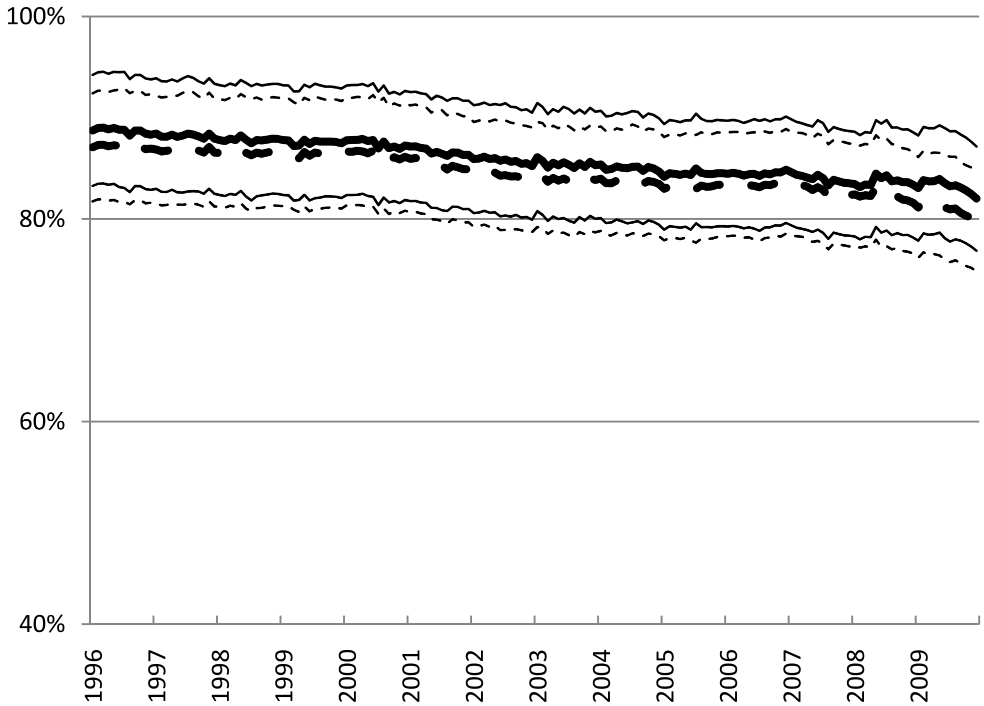
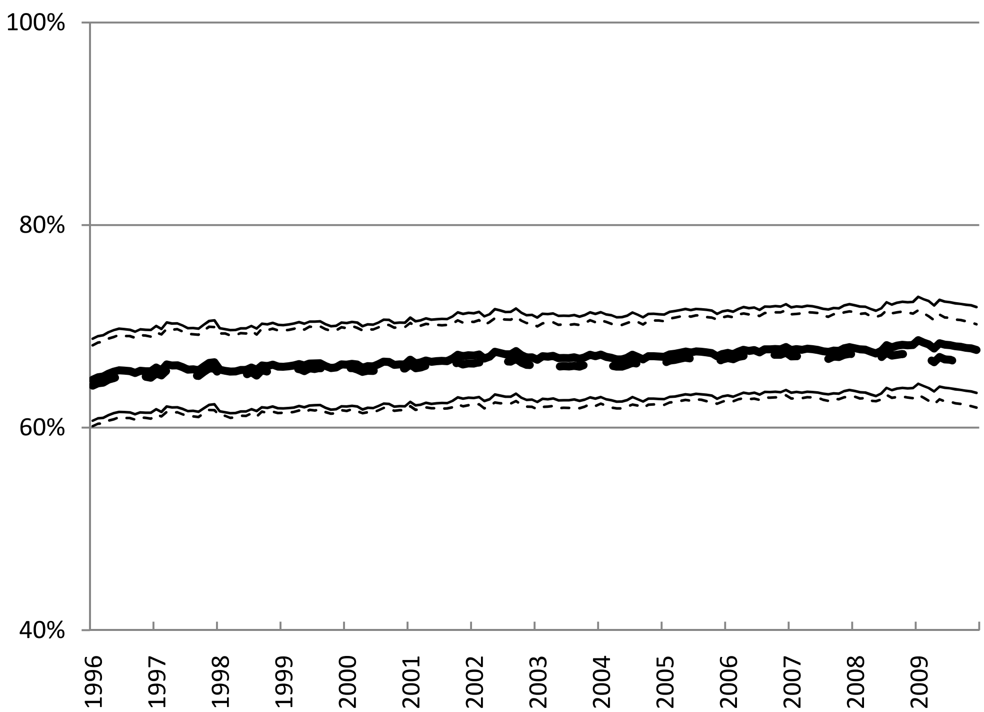


Figure A2: Reported and Corrected Labor Force Participation Rates for demographic groups

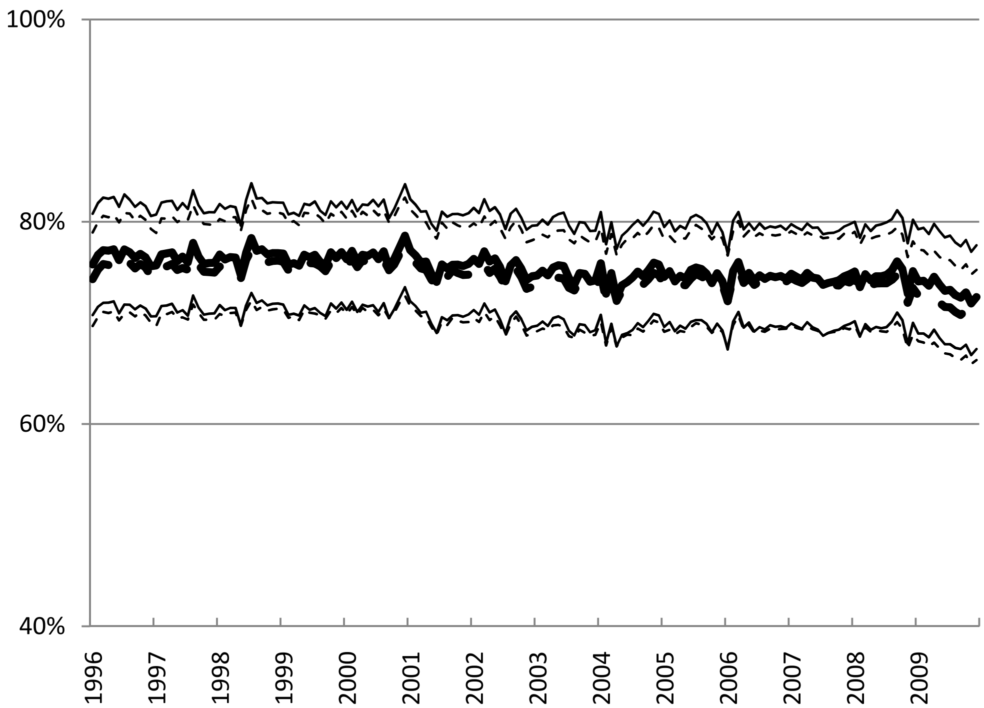
A: Young White Males



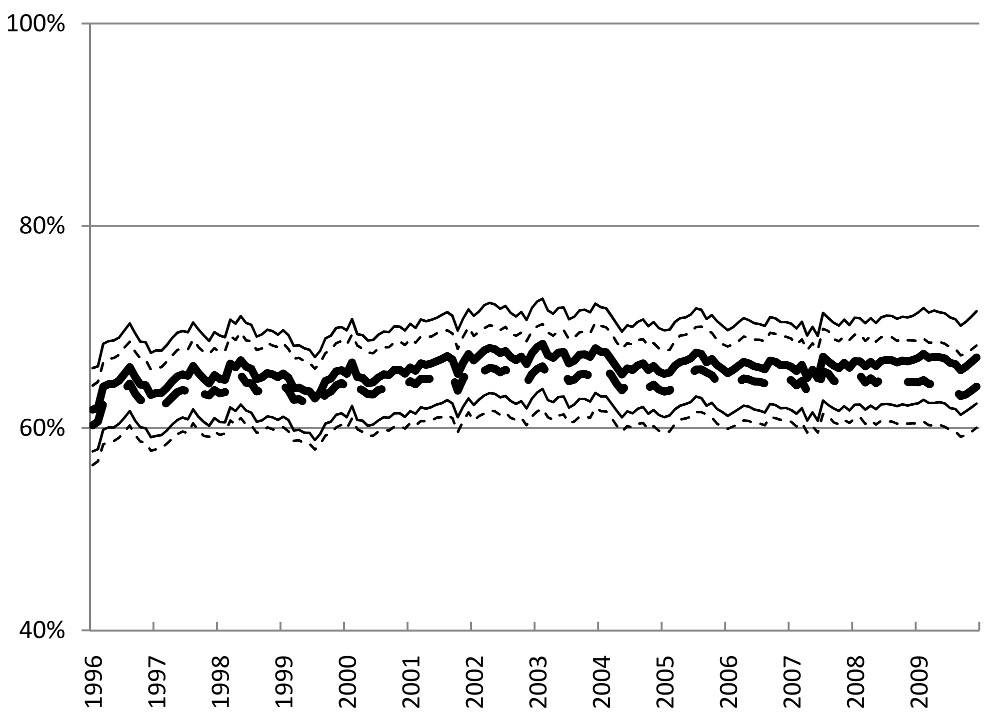
B: Old White Males



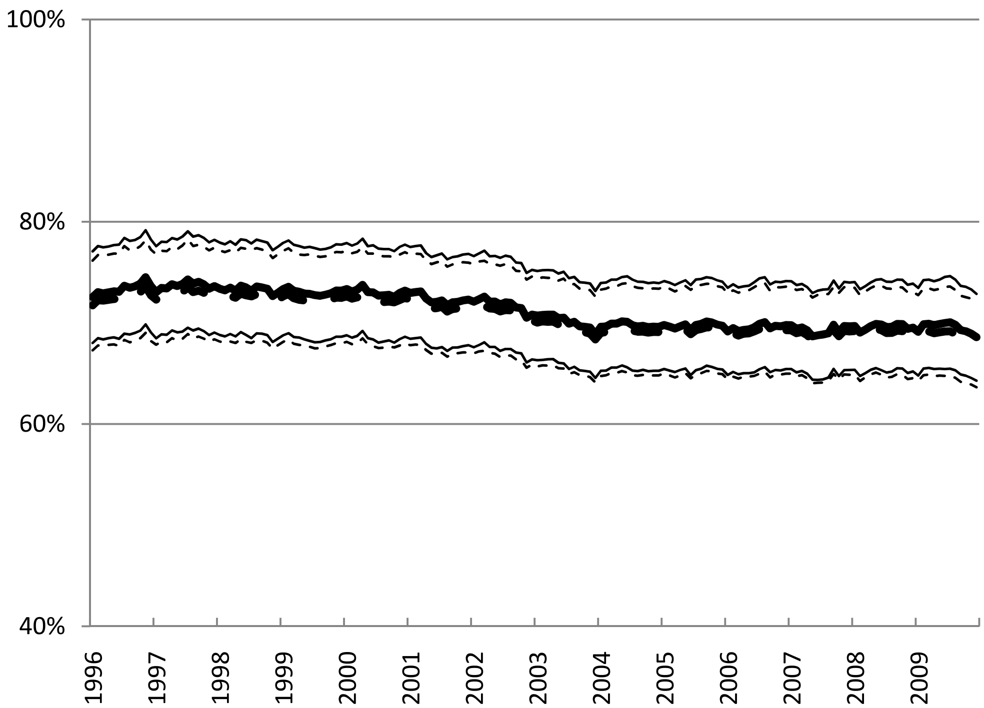
C: Young Nonwhite Males



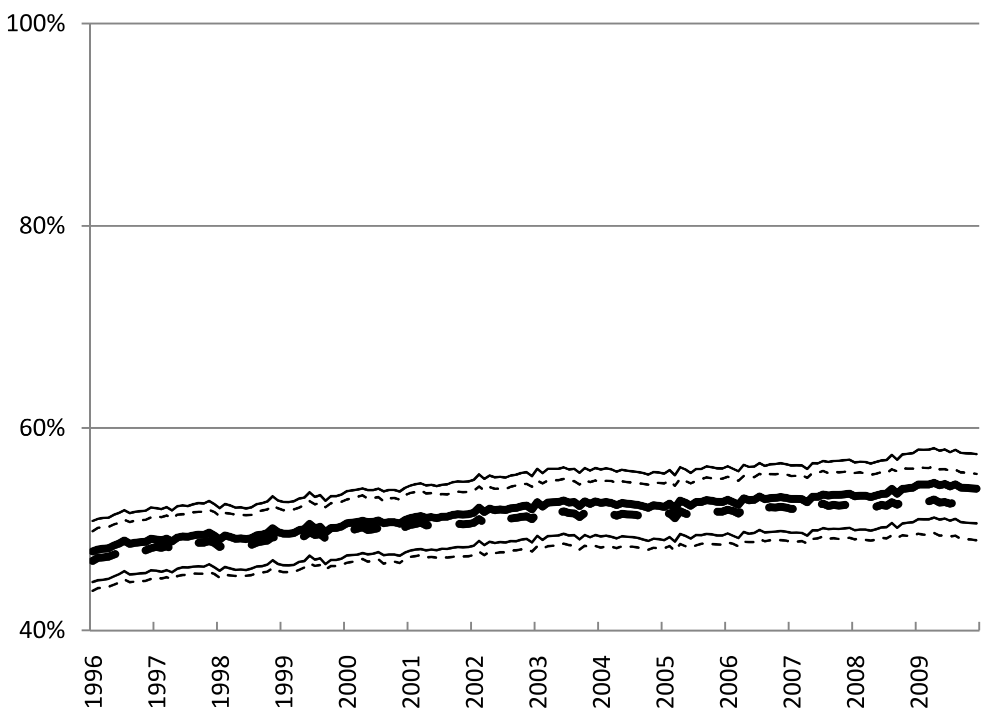
D: Old Nonwhite Males



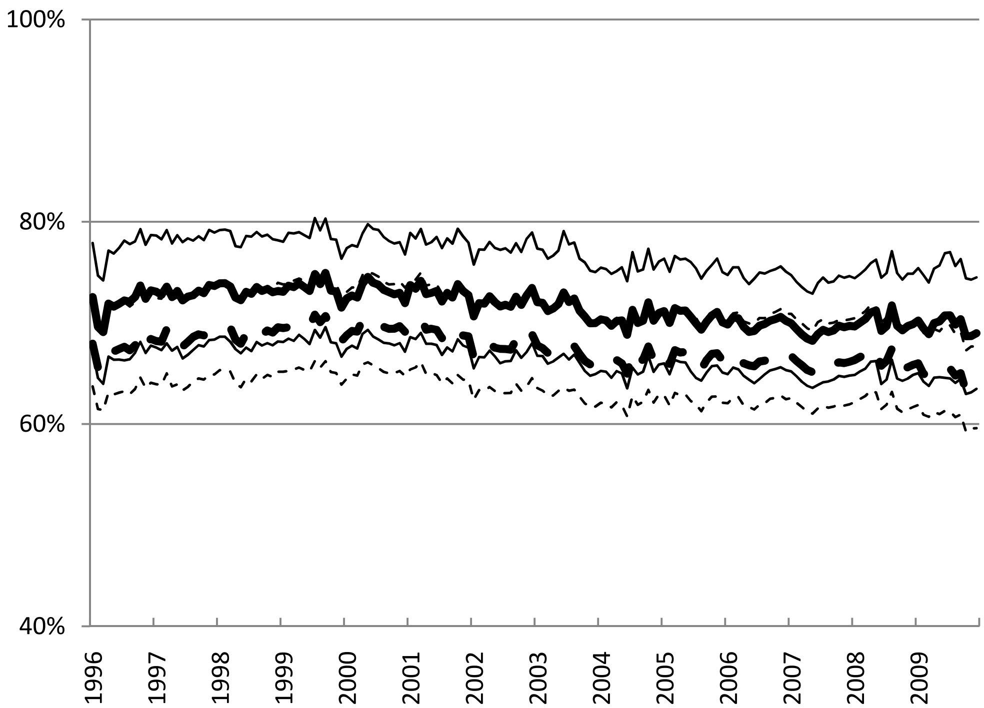
E: Young White Females



F: Old White Females



G: Young Nonwhite Females



H: Old Nonwhite Females