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On the robustness of alternative unemployment measures

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ABSTRACT

The unemployment rate is one of the most important economic indices. This article extends the work of Feng and Hu (2013) and examines the effects of potential misclassifications in labor force statuses on the different Bureau of Labor Statistics (BLS) unemployment measures. Compared to the official US unemployment rate U-3, the broader measure U-6 is more robust to such classification errors in the survey data that are used to calculate unemployment rates. If one prefers the definitions of U-3, then we offer an approach to use reported unemployment measures to proxy for the unobserved true U-3.

1. Introduction

The unemployment rate is probably one of the most important economic statistics, yet it is not straightforward to properly define unemployment and measure it using actual data. The U.S. Bureau of Labor Statistics offers six different unemployment rate series, from U-1 to U-6, of which the U-3 is the official unemployment rate and closest to the definition of unemployment by the International Labor Organization (see Table 1). The U-6 unemployment rate counts not only people without work seeking full-time employment (the more familiar U-3 rate), but also counts "marginally attached workers and those working part-time for economic reasons". The "marginally attached workers" include those who have gotten discouraged and stopped looking, but still want to work. Also, involuntary part-time workers are counted as employed by U-3 but may be actually closer to people's commonsense impression of unemployed people. The U-6 became more influential as its difference with U-3 increased substantially after the recent economic crisis, as many people are discouraged from participating labor market or forced to work part-time when the market is slack.

In this short article, we investigate the robustness of different measures of unemployment. It is well-known that labor force statuses in survey data are subject to measurement errors, and Feng and Hu (2013) correct for such misclassification and estimate the true U-3 using a latent variable approach. We extend their work to consider other measures, and find that U-6 is more robust to such measurement errors than U-3. In addition, if one still prefers the definitions of U-3, then we offer an almost accurate rule of thumb to predict the true unemployment rate U-3 from a linear combination of reported U-3, U-4, U-5, and U-6. Our regression shows that such a linear combination can account for 99% variation of the true U-3 after correcting the misclassification error.

Our methodology is different from the existing studies. There has been a literature on the proper classification of labor force statuses, which pays special attention to the labor force dynamics of people with different labor force status, especially the transition rates from unemployment (U) or out-of-labor-force (O) into employment(E). The idea is that if the probability of transition into E from U and O are the same, then the distinctions between U and O are meaningless from the Markov transition perspective. So far, the empirical results are somewhat mixed. Clark and Summers (1982) conclude that unemployment and out-of-labor-force are not distinct for teenagers. Flinn and Heckman (1982) report the opposite for white male high school graduates. Gönül (1992) examine whether unemployment and out-of-labor-force are distinct labor force statuses for high school graduates using NLSY79 data, and find mixed results. She found that the two states are distinct for women but not for men. Jones and Riddell (1999) conclude that "any attempt to dichotomize the nonemployed into unemployment and out-of-the-labor-force is unlikely to fully capture the complexity of labor force activity", and propose to classify at least four different labor force status: employment, unemployment, marginal attachment and not-attached-to-the-labor-force.

2. Methods

We use the method proposed by Hu (2008) and used in Feng and Hu (2013). Here we only provide a brief discussion on the

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Table 1
Definitions of alternative unemployment rates.
Source: U.S. Bureau of Labor Statistics (https://www.bls.gov/lau/stalt.htm).

	Definition
U-1	Persons unemployed 15 weeks or longer, as a percent of the civilian labor force.
U-2	Job losers and persons who completed temporary jobs, as a percent of the civilian labor force.
U-3	Total unemployed, as a percent of the civilian labor force (official unemployment rate).
U-4	Total unemployed plus discouraged workers, as a percent of the civilian labor force plus discouraged workers.
U-5	Total unemployed, plus discouraged workers, plus all other persons marginally attached to the labor force, as a percent of the civilian labor force plus all persons marginally attached to the labor force.
U-6	Total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons, as a percent of the civilian labor force plus all persons marginally attached to the labor force.

assumptions and methods, and refer interested readers to Feng and Hu (2013) for more detailed discussions. Suppose we observe an i.i.d. sample of self-reported labor status U for three periods $\{U_{t+1}, U_t, U_{t-9}\}_i$ for individual i $(i = 1, 2, \ldots, N)$. For example, if U_t stands for one's labor force status in January 2008, then U_{t+1} and U_{t-9} denote his or her labor force status in February 2008 and in April 2007, respectively. Although each person appears eight times in CPS, we choose to use data from the three periods $(t-9, t, t+1)$ for three reasons: (i) we want the three periods to be close enough to minimize sample attrition; (ii) we want the three periods to cover the 8-month break in the 4–8–4 rotation structure of CPS to ensure that there are enough variations in the labor force status; (iii) the assumption regarding the dynamics of the latent true labor force status (Condition 2 below) is more likely to be satisfied if we use the data reported a while ago, e.g., nine months earlier.

We assume that the latent true labor status U_t^* has the same support as U_t as follows:

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

This framework is general to the precise definitions labor force statuses in different measures used by BLS (U-1 to U-6). Let $f(\cdot)$ stand for probability density functions or probability mass functions of its arguments. Let $\Omega_{\neq t}$ denote all the variables in all the periods except period t, i.e., $\Omega_{\neq t} = \left\{\left(U_\tau, U_\tau^*\right) \text{ for } \tau = 1, \ldots, T \text{ and } \tau \neq t\right\}$. We assume that the misreporting error satisfies a local independence condition as follows:

Condition 1. $f\left(U_t|U_t^*, \Omega_{\neq t}\right) = f\left(U_t|U_t^*\right)$.

This condition implies that the misreporting error may be correlated with the true labor force status, and correlated with all other variables only through the true labor force status. In addition, we simplify the evolution of the true labor status as follows:

Condition 2. $f\left(U_{t+1}^*|U_t^*, U_{t-9}^*\right) = f\left(U_{t+1}^*|U_t^*\right)$.

This condition implies that the labor status in period $t-9$ does not have any prediction power on the labor status in the period $t+1$ beyond the labor status in the current period t. Under Conditions 1 and 2, the relationship between observed probabilities and unobserved ones is as follows:

$$f\left(U_{t+1}, U_t, U_{t-9}\right) = \sum_{U_t^*} f\left(U_{t+1}|U_t^*\right) f\left(U_t|U_t^*\right) f\left(U_t^*, U_{t-9}\right). \quad (1)$$

We may then use the identification results in Hu (2008) to show that all the unobservables on the right-hand side of Eq. (1) may be identified. Define $M_{U_t|U_t^*} = \left[f_{U_t|U_t^*}(i|k)\right]_{i,k}$, $M_{U_t|U_t^*} = \left[f_{U_t|U_t^*}(i|j)\right]_{i,j}$, $M_{U_t^*,U_{t-v}} = \left[f_{U_t^*,U_{t-v}}(j,k)\right]_{j,k}$, and $M_{1,U_t,U_{t-v}} = \left[f_{U_{t+s},U_t,U_{t-v}}(1,i,k)\right]_{i,k}$ and $D_{1|U_t^*} = diag\left[f_{U_{t+s}|U_t^*}(1|k)\right]_k$. We can show that Eq. (1) is equivalent to

$$M_{1,U_t,U_{t-v}} = M_{U_t|U_t^*} D_{1|U_t^*} M_{U_t^*,U_{t-v}} \quad (2)$$

and

$$M_{U_t,U_{t-v}} = M_{U_t|U_t^*} M_{U_t^*,U_{t-v}}. \quad (3)$$

Under the following technical condition,

Condition 3. *Matrix* $M_{U_t,U_{t-v}}$ *is invertible.*

we obtain

$$M_{1,U_t,U_{t-v}} M_{U_t,U_{t-v}}^{-1} = M_{U_t|U_t^*} D_{1|U_t^*} M_{U_t|U_t^*}^{-1}. \quad (4)$$

This equation implies that the observed matrix on the LHS of Eq. (4) has an eigenvalue–eigenvector decomposition on the RHS. In order to achieve a unique decomposition, we need the following two additional conditions:

Condition 4. $f_{U_{t+s}|U_t^*}(1|k)$ *are different for a different* k.

Condition 5. $f_{U_t|U_t^*}(k|k) > f_{U_t|U_t^*}(j|k)$ *for* $j \neq k$.

These two conditions guarantee that the eigenvalues are distinctive and that the eigenvectors can be ordered by the value of true labor force status.

Given that we have identified the misclassification error distribution $f_{U_t|U_t^*}$ in $M_{U_t|U_t^*}$, we may then identify the distribution of the latent true labor status $f_{U_t^*}$, and therefore, the true unemployment rate, from the observed the distribution f_{U_t} from $f_{U_t} = \sum_{U_t^*} f_{U_t|U_t^*} f_{U_t^*}$. This identification procedure is constructive in the sense that it directly leads to an estimator.

3. Results

We use the public-use micro Current Population Surveys data from January 1996 to December 2016, which are used to calculate the BLS unemployment rates including the official U-3. Because of the 4–8–4 rotational group structure, the CPS can be matched to form longitudinal panels, which enables us to obtain the joint probabilities of the self-reported labor force statuses in three periods. The matching method in this paper is the same as Feng and Hu (2013). We follow the algorithm proposed by Madrian and Lefgren (2000) to match CPS monthly files. Due to sample attrition, the matched sample is not representative of the cross-sectional sample in period t. To correct for biases introduced by sample attrition, we also estimate matching weights to ensure the matched panel to have the same marginal distributions on some key individual characteristics as the cross-sectional dataset for period t. We also pool different periods of data to increase sample sizes when estimating the misclassification matrices. Specifically, the misclassification matrix for period t is generated by pooling matched samples from period $t-70$ to $t-1$. Therefore, though the data we use is from January 1996 to December 2016, we will report our results from November 2001.

Fig. 1 shows all the seasonally-adjusted monthly values of each unemployment measures, including both the reported values that are directly calculated from CPS, and the estimated true ones using the latent variable approach we outlined in the previous section. We only report the results of U-3 to U-6 for two reasons. First, in our framework, Condition 5 fails to hold for U-1 and U-2. Second, the current policy debate is that whether U-3 is a too narrow measure to capture all unemployed people, but U-1 and U-2 are even narrower concepts than U-3.

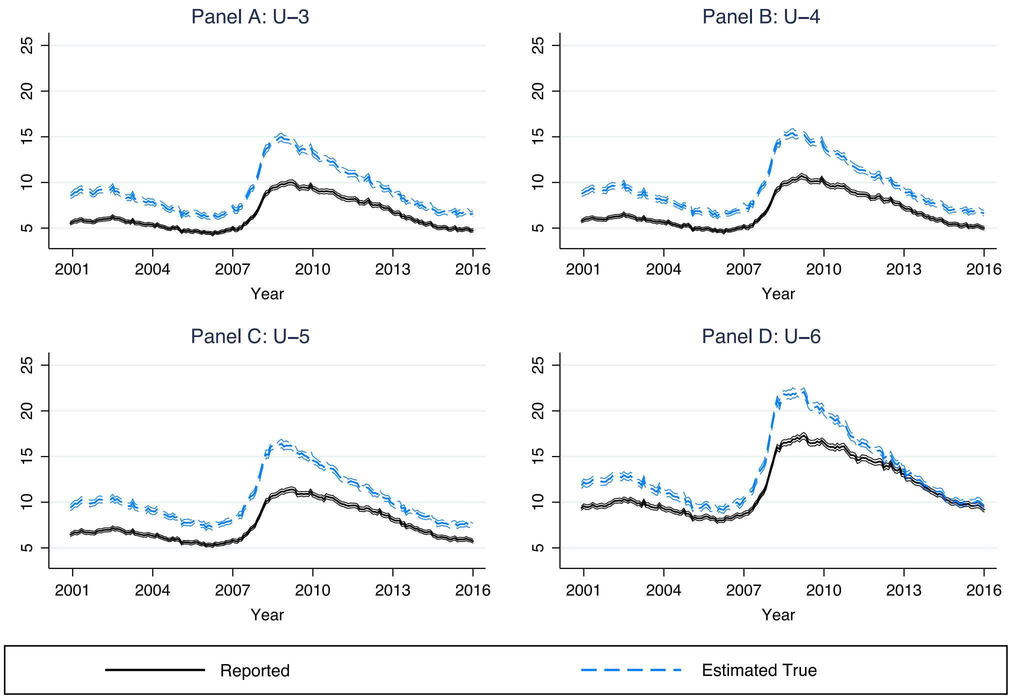

Fig. 1. Estimated true and reported unemployment rates. Note: Seasonally-adjusted estimated true unemployment rates (the dashed line) and reported unemployment rates (the solid line) from November 2001 to December 2016. The corresponding thin lines signify 95 percent upper and lower confidence bounds, which are based on bootstrapped standard errors with 200 repetitions.

We find that for U-3, U-4 and U-5, the estimated true numbers are always significantly higher than the reported ones, while for U-6, the estimated true numbers are no longer always significantly higher than the reported ones. Specifically, the estimated true U-6 rates almost coincide with the reported U-6 rates since 2013. Thus, simply eyeballing suggests that U-6 is a more robust measure than U-3, at least when the level of unemployment rate is not very high.

More rigorously, we report the average bias (both the level and percent) for each measure, which is defined as follows:

$$Average\_bias\_level = T^{-1}\sum_{t=1}^{T}(TU\text{-}i_t - RU\text{-}i_t) \tag{5}$$

$$Average\_bias\_percent = T^{-1}\sum_{t=1}^{T}\frac{TU\text{-}i_t - RU\text{-}i_t}{RU\text{-}i_t} \tag{6}$$

where $RU\text{-}i_t$ is the reported U-i rate in period t, and $TU\text{-}i_t$ is the estimated true U-i rate in period t. We also use Root Mean Squared Error (RMSE), which captures the difference in both the first and second moments, defined as:

$$RMSE\_level = \sqrt{T^{-1}\sum_{t=1}^{T}(TU\text{-}i_t - RU\text{-}i_t)^2} \tag{7}$$

$$RMSE\_percent = \sqrt{T^{-1}\sum_{t=1}^{T}\left(\frac{TU\text{-}i_t - RU\text{-}i_t}{RU\text{-}i_t}\right)^2}. \tag{8}$$

Panel A of Table 2 shows when comparing the reported values with estimated true values, U-6 has both the least absolute bias and relative bias. The average bias of U-3 is 2.7 percentage points, which is a 42.1 percent upward adjustment, while for U-6, the average bias is 2.0 percentage points, which is a 16.4 percent upward adjustment. It is also not surprising that U-6 posts the lowest RMSE, both on level and percent. Therefore, if someone prefers the

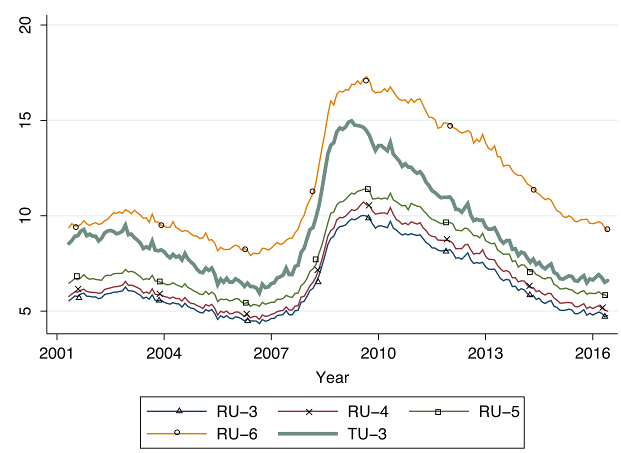

Fig. 2. Estimated true U-3 vs. reported U-3 to U-6. Note: Seasonally-adjusted reported unemployment measures and estimated true U-3 from November 2001 to December 2016. RU: reported unemployment rate, TU: estimated true unemployment rate.

definition of U-6, then our results lend additional support from the measurement perspective.

However, the official unemployment rate U-3 is still the most widely-used unemployment statistics. If people still prefer U-3 to other measures, then they must take the biases caused by measurement errors seriously. Taking our estimated true U-3 as the "true" values for U-3, Fig. 2 shows that the estimated true U-3 lies between the reported U-5 and reported U-6. In addition, the estimated true U-3 is closer to reported U-5 when the unemployment rate is going down, and to reported U-6 when unemployment is going up. Again, we consider the RMSE as follows,

$$RMSE = \sqrt{T^{-1}\sum_{t=1}^{T}(TU\text{-}3_t - RU\text{-}i_t)^2}. \tag{9}$$

Table 2
Results on average bias and RMSE: main results.

	U-3	U-4	U-5	U-6
Panel A: Comparison between *RU-i* and *TU-i*				
Average bias (level)	2.73	2.68	2.78	1.95
Average bias (percent)	42.1	39.2	36.8	16.4
RMSE (level)	2.88	2.86	2.95	2.39
RMSE (percent)	42.9	40.3	38.1	19.0
Panel B: Comparison between *RU-i* and *TU-3*				
Average bias (level)	2.73	2.34	1.58	−2.45
RMSE (level)	2.88	2.50	1.80	2.70

Note: CPS Data from November 2001 to December 2016. All unemployment rates are seasonally-adjusted.

Panel B of Table 2 reports the results of RMSE. We find that the reported U-5 has the lowest RMSE for the sample period that we cover, which implies that the reported U-5 is the closest to the estimated true U-3.

Table 3 compares U-3 with U-6 for different demographic groups. We use the same definitions of robustness as defined in Table 2 and report results by gender, race and levels of education. In all cases, we find that average biases and RMSE are substantially smaller for reported U-6 than for reported U-3, using estimated true measures as the standard. For males and females (Panel A of Table 3), the differences in average bias and RMSE are also much smaller for U-6 than for U-3. For example, RMSE is 2.41 for males and 2.4 for females in terms of U-6, but for U-3, the RMSE is 3.19 for females which is much larger than 2.77 for males. This suggests that if one uses U-3, there might be much more measurement errors for females than for males. This pattern also holds for different race and education groups, although to a lesser extent.

Finally, we explore whether linear combinations of these four reported unemployment measures would perform better in predicting the "true" U-3. We first regress the estimated true U-3 on the reported measures individually using the data from November 2001 to December 2013. The results are shown in the first four columns of Table 4. All four reported measures are positively correlated with the estimated true U-3, but the reported U-3 gives the best fit. However, column (5) shows a linear combination of all four measures perform even better with the R-squared being 0.99. More rigorously, we calculate the RMSE defined as follows:

$$RMSE = \sqrt{T^{-1}\sum_{t=1}^{T}(TU\text{-}3_t - \text{fitted } TU\text{-}3_t)^2}. \quad (10)$$

Panel B of Table 4 shows the corresponding RMSE for each regression in Panel A. We find column (5) has the lowest RMSE, not only for the in-sample prediction, but also for the out-of-sample prediction which covers the period from January 2014 to December 2016. This implies that one can proxy the estimated true U-3 very well by simply using a linear combination of reported

Table 3
Results on average bias and RMSE: heterogeneity among different demographic groups.

	U-3				U-6			
	Average bias		RMSE		Average bias		RMSE	
	Level	Percent	Level	Percent	Level	Percent	Level	Percent
Panel A: By Gender								
Male	2.53	37.0	2.77	37.8	1.88	15.1	2.41	17.6
Female	3.11	50.8	3.19	51.3	2.03	17.8	2.40	20.7
Panel B: By Race								
White	2.54	44.7	2.67	45.6	2.03	18.7	2.52	22.0
Non-white	3.43	34.0	3.82	35.6	1.84	11.1	2.15	12.4
Panel C: By Education								
High-edu	2.08	45.0	2.21	45.8	1.66	19.5	1.92	21.6
Low-edu	3.38	36.6	3.59	37.8	2.17	12.9	3.02	16.8

Note: CPS Data from November 2001 to December 2016. "High-edu" includes people with some college education and more, and "Low-edu" includes those with high school education and below. All unemployment rates are seasonally-adjusted.

Table 4
Regression results on estimated true U-3.

	(1)	(2)	(3)	(4)	(5)
Panel A: OLS Results					
RU-3	1.409***				7.202***
	(0.026)				(0.371)
RU-4		1.297***			−2.248***
		(0.027)			(0.492)
RU-5			1.238***		−2.596***
			(0.028)		(0.363)
RU-6				0.764***	−0.254***
				(0.021)	(0.076)
Constant	0.202	0.456**	−0.058	0.593**	0.668***
	(0.180)	(0.198)	(0.227)	(0.259)	(0.190)
Observations	146	146	146	146	146
R-squared	0.954	0.941	0.931	0.901	0.990
Panel B: Results on RMSE					
RMSE (in-sample)	0.55	0.62	0.68	0.81	0.26
RMSE (out-of-sample)	0.62	0.76	0.88	1.51	0.50
RMSE (total)	1.27	1.47	1.62	2.22	0.73

Note: The dependent variable is the estimated true U-3. All unemployment rates are seasonally-adjusted. The data used in regression is from November 2001 to December 2013. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. In-sample analysis is from November 2001 to December 2013, while out-of-sample analysis is from January 2014 to December 2016.

unemployment measures, i.e.,

$$TU\text{-}3 \approx \beta_0 + \beta_1 U\text{-}3 + \beta_2 U\text{-}4 + \beta_3 U\text{-}5 + \beta_4 U\text{-}6.$$

Our regression results provide estimates for these coefficients $\beta's$.

4. Conclusion

This article examines robustness of various BLS unemployment measures to misclassification errors in CPS. We follow the latent variable approach used in Feng and Hu (2013) to estimate the unobserved true unemployment rates from U-3 to U-6, and have reached a number of conclusions useful for users of unemployment statistics. First, we find that U-6, which is widely considered by many people as the "true" unemployment rate, are more robust than the official U-3. Second, taking U-3 as the golden standard definition of unemployment, we show that the reported U-5 is the closest to the estimated true U-3. Finally, one can actually use a linear combination of all four reported unemployment measures to proxy for the estimated true U-3 without evoking the more technically sophisticated latent variable approach that we use, as long as the weights used are regularly updated.

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