Utilizing Two Types of Survey Data to Enhance the Accuracy of Labor Supply Elasticity Estimation

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Abstract

We argue that despite its nonclassical measurement errors, the hours worked in the Current Population Survey (CPS) can still be utilized to enhance the overall accuracy of the estimator of the labor supply parameters based on the American Time Use Survey (ATUS), if done properly. We propose such an estimator that is a weighted average between the two stage least squares estimator based on the CPS and a non-standard estimator based on the ATUS.

Keywords: labor supply elasticity, averaging estimator, bias-variance trade-off, measurement error

JEL codes: C13, C21, C26, C52, C81, J22

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1 Introduction

Empirical studies of labor supply typically rely on one of two types of surveys for measuring how much time people spend on working — conventional surveys and time use surveys. On one hand, abundant evidence (e.g., Bound et al., 2001) reveals substantial nonclassical measurement errors in the recalled weekly hours worked in conventional surveys such as the Current Population Survey (CPS), which significantly bias the estimator of labor supply elasticities. On the other hand, time use surveys like the American Time Use Survey (ATUS) record much more accurate hours worked in a short period of time (e.g., one day in the ATUS). The resulting estimator is therefore robust against measurement error, but it has larger standard error due to the shorter reference period of the ATUS (see Barrett and Hamermesh, 2019; Chou and Shi, 2020, for details).

In this paper, we propose an estimator that combines the advantage of both types of survey data by taking a weighted average of the two estimators. The data-driven weight strikes a balance between the bias from the CPS and the efficiency loss from the ATUS, resulting in an averaging estimator that has smaller asymptotic mean squared error (MSE) than the robust ATUS-based estimator. Such bias-variance trade-off is common among averaging (or shrinkage) estimators (e.g., Fan and Ullah, 1999; Hansen, 2016), and the averaging estimator proposed by Cheng et al. (2019) possesses a unique uniform dominance property in a setting with two GMM estimators. The distinctive feature of this paper is that we recognize that the averaging approach of Cheng et al. (2019) could be generalized to the case where there are two separate types of survey data, and one of the two estimators is non-standard.

We apply our new averaging estimator to the ATUS and the CPS data for the years 2002-2017 to estimate weekly labor supply elasticities for various demographic groups, and compare its estimates with those obtained solely from the CPS or from the ATUS. The objective of this paper is not to solve the measurement error problem in the CPS using the ATUS as an auxiliary data (e.g., Chen et al., 2005), but to show that despite sizable bias resulting from the nonclassical measurement errors, the CPS still contains valuable information that can be utilized to improve the overall accuracy of the ATUS-based robust estimator.

2 The ATUS and the CPS Data

We use two samples for our empirical analysis. The baseline sample is from the 2003–2017 ATUS (Hofferth et al., 2018). The ATUS randomly draws its respondents from the outgoing rotation groups of the CPS respondents. Therefore, for all respondents in the ATUS, we have their answers to all the CPS questions as well. For our empirical analysis, we filter the baseline sample and keep hourly paid workers aged between of 25 and 54, whose wage rate is positive[1] and spouse earnings (if married) and total usual weekly hours worked (at current job reported in the last CPS interview) are observed.

The second enlarged sample contains all respondents from the 2003–2017 CPS, regardless of whether they took part in the ATUS or not. For the enlarged sample, we apply the same filtering criteria as used for the baseline sample. Table 1 shows that the baseline and the enlarged samples are similar in the aspects that are relevant for our analysis.

To prepare for our analysis in Section 3, some background information about the ATUS is needed here. Unlike the CPS that asks its participants to recall their hours worked in a week, the ATUS requires its respondents to record all their activities on a single day (known as the diary day, chosen completely at random). Adding all the spells spent on working by each respondent on that day yields his/her ATUS hours worked for the diary day. Since the ATUS records the time allocated to all the activities minute-by-minute and imposes a sum-to-24-hour constraint, the measurement errors in the ATUS hours are negligible compared to the CPS.[2] The shorter reference period of the ATUS, however, results in larger variance and the "time specificity" problem (see Barrett and Hamermesh, 2019; Chou and Shi, 2020, for details) when the period of interest is a week.

[1] The hourly wage rate was trimmed at percentiles 1 from below and 99 from above. After the trimming, the hourly wage in the sample ranges from $5.2 to $67.8 for men and from $3.6 to $63.1 for women (2017 US dollars).

[2] For a more detailed description of the ATUS, see Hamermesh et al. (2005); ATUS (2019). We acknowledge that the measurement errors in the ATUS hours might not be negligible, but this assumption is adequate and convenient for our purpose in this paper.

Table 1: Comparison Between the Baseline and the Enlarged Samples

	Baseline Sample	Enlarged Sample
Male (%)	40.5	48.2
College graduate (%)	21.3	18.1
Age	39.3	39.3
(s.d.)	(8.4)	(8.6)
Hours usually worked per week in CPS	36.1	38
(s.d.)	(9.0)	(8.5)
Hourly wage (2017 US dollars)	18.7	18.6
(s.d.)	(9.0)	(8.8)
Num. of children aged < 5	0.23	0.21
(s.d.)	(0.52)	(0.50)
Num. of children aged 5–18	0.79	0.93
(s.d.)	(1.00)	(1.11)
Num. of obs.	19,038	72,133

[1] The baseline sample contains the individuals who participated in both the ATUS and the CPS. The enlarged sample contains all individuals who participated the CPS, regardless of their participation status in the ATUS. The sample filtering criteria described in Section 2 is applied to both samples.

3 Model and Empirical Strategy

We are interested in estimating the parameters β in the following equation of weekly labor supply,

$$H_i^w = X_i'\beta + U_i, \tag{1}$$

where H_i^w is the weekly hours worked by individual i, X_i is a $p \times 1$ vector of observable explanatory variables and the first element of X_i is unity. The explanatory variables X_i, including log wage in particular, tend to be correlated with U_i, and hence is often endogenous. Suppose that a $q \times 1$ vector of instrumental variables (IVs) Z_i is available.

The CPS recalled weekly hours worked, H_i^{CPS}, serve as an error-ridden measure of H_i^w; that is, $H_i^{CPS} = H_i^w + E_i$, where E_i represents the nonclassical measurement error. Let N represent the sample size of the CPS data. Let $H^{CPS} \equiv (H_1^{CPS}, \ldots, H_N^{CPS})'$, $X \equiv (X_1, \ldots, X_N)'$, $Z \equiv (Z_1, \ldots, Z_N)'$ and $P_z \equiv Z(Z'Z)^{-1}Z'$. Then the standard two stage least squares (2SLS) estimator using the CPS recalled weekly hours is $\hat{\beta}_{CPS} \equiv (X'P_zX)^{-1}X'P_zH^{CPS} = \beta + (X'P_zX)^{-1} X'P_z(U+E)$, where $U \equiv (U_1, \ldots, U_N)'$ and $E \equiv (E_1, \ldots, E_N)'$. Since $\mathbb{E}(Z_iE_i) \neq 0$ due to the nonclassical nature of the measurement errors, $\hat{\beta}_{CPS}$ will be biased. We can show that under standard conditions, $\sqrt{N}\left(\hat{\beta}_{CPS} - \beta\right) \xrightarrow{d.} \mathcal{N}\left(\delta, \Omega_{CPS}\right)$, where δ is asymptotic bias and Ω_{CPS} is a covariance matrix.

In order to utilize the ATUS to estimate the weekly labor supply equation (1), Chou and Shi

(2020) recommended thinking of the hours worked on the ATUS diary day, H_i^{ATUS}, under the potential outcome framework. Formally, for $t = 1, \ldots, 7$, let H_{it} denote the actual hours worked by individual i on day t, which is not necessarily observed by economists. Let $d_{it} = 1$ if individual i is surveyed on day t and let $d_{it} = 0$ otherwise. Using this notation, we can express the observed ATUS diary day hours as $H_i^{ATUS} = \sum_{t=1}^{7} d_{it} H_{it}$. The potential outcome framework provides a context for the "time specificity" problem and facilitates the analysis of weekly labor supply using the ATUS data. In particular, Chou and Shi (2020) developed an *impute estimator*, denoted as $\hat{\beta}_{ATUS}$, which in practice can be obtained by following these steps using the ATUS data:

1. ("X first stage") Regress X_i on Z_i using the entire sample and take the fitted values $\hat{X}_i$;

2. ("H first stage") For each diary day t, regress H_i^{ATUS} on Z_i using the subsample $d_{it} = 1$ to get $\hat{\alpha}_t$, and impute the weekly hours worked by $\hat{H}_i^w = \sum_{t=1}^{7} \hat{H}_{it} = \sum_{t=1}^{7} Z_i' \hat{\alpha}_t$ for the entire sample;

3. ("Second stage") Regress $\hat{H}_i^w$ on $\hat{X}_i$ using the entire sample and get $\hat{\beta}_{ATUS}$.

The impute estimator is a simple modification of the standard 2SLS estimator, where the same IVs are used to impute the (unobserved) dependent variable within daily subsamples, as well as the (endogenous) independent variables within the entire sample. Chou and Shi (2020) derived the asymptotic normality for the impute estimator: $\sqrt{n}\left(\hat{\beta}_{ATUS} - \beta\right) \xrightarrow{d.} \mathcal{N}(0, \Omega_{ATUS})$, where n is the sample size of the ATUS data. Note that $\hat{\beta}_{ATUS}$ is consistent, since the ATUS does not suffer from the nonclassical measurement error as the CPS does. But Chou and Shi (2020, Theorem 3(ii)) showed that $\hat{\beta}_{ATUS}$ is less efficient than $\hat{\beta}_{CPS}$ (i.e., $\Omega_{CPS} \leq \Omega_{ATUS}$) even if they are based on the same respondents, since the reference period of the ATUS is one day, which is inherited with more noise if the period of interest is one week, the reference period of the CPS. This bias-variance trade-off between the two feasible estimators of β makes it a fruitful approach to average the two estimators.

In this paper, we generalize the idea proposed by Cheng et al. (2019) and Shi (2020) and propose an averaging estimator $\hat{\beta}_{AVE} \equiv (1 - \hat{w})\hat{\beta}_{ATUS} + \hat{w}\hat{\beta}_{CPS}$, where the weight is given by

$$\hat{w} \equiv \frac{\mathrm{tr}(\frac{N}{n}\hat{\Omega}_{ATUS} - \hat{\Omega}_{CPS})}{\mathrm{tr}(\frac{N}{n}\hat{\Omega}_{ATUS} - \hat{\Omega}_{CPS}) + N(\hat{\beta}_{ATUS} - \hat{\beta}_{CPS})'(\hat{\beta}_{ATUS} - \hat{\beta}_{CPS})}. \tag{2}$$

In equation (2), $\mathrm{tr}(\cdot)$ denotes the trace of a square matrix, and $\hat{\Omega}_{ATUS}$ and $\hat{\Omega}_{CPS}$ denote consistent estimators of Ω_{ATUS} and Ω_{CPS}, respectively. For our baseline sample, $n = N$; and for our enlarged sample, $n < N$. It should be remarked that when computing $\hat{\Omega}_{CPS}$ and $\hat{\Omega}_{ATUS}$, one needs a consistent estimate of β. For this purpose, one should use the consistent estimate $\hat{\beta}_{ATUS}$, instead of the biased $\hat{\beta}_{CPS}$, otherwise the weight $\hat{w}$ is likely to deviate from its optimal value.

In a setting with two GMM estimators, Cheng et al. (2019) showed that the averaging estimator has uniformly smaller asymptotic quadratic risk (e.g., mean squared error) than the consistent estimator (but less efficient) estimator. Shi (2020) generalized the approach and average between a parametric estimator and a semiparametric estimator. By similar argument, one can show that in this paper the averaging estimator $\hat{\beta}_{AVE}$ is going to have smaller asymptotic MSE than $\hat{\beta}_{ATUS}$.[3]

4 Results and Discussion

We apply the averaging estimator with the weight in Equation (2) to both the baseline and the enlarged samples. In Table 2, we report the results separately for married men, unmarried men, married women and unmarried women.[4] The numbers in Table 2 are weekly labor supply elasticity estimates (measured in hundredths, standard errors in parentheses). The standard errors for the baseline $\hat{\beta}_{CPS}$ (column II) are much smaller than those for $\hat{\beta}_{ATUS}$ (column I), although the two columns are based on the same respondents. The estimates in columns I and II differ substantially as well. The results for the enlarged sample (columns IV and V) are qualitatively similar.

It is worth emphasizing that the averaging estimator (column III) assigns sizable positive weights to $\hat{\beta}_{CPS}$ across all demographic groups. This demonstrates that despite the nonclassical measurement errors, there is still considerable amount of information about weekly labor supply to be utilized in the CPS. If the averaging is done properly, this information can raise the efficiency of the estimator without sacrificing too much on the bias front, such that the overall accuracy of the estimates is enhanced.[5]

[3] The proof is straightforward by conducting similar asymptotic analysis as in Cheng et al. (2019), and therefore is omitted here.

[4] In order to safeguard against the potential classical measurement error problem in wage and spouse weekly earnings, we use wage deciles and spouse earning deciles as IV.

[5] The standard errors for the averaging estimator are computed as if $\hat{w}$ were a constant. This is likely to be a lower bound for the actual standard errors since $\hat{w}$ is random and is correlated with $\hat{\beta}_{CPS}$ and $\hat{\beta}_{ATUS}$. Rigorous inference of averaging estimators which accounts for the dependence between $\hat{w}$ and the two constituent estimators is an active area of research and is outside the scope of this paper.

Table 2: Weekly Labor Supply Elasticity Estimates (In Hundredths)

	I $\hat{\beta}_{ATUS}$	**II** $\hat{\beta}_{CPS}$ (Baseline)	**III** $\hat{\beta}_{AVE}$ (I and II)	**IV** $\hat{\beta}_{CPS}$ (Enlarged)	**V** $\hat{\beta}_{AVE}$ (I and IV)
Panel A: Married Men					
Wage	1.47	5.39	3.52	8.54	3.15
	(3.36)	(0.89)	(1.93)	(0.38)	(2.60)
Spouse weekly earnings	−3.47	−0.19	−1.85	−0.33	−2.03
	(1.62)	(0.41)	(0.92)	(0.13)	(0.92)
Num. of kids age < 5	−1.08	−0.80	−0.96	0.21	−0.78
	(1.92)	(0.48)	(1.09)	(0.22)	(1.48)
Num. of kids age 5–18	−0.44	−0.00	−0.23	0.32	−0.27
	(1.12)	(0.26)	(0.63)	(0.11)	(0.87)
Weight assigned to CPS ($\hat{w}$)			0.51		0.24
n of obs.	3889	3889		19999	
R squared	0.16	0.08		0.10	
Panel B: Unmarried Men					
Wage	4.71	11.38	7.43	12.06	7.24
	(3.25)	(1.06)	(2.30)	(0.48)	(2.28)
Weight assigned to CPS ($\hat{w}$)			0.39		0.33
n of obs.	3816	3816		14802	
R squared	0.24	0.15		0.13	
Panel C: Married Women					
Wage	10.48	15.89	11.90	10.74	10.38
	(3.32)	(1.26)	(2.51)	(0.54)	(1.10)
Spouse weekly earnings	−5.79	−9.43	−6.76	−2.59	−3.03
	(2.12)	(0.77)	(1.59)	(0.24)	(0.52)
Num. of kids age < 5	−8.97	−8.58	−8.75	−6.37	−6.94
	(2.11)	(0.82)	(1.60)	(0.42)	(0.75)
Num. of kids age 5–18	−1.20	−2.87	−1.66	−2.26	−1.90
	(1.18)	(0.42)	(0.89)	(0.17)	(0.38)
Weight assigned to CPS ($\hat{w}$)			0.29		0.69
n of obs.	5602	5602		20891	
R squared	0.17	0.22		0.14	
Panel D: Unmarried Women					
Wage	8.14	11.72	9.88	13.58	9.67
	(3.30)	(1.07)	(2.06)	(0.57)	(2.33)
Weight assigned to CPS ($\hat{w}$)			0.46		0.30
n of obs.	5731	5731		16441	
R squared	0.17	0.15		0.13	

[1] The baseline sample contains the individuals who participated in both the ATUS and the CPS. The enlarged sample contains all individuals who participated in the CPS, regardless of their participation status in the ATUS. The sample filtering criteria described in Section 2 is applied to both samples.
[2] The standard errors are in parentheses.
[3] The standard errors for the averaging estimators are computed as if $\hat{w}$ were a constant.
[4] The elasticities are evaluated at the respective mean hours worked in each data source.
[5] The R squared for impute estimator is the average R squared of the seven linear regression of daily hours worked $H_{it} = X_i'\beta_t + U_{it}$ for $t = 1, \ldots, 7$.
[6] The other control variables are age, age-squared, the number of children aged below 5, the number of children aged between 5 and 18, two education dummies, eight Census division dummies, a metropolitan area dummy, race dummies, year dummies, occupation dummies and industry dummies. In order to safeguard against the potential classical measurement error problem in wage and spouse weekly earnings, we use wage deciles and spouse earning deciles as IV.

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