RECURSIVE REGRESSION ESTIMATION IN THE PRESENCE OF TIME-IN-SAMPLE EFFECTS

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1. Introduction

1.1 Problem Statement

The distinguishing feature of periodic surveys is that the same respondents are interviewed at several points in time. The sample for each period of data collection is divided into several panels or rotation groups. A major problem with most periodic surveys is the presence of time-in-sample effects. This problem arises when estimates of characteristics of interest from the different rotation groups relating to the same time period have different expected values, depending on the length of time they have been included in the sample. The effects of this phenomenon on the estimates of current level and change in level of characteristic of interest have been investigated and reported by many researchers and survey organizations. Bailar (1975) studied the effects of rotation group bias on both ratio estimates and composite estimates and compared the mean-squared errors of these estimates using data from the U.S. Current Population Survey (CPS). Breau and Ernst (1983) compared alternative estimators to the CPS ratio and composite estimators under the assumptions of time-in-sample effects and no time-in-sample effects on the basis of variance, bias, and mean-squared error. Ghangurde (1982) discussed the effects of rotation group bias on estimates of many characteristics in the Canadian Labor Force Survey. The effects of rotation group bias on the estimation and seasonal adjustment of population means was considered by Pfeffermann (1991). The present paper examines the impact of time-in-sample effects on the efficiency of the recursive regression estimator.

1.2 The Proposed Estimation Procedure

Yansaneh and Fuller (1997) proposed the recursive regression estimation procedure, which is a computationally efficient method of producing minimum variance estimators in repeated surveys. Using a linear model with no assumptions about time-in-sample effects, the recursive regression estimator (RRE) was shown to be uniformly more efficient than the present CPS method of composite estimation for all characteristics of interest. The focus of the present paper is to examine the impact of time-in-sample effects or rotation group bias on the RRE of current level and change in level of selected labor force characteristics in the CPS. The linear model used to produce optimal estimators with no assumptions on time-in-sample effects is modified to incorporate time-in-sample effects. Using CPS data, the resulting recursive regression estimator is compared with the estimator based on the linear model with no time-in-sample effects, in terms of the variances of the estimators. Even though the results of this paper are tailored to the CPS, they are applicable to a wide variety of rotation designs. Throughout our discussion, we shall consider the unknown true values to be fixed parameters.

1.3 Outline of the Present Paper

The paper is organized as follows: Section 2 provides a brief description of the CPS design. In Section 3, we present the linear model under consideration in this paper, along with the assumptions governing both the model and the estimation procedure. A detailed description of the recursive regression estimation procedure is presented in Section 4. Special attention is devoted to the extensions of the standard procedure in order to accommodate time-in-sample effects. In Section 5, we discuss an application of the proposed estimation procedure to CPS data. Numerical results are presented, comparing the variances of the RRE of current level and change in level of selected labor force characteristics under the assumption of time-in-sample effects, with those under the assumption of no time-in-sample effects.

2. The CPS Design

The CPS is a national household survey conducted by the U.S. Census Bureau in cooperation with the Bureau of Labor Statistics. It is designed to generate national and state-level estimates of labor force characteristics (such as *employed*, *unemployed*, and *civilian labor force*), demographic characteristics, and other characteristics of the non-institutionalized civilian population. The sample design of the CPS contains a rotation scheme that includes the replacement of a fraction of the households in the sample each month. For any given month, the sample consists of eight time-in-sample panels or rotation groups, of which one is being interviewed for the first time, one is being interviewed for the second time, ..., one is being interviewed for the eighth time. In other words, the interview scheme is balanced on time-in-sample. Households in a rotation group are interviewed for four consecutive months, dropped for the next eight months, and then interviewed for another four consecutive months. They are then dropped form the sample entirely. This system of interviewing is called the 4-8-4 rotation design. See Ernst (1983), Fuller et al (1993) and references cited therein, for a more detailed description of the CPS.

Table 1 provides an illustration of the 4-8-4 rotation scheme used in the CPS. The data for p periods is arranged in a $px8$ data matrix in such a way that the observations on a rotation group appear in a single column. In each column, the rotation groups rotate in and out of the sample in accordance with the 4-8-4 rotation scheme. The total number of elementary estimators is $n=8p$, where n is the number of entries Table 1. We call the columns of Table 1 *streams*. The first entry for the first month is for individuals that are being interviewed for the first time. That is, $A_{1,1}$ denotes the set of individuals being interviewed for the first time in month one. In general, $A_{t,k}$ represents a rotation group that is being interviewed for the $k-th$ time in month t.

The correlations between elementary estimates from the same rotation group several months apart have been computed by Adam and Fuller (1992), using a components of variance model for the covariance structure of the data from the CPS. See Fuller et al (1993) for a detailed description of the construction of the model, the estimation of its parameters, and the estimation of the covariance structure of observations within a given rotation group for various characteristics of interest. Because the rotation groups come from the same set of primary sampling units (PSUs), they are not independent. A component is included in the covariances to reflect the fact that the primary sampling units do not change.

Table 1. Data arrangement for the 1987 CPS data

	Streams							
Month	1	2	3	4	5	6	7	8
1	$A_{1,1}$	$D_{1,2}$	$G_{1,3}$	$J_{1,4}$	$M_{1,5}$	$P_{1,6}$	$T_{1,7}$	$X_{1,8}$
2	$A_{2,2}$	$D_{2,3}$	$G_{2,4}$	$K_{2,5}$	$M_{2,6}$	$P_{2,7}$	$T_{2,8}$	$Y_{2,1}$
3	$A_{3,3}$	$D_{3,4}$	$H_{3,5}$	$K_{3,6}$	$M_{3,7}$	$P_{3,8}$	$U_{3,1}$	$Y_{3,2}$
4	$A_{4,4}$	$E_{4,5}$	$H_{4,6}$	$K_{4,7}$	$M_{4,8}$	$Q_{4,1}$	$U_{4,2}$	$Y_{4,3}$
5	$B_{5,5}$	$E_{5,6}$	$H_{5,7}$	$K_{5,8}$	$N_{5,1}$	$Q_{5,2}$	$U_{5,3}$	$Y_{5,4}$
6	$B_{6,6}$	$E_{6,7}$	$H_{6,8}$	$L_{6,1}$	$N_{6,2}$	$Q_{6,3}$	$U_{6,4}$	$Z_{6,5}$
7	$B_{7,7}$	$E_{7,8}$	$I_{7,1}$	$L_{7,2}$	$N_{7,3}$	$Q_{7,4}$	$V_{7,5}$	$Z_{7,6}$
8	$B_{8,8}$	$F_{8,1}$	$I_{8,2}$	$L_{8,3}$	$N_{8,4}$	$R_{8,5}$	$V_{8,6}$	$Z_{8,7}$
9	$C_{9,1}$	$F_{9,2}$	$I_{9,3}$	$L_{9,4}$	$O_{9,5}$	$R_{9,6}$	$V_{9,7}$	$Z_{9,8}$
10	$C_{10,2}$	$F_{10,3}$	$I_{10,4}$	$J_{10,5}$	$O_{10,6}$	$R_{10,7}$	$V_{10,8}$	$\Gamma_{10,1}$
11	$C_{11,3}$	$F_{11,4}$	$G_{11,5}$	$J_{11,6}$	$O_{11,7}$	$R_{11,8}$	$W_{11,1}$	$\Gamma_{11,2}$
12	$C_{12,4}$	$D_{12,5}$	$G_{12,6}$	$J_{12,7}$	$O_{12,8}$	$S_{12,1}$	$W_{12,2}$	$\Gamma_{12,3}$
13	$A_{13,5}$	$D_{13,6}$	$G_{13,7}$	$J_{13,8}$	$\Psi_{13,1}$	$S_{13,2}$	$W_{13,3}$	$\Gamma_{13,4}$
14	$A_{14,6}$	$D_{14,7}$	$G_{14,8}$	$\Sigma_{14,1}$	$\Psi_{14,2}$	$S_{14,3}$	$W_{14,4}$	$Y_{14,5}$
15	$A_{15,7}$	$D_{15,8}$	$\Omega_{15,1}$	$\Sigma_{15,2}$	$\Psi_{15,3}$	$S_{15,4}$	$U_{15,5}$	$Y_{15,6}$
16	$A_{16,8}$	$\Lambda_{16,1}$	$\Omega_{16,2}$	$\Sigma_{16,3}$	$\Psi_{16,4}$	$Q_{16,5}$	$U_{16,6}$	$Y_{16,7}$

3. The Model With Time-In-Sample Effects

Let $y_{t,k}$ denote the elementary estimate from a rotation group which is in its k-th time-in-sample at time t, θ_t is the true level of the characteristic at time t. Thus at time j, θ_j is the *current level* of the parameter of interest. For example, in the context of the CPS, θ_j might represent the population mean or proportion of unemployed at time j.

Suppose τ_{tk} is the rotation group effect for time t associated with the rotation group which is in its k-th time-in-sample. Then, for each time t, we may write the model

$$y_{t,k} = \theta_t + t_{tk} + \varepsilon_{tk} \qquad (1)$$

where ε_{tk} is the random error. To simplify our analysis, and to ensure the estimability of change in level of the characteristics of interest, we assume that the time-in-sample effects are constant over time. That is,

$$\tau_{kt} = \tau_k \qquad \text{for all } t.$$

To ensure the unbiasedness of the basic estimator (defined as the simple mean of the 8 elementary estimators) at any given time, we generally assume that the sum of the time-in-sample effects is zero. That is,

$$\sum_{k=1}^{8} \tau_k = 0$$

This second assumption guarantees the estimability of the current level of the parameter of interest.

4. Recursive Regression Estimation

4.1 The Best Linear Unbiased Estimator of Current Level

The best linear unbiased estimator (BLUE) of the current level of a parameter of interest is defined to be the minimum-variance unbiased linear combination of the elementary estimators from the rotation groups available for estimation. It is possible in the process of computing the best linear unbiased estimator for the current level, to also compute the best linear unbiased estimators for all preceding periods using data available at the current time.

Suppose that the CPS has been in operation for p periods and that 8 streams of data collected over p periods are available for estimation. Let $\mathbf{y}_i = (y_{i,1}, y_{i,2}, \ldots, y_{i,p})'$ be the vector of p observations in the $i-th$ stream at time t. Let $\mathbf{Y}_p$ be the data vector formed by the streams or columns of the $p \times 8$ data matrix in Table 1 above, arranged chronologically. Thus, $\mathbf{Y}_p = (\mathbf{y}_1', \mathbf{y}_2', \ldots, \mathbf{y}_8')'$ is an $nx1$ vector of observations, where $n=8xp$. Let $\Theta_p = (\theta_1, \theta_2, \ldots, \theta_p)'$ be the $p \times 1$ vector of parameters of interest, and let $\mathbf{T}_8 = (\tau_1, \tau_2, \ldots, \tau_8)'$ be the $8x1$ vector of time-in-sample effects. Then, the parameter vector is given by $\mathbf{B} = (\mathbf{T}_8', \Theta_p')'$. Let $\mathbf{X} = \left(\mathbf{J}_{8\times 1} \otimes \mathbf{I}_{8\times 8}, \mathbf{J}_{8\times 1} \otimes \mathbf{I}_{p\times p}\right)$ be the $n \times (p+8)$ design matrix (which relates the observations in $\mathbf{Y}_p$ to their expected values in $\mathbf{B}$), where $\mathbf{J}_{8\times 1}$ is the $8x1$ vector of ones, $I_{d\times d}$ is the identity matrix of order d for any d; and $\otimes$ denotes the Kronecker product. Let $\mathbf{V}_p$ denote the covariance matrix of $\mathbf{Y}_p$. Note that since the matrix $\left(\mathbf{X}'\mathbf{V}_p^{-1}\mathbf{X}\right)$ is singular, the components of the parameter vector $\mathbf{B}$ are nonestimable (Searle, 1971). The restriction that the sum of the time-in-sample effects is equal to zero permits the estimation of the parameter vector $\mathbf{B}$. The linear model for $\mathbf{Y}_p$ may then be explicitly written as

$$\mathbf{Y}_p = \mathbf{XB} + \mathbf{U}_p \qquad (2)$$

where $\mathbf{B} = \left(\tau_1, \tau_2, \ldots, \tau_7, \theta_1, \theta_2, \ldots, \theta_p\right)'$, $\mathbf{X}$ is the model matrix with the specified restriction on the time-in-sample effects, $\mathbf{U}_p$ is the vector of error terms satisfying the assumptions $E\left(\mathbf{U}_p\right) = 0$ and $E\left(\mathbf{U}_p \mathbf{U}_p'\right) = \mathbf{V}_p$. By the Gauss-Markov Theorem, the BLUE of $\mathbf{B}$ is

$$\hat{\mathbf{B}} = \left(\mathbf{X}'\mathbf{V}_p^{-1}\mathbf{X}\right)^{-1} \mathbf{X}'\mathbf{V}_p^{-1} Y_p .$$

The covariance matrix of $\hat{\mathbf{B}}$ is $\Sigma\left(\mathbf{X}'\mathbf{V}_p^{-1}\mathbf{X}\right)^{-1}$.

4.2 The Recursive Regression Estimator

The computation of the BLUE becomes progressively more complicated as the number of periods increases. Instead of using all the available information in a large least squares computation, the RRE uses a judiciously chosen set of initial estimates, new observations at the current level, and all previous observations on the rotation groups at the current level, to produce the BLUE of current level. In the case of the CPS, there will be some observations as far as 15 months in the past that will appear in the estimator because, if a rotation group is being interviewed for the last time, then that is the sixteenth month that the rotation group has been associated with the CPS. The recursive regression estimator is constructed as follows:

At the current time, denoted by t, where $t \geq 15$, we desire an estimator of θ_t, the value of a particular characteristic. We assume that at time *t*, the following quantities are available:

(i) a vector of 22 initial estimates $\hat{\beta}_{t-1(22)} = \left(\hat{\mathbf{T}}'_{t-1(7)}, \hat{\Theta}'_{t-1(15)}\right)'$, consisting of seven least squares estimators $\hat{\mathbf{T}}_{t-1(7)} = \left(\hat{\tau}_1, \ldots, \hat{\tau}_7\right)'$ of the time-in-sample effects $\mathbf{T}_{t-1(7)} = \left(\tau_1, \ldots, \tau_7\right)'$, and fifteen least squares estimators $\hat{\Theta}'_{t-1(15)} = \left(\hat{\theta}_{t-15}, \ldots, \hat{\theta}_{t-1}\right)$ of the parameters of interest $\Theta_{t-1(15)} = \left(\theta_{t-15}, \ldots, \theta_{t-1}\right)'$. We assume that these estimates are based on data through time $t-1$;

(ii) the covariance matrix of $\hat{\beta}_{t-1(22)}$, given by:

$$\Gamma_{11,t-1(22)} = \begin{pmatrix} \Omega_{11,t-1(7)} & \Omega_{12,t-1} \\ \Omega_{12,t-1} & \Omega_{22,t-1(15)} \end{pmatrix},$$

where $\Omega_{11,t-1(7)} = Var\left\{\hat{\mathrm{T}}_{t-1(7)}\right\}$,

$$\Omega_{12,t-1} = Cov\left\{\hat{\mathbf{T}}_{t-1(7)}, \Omega_{22,t-1(15)}\right\},$$

$$\Omega_{22,t-1(15)} = Var\left\{\hat{\Theta}_{t-1(15)}\right\}; \text{ and}$$

(iii) a vector of eight independent observations $\mathbf{z_t} = (z_{1t}, \ldots, z_{8t})'$, obtained by a suitable transformation of the elementary estimates from the rotation groups at time *t*.

The transformed observations may be written as

$$z_{it} = y_{i,t} - \sum_{j=1}^{15} b_{k(i,t),j} y_{i,t-j},$$

$i = 1, 2, \ldots, 8$, where $y_{i,t}$ denotes the elementary estimator from the rotation group which is in stream i at time t. The coefficients b_{kj}, $k = 1, \ldots, 8$ and $j = 1, \ldots, 15$, are constructed so that for $i = 1, 2, \ldots, 8$, the transformed observations z_{it} are uncorrelated with $y_{i,t-j}$, for all $j > 0$. A linear model for the data available at the current time is

$$\mathbf{Z}_t = \mathbf{W}\beta_{t(23)} + \mathbf{E}_t \tag{3}$$

where $\mathbf{Z}_t = \left(\hat{\beta}'_{t-1(22)}, z'_t\right)'$, $\mathbf{z_t} = (z_{1t}, \ldots, z_{8t})'$, and $\beta_{t(23)} = \left(\tau_1, \tau_2, \ldots, \tau_7, \theta_{t-15}, \ldots, \theta_{t-1}, \theta_t\right)'$. The model matrix $\mathbf{W}$ is given by

$$\mathbf{W} = \begin{pmatrix} \mathbf{I}_{7\times7} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_{p\times p} & \mathbf{0} \\ \mathbf{W}_{31} & \mathbf{W}_{32} & \mathbf{J}_{8\times1} \end{pmatrix},$$

where $\mathbf{W}_{31}$ and $\mathbf{W}_{32}$ are matrices of dimensions *8x7* and *8x15*, whose entries are functions of the coefficients b_{kj}, which are in turn functions of the autocorrelations within rotation groups over time. Let Ω_{33} be the diagonal matrix with σ_i^2 as the diagonal entries, where $\sigma_i^2 = Var\{z_{it}\}$, $i = 1, 2, \ldots, 8$. It can be shown that the covariance matrix of $\mathbf{Z}_t$ is

$$\mathbf{V}_t = \begin{pmatrix} \Omega_{11,t-1(7)} & \Omega_{12,t-1} & 0 \\ \Omega'_{12,t-1} & \Omega_{22,t-1(15)} & 0 \\ 0' & 0' & \Omega_{33} \end{pmatrix} + \sigma_u^2 \begin{pmatrix} 0 & 0 & 0 \\ 0' & 0 & \mathbf{J}_{15\times1}\psi' \\ 0' & \psi\mathbf{J}'_{15\times1} & \psi\psi' \end{pmatrix},$$

where ψ is an 8 x 1 vector whose entries are functions of the coefficients b_{kj}, and σ_u^2 is the PSU or replicate variance. See Yansaneh (1992) for details. The RRE of the parameter vector $\beta_{t(23)}$ is defined as the least squares estimator based on the model (3).

Note that retaining θ_{t-15} in the parameter vector and $\hat{\theta}_{t-15}$ in the data vector does not affect the estimator at time $t+1$. Thus, to update the RRE for the next period, we drop the initial estimator $\hat{\theta}_{t-15}$ from the data vector, and drop θ_{t-15} from the parameter vector. We then add the parameter θ_{t+1} to the parameter vector. This way, the dimension of the basic model and the estimation problem are kept constant over time.

In the recursive regression estimation procedure, the current estimates of the time-in-sample effects are present in the data vector throughout the iteration process. Therefore, the variance of the estimators of each of the time-in-sample effects will converge to zero as the number of iterations increases indefinitely.

One may be unwilling to assume that the time-in-sample effects are constant over a long period. One way of permitting the estimates of the time-in-sample effects to change slowly over time is to perform some kind of *exponential smoothing* by adjusting the covariance matrix of the estimated effects used to construct the estimator at time *t*. One procedure is to multiply the covariance matrix of the initial estimates of the time-in-sample effects for time *t-1* used in the construction of estimates for time *t*, by a constant larger than one, so that the diagonal elements of the covariance matrix increase slightly as the number of iterations increases. The resulting estimator is similar to an exponentially smoothed estimator in the sense that the effect of the observations in the past dies out as the distance from the current period increases. Since, if no modification is introduced, the variance of each of the estimates of the time-in-sample effects decreases at the rate n^{-1}, the factor that is multiplied by the covariance matrix after, say, P periods (including the number of periods on which the initial estimates are based) is $1+P^{-1}$. In this particular case, we choose $P=36=15+21$, so that the resulting estimator will correspond to the BLUE based on 36 periods of data, which is approximately as efficient as the RRE.

In recursive regression estimation procedure, it is important to distinguish between the matrix used to define the estimator and the actual covariance matrix of the estimators. The covariance matrix of initial estimates used to construct the RRE will converge as the number of periods increases (Yansaneh and Fuller, 1997). Therefore, the matrix of coefficients defining the RRE of $\beta_{t(23)}$ will also converge. In the limit, we can write the RRE of $\beta_{t(23)}$ as

$$\hat{\beta}_{t(23)} = \mathbf{PZ}_t \qquad (4)$$

where **P** is the limit of the matrix of coefficients. Since $\hat{\beta}_{t(23)}$ is a function of preceding estimates, one can calculate the coefficients of the observations that define the estimator.

5. Numerical Results And Discussion

We now present results illustrating the impact of time-in-sample effects on the RRE. We will compare the variances of the RRE of current level and change based on a model with time-in-sample effects, using the model with no time-in-sample effects as the benchmark. The basic procedure used to calculate the variance of the RRE is first, to express the estimator as a linear combination of the observations; second, to compute the covariance matrix of the observations; and then finally, to compute the variance of the estimator from the coefficients of the linear combination and the entries of the covariance matrix. Note that in keeping with the tradition of the CPS, previous estimates are not revised when more data become available.

Variances of estimators are computed relative to the variance of the basic estimator of current level, for each of the characteristics of interest. Recall that the basic estimator of the current level (denoted by $\bar{y}_t$, where t is the current level or period) is the simple mean of the elementary estimators obtained from the eight rotation groups observed at the current period. That is, $\bar{y}_{t.} = 8^{-1}\sum_{k=1}^{8} y_{t,k}$, and $Var(\bar{y}_{t.}) = \sigma^2/8$, where $\sigma^2 = Var(y_{t,k})$ for all t and k. We shall restrict attention to the estimation of current level and change in level for multiple time periods and for three characteristics: *Employed*, *Unemployed*, and *Civilian Labor Force*. The variances of the current level and change over several periods in the presence and absence of time-in-sample effects are presented in Table 2 for the characteristics of interest.

In the presence of time-in-sample effects, the RRE of current level and change are biased relative to the expected value of the basic estimator. Under the added assumption that the sum of the time-in-sample effects is zero, the variances of the RRE of current level and change based on the model that incorporates time-in-sample affects are expected to be greater than those obtained under the assumption of no time-in-sample effects. However, the assumption that the sum of the time-in-sample effects is zero is not tenable in many practical situations. For example, in the CPS, it has been determined that of the eight rotation groups in the sample in any given month, the expected values of the estimates of employed based on the first and fifth time-in-sample households are greater than those based on the rest of the households (Bailar, 1975).

In our variance calculations, the sum of the time-in-sample effects is restricted to be zero for all characteristics of interest. It can be seen from Table 2 that in estimating current level, there is an increase in variance of about 6% for *employed,* 4% *civilian labor force,* and 1% *unemployed* as a result of restricting the estimator to have a mean equal to the mean of the eight rotation groups. For estimation of change in all characteristics, the increase in variance rises monotonically as the lag increases. For *employed,* the increase in variance is about 1% for one-period change, about 3% for six-period change and about 6% for twelve-period change. The results for *civilian labor force* are similar, but the increase in variance due to time-in-sample effects is modest. For *unemployed,* there is virtually no increase in the variance of the REE of change.

In summary, the inclusion of time-in-sample effects in the model for the data vector generally has the effect of slightly increasing the variance of the estimators, while reducing the bias. The increase in variance is a function of the type of restriction imposed and the length of the period used to estimate the time-in-sample effects.

Table 2. Variance of the RRE for selected labor force characteristics relative to the variance of the basic estimator of current level (TIS = time-in-sample)

Parameter	*Employed* Without TIS effects	*Employed* With TIS effects	*Unemployed* Without TIS effects	*Unemployed* With TIS effects	*Civilian Labor Force* Without TIS effects	*Civilian Labor Force* With TIS effects
Current Level	0.650	0.688	0.918	0.923	0.704	0.733
1-period change	0.432	0.438	1.073	1.075	0.474	0.480
2-period change	0.604	0.614	1.338	1.342	0.652	0.663
3-period change	0.711	0.725	1.473	1.479	0.774	0.789
4-period change	0.784	0.801	1.562	1.569	0.859	0.877
5-period change	0.829	0.849	1.606	1.613	0.914	0.934
6-period change	0.855	0.878	1.628	1.635	0.946	0.970
7-period change	0.865	0.891	1.636	1.644	0.962	0.987
8-period change	0.860	0.889	1.634	1.642	0.963	0.990
9-period change	0.832	0.864	1.614	1.622	0.942	0.972
10-period change	0.806	0.842	1.595	1.603	0.921	0.954
11-period change	0.782	0.822	1.578	1.587	0.903	0.939
12-period change	0.761	0.807	1.564	1.573	0.887	0.926

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