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A SIMULATION STUDY OF FIXED-B ASYMPTOTIC DISTRIBUTIONS IN LINEAR PANEL MODELS WITH FIXED EFFECTS

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Abstract: In linear models, panel data often violates the assumption that the error terms should be independent. As a result, the estimated variance is usually large and the standard inferential methods are not appropriate. The previous research developed an inference method to solve this problem using a variance estimator namely the Heteroskedasticity Autocorrelation Consistent of the Cross-Section Averages (HACSC), with some improvements. The test statistic of this method converges to the fixed-b asymptotic distribution. In this paper, the performance of the proposed inferential method is evaluated by means of simulation and compared with the standard method using plm package in R. Several comparisons regarding the Type I Error of these two methods have been carried out. The results showed that the statistical inference based on fixed-b asymptotic distribution out-perform the standard method, especially for the panel data with small number of individual and time dimension.

1. INTRODUCTION

Linear models are powerful tools in statistical analysis. The linear models assume that the expected value of error is zero, the error variance is constant and independent each other. Violating these assumptions will affect the accuracy and precision of the parameter estimates obtained. Whereas in statistical inference, the best estimator is which unbiased with minimum variance.

The data obtained by researchers often causes these assumptions to be not fulfill in the models, for example when the researchers deal with panel data, a combination of cross-section and time series data. The cross-section data consists of individuals observed at a certain time, whereas the time series data consists of an individual that is observed within a certain time interval. Consequently, the panel data consists of several individuals that are observed in a certain time interval. The advantages of panel data are being able to capture the heterogeneity of individuals and find the dynamics of the data (Baltagi, 2013). The ability of panel data to detect the influences that cannot be detected by cross-section or time series data has caused panel data to be frequently used in many studies, especially in the economic field.

The problem of panel data analysis is the existence of correlation among the error terms, implying that one of the linear model assumptions is not fulfilled. This violation will inflate the variance of estimates and the standard inference cannot be carried out. The estimation of variances of parameter estimates needs to be corrected to accommodate the correlation among the error terms. Driscoll and Kraay (1998) proposed Consistent Heteroskedasticity Autocorrelation from Cross-Section Averages (HACSC) to correctly estimate the variances. The technique is based on the proposed method by Newey and West (1987) in estimating the variance of models suffered by heteroscedasticity and autocorrelation problems, called Heteroskedasticity Autocorrelation Consistent (HAC) Estimator.

Moreover, Vogelsang (2012) proposed a new statistical inference method which has been claimed to be robust to serial correlation, spatial correlation, and heteroscedasticity in the linear panel model with fixed effect. In the proposed method, parameters are estimated using the Fixed-Effect Least Square (FE-LS) method and the variances are estimated using HACSC. It is shown that the test statistics converge to the fixed-b asymptotic distribution, which is a new asymptotic theory for testing HAC variance estimators by considering bandwidth as a fixed proportion (say b) of the sample size (Kiefer & Vogelsang, 2005). As shown by Vogelsang (2012) that the simulation showed that the fixed-b asymptotic distribution approach produced better results than the standard distribution approach, such as standard normal distribution for partial test and chi-square distribution for simultaneous test (Vogelsang, 2012).

The previous research of Vogelsang (2012) is limited to the use of HACSC variance estimator. Meanwhile, researchers generally use the standard variance estimator which is found in plm package (Croissant & Millo, 2008; Millo, 2017). Therefore, this paper will compare the performance of the inference method based on the asymptotic b-fixed distribution with the HACSC variance estimator and the standard inference method contained in the plm package. The measure of goodness used is the probability of type I error or p-value. The p-value shows the maximum risk that can be tolerated when H_0 is rejected even though H_0 is actually true (Beaver et al., 2009). Thus, a better method is one that produces a smaller p-value.

2. LITERATURE REVIEW

2.1. Panel Linier Models with Fixed Effects

Panel data is a combination of cross-section and time series data. Cross-section data is data of several individuals observed at a certain time, while time series data is data of one individual observed in a period of time. So that panel data is the data of several individuals observed in a certain period of time. Table 1 shows the panel data structure, with n individuals observed in 1 to T period. Data of the response variable and independent variables in panel data analysis are arranged based on the time units stacked by the cross-section units.

The standard fixed effects panel model is given by

$$y_{it} = \boldsymbol{x}'_{it}\boldsymbol{\beta} + u_i + \varepsilon_{it} \;\; ; i = 1,2,\dots,n \;\; ; t = 1,2,\dots,T \quad (1)$$

where y_{it} denotes a response of i-th individual and t-th time, x_{it} denotes a predictor of i-th individual and t-th time, β denotes a regression coefficient, u_i denotes the i-th individual effect which is fixed, and ε_{it} denotes a random effect of the i-th individual and t-th time error. The fixed effect model shows that the differences in individual effect can be captured in the form of different constants. Each of u_i is considered as an estimable parameter (Greene, 2012).

Table 1. Panel Data Structure

Individual	Time	$\boldsymbol{y_{it}}$	$\boldsymbol{x_{1it}}$	$\boldsymbol{x_{2it}}$	$\cdots$	$\boldsymbol{x_{kit}}$
$i = 1$	$t = 1$	y_{12}	x_{112}	x_{212}	$\cdots$	x_{k12}
	$t = 2$	y_{12}	x_{112}	x_{212}	$\cdots$	x_{k12}
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	$t = T$	y_{1T}	x_{11T}	x_{21T}	$\cdots$	x_{k1T}
$i = 2$	$t = 1$	y_{21}	x_{121}	x_{221}	$\cdots$	x_{k21}
	$t = 2$	y_{22}	x_{122}	x_{222}	$\cdots$	x_{k22}
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	$t = T$	y_{2T}	x_{12T}	x_{22T}	$\cdots$	x_{k2T}
		$\vdots$				
$i = n$	$t = 1$	y_{n1}	x_{1n1}	x_{2n1}	$\cdots$	x_{kn1}
	$t = 2$	y_{n2}	x_{1n2}	x_{2n2}	$\cdots$	x_{kn2}
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
	$t = T$	y_{nT}	x_{1nT}	x_{2nT}	$\cdots$	x_{nT}

One of the estimating parameter methods of linear panel models with fixed effects is Fixed-Effect Least Square (FE-LS). The parameter estimator of FE-LS on the model (1) is

$$\widehat{\boldsymbol{\beta}} = \left(\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{\boldsymbol{x}}_{it}'\right)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{y}_{it} \tag{2}$$

where $\tilde{y}_{it} = y_{it} - T^{-1}\sum_{t=1}^{T} y_{it}$ and $\widetilde{\boldsymbol{x}}_{it} = \boldsymbol{x}_{it} - T^{-1}\sum_{t=1}^{T}\boldsymbol{x}_{it}$

2.2. Variance Estimation using HACSC

Estimating variance is very important in the hypothesis testing. If the variance assumption of the error in model (1) is written as $Var(\varepsilon_{it}) = \Omega$, then the variance of FE-LS estimator in (2) is

$$Cov(\widehat{\boldsymbol{\beta}}) = \left(\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{\boldsymbol{x}}_{it}'\right)^{-1}\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\,\Omega\,\widetilde{\boldsymbol{x}}_{it}'\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{\boldsymbol{x}}_{it}'\right)^{-1} \tag{3}$$

To obtain robust inference towards autocorrelation and heteroscedasticity, the $\widehat{\boldsymbol{\beta}}$ variance will be estimated using Heteroskedasticity Autocorrelation Consistent of the Cross-Section Averages (HACSC), which is the development of Heteroskedasticity Consistent Variation (HAC) variance estimator proposed by Newey and West (1987) and developed by (Zeileis, 2004).

Let $\widehat{\boldsymbol{v}}_{it} = \widetilde{\boldsymbol{x}}_{it}\hat{\varepsilon}_{it}$ where $\hat{\varepsilon}_{it} = \tilde{y}_{it} - \widetilde{\boldsymbol{x}}'_{it}\widehat{\boldsymbol{\beta}}$. The cross-section average is formulated in the form of $\widehat{\overline{\boldsymbol{v}}}_t = \sum_{i=1}^{n} \widehat{\boldsymbol{v}}_{it}$. The variance estimator of $\widehat{\boldsymbol{\beta}}$ using HACSC with kernel $k(x)$ dan bandwith M is formulated as

$$\widehat{\boldsymbol{V}}_{HACSC} = T\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{\boldsymbol{x}}'_{it}\right)^{-1}\widehat{\Psi}\left(\sum_{i=1}^{n}\sum_{t=1}^{T}\widetilde{\boldsymbol{x}}_{it}\widetilde{\boldsymbol{x}}'_{it}\right)^{-1} \tag{4}$$

where

$$\widehat{\Psi} = \frac{1}{\mathrm{T}}\sum_{t,s=1}^{T} K_{ts}\widehat{\overline{v}}_t\widehat{\overline{v}}'_s$$

with $K_{ts} = k\left(\frac{|t-s|}{M}\right)$ and $M = bT,\ b\epsilon(0,1]$ (Vogelsang, 2012). There are several forms of kernel functions that can be used, but in this paper the Bartlett Kernel is used, namely $k(x) = 1 - |x|$ untuk $-1 \le x \le 1$ dan $k(x) = 0$ untuk lainnya (Andrews, 1991).

2.3. Wald-HACSC Test

Wald Test (also called The Chi-Squared Test) is one of parametric statistical test that is often used. The test is named after the statistician Abraham Wald. The purpose of the test is to test a variety of hypotheses in context of linear (in parameter) regression models (Gujarati, 2004). The linear hypotheses about β used in the test is

$$H_0 : \boldsymbol{R\beta} = \boldsymbol{r} \quad \text{vs} \quad H_1 : \boldsymbol{R\beta} \neq \boldsymbol{r}$$

where $\boldsymbol{R}$ is a $q \times k$ matrix of known constants with full rank with $q \le k$ and $\boldsymbol{r}$ is a $q \times 1$ vector of known constants.

The test statistics used are as

$$Wald = \left(\boldsymbol{R}\widehat{\boldsymbol{\beta}} - \boldsymbol{r}\right)'\left(\boldsymbol{R}\ \widehat{\boldsymbol{Cov}}\left(\widehat{\boldsymbol{\beta}}\right)\boldsymbol{R}'\right)^{-1}\left(\boldsymbol{R}\widehat{\boldsymbol{\beta}} - \boldsymbol{r}\right) \tag{5}$$

The Wald-HACSC test is a Wald test using the HACSC variance estimator. The test statistics on the Wald-HACSC test are obtained by substituting equation (4) into equation (5), namely

$$Wald_{HACSC} = \left(\boldsymbol{R}\widehat{\boldsymbol{\beta}} - \boldsymbol{r}\right)'\left(\boldsymbol{R}\ \widehat{\boldsymbol{V}}_{HACSC}\ \boldsymbol{R}'\right)^{-1}\left(\boldsymbol{R}\widehat{\boldsymbol{\beta}} - \boldsymbol{r}\right) \tag{6}$$

When $q = 1$, the Wald test statistics can be simplified as (Agresti, 2006).

$$Wald_{HACSC} = \frac{\left(\boldsymbol{R}\widehat{\boldsymbol{\beta}} - \boldsymbol{r}\right)}{\sqrt{\boldsymbol{R}\ \widehat{\boldsymbol{V}}_{HACSC}\ \boldsymbol{R}'}} \tag{7}$$

2.4. Bartlett Kernel Fixed-b Critical Value

A critical value is needed when conducting the statistical inference. When the null hypothesis is true and the $\widehat{\boldsymbol{\beta}}$ variance is estimated by the standard method, the wald test statistic converges in distribution to the chi-square or normal distribution. So that it is often used a critical value based on the chi-square and normal tables. However, when the $\widehat{\boldsymbol{\beta}}$ variance is estimated with $\widehat{\boldsymbol{V}}_{HACSC}$, the wald test statistic is no longer converges in distribution to the chi-squared or normal distribution, but rather converges in distribution to the b-fixed asymptotic distribution (Vogelsang, 2012).

High order expansions derived by Velasco and Robinson (2001) and Sun et al. (2008) showed that the fixed b-critical value for wald test statistics can be approximated by polynomials which are functions of normal and chi-square critical values where the coefficient depends on the statistical moment. Vogelsang (2011) showed that the p-value with a critical value for the fixed-b approach can be obtained by the invers transformation of the polynomial model as $2P\big(Z > z(|x|)\big)$ where Z is the standard asymptotic random variable (chi-square or normal) and

$$z(|x|) = \frac{-\big(1+\gamma(b)\big) + \sqrt{\big(1+\gamma(b)\big)^2 + 4\theta(b)|x|}}{2\theta(b)} \tag{8}$$

The x value is obtained from wald test statistics, and the value of $\gamma(b) = \gamma_1 b + \gamma_2 b^2 + \gamma_3 b^3$ and $\theta(b) = \theta_1 b + \theta_2 b^2 + \theta_3 b^3$ with $\gamma_1, \gamma_2, \gamma_3, \theta_1, \theta_2$, and θ_3 is a constant on the B-Table proposed by Vogelsang (2011).

3. METHODOLOGY

3.1. Data

The data used in this paper is simulation data generated based on a linear panel model with a fixed effect as equation (1). Two parameters are set in the model, namely $\beta_1 = 0.1$ and $\beta_2 = 0.2$. Next, the predictors are set by

$$x_{lit} = \rho\, x_{li,t-1} + \eta_{lit}\ ;\ x_{li0} = 0\ ;\ \eta_{lit} \sim N(0,1)\ ;\ l = 1, 2$$

while the random variable of error is assumed to contain autocorrelation generated by the equation

$$\varepsilon_{it} = \rho\, \varepsilon_{i,t-1} + \delta_{it}\ ;\ \varepsilon_{i0} = 0\ ;\ \delta_{it} \sim N(0,1)$$

Because the use of FE-LS will eliminate the individual effects in estimating its parameters, the model built for the simulation process is

$$y_{it} = 0.1\, x_{1it} + 0.2\, x_{2it} + \varepsilon_{it}\ ;\ \ i = 1,2,\dots,n\ \ ;\ \ t = 1,2,\dots,T \tag{9}$$

Equation (9) is used as a data generation process because this paper focuses is on the variance estimation and statistical inference method for the linear panel models with fixed effects whose errors contain autocorrelation.

3.2. Simulation

In this paper, the parameter testing of the linear panel models with fixed effects is carried out using the standard method, a Wald test in plm package, and the HACSC method, a Wald-HACSC test, both with normal approximation and fixed-b approximation. The stages of the simulation are divided into 2 parts as below.

First Simulation

The first simulation aims to find out a comparison between the standard method and the HACSC method both with normal approximation and fixed-b approximation for each repetition. The steps of data analysis in the first simulation are as follows:

1. Performing algorithm presented in Figure 1.
2. Repeating step 1 in 10 times.

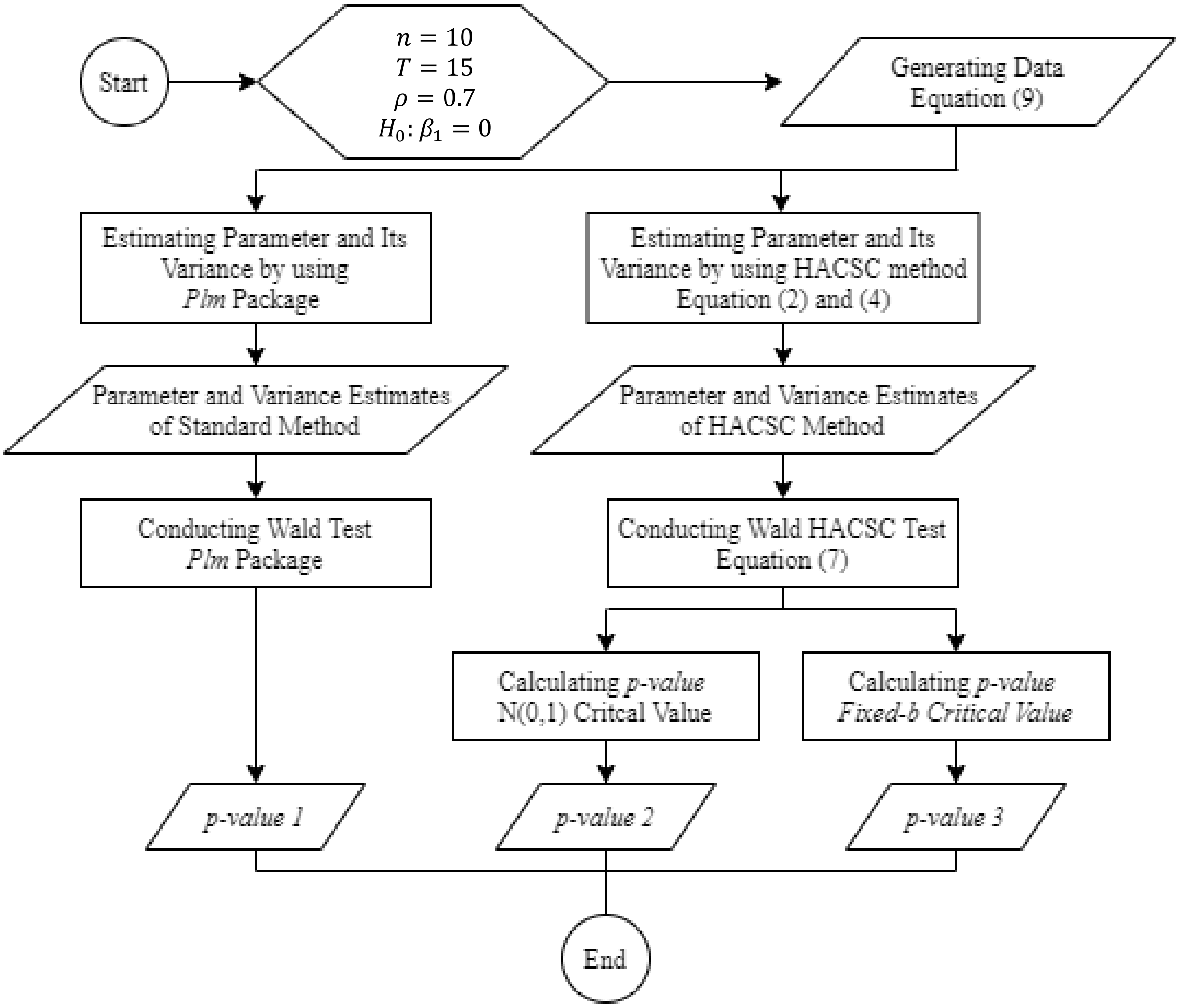

Figure 1. The First Simulation Algorithm

Second Simulation

The second simulation aims to find out a comparison between the standard method and the HACSC method fixed-b approximation for different n, T, and ρ. The steps of data analysis in the second simulation are as follows:

1. Performing algorithm presented in Figure 2.
2. Repeating step 1 in 1000 times.
3. Averaging the p-values obtained in step 2.

4. RESULTS AND DISCUSSION

4.1. The First Simulation

This study focuses on the statistical inference method. All inference methods tend to have same performance when the sample size is large. Therefore, the first simulation is carried out by taking the small values of n and T, $n = 10$ and $T = 15$. In addition, this study also focuses on violations of the autocorrelation assumption in linear panel models, so that the first simulation is carried out by taking a high enough correlation coefficient value, $\rho = 0.7$.

From the data that has been generated, the statistical inference is carried out using the standard method based on the plm package. In addition, the estimation of parameters using FE-LS and its variance estimation (HACSC) was also carried out. The results of parameter estimation β_1 and the standard error for 10 simulations is presented in Table 2.

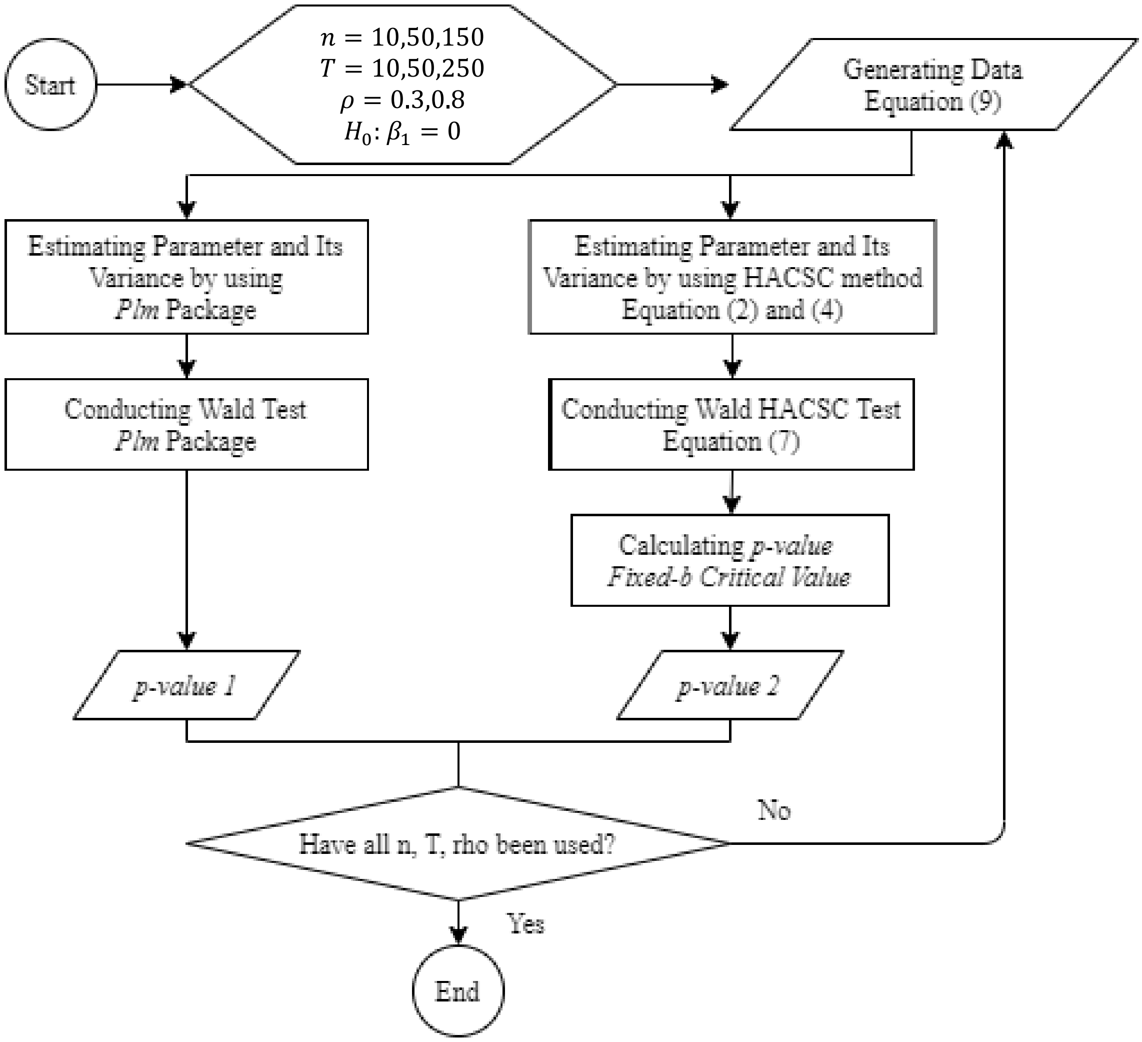

Figure 2. The Second Simulation Algorithm

Table 2 shows that a strong indication that both the standard and HACSC method produce the same parameter values. In the first repetition, the parameter estimation using both the standard and HACSC method is 0.0058. Likewise for the second to tenth repetition, the standard and HACSC method produce the same parameter estimates.

In contrast to the parameter estimation, the standard error between the standard and HACSC method is different. In the first repetition, the standard error obtained by standard method is 0.0870 and by HACSC method is 0.0900. It shows that the standard error obtained by standard method was slightly lower than the new method. This also happened on the sixth, seventh, and tenth repetitions. Whereas in the second test, the standard error obtained by standard method is 0.0801 and by HACSC method is 0.0798. It shows that the standard error obtained by standard method is greater than by HACSC method. This also happened in the third, fourth, fifth, eighth, and ninth repetitions.

Table 2 also shows that overall the HACSC method produces a slightly lower standard error than the standard method. It can be seen in the mean of standard error on the

HACSC method which is slightly lower than the standard method. Because it has a lower standard error, the HACSC variance estimator is better than the standard variance estimator in plm package. However, the standard method is able to produce a more stable variance estimate. It can be seen in Table 2 that the standard error obtained by the standard method is in the (0.07; 0.09) interval, unlike the standard error obtained by the HACSC method which is in the (0.06-0.10) interval.

Table 2. Result of Parameter Estimation and Its Standard Error on the First Simulation

Repetition	Method			
	Standard		HACSC	
	$\hat{\boldsymbol{\beta}}_1$	$se(\hat{\boldsymbol{\beta}}_1)$	$\hat{\boldsymbol{\beta}}_1$	$se(\hat{\boldsymbol{\beta}}_1)$
1	0.0058	0.0870	0.0058	0.0900
2	0.0984	0.0801	0.0984	0.0798
3	0.0675	0.0813	0.0675	0.0778
4	-0.0713	0.0933	-0.0713	0.0663
5	0.1517	0.0743	0.1517	0.0430
6	0.1753	0.0781	0.1753	0.1000
7	0.1762	0.0855	0.1762	0.0932
8	0.1131	0.0825	0.1131	0.0697
9	0.0608	0.0872	0.0608	0.0614
10	0.0659	0.0730	0.0659	0.1035
Mean	0.0843	0.0822	0.0843	0.0785

After obtaining the parameter β_1 estimation and its standard error, the next step is to test the significance of the coefficient using the Wald test. This test is carried out using three methods which will be compared, namely the standard method in plm package, the HACSC method with the normal critical value, and the HACSC method with the fixed-b critical value. The null hypothesis used is as follows:

$$H_0: \beta_1 = 0 \iff H_0: [1 \quad 0] \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = 0 \iff H_0: [1 \quad 0]\boldsymbol{\beta} = 0 \qquad (10)$$

The comparison that will be used is p-value, the probability to reject H_0 even though H_0 is true. The parameter set in the data generation process in equation (9) is $\beta_1 = 0.1$, while the null hypothesis to be tested in equation (10) is $\beta_1 = 0$. It means that in this first simulation, the better method is one that tends to reject the null hypothesis. In other words, the better method is one that produces a smaller p-value. The p-value of the test results is presented in Table 3.

Table 3 shows that the best statistical inference method on the linear panel models with fixed effects is by using HACSC method with a fixed-b critical value, because the HACSC method with a fixed-b critical value produces the lowest p-value. In the first repetition, the HACSC method with the fixed-b critical value produces the lowest p-value, 0.8969. It also happened on the second to tenth repetition. In the second to tenth repetition, the HACSC method with the fixed-b critical value also produces the lowest p-value.

Table 3. Result of P-value on the First Simulation

Repetition	Standard Method	HACSC Method	
		Normal(0,1)	*Fixed-b*
1	0.9467	0.9483	0.8969
2	0.2214	0.2171	0.0136
3	0.4075	0.3855	0.0827
4	0.4458	0.2823	0.0315
5	0.0432	0.0004	0.0000
6	0.0263	0.0795	0.0005
7	0.0412	0.0588	0.0002
8	0.1724	0.1045	0.0012
9	0.4871	0.3225	0.0479
10	0.3681	0.5243	0.2029
Mean	0.3160	0.2923	0.1277

Table 3 also shows that the HACSC method with normal critical value is better than the standard method. It can be seen from the mean of p-value obtained by the HACSC method with normal critical value is 0.2923, lower than that by standard method, 0.3160. However, this condition does not occur to all repetition. In the first repetition, the p-value of HACSC method with normal critical value is 0.9483, slightly higher than that of standard method, 0.9467. This also happened on the sixth, seventh, and tenth repetitions. Whereas in the second repetition, the HACSC method with normal critical value was 0.2171, slightly lower than that of standard method, 0.2214. This also happened in the third, fourth, fifth, eighth, and ninth repetitions.

Based on Table 2 and Table 3 in general, the HACSC method with fixed-b critical value produces the lowest p-value even though the standard error obtained is higher than the standard method, such as in the first, sixth, seventh, and tenth repetition. This differs from using the normal critical value in the HACSC method. HACSC method with normal critical value will produce p-value lower than standard method if the standard error obtained is also lower, such as in the second, third, fourth, fifth, eighth, and ninth repetition. Vice versa. If the standard error obtained is higher, the HACSC method with a normal critical value will also produce a higher p-value, as in the first, sixth, seventh, and tenth tests. These results indicate that the use of the HACSC method in estimating variance is able to correct the standard method due to the violation of the independent assumption.

4.2. The Second Simulation

The second simulation aims to find out the comparison between the standard and HACSC method in general. This is different from the first simulation which only compares when n, T, and ρ are 10, 15, and 0.7, respectively. Because the first simulation has shown that the HACSC method with a fixed-b critical value is better, the second simulation is carried out with a focus on testing $H_0: \beta_1 = 0$ using the standard method in plm package and HACSC method with fixed-b critical value for various combinations of $n, T,$ and ρ so that more aspects can be evaluated. The selected values for n and T were 10, 50, and 250, while the ρ values selected were 0.3 and 0.8. The results of the second simulation with 1000 repetition can be seen in Table 4.

Table 4. Result of P-value on the Second Simulation

n	T	ρ	Standard Method	HACSC Method
10	10	0.3	0.34181	0.14577
		0.8	0.31582	0.16488
	50	0.3	0.11280	0.04640
		0.8	0.17583	0.13729
	250	0.3	0.00051	0.00001
		0.8	0.02334	0.02233
50	10	0.3	0.11437	0.02996
		0.8	0.17440	0.07015
	50	0.3	0.00102	0.00005
		0.8	0.02480	0.01750
	250	0.3	0.00000	0.00000
		0.8	0.00000	0.00001
250	10	0.3	0.00131	0.00005
		0.8	0.00616	0.00071
	50	0.3	0.00000	0.00000
		0.8	0.00000	0.00000
	250	0.3	0.00000	0.00000
		0.8	0.00000	0.00000

There is some information that can be taken from Table 4. The first is that it is very clear that regardless of the values for n, T, and ρ, the HACSC method is better than the standard method. At $n = 10, T = 10$, and $\rho = 0.3$, the p-value of the HACSC method is 0.14557, lower than that of the standard method, 0.34181. Likewise all other combinations of n, T, and ρ. The HACSC method produce a lower p-value than the standard method.

The second information based on Table 4 is that regardless of the value of n and T, both the standard and HACSC method will produce better results at a smaller ρ. At $n = 10$ and $T = 10$, the HACSC method with $\rho = 0.3$ produce a p-value amounting to 0.14577, lower than that of $\rho = 0.8$, 0.16488. Likewise all other combinations of n and T, as well as for the standard method. The smaller ρ, the lower the p-value.

The third information is based on Table 4 is that regardless of the value of n and ρ both the standard and HACSC method will produce better results at a larger T. At $n = 10$ and $\rho = 0.3$, the HACSC method with $T = 10$ produce a p-value amounting to 0.14577, higher than that of $T = 50$, 0.04640. Likewise all other combinations of n and ρ, as well as for the standard method. The greater T, the lower the p-value.

The fourth information is based on Table 4 is that regardless of the value of T and ρ both the standard and HACSC method will produce better results at a larger n. At $T = 10$ and $\rho = 0.3$, the HACSC method with $n = 10$ yields a p-value amounting to 0.14577, higher than that of $n = 50$, 0.02996. Likewise all other combinations of T and ρ, as well as for the standard method. The greater n, the lower the p-value.

The last information based on Table 4 is that the HACSC method is significantly better than the standard method when the respective values for n, T, and ρ are small. At $n = 10, T = 10$, and $\rho = 0.3$, the p-value obtained by the HACSC method is 0.14577 which is considerably lower than the standard method, 0.34181. Whereas at $n = 50, T = 50$, and $\rho = 0.8$, the p-value obtained by the HACSC method is 0.01750 which is slightly lower than the standard method, 0.02480.

In general, the large values of n and T produce small p-values. This is because when the sample size is large, the $\hat{\beta}$ obtained by any method will be more homogeneous. Thus, the resulting standard error becomes small and the resulting p-value becomes small. So, the problem is the best method for linear panel models with autocorrelation at small n and T. The result shows by means of simulation that the HACSC method which is the Wald-HACSC test with a fixed-b critical value is more appropriate for it.

5. CONCLUSION

Based on the simulations that had been carried out, several conclusions obtained in order to evaluate the performance of the new inference method, namely the Wald-HACSC test with a fixed-b asymptotic distribution critical value were as follows.

First, overall the variance estimates obtained by HACSC method were slightly lower than by standard method. Second, the interval of variance estimates obtained by HACSC method was quite large, in other words, the variance estimates obtained by HACSC method was less stable. Third, overall the new inference method, Wald-HACSC test with fixed-b critical value, was better than the standard inference method in plm package because it produced a lower p-value. Fourth, both the new inference method, Wald-HACSC test with fixed-b critical value, and the standard inference method in plm package would give better results when the relationship between the observed and the previous observation is weak, the number of individuals is large, and the dimension of time period is long. Last, for data with a small number of individuals and a short time period, the new inference method, Wald-HACSC test with fixed-b critical value, was more appropriate than the standard inference method in plm package, because it produces a lower p-value significantly.

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