Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

Efficient Estimation With Panel Data: Bootstrap And Jackknife Method

Mohamed BIJOU 0000-0003-2567-0145

Mohamed V University Rabat

Said LAARIBYA[1] 0000-0003-3864-0612

Chouaib Doukkalli University – LREDD- El-Jadida *laaribya.s@ucd.ac.ma*

Article Type: Original Research Article
Vol 2 (Issue 2) 2020: 58-66

Received: 12.10.2020
Revised: 20.12.2020
Accepted: 29.12.2020

To Cite As: LAARIBYA, S . (2020). Efficient Estimation with Panel Data: Bootstrap and Jackknife Method. Quantrade Journal of Complex Systems in Social Sciences, 2 (2) , 58-66 . Retrieved from https://dergipark.org.tr/tr/pub/quantrade/issue/55193/708763

Abstract

Hausman and Taylor (1981) have proposed an effective instrumental variable estimator for the panel data regression models, where individual effects can be correlated with some of the regressors. Amemiya and MacCurdy (1986) also Breusch, Mizon and Schmidt (1986) suggested instrumental variables estimators potentially more efficient than the estimator of Hausman and Taylor. In our empirical exercise on educational returns inspired by the pioneering empirical work of Cornwell and Rupert 1988, we propose a new empirical covariance variance matrix revisited by bootstrap and jackknife methods to estimate robust standard deviations. The results show that three variables "smsa, union and black" become insignificant with robust standard deviation estimation via both Bootstrap and Jackknife methods. This modest contribution somehow qualifies the results revealed by BADI H. Baltagi and Sophon Khanti - Akom 1990 and Cornwell and Rupert 1988.

Keywords: Estimator, Panel Data, Covariance Variance Matrix, Bootstrap and Jackknife Methods

1. Introduction

It is well established that with panel data, individual specific effects can be controlled in a specification of a longitudinal econometric model (Longitudinal data analysis represents a marriage of regression and time series analysis. As with many regression data sets, longitudinal data are composed of a cross-section of subjects.). Since the specific effects may be correlated with some of the explanatory variables of the model, the choice of instrumental variables estimation techniques (IV) (instrumental variables) is more accurate, and more consistent. The traditional estimator of variance analysis is the "within" estimator. It is consistent with all the assumptions of the model and is simple to calculate: it is enough to transform the data into deviations from the individual averages and to perform ordinary least squares. However, the within estimator suffers from two significant defects. First, all time-invariant variables are eliminated by the within transformation, so that their coefficients cannot be estimated. Second, the within estimator is not entirely effective because it ignores the variation of individuals.

Hausman and Taylor (1981) propose an IV estimator by controlling all the defects observed by the within estimator. The HT estimator uses assumptions about explanatory variables that are not correlated with individual effects. The HT estimator is an improvement over the within estimator because it depends on the number of exogeneity restrictions that we want to impose. In general, if there are more exogenous variables who vary in the time than endogenous variables, the HT estimator is considered consistent and more effective than the within estimator.

Amemiya and MaCurdy (1986) propose an IV estimator, which is no less effective than the HT estimator is, in case it is consistent. Potential efficiency gains have been derived from the use of each exogenous explanatory variable as instruments (T + 1): as deviations from averages and separately for each of the available time periods. The HT estimator uses each of these variables as two instruments: the means and the deviations from the means.

Bruesch, Mizon, and Schmidt (1987) clarify the relationship between estimators HT and AM. In addition, they extend the reasoning of the MA to obtain an even more efficient IV estimator. Implicitly, the HT and AM estimators use the deviations from the average of the exogenous variables ranging th time as instruments. The BMS estimator uses the (T-1) linearly independent values of these deviations from the averages as additional instruments.

[1] *Corresponding Author: laaribya.s@ucd.ac.ma*

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

We discuss in this paper the empirical question `` the size of the efficiency gain for HT and AM after standard deviation correction " by the two methods, jackknife and bootstrap, in order to compare them with the work done by Cornwell and Rupert 1988, BADI H. Baltagi and Sophon Khanti -Akom 1990. The general context of our analysis is the Educational Performance inspired by these two works mentioned previously, we use in the empirical phase the same database used by BADI H. Baltagi and Sophon Khanti-Akom 1990. The choice of the framework and the database provides a special motivation for comparing these revised procedures with the results already conclude by BADI H. Baltagi and Sophon Khanti-Akom 1990 also Cornwell and Rupert 1988.

The remainder of the paper proceeds as follows: we begin in Section 2 with a brief review of these IV procedures, based on the theoretical work of Amemiya, T. and TE MacCurdy, (1986) ; Breusch, TS, GE Mizon and P. Schmidt, (1986) ;and Hausman and Taylor (1981). In Section 3, we apply at first the of HT and Amemiya MaCurdy estimators to a standard wage equation, with a highlighting on the differences observed between our robust covariance variance matrix (Bootstrap and jackknife) and the one in the two papers of BADI H. Baltagi and Sophon Khanti-Akom 1990, also of Cornwell and Rupert 1990 paper.

2. Methodological Approach: Model and Estimators

2.1. Methodology

We consider the models of the form

$$y_{it} = X'_{it}\beta + Z'_i\gamma + \alpha_i + \varepsilon_{it} \quad i=1,\ldots\ldots, N\ ;\ t=1,\ldots\ldots, T \qquad (2.1)$$

- **yi** represent as a variable to be explained
- $\mathbf{X_{it}}$ is a K x 1 vector of explanatory variables variations in time,
- $\mathbf{Z_i}$ is a vector G x 1 regressors are in varying over time,
- β and γ are parameters of the model vectors.

We assume that the disturbances ε_{it} are iid N (0, σ^2)) and the individual effects αi are iid N (0, σ^2)

It is assumed that the ε_{it} is not correlated with the explanatory variables and the individual effects, while the α_i can be correlated with parts of X and Z. By combining all NT observations, we can write (2.1) as follows:

$$y = X\beta + Z\gamma + V\alpha + \varepsilon \qquad (2.2)$$

Where

- **Y et ε** is NT x 1
- **X** is NT x K
- **Z** is NT x G
- **G et V** is an NT x N matrix of specific individual dummy variables

We follow HT and order the observations in N groups of length.

For any matrix A, we define $P_A = A(A'A)^{-1}A'$ as the projection on the space of the columns of A. Then, $Q_A = I - P_A$ is defined as the projection on the null space of A.

The most common IV estimator for models like (2.2) is the within estimator. It is calculated by projecting (2.2) over the null space of V and by performing ordinary least squares. Since $Q_V Z = 0$, alone β is estimated, so we have

$$\widehat{\beta}_w = (X' Q_V X)^{-1} X' Q_V y \quad \mathbf{(2.3)}$$

The within estimator is consistent (like N or T →□), whether the effects are correlated with the explanatory variables.

However, if we are willing to assume that the parts of X and Z are not correlated with the effects individual, potentially more effective IV procedures are available. Next HT, we partition X and Z:

$$X = (X_1, X_2)\ , Z = (Z_1, Z_2) \qquad (2.4)$$

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

And suppose that X_2 and Z_2 are correlated with the effects (eg plim $(NT)^{-1} X_2 V\alpha \neq 0$) , while and are not correlated with the effects. Note that X_1 at k_1 columns, X_2 at k_1 columns, and $k_1 + k_2 = K$; Z_1 at g_1 columns and Z_2 at g_2 columns and $g_1 + g_2 = G$.

The effective estimators of HT, AM and BMS are calculated in the same way. First, (2.2) is transformed so that the error term will have a scalar covariance matrix. Defining $\Omega = \mathrm{cov}(V\alpha + \varepsilon)$, the transformed model is

$$\Omega^{-1/2}y = \Omega^{-1/2}X\beta + \Omega^{-1/2}Z\gamma + \Omega^{-\frac{1}{2}}(V\alpha + \varepsilon) \qquad (2.5)$$

Or $\Omega^{-1/2} = Q_V + \theta P_V$ and $\theta^2 = \sigma^2(\sigma^2 + T\sigma^2)^{-1}$. Then, with a set of A instruments based on (2.4), IV is executed on (2.5). This gives form estimators

$$\begin{pmatrix}\hat{\beta}\\ \hat{\gamma}\end{pmatrix} = [(X,Z)'\Omega^{-\frac{1}{2}}P_A\Omega^{-\frac{1}{2}}(X,Z)]^{-1}(X,Z)'\Omega^{-\frac{1}{2}}P_A\Omega^{-\frac{1}{2}}y \qquad (2.6)$$

The HT estimator uses the set of instruments

$$A_1 = (Q_V X_1, Q_V X_2, P_V X_1, Z_1) \qquad \textbf{(2.7)}$$

Note that each variable in X_1 provides two instruments since averages ($P_V X_1$) and deviations from the averages (Q_V, X_1) are used separately. The order condition for the HT estimator to exist is $K + k_1 + g_1 \geq K + G$ or $k_1 \geq g_2$

To define the set of instruments used by AM, either X^* is an NT x TK matrix where each column contains values of X_{1it} for a single period. For example, the tth column of X^* is giveby $X^* = (X_{11t}, \dots\dots, X_{11t}, \dots\dots, X_{1Nt}, \dots\dots, X_{1Nt})$. So, the estimator AM is IV on (2.5) using the set of instruments

$A_2 = (Q_V X_1, Q_V X_2, X^*, Z_1)$

$$A_2 = (Q_V X_1, Q_V X_2, X^*, Z_1) \qquad \textbf{(2.8)}$$

While HT uses each variable X_1 as two instruments, AM uses each of these variables as instruments (T + 1) ($Q_V X_1$ et X^*). The condition of order AM for existence is $Tk_1 \geq g_2$.

The AM estimator, if consistent, is no less efficient than the HT estimator. However, in this case, the consistency depends on a stronger erogeneity assumption. Since plim (NT)−1

X′ Vα = 0 involves the plim (N)−1 ∑N X̄1i αi = 0 , HT requires only the averages of the

i=1variables are uncorrelated with the effects. For the AM estimator to be consistent, we need plim $(N)^{-1} \sum_{i-1}^{N} X'_{1it}\alpha_i = 0 \quad (t = 1, \dots\dots, T)$, or of non-correlated every moments

as suggested by AM and BMS, it is difficult to imagine a situation in which the HT hypothesis is true, but the AM hypothesis is not.

BMS derive a potentially more efficient AM estimator. Noting that the AM estimator is equivalent to IV of (2.5) on

$${}_2 = (Q_V X_1, Q_V X_2, P_V X_1, (Q_V X_1)^*, Z_1) \qquad \textbf{(2.9)}$$

or $(Q_V X_1)^*$ is defined in the same way as X_1^* : (that is, each column contains the variances of the means of the variables X_1 for a single period), BMS extends AM treatment of variables X_1 to the variables X_2 . The BMS estimator uses the set of instruments

$$A_3 = (Q_V X_1, Q_V X_2, P_V X_1, (Q_V X_1)^*, (Q_V X_2)^*, Z_1) \qquad \textbf{(2,10)}$$

with $(Q_V X_2)^*$ defined exactly like $(Q_V X_1)^*$ So, the BMS estimator exists when $Tk_1 + (T-1)k_1 \geq g_2$.

The potential efficiency gain of the BMS (Breush Mizon and shmidt) procedure depends on the fact that the $(Q_V X_2)^*$ are legitimate instruments. The $(Q_V X_2)^*$ are valid instruments if the variables of X_2 are not correlated with the effects only through invariant component in time. If that were true, $Q_V X_2$ would not contain this component, and using the spreads separately for each period would be legitimate.

2.2. Data

The data for our analysis are taken from the Income Dynamics Study (EDSP) from 1976 to 1982; we take into account in our empirical study only the part not included in the survey on economic prospects. The size of our sample amounted to 595 heads of households aged of 18 to 65 in 1976 , and who report a positive salary in a non-farm private job for all of the seven years.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

Thus, for each individual, we have seven annual observations on the following defining characteristics of salary:

- years of education (ED),
- years of full-time work experience (EXP),
- weeks worked (WKS),
- occupation (OCC = 1, if the individual has a working profession),
- industry (IND = 1, if the individual works in a manufacturing industry),
- residence (SUD = 1, SMSA = 1 if the individual resides in the south or in a standard metropolitan statistical area),
- marital status (MS = 1, if the person is married),
- union coverage (UNION = 1, if the individual's salary is set by a union contract),
- Gender and race (FEM = 1, BLK = 1, if the individual is female or black).

Before applying the HT, AM or BMS estimator to our salary equation, we have verified that the results observed by Cornwell and Rupert are the same as we find, with the objective of remaining on the same specification logic, and only of revisit the covariance variance matrix by the two methods of Bootstrap and jackknife. For each estimation method, four covariance variance matrices will be estimated.

1) A covariance variance matrix with robust deviations,
2) With standard deviations,
3) Standard deviations in bootstrap and
4) Standard deviations with the jackknife method.

Our models HT and AM are presented by the distinction of variables as follows: X_1 = (WKS, SUD, SMSA, MS), X_2= (EXP, EXP2, OCC, IND, UNION), Z_1= (FEM, BLK), and Z_2= (ED). Our reading and commentary of all the models will be cross-sectional according to the different estimation methods of the covariance variance matrix, making a comparison with the results found by Cornwell and Rupert 1988, and Baltagi and Sophon Khanti -Akom 1990.

3. Results and Discussions

In this section, we search to compare estimators with ROBUST-TYPE DEPTHS in order to measure educational results. When the model parameters are over-identified, the HT estimator represents a significant improvement over the within estimator, since more efficient estimates of β and consistent estimates of γ are possible. Potentially, even more efficient estimates of β and γ can be obtained with AM and BMS procedures. The size of the efficiency gains will be an empirical question. AM and BMS anticipate small gains in many applications.

Here we we study the potential efficiency gains from using these more refined IV procedures to estimate educational returns. Recent additions to back-to-school literature (eg, Griliches, 1977, Lillard and Willis, 1978, HT, and Chowdhury and Nickell, 1985) have focused on the potential correlation between individual ability and education. Typically, the unobserved capacity, is leading to the natural conclusion, that individual effects are correlated with education. One argument states that education is positively correlated with effects (capacity). In this case, the OLS (or GLS) estimate is biased upwards. However, as Griliches (1977) and Griliches, Hall and Hausman (1978) have shown, when schooling becomes endogenous, a negative correlation between effects and education may occur. These results are based on traditional IV procedures that define a reduced form for education in terms of excluded exogenous variables such as family characteristics. Higher returns from schooling estimates are also reported by HT. We are looking for additional evidence in our findings of a negative correlation between education and effects.

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

Table 1. Results of the within estimator with the set of covariance variance matrices

	Within (β)	Within (σ)	Within (β) VCE	Within (σ) VCE	Within (β) Bootstrap	Within (σ) Bootstrap	Within (β) Jackknife	Within (σ) Jackknife
wks	0.0008359	0.0005997	0.0008359	0.0005997	0.0008359	0.0008306	0.0008359	0.0008737
south	-0.0018612	0.0342993	-0.0018612	0.0342993	-0.0018612	0.1260892	-0.0018612	0.0965428
SMSA	-0.0424691	0.0194284	-0.0424691	0.0194284	-0.0424691	0.0287718	-0.0424691	0.0303851
ms	-0.0297259	0.0189836	-0.0297259	0.0189836	-0.0297259	0.0223029	-0.0297259	0.0277962
exp	0.1132083	0.002471	0.1132083	0.002471	0.1132083	0.0047786	0.1132083	0.0041087
expsq	-0.0004184	0.0000546	-0.0004184	0.0000546	-0.0004184	0.0001028	-0.0004184	0.0000834
occ	-0.0214765	0.0137837	-0.0214765	0.0137837	-0.0214765	0.0178477	-0.0214765	0.0195275
ind	0.0192101	0.0154463	0.0192101	0.0154463	0.0192101	0.0224549	0.0192101	0.0230723
union	0.0327849	0.0149229	0.0327849	0.0149229	0.0327849	0.0212205	0.0327849	0.0255552
fem	-	-	-	-	-	-	-	-
blk	-	-	-	-	-	-	-	-
ed	-	-	-	-	-	-	-	-
_cons	4.648767	0.046022	4.648767	0.046022	4.648767	0.0759275	4.648767	0.0906155
sigma_u	1.0338102		1.0338102		1.0338102		1.0338102	
sigma_e	0.15199444		0.15199444		0.15199444		0.15199444	
rho	0.97884144		0.97884144		0.97884144		0.97884144	

Source: Author

Beginning with the GLS estimator, we note that the standard deviations of all the variables are underestimated by the work of Cornwell and Rupert 1988 and BADI H. Baltagi and Sophon Khanti-Akom 1990. Compared to the significance of the parameters, the bootstrap and jackknife methods did not reverse the significance of the parameters of the whole GLS model, even though the standard deviations are a little different.

Beginning with the GLS estimator, we note that the standard deviations of all the variables are underestimated by the work of Cornwell and Rupert 1988 and BADI H. Baltagi and Sophon Khanti-Akom 1990. Compared to the significance of the parameters, the bootstrap and jackknife methods did not reverse the significance of the parameters of the whole GLS model, even though the standard deviations are a little different.

Table 2. Results of the GLS estimator with the set of covariance variance matrices

	GLS (β)	GLS (σ)	GLS (β) VCE	GLS (σ) VCE	GLS (β) Bootstrap	GLS (σ) Bootstrap	GLS (β) Jackknife	GLS (σ) Jackknife
wks	0.0010347	0.0007734	0.0010347	0.0007734	0.0010347	0.0010772	0.0010347	0.0009433
south	-0.0166176	0.0265265	-0.0166176	0.0265265	-0.0166176	0.0515652	-0.0166176	0.047013
SMSA	-0.0138231	0.0199927	-0.0138231	0.0199927	-0.0138231	0.0279209	-0.0138231	0.030818
ms	-0.0746283	0.0230052	-0.0746283	0.0230052	-0.0746283	0.0275097	-0.0746283	0.0281265
exp	0.0820544	0.0028478	0.0820544	0.0028478	0.0820544	0.0045376	0.0820544	0.0042877
expsq	-0.0008084	0.0000628	-0.0008084	0.0000628	-0.0008084	0.000099	-0.0008084	0.0000925
occ	-0.0500664	0.0166469	-0.0500664	0.0166469	-0.0500664	0.019984	-0.0500664	0.0210929
ind	0.0037441	0.0172618	0.0037441	0.0172618	0.0037441	0.0286112	0.0037441	0.0235052

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

union	0.0632232	0.01707	0.0632232	0.01707	0.0632232	0.0242657	0.0632232	0.0252174
fem	-0.3392101	0.0513033	-0.3392101	0.0513033	-0.3392101	0.0770409	-0.3392101	0.065948
blk	-0.2102803	0.0579888	-0.2102803	0.0579888	-0.2102803	0.0902292	-0.2102803	0.0852574
ed	0.0996585	0.0057475	0.0996585	0.0057475	0.0996585	0.0083001	0.0996585	0.0083477
_cons	4.26367	0.0977162	4.26367	0.0977162	4.26367	0.1428877	4.26367	0.1561258
sigma_u	0.26265814		0.26265814		0.26265814		0.26265814	
sigma_e	0.15199444		0.15199444		0.15199444		0.15199444	
rho	0.74913774		0.74913774		0.74913774		0.74913774	

Source: Author

Compared to the within estimator, we observe that the model within bootstrap and jackknife reverses the significance of some variables. The variables "smsa and union "become insignificant at a threshold of 5%.

As for the Hausman and Taylor model, our results show that the HT model by bootstrap and jackknife reverses the significance of certain variables. The variables "smsa union and black" become insignificant at a threshold of 5%.

Concerning the Amemiya Macurdy model, our results show that the AM model by bootstrap and jackknife reverses the significance of certain variables. The variables "smsa union and black "become insignificant at a threshold of 5%.

Table 3. Results of the Hausman and Taylor estimator with the set of covariance variance matrices

	HT (β)	HT (σ)	HT (β) VCE	HT (σ) VCE	HT (β) Bootstrap	HT (σ) Bootstrap	HT (β) Jackknife	HT (σ) jackknife
occ	-0.0207047	0.0137809	-0.0207047	0.0137809	-0.0207047	0.0181312	-0.0207047	0.0195239
south	0.0074398	0.031955	0.0074398	0.031955	0.0074398	0.0797143	0.0074398	0.084165
SMSA	-0.0418334	0.0189581	-0.0418334	0.0189581	-0.0418334	0.0282254	-0.0418334	0.0293561
ind	0.0136039	0.0152374	0.0136039	0.0152374	0.0136039	0.0220687	0.0136039	0.022573
exp	0.1131328	0.002471	0.1131328	0.002471	0.1131328	0.004297	0.1131328	0.0041106
expsq	-0.0004189	0.0000546	-0.0004189	0.0000546	-0.0004189	0.0000829	-0.0004189	0.0000832
wks	0.0008374	0.0005997	0.0008374	0.0005997	0.0008374	0.000844	0.0008374	0.0008741
ms	-0.0298508	0.01898	-0.0298508	0.01898	-0.0298508	0.0296329	-0.0298508	0.0277293
union	0.0327714	0.0149084	0.0327714	0.0149084	0.0327714	0.0257027	0.0327714	0.0255307
fem	-0.1309236	0.126659	-0.1309236	0.126659	-0.1309236	0.1225227	-0.1309236	0.1196553
blk	-0.2857479	0.1557019	-0.2857479	0.1557019	-0.2857479	0.1978291	-0.2857479	0.1749591
ed	0.137944	0.0212485	0.137944	0.0212485	0.137944	0.018654	0.137944	0.0218392
_cons	2.912726	0.2836522	2.912726	0.2836522	2.912726	0.2805748	2.912726	0.3116099
sigma_u	0.94180304		0.94180304		0.94180304		0.94180304	
sigma_e	0.15180273		0.15180273		0.15180273		0.15180273	
rho	0.97467788		0.97467788		0.97467788		0.97467788	

Source: Author

Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

Table 4. Results of the estimator Amemiya and Macurdy with the set of covariance variance matrices

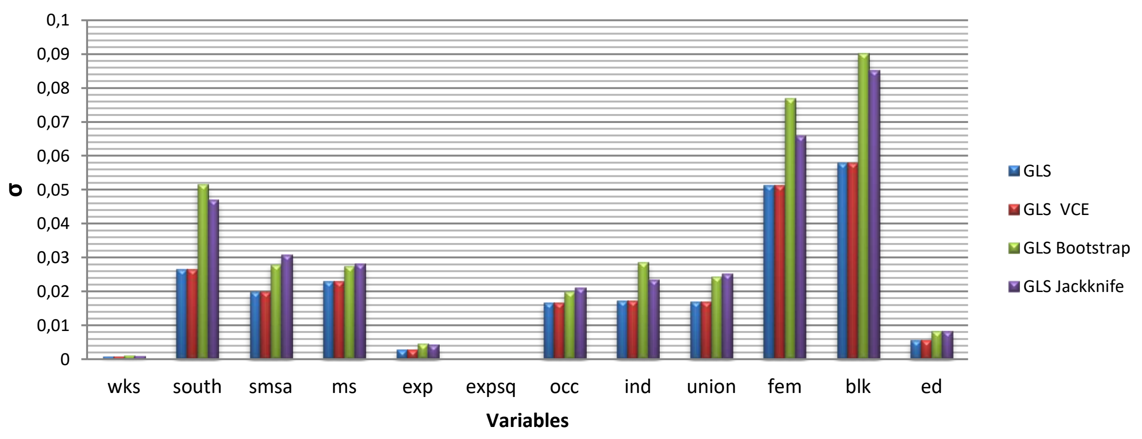
	AM (β)	AM (σ)	AM (β) VCE	AM (σ) VCE	AM (β) Bootstrap	AM (σ) Bootstrap	AM (β) Jackknife	AM (σ) jackknife
occ	-0.0208498	0.0137653	-0.0208498	0.0137653	-0.0208498	0.0201363	-0.0208498	0.0195073
south	0.0072818	0.0319365	0.0072818	0.0319365	0.0072818	0.0711183	0.0072818	0.0841492
SMSA	-0.0419507	0.0189471	-0.0419507	0.0189471	-0.0419507	0.0293418	-0.0419507	0.0293799
ind	0.0136289	0.015229	0.0136289	0.015229	0.0136289	0.0221828	0.0136289	0.0225711
exp	0.1129704	0.0024688	0.1129704	0.0024688	0.1129704	0.0036509	0.1129704	0.0040954
expsq	-0.0004214	0.0000546	-0.0004214	0.0000546	-0.0004214	0.0000773	-0.0004214	0.000083
wks	0.0008381	0.0005995	0.0008381	0.0005995	0.0008381	0.0007184	0.0008381	0.0008739
ms	-0.0300894	0.0189674	-0.0300894	0.0189674	-0.0300894	0.0257813	-0.0300894	0.0276782
union	0.0324752	0.0148939	0.0324752	0.0148939	0.0324752	0.0269478	0.0324752	0.0255395
fem	-0.132008	0.1266039	-0.132008	0.1266039	-0.132008	0.0875223	-0.132008	0.1191826
blk	-0.2859004	0.1554857	-0.2859004	0.1554857	-0.2859004	0.1570723	-0.2859004	0.1742587
ed	0.1372049	0.0205695	0.1372049	0.0205695	0.1372049	0.0251799	0.1372049	0.0212792
_cons	2.927338	0.2751274	2.927338	0.2751274	2.927338	0.346705	2.927338	0.3044036
sigma_u	0.94180304		0.94180304		0.94180304		0.94180304	
sigma_e	0.15180273		0.15180273		0.15180273		0.15180273	
rho	0.97467788		0.97467788		0.97467788		0.97467788	

Source: Author

After the two pioneering works in question of Cornwell and Rupert, BADI H. Baltagi and Sophon Khanti-Akom 1990, our contribution revisits the non-significance of these three variables « smsa union and black » after robust estimation the variance matrix by the two methods Bootstrap and Jackknife (the different estimates and bias deviations are illustrated in tables and graphs in appendix).

Annex

Figure 1. Estimation biases between GLS model differences



Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

Figure 2. Estimation biases between Within model differences

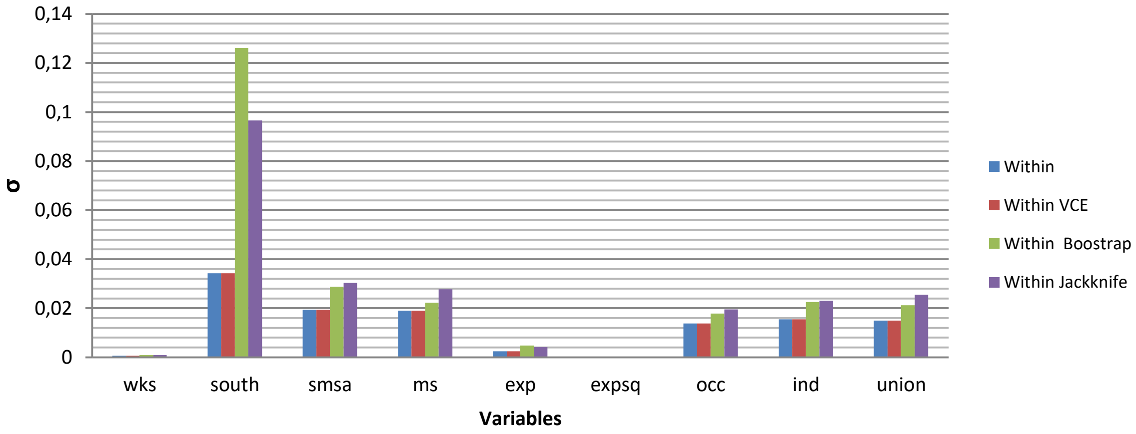


Figure 3. Estimation biases between Hausman Taylor model differences

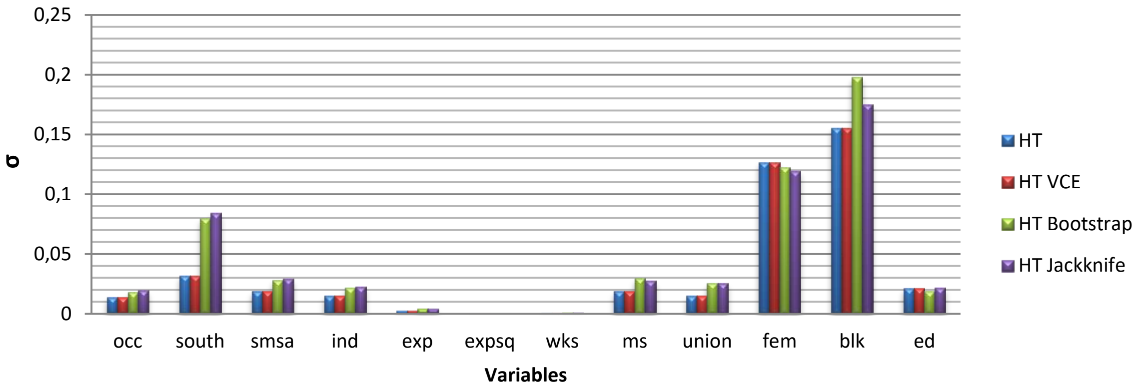
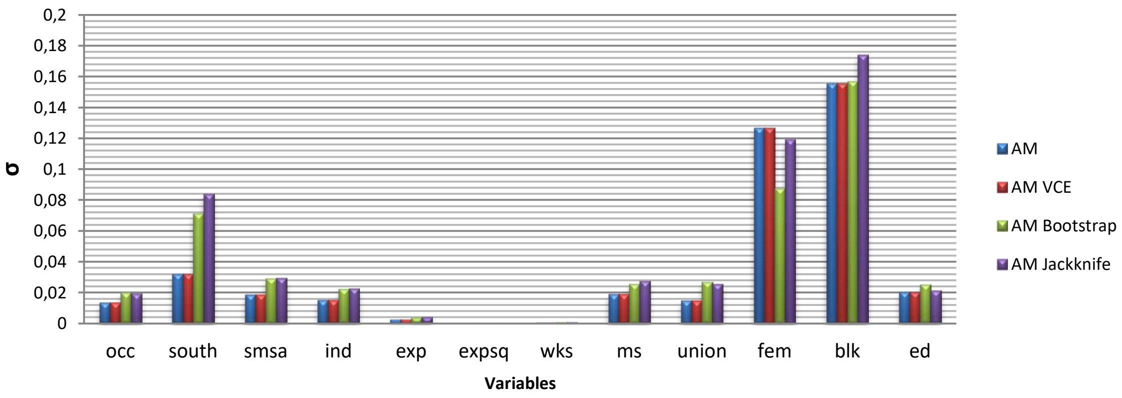


Figure 4. Estimation biases between Amemiya Macurdy model differences



Quantrade Journal of Complex Systems in Social Sciences e-ISSN: 2687-5098 Vol 2 (Issue 2) Fall 2020
http://www.dergipark.org.tr/quantrade

References

Amemiya, T. and MacCurdy, T.E., (1986). 'Instrumental Variables Estimation of an Error Model ', *Econometrica*, 54, 869-880.

Baltagi, B. H. and Khanti-Akom, S. (1990). 'On Efficient Estimation with Panel Data: An Empirical Comparison of İnstrumental Variables Estimators'. *Journal of Applied Econometrics, 5*(4), 401-406.

Breusch, T. S., Mizon, G. E. and Schmidt, P. (1986). 'Some Result on Panel Data'. *Econometrics Workshop Paper No. 8608*. Michigan State University.

Chowdhury, G. and Nickell, S. (1985). 'Hourly Earnings in the US: Another Look at Unionization, S Chooling, Sickness, and Unemployment Using PSID Data', *Journal of Labor Economics*, 3, 38-69.

Efron, B. (1979). 'Bootstrap Methods: Another Look at the Jackknife'. *The Annals of Statistics, 7* (1), 1-26.

Griliches, Z. (1977). 'Estimating the Returns to Schooling: Some Economic Problems'. *Econometrica,* 45, 1-22.

Griliches, Z., Hall, B. and Hausman, J.A. (1978). 'Missing Data and Self-Selection in Large Panels', *Annales de lInsee, 30*(31), 137-176.

Hausman, J.A. (1978). 'Specification Test in Econometrics'. *Econometrica*, 46, 1251- 1272.

Hausman, J.A. and Taylor, W. (1981). 'Panel Data and Unobservable Individual Effects'. *Econometrica*, 49, 1377-1399.

Lillard, L. and Willis, R. (1978). ' Dynamic Aspects of Earnings Mobility'. *Econometrica*, 46, 985-1012.

Tukey, J.W. (1958). ' Bias and Confidence Annals of Mathematical Statistics'. *Ann Math. Statist.*, 29, 614 .