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THE HAT MODEL : AN ESTIMATION METHOD OF CENSORED PANEL DATA WITH RANDOM-EFFECTS SPECIFICATION

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This paper suggests an estimation method of censored panel data under random-effects specification. The HAT model assumes a special type of heteroscedasticity which contains the information about cross-sectional and time-series properties of panel data. χ^2*-test statistic to evaluate the model specification is derived. Empirical study with COMPUSTAT data supports the specification of the HAT model.*

I . INTRODUCTION

The subject of this paper is to extend the Tobit model to censored panel data. Models which utilize panel data attempt to exploit the error covariance structure of the data generating process. As a result, we can obtain estimates of the parameters relating to the attributes which are common across the cross-sectional units in the panel. The conventional model specifications in panel studies are the fixed-effects model and the random-effects model. We are confronted with some problems when we try to apply the Tobit model for the estimation of censored panel data under the random-effects specification. The lack of the independence between observations increases the order of complexity of the likelihood function considerably and causes serious difficulty in estimation. In this paper, a special type of error covariance structure is suggested to circumvent the problems. It could be considered as heteroscedastically adjusted Tobit model(hereafter the HAT model) since all the off-diagonal elements of the error covariance matrix are assumed to be zeroes while assuming a special form of heteroscedasticity on its diagonal elements. The error covariance structure of the HAT model is not theoretically derived, thus it is subject to test.

Direct specification tests such as the Hausman specification test are not applicable to the model specification suggested in this study. For the purpose of evaluating the model specification, two indirect methods are used. The first one

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is testing the assumption of zero error covariance between time-different observations of every cross-sectional unit, which is critical for utilizing maximum likelihood estimation method. The second one is the parameter stability test suggested by Anderson(1987) which evaluates the model specification by comparing the predictive ability of the model. Those two statistics are used as criteria in evaluating the model specification.

II. SPECIFICATION AND ESTIMATION OF THE HAT MODEL

Recent availability of good panel data–cross sections of individuals over time–allows us to construct more realistic models. They help to explain the behavior that could not be explained using only cross-section or single time-series data. The other advantage of using panel data sets is that the efficiency of econometric estimates can be improved since using panel data increases the degree of freedom and reduces the collinearity between explanatory variables. Moreover, it resolves the problem of missing or unobserved variables.

Two conventional statistical model specifications which are used to analyze panel data are the fixed-effects model and the random-effects model. Consider the simple model of pooling procedure which does not contain a time specific component.

$$(1)\ y_{it}=\alpha_i+\beta X_{it}+\varepsilon_{it}, \qquad i=1,2,\ldots,N, \quad t=1,2,\ldots,T,$$

where α_i is the individual specific intercept and ε_{it} is a random error term which is independently identically distributed with mean zero and variance σ^2.

The fixed-effects model treats α_i's as fixed constants over time whereas the random-effects model considers α_i's as random variables just like ε_{it}.

Whether to treat α_i's as fixed or random is not an easy question to answer. However, it is important to try to specify an efficient model to analyze some panel data because the results from two different model specifications are significantly different (see Hausman, 1978, and Hsiao, 1986, p. 41).

The fixed-effects model can be estimated by the least-squares- dummy-variable (LSDV) method. The LSDV estimator of β is unbiased, and it is also consistent when N or T tends to infinity (see Hsiao, 1986, p.32).

The random-effects model which treats α_i's as random variables can be written as follows:

$$(2)\ y_{it}=\beta X_{it}+u_{it} \qquad \text{where } u_{it}=\alpha_i+\varepsilon_{it}.$$

From the conventional stochastic assumptions on α_i and ε_{it}, we can derive the following error covariance structure of the model:

$$
\begin{aligned}
(3)\ \operatorname{cov}(u_{it}, u_{js}) &= \sigma_a^2 + \sigma_\epsilon^2 && \text{for } i=j \text{ and } t=s,\\
&= \sigma_a^2 && \text{for } i=j \text{ and } t\neq s,\\
&= 0 && \text{otherwise.}
\end{aligned}
$$

The model must be estimated by the generalized least squares (GLS) method because the residuals are correlated.

The least squares method, however, cannot be extended directly to censored panel data where the dependent variable is restricted in some sense. Generally, the least squares method applied to Tobit-type censored regression models leads to biased estimates; thus we have to use other methods such as the maximum likelihood method.

The Tobit model can be easily extended to panel data under the fixed-effects specification. Heckman and MaCurdy (1980) suggest an iterative maximum likelihood estimation method for the fixed-effects model considering panel data with short time span. Their method can be understood as a two-step procedure. The fixed-effects a_i's which may be different across cross-section units are estimated given values for β and σ^2. The parameters β and σ^2 which are common for all observations are estimated given estimated value for a_i's. These two steps are iterated until the estimates for both the parameters and the fixed effects converge.

When we treat random effects, however, it is not as simple as the fixed-effects model to estimate parameters β and σ^2 since the covariances of the error terms between different time periods of each individual are not zeroes under the conventional assumptions on the error term and individual specific terms. The random-effects Tobit model can be written as follows:

$$
\begin{aligned}
(4)\ y^*_{it} &= X_{it}\beta + u_{it} && \text{where } u_{it} = a_i + \varepsilon_{it},\\
y_{it} &= y^*_{it} && \text{if } y^*_{it} \geq 0,\\
&= 0 && \text{otherwise.}
\end{aligned}
$$

The conventional assumptions on a_i and ε_{it} lead to the error covariance structure (3). That is, all the off-diagonal terms of the error covariance matrix are not zeroes because the off-diagonal elements of submatrices which represent serial correlations between cross-sectional units are not zeroes. The problem with serial correlation between time-periods is more serious than that of the dependence between cross sections. Therefore, we need alternative stochastic assumptions on error covariance structure to facilitate the estimation of the random-effects model. Given the appropriate specification of the random effects, a convenient alternative which obviates the above problem is to assume the off-diagonal elements of error covariance matrix to be zeroes and to accommodate the dependence between cross-sections into the diagonal elements of error covariance matrix.

In the panel study where stochastic error term is determined by both cross-sectional unit and time period and both the cross-sectional difference and time-specific difference are in interest, it would be reasonable to consider cross-sectional and time periodic characteristics to specify the stochastic assumptions. Therefore, a combination of two disturbance parameters is used to specify the error covariance structure of the model: σ_i^2, which represents the distribution of errors over the sample periods for each cross section, and θ_t^2 which represents the distribution of errors over the cross sections in each period. Among various possible combinations of σ_i^2 and θ_t^2, the geometric mean as the following is selected for the HAT model.

$$(5)\ u_{it} \sim IN(0, \sqrt{\sigma_i^2 \theta_t^2}),$$

The error covariance structure shows a kind of heteroscedasticity where all the off-diagonal elements are zeroes but the diagonal elements would be different for each individual and period.

The log-likelihood function of the HAT model where the error covariance structure is assumed to have a special type of heteroscedasticity as in (5) is as follows:

$$(6)\ lnL = \sum_i \sum_t (1-d_{it})(1-\Phi_{it}) + \sum_i \sum_t d_{it}[-\frac{1}{2} ln\sigma_i\theta_t) - \frac{1}{2\sigma_i\theta_t}(y_{it} - X_{it}\beta)^2]$$

where Φ_{it} is the standard normal distribution function for $\frac{X_{it}\beta}{\sigma_i\theta_t}$,

and $d_{it} = 1$ if $y^*_{it} \geq 0$,
$= 0$ otherwise.

The roundabout assumption such that the increasing rate of the number of parameters to be estimated is of a smaller order than that of sample size can be suggested to insure the consistency of the estimation. However, the consistency cannot be guaranteed in practical estimation with a relatively larger number of parameters to be estimated. Some parameters which are confined to a small number of observations may not be estimated consistently, and even the estimation of the system parameters is going to be troublesome.

An alternative is to use the concentrated likelihood estimation method to minimize the number of parameters to be estimated by iterative procedure. The concentrated maximum likelihood estimation method first estimates a subset of the parameters. Then it maximizes the remaining parameters after substituting the value of pre-estimated parameters. In this study, the estimated values for the variance parameters are substituted into the likelihood function then β is estimated. The formula should be calculated from the first order conditions of the log-likelihood function (6). However, the formula cannot be obtained because of the complexity of the equation. Instead of the unknown real formula, the formula which can be obtained from the first order conditions for the maximum of the log-likelihood function of the standard Tobit model is used (see Maddala, 1983, p.153).

$$(7)\ \sigma^2 = \frac{1}{N_1}\sum_1 (y_i - X_i\beta)y_i,$$

where $\sum_1$ is summing over the observations with $y_i > 0$ and N_1 is the number of the observations with non-zero dependent variable. This formula can be used as an approximation for the variances characterizing the error distributions of the time series for each cross section and for the variance representing the error distribution of the cross-sectional units given certain period. That is, the error variance of the time series for cross section i, denoted by σ_i^2, and the error variance of the cross-sectional units for the period t, denoted by θ_t^2, can be estimated as

$$(8a)\ \sigma_i^2 = \frac{1}{T_1}\sum_1 (y_{it} - X_{it}\beta)y_{it} \qquad i = 1, \ldots, N,$$

$$(8b)\ \theta_t^2 = \frac{1}{N_1}\sum_1 (y_{it} - X_{it}\beta)y_{it} \qquad t = 1, \ldots, T.$$

These estimated variances which are the functions of β are substituted into the log-likelihood function (6) to construct the concentrated log-likelihood function which is the function of β only.

$$(9)\ lnL(\beta) = lnL(\beta, \sigma_1^2(\beta), \ldots, \sigma_N^2(\beta), \theta_1^2(\beta), \ldots, \theta_T^2(\beta))$$

In maximizing the concentrated log-likelihood function, the dimension of gradient vector is reduced to k by 1 from $(k+N+T)$ by 1 of the case maximizing the standard log-likelihood function, and the dimension of Hessian matrix is k by k instead of $(k+N+T)$ by $(k+N+T)$. The advantages of using the concentrated maximum likelihood method are as follows: First of all, we can save computing time since the calculation of inverse is more simple. And, what is more critical is that the standard maximum likelihood method may not reach the maximum if there are too many variance parameters to be estimated. The log-likelihood function and the normal equations are very sensitive to the values of variance parameters, thus sometimes the convergence is not possible.

III. SPECIFICATION TEST OF THE HAT MODEL

Conventional stochastic assumptions on the individual specific term and error term lead to $E(u_{it}, u_{is}) \neq 0$ for $t \neq s$ as shown in the equation (3), and it has made estimation of censored panel data intractable and presents difficulty when model specification is dynamic. The problem is critical since presumably one of the attractions of pooling models over simple cross-section models is that they facilitate the incorporation of some form of dynamic behavior into the model. Therefore, the assumption of zero error covariance between observations of different time periods for each individual is very critical and should be tested.

The test statistic for the hypothesis of $E(u_{it}, u_{is}) = 0$, $t \neq s$ is derived from the formula for the truncated normal distribution. The mean of the truncated normal distribution can be expressed as the conditional mean of non-zero observations which is given by

$$(10)\quad E_c(u_{it}) = E(u_{it} | u_{it} > -X\beta) = \frac{\phi\left[\dfrac{-X_{it}\beta}{\sigma_{it}}\right]}{1-\Phi\left[\dfrac{-X_{it}\beta}{\sigma_{it}}\right]} \equiv M_{it}$$

Under the null hypothesis, a consistent estimator of u_{it} conditional on $u_{it} > -X_{it}\beta$ is obtained from

$$(11)\quad \hat{u}_{it} = Y_{it} - X\hat{\beta}_{it},$$

where $\hat{\beta}$ is the maximum likelihood estimator of β. Then a consistent estimator of $\mathrm{Cov}(u_{it}, u_{is})$ is obtained as

$$(12)\ \hat{C}_{its} = (u_{it} - M_{it})(u_{is} - M_{is}).$$

We can derive the asymptotic variance of $\hat{C}_{its}$ as the following:

$$(13)\ V(\hat{C}_{its}) = \mathrm{E}_c[(u_{it} - M_{it})(u_{is} - M_{is}) - \mathrm{E}_c\{(u_{it} - M_{it})(u_{is} - M_{is})\}]^2.$$

We can show that $\mathrm{E}_c[(u_{it} - M_{it})(u_{is} - M_{is})] = 0$ using the independence condition implicit in the null hypothesis. The fact that u_{it} and u_{is} are independent implies that

$$\begin{aligned}(14)\ \mathrm{E}_c(u_{it}u_{is}) &= \mathrm{E}_c(u_{it})\mathrm{E}_c(u_{is}) \\ &= \frac{\phi_{it}}{1-\Phi_{it}}\frac{\phi_{is}}{1-\Phi_{is}} \\ &= M_{it}M_{is}.\end{aligned}$$

Therefore, we have the following result:

$$\begin{aligned}(15)\ &\mathrm{E}_c[(u_{it} - M_{it})(u_{is} - M_{is})] \\ &= \mathrm{E}_c[u_{it}u_{is} - M_{it}u_{is} - M_{is}u_{it} + M_{it}M_{is}] \\ &= \mathrm{E}_c(u_{it}u_{is}) - M_{it}\mathrm{E}_c(u_{is}) - M_{is}\mathrm{E}_c(u_{it}) + M_{it}M_{is} \\ &= 2M_{it}M_{is} - M_{it}M_{is} - M_{is}M_{it} \\ &= 0.\end{aligned}$$

Hence, we get the result:

$$\begin{aligned}(16)\ V_c(\hat{C}_{its}) &= \mathrm{E}_c[(u_{it} - M_{it})(u_{is} - M_{is})]^2 \\ &= \mathrm{E}_c[(u_{it} - M_{it})^2]\mathrm{E}_c[(u_{is} - M_{is})^2] \\ &= V_c(u_{it})V_c(u_{is}).\end{aligned}$$

Since $V_c(u_{it}) = 1 - M_{it}(M_{it} + \frac{X_{it}\beta}{\sigma_{it}})$, the estimate will be

$$(17)\ \hat{V}_{its} = [1 - M_{it}(M_{it} + \frac{X_{it}\hat{\beta}}{\sigma_{it}})][1 - M_{is}(M_{is} + \frac{X_{is}\hat{\beta}}{\sigma_{is}})]$$

Now, we have the statistic which is asymptotically distributed N(0,1) :

$$(18)\ \Psi_i = \frac{1}{k_i}\Sigma[\hat{C}_{its}/\sqrt{\hat{V}_{its}}],$$

where the summation will be over all available covariance terms for the set of non-limit observations and k_i represents the number of covariance terms. The test statistic for testing the hypothesis of $E(u_{it}u_{is})=0$ for $t \neq s$ is obtained from summing the squares of standard normal statistics of the formula (18).

$$(19)\quad \sum_{i=1}^{N} \Psi_i^2 \sim \chi^2(N^*),$$

where the degree of freedom N^* represents the number of cross sections on which Ψ_i is defined.

Another test which can be used as a specification test is the parameter stability test like the Chow test. The Chow test has some power against a wide range of possible alternatives. Thus, it may provide a convenient specification test. Anderson (1987) developed the χ^2-statistic for the predictive power test of limited dependent variable models. The test compares the maximized value of the log-likelihood functions from two data sets; one is the subdata set excluding the samples which are reserved for the prediction, and the other is the data set with the whole samples. Usually, prediction tests are considered in the context of time-series models rather than cross-sectional studies because of the nature of the data. Limited dependent variable models are more frequently cross-sectional in nature, and a kind of prediction test seems inappropriate with limited dependent variable models. However, the structural change may not only be a function of passing time, and the prediction tests for cross-section models are demonstrated to have powers by Anderson.

The parameter stability test is an analogue of the Chow test which concerns only the maximum values of the log-likelihood functions over two sample periods; one is the full sample and the other is a subsample. While the statistic can be applied simply to Logit and Probit models, it is not so straightforward to apply it to Tobit model and the following approximation has been suggested.

$$(20)\quad 2\left[\frac{n_1+n_2}{n_1} lnL_{N_1T} - \frac{n_1+n_2}{2} ln\left(\frac{n_1}{n_1+n_2}\right) - lnL_{NT}\right],$$

where N_1 denotes the number of individuals in the first sub-sample, n_1 and n_2 are the numbers of non-zero observations in the observations 1 to N_1T and N_1T+1 to NT respectively, and L denotes the value of the log-likelihood function evaluated over the two samples. The statistic is asymptotically distributed as χ^2 with $NT-N_1T$ degree of freedom. This prediction test can be used for testing parameter stability, and a model which is correctly specified will show the stability when we compare the estimated parameters of the sub-sample and the full sample with those from misspecified models.

Therefore, the test may be used to evaluate the different model specifications such as fixed-effects specification versus random-effects specification or homoscedasticity versus heteroscedasticity.

IV. EMPIRICAL STUDY WITH COMPUSTAT DATA

The HAT model suggested in section II is applied to the panel data samples which are extracted from the COMPUSTAT tape. Only the manufacturing industry is selected, and the data set is divided into 10 industry groups. The structure of the data set is reported in Table 1 of Appendix. A dividend model which follows the framework of Lintner model is used to examine the practical validity of the HAT model for estimating censored panel data with random-effects specification.

Estimating dividend behavior model, we confront the censoring problem since some firms pay dividends and others do not.

The Tobit-type model for dividend behavior is written as follows:

$$(21)\quad \begin{aligned} D_{it} &= \alpha_i + X_{it}\beta + u_{it} && \text{if RHS} > 0, \\ &= 0 && \text{otherwise.} \end{aligned}$$

Dependent variable D_{it} is the dividend payment of firm i during the period t, X_{it} is the independent variable vector which is used to explain dividend payout behavior, α_i represents the firm specific effect, and u_{it} is conventional stochastic error term.

The HAT model is applied to the dividend model above, and the results of estimation and specification tests are compared to the results from the standard Tobit model in which all the stochastic error terms are independently and identically distributed.

The concentrated maximum likelihood method is used to estimate the HAT model, and for the estimation of the standard Tobit model, both of the maximum likelihood method and the concentrated maximum likelihood method are applied to check the differences due to estimation methods.

The practical estimation procedure of the HAT model is as follows: The OLS estimates, using observations with positive dividend payout, are used as the initial values for $\hat{\beta}$. The estimates of disturbance parameters, $\hat{\sigma}_i^2$ and $\hat{\theta}_t^2$ are obtained using the formula (8a) and (8b), then substituted into the concentrated log-likelihood function. New parameter values are obtained from the gradient vector and gradient matrix of the concentrated log-likelihood function using the BHHH algorithm. This procedure is iterated until all the parameters converge.

The resulting parameter estimates cannot be said to be consistent because the number of time-series observations for each firm is fixed with $T=12$. The inconsistency problem is very similar to the fixed effects problem of Heckman and MaCurdy's study. The estimates for σ_i^2 's are generally inconsistent since they are estimated using small numbers of observations, and that causes the incidental parameters problem such that the inconsistency carries through the other parameter estimates. However, following Heckman and MaCurdy, the fixed effects problem is not so severe to affect the other structural parameter estimates seriously. In this study, moreover, the estimates for disturbance parameters are obtained approximately to facilitate the estimation. That is, the inconsistency of the parameter estimates would be the cost to solve the estimation problem. Therefore, the incidental parameters problem is not concerned seriously in this study.

For the evaluation of the suggested specification, two test statistics (19) and (20), which are derived and suggested in section III, are obtained from the results of regression. The χ^2 -statistics reported in Table 2 are the test to examine the validity of the assumption that all the off-diagonal elements of the error covariance matrix are zeroes. Since both specifications assume zero error covariances, the test of zero error covariance can be a criterion for evaluating the error covariance specifications. The results from the test of the hypothesis that $\mathrm{Cov}(u_{it}, u_{is})=0$ for $t \neq s$ are as follows: With the specification of the standard Tobit model, the tests for 7 industries reject the null hypothesis, while the null hypothesis is rejected in only one industry with the HAT model. The test results imply that the error covariance specification of the HAT model is more appropriate to accommodate the assumption of zero off-diagonal elements in the error covariance matrix.

Another test, supplementary to the main test above is the parameter stability test. Since all the degrees of freedom for the test in this study are greater than 100, the standardized normal statistics are calculated and reported. The smaller value of the statistic indicates that the parameter estimates are more stable, thus the model with small value of statistic can be considered to be better specified than the other models which produce greater values of the stability test statistic.

The parameter stability test results show that the HAT model is relatively more stable: The null hypothesis of stable parameters cannot be rejected for 4 industries, while the null hypothesis cannot be rejected for only 2 industries with the standard Tobit model. It is hard to say that the parameter estimates of the HAT model are more stable than those of the standard Tobit model. However, the statistics from the standard Tobit model are smaller than those from the standard Tobit model in most industries regardless of the test results; rejecting or accepting the null hypothesis. Therefore, it may be said that the HAT model is parametrically more stable than the standard Tobit model. We can use the results to support the argument that the HAT model which utilizes the random-effects specification is a fairly good specification in spite of the artificial assumptions on its error covariance structure.

From the specification tests, we can draw an implicit conclusion that the HAT model, which assumes the heteroscedastic error covariance structure of (5), would be a practically acceptable estimation method of censored panel data with random-effects specification.

V. CONCLUDING REMARKS

When we estimate censored panel data where some values of dependent variable are limited, we are confronted with critical problems stemming from the error covariance structure. The least squares method cannot be used since the resulting estimators are not unbiased anymore, and the maximum likelihood method should be used.

Two common statistical model specifications for pooled regression models are fixed-effects model and random-effects model. Tobit model which utilizes censored data can be directly extended to censored panel data under fixed- effects specification. However, more general assumption of random-effects model leads to the complicated error covariance structure in which all the off-diagonal terms are not zeroes and may be different respectively, and the conventional maximum likelihood method is not applicable.

The HAT model suggested in this paper is an attempt to circumvent the estimation problem holding the random-effects assumption on individual specific terms. The error covariance structure of the HAT model assumes a special type of heteroscedasticity which accommodates the random nature of individual specific terms into the diagonal elements of the error covariance matrix.

χ^2-statistic to test the hypothesis that the off-diagonal elements of the error covariance matrix are zeroes is derived, and it is used for the model specification test.

From the results of estimations and tests using the data from the Industrial Compustat Tape, we can conclude that the HAT model is an acceptable model specification for estimating censored panel data with random-effects specification.

APPENDIX

[Table 1] Structure of the Data Set

Data Set	DNUM	firms	obs	% of zero observations	Industry
1	2000-2099	47	517	14.31	Food and kindred product
2	2200-2300	47	517	40.81	Textile mill product and Aparel industry
3	2600-2771	57	627	11.64	Paper and allied product, Printing and publishing
4	2800-2890	81	891	6.85	Chemical and allied product
5	2911-3079	63	693	18.76	Petroleum, Rubber, Plastic
6	3310-3499	80	880	18.98	Metal product
7	3510-3590	77	847	20.43	Machinery
8	3600-3679	107	1177	31.76	Electrical machinery
9	3680-3699	37	407	58.23	Computing machinery
10	3711-3790	53	583	22.30	Motor vehicle, Aircraft and Transportation equipment

Note: DNUM is the firm classification number in the Industrial Compustat tape.

[Table 2] Results of Specification Analyses

Data Set	Standard Tobit				HAT Model			
	-log$L$	R^2	Stab	χ^2	-log$L$	R^2	Stab	χ^2
1	143	.96	−1.2	113.8	79	.91	.2	6.0
2	9	.96	−1.3	135.5	16	.96	−1.2	31.2
3	24	.97	4.4	237.3	14	.92	3.4	86.7
4	145	.96	9.7	127.8	26	.94	4.5	11.3
5	198	.96	5.7	69.1	64	.94	−3.1	49.5
6	236	.94	6.3	74.4	53	.90	9.4	13.9
7	127	.96	−8.4	190.3	11	.92	3.1	25.6
8	64	.96	−2.8	416.9	37	.96	−2.2	9.2
9	238	.91	−2.8	69.0	129	.97	−1.9	19.7
10	295	.93	2.6	165.6	144	.92	−1.0	21.6

Notes: a) The stability test statistics are standardized normal.
b) The degrees of freedom of χ^2-statistics for the data sets are as follows: 1(43), 2(55), 3(55), 4(78), 5(54), 6(72), 7(69), 8(85),9(17), 10(47).

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