

Estimation of the Labor Participation and Wage Equation Model of Japanese Married Women by the Simultaneous Maximum Likelihood Method

K. Nawata^a and M. Ii^b

^aGraduate School of Engineering, University of Tokyo, 7-3-1 Bunkyo-ku, Tokyo 113-8656, [Japan](#)

^bFaculty of Economics, Yokohama National University, Hodogaka-ku, Yokohama 240-8501, [Japan](#)

Abstract: Econometric models consisting of female labor participation and wage equations have been widely used. Since wages of women are not observed unless they are working, problems of sample selection biases must be considered in estimations of the model. However, conventional estimation methods have not been sufficiently examined and therefore may result in misleading policy implications.

In this paper, the Japanese married female labor participation and wage equations are estimated by the conventional methods and by a newly proposed simultaneous maximum likelihood method using the “Panel Survey of Consumption and Lifestyle” by the Institute for Research on Household Economics. This paper is the first attempt to estimate the model as a system using a fully efficient maximum likelihood estimator.

Keywords: female labor participation, wage equation, Japanese female, Heckman’s two-step estimator, simultaneous maximum likelihood estimator

1. INTRODUCTION

The model consisting of female labor participation and wage equations has been widely used in labor economics as early as Gronau (1974) and Heckman (1974). Recently, the effects of wage levels on the work behavior of married Japanese women have been analyzed by various authors using individual survey data. Nagase (1997) has analyzed how women select a form of work from various choices, e.g., full-time, part-time, family business, piecework at home, and full-time housewife. Nakamura and Ueda (1999) have analyzed the factors which affect whether or not women with infants continue to work.

However, the estimation methods used in such models have not been sufficiently examined in previous studies. Heckman’s two-step estimator is typically used for the wage equation estimation. Although Heckman’s two-step estimator is a consistent estimator, it is not asymptotically efficient and it sometimes performs poorly (Nawata (1993, 1994), Nawata and Nagase (1996)). In addition, the decision among women about whether or not to work depends on their wage levels; however, wage levels are not observable unless the women are working. Although it appears reasonable to use predicted values of wages for non-working women, models using predicted wages in the labor participation equation give inconsistent estimators. Thus, the estimated results of such models may

produce misleading policy implications.

In this paper, we consider the simultaneous estimation of the wage and labor participation equations using maximum likelihood methods. The obtained simultaneous maximum likelihood estimator (MLE) is not only consistent but also asymptotically efficient and it outperforms the conventional estimators. By conventional and proposed methods, the wage and labor participation equations of Japanese married women were estimated using the data from the “Panel Survey of the Consumption and Lifestyle” by the Institute for Research on Household Economics.

2. MODEL

The model considered in this paper has been widely used by various authors. Allowing h_i to be the hours worked and w_i^* to be the reservation wage (the value of time at $h_i=0$), we suppose that w_i^* is given by the following:

$$w_i^* = x_{1i}'\alpha^* + u_i^*, \quad i = 1, 2, \dots, n, \quad (1)$$

where x_{1i} is a vector of explanatory variables which describe the woman’s characteristics and n is the number of observations. Let w_i be the woman’s (potential) market wage, w_i is not observed unless she is working, and works if and only if

$$w_i^* = x_{1i}'\alpha^* + u_i^* < w_i. \quad (2)$$

Dividing (2) by the standard deviation of u_i^* , we get the labor participation equation, given by

$$y_i = 1(y_i^* > 0), \quad (3)$$

$$y_i^* = x_{1i}'\alpha + \gamma w_i + u_i, \quad i = 1, 2, \dots, n,$$

where y_i is a dummy variable such that $y_i = 1$ if the i -th woman works and 0 otherwise. $1(\cdot)$ is the indicator function such that $1(\cdot) = 1$ if \cdot is true; and otherwise 0 is used.

Suppose that the wage equation is given by

$$w_i = x_{2i}'\beta + v_i \quad (4)$$

where x_{2i} is another vector of explanatory variables. x_{1i} and x_{2i} may contain different variables. $\{x_{1i}, x_{2i}\}$ are i.i.d. random variables and satisfy the standard assumptions. u_i and v_i are independent and follow normal distributions with means of 0, and with variances 1 and σ_v^2 , respectively. Equations (3) and (4) are the structural forms of the labor participation and wage equations.

Substituting (4) into (3), we obtain

$$y_i = 1(y_i^* > 0), \quad (5)$$

$$y_i^* = x_{1i}'\alpha + \gamma(x_{2i}'\beta) + u_i + \gamma v_i$$

$$= x_{1i}'\alpha + \gamma(x_{2i}'\beta) + \varepsilon_i,$$

where $\varepsilon_i = u_i + \gamma v_i$. Let x_i be the vector of all explanatory variables contained in x_{1i} and x_{2i} . The second equation of (4) is rewritten in the reduced form given by

$$y_i^* = x_i'\delta + \varepsilon_i. \quad (6)$$

3. ESTIMATION OF THE MODEL

Since the wage w_i is not observable unless the i -th woman is working, we must consider effects of sample selection biases when estimating the model given in Section 2. In the present section, we describe both conventional estimators and the simultaneous MLE, which is newly considered in this paper.

3.1 CONVENTIONAL ESTIMATORS

a) Wage Equation

The wage equation is estimated by either Heckman's (1976, 1979) two-step estimator or by the Type II Tobit MLE combining (4) with (6). Although these estimators are consistent, they are not asymptotically efficient estimators.

b) Labor Participation Equation

Let \hat{w}_i be the fitted value of w_i . Since w_i is not observable if $y_i = 0$, it appears reasonable to use \hat{w}_i when $y_i = 0$ and to estimate the model by the probit

MLE. (Ohkusa (1997) used this method.) However, this estimator cannot be consistent. When \hat{w}_i is substituted into w_i for $y_i = 0$, the following problems are encountered:

- the error terms of the equation do not become i.i.d. normal variables, and
- $w_i = y_i w_i + (1 - y_i) \hat{w}_i$ becomes an explanatory variable, and it is related to the error term.

If x_{2i} contains at least one variable which is not included in x_{1i} , the probit MLE using $\hat{w}_i = x_{2i}'\hat{\beta}$ for all observations yields a consistent estimator, as suggested by Blundell and Smith (1994). However, the problems the associated with this estimator are as follows: i) the estimator cannot be calculated if x_{1i} contains all variables belonging to x_{2i} , and ii) the estimator is not asymptotically efficient even if it can be calculated.

Moreover, since the error terms are not i.i.d. normal, the standard errors of the probit MLE cannot be calculated by the standard methods using the Fisher information and Hessian matrices. In this paper, the asymptotic variance-covariance matrix is calculated by the following equations:

$$V = A^{-1}BA^{-1}, \quad (7)$$

$$A = \frac{\partial^2 \log L_2}{\partial \theta^2}, B = \sum \frac{\partial \log g_i}{\partial \theta} \frac{\partial \log g_i}{\partial \theta'}$$

$$g_i(\theta) = y_i \log \Phi(z_i^* \theta) + (1 - y_i) \log \{1 - \Phi(z_i^* \theta)\},$$

$$\log L_2 = \sum g_i(\theta), \text{ and}$$

$$z_i^* = (x_{1i}, \hat{w}_i).$$

3.2 SIMULTANEOUS MLE

a) Likelihood Function

It is possible to consider the MLE in order to estimate the two equations simultaneously. Let $\theta' = (\alpha', \beta', \gamma, \sigma_v^2)$, and Φ and ϕ be the distribution and density functions of the standard normal distribution. Since $V(\varepsilon_i) = 1 + \gamma^2 \sigma_v^2$, and $Cov(v_i, \varepsilon_i) = \gamma \sigma_v^2$, we obtain the likelihood function, given by

$$L(\theta) = \prod_{y_i=1} \left[\Phi(x_{1i}'\alpha + \gamma w_i) \frac{1}{\sigma_v} \phi\left(\frac{w_i - x_{2i}'\beta}{\sigma_v}\right) \right] \quad (8)$$

$$\times \prod_{y_i=0} \left[1 - \Phi\left\{ \frac{x_{1i}'\alpha + \gamma(x_{2i}'\beta)}{\sqrt{1 + \gamma^2 \sigma_v^2}} \right\} \right],$$

by modifications of the standard Type II Tobit model (for details, see Amemiya (1985, 385-387)). It is now easy to show that the simultaneous MLE $\hat{\theta}$,

which maximizes (8), is consistent and asymptotically normal by the standard arguments of the MLE.

b) Algorithm

Since the likelihood function is not a concave function of γ and σ_v , the standard algorithms may not converge to the maximum value. The following method, a modification of the scanning procedure suggested by Nawata (1994, 1995) and Nawata and Nagase (1996), is used to calculate the simultaneous MLE.

- Choose γ from $[-2\eta, 2\eta]$ with an interval of 0.1η , where η is the sample standard deviation of w_i .
- Let $\gamma = 0$ and calculate $\hat{\alpha}_0, \hat{\beta}_0$ and $\hat{\sigma}_{v_0}$, which maximize the conditional maximum likelihood function. Note that $\hat{\alpha}_0$ is the probit MLE of $y_i = 1(y_i^* > 0), y_i^* = x_{1i}'\alpha + u_i$, and $\hat{\beta}_0$ and $\hat{\sigma}_{v_0}$ are the OLS estimators of (2.4) using $y_i = 1$ observations.
- Let $\hat{\alpha}_j, \hat{\beta}_j$ and $\hat{\sigma}_{v_j}$ be the j-th estimators. Increase γ by 0.1η , and choose the initial values of the iteration as $\hat{\alpha}_j, \hat{\beta}_j$ and $\hat{\sigma}_{v_j}$. Then calculate the (j+1)-th estimator by the Newton-Raphson method. Since the likelihood is a continuous function of γ , the previous estimators are in the neighborhood of the maximum value.
- Continue (iii) and calculate estimators up to 2η , the largest value of γ , as determined in (i).
- In the same manner, calculate the estimators from 0 to -2η , the smallest value of γ .
- Choose $\hat{\gamma}_1$, which maximizes the conditional likelihood function.
- Choose 20 points in the neighborhood of $\hat{\gamma}_1$ with an interval of 0.01η and choose $\hat{\gamma}_2$, which maximizes the conditional likelihood function.
- Determine the final estimators, $\hat{\alpha}, \hat{\beta}, \hat{\sigma}_v$ and $\hat{\gamma}$. Note that since the values determined in the previous step are sufficiently close to the maximum value, $\hat{\alpha}, \hat{\beta}, \hat{\sigma}_v$ and $\hat{\gamma}$ can be calculated by the Newton-Raphson method using the values determined in the previous step as the initial values of the iteration.

4. EMPIRICAL MODEL AND DATA

The data set used in this paper is the “1993 Panel Survey of Consumption and Lifestyle” by the Institute for Research on Household Economics.

The survey was completed by 1,500 women (age: 24-35) in 1993. The number of married women was 1,002. After excluding the observations with missing information, the surveys of 818 married women were used in this study. Among these 818 women, 287 (34.9%) were working and 551 (65.1%) were not working.

As regards the labor participation equation, the explanatory variables were as follows:

WAGE : Hourly Wage (yen),

J_COLLEGE: 1: Graduated Junior College or Job Training School; 0: Otherwise,

COLLEGE: 1: Graduated COLLEGE; 0: Otherwise,

AGE: Age,

H_INCOME: Income of the Husband (1000yen),

N_CHILD: Number of Children,

CHILD0: 1: Existing Children at Age 0; 0: otherwise

CHILDI_3: 1: Existing Children at Age 1-3;

0: otherwise,

CHILDA_6: 1: Existing Children at Age 1-3;

0: otherwise,

L_W_PARENT: 1: Living with Parents (Including

Husband’s Parents); 0: Otherwise,

P_NEIGHBOR: , 1: Parents are Living in

Neighborhood; 0: Otherwise,

MAJOR13: 1: Living in 13 Major Cities(Including

Tokyo 23 Districts); 0: Otherwise,

O_CITY: 1: Living Other Cities; 0: Otherwise, and

NURSERY : 1: Existing Day Nurseries,

0: Otherwise.

The labor participation equation (3) is given by

$$y^* = \alpha_1 + \alpha_2 J_COLLEGE + \alpha_3 COLLEGE \quad (9)$$

$$+ \alpha_4 AGE + \alpha_5 H_INCOME + \alpha_6 N_CHILD$$

$$+ \alpha_7 CHILD0 + \alpha_8 CHILDI_3 + \alpha_9 CHILDA_6$$

$$+ \alpha_{10} L_W_PARENT + \alpha_{11} P_NEIGHBOR$$

$$+ \alpha_{12} O_CITY + \alpha_{13} NURSERY + \gamma \log(WAGE)$$

Using this equation, the incentive to work becomes weaker as the husband’s income increases. Thus, the expected sign of *H_INCOME* is negative. Since the presence of preschool children and children at age 0 increases the amount of household tasks, the expected signs of these variables (*CHILD0*, *CHILDI_3*, and *CHILDA_6*) are negative. If the parents are living together or are living in the same neighborhood, the value of the woman’s reservation wage diminishes, since support for household tasks from parents is expected. Hence, the expected signs of *L_W_PARENT* and *P_NEIGHBOR* are positive.

On the other hand, as regards the wage equation, the following explanatory variables were used in addition to *J_COLLEGE*, *COLLEGE*, *AGE*, *MAJOR13*, and *O_CITY*.

EXPERIENCE: Years of Job Experience

L_FIRM: 1: Firms more than 1,000 Employees or

Governments; 0: Otherwise,
Q_MEDICAL: 1: Possessing Medical
 Qualifications; 0: Otherwise,
Q_EDUCATION: 1: Possessing Teaching
 Qualifications; 0: Otherwise,
Q_OTHER: 1: Possessing Other Qualifications; 0:
 Otherwise,
MANUFACTURE: 1: Manufacturing; 0: Otherwise,
SALE: 1: Retail and Wholesale; 0: Otherwise, and
FINANCE: 1: Finance, Insurance, Real Estate and
 Public Utility; 0: Otherwise.

The wage equation (4) is given by

$$\begin{aligned} \log(WAGE) = & \beta_1 + \beta_2 J_COLLEGE \quad (10) \\ & + \beta_3 COLLEGE + \beta_4 AGE + \beta_5 EXPERIENCE \\ & + \beta_6 MAJOR13 + \beta_7 O_CITY + \beta_8 L_FIRM \\ & + \beta_{11} Q_OTHER + \beta_{12} MANUFACTURE + \beta_{13} SALE \\ & + \beta_{14} FINANCE . \end{aligned}$$

The variables of education, job experience, and qualifications represent the human capital. Considering differences in the regional labor demand-supply conditions, the residential area variables were used. Since the size of the firm and types of industry are considered to be important determinants of wage in Japan, these dummy variables were used in the model.

5. RESULTS OF THE ESTIMATION

Table 1 gives the results of labor participation equation by i) the simultaneous MLE based on (8), ii) the consistent probit MLE, and iii) the Type II Tobit MLE (reduced form) based on (4) and (6). In the estimates of the labor participation equation by the simultaneous MLE, one of the most notable findings was that the probability of work decreased as the educational level increased. As pointed out by Higuchi (1991), Japanese women who only graduated from high schools or junior high schools were more likely to start working again in their thirties and forties after they had once left the labor market. On the other hand, Japanese women with higher educational backgrounds trended to remain working at one firm. However, once they left the labor market, they often did not return to the labor market. A higher spousal income and the presence of babies at age 0 reduced the probability of work, as expected. However, variables such as living with parents and the existence of day nurseries did not affect the probability of work. The t-value of $\log(WAGE)$ was quite large (5.861), suggesting that higher wages increased the probability of work.

In the estimates of the probit MLE, the predicted values of $\log(WAGE)$, \hat{w} , were calculated by Heckman's two-step estimator using variables observed for all 818 women. When the results of the probit MLE were compared with those of the

simultaneous MLE, the coefficient of the predicted wage \hat{w} was too high (17.78). Note that the standard errors calculated by the standard Hessian matrix (output of the computer software package programs) were much smaller than those calculated by (3.1), and they might therefore give incorrect implications.

Table 2 shows the results of the wage equation by i) the simultaneous MLE, ii) Heckman's two-step estimator, and iii) the Type II Tobit MLE. In the estimates of the wage equation by the simultaneous MLE, the effects of education and years of job experience were quite large. In particular, the coefficient of years of job experience was considerably higher than those observed in previous studies. The coefficient of age was negative, and wages declined as women aged. The wages of women with medical qualifications (e.g. medical doctor, pharmacist, nurse) were significantly higher than those of women without such qualifications. However, teaching qualifications such as teacher's certificates did not increase wages. The wages of manufacturing, retail and wholesale, finance, insurance, real estate and public utility industries were significantly higher than those in the service and other industries.

When the results of Heckman's two-step estimator were compared with those of the simultaneous MLE, the estimates revealed the similar tendencies, except regarding the years of job experience and type of industry (i.e., the dummy variables of manufacturing industry and retail and wholesale industry). The coefficients of the years of job experience were 0.121 and 0.042, which implies that the estimate of the simultaneous MLE is about three times as large as that of Heckman's two-step estimator. The signs of the coefficients were opposed as regards for the types of industries. The absolute values of the t-values of the simultaneous MLE were generally larger than those obtained by Heckman's two-step estimator. The reason for this finding is that the simultaneous MLE is asymptotically efficient, suggesting usefulness of the simultaneous MLE.

For the estimation of the Type II Tobit MLE, the TSP 4.5 was used. Unlike other software package programs, TSP 4.5 employs the method suggested by Nawata (1994,1995), this package can obtain the global maximum of the likelihood function, in which (6) is the reduced form. A disadvantage of Type II Tobit MLE is that the effects of wage on work cannot be directly observed. The present results were similar to those of Heckman's two-step estimator as regards the wage equation. When the results were compared with those of the simultaneous MLE, the relationships described above could be observed. Regarding the labor participation equation, the results were not directly comparable with those of the simultaneous MLE and the probit MLE because the Type II Tobit MLE represents a reduced form. However, when the common variables of the two equations were compared, we obtained the following results.

- Although education did not affect the probability of work in the Type II MLE, education did reduce the probability of work in the simultaneous MLE and the probit MLE.
- In the simultaneous MLE and the Type II MLE, the probability of work decreased as the husband's income increased. However, such a tendency could not be demonstrated by the probit MLE.
- In the Type II MLE, living with parents increased the probability of work. However, this tendency was not observed by either the simultaneous MLE or the probit MLE.
- In the Type II MLE, the existence of babies at age 0 and children aged 1-3 both had a negative effect on the decisions to work among these women. However, the existence of children aged 1-3 did not affect the probability of work in the simultaneous MLE and the probit MLE.

6. CONCLUSION

Analyses of the working behavior of women are potentially very influential in terms of future social security systems, and in particular pensions. However, conventional estimators, such as Heckman's two-step estimator and the probit MLE, sometimes perform poorly. In this paper, we evaluated the labor participation and wage equation model of the Japanese married women, using both the conventional estimator and the simultaneous MLE.

As regards the labor participation equation, the estimated coefficient of wage by the simultaneous MLE decreased to less than that of the probit MLE. The standard error of the simultaneous MLE was significantly smaller than that of the probit MLE. It is possible that the simultaneous MLE more accurately evaluates the effect of wage on the probability of work. As regards the wage equation, the effect of the years of job experience was greater than that obtained by the conventional estimators. Moreover, the standard errors of the simultaneous MLE were smaller because it is an asymptotically efficient estimator. Therefore, the comparative advantage of the simultaneous MLE was demonstrated in this paper.

In the present study, we did not distinguish between types of work, such as full-time, part-time, piecework, and family business. However, as pointed out by Nagase (1997), future studies to consider these various types of work will be needed.

REFERENCES

- Amemiya, T., 1985, *Advanced Econometrics*, Harvard University Press, Cambridge, Massachusetts.
- Blundell, R., and R. J. Smith, 1994, "Coherency and Estimation in Simultaneous Models with Censored or Qualitative Dependent Variables," *Journal of Econometrics*, 64, 355-373.
- Gronau, R., 1974, "Wage Comparisons - A

- Selectivity Bias," *Journal of Political Economy*, 82, 1119-1143.
- Heckman, J., 1974, "Shadow Prices, Market Wages, and Labor Supply," *Econometrica*, 42, 679-693.
- Heckman, J., 1976, "The Common Structure of Statistical Models for Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement* 5, 475-492.
- Heckman, J., 1979, "Sample Selection Bias as Specific Error," *Econometrica*, 47, 152-161.
- Nakamura, J. and A. Ueda, 1999, "On the Determinants of Career Interruption by Childbirth among Married Women in Japan," *Journal of the Japanese and International Economies*, Vol.13, No.1.
- Nawata, K., 1993, "A Note on Estimation of Models with Sample-Selection Biases," *Economic Letters*, 42, 15-24.
- Nawata, K., 1994, "Estimation of the Sample-Selection Models by the Maximum Likelihood Estimator and Heckman's Two-Step Estimator," *Economic Letters*, 45, 33-40.
- Nawata, K., 1995, "Estimation of Sample-Selection Models by the Maximum Likelihood Method," *Mathematics and Computers in Simulation*, 39, 299-303.
- Nawata, K., and N. Nagase, 1996, "Estimation of Sample Selection Models," *Econometric Reviews*, 15, 387-400.
- Nagase, N., 1997, "*Josei no Shūgyō Sentaku - Kateinai Seisan to Rōdō Kyōkyū* (Working Choices of Females - Domestic Production and Labor Supply)", in H. Chuuma and T. Suruga Eds., *Rōdō Kankō no Henka to Josei Rōdō* (Changes in Employment Practices and Female Labor), University of Tokyo Press, Tokyo. (In Japanese)
- Ohkusa, Y., 1997, "*Shin Gorudo Puran niyoru Rōdō Sōsetsu Kōka ni Kansuru Kenkyū* (An Empirical Analysis for the Effect of the "New Gold" plan on Labor Participation)", *Iryō to Keisai* (Journal of Health Care and Society), Vol. 7, No.2, 98-119. (In Japanese)

Table 1. Results of the Labor Participation Equation

Variable	Simultaneous MLE		Probit MLE		Type II Tobit MLE (Reduced Form)	
	Estimate	t-value	Estimate	t-value ²⁾	Estimate	t-value
Constant	-1.854	-0.758	4.119	0.255	-0.843	-1.554
J_COLLEGE	-0.316	-0.698	-3.181	-2.588	0.044	0.368
COLLEGE	-2.401	-2.672	-10.620	-1.683	0.121	0.590
AGE	0.282	0.622	0.220	0.293	0.053	2.747
H_INCOME	-0.0011	-1.767	-0.00056	-0.385	-0.0011	-3.989
N_CHILD	0.337	0.981	0.579	0.965	-0.034	-0.451
CHILD0	-1.705	-2.127	-2.335	-2.247	-1.366	-6.477
CHILD1_3	-0.690	-0.962	-1.725	-1.191	-0.838	-4.718
CHILD4_6	-0.962	-0.836	-0.436	-0.480	-0.031	-0.135
L_W_PARENT	0.229	0.506	-0.108	-0.294	0.463	4.082
P_NEIGHBOR	0.909	1.393	0.149	0.406	0.032	0.217
MAJOR13	-1.435	-2.177	-4.392	-2.234	-0.394	-2.566
O_CITY	-0.411	-0.761	-1.310	-1.858	-0.444	-3.523
NURSERY	0.187	0.434	0.072	-0.150	0.153	1.424
Q_MEDICAL					0.150	0.921
Q_EDUCATION					0.267	1.635
Q_OTHER					0.351	3.118
Log(WAGE) ¹⁾	6.975	5.861	17.780	1.754		
Number of Observations	818					

1) In the estimates of the probit MLE, the predicted values of $\log(\text{wage})$, \hat{w} , are calculated by Heckman's two-step estimator using variables observed for all 818 women.

2) t-values calculated by the standard Hessian matrix (outputs of TSP) are 2.904, -6.874, -8.238, 3.881, -0.948, 2.936, -3.799, -3.676, -0.683, -3.827, 0.393, -7.318, -3.769, -0.245, 9.937. These values are over-evaluated (standard errors are under-evaluated) by the results calculated from (3.1).

Table 2. Results of the Wage Equation

Variable	Simultaneous MLE		Heckman's Two-Step Estimator		Type II Tobit MLE	
	Estimate	t-value	Estimate	t-value	Estimate	t-value
Constant	0.378	1.603	0.010	0.038	0.010	0.040
J_COLLEGE	0.125	2.314	0.054	0.904	0.054	0.996
COLLEGE	0.557	6.221	0.416	2.942	0.091	4.600
AGE	-0.066	-7.735	-0.023	-2.584	-0.023	-2.638
EXPERIENCE	0.121	17.765	0.042	5.493	0.042	5.718
MAJOR13	0.217	3.232	0.227	3.231	0.227	3.277
O_CITY	0.037	0.694	0.045	0.911	0.045	0.849
Q_MEDICAL	0.161	2.428	0.238	3.101	0.237	3.306
Q_EDUCATION	-0.117	-1.622	-0.073	-0.969	-0.073	-0.977
Q_OTHER	0.046	1.000	0.037	0.765	0.037	0.760
L_FIRM	0.356	4.799	0.290	4.217	0.290	4.294
MANUFACTURE	0.137	2.009	-0.044	-0.726	-0.043	-0.686
SALE	0.141	2.110	-0.098	-1.587	-0.098	-1.573
FINANCE	0.260	3.053	0.133	1.655	0.134	1.714
Bias Correction Term			0.041	0.699		
σ_v ¹⁾	0.392	22.252			0.357	22.869
ρ ¹⁾					0.114	0.628
log likelihood	-25.9357				-551.126	
Number of Observations	283					

1) ρ is the correlation coefficient of v_i and ε_i .