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Estimating the Leverage Effect Using Panel Data with Large Number of Listed Issues over Fixed Daily Periods

by

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Modification of Errortum in Old Version (January 17, 1998):
In Main Document of Old Version,

[page 3, footnote2, line 2] : At “Due to the correlation between these effects and the dependent variables”, ”the dependent variables” is converted into “the independent variables”.

[page 5, line 14] : At “We estimate α by using “Generalized Method of Moments (hereafter GMM)” for this dynamic panel data model.”, adding “GMM is developed by Hansen (1982).”

[page 8, line 9] : Instead of

$$y_{it} = [\log(OP_{it}) - \log(CP_{it})]/100,$$

the modified is

$$y_{it} = [\log(OP_{it}) - \log(CP_{it})] \times 100,$$

In Tables of Old Version,

[page 3 and 4, column 3 in Table 5 and Table 6] : A series of Degree of Freedom (df) is “5” in all cases.

Estimating the Leverage Effect Using Panel Data with Large Number of Listed Issues over Fixed Daily Periods

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Abstract

This paper explores the leverage effect (the negative association between the stock return today and the stock return's volatility tomorrow), by utilizing the exponential ARCH type specification for panel data with large number of issues over fixed daily periods. We can find that the leverage effect is significantly estimated in the span from June 22 to June 29 at 1998, which is the period dominated by the "Good News".

Keywords: Conditional volatility, Leverage effect, Panel data

1 Introduction

There is a folklore in stock markets that there exists a negative association between the stock returns and future stock returns' volatilities. In incipient works, Black (1976) and Christie (1982) argue this association theoretically and statistically. In recent years, Nelson (1991) develops simple but full-fledged estimation models incorporating the notion of the conditional variance to estimate this so-called "leverage effect". These are EARCH (Exponential Autoregressive Conditional Heteroschedasticity) model and EGARCH (Exponential Generalized Autoregressive Conditional Heteroschedasticity) model.[1] Then it is corroborated in Engle and Ng (1993) and Watanabe (1997) that EGARCH specification model is very suitable for describing the Japanese stock returns model.

However, models mentioned above have been tested by the time series data over large sample periods. Time series model do not amply capture the short-run structural change of the parameter of the leverage effect. Allowing for the short-run structural change requires the estimation using the panel data specification with large number of issues over fixed (e.g. digit number) periods. Recently, Meghir and Windmeijer (1997) develop the panel data estimation method for estimating the structure in the conditional variance of returns, by solving the problems in panel data.[2] The aim of this paper is to investigate the association between the stock returns at current day and the stock returns' volatilities at next day, by utilizing this panel data estimation method. The data used is daily balanced panel data composed of the listed issues in the Tokyo Stock Exchange (hereafter the TSE) over the periods from June 1 to July 3 in 1998.

In section 2, the detail of the estimation models is described. Section 3 provides the explanation of the data used. In section 4, estimation results and discussion are presented. Section 5 concludes this paper.

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[1] These models are expansions of ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) model for capturing the asymmetricity of volatility change to the sign of the past shock.

[2] One well-known obstacle typical of panel data specification is the existence of the issue specific effects. Due to the correlation between these effects and the independent variables, the estimator become inconsistent in many cases.

2 Model and Estimation Strategy

This section describes the panel data model capturing the leverage effect in view of formulating the conditional volatility of the stock returns and shows the method of estimating it. A series of specification models and estimation methods is based on Meghir and Windmeijer (1997).

At first, we consider the case that the stock return of i th issues at period t is explained with that at period $t-1$, where $i = 1, \ldots, N$ with large number of issues N and $t = 2, \ldots, T$ with fixed time horizon T. That is, we capture the stock return of i th issue at period t, y_{it}, as simple AR(1) (Auto Regressive of Order 1) model as follows:

$$y_{it} = \alpha y_{i,t-1} + v_{it} \tag{1}$$

$$v_{it} = f_i + u_{it} \tag{2}$$

where we assume that α is common in all issues and the error process v_{it} is composed of the issue specific effect f_i and the disturbance u_{it}.

We estimate α by using "Generalized Method of Moments (hereafter GMM)" in Hansen (1982) for this dynamic panel data model. For the preparation for GMM estimation, we consider the case that the Standard Assumptions (SA.1)-(SA.3) of Ahn and Schmidt (1995) among the disturbance, u_{it}, the initial value of (1), y_{i1}, and the issue specific effect, f_i, hold:

(SA.1) For all i, u_{it} is uncorrelated with y_{i1} for all t,

(SA.2) For all i, u_{it} is uncorrelated with f_i for all t,

(SA.3) For all i, u_{it} is mutually uncorrelated.

Under these assumptions, we can obtain the moment restrictions proposed in Holtz-Eakin et al. (1988) and Arellano and Bond (1991) to estimate α consistently:

$$E[y_{is} \Delta v_{it}] = 0, \quad \text{for } t = 3, \ldots, T \text{ and for } s = 1, \ldots, t-2 \tag{3}$$

where Δ is the first difference operator.

In addition, Blundell and Bond (1998) point out the additional non-linear moment restrictions to estimate α:[3]

$$E[v_{it}\,\Delta v_{i,t-1}] = 0, \quad \text{for } t = 4, \ldots, T \tag{4}$$

That is to say, we can estimate α consistently and efficiently by using GMM under the information only of (SA1)-(SA3).

Next, we try to capture the leverage effect, by utilizing the model explaining the conditional variance of the ith stock issue's stock return at period t, $E_{t-1}[u_{it}^2]$ by the i issue's stock return at period $t-1$, $y_{i,t-1}$, where operator E_{t-1} represents the conditional expectation under the information set up to the period $t-1$. As an appropriate specification for this model, we consider the simple exponential ARCH(1) (Auto Regressive Conditional Heteroschedasticity of Order 1) type specification as below:

$$E_{t-1}[u_{it}^2] = \exp(g_i + \gamma y_{i,t-1}) \tag{5}$$

where γ is the estimated parameter and the negative γ implies the existence of the leverage effect, and g_i is the issue specific volatility.

To rule out g_i s and then estimate γ consistently, in joint system with the moment restrictions (3) and (4) (or (3) and (A2)), or conditional on the estimate of α estimated with the moment restrictions (3) and (4) (or (3) and (A2)), Meghir and Windmeijer (1997) utilize the moment restrictions below:

$$E[\, v_{it}\,\Delta v_{i,t+1}/\exp(\gamma y_{i,t-1}) - v_{i,t-1}\,\Delta v_{it}/\exp(\gamma y_{i,t-2}) \mid y_i^{t-2}] = 0, \quad \text{for } t = 3, \ldots, T-1 \tag{6}$$

where y_i^{t-2} is any transformation of y_{is}, where $s = 1, \ldots, t-2$.[4]

[3] These moment restrictions (4) are spiritually equivalent to those in Ahn and Schmidt (1995):

$$E[v_{iT}\,\Delta v_{it}] = 0, \quad \text{for } t = 3, \ldots, T-1 \tag{A1}$$

Furthermore, Blundell and Bond (1998) shows that if y_{it} ($t = 1, \ldots, T$) are stationary on initial conditions, the moment restrictions (4) are replaced with composed parts of the moment restrictions below and we can use them instead of (4):

$$E[\Delta y_{i,t-1}\, v_{it}], \quad \text{for } t = 3, \ldots, T. \tag{A2}$$

These moment restrictions are proposed in Arellano and Bover (1995).

[4] Dividing both sides of (6) by $\exp(\gamma y_{i,t-1})$, we can obtain the form of quasi-differenced

We succinctly describe the practical estimation procedure as follows: At the first stage, we estimate α only of AR part in specific sample periods, by using the moment restrictions (3) and (4), or (3) and (A2). If α is estimated consistently, at the second stage, we estimate α and γ jointly in their periods by using moment restrictions (3), (4) and (6), or (3), (A2) and (6). At the third stage, after calculating the residuals conditional on the estimated α in the first and second stages and then replacing v_{it} s with them, we estimate γ by utilizing the moment restrictions (6).

A series of methods for choosing the weighting matrices for 1 step and 2 step estimator is the same as Meghir and Windmeijer (1997).[5] In case of iterated estimator , we use the optimally updated weighting matrix composed using the estimates iterated out until the estimates converge, starting from the weighting matrix for 1 step estimator.

A series of estimations is carried out using TSP4.4.[6]

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transformation on the multiplicative fixed effect panel data model in Chamberlain (1992) and Wooldridge (1997):

$$E[\ v_{it}\ \Delta v_{i,t+1}\ -\ \exp(\gamma \Delta y_{i,t-1})\ v_{i,t-1}\ \Delta v_{it}\ |\ y_i^{t-2}] = 0, \quad \text{for } t = 3, \ldots, T-1 \qquad (A3)$$

[5]They use the weighting matrix $\sum_{i=1}^{N} Z_i' Z_i$ for 1 step estimator, where Z_i is the instrument matrix for i individual, and the updated weighting matrix composed using the 1 step estimate for 2 step estimator, respectively.

[6]Manual is written by Hall et al. (1997)

3 Data

Data used in this paper are gleaned from the daily stock prices in *Stock Price Chart CD-ROM Published In Autumn 1998* (*Kabuka Chart CD-ROM 1998 Nen Aki Gou*, in Japanese) published by *Toyo Keizai Inc.* (*Toyo Keizai Shinpou Sha*, in Japanese). The dataset is a daily balanced panel dataset consisting of opening prices and closing prices of 1167 issues listed on the 1st and 2nd section of the TSE over the periods from June 1 to July 3 in 1998 except for holidays. Accordingly the sample periods add up to 25.

As the stock return in a series of estimations, we use the overnight unexchange term stock return of issue i at period t, which is defined as

$$y_{it} = [\log(OP_{it}) - \log(CP_{i,t-1})] \times 100,$$

where OP_{it} and CP_{it} is the opening price and closing price of issue i at period (date) t, respectively.

We single out some spans of the sample periods to carry out the estimations.

4 Result and Discussion

At the first stage, we try to estimate the coefficient α of AR part. There are two spans where α is estimated consistently. One is the period from June 5 (Friday) to June 12 (Friday). Another is the period from June 22 (Monday) to June 29 (Monday). Both are of length 6 periods ($T = 6$), omitting the holidays of the TSE. We call the former and the latter as Span 1 and Span 2, respectively. The candidates of the watershed splitting both spans are the joint intervention into foreign exchange market by both Bank of Japan and Federal Bank of New York at the date of June 17 and the emergency meeting on currencies in Tokyo at the date of June 20. The results are depicted in Table 1 and 2.

At the second stage, in both spans, we estimate α and γ jointly to obtain the results depicted in Table 3 and 4. In Span 2, a series of the estimates of γ is significantly negative, while in Span 1, it is significantly positive. The former is consistent with the leverage effect often seen in many literature, while the latter is not so. Judging from $lm2$ test and $Sargan$ test statistics, we can recognize that the moment restrictions used are valid in each estimation.

At the third stage, we estimate γ, by utilizing the residuals conditional on the estimated α in the first and second stages.[7] In Span 2, we find that a series of the estimates of γ conditional on each fixed α is significantly negative (see Table 6), while in Span 1, we find that it is positive and not fully significant (see Table 5). $Sargan$ test statistics in all estimations say that the moment restrictions are valid.

Span 1 is the period dominated by the "Bad News". That is, in this span, we can find the conspicuous factors deteriorating the business condition: the descent of yen against US dollar and Nikkei Average, and possible devaluation of the Chinese yuan. On the other hand, Span 2 is the period dominated by the "Good News". That is, right before this span, the joint intervention is done and the emergency meeting for currencies is held, where measures to cope with bad loans by Japanese government is outlined and a promise of maintaining the Chinese yuan's stability is made. Furthermore, in this

[7] In addition, we estimate γ conditional on $\alpha = 0$, because the estimates of α in the first and second stages are often insignificant.

span, the rise of Nikkei Average is observed. It is intriguing that negative estimates of γ, which imply the existence of the leverage effect, are observed in Span 2 ("Good News" period), while positive estimates in Span 1 ("Bad News" period).

5 Conclusion

Utilizing an exponential ARCH type specification for panel data model with large number of issues over short periods and their estimation methods, this paper examined the daily overnight unexchange term return data composed of the 1167 issues over the periods from June 1 to July 3 at 1998, with the aim of corroborating the leverage effect in the TSE market. Results indicate that the leverage effect (the negative association between the stock return today and the future stock return's volatility tomorrow) was estimated in a time span of the sample periods. This span corresponds the period dominated by the "Good News".

REFERENCES

Ahn, S.C., and Schmidt, P. (1995) Efficient estimation of models for dynamic panel data, *Journal of Econometrics*, **68**, 5-27.

Arellano, M., and Bond, S. (1991) Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies*, **58**, 277-297.

Arellano, M., and Bover, O. (1995) Another look at the instrumental variable estimation of error-components models, *Journal of Econometrics*, **68**, 29-51.

Black, F. (1976) Studies of stock, price volatility change, *Proceedings of the 1976 meetings of the business and economics statistics section, American Statistical Association*, 177-181.

Blundell, R., and Bond, S. (1998) Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics*, **87**, 115-143.

Bollerslev, T. (1986) Generalized autoregressive conditional heteroschedasticity, *Journal of Econometrics*, **51**, 307-327.

Chamberlain, G. (1992) Comment: Sequential moment restrictions in panel data, *Journal of Business & Economic Statistics*, **10**, 20-26.

Christie, A. A. (1982) The stochastic behavior of common stock variances, value, leverage and interest-rate effects, *Journal of Financial Economics*, **10**, 407-432.

Engle, R. F. (1982) Autoregressive conditional heteroschedasticity with estimates of the variance of United Kingdom inflation, *Econometrica*, **50**, 987-1008.

Engle, R. F. and Ng, V. K. (1993) Measuring and testing the impact of news on volatility, *Journal of Finance*, **48**, 1749-1801.

Hall, B. H., Cummins, C., and Schnake, R. (1997) Time series processor version 4.4 user's guide, *TSP International*, August.

Hansen, L. P. (1982) Large sample properties of generalized method of moments estimators, *Econometrica*, **50**, 1029-1054.

Holtz-Eakin, D., Newey, W., and Rosen, H. S. (1988) Estimating vector autoregressions with panel data, *Econometrica*, **56**, 1371-1395.

Meghir, C., and Windmeijer, F. (1997) Moment conditions for dynamic panel data models with multiplicative individual effects in the conditional variance, *Institute for Fiscal Studies*, Working Paper No. 21.

Nelson, D. B. (1991) Conditional heteroschedasticity in asset returns: a new approach, *Econometrica*, **59**, 347-370.

Watanabe, T. (1997) Stochastic properties of volatility in Japanese stock market: analyses based on ARCH-type models, (Nihon no kabushiki shijou ni okeru volatility no hendou: ARCH gata model ni yoru bunseki, in Japanese), *Mitsubishi Keizai Kenkyuujo*

Wooldridge, J. M. (1997) Multiplicative panel data models without the strict exogeneity assumption, *Econometric Theory*, **13**, 667-678.

Table 1. Estimation of α Using the Moment Restrictions (3) and (4)
Number of Issues ($N = 1167$)

	Estimation Method	α (t-value)	$lm1$ [p-value]	$lm2$ [p-value]	$Sargan$ (df) [p-value]
Span 1	2 step	.0141	-13.907	1.257	18.215 (12)
		(.558)	[.000]	[.209]	[.109]
	Iterated	.0162	-13.926	1.292	18.202 (12)
		(.642)	[.000]	[.196]	[.110]
Span 2	2 step	-.0281	-14.176	-.753	17.171 (12)
		(-1.574)	[.000]	[.451]	[.143]
	Iterated	-.0289	-14.168	-.764	17.158 (12)
		(-1.621)	[.000]	[.445]	[.144]

Notes: (i) Span 1 and Span 2 imply the periods from June 5 to 12 except for June 6 and 7, and the periods from June 22 to June 29 except for June 27 and 28, respectively. (ii) $lm1$ and $lm2$ are test statistics for the null hypothesis of no first-order and second-order correlation in the residuals, which are $N(0,1)$ distributed asymptotically. (iii) $Sargan$ is a χ^2 test statistic of overidentifying restrictions under the null hypothesis of the validity of moment conditions, whose degree of freedom is located in (df).

Table 2. Estimation of α Using the Moment Restrictions (3) and (A2).
Number of Issues ($N = 1167$)

	Estimation Method	α (t-value)	$lm1$ [p-value]	$lm2$ [p-value]	$Sargan$ (df) [p-value]
Span 1	2 step	.0266	-14.015	1.465	19.885 (13)
		(1.083)	[.000]	[.143]	[.098]
	Iterated	.0289	-14.034	1.502	19.896 (13)
		(1.176)	[.000]	[.133]	[.098]
Span 2	2 step	-.0249	-14.207	-.711	17.659 (13)
		(-1.409)	[.000]	[.477]	[.179]
	Iterated	-.0304	-14.153	-.784	17.486 (13)
		(-1.756)	[.000]	[.433]	[.178]

Notes: (i) See Notes (i), (ii), and (iii) of Table 1.

Table 3. Joint Estimation of α and γ Using the Moment Restrictions (3), (4), and (6) *Number of Issues* ($N = 1167$)

	Estimation Method	α (t-value)	γ (t-value)	$lm1$ [p-value]	$lm2$ [p-value]	$Sargan$ (df) [p-value]
Span 1	2 step	.0032	.0388	-13.810	1.070	22.672 (16)
		(.136)	(2.007)	[.000]	[.284]	[.123]
	Iterated	.0049	.0475	-13.826	1.101	22.731 (16)
		(.211)	(2.437)	[.000]	[.271]	[.121]
Span 2	2 step	-.0489	-.0302	-13.966	-1.029	21.282 (16)
		(-3.051)	(-2.088)	[.000]	[.304]	[.168]
	Iterated	-.0321	-.0555	-14.136	-.807	20.904 (16)
		(-2.405)	(-5.548)	[.000]	[.420]	[.182]

Notes: (i) See Notes (i), (ii), and (iii) of Table 1. (ii) Here, the instruments set of the moment restrictions (6), y_i^{t-2}, is composed of y_{is}, where $s = t - 3$ and $t - 2$.

Table 4. Joint Estimation of α and γ Using the Moment Restrictions (3), (A2), and (6) *Number of Issues* ($N = 1167$)

	Estimation Method	α (t-value)	γ (t-value)	$lm1$ [p-value]	$lm2$ [p-value]	$Sargan$ (df) [p-value]
Span 1	2 step	.0127	.0389	-13.895	1.233	24.480 (17)
		(.555)	(1.998)	[.000]	[.218]	[.107]
	Iterated	.0174	.0475	-13.936	1.312	24.571 (17)
		(.764)	(2.425)	[.000]	[.189]	[.105]
Span 2	2 step	-.0648	-.0243	-13.796	-1.241	24.174 (17)
		(-3.369)	(-1.535)	[.000]	[.214]	[.115]
	Iterated	-.0336	-.0552	-14.121	-.826	21.327 (17)
		(-2.566)	(-5.540)	[.000]	[.409]	[.212]

Notes: (i) See Notes (i) and (ii) of Table 3.

Table 5. Estimation of γ Conditional on Each α Using the Moment Restrictions (6) in Span 1
Number of Issues ($N = 1167$)

α	γ (t-value)	*Sargan* (*df*) [p-value]
0	.0323	5.409 (5)
(fixed)	(1.541)	[.368]
.0032	.0323	5.409 (5)
(fixed)	(1.540)	[.368]
.0049	.0323	5.409 (5)
(fixed)	(1.540)	[.368]
.0127	.0321	5.409 (5)
(fixed)	(1.538)	[.368]
.0141	.0321	5.409 (5)
(fixed)	(1.537)	[.368]
.0162	.0320	5.409 (5)
(fixed)	(1.536)	[.368]
.0174	.0320	5.408 (5)
(fixed)	(1.535)	[.368]
.0266	.0318	5.406 (5)
(fixed)	(1.529)	[.368]
.0289	.0317	5.405 (5)
(fixed)	(1.528)	[.368]

Notes: (i) See Notes (i) and (iii) of Table 1. (ii) Here, the instruments set of the moment restrictions (6), y_i^{t-2}, is composed of y_{is}, where $s = 1, \ldots, t-2$. (iii) A series of the estimates of γ in this table is estimated by the iterated GMM estimator.

Table 6. Estimation of γ Conditional on Each α Using the Moment Restrictions (6) in Span 2
Number of Issues ($N = 1167$)

α	γ (t-value)	*Sargan* (*df*) [p-value]
0	-.0338	6.846 (5)
(fixed)	(-2.393)	[.232]
-.0249	-.0389	6.735 (5)
(fixed)	(-2.520)	[.241]
-.0281	-.0395	6.717 (5)
(fixed)	(-2.541)	[.243]
-.0289	-.0396	6.713 (5)
(fixed)	(-2.546)	[.243]
-.0304	-.0399	6.704 (5)
(fixed)	(-2.556)	[.244]
-.0321	-.0402	6.695 (5)
(fixed)	(-2.569)	[.244]
-.0336	-.0404	6.686 (5)
(fixed)	(-2.578)	[.245]
-.0489	-.0423	6.577 (5)
(fixed)	(-2.660)	[.254]
-.0648	-.0429	6.431 (5)
(fixed)	(-2.674)	[.266]

Notes: (i) See Notes (i), (ii), and (iii) of Table 5.