USING POOLED TIME-SERIES AND CROSS-SECTION DATA TO TEST THE FIRM AND TIME EFFECTS IN FINANCIAL ANALYSES

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I. Introduction

In financial analyses, both firm effect and time effect are of interest to the researcher. Bower and Bower [4] and Chung [5] have used the residual technique to deal with the firm effect, but the statistical property of the technique is ambiguous. To the knowledge of these authors, the importance of firm effect and time effect in evaluating alternative corporate policies has never been investigated formally. The main purpose of this study is to demonstrate how the pooled time-series and cross-section data can be used to test the importance of both the firm effect and the time effect in financial studies. Data on electric utility industry are used as examples. It is shown that both firm effect and time effect are statistically significant in this set of data, and therefore, should be taken into account empirically when the effect of alternative corporate policies is evaluated. Further, the transformation technique developed by Box and Cox [3] is integrated with the pooled time-series and cross-section data to draw additional methodological implications.

In the second section of this paper, the dummy variable technique and the error component model for analyzing pooled data will be introduced. In the third section, financial data on the electric industry from 1963 to 1973 are used to investigate the impacts of firm effect and time effect on the variation of stock price per share and on the change of regression coefficients associated with dividends and retained earnings. In the fourth section, methods of analyzing pooled time-series and cross-section data are combined with the transformation technique developed by Box and Cox [3]. Data from the previous section are used to investigate the possible impacts of firm effect and time effect on choosing the optimal functional form of a financial research study.

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The firm effect refers to the effect of factors affecting the behavior of an individual firm; it is constant over time. The time effect refers to the economic condition of particular time point; it varies over time.

II. The Dummy Variable Technique and the Error Component Model

Suppose we have observations on N firms over T periods of time. The model for analyzing both firm and time effects of an industry can be written as:

(1)
$$P_{it} = \sum_{k=1}^{K} \beta_k \chi_{kit} + u_{it}, i = 1, 2, ..., N \\ t = 1, 2, ..., T$$

where P_{it} represents the stock price per share of the i^{th} firm of the industry in period t; χ 's are the factors affecting the stock price; and u_{it} is the disturbance term. In actuality the factors affecting the stock price per share are often numerous and complex and may not be readily observable or measurable. Consequently, usually only a subset of these factors is included in regression analysis in empirical studies. In addition, when cross-section and time-series data are combined in the estimation of a regression equation, certain unobservable "other effects" may be present in the data. Without considering those other factors, the ordinary least squares (OLS) estimates of the β 's in (1), as indicated by Nerlove [10] and Wallace and Hussain [11], may be biased and inefficient. To consider other causal variables, Equation (1) is written as:

(2)
$$P_{it} = \sum_{k=1}^{K} \beta_k \chi_{kit} + w_i + v_t + u_{it}$$

$$(i = 1, 2,, N; t = 1, 2, T)$$

where $\mathbf{w_i}$ represents more or less time invariant, unobserved firm effects; $\mathbf{v_t}$ represents more or less cross-section invariant, unobserved time effects on the stock price per share of the industry; and $\mathbf{u_i}$ represents the remaining effects which are assumed to vary in both cross-section and time dimensions. Other notations remain the same as in equation (1).

One way to estimate the parameters in equation (2) is through the treatment of w_i and v_t as constants. Under the assumption that u_{it} are independent with zero means and constant variances, least squares regression of P on χ 's and firm and time dummies can be used. This approach is known as the least squares with dummy variable technique (LSDV). As indicated by Maddala [9], the use of this dummy variable technique eliminates a major portion of the variation among the dependent and explanatory variables if the between-firm and between-time period variation is large. In addition, in some cases, the loss of a substantial number of degrees of freedom occurs. Hence LSDV is not an efficient method for

 $_{
m For\ a\ discussion}^{
m 2}$ of the existence of unobservable effects, see Friend and Puckett [7].

estimating equation (2). In a Monte Carlo study, Nerlove [10] also found that LSDV produces estimates with serious bias in finite samples.

Another approach to dealing with equation (2) is to treat \mathbf{w}_1 and \mathbf{v}_t as rantom.³ In this case, instead of N w's and T v's, we estimate only the means and the variances of the distributions of w's and v's. This is known as the error component model, in which the regression error is assumed to be composed of three components—one associated with time, another with cross—section, and the third variable both with the time and cross—section dimensions. Hence in the error component model, equation (2) becomes:

(3)
$$P_{it} = \sum_{k=1}^{K} \beta_k \chi_{kit} + \epsilon_{it}$$

(4)
$$\varepsilon_{it} = w_i + v_t + u_{it}$$

$$(i = 1, 2,, N; t = 1, 2,, T)$$

The assumptions on the components of the error term are that they are independent random variables with constant variances. Without loss of generality, it is also assumed that they have zero means. To estimate the parameters in (3), Aitken's generalized least squares (GLS) can be used. In matrix notation, equation (3) can be written as:

$$Y = \chi \beta + \varepsilon$$

where Y is an NT x l vector, the elements of which are the observations on price per share of firm i in period t; χ is an NT x K matrix with the observations on the K explanatory variables; ε is an NT x l vector containing the error terms. Under the assumptions on the error components, the variance-covariance matrix of the disturbance terms ε_{it} is the following NT x NT matrix:

 $^{^3}$ For a discussion of this sort, see, for example, Balestra and Nerlove [2].

$$E (\varepsilon \varepsilon') = \Omega = \begin{bmatrix} \sigma_{\mathbf{w}}^2 \mathbf{A}_{\mathbf{T}} & \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} & \dots & \dots & \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} \\ \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} & \sigma_{\mathbf{w}}^2 \mathbf{A}_{\mathbf{T}} & \dots & \dots & \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} \\ \vdots & \vdots & & \vdots & & \vdots \\ \vdots & \vdots & & & \vdots \\ \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} & \sigma_{\mathbf{v}}^2 \mathbf{I}_{\mathbf{T}} & \dots & \dots & \sigma_{\mathbf{w}}^2 \mathbf{A}_{\mathbf{T}} \end{bmatrix}$$

$$(6)$$

where $I_{_{\bf T}}$ is a (T x T) identity matrix and $A_{_{\bf T}}$ is a (T x T) matrix defined as:

in which $\sigma^2 = \sigma_w^2 + \sigma_v^2 + \sigma_u^2$. Given equation (6), it is well known that the generalized least squares estimate of β , if σ_w^2 , σ_v^2 , and σ_u^2 are known, is

$$\hat{\beta} = (\chi' \Omega^{-1} \chi)^{-1} (\chi' \Omega^{-1} Y)$$

with variance-covariance matrix

(8)
$$\operatorname{Var}(\hat{\beta}) = (\chi' \Omega^{-1} \chi)^{-1}.$$

GLS estimates are more efficient than LSDV or OLS estimates because they enable us to extract some information about the regression parameters from the between-firm and between-time-period variation. In finite samples, Nerlove [10] has also found that it produces little bias.

In actuality σ_w^2 , σ_v^2 and σ_u^2 are usually unknown, but they can be estimated by the analysis of covariance techniques as follows (see, for example, Amemiya [1]):

(10)
$$\hat{\sigma}_{w}^{2} = \frac{1}{T} \begin{bmatrix} \frac{1}{(N-1)T} & \frac{N}{\Sigma} & \frac{T}{\Sigma} & e_{it} & -\hat{\sigma}_{u}^{2} \\ \frac{1}{(N-1)T} & \frac{1}{i-1} & t=1 \end{bmatrix}.$$

(11)
$$\hat{\sigma}_{v}^{2} = \frac{1}{N} \left[\frac{1}{N(T-1)} \begin{array}{ccc} T & N & 2 \\ \Sigma & \Sigma & E \\ t=1 & i=1 \end{array} \right] - \hat{\sigma}_{u}^{2}$$

where e_{it} represents residuals obtained by applying the least squares method to the pooled data, assuming that w_i and v_t are constants to be estimated rather than random variables.

If $\sigma_{\rm w}^2$ and $\sigma_{\rm v}^2$ are estimated to equal zero, then Ω in (6) is a NT x NT identity matrix and hence equations (7) and (8) are the same as the OLS estimators. On the other hand, if the estimate of $\sigma_{\rm w}^2/\sigma^2$ approaches one and $\hat{\sigma}_{\rm v}^2$ approaches zero, they are equivalent to LSDV with firm dummies; if $\hat{\sigma}_{\rm v}^2/\hat{\sigma}^2$ approach one and $\sigma_{\rm w}^2$ approaches zero, they are equivalent to LSDV with time dummies. Hence in applying GLS rather than OLS or LSDV, the existence of other time or firm effects can be determined by the sample rather than assumed. The relative weights given to between and within firm and time period variations for the estimation of the parameters are determined by the data. In OLS it is assumed that the between and within variations are just added up; in LSDV the between variation is ignored completely (see Maddala [9], p. 341-344).

III. Impacts of Firm Effect and Time Effect on Stock Price Variation

Either time-series or cross-section data are used generally to investigate variation of stock price per share within an industry. However, the firm effect and time effect have never been formally investigated by the technique described above. Gordon [8], Durand [6], and the others have claimed that stock price per share can be explained by dividends and retained earnings per share. Friend and Puckett [7] have argued that some unobservable variables are of importance in explaining the behavior of stock price per share. They have further demonstrated that both firm and time effects are the most important unobservable effects to be considered. However, they could not find a satisfactory method to handle these effects.

To allow both firm effect and time effect to be included in the Gordon-type model, following equations (3) and (4), a generalized Gordon-type model is defined as:

(12)
$$P_{i+} = \beta_1 + \beta_2 D_{i+} + \beta_3 R_{i+} + w_i + v_t + u_{i+}$$

where P. D. and R represent per share price, dividend, and retained earnings, respectively; and w, v, and u are the same as before. To test the importance of firm effect and time effect in explaining stock price variation, annual data of utility industry associated with P, D, and R are collected from Compustat tape. There are 110 firms used in this study. The sample period is from 1963 to 1973 which allows different economic conditions to be reflected in the empirical study. Both linear and log linear forms are used for the estimation, based upon OLS, LSDV, and GLS methods. Estimates on equation (12) were obtained by assuming that (a) w_i and V_{+} are identical to zero for all i and t (OLS); (b) v_{+} are identical to zero and w_i are constant (LSDV with firm dummies); (c) v_{\downarrow} are identical to zero, and w, is a random variable with zero mean and constant variance (GLS with firm effects); (d) w_i are identical to zero and v_{\downarrow} are constants (LSDV with year dummies); (e) w_i are identical to zero and v_{+} is a random variable (GLS with year effects); (f) both w_i and v_t are constants (LSDV with both firm and year dummies); and (g) both \mathbf{w}_{i} and \mathbf{v}_{t} are random variables (GLS with both firm and year effects). The estimated results of the seven assumptions are summarized in Tables I and II. Table I is based upon the linear form and Table II is based upon the log linear form.

The figures of adjusted coefficients of determination (\overline{R}^2) in the tables demonstrate the importance of both firm effect and time effect in explaining the variation of stock price per share. Unless either firm effect or time effect is considered, the two explanatory variables can account for only 30 percent of the dependent variable. As the firm effect and/or the time effect are included, the explanatory power is improved significantly. The tables also demonstrate that if either of the two effects is not taken into account, the coefficient for dividend will be seriously underestimated in both linear and log linear forms. The coefficient for retained earnings, on the other hand, will be overestimated in both functional forms if the firm effect is not considered; and it will be slightly underestimated in the log-linear form if the time effect is not taken

 $^{^4}$ Sample lists of these firms are available from the authors.

TABLE I ESTIMATED COEFFICIENTS FROM THE POOLED DATA (1.TNEAR FORM)

	Based on	Constant	Coefficient for Dividend	Coefficient for (Earning-Dividend)	<u>R</u> 2
(a)	OLS	9.64 (0.99)	8.65	12.01 (0.93)	0.31
(p)	LSDV with firm effects	19.59 (1.49)	5.94 (1.23)	3.12 (1.30)	0.48
(c)	GLS with firm effects	16.25 (1.42)	7.05 (1.06)	5.73 (1.17)	0.48
(d)	LSDV with time effects	2.87 (0.64)	12.67 (0.49)	13.97 (0.58)	0.74
(e)	GLS with time effects	2.91 (2.54)	12.64 (0.49)	13.96 (0.58)	0.74
(f)	LSDV with both effects	-2.44 (0.70)	20.72 (0.56)	6.18 (0.55)	0.91
(g)	GLS with both effects	-1.70 (2.71)	19.83 (0.54)	6.82 (0.54)	0.91

Note: Figures in parentheses are standard errors; and LSDV is OLS with dummy variables.

TABLE II

ESTIMATED COEFFICIENTS FROM THE POOLED DATA (LOG-LINEAR FORM)

R-2	0.33	0.49	0.49	0.78	0.78	0.94	0.94
Coefficient for (Earning-Dividend)	0.29	0.14 (0.03)	0.1 (0.02)	0.29 (0.01)	0.29 (0.01)	0.14 (0.01)	0.14 (0.01)
Coefficient for Dividend	0.35 (0.03)	0.05	0.16 (0.04)	0.57 (0.02)	0.57 (0.02)	0.83 (0.02)	0.81
Constant	3.37 (0.02)	3.38 (0.02)	3.37 (0.03)	3.32 (0.01)	3.32 (0.08)	3.18 (0.01)	3.19 (0.08)
Based on	OLS	LSDV with firm effects	GLS with firm effects	LSDV with time effects	GLS with time effects	LSDV with both effects	GLS with both effects
	(a)	(p)	(c)	(d)	(e)	(£)	(g)

Note: Figures in parentheses are standard errors; and LSDV is OLS with dummy variables.

into account. In sum, both firm and time effects are statistically significant in explaining the stock price variation and the omission of either effect will cause the estimated coefficients to be biased. Hence both firm effect and time effect should be handled carefully in this kind of financial analysis. In the following section, the transformation technique developed by Box and Cox [3] is integrated with the model discussed in this section to find an appropriate functional form for doing the pooled time-series and cross-section analysis.

IV. Functional Form and Pooled Time-Series and Cross-Section Data

The choice of a linear or log-linear functional form for financial analyses has often been arbitrary, usually based on the ease of estimation. Since the choice of one or the other form might have serious implications on the effect of explanatory variables on the dependent variable, the choice of a proper functional form should be based on the sample and determined on statistical grounds. In order to do so, the deterministic portion of equation (12) is written in terms of the following general form according to the suggestion of Box and Cox [3]:

(13)
$$p_{it}^{\lambda} = \beta_0 + \beta_1 p_{it}^{\lambda} + \beta_2 R_{it}^{\lambda}$$

where λ is the functional form parameter to be estimated. Equation (13) includes both the linear and the logarithmic form as a special case and provides a generalized functional form (GFF) for testing the dividend effect. For allowing the generalized functional form to be continuous at λ = 0, Box and Cox [3] and Zarembka [12] have shown that equation (13) can be rewritten as 5

(14)
$$P_{it}^{(\lambda)} = \beta_0' + \beta_1 D_{it}^{(\lambda)} + \beta_2 R_{it}^{(\lambda)}$$

where

$$P_{it}^{(\lambda)} = \frac{P_{it}^{\lambda} - 1}{\lambda}, \quad D_{ti}^{(\lambda)} = \frac{D_{it}^{\lambda} - 1}{\lambda},$$

$$R_{it}^{(\lambda)} = \frac{R_{it}^{\lambda} - 1}{\lambda} \text{ and } \beta_{0}^{\prime} = \frac{(\beta_{0} + \beta_{1} + \beta_{2}) - 1}{\lambda}.$$

Following Box and Cox [3] and Zarembka [12], for the true functional form (i.e., the true " λ "), it is assumed that additive disturbance terms, w_i' , v_t' , and u_{it}' , exist to allow equation (14) to be rewritten into a stochastic relationship:

⁵Zarembka [12] has employed the generalized functional form technique to determine the true functional form for money demand. The proof of this statement can also be found in his paper.

(15)
$$P_{it}^{(\lambda)} = \beta_{0}' + \beta_{1} D_{it}^{(\lambda)} + \beta_{2} R_{it}^{(\lambda)} + w_{i}' + v_{t}' + w_{it}'$$

where w_i , v_t , and u_{it} are normally and independently distributed with zero means and variances σ_w^2 , σ_v^2 and σ_u^2 .

Using the maximum likelihood method, Box and Cox [3] derived a maximum logarithmic likelihood for determining the functional form parameter:

(16)
$$\operatorname{Lmax}(\hat{\lambda}) = \operatorname{Constant} - n \log \hat{\sigma}_{\tau}(\lambda) + (\lambda - 1) \sum_{i=1}^{n} \log P_{it}$$

where n is the sample size, and $\hat{\sigma}_{\tau}(\lambda)$ is the estimated regression residual standard error of equation (15). For calculating $\hat{\sigma}_{\tau}(\lambda)$, P_{it} , D_{it} and R_{it} should be transformed in terms of equation (14). After $\hat{\sigma}_{\tau}(\lambda)$ is estimated, equation (16) will be employed to determine the optimum value of the functional form parameter, $\hat{\lambda}$. the optimum value of λ is obtained by plotting equation (16) for different values of λ to arrive at the maximized logarithmic likelihood over the whole parameter space. Using the likelihood ratio method, an approximate 95 percent confidence region for λ can be obtained from:

(17)
$$\operatorname{Lmax}(\hat{\lambda}) - \operatorname{Lmax}(\lambda) < 1/2\chi_1^2 (.05) = 1.92.$$

The 95 percent confidence region for λ will be used to determine the true functional form for the pooled time-series and cross-section models.

For determining the true functional parameters, P_{it} , D_{it} , and R_{it} are transformed in accordance with equation (14) by λ between -0.5 and 1.5 at intervals of length 0.1. These transformed data are then used to estimate the relationship among P_{it} , D_{it} , and R_{it} in accordance with OLS, LSDV with crosssection effect, GLS with cross-section effect, LSDV with time effect, GLS with time effect, LSDV with both effects, and GLS with both effects. Twenty-one regressions are estimated for each case and the results are listed in Table III. To estimate the optimal functional form parameters for every case above-mentioned, the logarithmic likelihoods are estimated in accordance with equation (16) and listed in Table IV. Using the χ^2 test indicated in equation (17) and Table IV, it is found that the linear form (λ = 1) has been rejected for all seven cases under 95 percent confidence interval. Under the same confidence interval, it also is found that the log-linear form has been rejected for LSDV

 $[\]hat{\sigma}_{\tau}(\lambda)$ is obtained either from OLS, LSDV, or GLS.

TABLE III ESTIMATED COEFFICIENTS FROM THE POOLED DATA (GENERALIZED FUNCTIONAL FORM)

OLS

44.73

(3.81)

32.16

23.14

16.66

(1.47)

(.57)

4.51

3.27

2.36

1.72

(.16)

1.25

(.12)

.91

(.08)

.66

(.06)

.48

(.05)

0.35

(0.03)

.26

(.02)

.19

(.02)

.14

(.01)

.10

(.01)

.08

(.01)

(.22)

(.30)

(.41)

(2.02)

(2.77)

LSDV

45.69

30.72

13.67

(.90)

2.51

1.62

(.47)

1.03

(.34)

.65

(.25)

.41

(.18)

.25

(.13)

.15

(.01)

.09

(.07)

0.05

.03

(.04)

.02

(.03)

.01

(.02)

.003

(.01)

.00

(.01)

(.65)

GLS

45.69

31.52

14.95

(.77)

3.31

2.26

(.40)

1.55

(.30)

1.06

(.22)

.72

(.16)

.50

(.12)

.34

(.08)

.23

(.06)

0.16

.11

(.03)

.08

(.02)

.05

(.02)

.04

(.01)

. 03

(.01)

(0.05) (0.04)

(.56)

20.55 21.72

(2.33) (2.00)

LSDV

60.78

44.35

32.39

23.66

(.96)

(.35)

6.79

(.25)

4.97

(.18)

3.65

(.13)

2.67

(.1)

1.96

(.07)

1.44

1.06

(.04)

.78

(.03)

0.57

(0.02)

. 42

(.01)

.31

(.01)

.23

(.01)

.17

(.01)

.12

(.00)

(.05)

(6.03) (5.18) (2.63) (2.62)

(4.40)(32.72)(1.88)(1.87)

(3.20) (2.75) (1.34) (1.34)

GLS

60.66

44.27

32.33

23.62

(.96)

(.35)

6.77

4.96

(.18)

3.64

(.13)

2.67

(.1)

1.96

(.07)

1.44

(.05)

1.06

(.04)

.78

(.03)

0.57

(0.02)

.42

(.01)

.30

(.01)

.23

(.01)

.17

(.01)

.12

(.00)

(.25)

LSDV

105.50

76.07

54.89

39.64

28.65

20.72

15.0

(.56)

(.40)

(.28)

7.88

(.20)

5.71

4.15

(.1)

3.01

2.18

(.05)

1.59

1.15

(.03)

0.83

(0.02)

.60

(.01)

.44

(.01)

.32

(.01)

.23

(.01)

.17

(.00)

(.04)

(.07)

(.14)

10.87

(.80)

GLS

99.64 (3.22) (3.06

72.02

52.11

37.73

27.34

(.76

19.83

14.39

(.38

10.45

(.27

7.60

(.19

5.52

(.13

4.01

(.1)

2.92

(.07

2.12

(.05)

1.54

(.04

1.12

(.05)

0.81

. 59

.43

(.01

.31

(.01

.22

(.01

.02

(.00

(.01

(0.02)

(.54

(2.28) (2.16)

(1.61) (1.53

(1.13) (1.08)

							
Cor	nstant		Coefficient	t for Dividend			
Cross Section Effects	Time Effects	Both Effect	Cross Section Effects	Time Effects	Both Effect		

77.91 81.56

60.99 63.45

(1.41)(10.72)

(.67) (5.32)

(.21) (1.87)

(.15) (1.32)

15.11

12.11

(.94)

9.77

(.66)

7.94

(.47)

6.51

(.34)

5.37

(.24)

4.48

(.17)

3.76

(.12)

3.19

(0.08)

2.73

(.06)

2.35

(.04)

2.05

(.03)

1.80

(.02)

14.90

11.97

(.10)

9.68

7.88

6.46

(.03)

5.34

4.46

(.02)

3.74

(.01)

3.18

(0.01)

2,72

(.01)

2.35

(.00)

2.04

1.79

(.00)

Figures in parentheses are standard errors, and LSDV: OLS with dummy variables. 467

(.02)

(.05)

(.62) (0.07)

49.49

38.71

GLS

LSDV

47.83

(7.05) (.97) (7.55)

37.60

1.1								12.0 (1.07)				
1.0								8.65 (.78)				
0.9	22.78	21.77	21.98	22.15	22.15	18.65	18.98	6.25	3.88	4.83	9.26	9.25

(.01)

1.62

(.01)

OLS

111.83

(3.03)

84.77

(2.14)

64.53

(1.51)

49.34

(1.07)

(.38)

17.82

17,04

11.15

(.19)

(.14)

8.92

(0.1)

7.21

5.87

(.05)

4.83

(.03)

4.01

(.02)

3.37

(0.02)

2.85

2.44

(.01)

2.11

1.84

(.00)

1.62

(.00)

(.01)

(.07)

(.27)

λ

1.5

1.4

1.3

1.2

0.8

0.7

0.6

0.5

0.4

0.3

0.2

0.1

0.0

-0.1

-0.2

-0.3

-0.4

-0.5

Note:

LSDV

96.03

(4.02)

74.50

(2.86)

57.91

45.13

(1.45)

(.52)

17.22

13.70

10.96

(.18)

8.82

(.13)

7.16

(.1)

5.86

(.06)

4.83

(.04)

4.02

(.03)

3.38

(0.02)

2.86

(.02)

2.45

(.01)

2.12

1.85

(.01)

1.63

(.00)

(.26)

(.37)

(2.04)

GLS

100.51

(5.05)

77.37

59.71

46.23

(1.75)

(.62)

17.32

13.74

10.97

(.31)

(.22)

8.82

7.15

(.12)

5.84

4.82

4.01

(.04)

3.37

(0.03)

2.86

(.02)

2.44

(.01)

(.06)

(.08)

(.16)

(.44)

(2.49)

(3.54)

LSDV

109.03

82.59

62.82

48.01

(.99)

(.69)

(.23)

17.34

13.67

10.86

(0.08)

8.71

(0.06)

7.04

(.04)

5.75

(.03)

4.74

(.02)

3.94

(.01)

3.32

(0.01)

2.82

(.01)

2.41

2.09

1.83

1.51

(.00)

(.00)

(.01)

(.16)

(.11)

(1.43) (10.0)

GLS

109.05

82.60

62.88

48.02

(4.97)

(1.75)

17.34

(1.24)

13.67

10.87

8.71

7.04

5.75

(.22)

4.74

(.16)

3.94

(.11)

3.32

(0.08)

2.82

2.41

2.09

1.83

(.02)

1.61

(.01)

(.04)

(.06)

(.03)

(.44)

(.88)

(2.06) (14.21) (2.05) (15.25)

1.59	1.59
(.00)	(.01)

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^{2.11} (.01)(.01)(.01)(.00)(.02)(.00)1.84

IABLE III (Continued)

	Coefficient for (Earning-Dividend)							R ²						
		Section ects	Time E	ffects	Both Ef	fects		Cross Se Effec		Time Ef	fects	Both Ef	fects	
OLS	LSDV	GLS	LSDV	GLS	LSDV	GLS	OLS	LSDV	GLS	LSDV	GLS	LSDV	GLS	
70.01 (5.91)	4.64 (8.02)	23.63 (7.24)	85.80 (4.05)	85.68 (4.05)	30.88 (4.08)	36.23 (3.96)	.2980	.4754	.4795	.6793	.6798	.8721	.8726	
49.41 (4.10)	5.29 (5.61)	18.24 (5.05)	60.01 (2.76)	59.93 (2.75)	22.79 (2.75)	26.34 (2.67)	.3013	.4750	.4802	.6959	.6927	.8808	.8812	
34.81 (2.84)	5.12 (3.91)	13.88 (3.52)	41.85 (1.87)	41.81 (1.87)	16.67 (1.85)	19.01 (1.80)	.3046	.4750	.4794	.7055	.7055	. 8891	.8897	
24.47 (1.96)	4.56 (2.72)	10.45 (2.44)	29.11 (1.27)	29.08 (1.27)	12.08 (1.24)	13.61 (1.20)	.3078	.4752	.4798	.7175	.7175	.8971	.8975	
17.16 (1.36)	3.84 (1.88)	7.78 (1.69)	20.19 (.86)	20,17	8.68 (.83)	9.67 (.80)	.3108	.4757	.4804	.7287	.7287	.9047	.9050	
12.01 (.93)	3.12 (1.30)	5.73 (1.17)	13.97 (.58)	13.96 (.58)	6.18 (.55)	6.82 (.54)	.3136	.4764	.4813	.7391	.7391	.9117	.9119	
8.38 (.64)	2.46 (.90)	4.19 (.81)	9.63 (.39)	9.63 (.39)	4.37 (.36)	4.78 (.36)	.3162	.4773	.4824	.7484	.7484	.9181	.9183	
5.84 (.44)	1.90 (.61)	3.04 (.55)	6.62 (.27)	6.62 (.27)	3.06 (.24)	3.33 (.24)	.3186	.4784	.4837	.7568	.7568	.9239	.9241	
4.05 (.30)	1.44 (.42)	2.18 (.38)	4.54 (.18)	4.53 (.18)	2.13 (.16)	2.30 (.16)	.3207	.4796	.4850	.7641	.7641	.9290	.9291	
2.81 (.21)	1.07 (.29)	1.56 (.26)	3.10 (.12)	3.10 (.12)	1.47 (.11)	1.58 (.10)	.3225	.4809	.4864	.7703	.7703	.9333	.9334	
1.94 (.14)	.79 (.20)	1.10 (.18)	2.11 (.08)	2.11 (0.1)	1.0 (.07)	1.08 (.07)	.3240	.4822	.4878	.7754	.7754	.9368	.9369	
1.33	.57 (.13)	.78 (.12)	1.43 (.06)	1.43 (.06)	.68 (.05)	.73 (.05)	.3252	.4835	.4892	.7793	.7793	.9395	.9396	
.92 (.07)	.41 (.01)	.54 (.08)	.97 (.04)	.97 (.04)	.46 (.03)	.49 (.03)	.3259	.4847	.4905	.7819	.7819	.9413	.9413	
.62 (.04)	.29 (.06)	.38 (.06)	.65 (.03)	.65 (.03)	.31 (.02)	.33	.3273	.4858	.4916	.7833	.7837	.9423	.9424	
.43 (.03)	.20 (.04)	.26 (.04)	.44 (.02)	.44 (.02)	.21 (.01)	.22 (.01)	.3259	.4867	.4926	.7835	.7835	.9423	.9424	
0.29 (0.02)	0.14 (0.03)	0.18 (0.02)	0.29 (0.01)	0.29 (0.01)	0.14 (0.01)	0.14 (0.01)	.33	.49	.49	.78	.78	.94	.94	
.19 (.01)	.10 (.02)	.12 (.02)	.19 (.01)	.19 (.01)	.09 (.01)	.10 (.01)	.3238	.4880	.4940	.7798	.7798	.9396	.9397	
.13 (.01)	.07 (.01)	.08 (.01)	.13 (.01)	.13 (.01)	.06 (.00)	.06 (.00)	.3218	.4883	.4943	.7761	.7761	.9369	.9370	

.04 .3191 .5353 .4951 .08 .08 .04 .08 .04 .05 (.00)(.00)(.00)(.00)(.01) (.01) (.01).02 .03 .3157 .4879 .4839 .06 .03 .04 .06 (.00)(.00)(.00)(.00)(.00) (.01) (.00).4872 .4931 .7570 .03 .3116 .02 .02 .04 .02 .16 .04

(.00)

(.00)

(.00)

.06

(.00)

(.00)

(.00)

(.00)

.7710 .9333 .9334 .7710 .9288 .7646 .7646

.9289

.7570 .9234 .9235

TABLE IV ESTIMATES OF LOG LIKELIHOOD

-1194

λ	(a)	(b)	(c)	(d)	(e)	(f)	(g,
1.5	-2751.31	-2584.67	-2580.22	-2303.24	-2303.23	-177.50	-1775
1.4	-2712.17	-2548.69	-2544.07	-2242.36	-2242.35	-1700.88	-1698
1.3	-2675.43	-2514.70	-2509.89	-2184.01	-2184.00	-1625.14	-1623
1.2	-2641.10	-2482.72	-2477.71	-2128.42	-2128.41	-1550.61	-1548
1.1	-2609.22	-2452.77	-2447.58	-2075.86	-2074.84	-1477.68	-1475
1.0	-2579.79	-2424.91	-2419.50	-2026.59	-2026.57	-1406.88	-1405
0.9	-2552.87	-2399.17	-2393.57	-1980.90	-1980.89	-1338.91	-1337
0.8	-2528.45	-2375.56	-2369.78	-1939.11	-1939.11	-1274.65	-1273
0.7	-2506.58	-2354.15	-2348.22	-1901.57	-1901.57	-1215.17	-1213
0.6	-2487.24	-2334.94	-2328.83	-1868.60	-1868.60	-1161.31	-1160
0.5	, -2470.60	-2318.21	-2311.81	-1840.07	-1840.07	-1114.48	-1114
0.4	-2456.39	-2303.69	-2297.03	-1817.75	-1817.75	-1075.42	-1075
0.3	-2445.12	-2291.09	-2284.46	-1800.55	-1800.55	-1045.15	-1045
0.2	-2435.88	-2280.65	-2274.09	-1787.23	-1787.23	-1038.86	-1038
0.1	-2431.47	-2275.52	-2266.92	-1780.53	-1780.52	-1022.96	-1022
0.0	-2426.51	-2268.93	-2262.17	<u>-1778.64</u>	<u>-1778.64</u>	-1028.76	-1027
-0.1	-2426.33	-2267.13	-2260.53	-1784.11	-1784.11	-1043.58	-1043
-0.2	-2428.74	-2265.79	-2259.36	-1796.64	-1790.64	-1066.68	-1066
-0.3	-2431.75	-2271.82	-2265.64	-1810.28	-1810.28	-1105.29	-1105
-0.4	-2440.42	-2275.28	-2268.09	-1830.43	-1830.48	-1146.91	-1146

Note: (a) = OLS

-2450.64

-0.5

(b) = LSDV with cross-section effects

- (c) = GLS with cross-section effects
- (d) = LSDV with time effects
- (e) = GLS with time effects
- (f) = LSDV with both effects
- (g) = GLS with both effects

-2281.53 -2276.93 -1856.91 -1856.91 -1194.85

with cross-sectional effect, GLS with cross-section effect, LSDV with both effects, and GLS with both effects. These results have demonstrated that the functional parameter estimation method can be integrated with the pooled time-series and cross-section data to improve the specification of a financial relationship.

V. Summary

In this study two alternative techniques to analyze pooled time-series and cross-section data are used to test the importance of firm effect and time effect in the financial analysis. These techniques are also integrated with the functional form parameter estimation method to show the importance of appropriate functional form in handling a pooled time-series and cross-section type econometric model. The data on the electric industry show that both the time effect and cross-section effect are of importance in explaining stock price variation. It is also found that linear form (and/or) log-linear form is not always appropriate in testing the importance of both time effect and firm effect in financial analyses.

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