An Empirical Evaluation of the Predictive Ability of Segment Data

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I. Introduction

Financial statement users have expressed concerns about the ability to assess earnings potential and riskiness of diversified firms as conglomerate mergers and acquisitions increased rapidly during the 1960's. As shown in congressional hearing records and survey, financial analysts and other financial statements users have contended that consolidated financial statements do not provide sufficient informaion to assist in analyzing diversified firms and thus segment data might be important in assessing future prospects of a diversified firm.(1)

As a result of continuing pressure from interested parties, segment reporting requirements have been imposed by the Securities Exchange Commission (SEC)(2) and expanded by the Financial Accounting Standards Board(FASB). The addition of segment information to consolidated financial statements is presumed to enhance the predictive value of accounting information. Their

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(1) For example, based on his survey, Mautz (1968) asserts that "there is virtually no successful way of judging future earnings or profits unless major areas of activity are spelled out in terms of revenue, direct cost, and net proffts." (p. 96)

(2) Securities and Exchange Commission, Securities Exchange Act of 1934 Release No. 8650, 1969.
Securities and Exchange Commission, Securities Exchange Act of 1934 Release No. 9000, 1970.

presumption is well presented in the stated purpose of the FASB's SFAS No. 14.

> The purpose of the information required to be reported by this statement is to assist financial statements users in analyzing and understanding the enterprise's financial statements by permitting better assessment of the enterprise's past performance and future prospects (FASB, 1978; para 5).

However, there have been arguments against the value of segmental information. Those arguments can be summarized into two points: (1) it contains measurement errors due to arbitrary common cost allocation and transfer pricing and (2) there is no objective criterion in segmentation schemes and consistency in segment information across firms. That is, it is claimed that problems related to potential measurement errors and lack of the comparability across firms may impair the relevance of segment information. Thus, opponents caution that disclosure of segment information may mislead financial statement users.

A considerable amount of empirical research has attempted to resolve the arguments on whether segment information is valuable. Although both the costs and the benefits of segment information disclosure should be examined to evaluate the relevance of segment reporting requirement, most studies have only assessed the benefits of segment reporting. The Fineness Theorem of the information literature (e.g., Marshak and Radner, 1971) provides a theoretical basis for the claimed benefits of segment reporting. It states that a finer information system is at least as valuable to decision makers as less fine information system. Thus, many empirical studies focus on whether segment data provide additional information to investors despite potential measurement errors and lack of the comparability of segment information.

The previous studies on the benefits of segment reporting can be summarized into two groups. One group of studies evaluates the impact of segment reporting on investors' ability to predict future earnings, investors' risk assessment, or return distributions of affected firms.(3) However, their findings are contradic-

(3) e.g., see Barefield and Cominsky [1975, as cited in Baldwin(1984)] and Baldwin(1984) for

tory. Many of those studies compare two disclosure environments, voluntary and mandatory, over the periods before and after the disclosure requirements, or evaluate cross-sectional differences between voluntarily disclosing firms and nondisclosing firms prior to the segment reporting requirement. The comparison of the mandatory disclosure environment with the regulation-free environment could provide a good control scheme in research designs. However, it necssarily involves complications due to potential changes in operating characteristics of multidivisional firms between the time periods and self-selection bias in the sampling process.(4) Several other aspects should be also considered for the assessment of a finer information system with changes in return distributions. Examples of these aspects are the cost of information production and disclosure, its impact on the payoff and probability functions at individual level, and wealth transfer problem among firms.

Another group of studies evaluates the value of segment information, focusing on the nature of information rather than merely the act of disclosure.(5) Those studies show how segment information can be used in the investment decision process, especially in future earnings prediction or risk assessment. However, those studies rely on rather simple forecasting models with a limited numbers of sample firms and only a few years of segment data disclosed voluntarily or in compliance with the SEC's reporting requirement.

Since the initial pronouncements of the SEC's segment reporting requirements in 1969 and 1970, the segment reporting requirements have been expanded through the FASB's SFAS No. 14(1976) and Regulation S-K of the SEC (1978). Under SFAS No. 14, segment reporting is also subject to the inde-

changes in financial analysts' predictive ability, Horwitz and Kolodny(1977), Collins and Simmond(1978) for changes in risk assessment and Horwitz and Kolodny(1977), Twombly (1980) and Ajinkya(1980) for changes in return distributions.

(4) Since multidivisional firms had discretion to disclose segment data prior to the segment reporting requirement of the SEC, there might be peculiar characteristics inherent in firms which chose to report segment data.

(5) See Kinney(1971) and Collins(1976) for the accuracy forecasting models, Collins(1975) for private value of segment information as evaluated in a trading strategy in security markets and Kinney(1972) and Mohr(1982) for the use of segment information in risk assessment.

pendent auditors' review, which may improve the overall quality of segment reporting. Segment information has been disclosed for more than a decade since the initial reporting requirement of the SEC. However, whether segment data contain information not available in the consolidated financial statements has not been resolved. Thus, more research on the value of segment information with different perspectives and more reliable data (as explained below) is likely to be worthwhile in addressing the shortcomings of previous research.

The purpose of this research is to provide empirical evidence concerning the predictive ability of segment data disclosed in accordance with SFAS No. 14 as a way to evaluate the benefits of segment reporting requirements. The predictive ability criterion is adopted to evaluate whether segment information can be used to improve information users' ability to predict future earnings, which is considered as one of the common information needs. Although the requirements of segment reporting should be evaluated by considering cost and benefits to both information users and affected firms, the evaluation of potential benefits in terms of future earnings prediction can provide some implications for future accounting policy decisions.

Predictive ability has been defined as "the ability to generate operational implications (i.e. prediction) and to have those predictions subsequently verified by empirical evidence." (Beaver, Kennelly, and Voss; 1968, p. 677) Therefore, the predictive ability of segment information can be evaluated by comparing the actual numbers with forecasts. However, this evaluation of the predictive ability is dependent upon the forecasting models adopted. The forecasting models should be chosen based on whether they are similar to investors' decision models. However, various decision models can be used by investors according to their available information and other resources.

Time series models can be used in evaluating predictive ability because time series models do not require us to specify functional relationships with other variables and theses models need only the past history of the variables to be

predicted. However, even the accuracy of time series models may be dependent upon the characteristics of underlying processes. Moreover, time series behavior of consolidated earnings and segment earnings of diversified firms has not been specifically examined despite considerable amount of time series research on accounting earnings numbers. Thus, this study uses general classes of Box-Jenkins' autoregressive integrated moving average (ARIMA) models as forecasting models for segment earnings and consolidated earnings and consolidated earnings.

The available time series observations for segment earnings are too small to apply Box-Jenkins time series analysis since segment reporting has been required on annual basis only since 1970. Thus, in this study time series models for segment earnings are identified and estimated from industry aggregated earnings series under the assumption that earnings of segments operating in the same industry follow an identical time series process. Earnings are presumed to be decomposable into two components; a firm-specific component which is affected by firm-specific factors, and an industry-specific component which is affected by external factors (macroeconomic and industry factors). If a multidivisional firm operates in several industries, its consolidated earnings are differently affected by industry or macroeconomic factors. Thus, if segment data contain information in addition to that of consolidated data, segment data are presumed to reflect the effects of external factors on earnings better than consolidated data. The accuracy of forecasting models incorporating segment data is compared to that of models incorporating consolidated data only.

II. Earnings Forecasting Models and Hypotheses

1. Earnings Forecasting Models

Previous analytical studies have suggested that the "gains" from disaggregation exist if (1) some of parameters of time series models for the disaggregated series are not identical or (2) non-zero serial correlations among disaggregate

series are present. These necessary conditions for potential gains from disaggregation may be very likely to be met in segment earnings series. [e.g., Nelson, 1975; Rose, 1977; Wei and Abrabam, 1981; Hopwood, Newbold, and Silhan, 1982] However, those conditions are derived under the strict assumption that the underlying processes are known without error. Thus, the gains from using segment data may be also dependent upon whether the potential errors in the specification of models for consolidated earnings series exceed those for segment earnings series.

An important part of segment reporting for a multidivisional firm is to disaggregate its overall operational results by its lines of business according to industry categories. Previous empirical research suggests that there exist commonalities of individual firms' earnings in the same industry. [e.g., Brown and Ball, 1967; Brealy, 1968; Gonedes, 1973; Magee, 1974; Foster, 1977] It has been also suggested that accounting earnings of firms in the same industry follow similar time series behavior since the operational characteristics of firms in the same industry are determined by similar factor input and output markets. [e.g., Dopuch and Watts, 1972; Lev, 1983; Lorek, Icerman, and Abdulkader, 1983]

This study utilizes the industry-specific time series models as forecasting models for segment earnings in order to overcome limited time series observations of segment data. The underlying presumption is that consolidated earnings of a multidivisional firm follows a more complex process than its segments' earnings and can be better analyzed and predicted using the differential industry-specific time series properties of earnings of its segments. Earnings of segments in the same industry are assumed to follow an identical time series process which is specific to the industry.

(1) The Effects of Industry Factors on Earnings

Factors affecting earnings of individual firms can be classified into two groups; firm-specific factors and external factors (industry-wide and economy-wide factors). Some examples of external factors are changes in inflation rates,

macroeconomic policies, technologies or consumer tastes pertaining to specific industries, and input and output prices. Differences in operational and financial decisions, management skill, and the choice of accounting methods can be firm-specific factors.

The effects of common external factors on a firm's accounting earnings have been found significant. For example, using a two-digit level of SIC aggregation as the definition of an industry, Brown and Ball(1967) find that industry-wide commonalities account for 10~15 percent of the variability of a firms' annual earnings after 35~40 percent of explanation by economy-wide commonalities. Brealey [1968, as cited in Foster (1978)] uses a three-digit level of SIC aggregation and finds that on average 21 percent of the variability of earnings is explained by industry commonalities in addition to 21 percent of explanation by economy-wide factors. Foster (1978) finds 18 percent of the variation in net income to be from industry influence after 27 percent is accounted for by economy-wide factors. Even multidivisional firms may be assigned to one industry group according to their main lines of business regardless of the level of fineness in industry classification. Thus, the influence of industry factors may be underestimated if many multidivisional firms are included in the sample.

The evidence about the existence of industry and economy-wide influences on accounting earnings can be utilized to describe potential problems in applying time series analysis to consolidated earnings series of multidivisional firms. Suppose that earnings of a segment or a firm are decomposable into two components, a firm-specific component which is determined by firm-specific factors and an industry-specific component which is determined by external factors, as follows:

$$SE_{1t}=FE_{1t}+IE_{1t} \qquad (\text{II}.1)$$

where

SE_{1t}=segment earnings for segment 1 (or single segment firm 1) at time t

FE_{1t}=firm-specific component for segment 1

IE_{1t}=industry-specific component for segment 1

Then we can show that the earnings of a multidivisional firm is generated from a more complex process than the earnings of a single segment. Take one simple case where a multidivisional firm operates in two unrelated industries. If the sum of two segment earnings series is equal to consolidated earnings series, then

$$\begin{aligned} E_t^m &= SE_{1t}+SE_{2t} \\ &= (FE_{1t}+IE_{1t})+(FE_{2t}+IE_{2t}) \\ &= (FE_{1t}+FE_{2t})+(IE_{1t}+IE_{2t}) \\ &= FE_t+(IE_{1t}+IE_{2t}) \end{aligned} \qquad (\text{II}.2)$$

where

E_t^m=consolidated earnings of a multidivisional firm at time t

Granger and Morris (1976), Rose (1977), Granger and Newbold (1979) provide analytical proof that the sum of two series results in a more complex series than component series when component series are independent each other and stationary. That is,

if $X_t \sim ARMA(p, m)$, $Y_t \sim ARMA(q, n)$, and $Z_t = X_t + Y_t$

then $Z_t \sim ARMA(x, y)$

where $x \leq p+q$ and $y \leq \max(p+n,\ q+m)$

(Granger and Morris; 1976)

The reduction of parameters can occur in "coincidental" situations. The sum of two series is identical to its component series, only when two series are identical process, which is called "perfectly coincidental" situations. To simplify the case, assume that FE_{1t} and FE_{2t} follow an identical process. Then, FE_{1t} in (II.1) and FE_t in (II.2) follow the same process. Although two industry component series cannot be perfectly independent because of the existence of economy-wide influence, consolidated earnings series (II.2) will follow a more complex process than its segment (II.1). This can be extended to the comparison between earnings series of a single-segment firm and a multi-segment

firm. In this case, however, the firm-specific component FE_t may be different across firms. Thus, we may state that on average earnings of multi-segment firms are more complex than those of single-segment firms within the same industry as the multi-segment firms.

When systematic stochastic processes are filtered [e.g., parsimonious ARIMA models are fitted as suggested by Box-Jenkins(1976)] for consolidated earnings series and segment earnings series, more random effects or noise are likely to remain for consolidated earnings series than for segment earnings series. However, the relative efficiency of estimation and prediction for segment earnings models versus consolidated earnings models is also affected by measurement errors. Thus, the question is whether gains from using segment data (in terms of specifying industry effects on earnings) exceed measurement errors of segment data and potential errors from the misspecification of segment earnings models.

(2) Industry Time Series Models

Extension of the above analysis can be useful in utilizing industry-specific time series characteristics in formulating forecasting models for segment earnings.[6] If the industry-specific time series models can be identified and estimated, use of those models for segment earnings series may reduce the potential errors of misspecification for time series models for consolidated earnings series.

One way of identifying and estimating the industry-specific time series models is to use industry aggregated earnings series. As in formulating an industry index, the industry aggregated earnings series can be constructed by aggregating (or by aggregating with weighting) earnings of firms in the same industry.

(6) This kind of framework is also suggested by Granger and Morris (1976). They suggest;

> If each component consists of two parts, the first a factor common to all components representing the influence of the whole economy on them and the second a factor relating just to the particular component and independent of the economy-wide factor, then simple models can be assumed for each factor and on aggregation the more general form of the basic model involving the sum of several series will apply. Such factor models have been successfully used with series of stock markets prices and firms' earnings. (p. 251)

The time series characteristics of industry aggregated earnings series can be shown by taking a simple example. Suppose that two single segment firms make one industry. Then industry aggregated earnings can be expressed as follows:

$$\begin{aligned} IAE_t &= E_{1t} + E_{2t} \\ &= (FE_{1t} + IE_{1t}) + (FE_{2t} + IE_{2t}) \\ &= (FE_{1t} + FE_{2t}) + (IE_{1t} + IE_{2t}) \quad (\text{II}.3) \end{aligned}$$

where

E_{1t}=earnings of firm 1 at time t

IAE_t=industry aggregated earnings at time t

Since industry components of earnings, IE_{1t} and IE_{2t}, are affected by industry-common factors, they will follow an identical process. Thus, the sum of two industry-specific components leads to the same process as its components. Thus,

$$\begin{aligned} IAE_t &= (FE_{1t} + FE_{2t}) + IE_t \\ &= \Sigma FE_{1t} + IE_t \quad (\text{II}.4) \end{aligned}$$

If we assume that the firm-specific component of earnings (FE_{1t}) follow a specific time series process such as a moving average process or mean reverting process or white noise process,(7) then the industry-aggregated earnings series will follow a process similar to the idustry-specific earnings process. For example, if FE_{1t} and FE_{2t} in (II.4) follow a MA(1) process and IE_t follows a AR(1) process, then (II.4) will follow

$$\begin{aligned} IAE_t &\sim MA(1) + MA(1) + AR(1) \\ &= MA(1) + AR(1) \end{aligned}$$

since $MA(m) + MA(n) = MA(y)$, where $y \leq \max(m, n)$

(Granger and Morris; 1976).

Segment earnings in the same industry will follow a similar process. That is,

(7) There are some indications that firm-specific earnings components follow one of these processes. For example, firm-specific decisions such as current expenditure on research and development or on advertising some products will affect future earnings for a few years, which can be described well by moving average process. On the other hand, some firm-specific events such as union strikes may have no memory in future earnings, which can be described by mean reverting process.

$SE_t \sim MA(1)+AR(1)$. The only difference between IAE_t and SE_t is parameters of firm-specific component series. If we increase the number of firms in the industry index, the parameters for aggregated firm-specific component earnings (ΣFE_{it}) series will become average values. Similarly, if component series follow mean reverting processes or white noise processes, their sum will follow the same process as the component series. Thus, models for industry-aggregated earnings can proxy for models for segment earnings if we assume that unrelated firm-specific components follow a process such as moving average process of the same order, mean reverting process or white noise.

Making the assumption that earnings of segments or single-segment firms operating in the same industry follow the identical time series process will lead to the results similar to the above. That is, the sum of component series will follow the same process as its components. Since the aggregation of earnings in the same industry will make unrelated firm-specific components into noise, aggregated earnings series may be close to the unknown industry-specific process. However, in the case where firm-specific components follow widely different processes across firms, the accuracy of earnings prediction based on the identified and estimated industry-specific models may be affected by how large portion of earnings is unobservable firm-specific component.

(3) Earnings Forecasting Models

This study uses time series models for industry aggregated earnings (S1) as the primary forecasting model for segment earnings. The assumption imposed is that the earnings of segments operating in the same industry follow an identical process. The industry-specific time series models are not presupposed. Rather, the general classes of Box-Jenkins' ARIMA models are fitted to identify and estimate industry-specific models. The difference in varying magnitude of series across segments are assumed to be reflected in constant terms.

The random walk model and the random walk with drift model (S2 and S3, respectively) are most widely used as earnings expectation models for their simplicity and support from previous studies. They are included as

benchmarks to evaluate the prediction accuracy of segment-specific forecasting model S1.

The forecasting models for segment earnings are summarized as follows;

S1. Industry-specific ARIMA Model

$E(SE_{i,j,t})$ = segment earnings predicted by j industry specific time series model

S2. Random Walk with Drift (RWD) Model

$E(SE_{i,j,t}) = SE_{i,j,t-1} + d_{i,j}$

S3. Random Walk (RW) Model

$E(SE_{i,j,t}) = SE_{i,j,t-1}$

where

$SE_{i,j,t}$ = segment earnings for firm i, industry j at time t

$d_{i,j}$ = estimated drift term for segment j of a firm i

In order to evaluate the predictive ability of segment information, the aggregate of segment earnings forecasts is compared with the forecasts from consolidated-based models which incorporate only past consolidated earnings. The prediction accuracy comparison is a joint test for the predictive ability of segment data and the validity of forecasting models. Thus, the use of the same class of forecasting models for two sets of data can separate the effects of the disaggregation on the prediction accuracy difference from the effects of model choice. Since the primary segment-based model is the industry-specific Box-Jenkins' ARIMA model, the firm-specific ARIMA model (C2) is used as the primary consolidated-based forecasting model to control the effects of forecasting model choice on the prediction accuracy comparison. That is, the effects of aggregation of different segment earnings series is presumed to be reflected in the relative prediction accuracy of segment-based models versus consolidated-based models.

According to previous studies on time series properties of annual earnings, predictions from the RW model (C3) and the RWD model (C4) are used as benchmarks. Since models C3 and C4 are simple models, the prediction

accuracy of these models can be used in evaluating the cost effectiveness of segment-based models. The sum of segment-based random walk processes also follows a random walk process. Thus, the aggregates of forecasts of models S2 and S3 are identical to those of consolidated-based models C3 and C4 respectively.

The forecasting models for consolidated earnings are summarized as follows:

C1. Segment-based Model

$E(CE_{i,t}) = \Sigma E(SE_{i,j,t})$

C2. Firm-specific ARIMA Model

$E(CE_{i,t})$ = predicted by i firm-specific time series model

C3. Random Walk with Drift (RWD) Model

$E(CE_{i,t}) = CE_{i,t-1} + d_i$

C4. Random Walk (RW) Model

$E(CE_{i,t}) = CE_{i,t-1}$

where

$E(SE_{i,j,t})$ = predicted segment earnings from models S1.

$CE_{i,t}$ = consolidated earnings for firm i

d_i = drift term for firm i

2. Statement of Hypotheses

Whether segment information can provide a more accurate prediction for future earnings is the specific question to be addressed in this study as a way to evaluate the potential benefits of segment information to investors. Thus, the prediction accuracy of segment-based earnings forecasts is compared to that of consolidated-based earnings forecasts. If we do not consider the effects of the model choice on the prediction accuracy, the question can be whether the forecasts based on the past segment earnings data are more accurate than those based on the past consolidated earnings data. It can be stated formally in a mean squared error sense in the following hypothesis.

H_0;

$$E[CE_t - E(CE_t | CE_{t-1}, CE_{t-2}, \cdots)]^2$$

$$=E[CE_t - E(CE_t | SE_{t-1}, SE_{t-2}, \cdots)]^2$$

H_A;

$$E[CE_t - E(CE_t | CE_{t-1}, CE_{t-2}, \cdots)]^2$$
$$< E[CE_t - E(CE_t | SE_{t-1}, SE_{t-2}, \cdots)]^2$$

where CE_t is consolidated earnings at time t

SE_t is a vector of segment earnings at time t

Consolidated earnings forecasts from the firm-specific ARIMA models are compared with those from the segmets-based (industry-specific) ARIMA models. As discussed in the prior section, use of disaggregated (segment earnings) series may provide more accurate forecasts for consolidated earnings than aggregated (consolidated earnings) data. The gains from using segment earnings data will be present if segment earnings data contain small measurement errors and reflect the industry-specific time series characteristics, and each segment in a firm does not follow an identical or similar process. However, the above hypothesis is not testable on an individual firm basis since we have very limited number of time series observations and thus only a few test periods. Thus, this study is designed to test the prediction accuracy on a cross-sectional basis. The hypothesis can be restated in a testable form as follows:

H_0; On average, the segment-based ARIMA models do not provide more accurate forecasts for future consolidated earnings than the consolidated-based ARIMA models.

H_A; On average, the segment-based ARIMA models provide more accurate forecasts for future consolidated earnings than the consolidated-based ARIMA models.

As suggested by several studies, even though the quality of forecasting models is identical, the potential gains from using segment earnings data are dependent upon the time series properties of segment earnings series. That is, the aggregation of similar and related time series processes can induce simpler time series process than might generally be expected (the 'coincidental'

situation). Thus, the potential gains from disaggregation are more likely for firms operating in heterogeneous industries (in terms of time series properties). However, the composition of lines of business varies widely across multidivisional firms. Thus, two potential factors are identified and examined to evaluate the predictive ability of segment earnings more carefully.

In the prior section, it is suggested that the gains from using segment information come from the reduction in misspecification errors of firm-specific time series models for consolidated earnings. That is, the aggregate of unrelated processes is presumed to be a more complex process or a noise process which cannot be filtered well with parsimonious ARIMA models. Thus, as the number of unrelated segments being aggregated into consolidated earnings increases, the consolidated earnings will follow a more complex process and the gains from using segment information will increase. For example, suppose that two firms, A and B, adopt the same level of industry segmentation (e.g., in three-digit SIC code level) and firm A has two segments while firm B has one more segment in addition to the two segments which are identical to firm A. Then the gains from using segment information will be larger for firm B than for firm A. That is, as the number of segments increase, the prediction gains from using segment earnings series will increase. Thus, the main hypothesis stated above can be divided into following sub-hypothesis.

H_{01}; The relative prediction accuracy of the segment-based ARIMA models versus the consolidated-based ARIMA models is not different between firms with different number of segments.

H_{A1}; The relative prediction accuracy of the segment-based ARIMA models versus the consolidated-based ARIMA models for firms with more segments is larger than that for firms with fewer segments.(8)

(8) On the condition that the main null hypothesis is rejected, this alternative sub-hypothesis can be restated as follows;

H_{A1}; The gains in the prediction accuracy from using segment-based models over consolidated-based models for firms with more segments are larger than the gains for firms with fewer segments.

Nelson (1975) and Rose (1977) suggest that the gains from using disaggregated information is maximized when the variance ratio of forecast errors is equal among the components. If we assume that the efficiency of the identification and the estimation is not different across components despite varying component-specific models, the variance ratio of forecast errors may be determined by the relative size of the components. Intuitively, its application to segment earnings appears to be appropriate. For example, suppose that each of two firms, A and B, has two unrelated segments which are similar except size. If firm A's main segment is so dominant that it contributes 90 percent of consolidated earnings while firm B's main segment covers 51 percent of its consolidated earnings, then the prediction gains from using segment information for firm A are relatively smaller than those for firm B. The relative size among multiple segments is hard to capture in a single measure. A proxy can be the relative size of the main segment in a firm since the contribution of the main segment to consolidated earnings is more significant than other segments. Thus, as the relative size of the main segment of a firm is getting larger, the prediction gains from using segment earnings series may increase. This can be stated as following sub-hypothesis:

H_{O2}; The relative prediction accuracy of the segment-based ARIMA models is not different between firms with different relative size of the main segment.

H_{A2}; The relative prediction accuracy of the segment-based ARIMA models versus the consolidated-based ARIMA models for firms for which the main segment is large relative to other segments is greater than that for firms of which main segment is small relative to other segments.

III. Research Design and Methodology

1. Operating Income as an Object of Prediction

The segment earnings figure disclosed in accordance with SFAS No. 14 is

operating earnings. It excludes general corporate expenses, interest expenses, income taxes, and gain or loss on discontinued operation, extraordinary items, etc. The aggregate of segment operating earnings is not identical to consolidated operating earnings disclosed in the income statement, which does not exclude general corporate expenses. That is, consolidated operating earnings before general corporate expenses had not been disclosed before segment reporting was required. Since more time series observations are needed to apply ARIMA models, consolidated operating earnings after depreciation expenses and general corporate expenses (Compustat items; #13～#14) is predicted. General corporate expense item is treated as a component in predicting consolidated operating earnings. Consolidated operating earnings of a firm are predicted by aggregating its segment earnings forecasts and forecasts of its general corporate expenses.

The use of operating earnings as an object of prediction will be helpful in detecting industry-specific time series properties because a number of firm-specific items such as interest expense (or revenue) and extraordinary items are excluded. That is, the operating earnings series may be less affected by firm-specific factors such as capital structure, capital intensity and unusual firm-specific events. As discussed in the prior chapter, the industry-specific time series models may proxy for segment earnings better when we reduce the firm-specific component of earnings.

2. Sample Design

(1) Sample Selection for Multidivisional Firms

The following steps and criteria are adopted for the selection of sample multidivisional firms and for data collection.

(i) The Value Line file (1982) is initially used to identify multidivisional firms which have disclosed segment information. Among those multidivisional firms in the Value line file, 175 manufacturing firms are selected according to the following criteria:

ⓐ Firms for which the fiscal-year-end is December 31 are selected to preserve the comparability in prediction accuracy tests.

ⓑ Firms operating in more than one industry by the two-digit SIC code level are selected since more diversified firms are more likely to have unrelated segments and thus to have more gains from using segment information.

ⓒ Firms for which segmentation schemes are too broad (e.g., roughly described as consumer goods or industry products) are dropped since the industries to which segments of those firms belong cannot be identified.

(ii) 109 firms are left after after checking the Compustat files (1975 and 1985) for 25～30 years' observations (from 1960～1984 to 1955～1984).

(iii) The data base of the National Automated Accounting Research System (NAARS) and published annual reports are examined. Annual reports for 89 firms are available. 8 years' segment data for those firms, which have been disclosed in accordance with SFAS No. 14, are collected (1977～1984). 18 firms are dropped for one of the following reasons:

ⓐ Segmentation schemes have been changed during the period 1977～1984.

ⓑ More than 25% of total sales (based on operational results in 1984) are coming from oversea operations. Since industry-specific time series are obtained by aggregating earnings of U.S. industry firms, industry-specific models may not be well fitted to industry segments of those firms of which oversea operations generate considerable portion of consolidated earnings.

ⓒ Inter-segment transactions cover more than 15% of total sales (based on operating results in 1984). This criterion is imposed to eliminate firms for which segments are closely interacting since segment earnings of those firms are more likely to be related and may have potential problems in measurement due to discretionary transfer pricing.

The remaining 71 firms are used as final sample. These sample firms are not selected randomly. It should be also noted that sample selection procedures are subject to well-known survivorship bias due to data requirements for long periods.

The distributions of sample firms by industry and the number of segments are shown in Table Ⅲ.1. Segments of which industries cannot be identified

Table III. 1. Distribution of Sample Firms by Industry and by Number of Segments

Sic	Description	Freq.	Number of Segments		
			two	Three	Four
20	Food	3	3	0	0
21	Tobacco	2	1	0	1
24	Lumber and Wood	3	3	0	0
26	Paper	6	3	3	0
28	Chemicals	11	1	5	5
29	Petroleum	2	2	0	0
30	Rubber and Plastic	3	1	1	1
32	Stone, Clay, and Glass	7	5	2	0
33	Primary Metal	9	3	6	0
34	Fabricated Metal	4	2	2	0
35	Machinery	7	5	2	0
36	Electric and Electronic	6	1	5	0
37	Transportation Equip.	4	1	2	1
OTHERS		4	1	1	2
	Total	71	32	29	10

(e.g., described as others or misc.) are not counted in the number of segments. Table Ⅲ.2 shows the distributions of size (sales) of sample firms and weights of the main segments of sample firms as a percentage of consolidated sales and as a percentage of the sum of absolute segment earnings.

(2) Formulation of Industry Aggregated Series

All industries to which segments of sample firms belong are identified by three-or four-digit SIC codes. Those identified industries are classified into 40 industry groups according to the classification scheme as applied in *U.S. Industrial Outlook*. December fiscal-year-end firms which belong to those industries and of which operating earnings numbers are available for 23 years (1961～1983) are selected using Compustat Files of 1981 and 1984.[9] Calendar-year firms are used so that the cross-sectionally aggregated series contain the

(9) If longer time series observations such as 30 years are required, the number of firms to be included in the formulation of aggregated series is reduced by 30～40%. The number of firms may be also reduced because a considerable number of firms are classified into different industries during the longer time periods.

Table III. 2. Distribution of Sample Firms by Sales Amount and by Weight of Main Segment

	Weight of Main Segment (Ratio of Sales)	Weight of Main Segment (Ratio of Earnings)	Sales Amount (in $ mil.)
Mean	0. 5790	0. 8134	2420. 4
Minimum	0. 2708	0. 3509	20. 5
25%	0. 4784	0. 4309	594. 9
Median	0. 5955	0. 5992	1386. 2
75%	0. 6705	0. 8655	4160. 5
Maximum	0. 9186	6. 5000	14890. 0

influences of industry-wide factors for each time period. Those firms of which industries are classified differently between two Compustat files are dropped to enhance the homogeneity of firms belonging to the same industry.

The number of firms included in the industry aggregated earnings series varies across industries. The inclusion of more firms would be helpful in averaging out firm-specific variation. However, the number of firms belonging to each industry are different by industry. Thus, all available firms in each industry group are used in the formulation of aggregated series without controlling the number and the size of firms.

3. Time Series Methodology

The Box-Jenkins methodology is well described in the time series literature [e.g., Box and Jenkins, 1976; Nelson, 1973; Granger and Newbold, 1977; and Pankratz, 1983]. Thus, a detailed description of the Box-Jenkins methodology is not provided. Rather, it points out some limitations of this study in employing the Box-Jenkins ARIMA models and describes the procedures adopted in this study.

(1) Time Series Observations

The Box-Jenkins methodology suggests that at least fifty or more observations should be used to identify and estimate a suitable model for the time series. Although a large sample size is desirable, ARIMA models have been applied for modest sample size by researchers. [e.g., Dopuch and Watts, 1972; Lorek, McDonald, and Patz, 1976; Albrecht, Lookabill, and Mckeown, 1977]

The effects of small sample size on the estimation and prediction efficiency are examined by Nelson (1974) and Lorek and McKeown (1978). Since this study applies ARIMA models on less than thirty years' observations of firm-specific earnings and industry aggregated earnings, special cautions are needed in the specification and the estimation of the models. In order to reduce the possibility of misspecification, several possible parsimonious ARIMA models are simultaneously examined in the identification procedure.

(2) The Procedures for ARIMA Model Specification

This study employs ARIMA models for samples of moderate size. Limited number of time series observations may lead to incorrect identification and inefficient estimation of ARIMA models. Thus, the Box-Jenkins iterative approach is implemented with caution. In this study, the identification, estimation and diagnostic checking are made by considering several alternative models to choose the most appropriate model. The procedures adopted in this study for the specifications of ARIMA models are as follows.

(i) The sample ACF, PACF, and inverse autocorrelation function (IACF) are examined to identify possible models.

(ii) Competing models are estimated using ARIMA procedure in SAS ETS (version 5). There are several estimation methods such as maximum likelihood method, conditional least square method, and unconditional least square method. Although there have been arguments about which method is more efficient for relatively small sample size [e.g., Nelson, 1974; Dent and Min, 1978; Ansley and Newbold, 1980; and Davidson, 1981], there has been no consensus. The maximum likelihood method is favored by Box and Jenkins (1976) and Dent and Min (1978). This study uses the maximum likelihood method in the estimation process. In the process, the conditions of the stationarity and the invertability are checked. If those conditions are violated, the model is rejected.

(iii) The final model for each series is chosen according to following two complementary criteria. (a) The autocorrelations in the residuals from the estimated models are checked using a Chi-squared test. (b) The model with

minimum Akaike Information Criterion (AIC) is chosen among competing models.

For checking the autocorrelations in the residuals, this study uses the test statistic (named here as LBQ) suggested by Davies, Triggs, and Newbold (1977) and Ljung and Box (1978), which modifies BPQ adjusting for small sample bias:[10]

$$LBQ = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}r_k^2(a) \qquad (\text{Ⅲ}.1)$$

where n is the number of observations used to estimate the model, K is the number of residual autocorrelations considered, and $r_k^2(a)$ is the autocorrelation of the k-th residual. The LBQ approximately follows a Chi-squared distribution with $(K-p-q)$ degree of freedom, where p and q are numbers of auregressive parameters and moving average parameters respectively in the estimated model. In this study, the LBQ for 12 residual autocorrelations are checked.

Akaike (1974) suggests that identification of models can be treated as an estimation problem. That is, the choice of model is formulated as maximizing following information measure, named as Akaike Information Criterion (AIC).[11]

$$AIC(\theta) = -2\log[\text{maximum likelihood}] + 2m \qquad (\text{Ⅲ}.2)$$

where θ is a set of p and q values

$m = p+q$, the total number of coefficients of the model to be estimated

(Ⅲ.2) can be restated under the assumption of normal distribution of residuals

(10) Box and Pierce(1970) suggest the test statistic, named as 'portmanteau' test of fiit or as Box-Pierce Q-statistic (BPQ), for checking whether the residuals of the estimated model are independent.

$$BPQ = n\sum_{h=1}^{k} r_k^2(a)$$

BPQ has been used in many studies as a way of diagnostic checking. However, as Davies, Triggs, and Newbold (1977) suggest, the significance levels of BPQ are likely to be much lower than predicted asymptotic theory for moderate sample size. That is, with the BPQ test, the ARIMA models estimated with relatively small sample are more likely to be regarded as adequate ones.

(11) See Akaike(1974) for details in deriving AIC and see Dharan(1983) for its application to accounting in selecting earnings time series models.

as follows.

$$AIC(\theta) = N \log(s^2) + 2m \qquad (\text{III}.3)$$

where s^2 is the estimate of the residual variance

The model which maxizes the criterion (Ⅲ.2) or minimizes (Ⅲ.3) is selected as the most appropriate model among competing mmodels. The use of AIC in model specification favors parsimonious models since the increase in parameters should result in a reduction in AIC due to reduction of residual variance. Since this study employs ARIMA models on small sample size, the AIC can be useful in selecting the parsimonious models.

(3) Time Periods for Estimation and Prediction

The years 1983～1984 are used as the holdout periods for testing the relative prediction accuracy among competing models. One-year-ahead forecasts from all models are used in prediction accuracy tests.

ARIMA models are identified and estimated separately for one-year-ahead prediction of 1983 earnings and 1984 earnings. About 80 percent of the firm-specific ARIMA models for consolidated earnings series are estimated based on 28 years' observations (1955～1982) and 29 years' observations (1955～1983) while some firm-specific models are identified and estimated based on minimum 23 years' and 24 years' observations. ARIMA models for industry aggregated earnings series are identified and estimated based on 22 years' (1961～1982) and 23 years' (1961～1983) observations, respectively.

The drift term of the RWD model is estimated from 6 years' observations (1977～1982 for forecasts of 1983 earnings and 1978～1983 for forecasts of 1984 earnings) for segment earnings series. On the other hand, 10 years' past observations before the prediction year are used to estimate the drift term of the RWD model for consolidated earnings series, following the suggestion by Watts and Lev(1976).

(4) Procedures for Segment-Based Forecasting

This study assumes that earnings series of a segment follows the same ARIMA model as industry aggregated earnings except constant terms. It simply

applies the estimated parameters of an industry-specific ARIMA model in forecasting segment earnings without re-estimating parameters based on sample segment earnings series. The following steps are taken to forecast segment earnings numbers.

(i) All the industry-specific ARIMA models are inverted so that the process can be expressed in terms of the current disturbance and past observations only.

(ii) The mean of the series is calculated based on all available past observations of segment earnings This mean is used to estimate the constant terms for each segment earnings series.

(iii) Forecasts of segment earnings are obtained by using past observations and autoregressive parameters and constant terms.

(iv) General corporate expense (and other adjustments, if needed) are predicted with the random walk model. Earnings of segments of which industries are not identified are also predicted with the random walk model.

(v) Finally, consolidated earnings forecasts are obtained by summing forecasts of segment earnings and general corporate expense.

4. Test Design

(1) Measure of Forecast Errors

Absolute Relative Error (ARE) is used as the primary forecast error measure to evaluate the prediction accuracy of competing forecasting models. ARE can be expressed as follows;

$$ARE_{i,m,t} = \left| \frac{E(X_{i,m,t}) - X_{i,t}}{X_{i,t}} \right|$$

where

$E(X_{i,m,t})$ = predicted segment or consolidated earnings for segment or firm i, forecasting model m, and fiscal year t

$X_{i,t}$ = actual segment or consolidated earnings for segment or firm i and fiscal year t

If actual earnings numbers are close to zero, even small difference in forecasted numbers can be magnified and significantly influence mean statistics. Thus, an

alternative forecast error measure [named here as "restricted absolute relative error (RARE)"] is also used to reduce the potential effects of outlier ARE's caused by small actual numbers. That is, if ARE's are greater than 1.0, those ARE's are replaced with 1.0. While the 'unrestricted' ARE assumes a linear loss function for forecast errors, the 'restricted' ARE assumes a constant loss function after ARE exceeds 1.0.

The rank of forecast errors among competing models is also used to eliminate the effects of outliers and to evaluate competing models all together. In computing the rank measure, the most accurate forecast is given a score of one and the next accurate forecast is given a score of two, and so on.

(2) Test Design

Employing the ARE as the accuracy measure, the main hypothesis can be formulated in the following operational form:

$$H_0 : MARE_c = MARE_s$$

$$H_A : MARE_c > MARE_s$$

where

$MARE_c$ = the mean ARE of the consolidated-based model across sample firms (and over test periods)

$MARE_s$ = the mean ARE of the segment-based model across sample firms (and over test periods)

The sub-hypotheses can be formulated in operational forms as follows:

$$H_{01} : \mu_{c-s,1} = \mu_{c-s,2}$$

$$H_{A1} : \mu_{c-s,1} > \mu_{c-s,2}$$

$$H_{02} : \mu_{c-s,3} = \mu_{c-s,4}$$

$$H_{A2} : \mu_{c-s,3} > \mu_{c-s,4}$$

where

$\mu_{c-s,1}$ = the mean of differences in ARE between the consolidated-based model and the segment-based model across sample firms within subgroup i (and over test periods), $i = 1, 2, 3, 4$

The main hypothesis and sub-hypotheses stated above are tested with the

paired comparison t-test. However, the parametric paired t-test may be inappropriate when distributional assumptions are violated because of potential outliers in ARE metrics as noted earlier. Thus, this study also adopts the nonparametric test for paired comparisons of competing models, the Wilcoxon Matched-Pairs Signed-Ranks Test, which is comparable to the parametric paired t-test. In addition to the paired comparison of competing models, this study also checks whethert the predictive ability of all forecasing models (C1~C4) are different from one another. Friedman's Analysis of Variance by Ranks test is used with the rank measures.

IV. Data Analysis

1. Identification and Estimation of Models

(1) Industry-specific ARIMA Models

Based on time plots of aggregated earnings series and sample autocorrelation functions, industry aggregated series are differenced to obtain stationary series. The first-order differencing is needed for 90 percent of the earnings series of sample industries to meet the stationarity condition. The Akaike Information Criterion (AIC) is used to choose the best model for each sample series given the conditions. Since AIC favors parsimonious models, the identified and estimated models have less than four coefficients (autoregressive coefficients and/or moving average coefficients).

The re-identification and re-estimation of the industry-specific models, however, suggests that some of the identified and estimated models are not stable. The value and the significance level of parameters of models identified and estimated with 1961~1982 earnings data are changed when 1961~1983 earnings data are used. When their original series and differenced series are examined, it appears to be caused by some serious outliers in 1980's. That is, the industries of which estimated ARIMA models are not stable over two estimation periods experienced sharp declines in earnings in the recession period of 1981 or 1982

Table IV. 1. Summary of Identified and Estimated Industry-Specific ARIMA Models

Models	(1)	(2)	(3)
AR	3	0	1
IAR	14	5	10
IMA	4	2	1
Total	21	7	12

(1) Models of which estimated parameters are consistently significant for two test periods.
(2) Models of which parameters' significance levels are changed between two test periods.
(3) Models of which estimated parameters are consistently insignificant between two test periods.

and sharp increase in the recovering period of 1982 or 1983. Thus, the differencing of those series may cause the non-constant variance problem because of the serious variation in 1980's. The higher order differencing or other forms of transformation (e.g., transformation into percentage change term) cannot resolve the problem since it may be related to the problem of small sample size. Thus, industry-specific ARIMA models are identified and estimated without any transformation other than differencing to meet the stationarity condition.

As shown in Table IV. 1, the autoregressive (AR) models are more frequently estimated than the moving average (MA) or the autoregressive and moving average (ARMA or ARIMA) models. The series which are close to a random walk process are estimated with the AR models because the MA models are not well estimated based on moderate sample size with the maximum likelihood method when the parameters of the MA models are close to zero (Nelson; 1973). Earnings series of nine industries out of forty sample industries appear to follow a random walk process since their estimated autoregressive parameters are close to zero and insignificant for both estimation periods. Diagnostic checking shows that identified and estimated models are adequate at reasonable level of confidence. No industry earnings series has significant residual autocorrelations at the 20 percent significance level.

(2) Firm-specific ARIMA Models

For two thirds of sample firms, their consolidated earnings series need to be differenced to have stationary series. However, the re-identification and re-

Table IV. 2. Summary of Identified and Estimated Firm-Specific ARIMA Models

Models	(1)	(2)	(3)
AR	19	1	2
IAR	10	8	11
MA	1	1	0
IMA	9	2	5
ARIMA	2	0	0
Total	41	12	18

(1) Models of which estimated parameters are consistently significant for two test periods.
(2) Models of which parameters' significance levels are changed between two test periods.
(3) Models of which estimated parameters are consistently insignificant between two test periods.

estimation reveals the problem of the non-stationarity of estimated models as discussed in the prior subsection. For 11 firms out of 71 sample firms, their differenced earnings series are affected by some outliers in the 1980's and thus the value and the significance level of estimated models have changed seriously. The identified and estimated ARIMA models for sample firms are summarized in Table Ⅳ. 2.

As summarized in Table Ⅳ. 2, the autoregressive models are more frequently identified than the moving average models and the mixed models such as ARMA and ARIMA models. For 16 firms out of 71 sample firms, the parameters of identified models are consistently insignificant and their values are close to zero, which may be considered as following a random walk process.

2. Results of Prediction Accuracy Test

Prediction accuracy is measured using three different forecast error measures: (a) absolute relative forecast error (ARE), (b) restricted absolute relative forecast error (RARE), and (c) rank of ARE's across competing models. Consolidated earnings are predicted using four different models: segment-earnings-based model, consolidated-earnings-based ARIMA model, RWD model, and RW model. Forecasts of segment earnings based on the industry-specific ARIMA models are aggregated to obtain the segment-based forecasts for consolidated earnings. Thus, before testing the prediction accuracy of competing models for consolidated earnings, the prediction accuracy of the industry-specific

ARIMA models for segment earnings are compared with that of simple forecasting models to evaluate the validity of the industry-specific ARIMA models in predicting segment earnings.

(1) Accuracy of Segment Earnings Prediction

As shown in Table Ⅳ.1, 30 percent of the identified and estimated industry-specific ARIMA models are insignificant. Models are considered as insignificant when all autoregressive coefficients and/or moving average coefficients are insignificant at the 10 percent level (two-tailed test). Since insignificant models may not reflect industry-specific time series characteristics properly, use of the insignificant ARIMA models in predicting segment earnings may produce inaccurate forecasts. Thus, segment earnings are predicted after replacing the insignificant models with the RWD model since many of the insignificant models are close to the random walk process.

Mean statistics for the ARE and RARE error measures for each prediction period are shown in Table Ⅳ.3. Table Ⅳ.4 provides the results of the paired comparison t-tests for models. The comparison between the industry-specific

Table Ⅳ.3. Mean Statistics of Forecast Errors for Segment Earnings

Forecast Year	OBS	Forecast Error Measure	Forecasting Models		
			IND*	RW	RWD
1983	189	ARE	2.202	2.367	3.151
		RARE	0.483	0.484	0.472
		RANK**	1.990	1.922	2.097
1984	191	ARE	1.004	0.966	1.082
		RARE	0.415	0.416	0.413
		RANK	2.036	2.012	1.952
1983~84	380	ARE	1.600	1.663	2.111
		RARE	0.449	0.442	0.450
		RANK	2.010	1.963	2.032

IND : industry-specific ARIMA model
RW : random walk model
RWD : random walk with drift model
* Industry-specific time series models of which estimated parameters are insignificant are replaced with random walk model.
** Ranks are measured after eliminating observations which have tied ranks.

Table IV. 4. Paired Comparison t-test for Prediction Accuracy of Segment Earnings Forecasting Models

Forecast Year	Error Measure	Mean Difference between Paired Forecasting Models		
		RW-IND	RWD-IND	RW-RWD
1983	ARE	0.271(0.74)	0.730(1.45)	−0.784(−1.89)*
	RARE	−0.018(−0.83)	−0.004(−0.14)	−0.012(−1.15)
1984	ARE	−0.062(−0.03)	−0.047(−0.01)	−0.106(−1.39)
	RARE	−0.005(−0.27)	−0.007(−0.41)	−0.003(−0.41)
1983~84	ARE	0.103(0.56)	0.340(1.31)	−0.448(−2.13)**
	RARE	−0.012(−0.82)	−0.006(−0.35)	−0.008(−1.16)

* : significant at $\alpha=10\%$ (two-tailed test)

** : significant at $\alpha=5\%$ (two-tailed test)

Remarks: (1) If mean difference between RW-IND (that is, mean of ARE_{rw}-ARE_{ind}) is less than zero, it means that the random walk model outperforms the industry-specific ARIMA model on average.

(2) The comparison of forecasting accuracy between the industry-specific ARIMA model and the RW model or the RWD model are based on lines of business of which industry-specific models are significant Thus, the sample size varies from 116 for the RWD-IND pair in 1983 to 191 for the RW-RWD pair in 1984.

ARIMA model and the RWD model suggests that the industry-specific ARIMA model is better than the RWD model although it is not statististically significant. The RW model performs better than the industry-specific ARIMA models on average. However, the mean statistics show that forecast accuracy of models vary between two prediction periods. As indicated in the prior section, earnings fluctuation during the period of 1981~1983 appears to affect the prediction accuracy of models. As shown in Table Ⅳ. 4, the RW model is significantly superior to the RWD model which is contrary to the findings of previous studies. It clearly reveals the test period effects on the prediction accuracy.

The assumption of a normal distribution in the t-test may be violated because of serious outliers in the ARE measure. Since t-test results of ARE measures may not be reliable, a nonparametric test is also applied. The paired comparison of models based on Wilcoxon signed rank test (in Table Ⅳ. 5) shows that the industry-specific ARIMA models are not significantly superior or inferior to the RW model or the RWD model. Moreover, it is found that the RW model is clearly superior to the RWD model especially in the prediction year 1983.

Table IV.5. Statistics for Wilcoxon Matched-Pairs Signed Ranks test for the Accuracy of Segment Earnings Prediction

Forecast Year	Error Measure	Wilcoxon Statistics for Paired Models		
		RW-IND	RWD-IND	RW-RWD
1983	ARE	−1.32	0.80	−4.78***
	RARE	−0.89	0.05	−1.26
1984	ARE	−0.78	0.21	−1.72*
	RARE	−0.53	−0.74	0.59
1983~84	ARE	−1.56	0.79	−4.72***
	RARE	−1.08	−0.42	−0.51

* : significant at $\alpha=10\%$
*** : significant at $\alpha=0.1\%$
Remarks: (1) Wilcoxon statistic is approximately normally distributed with zero mean and unit variance.
(2) Negative statistics of RW-IND indicate that industy-specific ARIMA model cannot outperform random walk model.
(3) Restricted Absolute Relative Error (RARE) is measured by replacing ARE's exceeding 1.0 with 1.0.
(4) In each pair, the observations which have the same ARE or RARE are dropped. Thus, the number of observations vary by pairs and by test periods.

However, when outliers exceeding 1.0 are eliminated as in the RARE measure, the significance of difference of two models is reduced. The RWD model is even better than the RW model in 1984 in terms of the RARE measure.

Considering the earnings fluctuation in 1980's, the results of the comparison of prediction accuracy cannot provide convincing evidence for the superiority or the inferiority of the industry-specific ARIMA models in predicting segment earnings. However, following several alternative interpretations of the results may be possible.

(i) The industry-specific ARIMA models may not be properly specified and estimated because of limited number of time series observations even though only the significant models are included in prediction accuracy tests.

(ii) Even the industry-specific ARIMA models are identified and estimated correctly, their predictive accuracy may be affected by the application of the models to individual segment earnings series. This study estimates constant terms based on seven years data for the prediction of 1984 segment earnings (6 observations if the first-order differencing is needed). Thus, the estimation

Table IV. 6. Spearman Rank Correlations Coefficients Between the Size of Frm and the Prediction Accuracy

Panel A: Abolute Earnings vs. Absolute Relative Errors

Forecast Year	Obs.	Models		
		IND	RW	RWD
1983	189	−0. 36(0. 00)	−0. 37(0. 00)	−0. 36(0. 00)
1984	191	−0. 32(0. 00)	−0. 31(0. 00)	−0. 35(0. 00)

Panel B: Abolute Earnings vs. Differences in ARE's

Forecast Year	ARE_{RW-IND}	$ARE_{RWD-IND}$
1983	0. 14(0. 05)	−0. 12(0. 34)
1984	−0. 03(0. 67)	−0. 03(0. 32)

Remarks: Numbers in parentheses are the significance levels under null hypothesis that Spearman rank correlation coefficient is zero.

of the constant term may be seriously affected by a sharp decline or increase in earnings.

(iii) The magnitude of the industry effects on time series properties of individual segments may vary across firms and industries. Better specification of various potential factors such as the type of products (e.g., durable-nondurable), the size of segments, and the entry barriers and/or the concentration ratios of industries may discriminate the differential magnitude of the industry effects. Among those potential factors, the size of segment is checked with the Spearman rank correlation between AREs of the industry-specific ARIMA model and model and the absolute value of segment earnings. As shown in Table Ⅳ. 6. AREs of the forecasting models are negatively correlated with absolute segment earnings. However, this may be attributable to the fact that segment earnings is used as the deflator in ARE measure. On the other hand, there is no evidence that the differences in forecast errors between paired models are related to the size of segment.

(2) Accuracy of Consolidated Earnings Prediction

The segment-based forecast for a firm's consolidated earnings is made by aggregating forecasts for segment earnings of the firm. Segment earnings are

Table IV.7. Mean Statistics for Forecast Errors of Consolidated Earnings Forecasts

Forecast Year (N=obs.)	Accuracy Measure	Forecasting Models			
		SEGMENT	ARIMA	RW	RWD
1983(N=71)	ARE	1.464	1.132	1.218	1.395
	RARE	0.453	0.465	0.469	0.480
	RANK*	2.493	2.423	2.437	2.662
1984(N=71)	ARE	0.576	0.802	0.899	0.714
	RARE	0.379	0.384	0.505	0.414
	RANK	2.162	2.352	3.246	2.239
1983~84(N=142)	ARE	1.020	1.054	1.058	0.967
	RARE	0.416	0.425	0.487	0.447
	RANK	2.327	2.387	2.842	2.451

* Remarks: Friedman test statistics (based on two-way anaylsis of variance by RANK measures) are as follows:

Year	Statistic	Prob.
1983	4.46	0.22
1984	27.88	0.00
1983~84	16.59	0.00

Friedman statistics follow Chi-square with 3 degree of freedom.

predicted by applying the significant industry-specific ARIMN models and the RWD models for the segments of which ARIMA models are statistically insignificant.

Table Ⅳ.7. presents the mean statistics of the forecast error measures by the prediction periods and by the forecasting models. Mean values of the RARE and the RANK measure favor the segment-based ARIMA model for 1984 earnings prediction. Results of the paired comparison t-tests in Table Ⅳ.8 show that the segment-based ARIMA model performs significantly better than the RW model for both ARE and RARE measures in 1984 and better than the RWD model in terms of the ARE measure in 1984. However, ARE's have a considerable number of outiliers. Thus, the results of the t-test based on the ARE measure may not be reliable. Also, since about 20 percent of ARE's have values of exceeding 1.0, use of the RARE measure truncates too many observations, which may make the paired comparison t-test not representative

Table IV. 8. Paired Comparison t-test for Consolidated Earnings Forecasting Models

Panel A: Comparison between Segment-based Model and Consolidated-based Models

Forecast Year	Error Measure	Mean Difference in Forecast Errors between Matched Forecasting Models (t-statistics)		
		BJ-SEG	RW-SEG	RWD-SEG
1983	ARE	−0.332(−1.04)	−0.246(−1.05)	−0.070(−0.39)
	RARE	0.012(0.37)	0.016(0.76)	0.028(1.02)
1984	ARE	0.226(0.69)	0.323(1.87)*	0.138(2.06)**
	RARE	0.005(0.16)	0.126(3.28)***	0.034(1.44)
1983~84	ARE	−0.053(−0.23)	0.034(0.26)	0.038(0.36)
	RARE	0.009(0.39)	0.071(3.16)***	0.031(1.72)*

* : significant at $\alpha=10\%$ in two-tailed test
** : significant at $\alpha=5\%$ in two-tailed test
*** : significant at $\alpha=1\%$ in two-tailed test
Remarks: (1) If mean of $ARE_{RW}-ARE_{SEG}$ (difference of ARE's between RW-SEG) is negative, it means that the random walk model outperforms the segment-based ARIMA model.
(2) RARE is measured by replacing outliers exceeding 1.0 with 1.0.

PANEL B: Comparison between Consolidated-based Models

Forecast Year	Error Measure	Mean Difference in Forecast Errors between Matched Forecasting Models (t-statistics)		
		RW-BJ	RWD-BJ	RW-RWD
1983	ARE	0.085(0.33)	0.262(1.03)	−0.176(−2.23)**
	RARE	0.004(0.16)	0.016(0.68)	−0.011(−0.88)
1984	ARE	0.097(0.30)	−0.088(−0.26)	0.184(0.97)
	RARE	0.121(3.03)***	0.138(3.51)***	0.913(2.43)**
1983~84	ARE	0.091(0.44)	0.087(0.41)	0.004(0.04)
	RARE	0.062(2.57)**	−0.080(1.24)	0.040(2.00)**

* : significant at $\alpha=10\%$ in two-tailed test
** : significant at $\alpha=5\%$ in two-tailed test
*** : significant at $\alpha=1\%$ in two-tailed test
Remarks: (1) If mean of $ARE_{RW}-ARE_{BJ}$ (difference of ARE's between RW-BJ) is negative, it means that the random walk model outperforms the consolidated-based ARIMA model.
(2) RARE is measured by replacing outliers eceeding 1.0 with 1.0.

for the whole sample. Thus, the nonparametric Wilcoxon test is also applied. Table Ⅳ.8 summarizes the results of the Wilcoxon matched pairs signed ranks test for pairs of four competing models.

Before the results of hypotheses tests (based on the comparison between the segment-based ARIMA model and the consolidated-based ARIMA model) are

discussed, the relative prediction accuracy of other pairs of models is examined. Table Ⅳ.7 shows the results of Friedman's analysis of variance by ranks test. Based on rank measure among four competing models, it tests the null hypothesis that four competing models are not different in terms of the prediction accuracy. The results indicate that unll hypothesis cannot be rejected for the 1983 test period.

Wilcoxon test results in Table Ⅳ.9 show that the RW model outperforms the RWD model at the 0.5 percent significance level in the 1983 test period. However, it is found that the RWD model is superior to the RW model at the 0.1 percent significance level in 1984. Similar results are found in the t-tests for the ARE measure and the RARE measure (in Table Ⅳ.8) although test results for one of two measures are insignificant for one of two test periods. These test results confirm the test period effects on the prediction accuracy which was found in the case of segment earnings prediction.

The paired comparison between the RW model and the consolidated-based ARIMA model (based on the t-test for RARE measure in Table Ⅳ.8 and the Wilcoxon test in Table Ⅳ.9) indicates similar test period effects. That is, while there is no difference in the predictive ability between two models in 1983, the firm-specific ARIMA model is significantly superior to the RW model in 1984. On the other hand, it is found that the prediction based on the firm-specific ARIMA models is not significantly more accurare than the RWD model although the sign of the Wilcoxon statistic favors the firm-specific ARIMA model.

Table IV.9. Statistics for Wilcoxon Signed Ranks Test

PANEL A: Paired Comparison of Prediction Accuracy for Segment-Based Model and Consolidated-Based Models

Forecast Year	Error Measure	Wilcoxon statistics for paired models		
		BJ-SEG	RW-SEG	RWD-SEG
1983	ARE	−1.27	−0.73	1.25
1984	ARE	0.44	4.11***	2.08*
1983~84	ARE	−0.69	3.22**	2.31*

PANEL B: Paired Comparison of Prediction Accuracy Between Consolidated-Based Models

Forecast Year	Error Measure	Wilcoxon statistics for paired models		
		RW-BJ	RWD-BJ	RW-RWD
1983	ARE	0.69	1.56	−3.12**
1984	ARE	3.03**	0.21	3.65***
1983~84	ARE	2.76**	1.07	1.41

* : significant at $\alpha=5\%$ (two-tailed test)
** : significant at $\alpha=1\%$ (two-tailed test)
*** : significant at $\alpha=0.1\%$ (two-tailed test)
Remarks: (1) Positive statistics in A-B pair indicate that model A outperforms model B.
(2) Wilcoxon statistic is approximately normally distributed with zero mean and unit variance with large sample.

The paired comparisons between the segment-based ARIMA model and the RW model and between the segment-based ARIMA model and the RWD model suggest that the segment-based model is superior to the two simple models in the test period of 1984. That is, in predicting 1983 consolidated earnings, there is no significant difference between the segment-based ARIMA model and one of the two simple models. However, the forecasts of 1984 earnings based on the segment-based ARIMA models are more accurate than those based on the RW model or the RWD model although the significance levels vary by pairs, error measures, and test methods. Considering that forecasts of segment earnings based on the industry-specific ARIMA model are not significantly more accurate than two simple models, discussion may be needed on what may contribute to the improvement of the prediction accuracy. These results can be interpreted in several ways.

(i) Forecast errors of the industry-specific ARIMA models may be more negatively correlated than those of the RW model or the RWD model. Thus, the aggregation of forecast errors for segment earnings may induce smaller forecast errors for consolidated earnings. Since we do not incorporate forecast errors in the forecasting models, we cannot utilize systematic correlations among forecast errors, if any. Thus, the superior prediction accuracy of the segment-based ARIMA model to the simple models may not extend to other

test periods and for different sample firms. If we can identity any systematic correlations of forecast errors among industries, we may utilize this information in the prediction of consolidated earnings. However, since we predict only two years' earnings, this cannot be done in this study.

(ii) The prediction accuracy of the segment-based ARIMA model for consolidated earnings may be different from that for segment earnings. The relative forecast error for each segment is counted as one observation in the prediction accuracy test for segment earnings while the prediction accuracy test for consolidated earnings is based on the relative forecast error for each firm. Thus, the results of the prediction accuracy tests for segment earnings may not be similar to those for consolidated earnings. If the main segment of a firm is relatively large and forecast errors of its earnings are smaller than those of other segments, the relative forecast errors for consolidated earnings will show improved results from the mean of the relative forecast errors for segment earnings. However, it conflicts with one of the subhypotheses. That is, it is hypothesized that the gains from using disaggregated data may be smaller when the relative size of the main segment is large. This can be regarded as the problem of the trade-off between the large relative forecast errors for the small components and the gains from using finer information in the prediction. These things will be further explored in the process of hypothesis testing in the next section.

(iii) The improvement of the prediction accuracy of the segment-based ARIMA models for consolidated earnings can be explained differently with the effects of acquisition or divestiture activities. That is, the utilization of segment information can minimize the effects of acquisition and/or divestiture on the prediction accuracy of undeflated earnings since divested segments are not considered in the prediction and earnings of newly acquired segments are predicted with available information.

(iv) Finally the prediction of unallocated general corporate expenses using the RW model may contribute to the improvement of prediction accuracy.

Unlike other segment earnings, general corporate expense should be subtracted from aggregated segment earnings. That is, since the expense is a subtractive component, its forecast errors may behave differently from those of additive components. However, it is hard to believe that its forecast errors have a different sign from forecast errors of segments earnings consistently across firms and over test periods. Also, the general corporate expense represents only a small portion of consolidated earnings.

(3) Hypothesis Testing

Parametric t-tests for matched pairs of the segment-based model and the consolidated-based model are applied in testing the main hypothesis. Wilcoxon matched-pairs signed rank tests are also used for testing the main hypothesis. Tests of the subhypotheses are conducted with only the Wilcoxon signed rank test because of relatively small sample size in each subgroup.

The main hypothesis of no difference in the prediction accuracy between the segment-based ARIMA model and the consolidated-based ARIMA model is tested separately for each test period and by combining two test periods. Table Ⅳ.8 presents the results of t-tests based on the ARE measure and the RARE measure and Table Ⅳ.9 presents the results of Wilcoxon signed ranks sum test.

Results of all tests consistently indicate that the null hypothesis cannot be rejected at a reasonable significance level. The signs of test statistics are inconsistent across tests and over the test periods. That is, mean differences based on the RARE measure favor the the segment-based ARIMA model for all test periods. However, the Wilcoxon test favors the consolidated-based ARIMA model in the test period of 1983 while it favors the segment-based model in the 1984 test period at a much lower significance level.

The sub-hypotheses are tested to further explore whether there are any differences in the relative prediction accuracy of two models between subgroups. Two subgroups are formed based on each of two variables, the number of segments and the weight of the main segments of sample firms. Two variables

vary by the industry to which sample firms belong. Also, the composition of lines of business is similar in firms operating in some industries. Thus, sample firms are grouped by the two-or three-digit SIC codes depending upon the available number of sample firms for each industry. Among those firms in the same industry group, firms which have two segments are assigned to Subgroup One. Equal number of firms which have more than two segments are assigned to Subgroup Two. 24 sample firms are assigned to Subgroup One and Subgroup Two each.

In a similar way, firms in the same industry are assigned to Subgroup Three when the weights of their main segments are small. Also, firms are assigned to Subgroup Four when the weights of their main segments are large. As discussed in Chapter II, the weight of the main segment may be related to the number of segments. Although the number of segments cannot be well controlled in forming Subgroups Three and Four, the number of segments are considered in matching process by assigning firms with the same number of segments to different group. The weight of the main segment is measured as

Table IV. 10. Statistics of Wilcoxon Matched-pairs Signed Ranks Test Between Segment-based ARIMA Model and Consolidated-based ARIMA Model

PANEL A: Subgroups by Number of Segments

Forecast Year	Obs.	Number of Segments	
		Two(Subgroup One)	More than two (Subgroup Two)
1983	24	1.39	−0.47
1984	24	0.97	−0.34
1983~84	48	0.63	−0.22

PANEL B: Subgroups by Weight of Main Segment

Forecast Year	Obs.	Weight of main segment	
		Small(Subgroup Three)	Large(Subgroup Four)
1983	31	−1.25	0.18
1984	31	−0.88	0.38
1983~84	31	−1.62	0.25

Remarks: (1) Positive statistics indicate that segment-based model outperforms consolidated-based models.

the ratio of its earnings to the sum of absolute earnings of all segments.

Table Ⅳ. 10 shows the Wilcoxon test results for each subgroup and for each test period. For any of the subgroups, the null hypothesis cannot be rejected at a reasonable significance level (10 percent in two-tailed test). The signs of Wilcoxon test statistics are consistently contrary to the expectation of this study. That is, this study expects that the gains from using segment data increase as the number of segments increases. On the other hand, the gains from using segment information are expected to increase as the weight of the main segment decreases. However, as shown in Table Ⅳ. 10, the segment-based ARIMA model is favored over the consolidated-based ARIMA model in Subgroup

Table IV. 11. Statistics for Wilcoxon Matched-pairs Signed Ranks test Between Segment-based ARIMA Model and Simple Models

PANEL A: Subgroups by Number of Segments

Model Pairs	Forecast Year	Obs.	Number of Segmnets	
			Two	More than Two
RW-SEG	1983	24	1.16	0.12
	1984	24	3.43**	0.71
	1983~84	48	2.12*	0.93
RWD-SEG	1983	24	0.40	0.93
	1984	24	2.92**	−0.04
	1983~84	48	2.14*	0.67

PANEL B: Subgroups by Weight of Main Segment

Model Pairs	Forecast Year	Obs.	Weight of Main Segment	
			Small	Large
RW-SEG	1983	30	1.09	0.46
	1984	30	2.14*	3.60**
	1983~84	60	1.25	3.27**
RWD-SEG	1983	30	−0.94	2.20**
	1984	30	1.48	0.10
	1983~84	60	0.66	2.01*

* : significant at $\alpha=5\%$ (two-tailed test)
** : significant at $\alpha=1\%$ (two-tailed test)
Remarks: (1) Positive statistics indicate that segment-based model outperforms consolidated-based model

One (firms with two segments) while the consolidated-based ARIMA model is favored in Subgroup Two. Also, in Subgroup Three (firms with the main segment of small weight), the signs of the Wilcoxon test statistics consistently favor the consolidated-based ARIMA model. On the other hand, in Subgroup Four, the segment-based ARIMA model is favored.

In order to check whether the above results are specific to the pair of the segment-based ARIMA model and the consolidated-based ARIMA model, the Wilcoxon test is also applied to other pairs of models for the same subgroups. As shown in Table Ⅳ. 11, the results are similar to those of the above pair.

These results can be interpreted in relation to the discussion in the prior subsection. That is, the relative forecast errors of small segments may be large. Thus, the gains from using finer segment information may be offset by the large forecast errors for smaller segments.

Since the absolute size of segments of a firm may be related by the size of the firm, a check is made of whether the size of sample firms is related to the relative prediction accuracy of the segment-based ARIMA model versus the consolidated ARIMA model. Sales and absolute earnings are used as size

Table IV. 12. Spearman Rank Correlations Between the Size of Firm and the Prediction Accuracy of Segment-based ARIMA Model and Consolidated-based ARIMA Model

PANEL A: Size vs. ARE (Absolute Relative Errors)

Forecast Year	Obs.	Sales		Earnings	
		BJ	Segment	BJ	Segment
1983	71	−0. 05(0. 68)	−0. 23(0. 05)	−0. 41(0. 00)	−0. 50(0. 00)
1984	71	−0. 12(0. 17)	−0. 26(0. 00)	−0. 37(0. 00)	−0. 49(0. 00)

PANEL B: Size vs. Difference in ARE's (ARE_{BJ}-ARE_{SEG})

Forecast Year	Obs.	Sales	Earnings
1983	71	0. 31(0. 01)	0. 37(0. 00)
1984	71	−0. 01(0. 97)	0. 09(0. 44)

Remarks: (1) Numbers in parentheses are significance levels under the null hypothesis that Spearman correlation coefficient is zero.
(2) Absolute earnings are used for size variable.

variables. Panel A of Table Ⅳ. 12 shows the results of Spearman rank correlations between ARE's and the size variables. Rank correlation coefficients are significantly negative for the segment-based ARIMA model for both size variables. However, the coefficients for the consolidated-based ARIMA model are not significant for the sales variable although the sign is negative. This suggests that forecast errors of the segment-based ARIMA model are negatively correlated with size of the firm. Panel B of Table Ⅳ. 12 shows the results of rank correlations between the differences in ARE's between two models and the size variables. The results indicate that in the 1983 test period the segment-based ARIMA model is superior to the consolidated-based ARIMA model for large firms and is inferior to the consolidated-based ARIMA model for small firms. However, in 1984, two models' relative performance is not related to the size of sample firms.

The above results of rank correlations are contrary to Silhan's (1983) findings. That is, Silhan finds that firms with larger segments have smaller gains from using segment earnings forecasts in predicting consolidated earnings. He hypothesizes that larger segments are more likely to have identical forecasting models and thus less gains from the disaggregation. However, the results of this study suggest that the misspecification errors or the measurement errors may be relatively small for segments of large firms. The finding that the segment-based ARIMA model is favored over the consolidated-based model for large firms can be interpreted in relation to the misspecification errors for the consolidated-based ARIMA model. That is, as this study justifies for the segment-based model, the consolidated-based ARIMA model may be more misspecified for larger firms because more heterogeneous processes may be mixed and thus earnings process may have more noise. However, this may be only possible explanation since the results are not statistically significant and the analysis may not be precise. We may need more studies to explore the size effects on the potential misspecification of the firm-specific ARIMA model.

V. Conclusions

Before concluding this research, the following limitations of this research should be explicitly noted.

(i) The most critical but unavoidable limitation of this research is related to the small time series observations of segment earnings data. The industry-specific ARIMA model was used to overcome data limitations of segment earnings. However, the small time series observations might affect the estimation of means of the segment earnings series and thus might affect the prediction accuracy of the model.

(ii) This study employed the Box-Jenkins ARIMA models to the earnings series with less than 30 years' time series observations. Thus, some of identified and estimated ARIMA models were found unstable when one more observation was added and then the models were re-identified and re-estimated. Although the relatively moderate sample size might reduce the potential structural change problem, it might induce the inefficient and inconsistent estimation of the model. This study replaced the insignificant industry-specific ARIMA models with the random walk with drift model. However, when the underlying process for those insignificant models was not a random walk, use of the random walk with drift model might complicate the comparison of the prediction accuracy of competing models.

(iii) This study can be criticized because it did not verify the feasibility of the industry-specific ARIMA model in predicting earnings. Although previous studies identified the same class of ARIMA model for annual earnings and quarterly earnings for some industries, their predictive ability has not been proven. The industry classification scheme, the way of identifying the industry-specific ARIMA model, and the way of applying the identified and estimated model to the earnings series should be further explored (for example, using single-segment firms).

(iv) This study tested the hypotheses based on two years' prediction results. However, test period effects were detected in the test results of the prediction accuracy. Considering the poor performance of competing models in the test period of 1983, the comparison of the prediction accuracy based on the prediction of 1983 earnings might not be reliable. We may need a few more years' predictions for more convincing results.

The primary finding of this study is that the forecasting model incorporating past segment earnings data does not provide more accurate predictions for future consolidated earnings than the forecasting model incorporating past consolidated earnings data. Thus, this study does not support the contention of the proponents for segment reporting requirements that the industry segment earnings data are beneficial to financial statement users in predicting annual earnings of the diversified firms. However, because of limitations in formulating the forecasting models for segment earnings and consolidated earnings, the conclusion of this study should be accepted with caution.

The secondary finding is that the predictive value of segment earnings data does not increase with their level of disaggregation and rather appears to be affected by the size of the diversified firms. This finding suggests that segment earnings data may be of limited usefulness because of the potential misspecification errors of forecasting models and/or measurement errors of segment earnings which are increasing as consolidated earnings compose of finer segment earnings data. Thus, the contention for the benefits of segment data are not supported in this respect either.

Implications of these findings are limited since only segment earnings information was considered and only one aspect of benefits (predicting consolidated earnings) were examined. Moreover, this study has some limitations. In order to provide more convincing evidence, the following is suggested for the refinement and the extension of the current study.

(i) Segment sales margin data can be used rather than undeflated earnings data to predict consolidated earnings. For example, sales margins of segments

for the next year can be predicted in the same way as in this study and the sales amount can be predicted applying simple time series model such as the random walk with drift model. With sales margin data, the industry-specific ARIMA models can be better identified and estimated by reducing the non-stationarity problem observed in this study. Also, the sales margin series of firms in the same industry may behave in a more similar pattern than the undeflated earnings series.

(ii) With the availability of more segment data, it may be desirable to include more years' data to mitigate the test period effects observed in the prediction accuracy tests in this study. It will also help to evaluate the validity of applying Box-Jenkins' models to undeflated annual accounting earnings by examining the stability of the parameters estimated.

(iii) Related to (ii), the research design of this study can be refined in order to examine the effects of several variables on the relative prediction accuracy of the segment-based model and the consolidated-based model at the same time. That is, with more test periods, the paired comparison t-test or the Wilcoxon signed ranks sum test can be extended to more complex tests for multiple treatments such as the test with an analysis-of-covariance model with repeated measures.

(iv) This study simply compared the prediction accuracy of competing models. Thus, it cannot provide enough implications on whether the predicted earnings of the segment-based model can be a better proxy for the market earnings expectation. With a security price association test for each competing model, we may be able to examine whether the segment-based model better captures the the way the market forms expectations of security prices.

REFERENCES

Ajinkia, B., "Line of Business Reporting," *Journal of Accounting Research*, (Autumn 1980), pp. 343-361.

Akaike, H., "A New Look at the Statistical Model Identification," *IEEE Transactions on Automatic Control*, AC-19, 1974, pp. 716-723.

Albrecht, W.S., L.L. Lookabill, J.C. McKeown, "The Time Series Properties of Annual Earnings," *Journal of Accounting Research*, (Autumn 1977), pp. 226-244.

Ang, J.S., "Aggregated Versus Component Forecasts of Financial Statement Items," *Review of Business and Economic Research* 15, (Fall 1979), pp. 30-42.

Ansley, C.F. and P. Newbold, "Finite Sample Properties of Estimators for Autoregressive Moving Average Models," *Journal of Econometrics* 13, (1980), pp. 159-183.

Baldwin, B.A., "Segment Earnings Disclosure and the Ability of Security Analysts to Forecast Earnings Per Share," *The Accounting Review*, (July 1984), pp. 376-389.

Ball, R. and R. Watts, "Some Properties of Accounting Income," *Journal of Finance* (June 1972), pp. 300-323.

Barefield, R.M. and E.E. Cominskey, "Segmental Financial Disclosure by Diversified Firms and Security Prices; A Comment," *The Accounting Reiew* (October 1975), pp. 818-821.

Beaver, W.H., "The Time series Behavior of Earnings," *Empirical Studies in Accounting: Selected Studies*, 1970, supplement to *Journal of Accounting Research*, (Autumn 1970), pp. 62-99.

Beaver, W.H., J. Kennelly, and W. Voss, "Predictive Ability as a Criterion for Evaluation of Accounting Data," *The Accounting Reiew*, (October 1968), pp. 675-683.

Box, G. E.P. and D.A. Pierce, "Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models," *Journal of the American Statistical Association*, (December 1970), pp. 1509-1526.

Box, G.E.P. and G.M. Jenkins, *Time Series Analysis Forecasting and Control*, revised edition, San Francisco, California, Holden-Day, Inc., 1976.

Brooks, L.D. and D.A. Buckmaster, "Further Evidence of the Time Series Properties of Accounting Income," *The Journal of Finance* (Dec. 1976), pp. 1359-1373.

Brooks, L.D. and D.A. Buckmaster, "First Difference Signals and Accounting Income Time Series Properties," *Journal of Business Finance & Accounting* 7. 3(1980), pp. 437-454.

Brown, P. and R. Ball, "Some Preliminary Findings on the Association between the Earnings of a Firm, Its Industry and the Economy," *Empirical Research in Accounting;*

Selected Studies, 1967, *Supplement to Journal of Accounting Research*. pp. 1-14.

Chant, P.D., "On the Predictability of Corporate Earnings Per Share Behavior," *The Journal of Finance* (1980), pp. 13-21.

Collins, D.W., "SEC Product-Line Reporting and Market Efficiency," *Journal of Financial Economics* (June 1975), pp. 125-164.

Collins, D.W., and R. Simmonds, "SEC Line of Business Disclosure and Market Risk Adjustments," *Journal of Accounting Research* (Autumn 1979), pp. 352-383.

Collins, D.W. and W.S. Hopwood, "A Multivariate Analysis of Annual Earnings Forecasts Generated from Quarterly Forecasts of Financial Analysts and Uniariate Time Series Models," *Journal of Accounting Research* (Autumn 1980), pp. 390-400.

Davis, N., C.M. Triggs, and P. Newbold, "Significance Levels of the Box-Pierce Portmanteau Statistic in Finite Samples," *Econometrika*, (1977), 64, 3, pp. 517-522.

Davidson, J.E.H., "Problems with the Estimation of Moving Average Process," *Journal of Econometrics*, 16 (1981), pp. 295-310.

Dent, W. and A. Min, "A Monte Carlo Study of Autoregressive Integrated Moving Average Processes," *Journal of Econometrics*, 7 (1978), pp. 23-25.

Dharan, B.G., "Empirical Identification Procedures for Earnings Models," *Journal of Accounting Research* (Spring 1983), pp. 256-270.

Dopuch, N. and R. Watts, "Using Time Series Models to Assess the Significance of Accounting Changes," *Journal of Accounting Research*, 10 (Spring 1972), pp. 180-194.

Dunn, D.M., W.H. Williams, and T.L. DeChaine, "Aggregate Versus Subaggregate Models in Local Area Forecasting," *Journal of American Statistical Association* (March 1976), pp. 68-71.

Financial Accounting Standards Board, *Discussion Memorandum: Financial Reporting for Segments of a Business Enterprise*, Stamford, Conn., FASB, 1974.

Financial Analysts Federation, *Ealuation of Corporate Financial Reporting in Selected Industries for the Year 1971*, New York, FAF, 1972.

Foster, G., "Quarterly Accounting Data; Time-Series Properties and Predictie Ability Results," *The Accounting Reiew* (Jan. 1977), pp. 1-21.

Foster, G., *Financial Statement Analysis*, Prentice-Hall, 1978.

Gonedes, N.J., "Properties of Accounting Numbers; Models and Tests," *Journal of*

Accounting Research (Autumn 1973), pp. 212-237.

Gonedes, N.J. and N. Dopuch, "Economic Analyses and Accounting Techniques; Perspective and Proposal," *Journal of Accounting Research* (Autumn 1979), pp. 384-410.

Granger, C.W.J. and M.J. Morris, "Time Series Modelling and Interpretation," *Journal of Royal Statistical Society A* (1976), 139, Part 2, pp. 246-257.

Granger, C.W.J. and P. Newbold, *Forecasting Economic Time Series*, New York, Academic, 1977.

Green, H.A.J., *Aggregation in Economic Analysis: An Introductory Survey*, Princeton University Press, Princeton, NJ, 1964.

Greenberg, R., "Adaptive Estimation: An Alternative to the Traditional Stationarity Assumptions," *Journal of Accounting Research*, (Autumn 1984), pp. 719-730.

Grunfeld, Y. and Z. Griliches, "Is Aggregation Necessarily Bad?" *Review of Economics and Statistics*, 42 (1960), pp. 1-13.

Gupta, K.L., *Aggregationin Economics: A Theoretical and Empirical Study*, Rotterdam University Press, 1969.

Hopwood, W.S., J.C. MeKeown, and P. Newbold, "The Additional Information Content of Quarterly Earnings Reports; Intertemporal Disaggregation," *Journal of Accounting Research*)Autumn 1982), pp. 343-349.

Hopwood, W.S., P. Newbold, and P.A. Silhan, "The Potential for Gains in Predictive Ability Through Disaggregation; Segmented Annual Earnings." *Journal of Accounting Research* (Autumn 1982), pp. 724-731.

Hopwood, W.S. and J.C. McKeown, "The Incremental Information Content of Interim Expenses over Interim Sales," *Journal of Accounting Research* (Spring 1985), pp. 724-731.

Horwitz, B. and R. Kolodny, "Line of Business Reporting and Security Prices; An Analysis of An SEC Disclosure Rule," *Bell Journal of Economics and Management Science* (Spring 1977), pp. 234-249.

Kinney, W.R., Jr., "Predicting Earnings; Entity versus Subentity Data," *Journal of Accounting Research* (Spring 1971), pp. 127-136.

Kinney, W.R., Jr., "Covariability of Segment Earnings and Assets," *The Accounting Reiew* (April 1972), pp. 339-445.

Kohn, R., "When Is an Aggregate of a Time Series Efficiently Forecast by Its Past?"

Journal of Econometrics 18 (1982), pp. 337-349.

Lev, B., "The Aggregation Problem in Financial Statements: An Informational Approach," *Journal of Accounting Research*, (Autumn 1968), pp. 247-261.

Lev, B., "Determinants of Time-series Properties of Earnings," *Journal of Accounting and Economics* 5 (1983) pp. 31-48.

Ljung, G.M. and G.E.P. Box, "On a Measure of Lack of Fit in Time Series Models," *Biometrika*, 65 (1978), pp. 517-522.

Lookabill, L.L., "Some Additional Evidence on the Time Series Properties of Accounting Earnings," *The Accounting Review* (October 1976), pp. 724-738.

Lorek, K.S. and A.W. Bathke, Jr., "A Time-Series Analysis of Nonseasonal Quarterly Earnings Data," *Journal of Accounting Research* (Spring 1984), pp. 369-378.

Lorek, K.S., J.D. Icerman, and A.A. Abdulkader, "Further Descriptive and Predictive **Evidence** on Alternative Time Series Models for Quarterly Earnings," *Journal of Accounting Research* (Spring 1983), pp. 317-328.

Lorek, K.S., R. Kee, and H. Vass, "Time Series Properties of Annual Earnings Data; The State of the Art," *Quarterly Review of Economics and Business*, Spring 1981, pp. 97-113.

Lorek, K.S., C.L. McDonald, and D.M. Patz, "A Comparative Examination of Management Forecasts and Box-Jenkins Forecasts of Earnings," *The Accounting Review* (April 1976), pp. 321-330.

Lorek, K.S. and J.C. McKeown, "The Effects on Predictive Ability of Reducing the Number of Observations on a Time-Series Analysis of Quarterly Earnings Data," *Journal of Accounting Research* (Spring 1978), pp. 204-214.

Lutkepohl, H., "Differencing Multiple Time Series: Another Look at Canadian Money and Income Data," *Journal of Time Series Analysis*, 3(1982), pp. 235-243.

Lutkepohl, H., "Forecasting Contemporaneously Aggregated Vector ARIMA Processes," *Journal of Business & Economic Statistics* (July 1984), pp. 201-213.

Magee, R.P., "Industry-wide Commonalities in Earnings," *Journal of Accounting Research* (1974), pp. 270-287.

Mautz, R.K., *Financial Reporting by Diversified Companies*, New York, Financial Executives Research Foundation, 1968.

Marschak, J. and R. Radner, *Economic Theory of Teams*, New Haven, Yale University

Press, 1972.

Nelson, C.R., *Applied Time Series Analysis*, San Francisco, California, Holden-Day, Inc., 1973.

Nelson, C.R., "The First-Order Moving Average Process," *Journal of Econometrics*, 2 (1974), pp. 121-141.

Nelson, C.R., "Rational Expectations and the Predictive Efficiency of Economic Models," *The Journal of Business* (July 1975), pp. 331-343.

Orcutt, G.H., W.H. Watts, and J.B. Edwards, "Data Aggregation and Information Loss," *American Economic Review* 58 (1968), pp. 773-787.

Pankratz, A., *Forecasting with Univariate Box-Jenkins Models*, New York, John Wiley & Sons, 1983.

Pierce, D.A., "Forecasting in Dynamic Models with Stochastic Regressors," *Journal of Econometrics*, 3 (1975), pp. 349-374.

Rose, D.E., "Forecasting Aggregates of Independent ARIMA Processes," *Journal of Econometrics*, 5 (1977), pp. 323-345.

Schwarz, G., "Estimating the Dimension of a Model," *The Annals of Statistics*, 1978, pp. 461-464.

Securities and Exchange Commission, Adoption of Amendments to Forms S-1, S-7 and 10. Securities Exchange Act of 1934 Release No. 8650, Washington, D.C., SEC, 1969.

Securities and Exchange Commission, Adoption of Revised Form 10-K, Securities Exhange Act of 1934 Release No. 9000, Washington, D.C., SEC, 1970.

Silhan, P.A., "Simulated Mergers of Existent Autonomous Firms; A New Approach to Segmentation Research," *Journal of Accounting Research* (Spring 1982), pp. 255-262.

Silhan, P.A., "The Effects of Segmenting Quarterly Sales and Margins on Extrapolative Forecasts of Conglomerate Earnings; Extension and Replication," *Journal of Accounting Research* (Spring 1983a), pp. 341-347.

Silhan, P.A., "Company Size and the Issue of Quarterly Segment Reporting," *Journal of Accounting and Public Policy* (1983b), pp. 185-197.

Steece, B.M. and S.D. Wood, "An ARIMA-Based Methodology for Forecasting in a Multi-Item Environment," *TIMS Studies in the Management Sciences* 12 (1979), pp. 167-187.

Theil, H., *Linear Aggregation of Economic Relations*, Amsterdam, North-Holland

Publishing Company, 1954.

Theil, H., *Applied Economic Forecasting*, Chicago, RAND McNally & Company, 1966.

Theil, H., *Economics and Information Theory*, Chicago, RAND McNally & Company, 1967.

Tiao, G.C. and I. Guttman, "Forecasting Contemporal Aggregates of Multiple Time Series," *Journal of Econometrics* 12 (1980), pp. 219-230.

Watts, R.L. and R.W. Leftwich, "The Time Series Properties of Annual Accounting Earnings," *Journal of Accounting Research* (Autumn 1977), pp. 253-271.

Zeghal, D., "Industry, Market Structure and the Information Content of Financial Statements," *Journal of Accounting and Public Policy* (1983), pp. 115-121.