ACTA ACADEMIAE OECONOMICAE HELSINGIENSIS

Series A:58

JUHA KINNUNEN

THE TIME SERIES PROPERTIES OF ACCRUAL VERSUS CASH-BASED INCOME VARIABLES:

EMPIRICAL EVIDENCE FROM LISTED FINNISH FIRMS

Helsinki 1988

THE HELSINKI SCHOOL OF ECONOMICS AND BUSINESS ADMINISTRATION

ACTA ACADEMIAE OECONOMICAE HELSINGIENSIS

Series A:58

JUHA KINNUNEN

THE TIME SERIES PROPERTIES OF ACCRUAL VERSUS CASH-BASED INCOME VARIABLES:

EMPIRICAL EVIDENCE FROM LISTED FINNISH FIRMS

Helsinki 1988

THE HELSINKI SCHOOL OF ECONOMICS AND BUSINESS ADMINISTRATION

ISSN 0356-9969
ISBN 951-700-390-0
1988

ABSTRACT

This study compares the time series properties of accrual and cash-based income variables in order to determine the basic (dis)similarities in the underlying mechanisms of their behavior over time. The main motive behind this research objective lies in the observation that while the relevant literature almost unanimously suggests that annual accrual-based income follows a submartingale (random walk with or without a drift) or similar process, the explanations for such behavior are virtually non-existent. It has been particularly unclear whether the submartingale behavior is primarily due to industrial-organization-based or accounting-method-based factors. The comparative analysis of accrual vs. cash-based income time series performed in this study tackles the relative strengths of these competing explanations.

Theoretical analysis of serial dependences at the sales and operating income levels produced inconclusive results with respect to the relative magnitudes of autocorrelation in accrual vis-a-vis cash-based variables. Empirical analysis was needed to provide an answer to the research question.

The empirical time series analysis was performed on accrual-based sales, operating income and net income variables, and on their direct cash-based counterparts. The time series data was obtained from the financial statements of 39 listed Finnish firms representing various industries. The data covered the 34-year period 1951-84.

The empirical inquiry involved three main phases. First, the degree of randomness was analyzed with distribution-free tests and autocorrelation analysis. Second, some parsimonious univariate time series models were estimated from the data. Third, the predictive ability of the models was tested in non-overlapping hold-out prediction periods.

The main findings of the empirical time series analysis were as follows. First, the analysis confirmed with data from Finnish firms the prior results obtained in other countries that, on average, the underlying mechanism descibing the behavior of annual accrual accounting income variables is a submartingale or similar process. Second, submartingale-type behavior in accrual variables was observed across all income measurement levels analyzed in this study. Third and most important, at the operating and net income levels the submartingale model did not turn out to be robust across the accounting systems: the behavior of the cash-based operating and net income variables were much better described by constant processes than by submartingales. Thus, the main conclusion of this study is that the <u>accounting-method-based</u> explanation for the observed patterns in annual accrual income numbers is obviously much stronger than the competing industrial-organization-based explanation. Furthermore, another implication of the results is that insofar as market expectations can be proxied with past realizations, the information content of the most recent cash flow number should be relatively small.

ACKNOWLEDGMENTS

Now that my dissertation is complete, I have the pleasure of expressing my gratitude to everyone who has contributed to the project.

First of all, I am particularly grateful to my thesis advisor, Professor Eero Artto of the Helsinki School of Economics, whose guidance, encouragement and support have been most valuable to me in traversing the jungles along the way. Without his help and devotion this dissertation would not have been completed. Thank you very much, EA.

I am also greatly obliged to my official thesis examiners, Professor George Foster of Stanford University, and Professor Timo Salmi of the University of Vaasa. George Foster's constructive and favorable comments on the manuscript have been very important to me, not only because they have provided the necessary external feedback, but also because they have given me more self-confidence than he may ever realize. Timo Salmi's detailed comments were most valuable in improving the final version of the thesis. Thank you, George and Timo.

In the course of the dissertation process I had the opportunity to attend the first doctoral colloquium of the European Accounting Association, which was held in Brussels in 1985. I would like to acknowledge the constructive comments and suggestions that I received on an early version of this thesis from the excellent faculty there; the comments of Professor Hein Schreuder of the University of Limburg, Professor Ray Ball of the University of Rochester, and Professor Gary Sundem of the University of Washington (Seattle) have been especially helpful.

Being an accountant rather than a statistician I would not have been able to solve some of the methodological problems without good advice from Dr. Tapani Lehtonen of the Helsinki School of Economics, Dr. Antti Kanto of the University of Vaasa, and Dr. Pentti Saikkonen of the University of Helsinki. I would like to thank them all for their expertise, which has been very valuable.

Thanks are also due to all my colleagues at the HSE Research Institute and at the Department of Accounting and Finance for the discussions I have had with them. Professor Kalervo Virtanen, Dr. Pekka Hietala, and Ms. Margareta Soismaa, Lic.Sc. (Econ.) in particular have given helpful comments for which I am most grateful.

I would also like to extend my thanks to Mr. Juha Kaiponen, Vice Director of the Helsinki Stock Exchange, who provided data needed for this study, and to Mr. David Miller, MA, who proofread the manuscript.

I wish to express my deep gratitude to the Helsinki School of Economics for providing an excellent infrastructure to carry out this research, and to Jenny ja Antti Wihurin rahasto, Yksityisyrittäjäin säätiö and Liikesivistysrahasto for their financial support which has been crucial in providing me the opportunity to work full-time on this dissertation project for the last fourteen months.

Furthermore, I am much obliged to my family, Heli, Samuli and Joonas, for their love, care and patience. Without them my research would have become a never-ending random walk process.

Finally, I am grateful to my PC for its amazing number crunching capability. Without it this study would be still in progress.

Chydenia, February 1988

TABLE OF CONTENTS

LIST OF TABLES AND FIGURES

1. INTRODUCTION

1.1. Background of the Study

This study relates to two interrelated areas in the broad domain of empirical research on financial accounting. The first is the time series analytic research area which deals with the behavior of financial statement numbers over time.

The origin of the time series research tradition can be traced back to the early sixties, when the first noteworthy study in this area was published in the United Kingdom (Little, 1962). Research activity subsequently moved quite rapidly to the United States in the late sixties, where the early findings suggesting independence in consecutive earnings changes were soon confirmed by large samples of firms and more rigorous statistical methods.

The methodological development that took place in time series analysis in the early seventies, especially the approach suggested by Box and Jenkins [1], gave a new additional thrust to many further studies in the late seventies and early eighties with new research questions and objectives. In addition to modeling the behavior of annual earnings and rates of return, the time series properties and predictive content of interim income numbers were analyzed, comparative studies of the predictive ability of management and financial analysts vis-a-vis time series models and each other were performed, the predictive content of variables exogenous to past historical time series were explored, aggregation issues were tackled across various dimensions, and so on. Although not always explicitly recognized, one of the main driving motives behind many of these studies has been the aim to develop new and better expectation models for corporate earnings. This, in turn, has been based on the belief that such models might be useful e.g. for the valuation of the firm's shares.

As a general observation on the research in this area, it can be said that whatever their exact question might have been, the vast majority of the studies have analyzed earnings or rates of return variables obtained from financial statements based on the accruals principle and historical costs. Furthermore, it is evident that the research tradition in the area has been highly empirical with little efforts on a priori or even a posteriori hypothesis formation. In the trichotomy "descriptive - positive - normative research", the time series studies of financial statement numbers serve as a good example of the first mentioned research type. This is because they typically search for answers to the question of what things exist rather than seek explanations for the existence of things, or recommendations of how things should be.

Since the bulk of the time series research has been carried out in the U.S., it is perhaps not very surprising that a capital market linkage was also introduced into some of the studies quite early. The pioneering work in this second area in the background of the present study was published in the late sixties (Ball and Brown, 1968), and it formed a basis for a subsequent research tradition known as "information content studies".

As is well-known, the main impulse to this research area was the emergence of the notion of capital market efficiency in the early sixties, implying that share prices reflect all relevant information available to the market. Since it is the task of the accounting profession to produce relevant information for users of financial statements, the information content studies examined the extent to which accountants have succeeded in the accomplishment of this basic task by examining market reactions to published earnings numbers. It was assumed that insofar as the capital market efficiently utilizes all relevant information, the stronger the market reacts to earnings announcements, the greater the information content of the announced earnings.

Besides the information content of published annual earnings analyzed in the early studies of the late sixties and early seventies, many other subsequent studies have examined the content of various aspects of accounting information in the market context. For example, market reactions to interim earnings, interim sales and expenses, valuation of inventories, components of earnings, replacement cost accounting, as well as cash flows derived from financial statements have been analyzed in the framework provided by the efficient market hypothesis.

The relation between the two research areas (the time series research and the information content research) lies in the proxies the former provides for market expectations of earnings needed in the latter. For example, the original study of Ball and Brown (1968) mentioned above assumed that if succesive earnings changes are independent, then the most recent earnings number might serve as a useful surrogate for earnings expectations in the market. Based on that assumption, Ball and Brown then measured the unexpected earnings with the difference between two consecutive earnings numbers and found a clear-cut relationship in the market reaction to the sign of unexpected earnings. Following this basic design, many subsequent studies (e.g. the studies analyzing the information content of interim reports) have relied on the results which time series analysis could provide about the behavior of earnings variables.

1.2. Research Objective and Its Relevance

Relating to the background framework briefly described above, this monograph has the following objective:

> The present study aims to compare the time series properties of accrual versus cash-based income variables in order to determine the basic (dis)similarities in the underlying mechanisms of their behavior over time.

The main thrusts motivating this research objective are discussed below.

(i) Literature reviews of the time series research in corporate financial reporting reveal that the bulk of prior studies in the area have analyzed the behavior of accounting income variables and their derivatives such as earnings per share or rate of return obtained from financial statements based on the accruals principle and historical costs. Empirical results obtained from annual data have almost consistently showed that, on average, accrual accounting earnings tend to behave like a submartingale process (random walk with or without a drift). The important point motivating this study is that the explanations proposed in the literature for this observed tendency are, however, very meager.

As is the case with some other areas of empirical research on corporate financial reporting, time series research has suffered from a lack of theoretical underpinning for empirical inquiries. Both literature reviews and individual studies have explicitly recognized this state of the art. For example, Ball and Watts (1972, p. 667) note the following:

> "While the theory of efficient markets may yield specific hypotheses for the time series behavior of market prices of securities, there is no such theory for firms' incomes."

Lev (1977, p. 6) also notes the same deficiency:

> "...a dynamic theory of the firm under uncertainty, which is required for the time series hypotheses, is as yet non-existent."

Although by now some time has elapsed since those statements were made, the state of the art is still virtually the same. It seems that the literature has so far provided little theoretical (and empirical) explanations for the observed tendencies in the time series properties of income variables. The scarcity of explanations is obvious from the following remarks in more recent reviews of the area:

> "In fact, the random-walk hypothesis for earnings is not theory-based." (Lorek, Kee and Vass, 1981, p. 110)

> "Although discussions of economic and other explanations for observed statistical patterns are sometimes provided, typically, these discussions are included in either the introduction or the conclusion of the paper rather than being factored into the research design. ... At present, our knowledge as to why certain statistical properties are found for the annual earnings series of firms is very meager indeed." (Ball and Foster, 1982, pp. 211-212)

> "There have been few attempts to develop a theory that explains why reported earnings follow one particular process or another". (Watts and Zimmerman, 1986, p. 136)

Thus, it can be seen that the situation in the current research area is at present similar to what it was in the finance literature over two decades ago; although empirical observations suggesting the independence of successive security price changes had a long history, explanations of the phenomenon were not available until the mid-sixties when Samuelson (1965) provided theoretical proof for the observed random walk behavior. (As is well-known, that explanation gave thrust to the development of the efficient market hypothesis which in turn formed a basis for one of the main-stream research areas in financial accounting.)

Although a well-articulated explanation of the random walk-type behavior in corporate income numbers has so far not been provided, it would be inaccurate, however, to say that the knowledge of the determinants of the time series behavior of corporate income numbers is a 'tabula rasa' or that the question would not at all have been tackled in the literature. In fact, some hypotheses have been presented which can be grouped under the broad categories of <u>industrial-organization-based</u> and <u>accounting-method-based</u> explanations (See Ball and Foster, 1982, p. 211-212. See also Gonedes and Dopuch, 1976 p. 3, who argue that the properties of accounting numbers are jointly determined by accounting techniques and the attributes of the firm's decisions). The effects of these explanations can be formally summarized with the following general model:

$$\Omega = f(\alpha, \beta) \tag{1-1}$$

where

Ω = the underlying stochastic processes of income variables

α = factors relating to the industrial-organization-based explanation including:

- $\alpha 1$ = factors attributable to the economy as a whole; e.g. growth rate of the economy, cyclical fluctuation, rate of inflation, degree of regulation etc.,
- $\alpha 2$ = factors attributable to the industry; e.g. characteristics of supply and demand markets, competitive situation within the industry, barriers to entry etc.,
- $\alpha 3$ = factors attributable to the firm; e.g. size, growth, capital intensity, competitive capacity, cost structure, type of control, acquisition/divestiture behavior etc.,
- $\alpha 4$ = managerial decisions on the amount, value, and timing of the firm's transactions with external parties.

β = factors relating to the accounting-method-based explanation including:

- $\beta 1$ = the nondiscretionary choice of the basic accrual accounting system including the principle of recognizing revenues and expenses on the accrual basis, the principle of matching costs with revenues, and the principle of using historical costs as expenses,
- $\beta 2$ = discretionary choices within the basic accrual accounting system, viz. the particular valuation and allocation rules followed in the preparation of financial statements,
- $\beta 3$ = manipulative actions taking place through classificatory smoothing practices across different levels of income statements; e.g. the classification of expenses as ordinary vs. extraordinary.

With regard to the role of the economy-wide and industry-wide determinants ($\alpha 1$ and $\alpha 2$), the literature on the association between income variables and various indices constructed across the economy and within different industries shows that the variation of income numbers over time may to some extent be explained by the economic factors captured by these indices (see Brown and Ball, 1967, which was the seminal paper in the area). Moreover, observations that the economy-wide and industry-wide indices have not been able to explain all of the variation in income numbers and the findings that the income variables of different firms may have different underlying processes (see e.g. Watts and Leftwich, 1977; Albrecht et al., 1977) have given rise to studies showing the association between time series properties of income numbers and some firm-specific determinants ($\alpha 3$) (see Lev, 1977, 1983). Furthermore, managerial decisions ($\alpha 4$) on individual transactions with external parties (customers, suppliers and financial markets) obviously also have a direct effect on the monetary consequences of these transactions and thus on the behavior of income variables.

In regard to the importance of the basic accrual accounting system ($\beta 1$), several studies support the notion that it may have a role to play as a determinant of the underlying process(es) of income variables. For example, Beaver (1970, pp. 69, 88) and Lookabill (1976, p. 736) suggest that the accounting measurement rules based on historical costs may give rise to certain behavior in the accounting rates of return. Furthermore, recent theoretical analysis by Dharan (1985) suggests that the use of the accrual principle may result in a lower variance in the income variable than an alternative cash-basis.

With respect to the role of the discretionary smoothing actions through accounting choices within the accrual system ($\beta 2$), e.g. the results obtained by Dopuch and Watts (1972) suggest that accounting changes in the depreciation method may cause changes in the underlying processes of reported earnings numbers. Furthermore, in regard to the manipulative actions through classification of accounting items across income statement (β3) the income smoothing literature supports the notion that such actions exist and, therefore, may also have an effect on the underlying processes of accrual income variables. (For a comprehensive review of the income smoothing literature, see Ronen and Sadan, 1981.)

In conclusion, although a number of explanations have been proposed in the literature for the observed time series properties of income numbers, it still seems to be unclear why the tendency towards submartingale-type behavior in (accrual-based) income variables exists. Particularly, the relative strengths of the competing industrial-organization-based and the accounting-method-based explanations have remained ambiguous in the literature. As a motive for this study, it was assumed that a rigorous analysis of the (dis)similarities between the underlying processes of accrual-based versus cash-based (i.e. non-accrual-based) income variables might provide some insight into this issue. The rationale of such comparative time series analysis is based upon the following alternative filter models of cash flows and reported accrual income variables:

FIGURE 1-1: Alternative Filter Models of Accrual and Cash-Based Income Variables

A) <u>A Serial Filter Model:</u>

```
                                                     -----
                                                     ‖ β ‖
      -----                                          -----
      ‖ α ‖                                            ‖
      -----                                            v
        ‖                                         ------------
        v                                         ‖Accrual    ‖
 --------------    ------------                   ‖Accounting ‖ ----->
 ‖Transactions‖ --> ‖Cash Flows‖ -------->        ‖System     ‖   Ω(A)
 --------------    ------------     Ω(CF)         ------------
```

B) <u>A Parallel Filter Model:</u>

```
                                   -----
                                   ‖ β ‖
                                   -----
                                     ‖
      -----                          v
      ‖ α ‖                     ------------
      -----                     ‖Accrual    ‖
        ‖             ------->  ‖Accounting ‖ -------->
        v            |          ‖System     ‖    Ω(A)
 --------------      |          ------------
 ‖Transactions‖ ----|
 --------------      |          ------------
                      ------->  ‖Cash Flows‖ -------->
                                ------------    Ω(CF)
```

Legend:

α = economic factors relating to the industrial-organization -based explanation (see 1-1)

β = accounting factors relating to the accounting-method -based explanation (see 1-1)

Ω(A) = the underlying processes of accrual accounting income variables

Ω(CF) = the underlying processes of cash-based income variables

Irrespective of whether a serial or parallel filter system is assumed for accrual income and cash flows, figure 1-1 suggests the following:

0) If the effect of β is insignificant, then $\Omega(A) = \Omega(CF)$, and

1) If the effect of β is significant, then $\Omega(A) \neq \Omega(CF)$.

Based on these suggestions, the following alternative hypotheses are defined for this study:

> H0: If the economic factors relating to the <u>industrial-organization-based</u> explanation are of primary importance as determinants of the underlying processes of accrual-based income variables, then <u>similar</u> processes underlie the accrual-based variables and their cash-based (non-accrual) counterparts.
>
> H1: If the accounting choices relating to the <u>accounting-method-based</u> explanation are of primary importance as determinants of the underlying processes of accrual-based variables, then <u>different</u> processes underlie the accrual-based variables and their cash-based (non-accrual) counterparts.

With respect to the general model of the underlying determinants (1-1), it should be readily recognized that the comparative analysis of the cash-based and reported accrual income variables performed in this study mainly concerns the <u>joint effect</u> of the nondiscretionary choice of the basic accrual accounting system (β1) and the discretionary accounting choices within the accrual system (β2). It should be noted that the effects of the manipulative actions taking place through classificatory smoothing practices (β3) can be controlled by analyzing net income variables appearing on the bottom line of the income statement. Furthermore, it should also be recognized that some of the discretionary accounting method choices in β2 affect not only the accrual income but also cash-based income because of their potential tax effects. However, insofar as such accounting choices have any material effects on the cash-based variables, they can be controlled by examining the behavior of income variables both before and after tax.

Having now elaborated upon the main starting point for this study, the other motives giving thrust to this research are discussed below.

(ii) Studies examining the information content of income numbers through measuring capital market reactions to unexpected income changes typically require the specification of an expectancy model for income variables. Consequently, insofar as the information content of accrual and cash-based income variables is to be measured with market reactions, and if the market income expectations are approximated by expectancy models based on observations of past income, then the knowledge of the underlying processes of accrual versus cash-based income variables is of primary importance for such information content studies.

For example, the early studies addressing the question of the information content of cash flows typically used surrogates such as earnings plus depreciation as measures of cash flow in analyzing its potential information content (see Ball and Brown (1968); Beaver and Dukes (1972); Patell and Kaplan (1977)). As Watts and Zimmerman (1986, p. 66) note, the result obtained in these early studies suggesting that market reactions to unexpected cash flows are smaller than to unexpected earnings, and that unexpected cash flows may not have any additional information content beyond earnings, may well arise from the poor validity of the cash flow surrogates used in these studies to describe true underlying cash flows.

However, another possible explanation may be provided by the fact that the information content studies mentioned above also used similar expectancy models (random walk -type models) for both earnings variables and for cash flow surrogates, i.e. it was implicitly assumed that there is no difference between the underlying processes of the accrual vis-a-vis cash-based income variables. This being the case, it can be argued that the negative results of the existence of information content in income variables may well have been an outcome of the joint effect of the use of a poor cash flow surrogate <u>and</u> a poor expectancy model for cash flows.

(iii) In addition to the information content studies, cash flow expectations are also needed in direct applications of valuation models of firm's shares. For example, the well-known capital asset pricing model (CAPM) developed in the sixties requires the specification of future cash flow expectations in one way or another for valuation purposes [2].

However, because direct measures of future cash flow expectations needed for the valuation models have not been available, it has been a common practice to use accrual earnings variables as proxies for cash flows. In fact, as Watts and Zimmerman (1986) note, the rationale for using accrual-based income variables as proxies for cash flows in valuation context could be based on arguments such as the following:

> "Empirically, accounting earnings can be associated with cash flows. If they are associated, then accounting earnings of a firm for the current period can provide information on the firm's current cash flows and (if current cash flows provide information on future cash flows) on expected future cash flows." (ibid., p. 27), or

> "Indeed, some accountants think that the accrual process could cause current earnings to be a better index of future cash flows than current cash flows." (ibid., p.131)

The critical assumption behind the first statement is the condition that "current cash flows provide information on future cash flows" implying that succesive cash flow numbers are serially correlated. However, the second statement is based on an opposite assumption: the lower the serial dependence between successive cash flows, the less the predictive content of current cash flows, and hence current accrual earnings may provide a superior expectation of future cash flow. Despite the seeming conformity between the two arguments in their support to accrual earnings, it can be seen that they are quite obviously based on contradicting assumptions about the underlying processes of corporate cash flows.

Apart from the question of whether or not current earnings provide better cash flow expectations than current cash flows, the important point motivating this study is the assumption that insofar as income variables from the accrual accounting system are to serve as valid proxies for cash flows, the relevant time series properties, and hence the underlying processes of accrual versus cash-based income variables must be similar. The extent to which such similarities exist can be seen from a comparative analysis of the time series describing the behavior of these variables.

(iv) A knowledge of the (dis)similarities of accrual and cash-based income variables may also have a role to play in the income smoothing literature. As noted by Ronen and Sadan (1981), the income smoothing studies are typically based on the notion that (through the exploitation of actions included in $\beta 2$ and $\beta 3$ in 1-1) managers try to smooth income series by reducing the variance of income numbers around a trend or some other level of income.

However, it can be argued that tests of the smoothing hypothesis are joint tests of "the assumed time series of cash flows before management applied accounting procedures and smoothing" (Watts and Zimmerman, 1986, p. 137, emphasis added.) It can also be shown with simple exercises that while the smoothed (reported) earnings behave like a random walk, the presmoothed series may follow a process other than random walk (ibid., p. 145). Insofar as the time series of cash-based income can constitute the "presmoothed series", it must be recognized that knowledge of the (dis)similarities in the underlying processes of accrual and cash-based income variables also has important implications for the income smoothing literature.

(v) As a final motive for the present study, it can be speculated that the knowledge of the basic characteristics of the underlying processes of accrual and cash-based income variables may provide an important contribution to what could be labelled as "dynamic theories for the behavior of the operating, investing and financing flows of the firm".

So far, the fragments of such theories are scattered over a number of disciplines such as microeconomics, operations research and accounting. Typically, such theories take the form of a causal multivariate econometric model describing the behavior of income variables as functions of some exogenous and endogenous variables. It is reasonable to assume that at the very minimum, the relevance of knowledge of a firm's income time series processes can be in empirical tests of the forecast performance of econometric models for which univariate time series models can provide useful benchmarks.

1.3. Outline of the Research Report

The remainder of this research report is organized as follows:

Chapter 2 reviews the prior literature on the time series properties (and predictability) of accrual and cash-based income variables. It aims to describe the current state of the art by examining relevant results of prior studies and their technical solutions. The chapter ends with a discussion of some relevant issues in the previous literature.

Chapter 3 contains a tentative theoretical analysis of serial dependence (autocorrelation) in income variables at sales and operating income levels. The purpose of that analysis is to provide insight into the question of whether different accounting systems (i.e. the accrual and cash accounting systems) may produce (dis)similar autocorrelations in income variables. It may be worthwhile to note here that the analysis of autocorrelations is relevant for the present study, because their (dis)similarities have direct implications to the (dis)similarities of the underlying processes of the income variables.

In chapter 4, the exact variable definitions for empirical analysis are discussed. It also reports on the sample selection and adjustments performed to the raw time series data.

Chapter 5 is a methodological description of the empirical time series analysis. The chapter begins with a description of the general design of the empirical inquiry. Thereafter, the competing time series models and the rationales of their selection are discussed. The details of the model estimation are also discussed in this chapter as well as the most important issues in the predictive ability tests.

The results from the empirical inquiry are reported in chapter 6. The first three sections report on the results of the tests of randomness, results from an analysis of cross-sectional dependences in randomness and from the tests of the theoretical models, and results from the tests of stationarity. The estimation results and the results of the predictive ability tests are subsequently given. The chapter concludes with a summary of the test results.

Chapter 7 provides an overall summary of the study. Of course, the main findings and their implications are also discussed in this concluding chapter.

NOTES TO CHAPTER 1:

[1] For a brief description of the Box-Jenkins approach of modeling and forecasting of time series, see e.g. Mabert and Radcliffe (1974).

[2] For expositions of the theoretical valuation model based on capital market equilibrium under uncertainty, see e.g. Fama and Miller (1972, p. 298) or Haley and Schall (1979, p. 158). In the single period case the model has the following form (see Haley and Schall, 1979, pp. 194-202 for a generalization to multi-period valuation):

$$W(S) = X(0) - I(0) + \frac{E[X(1)] - \tau \, Cov[X(1), r(m)]}{1 + i}$$

where $W(S)$ = the value of the firm, i.e. the wealth provided by the firm to its shareholders in capital market equilibrium

$X(0)$ = current cash income of the firm (current cash revenues minus cash expenses)

$I(0)$ = cash outlay on current investments (including the increase in cash and other liquid assets)

$E[X(1)]$ = expected value of cash income in period 1 (in the single period case this includes the cash received from liquidating the assets in period 1)

τ = $\{E[r(m)] - i\}/\sigma^2(m)$, i.e. the difference between the expected return on the market portfolio and the risk-free rate of return divided by the variance of the return on the market portfolio

$Cov[X(1),r(m)]$ = covariance between the firm cash income in period 1 and the return on the market portfolio

i = risk-free rate of return

This theoretical valuation model is a direct derivative of the well-known Capital Asset Pricing Model (CAPM) developed by Sharpe, Lintner and Mossin in the 1960s. An important conclusion that can be drawn from the above model is that "... the wealth provided by the firm is independent of financing policy since neither X(0), X(1), nor I(0) is affected by financing policy. The wealth is solely a function of the basic cash flows of the firm and investment policy." (Haley and Schall, 1979, pp. 158-159.)

2. A REVIEW OF RELEVANT PRIOR LITERATURE

By the 1980s, studies on the time series properties and predictability of financial statement numbers had provided a substantial amount of empirical research on corporate financial reporting. This chapter reviews a relevant part of this literature in an organized manner with the aim of providing a comprehensive view of the specific topics and their development in the current research area. (The literature review below is based on Kinnunen (1984), which has been reorganized and updated for the present report.) The final purpose of the chapter is to provide a framework against which the present study can be put into perspective.

The literature review below is organized into four main sections. First, the motives and results of studies analyzing the time series properties and forecasts of accrual-based income variables is explored (section 2.1.) Second, the research findings from studies examining the behavior and forecasts of cash-based income variables is examined (section 2.2.). Then, a brief methodological summary of some technical issues (such as sample sizes and statistical methods) of prior studies is presented (section 2.3.). Finally, the chapter ends with a discussion, including a review of prior reviews and conclusions from the literature review.

2.1. Prior Time Series Research on Accrual Income Variables

Since the number of prior studies examining the behavior of accrual accounting income variables is very large, the literature covered by the current review is certainly not exhaustive. However, it is the author's contention that the most relevant part of the literature is included so that the conclusions drawn from the review are justified.

2.1.1. The Main Motives behind Prior Studies

In the very beginning, the size of the literature necessitates the question concerning the underlying motivation. In other words, it is reasonable to pose the question: What prompted earlier research in this area? That question has usually been answered with references to the following arguments.

(i) It has been stated that theoretical and empirical studies on the valuation of a firm's securities require a knowledge of future earning power and income expectations. Such a view is explicitly manifested for example in the following propositions released by the FASB in the late 1970s (see e.g. Hopwood, McKeown and Newbold, 1981, footnote on p. 927):

> "Fundamental financial analysis focuses on earning power of an enterprise in estimating the intrinsic value of the stock", and
>
> "The most important single factor determining a stock's value is now held to be the indicated average future earning power".

Since the accounting profession commonly regards accrual earnings as a superior measure of earning power, it is then quite understandable that earnings forecasts provided e.g. by the knowledge of the earnings time series behavior have been found important.

(ii) As noted e.g. by Brown and Rozeff (1978, p. 1), the rational market expectations hypothesis implies that market expectations should be measured with the 'best' forecasts available. This argument provides a clear motive for studies where the relative predictive ability of various forecasting agencies (e.g. time series models and financial analysts) have been examined. Furthermore, the results from these studies also provide a starting point for market-based studies examining the market reactions to published accounting information.

(iii) Studies on the relative accuracy of forecasts provided by such agencies as management and financial analysts may also have been partly motivated by the debate that took place in the U.S. in the 1970s. That debate concerned the question of the 'usefulness' of forecast disclosure. The rationale behind this research was that insofar as time series models were able to provide (at least) as accurate earnings forecasts as management and/or financial analysts, the forecasts provided by the latter would be futile and therefore should (or need not) be disclosed. (However, this argumentation assumes that the costs incurred from acquiring time series model and management or analysts forecasts are identical.)

(iv) The relevance to the income smoothing literature has also been commonly recognized as one important motive underlying the time series research of income variables. The rationale behind this is that studies in this area have been recognized as dependent on the assumptions concerning the underlying stochastic process of income numbers. On the one hand, it has been argued that income smoothing is futile when the net income of the firm follows a submartingale process (see Ball and Watts, 1972, pp. 663-665). On the other hand, theoretical models for optimal income smoothing under different stochastic processes have been presented with results supporting the income smoothing practices (see Gonedes, 1972).

(v) It has also been argued that time series analysis of income variables could be used as a means for deciding whether or not to adopt a considered accounting method. The relevant decision criterion should be the effect which the particular method might have on the time series behavior of the resulting income numbers

(Dopuch and Watts, 1972. See also Gonedes and Dopuch, 1976, pp. 18-22 for a discussion on the use of time series analysis in the evaluation of the effects of alternative accounting methods). According to this view, for example, the effect of the change from straight line to accelerated depreciation method should be determined on the basis of the potential change in the structure of the underlying stochastic process of the income variable.

(vi) Finally, it has been suggested that the time series analysis of accounting numbers is useful for analytical review or auditing of financial statements (see e.g. Kinney, 1978). The rationale behind this proposition is the task allocation of the reviewing or auditing work: accounting items that are found to be relatively far from their predictions (generated by time series models) should be reviewed in greater detail than the items which are close to their expectations. In this way time series analysis should help the reviewer/auditor to focus on the relevant points of the financial statements being analyzed.

Having now listed the main motives for research in the area, we shall turn below to a closer examination of individual topic areas.

2.1.2. Relevant Topics and Research Results

The research results in the following topic areas will be explored below:

(1) Time series properties of annual income;
(2) Determinants of annual income behavior;
(3) Time series properties of interim (quarterly) income;
(4) Predictive content of interim (quarterly) income;
(5) Managers' and financial analysts' relative forecasting ability;
(6) Predictive content of specified economic information; and
(7) Information content of accrual income

In order to highlight the essentials of prior research findings, the technical and methodological issues of the studies reviewed here are deliberately omitted from this section. Instead, they are briefly summarized in a separate section (2.3.) and in <u>appendix 2-1</u> relating to it.

(1) Time Series Properties of Annual Income

A major topic area concerns the temporal behavior of annual income numbers. The most important research questions asked in these studies are as follows:

(i) Is there any systematic pattern (serial dependence) in the growth of corporate annual income?

(ii) What kind of stochastic process provides <u>on average</u> the best description of the observed behavior of income numbers over time? To what extent does the behavior of income numbers of <u>individual firms</u> differ from each other?

(iii) What kind of time series model(s) would provide the best forecasts for the annual income?

The substantive answers provided by the literature to these questions are as follows.

(i) The behavior of corporate annual income seems to be characterized by "higgledy piggledy growth" which means that successive <u>changes</u> in annual income are random, i.e. independent of each other. This evidence was first obtained with data from the U.K. (Little, 1962; Rayner and Little, 1966) and was subsequently verified with data from the U.S. (Lintner and Glauber, 1967; Fama and Babiak, 1968). The very important implication of this finding is that, because successive earnings changes are essentially random, the earnings growth observed in the past does not provide a reliable forecast for future growth in earnings.

(ii) It has been found that, <u>on average</u>, annual income numbers follow the submartingale or similar process. This result, which is consistent with the previous findings, was explicitly stated first by Ball and Watts (1972), and it has been repeatedly supported by several subsequent studies in the U.S. (e.g. Brooks and Buckmaster, 1976; Ball and Watts, 1979; Brooks and Buckmaster 1980; Hopwood, Newbold and Silhan, 1982). Moreover, Ball and Foster (1982, p. 187) mention that results consistent with the submartingale behavior of annual earnings have also been found in Australian and New Zealand firms. Furthermore, Kodde and Schreuder (1984a) report results supporting submartingale behavior in Dutch firms.

At this point it should be noted that, under certain conditions, the general result supporting submartingale behavior has not been found to be a valid description of income behavior. This is the case in the years immediately following an exceptionally high or low annual income (due to e.g. the firm taking a 'financial bath')., when some mean reverting or moving average behavior has been noted (Brooks and Buckmaster, 1976 and 1980). Furthermore, as regards the income behavior in <u>individual firms</u>, the evidence suggests that different firms have different underlying processes (Salamon and Smith, 1977; Albrecht et al., 1977; Watts and Leftwich, 1977).

(iii) When the predictive ability of submartingales has been compared with individually identified firm-specific ARIMA models, it has turned out that the former can do (at least) as good a job in predicting annual earnings as the latter (Albrecht at al., 1977; Watts and Leftwich, 1977). This result is manifested e.g. in the following statements:

> "The ability of random walk to 'outpredict' the identified Box-Jenkins models suggests that the random walk is still a good description of the process generating annual earnings in general and for individual firms." (Watts and Leftwich, 1977, p. 269)

> "To summarize, the evidence suggests that, for forecasting annual earnings using annual data, individual firm ARIMA models perform no better than random walk models that allow for a drift parameter." (Bao et al., 1983, p. 408)

The research results mentioned above concern primarily the time series properties of absolute income numbers such as net income available to common equity holders or earnings per share. In addition, there is also evidence on the time series properties of relative income numbers expressed in the form of rates of return on common equity. In the early study of Beaver (1970), it was found that the underlying process of market-based as well as accounting rates of return might be of the mean reverting type. This conclusion was subsequently supported by Lookabill (1976) and Freeman et al. (1982) who also found mean reverting behavior for rates of return on common equity. Furthermore, Albrecht et al. (1977) found that individually identified ARIMA models from accounting rate of return series did not provide forecasts that were any better than those given by the simple random walk. It should be noted, however, that the mean reverting model was not tested in that study.

(2) Determinants of Annual Income Behavior

This body of time series research has tackled the following questions:

(i) What is the effect of economy- and industry-wide factors on the variation of annual income numbers over time?

(ii) Is there any association between the time series behavior of rate of return and the systematic ('beta') risk of a firm?

(iii) Could some specified industry and firm-specific determinants affect the degree of dependence between successive earnings changes?

(i) The first question concerning the role of economy and industry-wide factors was examined by Brown Ball (1967). They found that an important variable explaining the temporal variation of income numbers was an economy-wide index obtained by a cross-sectional average of income over all firms in the sample. Depending on the exact income definition, the economy-wide index explained on average some 40 - 60 % of the total variation in the income variables over time. Furthermore, an industry-wide index (average income of firms within the same industry) increased the explanatory power to about 70 % (see Brown and Ball, 1967, table 4, p. 64). Taken at face value, these results would suggest that firm-specific factors might play a minor role as determinants of income behavior. However, it should be noted that the results were obtained from the levels of the income variables, and therefore the coefficients of determination may be biased upwards (due to e.g. a common trend).

(ii) The results on the relationship between the time series behavior of rate of return and the systematic risk of the firm suggest that the mean reverting or moving average behavior of market-based as well as accounting rates of return does not seem to be explained by mean reversion in systematic risk (Lookabill, 1976). Therefore,

> "This leaves the explanation that the historical cost accounting system (as well as, perhaps, managerial manipulation) induces averaging into the accounting system." (ibid., p. 736)

(iii) With regard to the industry and firm-specific determinants, the evidence provided by Lev (1977 and 1983) indicates that such economic factors as product type (nondurables vs. durables), barriers to entry (competition) and capital intensity (operating leverage) are associated with the degree of serial dependence in earnings changes. Furthermore, Lev (1983) also suggests that earnings variability is affected by product type and firm size. On the other hand, factors such as firm size and type of control (owner vs. management control) were not found to be significant determinants of serial dependence in earnings changes. On the whole, Lev's studies suggested that

> "... corporate earnings behavior is systematically affected by substantive economic factors." (Lev, 1977, p. 27), and

> "... the association found between economic factors which <u>vary across firms</u> and the degree of dependence in earnings changes appears to suggest that different stochastic processes generate corporate earnings." (ibid., p. 28)

Furthermore, some studies mentioned in the preceding subsection have also shown that certain industry-specific determinants may be associated with the underlying processes. This was indicated e.g. by Albrecht et al. (1977, p. 228-229) who identified models of the autoregressive type for firms in the steel industry. Similar models were also obtained by Watts and Leftwich (1977, p. 262) for railroad companies. In all, these findings are consistent with Lev's results (1977, 1983), because the significant determinants found by him can largely be traced to the industry of the firm.

Finally, interesting analytical results have been derived by Dharan (1983a), who indicates that under a theoretical decision model of the firm's production, investments and inventory accounting, and assuming that sales behave like a white noise process (i.e. each period's sales level is an identically and independently distributed random variable), a particular stochastic process (viz. ARMA(3,3)) could be expected to underlie earnings behavior. Thus, there are also some theoretical results available which indicate the mechanisms of the effect of firm-specific decisions on the time series behavior of earnings.

(3) Time Series Properties of Interim (Quarterly) Income

In addition to annual income series, there are a number of studies examining the behavior of interim (quarterly) numbers. It should be noted that the findings from these two data sets are related to each other, because findings from quarterly series have direct implications for expected processes from annual series.

The main research questions motivating time series analysis of quarterly earnings have been as follows:

(i) Can the random walk-type behavior observed from annual earnings series be generalized to quarterly earnings as well?

(ii) In case the answer to the above question is negative, what kind of a stochastic process might provide the best description of quarterly earnings behavior?

(iii) What are the implications of findings from quarterly data with respect to the behavior of annual earnings?

(i) The empirical evidence shows indisputably that, in fact, the submartingale (random walk) hypothesis is not descriptive of quarterly income behavior. The reason for this is that, quite obviously, the simple random walk (with or without a drift) is unable to capture the seasonal variation inherent in quarterly income series, and that this property should be incorporated into the model. This is what all researchers in the field seem to agree upon.

(ii) However, the views diverge with respect to the exact form of the most descriptive time series model; at least three different competing 'premier' models have been suggested for quarterly earnings in the literature. These include the models proposed by Foster (1977), Griffin (1977), and Brown and Rozeff (1979). Interestingly, one of these, viz. the Brown-Rozeff's model, has also been supported by Deschamps and Mehta (1980), who found that a MCGS-model (Mixture of Constant Growth and Submartingale) performed about as well as firm-specific seasonal ARIMA models in their data [1], while Abdel-khalik and El-sheshai (1983) found that the Griffin model also had a good fit in quarterly sales time series. On the other hand, the comparative results by Lorek (1979) showed that the predictive ability of some of the previous 'premier' models was dependent on the length of the forecast horizon and that the Griffin model, which was consistently more accurate than the other two models, was unable to forecast quarterly income significantly any better than individually identified firm-specific seasonal ARIMA models. In conclusion, Lorek (1979, p. 202) noted:

> "Perhaps this phenomenon is simply a reflection of the diversity exhibited by underlying time series, so the search for an optimal parsimonious model for quarterly earnings may prove futile."

A similar conclusion was also drawn by Bao et al. (1983, p. 411):

> "To summarize the quarterly-data studies, there still remain questions about whether any single 'premier' univariate time-series model exists in a forecasting context."

(iii) Because annual earnings can be viewed as an aggregate of quarterly earnings, several researchers have noted the implications which identified quarterly earnings models have for appropriate models for annual earnings behavior. For example, Watts and Leftwich (1977, pp. 269-270) note that Foster's model for quarterly earnings implies that some negative dependence could be expected between successive changes in annual earnings. Furthermore, Hopwood and Newbold (1980, p. 141) show that Foster's model implies ARIMA(1,1,1) for the annual earnings, Griffin's model implies ARIMA(0,2,2) for the annuals, and Brown-Rozeff's model implies ARIMA(1,1,2) for the annuals, none of which is consistent with the submartingale (random walk) process of annual earnings behavior [2]. Furthermore, empirical tests by Hopwood, McKeown and Newbold (1982) indicated that random walk predictions for annual earnings were outperformed by the predictions obtained by annual models inferred from quarterly series:

> "...Procedure C [random walk] does worse than A [annual from quarterly] since it is based on an incorrectly specified model - the random walk - for the annual totals. Apparently the random walk model is not a very satisfactory premier model for corporate [annual] earnings." (ibid., p. 347)

(4) <u>Predictive Content of Interim (Quarterly) Income</u>

A pragmatic motive behind these studies has been the question of whether interim income information is useful for investors [3]. In the time series research context, this question has been approached by examining the extent to which interim income numbers can be utilized in the prediction of annual income which has been regarded as the more relevant income number. If published interim income numbers contribute to generating more accurate annual income forecasts, then it might be reasonable to assume that such information is useful and, therefore, should be disclosed [4].

With one exception (Green and Segall, 1967), the empirical evidence obtained on this topic indicates that quarterly income time series can be succesfully employed to produce annual income forecasts which outperform forecasts based on annual income series alone. This conclusion emerged at least in the studies performed by Brown and Niederhoffer (1968), Coates (1972), and Hopwood, McKeown and Newbold (1982). These studies also showed the obvious result of improving annual income forecasts as more observations of quarterly income numbers become available.

(5) Managers' and Financial Analysts' Relative Forecasting Ability

An interesting and very popular topic area within time series research concerns managers' and financial analysts' forecasting ability vis-a-vis each other and time series models. One motive for these studies has been the need to obtain valid surrogates for market's earnings expectations. For example, if judgmental forecasts by managers and financial analysts turned out to be superior (as measured by accuracy or by the strength of the association between forecast errors and market reactions), then their forecasts should be preferred to time series models in studies requiring such market proxies.

Another motive especially for some early studies is parallel to studies of the above subsection, i.e. do income forecasts provided by managers or financial analysts contain useful information for investors? This question is closely connected with the debate about the need for disclosing such forecasts, a problem that was discussed in the U.S. especially in the 1970s [5].

Using the predictive ability criterion, time series research has assessed the desirability of forecast disclosure by comparing the accuracy of income forecasts by managers and financial analysts with that of time series models. The underlying hypothesis of these comparisons has been that because managers and analysts are able to process much more information than is included in the time series of past income numbers alone, this larger information set should produce more accurate income forecasts (see e.g. Brown et al., 1985, pp. A.53-A.55, who recognize that besides information sets, there may also be differences between the time, aggregation and efficiency of forecast preparation). Furthermore, it has been stated that the mere existence of financial analysts and the continuous demand for their forecasts should indicate the superiority of their forecasts over time series models (Brown and Rozeff, 1978, p. 1). However, with regard to the intuitively strong arguments for the superiority of managers' and analysts' income forecasts, it may be surprising that the evidence provided by empirical studies has not been exclusively supportive for the hypothesis.

For example, the results obtained in studies where managers' income forecasts have been compared with time series models are mixed. On the one hand, Lorek, McDonald and Patz (1976) argued that seasonal ARIMA models are able to outperform managers in terms of predicting quarterly earnings, and Kodde and Schreuder (1984a) found that the simple random walk with drift outperformed managers in forecasting annual sales. On the other hand, no consistent or significant differences between managers and time series models in predicting earnings numbers were found by Green and Segall (1967), and Kodde and Schreuder (1984a). Finally, results supporting managers' superiority over time series models have been provided by Copeland and Marioni (1972) as well as Imhoff and Pare (1982). The findings being so mixed, it is then no wonder that Brown et al. (1985, p. A.64) note that "a consistent result does not emerge from this research."

As regards the relative forecasting accuracy of financial analysts vis-a-vis time series models, Cragg and Malkiel (1968), Elton and Gruber (1972), Imhoff and Pare (1982) as well as Kodde and Schreuder (1984a) found no significant differences between their ability to forecast earnings [7]. However, findings supporting the superiority of financial analysts have been provided by Barefield and Comiskey (1976), Brown and Rozeff (1978), Collins and Hopwood (1980), Fried and Givoly (1982), Brown, Hagerman et al. (1987), Brown, Richardson and Schwager (1987), as well as Conroy and Harris (1987). Moreover, Fried and Givoly (1982) found that financial analysts' earnings forecasts were not only more accurate than time series models (e.g. the submartingale model), but also their forecast errors had a stronger association with the reactions in the capital market. Furthermore, Brown, Richardson and Schwager (1987) showed that analysts' superiority is directly related to firm's size and inversely related to the agreement among analysts as measured by the dispersion of their forecasts.

The comparisons of management vis-a-vis financial analysts can be divided into two subclasses: the studies showing no significant differences between their forecasting ability, and the studies supporting the superiority of managers over analysts. The evidence belonging to the first class (i.e. no significant difference) includes the results by Basi et al. (1976), Imhoff and Pare (1982), and Schreuder and Klaassen (1984), whereas the second class (significant managers' superiority) includes the studies by Jaggi (1980), Armstrong (1983), Waymire (1986) and Hassel and Jennings (1986). It should be noted, however, that three of these studies (viz. Jaggi 1980, Waymire 1986, and Hassel and Jennings 1986) report the significance of management forecast superiority to be conditional on the timing difference between the forecast releases.

All studies included in this subsection are examples of research where <u>unspecified</u> information sets have been incorporated into the analysis in addition to mere historical time series. This has been implicitly done by examining managers' and analysts' income forecasts which are evidently based on such larger information sets. An interesting yet largely unexplored research topic concerns the benefits of combining the forecasts from one agent with those obtained from another. Some theoretical considerations on this issue are given by Kodde and Schreuder (1984b). Empirical evidence has recently been provided by Conroy and Harris (1987), who indicate that combining consensus (mean) analyst forecasts with time series models may generate improvement in forecast accuracy especially if the forecast horizon is not very short.

In the next subsection, results from studies analyzing the predictive content of more <u>specified</u> economic information exogenous to income time series will be examined.

(6) Predictive Content of Specified Economic Information

An important research area covered by this subsection deals with the question of whether desaggregated income numbers provide useful information for improving income forecasts. The dimensions of desaggregation that have been examined in the literature are [8]:

(i) Industry-specific subentity income information of multi-industry conglomerate firms, and

(ii) Desaggregated information included in the various items (e.g. sales revenues, costs of goods sold, interest expenses, taxes, etc.) of income statements.

(i) As regards industry-specific subentity income information, the evidence presented in the literature is mixed. The first two studies addressing this issue indicated that subentity income information may be useful in improving aggregate income forecasts (see Kinney 1971 and Collins 1976). However, the results of some more recent studies have shown the opposite. First, theoretical and empirical results by Barnea and Lakonishok (1980) indicated that desaggregated income information does not necessarily improve the forecasts of the aggregate income number. Furthermore, Silhan (1982) obtained empirical results showing that forecasts based on segmented (i.e. subentity) income time series did not generate forecasts of the aggregate income number which would have been significantly more accurate than forecasts based on the time series of the aggregate income. This result was manifested e.g. in the following conclusion drawn by Silhan (1982, p. 261):

> "...SG (segmented) earnings may be of limited usefulness in making predictions of enterprise profits."

A similar result was also obtained by Hopwood, Newbold and Silhan (1982), who showed that the theoretical conditions for this conclusion were met in their data. Moreover, the recent results provided by Garrod and Emmanuel (1987) from the U.K. showed that although company profile (proxied by diversification) was associated with the predictive content of desaggregated data, segmental sales and industry output forecasts turned out to be of limited usefulness in forecasting corporate turnover irrespective of the company profile.

(ii) With respect to the predictive content of various items appearing in income statements, the evidence provided by Ang (1979) is available. This study showed that the operating income numbers in selected industries were better (more accurately) predicted directly from the time series of operating income itself than by first forecasting the sales and expense numbers separately from their time series and then obtaining the operating income forecast as the difference between predicted sales and expenses [9].

In addition to desaggregated information, the literature also contains evidence on the predictive content of some <u>other economic variables</u>. For example, in the study performed by Elliot and Uphoff (1972), it was shown that an econometric model including such exogenous variables as indices of industrial production, materials price, total industry unit sales, and population, was able to predict virtually all items (operating profits inclusive) in the monthly income statements of a firm more accurately than time series models based on exponential smoothing. The authors could, therefore, conclude that the economic information included in the exogenous variables apparently had some additional predictive content beyond time series of income statement items [10].

Another subset of time series studies has examined the information content of various economy and industry-wide indices in a predictive setting. For example, Gonedes (1973) found that a regression model, where the firm's rate of return on equity was predicted with the expected average [11] of rates of return for all other firms in the sample, produced forecasts which were at least as accurate as forecasts obtained with some univariate time series models [12]. Also, Hopwood and McKeown (1981) using quarterly data found support for the contention that market-wide indices computed as a weighted average of earnings per share of individual firms may have some predictive power with respect to future earnings per share. This was indicated by the observation that when such indices were used as input series for transfer function models [13], their predictive power was superior to firm-specific univariate ARIMA models.

However, some studies have shown that the information included in share prices has no predictive power with respect to corporate earnings per share. This result was obtained by Chant (1980) who found that observed changes in the Standard & Poor's 425 industrial index were not able to predict future changes in earnings per share significantly more accurately than submartingales. Furthermore, Hopwood (1980) compared earnings forecasts generated by univariate ARIMA models with forecasts obtained with transfer function models using market and industry-wide share price indices as input series. Nevertheless, he was not able find significant superiority in the forecasting performance of the transfer function models.

Finally, some evidence on the non-existent predictive content of firm-specific economic variables is available. For example, Manegold (1981) compared transfer function forecasts of corporate earnings before tax with forecasts obtained with univariate ARIMA models.

Despite the fact that the transfer function models contained such input series as e.g. industry sales, operating margin, gross investments, liabilities, and bond rates, the multivariate models did not appear to forecast earnings more accurately than the less sophisticated univariate models. In conclusion, Manegold (1981, pp. 371-372) stated that

> "Forecasting results indicate that little seems to be gained by using the multivariate component model, especially if one considers the additional costs of developing such a model." [14]

(7) <u>Information Content of Accrual Income Numbers</u>

From the present perspective, a very important body of research also motivating the present study (see the introduction) concerns the (capital market) information content of income variables. Unfortunately, the number of individual studies examining these issues is too large to be covered by this brief review. (In fact, it can be argued that some of their <u>specific</u> research questions are also of marginal relevance for the current research objective.) Therefore, the main results of only a few studies in this area are presented below. (For more comprehensive reviews of the information content studies, see e.g. Foster (1986, pp. 373-420); and Watts and Zimmerman (1986, pp. 37-70.))

The seminal study of the area was performed by Ball and Brown (1968). Assuming market efficiency, Ball and Brown hypothesized that, if earnings numbers contain information, then the capital market should react to unexpected earnings changes. The expected earnings changes were generated in the study with the random walk expectation of no change in earnings, and with changes in earnings after removing market-wide effects as measured by average earnings changes of different firms in the market. When the signs of unexpected earnings changes were then related to the cumulative residual return of the shares (the residual return was defined as the excess return over the prediction of market-wide share index), it was found that the firms with positive (negative) unexpected earnings change had, on average, positive (negative) cumulative residual return by the month of the annual report announcement.

Similar results supporting the contention that accrual accounting income variables contain information on the capital market were obtained in a large number of subsequent studies. However, there has been variation across the studies in the way in which the predicted (expected) income numbers have been generated. For example, Foster (1977) analyzed the predictive content of interim earnings and generated expected earnings with some premier quarterly earnings time series models, while Manegold (1981) used firm-specific ARIMA and transfer function models in obtaining expectations for annual earnings. Despite these methodological differences, the results of these studies were, however, identical in that they showed a clear-cut association between the cumulative residual return and the sign of unexpected earnings change. An important conclusion for the present study would thus be that the time series modeling of past income numbers have been effectively used as proxies for market income expectation.

2.2. Prior Time Series Research on Cash-Based Income Variables

Studies on corporate cash flows and cash flow reporting form a highly fragmentary body of research, which is indicated e.g. by the fact that individual study reports have been scattered over a large number of journals and other publications. Therefore, it is a difficult task to form a comprehensive and organized view of that literature. With the risk of making violations, one classification scheme that may be useful for the current purpose is to distinguish the general conceptual cash flow research from the research with an empirical emphasis.

As regards the conceptual literature, it can be noted briefly that since the basic accounting reporting system presently used in most (if not all) countries is based on the accrual and matching principles and on the use of historical costs, most conceptual studies in the area have addressed the principles and formats of an alternative system, i.e. cash flow reporting. Typical examples of such research are Hawkins (1977) and Ijiri (1978) from the U.S., Lawson (1978) and Lee (1984) from the U.K., and Artto (1978, 1985) from Finland.

The thread running throughout the conceptual research tradition is that it is <u>normatively</u> inclined because these studies typically first recognize the problems relating to the accrual accounting system (e.g. the arbitrary allocation of expenditures over time), and then propose formats of an alternative cash-based reporting system which might provide more useful information for users. In fact, some of these researchers have gone a step further and analyzed the performance of firms and industries using their proposed frameworks (see e.g. Lawson, 1978; Artto, 1982, 1985, 1987).

The empirical cash flow literature that is more relevant for the present study will be examined below. The main motive(s) behind prior studies are first identified and then the results in some relevant topic areas are examined.

2.2.1. The Main Motives behind Prior Studies

Two main motives underlying time series research of cash flow numbers can be identified. They are parallel with the studies on accrual-based income numbers (see section 2.1.1.), and also with the present study (see section 1.2.).

The first and perhaps the most important motive seems to be the relevance of cash flow expectations for valuation of the firm's securities. This motive has been explicitly recognized e.g. by Icerman (1977, pp. 16-21) and by Adam (1984, p. 8).

The second motive discussed e.g. by Adam (1984, pp. 6-7) relates to the studies examining the incremental information of cash flows for the capital market. Since proxies for market expectations of cash flows are a prerequisite of such inquiries, the knowledge of cash flow time series behavior may be important in providing the required proxies. Because these motives have already been discussed above, no further elaboration is needed here.

Finally, it is evident that the motive behind the studies analyzing the lead relationship between accrual income and cash flows lies in the contention that accrual earnings numbers contain superior information for predicting future cash flows which are commonly recognized to be of primary importance in decision making by users of financial statements. Such a view is well documented e.g. in the following statement by the FASB in the late 1970s (see e.g. Bowen et al., 1986, pp. 714-715):

> "Information about enterprise earnings based on accrual accounting generally provides a better indication of an enterprise's present and continuing ability to generate favorable cash flows than information limited to the financial aspects of cash receipts and payments."

2.2.2. Relevant Topics and Research Results

The relevant research findings in the following topics will be reviewed below [15]:

(1) Time series properties of cash flows;
(2) Determinants of cash flow behavior;
(3) Predictability of cash flows; and
(4) Information content of cash flows.

(1) Time Series Properties of Cash Flows

The number of studies exploring the underlying processes of corporate cash flows is not very large; only three studies where this issue has been among the main research objectives were identified in the literature. One of the early studies in this area was Khumawala (1978), who analyzed the behavior of quarterly cash flows from operations defined by adjusting quarterly net income for non-cash charges and changes in the current accounts other than cash. Khumawala identified and estimated firm-specific ARIMA models from these time series and compared their predictive ability with four variants of submartingales and with a "financial analyst's model", which was a simple linear trend. One interesting finding of the study was that while no significant difference could be found between the predictive ability of invidually identified ARIMAs and the financial analyst's model, the submartingales performed poorly and were generally outperformed by the former models:

> "The interesting result... is that the financial analyst's model [linear trend] has performed equally well as the Box-Jenkins model. ... Further, the result indicates that the four naive models [submartingales] performed poorly and thus can be said are not useful for predicting future cash flows" (ibid., p. 106)

One should note, however, that since the sample of firms used by Khumawala was restricted to one single industry (airline), it may prevent generalization of the results to other industries.

Adam (1984) analyzed the behavior of historical cost and constant dollar operating cash flows (defined virtually in the same way as in the study above) on an annual basis. Using the Box-Jenkins methodology, Adam identified autoregressive-type models from approximately one half of the sample series. Interestingly, the proportion of submartingales identified in the study was quite small; approximately 15 % and 3 % of the models identified from historical cost and constant dollar cash flow series were of this type, respectively. Moreover, the predictive ability results were mixed. The one-year-ahead cash flow forecasts generated by ARIMA models were significantly more accurate than submartingale forecasts in one year (1980) but not in the other (1981). Furthermore, while submartingales and firm-specific ARIMA models did not show significant difference in the historical cost series, the ARIMAs were significantly superior in predicting the constant dollar cash flows two years in advance.

Kinnunen (1984) explored the underlying processes of three different versions of corporate annual cash flows. The first variable was cash margin for dividends obtained by subtracting the cash outflows for short term operating expenses, interests and taxes from sales cash inflows. The second variable was defined by the net cash flow realized between the firm and its shareholders, and the third variable was similar to the second, except for the net increase in liquid assets which was included. A general price level index was used in the study in order to express the nominal time series of these cash flow variables in a uniform purchasing power of money. The results from distribution-free tests of randomness, autocorrelation analysis and predictive ability tests indicated that the behavior of these cash flow variables were much better approximated by constant processes such as a mean reverting model than by a random walk (with or without a drift). However, it should be noted that the sample of firms analyzed by Kinnunen (1984) was very small (only eight firms) and they were all from one single industry (manufacturers of wood-processing products.)

(2) <u>Determinants of Cash Flow Behavior</u>

At least two studies can be found in which the determinants of cash flow time series behavior have been tackled. Koskela (1978) analyzed the determinants of the volatility of annual operating cash flows in four industries. The volatility of cash flows was measured with the relative dispersion of cash flows around their quadratic trend. Koskela found some support to his a priori hypothesis that differences in the operating leverage of the firms might provide an explanation for the cross-sectional variation in the degree of cash flow volatility. In particular, financial ratios such as working capital per total assets and fixed long-term assets per wages turned out to be significant variables explaining the cash flow volatility.

Another study examining the determinants of cash flow behavior is provided by Niskanen (1986). Using the familiar index model technique and an international sample containing wood-processing companies from four different countries (Finland, Sweden, Canada, and the U.S.A.), Niskanen explained the behavior of annual operating cash flows deflated by sales with an international and national industry indices computed as the averages of international and national samples, respectively. On average, the international and national industry-wide indices explained 19 % and 21 %, respectively, of the total variation in cash flows, and when both indices were included in the model, their explanatory power was about 35 % (see Niskanen, 1986, table 6, p. 75). On the whole, these percentages are somewhat lower than in some prior index studies examining accrual earnings with national samples (e.g. Brown and Ball, 1967). The results also imply the existence of firm-specific (and perhaps economy-wide) determinants of cash flow behavior.

(3) <u>Predictability of Cash Flows</u>

A number of studies have tackled the (FASB's) contention that accrual earnings provide relevant information for the prediction of future cash flows. However, none of the studies performed so far on this issue has found strong support for that contention.

For example, Cheung (1977) using a small sample of ten firms compared the ability of univariate ARIMA models to predict quarterly net cash flows realized between the firm and its security holders (shareholders and lenders) with transfer function models including quarterly accrual net income as input series. However, because he could not find any significant differences in their predictive ability, Cheung (1977, p. 112) conluded:

> "... a knowledge of past cash flows would render earnings data redundant as an additional predictor of cash flows."

Some results of the non-existent predictive content in accrual net earnings were provided also by Adam (1984), who identified transfer function relationships between earnings and operating cash flow series. For example, in the historical cost time series data Adam (1984) found no relationship between earnings and cash flows in 17 % of the firms, in only 25 % of the firms the earnings were found to be a leading indicator of cash flows, while in 23 % of the sample firms cash flow was a leading indicator of earnings (Adam, 1984, pp. 93-94). Since similar results were also obtained from the constant dollar time series data, Adam (1984, p. 130-131) concluded:

> "... there was no empirical evidence that income was the leading indicator of cash flow for either the historical cost or constant dollar measurement method."

Further evidence of the non-existent predictive content of accrual earnings has recently been provided by Bowen et al. (1986), who found that, while a relatively high cross-correlation existed between changes in accrual earnings and cash flow surrogates such as earnings plus depreciation, the cross-correlation was quite small between changes in accrual earnings and proper cash flow variables including adjustments in current accounts. Furthermore, past accrual earnings did not provide more accurate predictions of future (proper) cash flows than past cash flows themselves. In conclusion, Bowen et al. (1986, p. 723) noted:

> "In summary, the results do not clearly support the FASB's claims of the superiority of accrual numbers for predicting future cash flows."

As regards the predictive content of variables other than accrual earnings, some evidence is provided by Icerman (1977), who analyzed annual operating cash flows defined by net income adjusted for non-cash expenses and changes in current accounts excluding cash. The model set examined by Icerman included a market model with a market-wide index for cash flows as independent variable, a model based on industry sales, a regression model including several financial ratios as independent variables, exponential smoothing models, and naive models including a random walk, a mean reverting model, and four variants of random walk with drift. On the whole, Icerman found significant differences between the predictive abilities of these models. In the first year tested (1973), the prediction model based on an estimate of industry sales proved to be the best, while the random walks with drift performed worst. In the second year (1974), all models performed worse than in the preceding year, and none of the models was consistently superior across all forecast error measures. However, with one error measure, the industry sales model was once again superior. Interestingly, the mean reverting model also performed significantly better than random walk in that year.

Furthermore, Asp (1979) has analyzed cross-correlations between pre-whitened [16] time series of operating cash flows and investments in fixed long-term assets. Contrary to the intuitively appealing economic hypothesis that a positive cross-correlation at some lag(s) should exist between these variables, the number of significant coefficients was, however, not larger than could be expected under perfect independence. In essence, this result supports the (unappealing) contention that the amount of investments in fixed assets does not contain predictive information with respect to future cash flows of the firm [17].

(4) Information Content of Cash Flows

Several researchers have tackled the question of whether corporate cash flows or cash flow surrogates contain information relevant to the capital market. However, as shown below, the results obtained from the empirical inquiries into this issue are mixed.

An early study into the association between share values and a cash flow surrogate is provided by Staubus (1965), who analyzed cross-sectional correlations between discounted stock values and 'current flow' defined by adding depreciation, depletion and amortization expenses to earnings. The empirical results showed that this cash flow surrogate had a closer association with discounted stock values than accrual (net) earnings.

Three years later, Ball and Brown (1968) using their abnormal performance index, reported that 'cash flow' approximated by operating income (i.e. net sales less cost of sales and operating expenses before deducting depreciation, amortization, etc.) was not as successful in predicting the signs of stock return residuals as net income and earnings per share.

Also, similar results were subsequently reported by Beaver and Dukes (1972) who found that reported earnings had a higher association with capital market reactions (as measured by the abnormal performance index) than 'cash flows' defined by adding depreciation, depletion and amortization to earnings before tax deferrals.

Furthermore, Patell and Kaplan (1977) analyzed the incremental information content of 'cash flows' approximated by total funds from operations (i.e. net income plus depreciation etc.). The main result of their study was, however, that they were not able to find support for the hypothesis of cash flow information content over and above annual earnings.

Using a sample of U.K. manufacturing firms, Lawson (1980) found that the time series variation in the (cost-of-living-adjusted) equity price index was better explained by previous year's 'equity cash flow' (i.e. the net cash flow realized between the firm and its shareholders) together with its variability over the past four years than respective variables based on historical cost accrual earnings. As a result, Lawson (1980, p. 33) argued:

> "It is tempting to conclude that cash flow data ... constitute highly relevant information for stock market investors, and that historic cost accounts per se are apparently ignored by the market while being taken seriously by lenders, company directorates, and tax authorities."

Beaver et al. (1982) used a two-stage regression model in examining the incremental information content of replacement cost earnings and 'cash flows' (defined as net income + depreciation, depletion, and amortization) over historical cost earnings. However, their results showed that while the historical cost earnings contained significant incremental information over replacement cost earnings and the cash flow surrogate, these variables did not appear to contain significant information beyond the historical cost earnings. The results with respect to the information content of the cash flow surrogate thus proved to be similar to those of some prior studies (e.g. Beaver and Dukes, 1972) analyzing this cash flow definition.

Koskela (1984) found that some cash-based financial ratios were able to explain time series variation of market prices of shares traded in the Finnish security market. The financial ratios examined by Koskela were operating cash margin deflated by total assets, net investments in fixed assets deflated by cash receipts from sales, net cash margin after taxes, interest and dividends deflated by debt capital, and the coefficient of variation of operating cash margin deflated by cash receipts from sales. Empirical results indicated that these ratios had significant correlations with share prices in some of the sample firms. Furthermore, regression models including the ratios as independent variables turned out to be significant in over one half of the sample firms. However, since Koskela did not report results on respective accrual-based ratios, it remains unclear whether the explanatory power of the cash-based ratios were able to outperform respective ratios expressed on the accrual basis.

Recently, three studies examining operating cash flows and accrual components of earnings have found support for the hypothesis that they may, indeed, have information content for the capital market.

Rayburn (1986) regressed cumulative abnormal returns on unexpected changes of operating cash flow variable (defined by the sum of accrual earnings and total accruals, i.e. depreciation etc., changes in deferred taxes, and changes in current accounts other than cash), and on unexpected changes in the total accrual adjustments between the cash flow and accounting earnings. Using both random walk and holdout regression expectations for the operating cash flow and the total accruals, Rayburn could reject the null hypothesis that unexpected changes in these variables are not associated with the abnormal returns. Moreover, when the information content of the components of the total accruals were analyzed, it turned out that primarily the changes in the current accounts were associated with capital market reactions while the long-term accruals (depreciation etc.) were not.

Recognizing that information about earnings and its accrual and funds components become available to the market at two distinct event dates, Wilson (1986) constructed a 'two-return model' for analyzing the relative information content of the components of earnings. In order to define the required expectations for these components, Wilson regressed them on their lagged values, lagged revenues, and current capital expenditures. The main findings obtained by Wilson (1986) suggested that (i) total accruals (i.e. the sum of depreciation etc., and the net change in current accounts other than cash) and the cash flow from operations have information content beyond earnings, (ii) total accruals have information content beyond cash flow from operations, and (iii) the information content of total accruals is mainly attributable to its current component (i.e. the net change in the current accounts) rather than to the non-current component (i.e. depreciation etc.) These results thus fall well in line with similar findings of Rayburn (1986) noted above.

Furthermore, in a subsequent paper relating to the previous one, Wilson (1987) used a 'single-return, funds-event model' specifying only one event date, i.e. the date the annual report arrives at the SEC, and thus information about all funds and accrual components of earnings are available to the market. Using the regression approach similar to that of the related paper, Wilson (1987) defined the required expectations for the funds and accruals variables. Moreover, both a cross-sectional regression as well as a portfolio approach was used in order to detect the market reactions around the funds-event date to the unexpected components of earnings. Not so surprisingly, the main results provided by Wilson (1987) are consistent with the related paper: he showed that both the total accruals and cash flow from operations have information content beyond earnings. However, the findings were inconclusive with respect to whether non-current accruals (i.e. depreciation etc.) and working capital from operations (i.e. earnings plus non-current accruals) had information content.

Recently, similar findings were obtained by Bowen et al. (1987) suggesting that cash flow variables (defined after adjustments for changes in non-cash current accounts) have incremental information content beyond accrual earnings and working capital from operations, while working capital from operations may not have incremental information content relative to earnings. Moreover, their results were consistent with accrual data having incremental information content in addition to cash flows.

Finally, it may be worthwhile to note that the recent findings by Rayburn (1986), Wilson (1986, 1987) and Bowen et al. (1987) suggesting that cash-based income variables may, indeed, have information content for the capital market, are based on analyses of proper cash flow variables where appropriate adjustments for changes in currents accounts have been made. In other words, the inadequacy of working capital from operations (i.e. earnings plus depreciation and amortization) as a poor measure of cash flow may well explain the findings of the early studies suggesting non-existent information content in 'cash flows'.

2.3. Summary of Technical Issues

In surveying the research topics and results above, methodological and technical issues such as the sample sizes, detailed time series models, measures of their forecasting performance etc. used in individual studies were deliberately ignored. This was done not to underestimate their importance, but in order to emphasize the substantial side of the findings in prior studies. Furthermore, the number of individual studies examined above was so large that it was considered advisable to cover the technical issues in a table format appearing in appendix 2-1 to this chapter. The table gives information on the following technical issues in prior related studies:

(1) Number of sample firms
(2) Time period covered by the (time series) data
(3) Time interval of the data
(4) Variables examined
(5) Time series (and other) models considered
(6) Forecast accuracy measures employed
(7) Statistical testing methods used

In brief, the table indicates that the individual prior studies have diverged largely from each other in these dimensions, and therefore, the literature is heterogeneuos with respect to technical solutions. For instance, the number of sampled firms has varied between one (e.g. Elliot and Uphoff, 1972) and nine hundred (Ball and Watts 1972); the time span of the data has covered periods from a few years (e.g. Barefield and Comiskey, 1976) to over sixty years (Watts and Leftwich, 1977); and statistical analysis may have involved either no tests of statistical significance (e.g. Brooks and Buckmaster, 1976) or multiple tests (e.g. Brown and Rozeff, 1978). When statistical significance has been considered (which is certainly the case in a vast majority of the studies), it may have been based either on a parametric testing (e.g. Watts and Leftwich, 1977), non-parametric testing (e.g. Foster, 1977) or both (e.g. Chant, 1980).

As a conclusion, it may thus be noted that the literature has been, at least so far, free of strict methodological paradigms in these technical issues.

2.4. Discussion

2.4.1. A Review of Prior Reviews

One indication of the size and importance of the current research domain is that there presently exist a number of independent reviews of the area. It is worthwhile to briefly review here these prior discussions by examining how they have organized the literature and what kind of observations they have made. The following articles and discussions will be covered:

(1) Richards and Fraser (1978);
(2) Abdel-khalik and Thompson (1977-78);
(3) Lorek (1977-78);
(4) Hopwood and Newbold (1980);
(5) Lorek, Kee and Vass (1981);
(6) Ball and Foster (1982, Appendix);
(7) Armstrong (1983);
(8) Bao, Lewis, Lin and Manegold (1983);
(9) Brown and Griffin (1983); and
(10) Brown, Foster and Noreen (1985, Appendix, Section V.)

(1) The early review by Richards and Fraser (1978) is relatively limited in scope (only 17 references are included). It discusses four subareas, including research on earnings time series, analysts' earnings forecasts, management earnings forecasts and determinants of forecast errors. The finding of early studies suggesting random earnings changes is recognized. The authors also note e.g. that earnings numbers are obviously affected by economy-wide, industry-wide and firm-specific factors, and that there is consensus in the literature that neither analysts nor management can clearly outperform mechanical time series models.

(2) Abdel-khalik and Thompson (1977-78) offer the first comprehensive review of the area. Relying on 56 references, the authors structure their discussion under four main themes, including e.g. an update to early findings concerning the random behavior of

earnings. They also identify some shortcomings in the studies aiming at modeling the time series behavior of earnings numbers (e.g. studies assume that the earnings process can be modeled from the time series of <u>reported</u> earnings), and note that researchers are in disagreement on the forecasting ability of management and analysts relative to time series models. With respect to underlying processes of annual earnings, Abdel-khalik and Thompson note that the evidence is suggestive of a moving average process, submartingale, martingale, or a moving average autoregressive process. The authors regard these as refinements of the early findings in the literature.

(3) Lorek (1977-78) is essentially a commentary article on the previous one, and for that reason obviously uses only 29 references. The discussion is organized around three main themes including predictive ability and accuracy, random behavior of earnings, and additional commentary and suggestions. Lorek identifies some important problems such as the consistency of the error metrics with loss function and with each other. He also asks whether the relevant object of prediction is earnings per share, net earnings, rate of return, or cash flow. Furthermore, Lorek recognizes some trends in the literature: e.g. 'naive' models are replaced by 'descriptively valid' models, multiple error metrics are reported, and longer and more current data bases and holdout samples are used. The author also notes that empirical studies support the contention that nondeflated annual earnings (EPS and net earnings) follow a submartingale whereas deflated earnings (rate of return) follow a moving average or mean reverting process. Finally, Lorek recognizes some problems relating to the use of the Box-Jenkins methodology in the area: in addition to requiring user familiarity and preparation, it requires long data bases which may in turn introduce structural

changes into the time series data.

(4) Including 56 references, the survey article by Hopwood and Newbold (1980) discusses two main themes: the areas of application of time series research in accounting and the methodological problems relating to it. The authors argue that the series used in the studies have been relatively short and the focus has been on ARIMA model building with the Box-Jenkins methodology. As motivation for the studies, Hopwood and Newbold discuss seven areas of application including e.g. the studies dealing with the impact of accounting changes, the need for earnings forecasts for valuation models, the relevance for the income smoothing literature, etc. The methodological problems discussed in the article include e.g. the problems caused by short time series for parameter estimation, and the problems relating to heteroscedasticity and the transformations required by it. Finally, the authors note the implications which the findings from analyzing quarterly data have for the models of the behavior of annual earnings: none of the models identified from quarterly earnings series is consistent with the notion that annual earnings follow a random walk model. Hopwood and Newbold suggest that the inconsistency might be explained by a near cancellation in the autoregressive and moving average parts of the models and hence the annual models can be close to random walks.

(5) Lorek et al. (1981) concentrate on reviewing studies analyzing the behavior of annual earnings. Relying on 29 references, the authors organize their discussion around a description of some relevant stochastic processes (martingales, mean reverting processes and moving average processes), findings from cross-sectional analysis of earnings behavior, and findings from firm-specific analysis of earnings behavior. In the introductory part of the

article, Lorek et al. list six important motives behind the time series research, such as valuation of securities, associational testing of accounting earnings with security returns, and smoothing studies. As regards the underlying processes of annual earnings, the general difficulties in discriminating random walk models from certain other processes is recognized in the paper. The authors suggest that this problem may be increased by the 'noisy nature' of annual earnings behavior. Nevertheless, Lorek et al. conclude that empirical time series analysis has shown that a moving average process provides the best description of deflated (rate of return) earnings series, while the behavior of undeflated earnings is best described by a submartingale process. However, in the end of their article the authors argue that the fact that individually identified and estimated Box-Jenkins models have not been able to outperform these models (in the predictive ability tests) is rather a result of the problems relating to the use of the Box-Jenkins methodology in annual data than supportive evidence for the submartingale process.

(6) Ball and Foster (1982, Appendix) organize their 60 references under four main topic areas: (1) time-series modeling of annual and interim data; (2) aggregation issues; (3) smoothing and earnings management issues; and (4) miscellaneous issues. In discussing the studies in the first topic area, Ball and Foster recognize e.g. that the 'exercises are statistical in their orientation'; that they seldomly provide explanations for the statistical patterns; and, consequently, there is a lack of knowledge of why earnings behave as they do. With respect to the third area (smoothing and earnings management), the authors note as a main development that the empirical studies recognize to an increasing extent the many ways reported earnings numbers can be affected by management, for example through transactions with the market, and through

discretionary accounting choices.

(7) Armstrong (1983) concentrates on reviewing the studies dealing with the accuracy of judgmental (i.e. analysts and management) forecasts of annual earnings relative to forecasts of time series models. Armstrong relies on 55 references and structures his article on four issues: (1) hypotheses on methods and accuracy; (2) management vs. analysts forecasts; (3) judgment vs. extrapolation forecasts; and (4) proposals for further research. In regard to management vs. analysts, Armstrong identifies five studies allowing direct comparisons, and in three of them management forecasts significantly outperformed those of analysts. The author offers the following explanations for management's superiority: it has inside information; it has control over firm performance; it has control over reported earnings numbers; and it may possess more timely information than analysts. In regard to judgment vs. time series forecasts, Armstrong notes that prior studies provide 17 comparisons, and in eight of them judgmental earnings forecasts turn out to be significantly more accurate than forecasts from time series models. Armstrong suggests that the superiority of judgmental forecasts may be due to sampling bias, to inside information and the control over earnings by management, and to additional and more timely information used by management and analysts than time series models.

(8) Bao et al. (1983) review applications of time series analysis in accounting with 41 references. They organize the studies in the area into two main categories: (1) studies including univariate modeling and (2) studies including multivariate modeling of earnings and other accounting data. In the introduction, the authors view the accounting system as a filter which transforms and aggregates

economic events and releases the output as financial statements. They also recognize that the generally accepted accounting principles allow some discretion so that the financial statements of firms operating in the same industry may be based on different accounting procedures and hence the earnings numbers may not be a result of consistent accounting rules across firms or over time. In discussing the studies aiming at univariate modeling of earnings behavior, Bao et al. recognize the difficulties in identifying a single appropriate ARIMA model from annual accounting data. They suggest that such difficulties may be a result of the non-stationarity of the series, the limited number of observations that are available, or of a sampling variation. The authors also note that there is evidence suggesting that individual firm-specific ARIMA models perform no better in predicting annual earnings numbers than random walk models including a drift. However, due to the Box-Jenkins methodology not being able to overcome the data deficiencies, the authors conclude that it is not certain that annual earnings actually follow a random walk process. Relating to univariate analysis, Bao et al. also discuss such methodological issues as problems in achieving stationarity, impact of power transformations, aggregations issues (especially the implications of quarterly earnings behavior to appropriate annual models), and automated algorithms for Box-Jenkins analysis. With respect to multivariate modeling, the authors conclude that these studies suffer from the same problems as the univariate studies. Finally, Bao et al. identify some areas for future research such as studies examining the characteristics of accounting data affecting the application of the Box-Jenkins methodology, and studies aiming at multivariate modeling of accounting data.

(9) Brown and Griffin (1983) discuss univariate time series modeling, multivariate modeling, and experts' forecasts using 27 references. The authors argue that data exigencies have often necessicated the selection of one particular accounting variable for time series analysis, viz. the reported earnings and, therefore, the analysis of other accounting variables has been largely ignored. Brown and Griffin also note the lack of studies using multivariate analysis and techniques which are more appropriate than the Box-Jenkins methodology for small finite samples. In the epilogue, the authors provide some potential explanations for the persistent use of time series forecasts as measures of market expectations despite the evidence of the superiority of experts' (i.e. analysts and management) forecasts: the results suggesting expert superiority have not been known or accepted by the researchers; the results of the studies using proxies for market expectations may be robust with respect to experts vis-a-vis time series model forecasts; and experts' forecasts (especially management) have not been available at all or they have not been available in a machine readable form.

(10) Brown et al. (1985, Appendix) review 50 studies examining four topic areas, viz. (1) earnings forecasts of security analysts vs. mechanical models; (2) earnings forecasts of security analysts vs. management; (3) earnings forecasts of management vs. mechanical models; and (4) composite earnings forecast analysis. As a starting point, the authors identify four explanations why different forecasting performance could be expected between management, analysts and mechanical time series models: there are differences in the information set utilized; differences in the time at which forecasts are made; differences in the aggregation level underlying the forecasts (i.e. whether individual or a consensus of analyst forecasts is used); and differences in the efficiency of

information processing between these forecasting agencies. With respect to research concerning the relative accuracy of analysts vs. mechanical models, Brown et al. note that while early studies found little difference, subsequent literature is almost unanimous that security analysts outperform time series models. The authors suggest that although the timing difference explanation for this finding has been probed in some studies with inconsistent results, the differences between these agencies might be due to inefficient information processing of the mechanical time series models. With respect to relative accuracy of analysts vs. management, Brown et al. conclude that the evidence is mixed, and many studies report no significant differences between these agencies. However, the authors identify several difficulties in making comparisons between them: e.g. the loss functions of management and analysts may not be the same; management forecasts are sometimes reported in an interval form rather than in a point form; and management has the ability to influence the predicted earnings variable. With respect to management vs. mechanical model forecasts, Brown et al. find that the results provided by the literature are inconsistent. Finally, in regard to composite forecast analysis, Brown et al. note that although there is some evidence suggesting that there is not much to be gained from combining forecasts from mechanical models with analysts' forecasts (primarily because the latter include all relevant information from past earnings series), the combination of analyst forecasts with those of management might prove useful because there is not a perfect overlap in the information sets which these forecasting agencies can access.

2.4.2. Conclusions: Present Study in Perspective

On the basis of the survey of individual research topics and prior reviews of the literature, some conclusions can be drawn which will help put the present study into perspective.

(1) There is almost unanimity among researchers that annual earnings produced by the accrual accounting system follow a submartingale process similar to random walk with or without a drift. However, while this finding is prevalent especially in firms operating and reporting income numbers according to the accounting practice in the Anglo-Saxon world, the evidence from other countries is very scarce (the Netherlands is an exception). It is therefore unclear, whether the submartingale behavior of accounting income numbers can be generalized to firms operating under different economic conditions and using different accrual accounting practice from those previously analyzed.

Therefore, an analysis of the underlying processes of accrual income numbers reported by Finnish firms may shed some additional light on the robustness of the submartingale process across national boundaries. Given the strong evidence presented in the literature for the submartingale process, it can be expected that similar behavior might be also found from Finnish firms. If this turned out to be the case, then such finding would undoubtedly contribute to the robustness of the submartingale model. This, in turn, would imply that the general economy-wide factors as well as the international variation in the accounting-method-based factors from country to country may be of minor importance as determinants of the underlying processes of income variables.

(2) Although the notion of submartingale behavior of annual income

numbers seems to be something like a paradigm in the literature, the review indicated, however, that there are also some doubts. The concerns presented are as follows. First, it has been argued that due to e.g. structural changes and relatively short observation series, estimation problems are likely to be encountered with annual data, and therefore, the random walk-type behavior may be a result of an estimation bias rather than a description of the true underlying process (see e.g. Gonedes and Roberts, 1976; Lorek et al., 1981, p. 110; Bao et al., 1983, p. 408). Second, the findings from quarterly income series imply models other than a random walk for annual income (see e.g. Hopwood and Newbold, 1980; Cogger, 1981; Hopwood, McKeown and Newbold, 1982). Third, theoretical results presented in the literature so far do not lend support to the random walk process (see Dharan, 1983a).

Undoubtedly, the present study will also be subject to this critique. Since annual income numbers will be considered here, estimation problems similar to prior studies will certainly be encountered. It should be noted, however, that there is no reason to assume that their effect on the results of accrual variables would be <u>systematically</u> <u>different</u> from the effect on the results of cash-based variables. Consequently, the findings concerning the <u>(dis)similarities</u> of the underlying processes of accrual versus cash-based income variables should be unbiased.

(3) The studies analyzing the time series properties of cash flows were found to be relatively rare compared with studies examining accrual income numbers. The few studies that have so far analyzed the behavior of cash flows on an annual basis, have found that cash flows (defined in terms of cash inflows and outflows) may behave differently from the submartingale process (see Adam, 1984;

Kinnunen, 1984). The important point to note here is, however, that since these studies do <u>not</u> provide comparable evidence with respect to the behavior of accrual variables, it remains unclear whether the tentative results have been a sample-specific phenomenon or whether they were manifestations of true deviations from the submartingale processes. Consequently, a time series analysis of accrual and cash-based income variables obtained from the same sample of firms and the use of identical time series methods for both data sets hopefully eliminates some of the problems relating to contrasting the findings from these studies with those of others in the area.

(4) Although no study was found in the literature addressing directly the present research question, some <u>indirect</u> evidence exists supporting the notion that the underlying processes of accrual vis-a-vis cash-based income may be different from each other. Such conclusion might be drawn from findings showing that accrual earnings numbers are poor predictors of subsequent cash flows and that a low cross-correlation exists between them at lag zero (see e.g. Bowen et al., 1986). On the one hand, it can be assumed that <u>if</u> a high cross-correlation had been found between the variables or <u>if</u> cash flows could have been predicted with a high accuracy using a linear relationship between the variables, <u>then</u> the accrual and cash-based income variables would have varied together and, consequently, their behavior would have been similar, therefore implying similar underlying processes.

However, since no such finding was made, it may have been a result of at least the following explanations: (i) the accrual and cash-based variables have different underlying processes, or (ii) the variables have similar underlying processes but there is a high variance in the noise term of the linear relationship between the variables. Therefore, the most that can be concluded from this prior indirect evidence is that it is inadequate to show the (dis)similarity of the underlying processes of accrual versus cash-based income, and consequently some direct analysis is needed to provide an answer to the question.

(5) Several information content studies have assumed that cash flows behave like a submartingale process, and that there is therefore no difference in the underlying processes of accrual versus cash-based income variables. Such assumptions have been made at least by Ball and Brown (1968), Beaver and Dukes (1972) and Patell and Kaplan (1977) in analyzing the information content of cash flow surrogates (earnings plus depreciation). Also, more recent studies by Rayburn (1986) and Wilson (1986) analyzing the information content of operating cash flows used random walk expectations for operating cash flow as a benchmark to which they contrasted the performance of their own prediction models. Furthermore, Bowen et al. (1987) recently assumed random walk-behavior for cash flows in analysis of their incremental information content. It can be argued, however, that if the underlying processes of cash flows did not follow the submartingale process, the results from these information content studies would be difficult to interpret.

In addition, among the conclusions that can be drawn from the review of reviews are the following:

(6) Besides the appropriateness of the Box-Jenkins methodology, some reviewers of the area have also noticed some other methodological problems, such as e.g. the need and effects of transformations of the data, and the need for multivariate modeling of earnings behavior. As regards the multivariate modeling approach, it has to be recognized that the problems relating to the univariate modeling

are likely to be encountered perhaps even to a larger extent in the multivariate approach.

(7) The reviews also suggest that there is an increasing focus in the area on analyzing the relative accuracy of judgmental forecasts (provided by management and financial analysts) vis-a-vis each other and vis-a-vis mechanical time series models. It can also be noted that one change in the knowledge of these questions is manifested in the reviews. While the early reviewers argue that empirical studies have failed to indicate significant differences between analysts and time series models, the more recent reviewers recognize that this has been the case only in the early studies and subsequent evidence has unanimously showed the analysts' superiority.

(8) Interestingly, while some reviewers note the lack of studies analyzing other than reported earnings-related accounting series, none of them is able to report on any single study analyzing these alternative series, for example cash flows. On the basis of prior reviews, one might conclude that time series analysis of the alternative series is a perfect tabula rasa in the literature, although this is not exactly the case.

(9) A relatively new topic introduced into the literature mainly in the 1980s seems to be the composite (or consensus) forecast analysis. One reason for the delay might be that observations about the absolute inaccuracy of each individual forecasting agency (i.e. management, analysts and time series models) were first needed in order to detect the potential gain in combining the forecasts of different agencies.

NOTES TO CHAPTER 2:

[1] The MCGS (Mixture of Constant Growth and Submartingale) model defined by Deschamps and Mehta (1980, p. 936) is identical with the model proposed by Brown and Rozeff (1979) which has the following form:

$$Q(t) = Q(t-4) + \Phi 1[Q(t-1) - Q(t-5)] + a(t) + \theta 1' a(t-4) + \delta$$

where Q(t) = income in quarter t; $\Phi 1$ = first order autoregressive parameter; $\theta 1'$ = first order moving average parameter in seasonal; a(t) = white noise in quarter t; δ = a constant

[2] See also Cogger (1981) for an analytical discussion on the derivation of models for aggregated (annual) variables from the models of desaggregated (quarterly) variables.

[3] For a discussion on the debate on interim reporting in the U.S.A., see Coates (1972, pp. 134-135).

[4] This rationale can be seen as an application of the general predictive ability criterion represented by the Chicago school of thought. In brief, "according to this criterion, alternative accounting measurements are evaluated in terms of their ability to predict events of interest to decision-makers." (Beaver, Kennelly and Voss, 1968, p. 675). Subsequently, e.g. Beaver (1970, p. 64), Abdel-khalik and Thompson (1977-78, p. 182) and Lorek (1977-78, p. 211) have referred to this criterion as a basis of time series research in accounting.

[5] The problem has been discussed by such bodies as e.g. the SEC, the FASB, and the FAF. (See Foster, 1977, p. 1; Griffin, 1977, p. 72; Barefield and Comiskey, 1976, p. 59; Lorek, McDonald and Patz, 1976, p. 321; Basi, Carey and Twark, 1976, p. 244; Hopwood, McKeown and Newbold, 1981, p. 927.) For a more recent practice of corporate forecast disclosure in the U.K., the U.S.A. and the Netherlands, see Klaassen and Schreuder (1982, pp. 1-2)

[6] As Brown et al. (1985, p. A.53-A.55) note, there may also be other differences between judgmental and time series forecasts, such as differences at the time, aggregation level, and efficiency of forecast preparation.

[7] Cragg and Malkiel (1968) found that income forecasts of financial analysts were relatively consistent with each other, which was indicated by a high cross-sectional correlation between their forecasts. Moreover, a relatively low partial correlation after removing the effects of past growth in income numbers suggested that it was a common practice among the financial analysts to base their income forecasts on past growth rates. Furthermore, the results obtained by Richards (1976) supported the previous evidence about consistent income forecasts between different financial analysts.

[8] As noted e.g. by Ball and Foster (1982, p. 213), there is also the dimension of temporal desaggregation which means that annual income numbers are regarded as aggregates of interim (quarterly) income numbers. The predictive content of this information, however, has already been covered in preceding subsections.

[9] Ang (1979) also examined the general conditions under which aggregate forecasts are inferior to forecasts obtained via its components. Because the answer is dependent e.g. on the correlation between the component forecasts, Ang (1979, p. 34) concluded that "a general answer is again impossible". However, perhaps the most important result was that "the component forecast may not always give superior results in comparison to the aggregate forecast" (ibid., p. 35).

[10] It should be noted that the results of Elliot and Uphoff (1972) supporting the superiority of econometric models in predicting corporate income statement numbers are based at least on the following implicit assumptions:
(i) Because only exponential smoothing models were considered from the class of univariate time series models, it must be assumed that they are the best description of the stochastic process which generate monthly income statement numbers.
(ii) Because the ex-post realizations of the exogenous variables in the periods being forecasted were used in the econometric model, it must be assumed that in an actual forecasting situation the future values of the exogenous variables are known with certainty.
(iii) Because data from one single firm was used, it must be assumed that the firm was representative of all firms, if the results are to be generalized.

[11] 'Expected average' refers to the mean that was forecasted by martingale from the time series of past means.

[12] These included the pure mean reverting model and five variants of submartingales, see Gonedes (1973, p. 217)

[13] In brief, transfer function modeling can be described as a multivariate counterpart of the more specific univariate ARIMA-modeling. For a thorough discussion of transfer function model building, see Box and Jenkins (1976, part III). See also Hillmer et al. (1983), who note that the transfer function modeling is a special case of more general multiple time series analysis aiming at modeling vectors of time series.

[14] Another study examining the relative forecasting preformance of multiple and univariate time series models with accounting data is Hillmer et al. (1983). They modeled dollar values of production and costs from monthly time series data of a firm. They found that both of these monthly series were better (more accurately) predicted by the multiple approach than by the univariate approach. However, it should be noted that this finding was obtained from one single firm and that the authors did not provide evidence on income (earnings) forecasts.

[15] In addition to the studies reviewed here, there are also some results available from cross-sectional factor analyzes indicating that, for a given year or period, cash-based financial ratios may contain different information from accrual-based ratios. This has been shown with data from U.S. firms by Gombola and Ketz (1983), and from Finnish firms by Yli-Olli (1983). However, on the basis of such cross-sectional analysis alone, it would be uncertain to conclude anything about the behavior of cash flows over time.

[16] In brief, 'pre-whitening' means that temporal regularities in a time series are removed and the resultant residual series is used in the analysis.

[17] As Asp (1979, p. 270) notes, this unappealing result may have been caused by the relatively short time series used in the study as well as by changes in the investment strategies of the firms.

APPENDIX 2-1: Some Technical Solutions in Related Prior Studies

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
1. Studies on Accrual Income Variables							
(1) Time Series Properties of Annual Income							
Little (1962)	441+81	1951-59	Annual	Dividends, Net earnings, Earnings before taxes	-	-	Correlation analysis, Regression analysis
Rayner and Little (1966)	- " -	1951-61	Annual	- " -	-	-	- " - + Variance analysis
Lintner and Glauber (1967)	323	1946-65	Annual	Sales, Oper.income, Earnings before interest and taxes, EPS, Dividends/share	-	-	Regression analysis, Correlation analysis
Fama and Babiak (1968)	392	1947-65	Annual	Dividends, Earnings	-	Standardized prediction error	Regression analysis
Beaver (1970)	57	1949-68	Annual	Market and accounting-based rates of return, Net income	Mean reverting, Moving average, Random walk	-	Autocorrelation analysis, Rank correlation anal., Run-tests, Analysis of high-low groups
Ball and Watts (1972)	≈900	1947-66	Annual	Net income after taxes, EPS, Net income/total assets, Net sales	Partial adjustment models (incl. exponential smoothing)	Mean absolute error	Run-tests, Autocorrelation analysis, Analysis of optimal smoothing coefficients
Brooks and Buckmaster (1976)	Not reported	1954-73	Annual	Net income after taxes	Exponential smoothing	Mean absolute error, Standard error of estimate	Analysis of optimal smoothing coefficients in stratified sample (no statistical tests)
Salamon and Smith (1977)	110	1954-62	Annual	EPS	Exponential smoothing	Mean absolute error	Analysis of distributions of optimal smoothing coefficients (no statistical tests)
Albrecht, Lookabill and McKeown (1977)	49	1947-75	Annual	Earnings available to common, Earnings/equity	Firm-specific ARIMA models, Submartingales	Mean percentage, absolute, and squared errors	Analysis of various error measures, Analysis of variance for average ranking
Watts and Leftwich (1977)	32	1908-74	Annual	Earnings available to common	Firm-specific ARIMA models, Submartingales	Sum of ranks based on squared errors, Weighted sums of abs. and sqr. error	F-test, t-test

Appendix 2 - 1 - 2

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Ball and Watts (1979)	71	1910-65	Annual	EPS	-	-	Autocorelation analysis, t-test
Brooks and Buckmaster (1980)	Not reported	1955-74	Annual	Ordinary annual income (per share), Net income (per share)	Exponential smoothing	Mean absolute error	Analysis of optimal smoothing coefficients in stratified sample (no statistical tests)
Freeman, Ohlson and Penman (1982)	30	1946-77	Annual	EPS, Book rate of return on common equity	Logit-model for the sign of earnings change	-	Chi-square, Fisher's exact test, t-test
(2) Determinants of Annual Income Behavior							
Brown and Ball (1967)	316	1947-65	Annual	Net income, Oper. income (per assets), Net income + int.exp (per assets), EPS	-	-	Regression analysis
Lookabill (1976)	65	1951-68	Annual	Market rate of ret., Earnings/market val. Earnings/net worth, Systematic risk	Mean reverting, Moving average, Autoregressive	-	Analysis of high-low groups
Lev (1983)	385	1947-73	Annual	Earnings, Earnings per equity, Sales	-	-	Autocorrelation analysis, Regression analysis
(3) Time Series Properties of Interim Income							
Foster (1977)	69	1946-74	Quarterly	Earnings, Sales, Security returns	Firm-specific seasonal ARIMA, Five variants of submartingale	Mean absolute percentage error, Mean square percentage error	Friedman analysis of variance
Griffin (1977)	94	1958-71	Quarterly	Earnings	Firm-specific seasonal ARIMA	-	Autocorrelation analysis
Brown and Rozeff (1979)	23	1951-75	Quarterly	EPS	Firm-specific seasonal ARIMA, Three premier models	Mean absolute percentage error, Mean square error	Autocorrelation analysis, Wilcoxon test

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Lorek (1979)	30	1958-73	Quarterly	Earnings	Firm-specific seasonal ARIMA, Three premiers, Four submartingales, MovAvg	Mean absolute percentage error	Friedman analysis of variance
Deschamps and Mehta (1980)	91	1961-73	Quarterly	Earnings	Firm-specific seasonal ARIMA, Mixture of Constant Growth and Submart.	Mean square error	t-test
Abdel-khalik and El-sheshai (1983)	86	1963-74	Quarterly	Sales	Two premier models, Firm-specific seasonal ARIMA	Absolute percentage error, Squared percentage error	(Parametric) two-way analysis of variance (ANOVA)
(4) Predictive Content of Interim Income							
Green and Segall (1967)	46	1959-64	Annual, Quarterly	EPS	Submartingales	Mean absolute error Mean square error, Mean absolute percentage error	Friedman analysis of variance
Brown and Niederhoffer (1968)	519	1961-65	Annual, Quarterly	EPS	Submartingales	Mean perc. error, Mean absolute perc. error, Mean square percentage error	Analysis of accuracy measures (no statistical tests)
Coates (1972)	27	1945-66	Annual, Quarterly	EPS	Submartingales	Mean abs. error, Root mean square error	Analysis of accuracy measures (no statistical tests)
Hopwood, McKeown and Newbold (1982)	267	1962-77	Annual, Quarterly	EPS	Two premier models, Random walk for annual data	Mean square error	Analysis of variances of forecast errors
(5) Managers' and Financial Analysts' Relative Forecasting Ability							
Cragg and Malkiel (1968)	185	1962-67	Annual	EPS	-	Theil's U	Correlation analysis, Kendall's coefficient of concordance
Copeland and Marioni (1972)	50	1966-68	Annual, Quarterly	EPS	Submartingales	Mean absolute error, Mean percentage error	Chi-square, Kolmogorov-Smirnov test

Appendix 2 - 1 - 4

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Elton and Gruber (1972)	180	1948-67	Annual	EPS	Exponential smoothing, Autoregr models, Linear trends, Random Walk	Square error, Theil's U	Friedman analysis of variance, t-test
Lorek, McDonald and Patz (1976)	37	1958-70	Annual, Quarterly	Earnings	Firm-specific seasonal ARIMA	Percentage error	Wilcoxon test
Barefield and Comiskey (1976)	38	1967-72	Annual	EPS	Random Walk	Mean absolute perc. error, Net perc. error, Theil's U	Analysis of accuracy measures (no statistical tests)
Basi, Carey and Twark (1976)	88	1970-71	Annual	EPS	-	Mean percentage, absolute, and square errors	Kolmogorov-Smirnov test, Correlation analysis, t-test
Richards (1976)	93	1972	Annual	Earnings	-	Mean perc. error, Mean absolute percentage error, Theil's U	Correlation analysis, Analysis of variance
Brown and Rozeff (1978)	50	1951-75	Quarterly	EPS	Firm-specific seasonal ARIMA, Submartingales	Absolute percentage error	Wilcoxon test, Friedman analysis of variance
Collins and Hopwood (1980)	50	1951-74	Quarterly	EPS	Firm-specific seasonal ARIMA, Three premier models	Mean absolute percentage error	(Parametric) multivariate analysis of variance (MANOVA)
Jaggi (1980)	121	1971-74	Annual	Earnings	-	Absolute percentage error	Wilcoxon test
Fried and Givoly (1982)	424	1969-79	Annual	EPS	Two variants of submartingale	Mean percentage error, Mean absolute percentage error	t-test, Correlation analysis
Imhoff and Pare (1982)	46	1971-74	Annual, Quarterly	Earnings	Firm-specific seasonal ARIMA, Three premier models	Absolute error, Absolute percentage error, Prediction error/std. dev.	Friedman analysis of variance, t-test
Schreuder and Klaassen (1984)	53	1980	Annual	Earnings, Sales	-	Absolute error, Absolute percentage error	Sign test, Wilcoxon test

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Kodde and Schreuder (1984a)	63-67	1974-80	Annual	Earnings, Sales	Five variants of submartingale, Linear and exp. trends, EWMAs	Mean error, Mean abs. perc. error, Mean square error, etc.	Sign test, Wilcoxon test
Hassel and Jennings (1986)	93	1979-82	Annual	EPS	-	Absolute percentage error	t-test, Wilcoxon test
Waymire (1986)	Not reported	1970-73	Annual	EPS	-	Absolute error, Absolute percentage error	Sign test, Wilcoxon test
Brown, Hagerman et al. (1987)	233	1960-80	Quarterly	EPS	Three premier models	Four variants of percentage error	Friedman analysis of variance
Brown, Richardson and Schwager (1987)	702	1977-82	Annual, Quarterly	EPS	(Random walk)	Squared ratio of random walk error to analyst error	Regression analysis
Conroy and Harris (1987)	> 600	1963-83	Annual	EPS	Random walk, Three variants of EWMA, Moving average	Absolute percentage error, Mean absolute percentage error	t-test
(6) Predictive Content of Specified Economic Information							
Kinney (1971)	24	1960-69	Annual	Earnings	Submartingale, Exponential smoothing	Absolute percentage error	t-test
Elliot and Uphoff (1972)	1	1969-71	Monthly	Various income statement items incl. operating income	(Econometric model) Exponential smoothing	Percentage error	Analysis of accuracy measure (no statistical tests)
Gonedes (1973)	316	1947-68	Annual	Net sales/equity, Net income/equity	Submartingales	Mean error, Mean square error, Mean absolute error	Analysis of the distributions of accuracy measures
Collins (1976)	96	1951-70	Annual	Earnings before taxes and extraordinary items	Submartingales, Mean reverting, Exponential smoothing	Mean absolute percentage error	t-test

Appendix 2 - 1 - 6

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Ang (1979)	22 industries	1956-73	Quarterly	Operating income	Industry-specific seasonal ARIMA	Theil's U	Analysis of accuracy measures (no statistical tests)
Chant (1980)	218	1958-77	Annual	EPS	Submartingales, Exponential smoothing	Mean absolute percentage error	Hotelling T^2, Friedman analysis of variance
Hopwood (1980)	67	1962-77	Quarterly	EPS	Firm-specific seasonal ARIMA, Transfer function models	Absolute error	Chi-square, Exact probability (binomial) test
Barnea and Lakonishok (1980)	5	1946-71	Annual	Net income	Exponential smoothing	Theil's U	Correlation analysis, Binomial test
Hopwood and McKeown (1981)	267	1962-77	Quarterly	EPS	Three premiers, Firm-specific ARIMA Two premier transf. function models	Mean absolute percentage error	Analysis of accuracy measures (no statistical tests)
Manegold (1981)	27	1954-75	Annual	Earnings before taxes	Firm-specific ARIMA, Transfer function models	Normalized absolute error, Mean deflated absolute and squared errors	Sign test
Silhan (1982)	60	1967-77	Quarterly	Net income (after extraordinary items)	Firm-specific seasonal ARIMA	Mean percentage error, Mean absolute percentage error	t-test, Wilcoxon test
Hopwood, Newbold and Silhan (1982)	35	1950-79	Annual	Earnings (before extraordinary items)	Firm-specific ARIMA, Random Walk, EWMA	Mean absolute percentage error	Analysis of accuracy measure (no statistical tests)
Garrod and Emmanuel (1987)	511	1970-79	Annual	Turnover	Four variants of submartingale	Absolute error	t-test
(7) Information Content of Accrual Income							
Ball and Brown (1968)	261	1946-66	Annual	Net income, EPS	Random Walk (Linear regression)	-	Analysis of the sign of forecast error and cumulative residual return, Chi-square

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
2. Studies on Cash-Based Income Variables							
(1) Time Series Properties of Cash Flows							
Khumawala (1978)	30	1965-76	Quarterly	Cash flow from operations	Four variants of submartingale, Linear trend	Mean error, Mean square error, Mean absolute percentage error	Friedman analysis of variance
Adam (1984)	64	1951-81	Annual	Cash flow from operations	Firm-specific ARIMA, Submartingale, Transfer function models	Absolute percentage error, Squared percentage error	Wilcoxon test, (Parametric) analysis of variance
Kinnunen (1984)	8	1951-82	Annual	Cash margin for dividends, Two versions of equity cash flow	Submartingales, Mean reverting, Linear trend, EWMA, Firm-spec. ARIMA	Mean absolute perc. error, Mean square error, Absolute sum of discounted error	Distribution-free tests of randomness, autocorrelation analysis, Friedman analysis of variance
(2) Determinants of Cash Flow Behavior							
Koskela (1978)	17	1962-71	Annual	Cash flow from operations	-	-	Regression analysis
Niskanen (1986)	70	1970-81	Annual	Cash flow from operations deflated by net sales	-	-	Regression analysis, (Factor analysis)
(3) Predictability of Cash Flows							
Cheung (1977)	10	1962-75	Quarterly	Net cash flow between the firm and its equity and debt holders	Firm-specific ARIMA, Transfer function models	Mean square error, Mean perc. error, Mean absolute percentage error	F-test, t-test, Mann-Whitney test, Kruskall-Wallis test
Icerman (1977)	117	1956-74	Annual	Cash flow from operations	Index models, Regression models, EWMA, Mean reverting, submartingales	Percentage error, Absolute percentage error	Friedman analysis of variance, Wilcoxon test
Asp (1979)	9	1951-77	Annual	Cash flow from operations, Net investments in fixed assets	-	-	Cross-correlation analysis of pre-whitened series

Study	Number of Sampled Firms	Time Period of the Data	Time Interval of the Data	Examined Variables	Considered Time Series Models	Forecast Accuracy Measures	Statistical Analysis
Bowen et al. (1986)	324	1972-81	Annual	Net income, Working capital from oper., Cash flow from oper. Cash flow after inv.	Random Walk	Absolute Forecast Error	Cross-correlation analysis, Friedman analysis of variance, Sign test
(4) Information Content of Cash Flows							
Staubus (1965)	40-44	1949-60	Annual	Net earnings, Current flow, Net recurring funds flow, Dividends	-	-	Correlation analysis
Beaver and Dukes (1972)	123	1963-67	Annual	Net earnings, Earnings before deferral entries, Cash flow: earnings+depr.	Index model, Submartingales, Moving average	Forecast error (with sign)	Binomial test, Mann-Whitney test
Patell and Kaplan (1977)	450-540	1972-75	Annual	Net income/share, Total funds from operations: earnings + depreciation	(Random walk implicitly assumed)	Ratio of realized value to previous realized value	Modification of Hotelling T^2
Lawson (1980)	≈1000 -3000	1954-76	Annual	Post-tax equity cash flow	-	-	Regression analysis with aggregate data
Beaver et al. (1982)	313	1976-78	Annual	Historical and replacement cost earnings, Cash flow: earnings + deprec.	-	-	Two-stage regression analysis
Koskela (1984)	20	1951-80	Annual	Operating cash margin, Net cash margin, Net investments	-	-	Regression analysis, Discriminant analysis
Rayburn (1986)	175	1962-82	Annual	Accrual earnings, Operating cash flow,	Regression model (Random walk as a benchmark)	-	Regression analysis
Wilson (1986, 1987)	300	1981-82	Annual	Accrual earnings, Cash flow from operations	Regression model (Random walk as a benchmark)	-	Two-stage regression analysis, A portfolio approach
Bowen et al. (1987)	98	1972-81	Annual	Net income, Working capital from oper., Cash flow from oper. Cash flow after inv.	Random walk	-	Regression analysis

3. A THEORETICAL ANALYSIS OF SERIAL DEPENDENCE IN INCOME VARIABLES AT SALES AND OPERATING INCOME LEVELS

A common definition of income smoothing is that it dampens or levels the fluctuation of reported income "about some level of earnings that is currently considered to be normal for a firm" (Beidleman, 1973, p. 653). With respect to the "normal income", at least two possible interpretations exist: (i) The "normal income" is equal to what management regards as the target income of the firm for a given period (this could be defined e.g. by the industry average [1]), or (ii) it is the average income achieved by the firm over a number of periods. In the former case, income smoothing implies decreasing the difference between the target and reported income figures, whereas in the latter case, income smoothing means decreasing the volatility or variance of reported income figures over time.

Recently, Dharan (1985) examined the conditions under which the accrual accounting system may result in income smoothing in the variance reduction sense. The benchmark for comparing the effect of the accrual accounting was a cash accounting system where revenues and expenses are recognized only after their realization in cash. The analytical results derived by Dharan showed that, under certain conditions, the accrual accounting income variable contains lower variance than the income variable produced by the cash accounting system and hence income smoothing, in the variance reduction sense, may be a basic characteristic of the accrual accounting system.

This chapter extends Dharan's (1985) analysis by examining the role of the accounting system as a determinant of income smoothing from a slightly different viewpoint. While Dharan compared the effects of accrual and cash accounting systems on the <u>variances</u> of income variables, our focus will be on their <u>serial dependences</u> (i.e.

autocorrelations). The motive for this analysis lies in the correspondence between the autocorrelations and underlying processes: insofar as (dis)similar autocorrelations could be assumed for income variables, then the stochastic processes underlying the income number series are likely be (dis)similar.

At this point it should readily be recognized that, because autocorrelation is defined as the ratio of autocovariance to variance, the measures of serial dependence and variance are inversely related to each other. This implies that insofar as accrual accounting income contains lower variance than cash-based income (as Dharan suggests), the serial dependence in the former should be higher than in the latter. It must be noted, however, that such a conclusion would be too early because it is not valid without a ceteris paribus assumption, i.e. the autocovariances of income variables are identical under the two accounting systems.

As regards prior empirical results, the literature review in the preceding chapter (section 2.1.2.) indicated that many empirical studies exist supporting the random walk (with drift) model for annual accrual accounting income numbers, which implies a high (near unity) positive autocorrelation. It was also noted that comparable empirical evidence from cash flow time series is scarce, and the conclusions with respect to cash-based income variables therefore remain more uncertain. At least a couple of studies examining the time series behavior of annual cash flows have found that cash flows may follow a mean reverting-type process implying a low (near zero) autocorrelation (see section 2.2.2.). However, because these studies have not provided comparable results from accrual income data, it remains unclear whether their results were sample-specific or whether they were an indication of true differences in the underlying processes.

The theoretical analysis below aims to tentatively illustrate the effect of the accounting system on the serial dependence relaxing the ceteris paribus-assumption mentioned above. Assuming simple frameworks for the accrual and cash-based accounting systems, their potential effects on the variances and autocovariances will be explicitly considered in order to see the net effect of the accounting system on the serial correlation.

The analysis is divided into two subsections. First, the case of sales revenues is examined, where an expression for the theoretical autocorrelation of cash revenues received from customers is derived in terms of autocovariance and variance of accrual sales. Second, the case of operating income is examined, in which the expressions for the autocorrelations of accrual operating income and its cash-based counterpart are derived. In both cases, it will be assumed that the examined variables have a simple linear relationship to accrual sales, an assumption which will be given a descriptive content within the two accounting systems. Furthermore, it will be assumed that the behavior the firm's sales and fixed costs fulfil the requirements of weak stationarity, i.e. their expectations and variances are independent of time [2].

3.1. An Analysis of Sales Revenues

Assume that a firm follows a credit policy so that the long-term average of the turnover ratio of its sales receivables is:

$$\frac{\text{Sales}}{\text{Receivables}} = 1/k \qquad (0 < k < 1) \qquad (3\text{-}1)$$

The inverse of the turnover ratio, k, presents the fraction of sales which, on average, stands as a receivable in the end of each period, and (1-k) is the fraction of sales which, on average, is received from customers in the same period [3]. Now, the total cash sales in any period t can be expressed as a linear function of accrual sales in periods t and t-1 as follows:

$$\begin{aligned} CSA(t) &= (1-k)\ ASA(t) + (k)\ ASA(t-1) + a(t) \\ &= (\alpha 1)\ ASA(t) + (\alpha 2)\ ASA(t-1) + a(t) \qquad (3\text{-}2) \end{aligned}$$

where
- CSA(t) = cash sales in period t
- ASA(t) = accrual sales in period t
- $\alpha 1$ and $\alpha 2$ = constant parameters approximating (1-k) and k, respectively
- a(t) = an identically and independently distributed random variable with zero mean and constant variance

One should note that the random variable a(t) has been appended to the above model for several reasons. First, it includes the variation that occurs in the turnover of the firm's receivables (1/k) over time. Since parameters $\alpha 1$ and $\alpha 2$ are assumed to be constants approximating long-term averages (1-k) and k, the variation that takes place around these constants is 'absorbed' by a(t). Second, a(t) also includes the bad debts which the firm may incur and which also give rise to the fact that $(\alpha 1 + \alpha 2)$ may be < 1 rather than = 1, i.e. all sales may never be received in cash from customers. Finally, it includes the advance payments received from customers before the corresponding sales are recognized in accrual accounting. (Of course, the possibility of advances might have been incorporated in expression (3-2) by adding an appropriate term to the model, but the present form was preferred for the sake of simplicity.)

Assuming that the behavior of accrual sales is stationary so that Var[ASA(t)] = Var[ASA(t-1)], the variance of cash sales based on expression (3-2) is as follows:

$$\mathrm{Var}[CSA(t)] = \mathrm{Var}[(\alpha 1)ASA(t)+(\alpha 2)ASA(t-1)+a(t)]$$

$$= (\alpha 1)^2\mathrm{Var}[ASA(t)] + (\alpha 2)^2\mathrm{Var}[ASA(t-1)] + \mathrm{Var}[a(t)] + 2(\alpha 1)(\alpha 2)\mathrm{Cov}[ASA(t),ASA(t-1)] + 2(\alpha 1)\mathrm{Cov}[ASA(t),a(t)] + 2(\alpha 2)\mathrm{Cov}[ASA(t-1),a(t)]$$

$$= [(\alpha 1)^2+(\alpha 2)^2]\mathrm{Var}[ASA(t)] + 2(\alpha 1)(\alpha 2)\mathrm{Cov}[ASA(t),ASA(t-1)] + \mathrm{Var}[a(t)] \quad (3\text{-}3)$$

Correspondingly, the autocovariance of accrual sales at lag 1 can be derived as follows:

$$\mathrm{Cov}[CSA(t),CSA(t-1)]$$

$$= \mathrm{Cov}[((\alpha 1)ASA(t)+(\alpha 2)ASA(t-1)+a(t)), ((\alpha 1)ASA(t-1)+(\alpha 2)ASA(t-2)+a(t-1)]$$

$$= (\alpha 1)^2\mathrm{Cov}[ASA(t),ASA(t-1)] + (\alpha 1)(\alpha 2)\mathrm{Cov}[ASA(t),ASA(t-2)] + (\alpha 1)\mathrm{Cov}[ASA(t),a(t-1)] + (\alpha 1)(\alpha 2)\ \mathrm{Cov}[ASA(t-1),ASA(t-1)] + (\alpha 2)^2\mathrm{Cov}[ASA(t-1),ASA(t-2)] + (\alpha 2)\mathrm{Cov}[ASA(t-1),a(t-1)] + (\alpha 1)\mathrm{Cov}[a(t),ASA(t-1)] + (\alpha 2)\mathrm{Cov}[a(t),ASA(t-2)] + \mathrm{Cov}[a(t),a(t-1)]$$

$$= [(\alpha 1)^2+(\alpha 2)^2]\mathrm{Cov}[ASA(t),ASA(t-1)] + (\alpha 1)(\alpha 2)[\mathrm{Cov}[ASA(t),ASA(t-2)]+\mathrm{Var}[ASA(t)]] \quad (3\text{-}4)$$

Now, dividing (3-4) by (3-3) yields the theoretical autocorrelation of cash sales at lag 1 expressed as a function of the variance and autocovariances of accrual sales:

$$R[CSA(t),CSA(t-1)] = Cov[CSA(t),CSA(t-1)]/Var[CSA(t)]$$

$$= \frac{[(\alpha 1)^2+(\alpha 2)^2]Cov[ASA(t),ASA(t-1)] + (\alpha 1)(\alpha 2)[Cov[ASA(t),ASA(t-2)]+Var[ASA(t)]]}{[(\alpha 1)^2+(\alpha 2)^2]Var[ASA(t)] + 2(\alpha 1)(\alpha 2)Cov[ASA(t),ASA(t-1)] + Var[a(t)]} \qquad (3-5)$$

Since the autocorrelation of accrual sales at lag 1 is simply

$$R[ASA(t),ASA(t-1)] = Cov[ASA(t),ASA(t-1)]/Var[ASA(t)], \qquad (3-6)$$

one can see from (3-5) and (3-6) that <u>a general answer cannot be given to the question of whether accrual sales contain a higher (or lower) first order serial dependence than its cash-based counterpart</u>. That is, depending on parameters $\alpha 1$ and $\alpha 2$, on the autocovariance of accrual sales at the first two lags, and on the variance of the random variable a(t), the serial dependence of cash receipts from customers (CSA) may or may not be smaller than that of its accrual counterpart (ASA).

To be more exact, the necessary condition for a higher serial dependence in accrual sales than in cash sales requires that (3-6) be greater than (3-5). Assuming $\alpha 1$, $\alpha 2$ and Cov[ASA(t),ASA(t-1)] are non-negative, this leads (after some algebraic manipulation) to the following inequality:

$$2(\alpha 1)(\alpha 2)R1^2 + cR1 - (\alpha 1)(\alpha 2)(R2+1) > 0 \qquad (3-7)$$

where R1 = R[ASA(t),ASA(t-1)], i.e. the autocorrelation of accrual sales at lag 1
R2 = R[ASA(t),ASA(t-2)], i.e. the autocorrelation of accrual sales at lag 2
c = Var[a(t)]/Var[ASA(t)], i.e. the variance of the random term divided by the variance of accrual sales

Since $\alpha 1$ and $\alpha 2$ were assumed to be non-negative, the above ineqality holds true whenever the first order autocorrelation coefficient of accrual sales is <u>outside</u> the range defined by the following roots of the left hand side of (3-7):

$$R1 = \frac{-c \pm [c^2 + 8(\alpha 1)^2(\alpha 2)^2(R2+1)]^{\frac{1}{2}}}{4(\alpha 1)(\alpha 2)} \qquad (3\text{-}8)$$

Since the plausibility of the above condition is solely dependent on its parameter values, it can be concluded that empirical data is needed in order to provide estimates for them and in order to see whether (3-8) holds true, that is, whether (3-6) is higher than (3-5).

3.2. An Analysis of Operating Income

In order to derive a theoretical expression for the autocorrelation of accrual operating income, the following accrual accounting system will be assumed for any period t:

	Sales	ASA(t)
-	Variable Expenses	(1-m)ASA(t) + u(t)
-	Fixed Expenses	F + v(t)
	Accrual Operating Income AOI(t) =	(m)ASA(t) - F - (u(t)+v(t)) (3-9)

According to the accounting model assumed above, the firm's total operating expenses can be divided into variable and fixed components depending on whether an expense item is proportional to the volume of operations. It is assumed that the variable expenses are, on average, (1-m) marks per every mark of sales so that the firm is able to earn an amount of m marks per every mark of sales to cover the fixed operating and non-operating expenses. Furthermore, a random variable u(t) is included in the variable expenses in order to take into account the fluctuation around the average variable unit costs over time. Specifically, it will be assumed that u(t) is identically and independently distributed with zero mean and constant variance.

Moreover, the fixed expenses, which by definition are independent of the volume of the firm's operations, are assumed to follow a pure mean reverting process around a constant (F). This implies that, similarly to u(t), the random variable v(t) is identically and independently distributed with zero mean and constant variance. It should be noted that because fixed costs are thus assumed to be stationary, the firm is therefore assumed to experience no persistent growth in its fixed costs, an assumption made only for the sake of simplicity.

Denoting z(t) = u(t)+v(t), the variance of the accrual operating income is

$$\begin{aligned}
Var[AOI(t)] &= Var[mASA(t)-F-z(t)] \\
&= m^2 Var[ASA(t)] + Var[F] + Var[z(t)] \\
&\quad - 2mCov[ASA(t),F] - 2mCov[ASA(t),z(t)] + 2Cov[F,z(t)] \\
&= m^2 Var[ASA(t)] + Var[z(t)] \qquad (3\text{-}10)
\end{aligned}$$

and the autocovariance at lag 1

$$Cov[AOI(t),AOI(t-1)] = Cov[(mASA(t)-F-z(t)),(mASA(t-1)-F-z(t-1)]$$

$$= m^2Cov[ASA(t),ASA(t-1)] - mCov[ASA(t),F] - mCov[ASA(t),z(t-1)]$$
$$- mCov[F,ASA(t-1)] + Cov[F,F] + Cov[F,z(t-1)]$$
$$- mCov[z(t),ASA(t-1)] + Cov[z(t),F] + Cov[z(t),z(t-1)]$$

$$= m^2Cov[ASA(t),ASA(t-1)] \tag{3-11}$$

Now, the autocorrelation of the accrual operating income at lag 1 is:

$$R[AOI(t),AOI(t-1)] = Cov[AOI(t),AOI(t-1)]/Var[AOI(t)]$$

$$= \frac{m^2Cov[ASA(t),ASA(t-1)]}{m^2Var[ASA(t)] + Var[z(t)]} \tag{3-12}$$

From the expression above we can conclude that, since $Var[z(t)] > 0$, <u>the first order serial dependence in accrual accounting operating income numbers is always lower than in accrual sales</u> under the accounting model assumed in (3-9). Thus, the subtraction of variable and fixed operating expenses from accrual sales in the income statement can be expected to lead to a decrease in the autocorrelation of the resulting operating income variable.

For the cash-based counterpart of the accrual operating income, the following cash accounting system is assumed:

Cash Sales	$(1-k)ASA(t) + (k)ASA(t-1) + a(t)$
- Cash Outflows for Variable Expenses	$(1-p)[(1-m)ASA(t)+u(t)] + p[(1-m)ASA(t-1)+u(t-1)] + s(t)$
- Cash Outflows for Fixed Expenses	$[F+v(t)] + q(t)$

$$
\begin{aligned}
\text{Cash Operating Income } COI(t) &= (1-k)ASA(t) + (k)ASA(t-1) + a(t) \\
&\quad - (1-p)[(1-m)ASA(t)+u(t)] \\
&\quad - p[(1-m)ASA(t-1)+u(t-1)] - s(t) \\
&\quad - F - v(t) - q(t) \\
&= [(1-k)-(1-p)(1-m)]ASA(t) \\
&\quad + [k-p(1-m)]ASA(t-1) \\
&\quad + a(t)-(1-p)u(t)-pu(t-1)-s(t)-v(t)-q(t) \\
&\quad - F
\end{aligned}
\tag{3-13}
$$

The rationale behind the above expression for cash operating income is as follows.

First, the function describing cash revenues from customers is identical to expression (3-2) and therefore needs no further comment.

Analogously to cash sales, it is assumed that the firm follows a credit policy according to which the long-term average of the turnover of its accounts payable is $1/p$, and its inverse, p ($0 < p < 1$), is therefore the fraction of variable expenses that are, on average, outstanding at the end of any period. Thus, cash outflows for variable expenses in the current period are $(1-p)$ times the variable expenses of the current period plus p times variable expenses of the previous period plus a random variable $s(t)$, which takes into account the fluctuation around the average turnover ratio $1/p$ as well as changes in inventories.

Finally, the cash outflow for fixed expenses contains its accrual counterpart, $F+v(t)$, plus a random variable $q(t)$ which includes the net change in related accruals and deferrals, i.e. the difference between the amount expensed and actually paid. As was the case with $a(t)$, $u(t)$ and $v(t)$, the random variables $s(t)$ and $q(t)$ are also assumed to be independently distributed with zero means and constant variances.

Denoting
$$\beta 1 = (1-k)-(1-p)(1-m),$$
$$\beta 2 = k-p(1-m), \text{ and}$$
$$e(t) = a(t)-(1-p)u(t)-pu(t-1)-s(t)-v(t)-q(t)$$

expression (3-13) can more conveniently be written

$$COI(t) = (\beta 1)ASA(t) + (\beta 2)ASA(t-1) - F + e(t) \qquad (3\text{-}14)$$

Besides the contents of the parameters $\beta 1$ and $\beta 2$ and the constant F which is irrelevant for the autocorrelation of COI, the only noteworthy difference between expression (3-14) for cash operating income and (3-2) for cash sales is that, while $a(t)$ was assumed to be independently distributed in (3-2), such an assumption cannot be made with respect to $e(t)$ in (3-14). This is because consecutive terms $e(t)$ and $e(t-1)$ contain common element $u(t-1)$ and are therefore positively correlated. If the appropriate adjustment is made by adding the autocovariance of $e(t)$ in the nominator, expression (3-5) can, however, be applied for cash operating income as well:

$$R[COI(t),COI(t-1)] = Cov[COI(t),COI(t-1)]/Var[COI(t)]$$

$$= \frac{[(\beta 1)^2+(\beta 2)^2]Cov[ASA(t),ASA(t-1)] + (\beta 1)(\beta 2)[Cov[ASA(t),ASA(t-2)]+Var[ASA(t)]] + Cov[e(t),e(t-1)]}{[(\beta 1)^2+(\beta 2)^2]Var[ASA(t)] + 2(\beta 1)(\beta 2)Cov[ASA(t),ASA(t-1)] + Var[e(t)]} \qquad (3\text{-}15)$$

Comparing expressions (3-12) for accrual operating income and (3-15) for its cash-based counterpart, we can see that, once again, a <u>general answer cannot be given to the question of whether accrual operating income is likely to contain a higher (or lower) first order serial dependence than its cash-based counterpart</u>. Depending on parameters m, β1 and β2, on the autocovariances and variances of accrual sales and the random term e(t) as well as on the variance of random term z(t), the serial dependence of cash operating income (COI) may or may not be smaller than that of its accrual counterpart (AOI).

Of course, an exact condition (similar to 3-7 and 3-8 above) for a higher serial dependence in the accrual operating income could be derived as a function of the terms appearing in (3-12) and (3-15). However, since it would lead to a cumbersome expression with little additional insight into the main issue, such a condition will not be derived here. Instead, we conclude that the final answer can be given only with empirical data, which will provide the necessary estimates needed in (3-12) and (3-15).

To summarize the conclusions from the theoretical models derived above for serial dependences in income variables at the sales and operating income levels, it can be stated that, <u>a priori</u>, there is no general answer to the question of whether income smoothing (in the serial correlation increasing sense) might be a basic characteristic of the accrual accounting system. Assuming that cash sales, accrual operating income and cash operating income are simple linear functions of accrual sales, the analysis indicated that the difference between the first order autocorrelation of accrual income variable and that of its cash-based counterpart remains dependent on the parameter values of those linear relationships. A 'final' answer to the main question can therefore be given only by an empirical inquiry.

Empirical data will also provide us an opportunity to test the descriptive validity of the theoretical autocorrelation models derived above. Using empirical time series of the examined variables as our data, we can estimate the parameters of the assumed relationships. Those estimates enable us to compute the autocorrelation coefficients predicted by the theoretical expressions derived above. Comparing the predicted autocorrelations with the actual values estimated from the empirical time series then gives us the opportunity to see whether the theoretical examples have any descriptive validity.

NOTES TO CHAPTER 3:

[1] See Lev (1969) for empirical evidence consistent with the hypothesis that firms adjust their financial ratios according to industry-wide averages.

[2] Note that the assumption of weak stationarity does not preclude that successive realizations of a random variable and the dispersion of those realizations may increase or decrease in some consecutive periods of time. However, such change is not allowed to be persistent since it would lead to a revision in the expectation and the variance of the random variable.

[3] The question of whether the beginning or ending balances of receivables are used in the denominator of (3-1) is a problem one encounters in computing the turnover ratio in practice. Consistent with (3-2), it is assumed here that (3-1) is determined using the ending balance of receivables in the denominator.

4. VARIABLE DEFINITIONS AND THEIR DATA

As was seen in the preceding literature review, there is no unique income definition that has been consistently analyzed in related studies. On the contrary, a number of variables can be encountered in the area which differ e.g. with respect to whether income has been measured before or after extraordinary items, whether it has been deflated by firm size (as measured by total assets or sales) or whether it has been measured on a per share basis. Taking into account the present accounting system where cash flows are not directly reported, the mixture of definitions is even more apparent with cash-based variables. Different measures of cash flow have been defined in different studies on the basis of judgments and views of the researcher on how it should actually be measured.

The primary purpose of this chapter is to define in detail the accrual and cash flow variables to be taken into empirical time series analysis (section 4.1.). The second section (4.2.) aims to describe the selection of the time series sample to be used, and the third section (4.3.) discusses the measures that were taken in order to transform the raw data into a form which was more appropriate for our analysis.

4.1. Defining Relevant Accrual and Cash-Based Income Variables

In order to define the variables of interest, a set of requirements was imposed on them. The first requirement was that the variables must be of interest to the shareholders of a firm for two reasons. First, the shareholders' viewpoint was consistent with the argument that the knowledge of income time series behavior is important in the valuation of a firm's shares. The aspect of share valuation required that the income variables had to be defined from the shareholders' point of view. Second, the relevance to the shareholders also had the obvious advantage of preserving consistence with prior studies in the area. As was noted in the literature review, most prior studies have examined the time series behavior and predictability of such accrual earnings-related variables as total net income, earnings per share or accounting rate of return, all of which are relevant to the shareholders of the firm.

The second requirement for the variables was their operationality in the sense that they had to be readily available (or computable) from published financial reports and other publicly available sources. This requirement, although self-evident, was important because it explicitly excluded the consideration of any variable requiring inside information (such as interim or segmental reports of the firm) which is not publicly disclosed.

The third requirement concerned the number of levels of income measurements. Our analysis was not constrained to one single measurement level (e.g. the net income level on the bottom row of an income statement); multiple levels were considered instead. The primary reason for the inclusion of multiple measurements was twofold. First, the debate about the "correct" income measurement level was avoided when income was measured on different levels. E.g. the debate concerning current operating income vs. all-inclusive concept of income (see e.g. Hendriksen, 1977) or the debate about whether income should be measured before or after extraordinary items could be avoided when income was measured on both of these levels. Second and more important, selecting variables from different levels of an income statement also enabled us to observe how the time series properties vary across the income statement. These observations may provide interesting insights into the relative importance of the operating, investing and financing functions of the firm as determinants of the time series properties of income numbers.

In this study, variables from three different levels of the income statement were examined. The first was the net sales level which contains aggregate information of one single operating function of the firm. The obvious advantage of selecting the net sales variable was that while it is a basic constituent of other (lower level) income numbers, it is unaffected by such major accounting decisions as the allocation of expenditures over time or across the income statement, valuation of inventories, etc. The selection of net sales as one of the variables was also supported by its popularity, clarity and ease of interpretation. Furthermore, empirical evidence exists indicating that market share and profitability (as measured by return on investment) may be positively correlated over time and market share may therefore serve as a proxy for other measures of corporate performance such as profits (see e.g. Buzzell et al., 1975).

The second income variable was selected from the operating income level. Since the operating income is measured deducting operating expenses from net sales, the resulting income variable only contains information on the basic operating functions of the firm (sales and production), while such non-operating activities as investing and financing functions, which are of a less regular nature, have no direct effect on it. This is in fact the point of the advocates of the concept of current operating income (see Hendriksen, 1977) since operating income - as opposed to the all-inclusive concept of income - is more comparable from period to period, it should also be more predictable and therefore more appealing to the users of financial statements. Selecting operating income as one of our income variables provided us with the opportunity to obtain some empirical evidence for that contention. Moreover, from an accounting viewpoint it should also be noted that while decisions with respect to inventory valuation have a direct effect on reported operating income numbers, decisions concerning the valuation and allocation of fixed assets have not, because the operating income is measured before depreciation, depletion, amortization, and similar items.

The net income level was selected as the third income variable for several reasons. First, the proponents of accrual accounting earnings usually argue that accounting net income contains more relevant information for the prediction of future cash flows than any other single variable (see e.g. the statement by the FASB quoted in section 2.2.1. above).

Second, inclusion of the net income variable in the analysis also preserved consistence with prior studies in the area better than the preceding variables (net sales and operating income). As we noted already, the focus of these studies has been on the behavior of net earnings and its derivatives. It is therefore consistent that this central variable was also analyzed in the present study. Furthermore, inclusion of net income was justified on the grounds that it preserved 'symmetry' with respect to the selection of income measures; while net sales were selected from one extreme of the vertical 'continuum' of an income statement, it was therefore advisable to select net income from the other. Since the net income variable also includes information on the investment and financing functions of the firm, it should provide additional information not conveyed by the net sales or operating income variables discussed above. Last but not least, because "the primary focus of financial reporting is information about earnings and its components" (FASB, 1978), the analysis of the net income variable was also justified on its own account.

The fourth requirement imposed on the selected variables concerned the relationship between accrual and cash-based variables. In this respect a strict adherence to consistent inclusion of operating, investment and financing flows in accrual incomes vis-a-vis their cash-based counterparts was required. For example, the cash flow variable analyzed in some prior studies (see section 2.2.2. above) defines cash flow as the sum of net income, depreciation, depletion and amortization (+/- net change in current accounts other than cash) which cannot, under this requirement, be regarded as a valid counterpart of accrual net income. The reason is that while net income is reported <u>after</u> expenses for fixed assets (as measured by depreciation), the above cash flow variable measures cash flow from operations <u>before</u> outflows for long-term expenditures. Since the two variables include investment flows in an inconsistent manner, it would be unreasonable to compare their time series properties or information content with each other: if differences were found, it would remain unclear whether they would be due to the difference between the accounting principle (accrual vs. cash accounting) or to the difference between the inclusion of investment flows. To avoid such difficulties, the accrual accounting variables and their cash-based counterparts were, therefore, defined on a "<u>matched-pair</u>" - basis for this study.

On the basis of the requirements discussed above, the following variables were selected for empirical time series analysis:

TABLE 4-1: Selected Variables for the Study

Accrual Accounting Income Variables:		Cash Accounting Income Variables:
1) Accrual Sales (ASA)	<---->	4) Cash Sales (CSA)
. . . .		. . . .
2) Accrual Operating Income (AOI)	<---->	5) Cash Operating Income (COI)
. . . .		. . . .
3) Accrual Net Income (ANI)	<---->	6) Cash Net Income A (CNIA)
		7) Cash Net Income B (CNIB)

The description below aims to illustrate briefly how these variables were defined with the items appearing in the financial statements disclosed by Finnish firms. More detailed formulae for the computation of the cash-based variables are given in appendix 4-1 to this chapter.

Variable #1 (ASA) is equal to the net sales as reported, i.e. net of discounts allowed, bad debts incurred and any indirect taxes such as the sales tax and the excise tax.

Variable #4 (CSA) is the cash-based counterpart of ASA. It was computed by adjusting net sales for changes in accounts receivable and advance payments from customers.

Variable #2 (AOI) is the operating income as reported, i.e. net sales less variable and fixed expenses. Variable expenses include direct costs of the products sold such as raw materials, wages, energy, services etc. Fixed expenses include any indirect costs relating to the production process such as administrative expenses, salaries, rents, etc.

Variable #5 (COI) is the cash-based counterpart of AOI. It was computed by subtracting from cash sales (CSA) all cash outflows for short-term operating expenses. In brief, these were obtained by adjusting the expenses with changes in inventories, accounts payable and prepayments to suppliers of goods and services.

Variable #3 (ANI) is the net income as reported, i.e. operating income less depreciation, non-operating revenues and expenses, net change in untaxed reserves, interest expenses and direct taxes [1].

For the accrual net income variable, two cash-based counterparts (variables #6 CNIA and #7 CNIB) were defined, primarily because of the conceptual difficulties in taking into account the long-term expenditures in fixed assets deducted as depreciation in the income statement. The common element in both of the cash net income variables is cash net income before long-term expenditures. This was obtained by deducting non-operating revenues and expenses, interest expenses and direct taxes adjusted for their deferrals and accruals from the cash operating income (COI). The next step was to compute the total amount of net investments in fixed assets. In brief, this was obtained by adding depreciation to the net increase in fixed assets adjusted for any changes of advance payments and revaluations relating to them.

However, the two cash net income variables take different views with respect to the amount of net investments deducted in order to arrive at the final net income figure. For variable #6 (CNIA), the accounting principle of matching expenditures with revenues was followed and, consequently, only the proportion of replacement investments in total net investments was deducted. The basic method applied in this study for estimating the amount of replacements was developed by Artto (1985, pp. 49-77). His method was used here because it is the only serious attempt known by the author to reconcile (in a cash accounting setting) the basic dilemma of expenditure allocation with the matching principle of accounting theory [2].

While the former variable tries to follow the matching principle in deducting the long-term expenditures of fixed assets, variable #7 (CNIB) takes the opposite view. For this variable, the amount of net investments in fixed assets was deducted in its entirety without any prior attempt to split it into replacement and growth components. In doing this, the CNIB variable follows the line of reasoning in the financial theory where no attempt in matching expenditures with revenues is made. According to the financial theory, no dilemma of expenditure allocation exists because all expenditures (no matter whether short- or long-term) are deducted for the period when they are realized as cash outflows (see note 2 to chapter 1). Thus, it can be argued that the CNIB variable analyzed in this study falls in line with that view with one (minor) exception: while the financial theory suggests that the increase in liquid assets (i.e. the increase in cash and cash-equivalent deposits and marketable securities) should be regarded as a part of net investments and thus should be deducted in determining the relevant cash net income (see Haley and Schall, 1979, p. 12), such a deduction was, however, not made here in the computation of the CNIB variable. The main reason was that if CNIB were defined after the increase in liquid assets, the resulting variable would not have been comparable with its counterpart in accrual accounting (ANI), where investment outflows in liquid assets are not deducted in any form [3].

Finally, in order to summarize and to put the selected variables in perspective, the following remarks can be made:

(i) While prior time series research in the accounting literature has mainly concentrated on analyzing the behavior of accrual accounting net income and its derivatives, the present study examined two sets of variables; one comprised the income numbers from the accrual accounting and the other their direct cash-based counterparts. This setting enabled us to observe what effect, if any, the principles of accrual vs. cash accounting have on the time series properties of resulting income numbers.

(ii) Income was measured on the accrual and cash-basis from three different levels of an income statement: (1) the net sales level; (2) the operating income level; and (3) the net income level. The primary purpose of this stratification was to provide observations of how the time series properties of income numbers change across the income statement, i.e. what is the effect of different operating, investment and financing flows on the phenomena under examination. It should be noted that since the cash-based variables serve as 'control variables' in the current setting, it was assumed possible to observe the marginal effect of the accounting treatment of those flows.

(iii) The cash-based variables defined above also differ from related studies in the method of measuring cash flow from operations. While prior empirical studies on this variable have mainly used the indirect (upwards) method of computation (i.e. they have taken the reported net income as the starting point, which has then been adjusted for depreciation, changes in working capital and other non-cash items), the present study adopted the direct (downwards) method, starting from the cash revenues received from customers from which the (short-term) operating cash outflows were then deducted. As a result, some of the pitfalls included in the indirect method were hopefully avoided and a more reliable measure of operating cash flow was obtained. (For a discussion on the problems relating to the indirect method frequently used in related studies, see Drtina and Largay, 1985).

4.2. Sample Selection

The sample of firms analyzed in the study comprises industrial and commercial firms listed on the Helsinki Stock Exchange in the early 1980s. The sample was selected from among listed firms for at least the following reasons: (i) being relatively old and established firms, financial statement data was readily available for most of the listed companies over a longer period needed for time series analysis purposes; (ii) it will be possible to measure in future studies the information content (market reaction) of different information sets disclosed by these firms; and (iii) although small in number, the listed companies are very significant in the Finnish economy.

In 1982 there were thirty-three industrial firms, one transportation company, and eight commercial companies listed on the Helsinki Stock Exchange. (Banks and insurance companies were not considered for this study because of the essentially different nature of their operations and accounting practices which would have caused considerable difficulties in deriving comparable income variables defined in the previous section.) Of these firms two manufacturing firms (Marimekko Oy and Medica-yhtymä Oy) had to be omitted from the final sample because complete financial statements could not be obtained from them for the whole time period examined. In addition, one commercial company (SMK Oy) was omitted because its business changed essentially in the mid-70s so that the firm before and after the change was not comparable at all. Thus, the final sample of firms consisted of thirty-nine firms comprising thirty-one manufacturing companies (nine of which represent the wood-processing industry), one transportation company, and seven commercial companies. A complete list of the sample firms appears in appendix 4-2 to this chapter.

As regards the economic importance of the sample analyzed in this study, table 4-2 below gives some facts about its relative size compared with all Finnish firms (liable to turnover tax) in corresponding industries.

TABLE 4-2: The Sample Size in Relation to All Finnish Industrial, Commercial, and Transport Firms Liable to Turnover Tax in 1982 [4].

	All Firms:		Sample Firms:			
	Number of firms	Total Turnover Million FIM	Number of firms	%	Total Turnover Million FIM	%
Industrial	17130	172490.4	31	0.18 %	44639.8	25.9 %
Commercial	31957	196869.0	7	0.02 %	19011.3	9.7
Transport.	431	4660.7	1	0.23 %	962.8	20.7 %
Total	49518	374020.1	39	0.08 %	64613.9	17.3 %

On the one hand, the broad tenor of table 4-2 suggests that although the sample is only a tiny percentage (under 0.1 %) of all Finnish industrial, commercial and transport firms, its economic importance is, however, far from being insignificant. In 1982 the sample covered approximately one fourth, one tenth, and one fifth of the total turnovers of all industrial, commercial and transport enterprises in Finland. It thus is unambigious that the firms analyzed in this study play a very important role in the Finnish economy, and from that point of view their inclusion in the present sample was more than justified.

On the other hand, it has to be recognized that the relatively large size of the sample firms may restrict the generalizability of the results obtained in this study. As the general model of the underlying determinants (see expression 1-1 in chapter 1) hypothesized, the firm's size may affect the underlying processes of income variables, and therefore the findings of this study may not be generalizable to other (smaller) firms. However, the literature review (section 2.1.2.) indicated, that the empirical findings obtained so far do <u>not</u> support the hypothesis of the firm's size being a significant determinant of autocorrelation in income numbers (Lev, 1983). If this is indeed the case, the properties of the present sample do not prevent generalizations to smaller firms as well.

The financial statements of each sample firm were gathered over the 35-year period 1950-1984 [5]. Most of the financial statements (about 91 %) were readily available in form of computer printouts at the Department of Accounting and Finance of the HSE. The remaining 9 % were gathered from Patentti- ja rekisterihallituksen taseosasto (a govermental bureau where certain companies must submit their annual financial statements) and directly from the firms. From the financial statement data the income variables defined in the preceding section were then computed over the 34-year period 1951 - 1984. (Note that the balance sheets of the first year 1950 were needed in computing the cash flow variables for 1951). The total sample of empirical time series thus consisted of 273 series (= 39 firms * 7 variables per firm) each containing 34 annual income observations [6].

As regards the horizontal size (length) of the time series data, at least three reservations have to be made. On the one hand, the horizontal size of the sample time series is only 34 (annual) observations which is not very much for statistical estimation purposes especially when one considers the need for a hold-out sample that has to be left for predictive ability analysis (to be explained in the next chapter). Although the sample is therefore very small from this perspective, it should be noted, however, that it is quite comparable to sample sizes used in some prior related studies (see appendix 2-1).

On the other hand, it may be argued that the horizontal size of the sample is too large because structural changes undoubtedly are present in any time series covering over three decades. In this case, structural changes may rise due to (i) economic changes experienced by firms themselves in course of time, and (ii) changes in the accounting methods adopted by the firms. With respect to the economic changes, non-stationarities and other discontinuities can be expected to be encountered for reasons attributable to the economy as a whole (e.g. inflation), to the firm's industry (e.g. the measures taken by the government for regulation and deregulation of certain industries), and to the firm itself (e.g. the acquisition and divestiture behavior). With respect to accounting changes, some new acts have been made especially in the late sixties and mid-seventies affecting the accounting practices of Finnish firms [7]. All these structural changes will undoubtedly increase the noise in the time series data and therefore it will become more difficult to discern the 'regularities' from that noise.

Finally, the third problem relating to the horizontal size of the sample is the 'survivorship bias' caused by the fact that the time series analyzed in this study were obtained from firms that had survived for a long period of time and therefore the results may not be generalizable to younger firms with shorter history. Although the potential for the existence of such bias has to be recognized, prior empirical findings obtained by Ball and Watts (1979) on this issue suggest, however, that the effect of the 'survivorship bias' is non-existent or very small. Relying on that evidence, the 'survivorship bias' can therefore be expected to pose a less serious problem for this study.

4.3. Data Adjustments

In order to alleviate the problems caused by the structural changes noted above, several adjustments were applied to the original raw data in order to make it more appropriate for time series analysis. These included (i) an adjustment for exceptional fiscal years, (ii) an adjustment for inflation, and (iii) adjustments for outliers in individual years and sudden shifts in the level of some sample series.

(i) An adjustment for exceptional fiscal years was needed because 13 firms (33 %) in the sample had changed the ending date of their fiscal year from calendar to non-calendar year and/or vice versa, thus producing exceptional fiscal years the lengths of which were not 12 months. In the whole sample consisting of 1324 firm-years ($\approx$ 39 firms * 34 years) 23 such fiscal years were encountered. The adjustments for the length of fiscal years thus concerned 1.7 % of the whole sample.

The adjustment for exceptional fiscal years was based on the following linear transformation:

$$X(t) = (12/M) * X(t') \tag{4-1}$$

where X(t) = adjusted variable for fiscal year t
M = number of months in the non-twelve-month fiscal year
X(t') = unadjusted variable obtained from the non-twelve-month fiscal year t'

(ii) Next, the growth pattern caused by inflation was removed from the data for the following reasons. First, the focus of our interest was on the time series of accrual vs. cash-based income expressed at a uniform purchasing power of money. If no adjustment for inflation had been made, the time series data would have described the behavior of a hybrid phenomenon where inflation would have been an essential component. Second, it can be argued that the best way to take the inflation into account in a valuation context is to discount future cash flows expressed in a uniform purchasing power of money with required real rate of return. One can then avoid the complexities which would otherwise arise, viz. the allowance for the dependence between future cash flows and inflation [8]. Third, an adjustment for inflation was also desirable from a statistical point of view, because it removed a major part of the non-stationarity in the data (i.e. the trend introduced by inflation to the nominal income series).

For the inflation adjustment, the wholesale price index series published by the Central Statistical Office of Finland was employed. This index series was chosen for a number of reasons (see Kinnunen, 1983): (i) it was available over the entire period 1951 - 1984; (ii) it was considered a valid index for measuring changes in the general price level from the shareholders' point of view; (iii) the inflation behavior as measured by this index had been found to be an average of some other indices; and (iv) the wholesale price index has been widely used in financial statement analysis of Finnish firms for inflation measurement purposes.

With this price index each year's nominal income numbers were inflated to the price level of 1984 which was the last year of the time series data:

$$X(t)' = [I(84)/I(t)] * X(t) \qquad (4\text{-}2)$$

where

- $X(t)'$ = income number in year t expressed at the price level of 1984
- $I(84)$ = the wholesale price index in 1984
- $I(t)$ = the wholesale price index in year t
- $X(t)$ = income number in year t expressed at the nominal price level of year t

At this point it should be noted that the above transformation was not intended to do the job of such accounting methods as e.g. the CPP or the CCA recommended by some rule-making bodies for eliminating inflationary profit from the accounting income. What formula (4-2) does instead, is that it expresses those profits in a uniform scale. (Note also that the amount of inflationary profit in the cash-based income variables is much less than in the income variables produced by the accrual accounting practice based on historical costs. Of course, this is because the cash-based variables expressed in terms of proper cash inflows and outflows contain items of almost identical purchasing power of money.)

(iii) After the adjustments for exceptional fiscal years and inflation, the graphs of the time series data were visually examined in order to obtain a rough idea of the behavior of the selected income variables. The focus of the visual inspection was on identifying those series which contained trend, heteroscedasticity (i.e. instability in variance), sudden shifts in the levels or outliers in individual years. The findings from the graphs are summarized in the following table:

TABLE 4-3: Findings from the Visual Inspection of the Time Series Graphs (n = 273 time series, 39 time series per variable)

	Trend		Instability in variance		Shift in the level		Individual outliers	
Variable	fr.	%	fr.	%	fr.	%	fr.	%
ASA	36	92.3	8	20.5	3	7.7	0	0.0
AOI	30	76.9	29	74.4	3	7.7	2	5.1
ANI	11	28.2	13	33.3	1	2.6	20	51.3
CSA	36	92.3	7	17.9	3	7.7	3	7.7
COI	15	38.5	22	56.4	0	0.0	8	20.5
CNIA	5	12.8	19	48.7	2	5.1	7	17.9
CNIB	1	2.6	28	71.8	0	0.0	10	25.6
Total	134	49.1	126	46.2	12	4.4	50	18.3

Almost half (49.1 %) of the 273 time series examined seemed to contain a (usually positive) trend. It was indeed very common in the time series of accrual and cash-based sales where virtually all firms (92.3 %) exhibited real growth. A similar pattern was also found in the accrual operating income series where most firms (76.9 %) showed some kind of trend. Interestingly, the number of firms where trend was a salient feature in the behavior of the cash-based counterpart of the accrual operating income, was only half of those exhibiting trend on the accrual basis. The same kind of difference could also be found between the number of firms showing trend in the accrual net income and its cash-based counterparts.

Heteroscedasticity was also present in a large number of the sample time series (46.2 %). It was most commonly found in the accrual operating income and in one of the cash net income variables (CNIB) where approximately three fourths of the firms showed instability in variance. The other two cash-based variables (COI and CNIA) also seemed to have this property in half of the firms.

Sudden shifts of a permanent nature in the level of time series were relatively uncommon; only 12 series (4.4 %) were found which showed such a phenomenon. Although the underlying factors behind these shifts were not examined in detail, it can be assumed that mergers and divestitures explain most (if not all) of these shifts.

Outliers in individual years could be found approximately in one fifth (18.3 %) of the sample series. Most of these occurred in the time series of accrual net income, where outliers were encountered in approximately one half (51.3 %) of the firms. These were usually negative outliers in the late 1970s when the Finnish economy experienced one of its severiest slumps in the aftermath of the world-wide oil crisis. Interestingly, this slump produced outliers observable only in the accrual net income variable, not in the other variables examined [9].

The outliers and the shifts in the levels were 'cleaned' from the data using the following techniques.

The sample mean and standard deviation were estimated from each of the sample series containing an outlier (of course, the outlier itself was omitted from the estimation). Assuming normality, the limits of the 95 % confidence interval were then determined for the series, and the outliers were drawn back to these limits. Of the 9268 annual observations in the data, 37 individual outliers (0.4 %) were adjusted in this way [10]. Thus, a positive (negative) outlier was pull down (up) to

$$\mu + (-)\ 1.96 * \sigma \tag{4-3}$$

where μ = estimated mean of the series
σ = estimated standard deviation of the series

For the series containing a sudden shift in the level, the following model containing a dummy variable was estimated using the method of ordinary least squares (the variable denoting time (year) was also included in the model in order to take into account the possible trend in the series):

$$X(t) = \beta 0 + \beta 1 * t + \beta 2 * d + e(t) \tag{4-4}$$

where t = a variable denoting time (year)
d = a dummy variable defined as 0 in the years prior to the shift in the level and 1 in the years after the shift in the level of the series
e(t) = a residual with usual assumptions
$\beta 0$, $\beta 1$ and $\beta 2$ = estimated parameters

The magnitude of the shift in the level of the series as measured by the estimate of $\beta 2$ was then added to all annual observations preceding or following the shift. Thus, if a sudden positive (negative) shift occured in a series in, say 1976, a positive (negative) constant determined by the estimate of $\beta 2$ was added to all observations in the period 1951 - 1975. Since shifts in the levels were encountered in 12 series, dummy adjustments accounted for approximately 0.1 % of the total number of differences (8995) in the sample time series.

NOTES TO CHAPTER 4:

[1] The main reasons for <u>not</u> adjusting the reported accrual net income variable analyzed in this study for the net change in untaxed reserves (inventory reserve, reserves for bad debts, for warranty repair costs, etc.) were as follows:
(i) In the Finnish accounting practice, changes in untaxed reserves provide management with an important device for interperiod income smoothing. Since similar opportunities (at least to such an extent) are seldomly encountered in other countries (especially in the Anglo-Saxon world), the analysis of the time series behavior of the net income numbers as reported by the Finnish firms sheds light on how the use of such smoothing opportunities may affect the underlying processes of resulting income variables. For example, if similar tendency to submartingale (random walk with or without a drift) behavior could be identified from Finnish net income numbers as it has been the case in other countries, then such a result would imply that the smoothing opportunities by changes in untaxed reserves may have, afterall, an insignificant impact on the underlying process.
(ii) Review of the relevant literature reveals that adjustments for particular income statement items have not, in general, been made in related prior studies. It thus seems that because prior studies in the area have analyzed accrual income variables as reported, attempts have not been made to remove the potential effects of some of the discretionary accounting choices in $\beta 2$ (see 1-1).
(iii) Since income determination (c.f. reported net income) is a separate task from income evaluation (c.f. the financial analyst's net income obtained via adjusting the reported income numbers for changes in the untaxed reserves, etc.), and since the focus of this study is <u>not</u> on analyzing financial analyst's income numbers with the aim to evaluate firm performance, there was no basic need to make adjustments for accounting items such as changes in untaxed reserves. Furthermore, <u>if</u> this study had any such evaluative purposes, adjustments for items other than changes in untaxed reserves would also have been necessary (e.g. there would also have been a need to "normalize" the depreciation amount). In that case, considerable difficulties would have been encountered because there is no applicable theoretical guidelines for such adjustments (e.g. it would have been impossible to determine theoretically 'correct' depreciation amounts for the sample firms.) Finally, as a practical matter it should also be noted that in the 1950s and 1960s Finnish firms did not, in general, report their changes in inventory reserves, which makes it impossible to adjust the income numbers reported at that time.

[2] In brief, Artto's method for estimating the amount of replacements is a two-stage allocation process. In the first stage, the total amount of replacements is determined for a time period comprising a number of consecutive years on the basis of the amount of operating cash flows and the change of the market value of the firm . In the second stage, the amount of replacements determined in the first stage is allocated on the basis of the volume of the firm's operations (proxied by the amount of sales) for individual years within the time period. Denoting

R(t) = replacements of fixed assets (subscript t denotes year)
A(t) = growth investments in fixed assets
Y(t) = divestments (sale) of fixed assets
OCF(t) = operating cash flow (= COI defined for this study)

$T(t)$ = income taxes
δV = change in the market value of the firm during a period
r = internal rate of return determined by the change in the market value and the entity cash flow of the firm (i.e. the net cash flow between the firm and its debt and equity holders) during a period $t = 1, \ldots, n$

Artto (1985, p. 63) suggests that the amount of replacements attributable to period $t = 1, \ldots, n$ is given by the following expression:

$$\sum_{t=1}^{n} R(t) = \sum_{t=1}^{n} [A(t)+R(t)-Y(t)] * \frac{\sum_{t=1}^{n} [OCF(t)-T(t)]\,[1+r]^{n-t}}{\sum_{t=1}^{n} [OCF(t)-T(t)]\,[1+r]^{n-t} + \delta V}$$

That is, the amount of replacements attributable to period $t = 1, \ldots, n$ is directly proportional to the amount of (prolonged) after tax operating cash flow realized during the period and inversely proportional to the change in the market value of the firm. Denoting $L(t)$ = the volume of firm's operations in year t (proxied e.g. by the amount of sales), the amount of replacements in any single year within the period $t = 1, \ldots, n$ is (see Artto, 1985, p. 63):

$$R(t) = L(t) * \frac{\sum_{t=1}^{n} R(t)}{\sum_{t=1}^{n} L(t)}$$

In this study, the proportion of replacements as measured by the term $\Sigma R(t) / \Sigma L(t)$ on the right-hand side of the above expression was first determined for each sample firm separately from three different time periods (1951-62, 1963-73, and 1974-84). Thereafter, each firm's percentages were averaged across the three periods, and the resulting means were used as a basis of final estimates of replacement investments. Consequently, the firm-specific percentages used in this study for measuring replacements were constants over the entire data base 1951-84.

[3] Another reason for not deducting the net increase in liquid assets in the computation of cash net income is that it can be interpreted to represent (a part of) cash accounting "earnings" and therefore its deduction would not make sense any more than the deduction of net income in the computation of accrual earnings.

[4] See Suomen Tilastollinen Vuosikirja 1985/86 (p. 164) and Tilastotiedotus YR 1985:4 (p. 32) for the numbers and turnovers of all Finnish firms liable to turnover tax.

[5] There was one firm in the sample (Rauma-Repola Oy) which was founded in 1952, and the financial statements of this firm thus covered the period 1952-84.

[6] The only exception was the firm referred to in the preceding note. The time series of this firm covered the 32-year period 1953-84.

[7] The changes in the relevant legislation took place in 1969, 1974 and 1980, when the Corporate Income Taxation Act (EVL), the Accounting Act (KPL, KPA) and the Company Act (OYL), respectively, replaced the corresponding old legislation. The first one (the 1969 Corporate Income Taxation Act) had profound effects e.g. on inventory valuation rules (direct historical acquisition cost replaced the old valuation rule which was based on direct and indirect production costs) and on depreciation methods (straight-line depreciation was replaced by degressive methods). It should be noted that although this act primarily concerned corporate direct income taxation, it also affected accounting practices because firms commonly adjusted their accounting methods to the new tax legislation. Furthermore, some of these changes were subsequently taken into account in the 1974 Accounting Act, which also introduced a new format for income statements. Finally, the 1980 Company Act included rules governing e.g. the presentation of the inventory reserve which the former acts permit. It also specified the presentation formats of financial statements for limited (joint stock) companies. For a discussion (in English) of the theoretical foundation of the Finnish accounting practice, see Salmi (1978).

[8] To clarify this point, consider the following example. Assume π = average future annual inflation (a random variable), i = required real rate of return p.a. (a constant), and CF(t) = nominal cash flow in year t (a random variable). Now, the present value PV of CF(t) expressed at the price level of the base year is:

$$PV = (1+i)^{-t} * [(1+\pi)^{-t} * CF(t)]$$

Because the present value is the product of two random variables, the computation of its expected value as well as its variance requires the knowledge of the covariance of these random variables.

[9] One explanation might be that in the recession which began with the oil crisis, the firms used their accounting reserves to absorb their losses until these reserves were eventually exhausted in the late 70s producing the observable negative outliers. It is also worthwhile to note that, contrary to expectations, the accounting changes that took place in the time period examined (see note 6 above) did <u>not</u> produce systematic outliers or other discontinuities that would have been visually discernible from other variability in the data. One explanation may be that, after all, these accounting changes had but a small effect on reported accounting numbers relative to other changes in the firms and their environment.

[10] In addition, there were 24 outliers (0.3 %) of two consecutive years which were adjusted using the dummy technique described below.

APPENDIX 4-1: Formulae for the Computation of Cash Flows

The following formulae describe the basic schemes for the computation of the cash-based income variables from the financial statements prepared under current Finnish accounting practice (the 1974 Accounting Act, the 1980 Companies Act, Generally Accepted Accounting Principles). More detailed item-by-item formulae are available from the author on request.

Variable #4: Cash Sales (CSA)

Net Sales (after discounts allowed, bad debts incurred, and indirect taxes)
- Increase in accounts receivable
+ Increase in prepayments from customers

= CSA

Variable #5: Cash Operating Income (COI)

CSA
- Purchases of goods and services (incl. raw materials, accessories, wages, energy, salaries, administrative expenses and other short-term goods and services valued at direct historical acquisition cost)
+ Increase in accounts payable to suppliers of goods and services
- Increase in prepayments to suppliers of goods and services

= COI

Variable #6: Cash Net Income A (CNIA)

```
      COI
    + Other (non-operating) revenues
    - Other (non-operating) expenses
    - Interest expenses
    - Direct tax expense
  +/- Net change in accruals and deferrals relating to
      other revenues and expenses, interests and taxes
    - Replacement investments in fixed assets [1]
    ----------------------------------------------------
    = CNIA
```

[1]: See note [2] to chapter 4.

Variable #7: Cash Net Income B (CNIB)

```
      COI
    + Other (non-operating) revenues
    - Other (non-operating) expenses
    - Interest expenses
    - Direct tax expenses
  +/- Net change in accruals and deferrals relating to
      other revenues and expenses, interests and taxes
    - Net investments in fixed assets [2]
    ----------------------------------------------------
    = CNIB
```

```
[2]:      Book value of fixed assets at the end of fiscal year
        - Book value of fixed assets in the beginning of
          fiscal year
        - Increase in the accounting revaluation of fixed assets
        - Accounting net proceeds from the sale of fixed assets
        + Depreciation expense from fixed assets
        + Investments in fixed assets debited from investment
          reserve
        + Increase in prepayments to suppliers of fixed assets
        --------------------------------------------------------
        = Net investments in fixed assets
```

As regards financial statements prepared under the 1945 Accounting Act, the general formulae given above were adjusted for the old law. The most important adjustment concerned the computation of Cash Operating Income (COI), because under the old accounting practice, the income statement did not report the direct cost of goods sold.

Therefore, the basic formula for the computation of COI from the financial statements prepared under the old Accounting Act took the following form:

```
     CSA
   - Cash outflows for short-term operating expenses [3]
   ----------------------------------------------------
   = COI
```

```
[3]:     Net sales (reported in the margin of income
         balance sheet)
       - Sales margin as reported (so-called "TLH")
       ------------------------------------------------
       = Direct cost of goods sold (the expensed amount)
       + Increase in inventories
       ------------------------------------------------
       = Direct cost of goods produced
       + Salary, rents and other short-term expenses
     +/- Net increase in accounts payable and prepayments
         to suppliers of goods and services
       ------------------------------------------------
       = Cash outflows for short-term operating expenses
```

N.B. The term "increase" in the above formulae means the following difference (with sign): Item at the end of the fiscal year minus item at the beginning of the fiscal year.

APPENDIX 4-2: List of the Sample Firms

#	Firm
1	Amer-yhtymä Oy
2	Enso-Gutzeit Oy
3	Farmos-yhtymä Oy
4	Oy Finlayson Ab
5	Oy Fiskars Ab
6	Huhtamäki Oy
7	Instrumentarium Oy
8	Kajaani Oy
9	Oy Kaukas Ab
10	Kemi Oy
11	Kone Oy
12	Kymi Kymmene Oy
13	Lassila & Tikanoja Oy
14	Oy Lohja Ab
15	Metsäliiton Teollisuus Oy
16	Oy Nokia Ab
17	Kustannusosakeyhtiö Otava
18	Oy Partek Ab
19	Rauma-Repola Oy
20	Oy Rettig Ab
21	Oy W. Rosenlew Ab
22	Oy Wilh Schauman Ab
23	G.A. Serlachius Oy
24	Oy Strömberg Ab
25	Suomen Sokeri Oy
26	Suomen Trikoo Oy Ab
27	Tamfelt Oy Ab
28	Oy Tampella Ab
29	Werner Söderström Osakeyhtiö
30	Oy Wärtsilä Ab
31	Yhtyneet Paperitehtaat Oy
32	Suomen Höyrylaiva Oy
33	Oy Ford Ab
34	Kesko Oy
35	Kuusinen Oy
36	Rake Oy
37	Oy Stockmann Ab
38	Talous-Osakekauppa
39	Oy Tamro Ab

5. METHODOLOGY FOR EMPIRICAL INQUIRY

5.1. The General Design

It was found in the preceding literature review (chapter 2) that prior time series research of financial statement numbers has been devoid of a well-defined theoretical framework to guide the empirical research. This state of the art has repeatedly been noted in some prior surveys of the area (Ball and Foster, 1982; Watts and Zimmerman, 1986) and has also been found to be characteristic of other subareas in the domain of empirical research in corporate financial reporting (Ball and Foster, 1982, p. 169-170).

As regards the role of theory, this study makes no exception to the state of the art. Besides the tentative theoretical analysis presented in chapter 3 above, there is no dynamic theory of the firm and of the mechanisms of its financial accounting system that would have allowed us to derive conclusive a priori hypotheses of the (dis)similarities in the underlying time series processes of accrual accounting vis-a-vis cash flow income variables. Consequently, this study was performed in a position where the most plausible way to increase the knowledge of the role of the accrual accounting system was to perform a comparative empirical inquiry into the time series behavior of accrual and cash-based income variables.

The inquiry involved the following phases and tests. In the very beginning, distribution-free tests with the numbers of turning points and difference signs were performed in order to obtain a preliminary view of the (dis)similarities in the degree of randomness between the variables. Those preliminary tests were supplemented by autocorrelation analysis not only because it is the principal method for measuring the degree of serial dependence but also because it provided the starting point for subsequent model identification. Furthermore, autocorrelation analysis gives the opportunity to test the descriptive validity of the theoretical models for serial correlations derived in chapter 3.

At the second stage, some parsimonious time series models were estimated from the data. (The models considered will be briefly described in the following section.) The descriptive validity and adequacy of the models in the estimation period were then examined with some standard statistics.

Finally, the predictive abilities of the estimated models vis-a-vis each other were analyzed in a hold-out prediction period not used in the estimation of the models. For that purpose, the time series data were split into separate estimation and prediction periods as follows:

1. Estimation period 1951 - 1975	1. Prediction period 1976 - 1978
2. Estimation period 1951 - 1978	2. Prediction period 1979 - 1981
3. Estimation period 1951 - 1981	3. Prediction period 1982 - 1984

All time series models considered in this study were thus first estimated from the 25-year period (1951-75), and the predictive ability of the estimated models was then analyzed in the hold-out prediction period of three subsequent years (1976-78). The model estimation and the predictive ability analysis were then repeated twice, appending the preceding prediction period each time to the estimation base and taking three subsequent years for a new prediction period. It should be noted that this procedure provided prediction periods which were non-overlapping not only with the corresponding estimation base, but also with each other because each time 'fresh' years were taken for prediction purposes.

As is a common practice in the area, predictive ability tests serve as a validation method for the estimation results. However, an attempt was made in this study to avoid the difficulties usually encountered in such tests (viz. the measurement of forecast performance in a valid manner) by a careful selection of forecast accuracy measures. Also, the predictive ability tests were repeated twice with new hold-out data in order to observe the persistence of the results.

Before proceeding any further, the following comments on the general design of the empirical inquiry should be made.

(i) Since the income variables examined in this study were selected from three different levels of an income statement (see the preceding chapter), comparisons of the time series patterns could be performed not only across the accounting systems (accrual vs. cash flow) but also across those levels (net sales, operating income and net income levels). It was thus possible to observe what kind of effect, if any, the operating, investment and financing flows between these levels have on the time series properties income variables. In this sense the study provides some evidence of different economic determinants in the general omega-model (1-1), although the focus is on the role of the accounting factors (β) in order to preserve consistency with the original research objective.

(ii) Furthermore, the time series analysis was performed in this study on a purely univariate basis. Multivariate methods (e.g. transfer function model building) were not considered here because our primary interest was not to search for economic determinants and because, at this stage of the research, there were no a priori grounds for believing that multivariate modeling of the data would have produced better accrual and/or cash income forecasts than parsimonious univariate models [1].

(iii) Moreover, prior results obtained from using desaggregated data in predicting operating income numbers have indicated that such desaggregation may be of little use in improving the resulting income forecasts (see Ang, 1979). Therefore, decomposed income series were not used in this study; the analysis was instead based entirely on the aggregated income variables.

(iv) Since the analysis was restricted to data from Finnish firms, it was only possible to examine time series properties of annual income variables. This was because interim information such as quarterly financial reports is not generally published by Finnish firms [2].

(v) Finally, since forecasts by managers or financial analysts for the accrual and cash-based income variables were not available from public sources it was not possible to compare the performance of the time series models with them.

5.2. The Selection of Competing Time Series Models

At the outset it should be made clear that the time series models selected for the study must be considered tentative rather than being defined by a well-established theory or prior empirical knowledge. Moreover, it should be recognized that the empirical phenomena manifested in the time series data are quite obviously far too complicated to be captured in their entirety by the models listed below. Nevertheless, it was assumed that the selected model set provided useful approximations of potential time series patterns in the data. By 'usefulness' we mean here that the models allows us to observe the degree to which the basic nature of the underlying time series processes varies across accounting systems and/or income measurement levels.

Three criteria were followed in the selection of the tentative models. The first was the principle of parsimony, which implies thriftiness in the number of parameters to be estimated for each model. Consequently, the model set includes some very simple and naive time series models. However, this was regarded as a virtue rather than a vice of the study because the performance of naive models provide useful benchmarks for measuring the performance of more complicated models.

Another criterion for selecting the tentative models was their appearance in related studies. Standard models frequently encountered in the literature were selected for two reasons: (i) standard models were adequate for the present research purposes, and (ii) they also enabled us to contrast present findings with those of the prior literature.

Finally, the models were selected so that the whole set covered a wide range of essentially different stochastic processes in terms of autocorrelation and the importance of the most recent income observation for future expectations.

The following time series models were an outcome of these criteria:

A. Submartingale Processes:

1. Random Walk (RW)

$$X(t) = X(t-1) + e(t) \tag{5-1}$$

2. Random Walk with Drift (RWWD)

$$X(t) = X(t-1) + \delta + e(t) \tag{5-2}$$

B. Constant Processes:

3. Mean Reverting Process (or White Noise) (MR)

$$X(t) = \mu + e(t) \tag{5-3}$$

4. Linear Trend (with noise) (LT)

$$X(t) = \beta 0 + \beta 1\ t + e(t) \tag{5-4}$$

C. Autoregressive and Moving Average Processes:

5. Exponentially Weighted Moving Average (EWMA)

$$X(t) = \alpha X(t-1) + (1-\alpha)E[X(t-1)] + e(t) \tag{5-5}$$

6. Autoregressive Integrated Moving Average processes (ARIMA)

$$\Phi(B)(1-B)^{d} X(t) = \theta 0 + \theta(B)e(t) \tag{5-6}$$

where $X(t)$ = a random variable in period t (i.e. an accrual or cash-based income variable in year t)

$e(t)$ = an identically and independently distributed random (normal) variable with zero mean and constant variance: $E[e(t)] = 0$, $Var[e(t)] = \sigma^2(e)$, $Cov[e(t),e(t-s)] = 0$ when $s \neq 0$

δ = a non-negative constant drift

μ = a constant mean of the process

$\beta 0$ and $\beta 1$ = constant parameters

α = a constant weighting parameter ($0 < \alpha < 1$)

E = an expectation operator

$\Phi(B) = 1 - \Phi 1\ B - \Phi 2\ B^2 - \ldots - \Phi p\ B^p$

(an autoregressive operator of order p in B)

$\theta(B) = 1 - \theta 1\ B - \theta 2\ B^2 - \ldots - \theta q\ B^q$

(a moving-average operator of order q in B)

$\theta 0$ = a constant defined by $\Phi(B)\ \mu$ where $\mu = E[(1-B)^d X(t)]$

B = a back-shift operator defined by $B^m X(t) = X(t-m)$

d = order of differencing of the series $\{X(t)\}$

The first two model classes (submartingales and constant processes) were selected not only because of their important role in the literature but also because they represent two extremes in terms of serial dependence and the relevance of the most recent observation for future expectations. Both of these model types include variants both without (RW and MR) and with a drift term (RWWD and LT). It is also evident that the selection of the simple linear trend instead of the quadratic or other non-linear model was supported by a visual inspection of the data showing that the trend in the data was approximately linear rather than non-linear. (The reader should recall that the data were restated in a uniform purchasing power of money.)

Model #5 (EWMA) was selected because it provided a very simple yet flexible compromise for the above extremes. Depending on the value of the weighting coefficient, the EWMA-model can take the form of the random walk or of the pure mean reverting model, or be an average of them. The version of EWMA considered in this study was the simplest one not including linear or quadratic trend. The exclusion of such versions was due partly to the aim of keeping the total number of different models in manageable limits, partly to prior empirical findings unequivocally showing that such models are not warranted in predicting corporate income numbers (Ball and Watts, 1972; Brooks and Buckmaster, 1976, 1980).

The general class of non-seasonal linear AutoRegressive Integrated Moving Average (ARIMA) processes (model #6) covers a wide range of different time series models depending on the orders (p,d,q). These models (sometimes called the Box-Jenkins models) were examined in this study because of their popularity in many prior studies of the area (see the literature review).

They also provided an extremely flexible way to take into account some more complicated processes in addition to those represented by the first five models which can be seen as special cases of the general ARIMA-class. For example, the ARIMA(0,0,0) process is equivalent to the mean reverting process (5-3) because $\theta 0 = \mu$. Moreover, ARIMA(0,1,0) can be written $(1-B)X(t) = \theta 0 + e(t)$, which is the submartingale with $(1-B)X(t) = X(t) - X(t-1)$ and $\theta 0 = \delta$. Furthermore, the EWMA-model (5-5) can be seen as a special case of the more general ARIMA(0,1,1) process where $\theta 0 = 0$ [3].

On the one hand, since submartingales, constant processes and exponentially weighted moving averages were separately estimated from the data, they were therefore excluded from the ARIMA(p,d,q)-class in (5-6). On the other hand, for the sake of parsimony, models with p or q higher than 2 were not considered. On the whole, for each level of differencing (d), the following eight ARIMA-models were thus considered:

1. (0,d,1); 2. (0,d,2); 3. (1,d,0); 4. (1,d,1);
5. (1,d,2); 6. (2,d,0); 7. (2,d,1); 8. (2,d,2)

The selected time series models (5-1) - (5-6) and some of their most important statistical properties are summarized in appendix 5-1 of this chapter.

5.3. Details of Model Estimation

The details of the procedures employed in the estimation of time series models described above are as follows:

For the RWWD model (5-2) the drift parameter δ was estimated by computing the arithmetic mean of annual changes in the income variable (c.f. e.g. Albrecht, Lookabill and McKeown, 1977, p. 238 who also computed the drift in this way).

For the MR model (5-3) the constant mean was estimated by computing the arithmetic average of annual income observations.

The parameter values of the LT model (5-4) were obtained by regressing annual income observations on time (years) and using the standard estimators given by the ordinary least squares method.

For the EWMA model (5-5), the optimal weighting parameter was obtained using an enumerative method, i.e. alternative values were tried and the value minimizing the sum of squared errors in the estimation period was chosen for each income series (see e.g. Ball and Watts, 1972, p. 675 who used a similar method in estimating the optimal parameters for their EWMAs). In this study, the range of parameter values enumerated was from .05 to .95 with steps of .05 thus giving the total number of 19 alternative values from which the optimum was chosen. The reason why the extreme values of .00 and 1.00 were not considered was that, in fact, they were already taken into account by the mean reverting and random walk models, respectively.

For the ARIMA models (5-6), a two-stage process was followed for their identification and estimation. First, the order of differencing (d) was determined by the ordinary method suggested by Box and Jenkins (1976, p. 174-175) in which the appropriate degree of differencing is assumed to have been achieved when the estimated autocorrelation function tends to "die out quickly". Therefore, the autocorrelation function was first estimated from each of the original series (d = 0), and in the event it did not approach zero quickly, the function was re-estimated from the first differences (d = 1). (As will be seen from the results, orders of differencing higher than 1 were not needed in the data to produce stationarity in this sense.)

At the second stage, the orders of the autoregressive and moving-average parts of the model were determined using an enumerative approach rather than the analytic inference suggested by Box and Jenkins (1976, chapter 6). The primary reason for this was the large number of ARIMA models that had to be identified (39 firms * 7 income variables per firm * 3 estimation periods = 819 ARIMA models). The identification of appropriate models for such a large number of time series from estimated autocorrelation and partial autocorrelation functions would have been too time consuming and would have required a large number of subjective decisions with respect to the orders of autoregressive and moving-average parts. Furthermore, automated identification algorithms (see e.g. Hopwood, 1980) were not available for this study.

To avoid these problems and to ensure the reproducability of the results, each of the eight ARIMA models below were first estimated for each of the 819 time series (the total number of ARIMAs estimated in this study was thus over 6500):

1. (0,d,1): $Z(t) = \theta 0 + e(t) - \theta 1\ e(t-1)$
2. (0,d,2): $Z(t) = \theta 0 + e(t) - \theta 1\ e(t-1) - \theta 2\ e(t-2)$
3. (1,d,0): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + e(t)$
4. (1,d,1): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + e(t) - \theta 1\ e(t-1)$
5. (1,d,2): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + e(t) - \theta 1\ e(t-1) - \theta 2\ e(t-2)$
6. (2,d,0): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + \Phi 2\ Z(t-2) + e(t)$
7. (2,d,1): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + \Phi 2\ Z(t-2) + e(t) - \theta 1\ e(t-1)$
8. (2,d,2): $Z(t) = \theta 0 + \Phi 1\ Z(t-1) + \Phi 2\ Z(t-2) + e(t) - \theta 1\ e(t-1) - \theta 2\ e(t-2)$

where $Z(t) = (1-B)^d X(t)$, i.e. the dth order (0 or 1) difference of the original variable $X(t)$

After the above candidates were estimated for each time series [4], the optimal models were selected from among them using the Schwarz criterion based on the minimization of the following function [5]:

$$S(p,q) = N \log \sigma^2(e) + (p+q) \log N \quad (5\text{-}7)$$

where N = the number of observations in the time series

$\sigma^2(e)$ = the residual variance of the series

p and q = the orders of autoregressive and moving-average parts, respectively

As can be seen from the above expression, this selection criterion favors a model with a low residual variance and low orders of autoregressive and moving-average parts, i.e. a parsimonious model with (relatively) high goodness of fit. For comparative purposes, the value of the Schwarz criterion was also computed for ARIMA(0,0,0) and ARIMA(0,1,0) in order to see the relative performance of the MR models (5-3) and RWWD models (5-2), respectively, in the Schwarz sense.

5.4. Predictive Ability Tests

One major problem in the use of the predictive ability criterion in the evaluation of different time series models is the measurement of their forecast performance [6]. Theoretically, optimal forecasts should be determined by a decision-maker's loss function. This is a theoretical concept referring to the loss which the decision is assumed to cause when the decision-maker uses a particular forecasting model under uncertainty. The loss is the difference between the return which could be earned if the future value of the variable being predicted were known with certainty and the actual return which can be achieved when uncertain forecasts are used as a basis for decisions. If the decision-maker is rational, he then chooses the forecasting model which minimizes the sum of the expected loss and the direct costs incurred for using that particular model [7].

Unfortunately, the theoretical loss function is unknown in empirical studies, and therefore the forecast performance of different models is usually evaluated with some forecast accuracy measures which are assumed to be valid surrogates of a decision-maker's loss function [8]. It can also be argued that in a descriptive study like this, the primary interest is not in finding the most appealing forecast model for a decision-maker (in fact, this would be the task of a purely normative research). According to the present research objective, the focus is on finding appropriate characterizations for the underlying processes of corporate income variables and, in this search, the predictive ability criterion not only allows but even requires the use of forecast accuracy measures for forecast evaluation [9].

In this study, the forecasts generated by different models were evaluated with the following accuracy measures which differ significantly from each other with respect to the assumptions concerning a decision-maker's (shareholders') loss function. (Note that the divergence of the assumptions is desirable because a set of measures with different assumptions quite obviously has a greater descriptive validity with respect to the unknown theoretical loss function than a set of measures with similar assumptions.)

1. Mean Square (Prediction) Error:

$$MSE = (1/n) \sum_{t=1}^{n} \{E[X(t)]-X(t)\}^2 \tag{5-8}$$

2. Mean Absolute (Prediction) Error:

$$MAE = (1/n) \sum_{t=1}^{n} \| E[X(t)]-X(t) \| \tag{5-9}$$

3. Absolute Sum of Discounted (Prediction) Errors:

$$ASDE = \| \sum_{t=1}^{n} \{E[X(t)]-X(t)\} (1+i)^{-t} \| \tag{5-10}$$

where $E[X(t)]$ = forecast of the income variable for year t, i.e. the expectation of the income variable for year t conditional on past realizations in t-1, t-2, ..., and on the time series model in question

$X(t)$ = actual value of the income variable in year t

n = length of the forecasting horizon

i = discount rate (100i % p.a.)

The first measure (MSE) was selected because of its widespread use in the literature and because it has been found to be the most attractive error measure among academicians as well as practioners [10]. Furthermore, the use of the MSE criterion is consistent with the estimation methods based on the minimization of residual variance also used in this study.

While the mean square error assumes that the loss function is a quadratic function of the error size for the individual year, the mean absolute error (MAE) (also selected because of its popularity and wide-spread use) assumes linearity [11]. Despite this essential difference, both measures are similar in the sense that they assume indifference with respect to the sign of the individual forecast error.

The third measure (ASDE) was especially designed for the present study because it complemented the assumptions of the above measures in two important ways. Firstly, because it sums individual forecast errors over years, errors of opposite signs are allowed to cancel each other out. Secondly, due to the discount operation included in the formula, forecast errors have different weights according to the year they occur. It was assumed that these properties of ASDE justified its use in this study because they make it a valid criterion in a valuation context where, depending on the discount rate employed, forecast errors in the distant future are less important and have a smaller impact on the bias of the firm's value than errors of the more immediate future.

Also, the allowance for different signs of individual errors was consistent with any valuation convention where the sign of the amount being discounted is far from being irrelevant. However, it should be noted that when taking the absolute value of the sum of discounted errors, it was assumed that the decision maker's (shareholders') loss function is symmetric with respect to the sign of the sum.

A discount rate of 5 % p.a. was employed in computing ASDE. This was a purely subjective selection after taking into account that inflation had been eliminated from the data (see section 4.3.) and that in the relevant time period (1976-84) the average real return on shares listed at the Helsinki Stock Exchange was only about 2.1 % p.a.. It is also worthwhile to note that the model ranking given by the ASDE has previously been found to be rather robust with respect to the size of i (Kinnunen, 1984, p. 54).

With respect to the length of forecast horizon (n), the error measures were computed separately over one, two and three years in order to see the effect of the horizon length on the predictive ability results. Of course, since the results of forecasts for one year ahead are identical across all error measures (i.e. the ranking of the time series models with respect to their forecast accuracy is independent of the error measure used), predictive ability analysis was performed using only one error measure on this horizon.

As can be seen, the selected error measures do not scale the error size to the firm's size. However, this did not prevent their use in the study, because each measure was separately computed for each sample firm, after which rank orders were assigned to each time series model according to their relative forecasting ability within that particular firm. Because the error measures were not averaged cross-sectionally at any stage, there was no need for scaling the forecasting errors to the size of the firm. The obvious advantage of this was that the notorious problems relating to the use of relative error measures (such as mean percentage error and its derivatives) could be avoided [12].

To complete this section, a few words should be said about the statistical tests used in the predictive ability analysis. Unfortunately, it must be recognized that, strictly speaking, the distributional properties of the error measures are unknown which makes the use of more powerful parametric tests unjustified. Of course, the distributional assumptions (normality) underlying such tests could have been analyzed, but since the outcome of that analysis would have been unpredictable (it might have turned out that the null hypothesis of normality should have been rejected), it was decided not to perform such an exercise.

Therefore, the non-parametric Friedman two-way analysis of variance was selected as the principal method of statistical analysis for the predictive ability tests. Based on ranks, this method has very loose requirements with respect to the properties of the data. In fact, the only assumption is that the measurements are made at least in an ordinal scale, which was certainly true with the selected accuracy measures. Furthermore, the Friedman analysis of variance has previously been used in several prior studies in the area (e.g. Brown and Rozeff, 1978; Chant, 1980 and many others, see the technical appendix 2-1 to chapter 2).

By the same reasoning, the Binomial test (or the Sign test) and the Spearman rank correlation analysis, respectively, were used for pairwise comparisons of the time series models and for the analysis of the persistence in relative predictive abilities over time.

NOTES TO CHAPTER 5:

[1] For a brief discussion on the pros and cons of multivariate model building, see Manegold (1981). He tested bivariate transfer function models against univariate models on earnings before tax with somewhat discouraging results in the predictive ability of the former. For a thorough discussion on transfer function model building, see Box and Jenkins (1976, part III).

[2] This is true of most Finnish companies. The exceptions include banks which do disclose interim (monthly) financial reports, but because our analysis was restricted to industrial and commercial firms, they were not used in this study.

[3] This can be seen as follows. Assuming ARIMA(0,1,1,) with $\theta 0 = 0$, we have the model $(1-B)\ X(t) = (1-\theta 1)\ e(t)$, which by definition of B can as well be written: $X(t) = X(t-1) + e(t) - \theta 1\ e(t-1)$. Taking expectation yields $E[X(t)] = X(t-1) - \theta 1\ e(t-1)$. Since $e(t-1) = X(t-1) - E[X(t-1)]$, then $E[X(t)] = X(t-1) - \theta 1\ \{X(t-1) - E[X(t-1)]\} = (1-\theta 1)\ X(t-1) + \theta 1\ E[X(t-1)]$, which is equal to the expectation of the EWMA-process with $\alpha = 1-\theta 1$, see 5-5.

[4] The model estimation was performed with a PC version of RATS (Regression Analysis of Time Series). This program uses the so-called Gauss-Newton algorithm in the determination of final parameter estimates of an ARIMA model.

[5] This selection criterion is originally based on Schwarz (1978). For a comprehensive survey of different methods and criteria for determining the order of an ARIMA process, see Gooijer et al. (1985). It can be noted that the Schwarz criterion used in this study is virtually identical to the Akaike Information Criterion (AIC) tested by Dharan (1983b). Using quarterly earnings series from 30 firms he found that the AIC criterion "produced the same sample-wide earnings models as reported by researchers using the iterative Box-Jenkins procedure" (ibid., p. 269). See also Hopwood (1980b) for a test of an automated identification algorithm for ARIMA modeling.

[6] See Beaver, Kennelly and Voss (1968) for a discussion of the background of the predictive ability criterion in an accounting context.

[7] For a closer theoretical discussion on forecast evaluation, see Demski and Feltman (1972).

[8] In fact, what is assumed is that the ranking of various time series models by accuracy measures is identical to the ranking by the loss function. Furthermore, the ignorance of the direct costs associated with the use of different time series models implies that they are equal and hence irrelevant. Quite obviously, the assumption of equal costs between different models is far from reality. For example, the costs associated with the use of the pure random walk model with no computational efforts are certainly lower than the costs associated in the identification, estimation and forecasting of ARIMA models.

[9] Note that the predictive ability criterion as used here makes disregard of the costs associated with the use of different time series models more justified.

[10] See the survey results by Carbone and Armstrong (1982), who found that the MSE was considered by far the most attractive error measure among researchers as well as practioners. Moreover, it was found that accuracy, in general, was regarded as the most important criterion in selecting forecasting methods, whereas other criteria (e.g. ease of interpretation, cost/time, capture of turning points, robustness, universatility etc.) were found to be less important.

[11] Note that accuracy measures are used in empirical studies as surrogates for a theoretical loss function. Therefore, in so far as an accuracy metric is a (non)linear function of individual year's forecasting error, it must be assumed that the loss function is also (non)linear with respect to that error size.

[12] Typically, two problems relate to the use of relative forecasting errors where errors of individual years are divided by the actual value of the predicted variable. The problems arise when the denominator is either negative and/or near zero. Prior studies have treated these problems by taking absolute values or squares of the original ratios and by imposing a truncation rule for the outliers (see e.g. Brown and Niederhoffer, 1968; Brown and Rozeff, 1979; Chant, 1980; Kinnunen, 1984).

APPENDIX 5-1: Summary of the Selected Time Series Models and Some of Their Properties.

(For discussions of these processes, see e.g. Beaver (1970); Ball and Watts (1972); Lookabill (1976); Foster (1986, pp. 230-234); Lorek, Kee and Vass (1981); and Watts and Zimmerman (1986, chapter 6).)

Submartingale Processes

Under a submartingale process, the expected value of random variable X in period t (t = 1, 2, ...) is

$$E[X(t) \| X(0),...,X(t-1)] \geq X(t-1) \tag{A5-1}$$

Thus, the following model can be characterized as a submartingale:

$$X(t) = X(t-1) + \delta + e(t) \tag{A5-2}$$

where δ = a non-negative drift term ($\delta \geq 0$)

$e(t)$ = a random variable with zero mean and constant variance: $E[e(t)] = 0$ and $Var[e(t)] = \sigma^2(e)$

A martingale process is a special case of the more general submartingale when $\delta = 0$. Consequently, a martingale is the following expression

$$X(t) = X(t-1) + e(t) \tag{A5-3}$$

and its conditional expectation is

$$E[X(t) \| X(0),...,X(t-1)] = X(t-1) \tag{A5-4}$$

Now, if the restrictive assumption is imposed on the random variables {..., e(t-1), e(t), e(t+1), ...} that they are iid (identically and independently distributed so that $Cov[e(t),e(t-s)] = 0$ when s is non-zero), then, strictly speaking, model (A5-3) is a random walk (RW) and model (A5-2) a random walk with drift (RWWD).

Assume that we have a RWWD and that the initial value of the process is $X(0) = \delta + e(0)$. Expression (A5-2) can then be written

$$X(t) = (t+1)\delta + \sum_{j=0}^{t} e(j) \tag{A5-5}$$

From (A5-5) we note that the expected value and variance of $X(t)$ are

$$E[X(t)] = (t+1)\delta \tag{A5-6}$$

$$Var[X(t)] = (t+1)\ \delta^2(e) \tag{A5-7}$$

which imply that both the expectation and the variance of the submartingale process increase over time, i.e. the process is non-stationary.

It is very important to note that under the pure random walk process ($\delta = 0$) the autocorrelation coefficient at lag one of <u>differenced series</u> is zero because the corresponding autocovariance reduces to zero:

$$Cov\{[X(t+1)-X(t)],[X(t)-X(t-1)]\} =$$

$$Cov[e(t+1),e(t)] = 0 \tag{A5-8}$$

<u>Mean Reverting Process</u> (or White Noise)

A pure mean reverting process is the following

$$X(t) = \mu + e(t) \tag{A5-9}$$

where μ = a constant mean of the process

(e(t) as above)

Now, in contrast with the preceding submartingale, the expectation as well as the variance of the mean reverting process are constant and independent of time, i.e. the process is stationary:

$$E[X(t) \| X(0),...,X(t-1)] = \mu \qquad (A5\text{-}10)$$

$$Var[X(t)] = \sigma^2(e) \qquad (A5\text{-}11)$$

Also, the autocovariance and the autocorrelation coefficient differ from those of the submartingale process. Zero autocovariance and autocorrelations are obtained for original (non-differenced) series at all lags, whereas for the first order <u>differenced</u> series they are non-zero at lag one:

$$\begin{aligned} & Cov\{[X(t+1)-X(t)],[X(t)-X(t-1)]\} = \\ & Cov\{[e(t+1)-e(t)],[e(t)-e(t-1)]\} = \\ & E\{[e(t+1)-e(t)][e(t)-e(t-1)]\} = \\ & - E[e(t)^2] = - \sigma^2(e) \end{aligned} \qquad (A5\text{-}12)$$

$$\begin{aligned} => \quad & R\{[X(t+1)-X(t)],[X(t)-X(t-1)]\} = \\ & - \sigma^2(e)/Var[X(t+1)-X(t)] = \\ & - \sigma^2(e)/Var[e(t+1)-e(t)] = \\ & - \sigma^2(e) \ / \ 2\sigma^2(e) = - 1/2 \end{aligned} \qquad (A5\text{-}13)$$

It must be emphasized that an essential difference between the submartingale and the mean reverting processes lies in the weight given to the most recent observation in forming future expectations. While in the case of the mean reverting process, the most recent observation X(t-1) has virtually no importance for the expectation of X(t), the random walk model, for example, relies entirely on X(t-1) in forming the expectation of X(t).

Linear Trend (with noise)

A simple linear trend model

$$X(t) = \beta 0 + \beta 1\ t + e(t) \tag{A5-14}$$

where $\beta 0$ and $\beta 1$ = constant parameters

(e(t) as above)

is very similar to the mean reverting model above in that its autocorrelations (at lag one) for the original series and for the first differences are 0 and -1/2, respectively, as shown below.

For the original (undifferenced) series we have

$$Cov[X(t+1),X(t)] = Cov\{[\beta 0+\beta 1(t+1)+e(t+1)],[\beta 0+\beta 1(t)+e(t)]\} =$$

$$E\{[\beta 0+\beta 1(t+1)+e(t+1)-\beta 0-\beta 1(t+1)]\ [\beta 0+\beta 1(t)+e(t)-\beta 0-\beta 1(t)]\} =$$

$$E[e(t+1)\ e(t)] = 0, \Rightarrow R[X(t+1),X(t)] = 0 \tag{A5-15}$$

while for the first differences we obtain

$$Cov\{[X(t+1)-X(t)],[X(t)-X(t-1)]\} =$$

$$Cov\{[\beta 0+\beta 1(t+1)+e(t+1)-\beta 0-\beta 1(t)-e(t)], [\beta 0+\beta 1(t)+e(t)-\beta 0-\beta 1(t-1)-e(t-1)]\} =$$

$$Cov\{[e(t+1)-e(t)+\beta 1],[e(t)-e(t-1)+\beta 1]\} =$$

$$E\{[e(t+1)-e(t)]\ [e(t)-e(t-1)]\} =$$

$$- E[e(t)^2] = -\sigma^2(e) \tag{A5-16}$$

$$Var[X(t+1)-X(t)] = Var[e(t+1)-e(t)+\beta 1] =$$

$$Var[e(t+1)] + Var[e(t)] = 2\sigma^2(e) \tag{A5-17}$$

$$\Rightarrow R\{[X(t+1)-X(t)],[X(t)-X(t-1)]\} =$$

$$-\sigma^2(e)/2\sigma^2(e) = -1/2 \tag{A5-18}$$

Exponentially Weighted Moving Average

Under this process, the value of X in period t can be expressed (c.f. e.g. Brooks and Buckmaster, 1976, p. 1372):

$$X(t) = \alpha X(t-1) + (1-\alpha)E[X(t-1)] + e(t) \tag{A5-19}$$

where α = a constant weighting factor $(0 < \alpha < 1)$
(e(t) as above)

The expectation of this process is:

$$\begin{aligned} E[X(t)] &= \alpha X(t-1) + (1-\alpha)E[X(t-1)] \\ &= \alpha X(t-1) + (1-\alpha)\alpha X(t-2) + (1-\alpha)^2\alpha X(t-3) + \ldots \end{aligned} \tag{A5-20}$$

that is, the expectation is a weighted average of the most recent realization and its expectation, or an weighted average of all past realizations. As the weighting coefficient α approaches unity, the EWMA-process in (A5-19) approaches the random walk process with all its characteristics (e.g. the expectation becomes dependent solely of the most recent realization), and conversely, as α approaches zero, the process becomes more like the mean reverting process with a constant expectation.

ARIMA Processes

As explained in the body of the text, the general class of non-seasonal ARIMA processes

$$\Phi(B)(1-B)^d X(t) = \theta 0 + \theta(B)e(t) \tag{A5-21}$$

(for notation, see formula 5-6 in the body of the text)

covers a wide range of different time series models depending on the orders of the parameters (p,d,q). Box and Jenkins (1976) suggest the building of ARIMA models in a four-stage process consisting of (i) model identification, (ii) parameter estimation, (iii) diagnostic checking, and (iv) forecasting. The Box-Jenkins approach has been widely applied in many prior studies (see the literature review) so that it can almost be regarded as an 'industry standard' method for univariate time series analysis and forecasting of accounting data. The details of the approach have also been well documented elsewhere so that there is no need to repeat them here. (For brief summaries, see e.g. Mabert and Radcliffe (1974); Foster (1986, pp. 234-238); Makridakis and Wheelwright (1978); and Leskinen (1977). For more detailed and comprehensive presentations, see Box and Jenkins (1976); Nelson (1973); and Anderson (1976).)

6. EMPIRICAL RESULTS

This chapter reports in detail the results of the empirical time series analysis of the data. The first section (6.1.) presents the findings from the distribution-free tests of randomness and from the autocorrelation analysis. Thereafter, the dependences in the degree of randomness are examined across firms, and the descriptive validity of the theoretical models for autocorrelations derived in chapter 3 are tested (section 6.2.). In the following section (6.3.) the results obtained from some simple tests of stationarity are presented. The estimation and predictive ability results of the competing time series models are presented and discussed in sections 6.4. and 6.5., respectively. Finally, the chapter is concluded with a summary of main empirical findings (section 6.6.).

6.1. Tests of Randomness

The first test of randomness concerned the number of turning points in the data. By definition, a turning point in a time series occurs whenever $X(t-1) < X(t) > X(t+1)$, or $X(t-1) > X(t) < X(t+1)$.

It can be shown (Kendall, 1973, pp. 22-24) that if a series with N observations is random, the expected value and the variance of the number of turning points (p) are:

$$E(p) = (N-2)*2/3 \qquad (6\text{-}1)$$

$$Var(p) = (16N-29)/90 \qquad (6\text{-}2)$$

Using a normal approximation, the observed value of p can be tested against its expected value in the normal distribution with the standard deviation $\sqrt{[Var(p)]}$. If the observed number of turning points is greater than expected under the null hypothesis of randomness, then the series fluctuates rapidly in a manner which is not due to mere chance and, conversely, if the expected number of turning points is greater than observed, then successive observations in the series are positively correlated.

For each of the examined variables, the cross-sectional distributions of the standardized numbers of turning points and the numbers of firms where the null hypothesis of randomness could be rejected appear in table 6-1A.

Another test of randomness similar to the one described above is the difference-sign test where the number of positive differences in the series is counted. By definition, a positive difference occurs whenever $X(t+1) > X(t)$. Because there are N-1 differences in a series of N observations, then, if the series is random, the expectation and the variance of the number (c) of positive differences are (Kendall, 1973, p. 26):

$$E(c) = (N-1)/2 \qquad (6\text{-}3)$$

$$Var(c) = (N+1)/12 \qquad (6\text{-}4)$$

Again, using a normal approximation, the observed value of c can be tested against its expectation in the normal distribution with the standard deviation $\sqrt{[Var(c)]}$. It should be noted that the difference-sign test of randomness is useless for oscillatory series with c approximately N/2, and that this test has been advocated as a test against linear trend (ibid., p. 26).

The results from the tests of the difference-sign are presented in table 6-1B below.

TABLE 6-1A: Results from the Tests of the Numbers of Turning Points

a) Distributions of the Standardized Numbers of Turning Points

	Variable:						
(n = 39)	ASA	AOI	ANI	CSA	COI	CNIA	CNIB
1. quart.	-4.320	-3.066	-3.484	-3.902	-0.975	-0.557	-1.393
Median	-3.484	-1.812	-2.230	-3.066	-0.139	-0.139	-0.557
3. quart.	-2.648	-1.393	-1.393	-1.812	0.697	0.697	-0.139
Mean	-3.558	-2.023	-2.100	-2.851	0.013	-0.008	-0.747
Std. dev.	1.216	1.194	1.254	1.650	1.083	1.017	0.899

b) Numbers of Firms where H0: The Series Fluctuates Randomly Could Be Rejected (n = 39)

Signific.	Variable:						
Level α	ASA	AOI	ANI	CSA	COI	CNIA	CNIB
.10	38	25	28	31	3	3	3
.05	38	19	21	28	1	1	2
.01	33	15	16	26	0	1	1
.001	21	5	10	16	0	0	0

TABLE 6-1B: Results from the Tests of the Difference-Sign

a) Distributions of the Standardized Numbers of Posit. Differences

	Variable:						
(n = 39)	ASA	AOI	ANI	CSA	COI	CNIA	CNIB
1. quart.	2.049	0.878	-0.293	1.464	-0.293	-0.878	-0.293
Median	3.806	2.049	0.878	2.635	0.293	-0.293	0.293
3. quart.	4.977	2.635	2.049	4.392	0.905	0.878	0.878
Mean	3.269	2.006	0.849	2.863	0.436	-0.052	0.248
Std. dev.	2.528	1.205	1.525	2.060	1.242	1.192	0.843

b) Numbers of Firms where H0: The Series Fluctuates Randomly Could Be Rejected (n = 39)

Signific.	Variable:						
Level α	ASA	AOI	ANI	CSA	COI	CNIA	CNIB
.10	32	22	11	28	5	2	1
.05	32	22	11	28	5	2	1
.01	28	12	6	20	4	1	0
.001	21	6	2	15	0	0	0

The cross-sectional distributions of the standardized numbers of turning points (panel a of table 6-1A) indicate that, in the majority of firms, the observed number of turning points is smaller than can be expected under the null hypothesis of randomness (see the negative signs). As noted above, this implies some tendency towards positive serial correlation in the data rather than to a rapid non-random fluctuation. The distributions also indicate that the standardized numbers of turning points are most negative in the two sales variables ASA and CSA (see e.g. the medians), whereas in the other variables the number of turning points is closer to its expectation under randomness.

The variation of the numbers of turning points across firms is largest for CSA (see the estimated standard deviation) indicating firm-specific differences in the degree of randomness in the behavior of this variable. For the other variables, the cross-sectional variation in the degree of randomness is much smaller and closer to the theoretical standard deviation (of course, it equals unity for standardized variables).

Pairwise comparisons of the mean and median numbers of turning points in the accrual-based variables with their cash-based counterparts also reveal that the numbers of turning points for ASA, AOI and ANI are consistently smaller (more negative) than for CSA, COI, CNIA or CNIB, respectively. The conclusion from this would be that, on average, the accrual-based variables tend to behave in a less random manner than their cash-based counterparts.

The results from the turning point tests reported in the lower panel (b) of table 6-1A show that e.g. at the 5 % level of significance the null hypothesis of randomness could be rejected in virtually all of the sample firms (38 out of 39) for ASA, in a vast majority of firms (28 or 71.8 %) for its cash-counterpart CSA, and approximately one half of the firms for the other accrual variables, AOI and ANI. However, the test results for their cash-based counterparts COI, CNIA and CNIB are in sharp contrast: with a few exceptions (3 firms or 7.7 %), the null hypothesis of randomness could not be rejected even at 10 % level of significance.

The main findings from the analysis of the numbers of positive differences (table 6-1B) fall well in line with those of the above analysis of turning points. For most variables, the distributions indicate a tendency towards positive signs implying that more positive differences are present in the time series data than can be expected under randomness. Quite obviously, this is due to a positive (linear) trend which some of the variables (especially ASA and CSA) contain, a phenomenon that was already noticed in the preceding visual inspection (table 4-3) and which is also consistent with the tendency towards positive serial correlation revealed by the numbers of turning points.

The results given by the pairwise comparisons of the accrual-based income variables with their cash-based counterparts are similar for both the numbers of positive differences and for the numbers of turning points. In all of the comparisons (see e.g. the mean and median results in panel a of table 6-1B) it seems clear that the accrual-basis generates income variables which tend to behave in a less random manner than their cash-based counterparts.

As regards the cross-sectional differences in the randomness, the estimated standard deviations show that the two sales variables ASA and CSA contain much more firm-specific differences than the other variables, where the estimates are closer to the theoretical value of unity. Compared with the above analysis of turning points, the ASA variable now exhibits more firm-specific variation in the degree of randomness.

On the whole, the lower panel (b) of table 6-1B gives results similar to the tests of the turning points. In a large number of firms the null hypothesis of randomness can be rejected for all the accrual-based variables ASA, AOI and ANI as well as for cash sales CSA, whereas the rejection of the null is the exception rather than the rule for the cash-based variables COI, CNIA and CNIB. For ANI, however, compared with the results from turning points, the number of firms where the null can be rejected with the difference-sign test is much smaller. Nevertheless, the broad tenor of the results is the same in the two tests.

In addition to the cross-sectional analysis above, the degree of randomness in the accrual vs. cash-based variables was further examined in individual firms by examining the numbers of firms where the deviation from randomness was larger in the accrual variables than in their cash-based counterparts. The absolute differences of the observed numbers of turning points and positive differences from their expectations under complete randomness (expressions 6-1 and 6-3) were used as measures for the deviation from randomness. The results from each of the four comparisons appear in table 6-2 below.

TABLE 6-2: Pairwise Comparisons of the Numbers of Turning Points (Panel A) and Positive Differences (Panel B) in Accrual vs. Cash-based Time Series in Individual Firms

A) Comparisons of the Numbers of Turning Points

Number (percentage) of firms where:

Variables compared	‖A(p)-E(p)‖ > ‖C(p)-E(p)‖	‖A(p)-E(p)‖ < ‖C(p)-E(p)‖	‖A(p)-E(p)‖ = ‖C(p)-E(p)‖	α
ASA vs. CSA	23 (59.0%)	7 (17.9%)	9 (23.1%)	.003
AOI vs. COI	30 (76.9%)	8 (20.5%)	1 (2.6%)	<.001
ANI vs. CNIA	32 (82.1%)	5 (12.8%)	2 (5.1%)	<.001
ANI vs. CNIB	30 (76.9%)	5 (12.8%)	4 (10.3%)	<.001

Legend: A(p) = observed number of turning points in the time series of the accrual-based variable
C(p) = observed number of turning points in the time series of the cash-based variable
E(p) = expected number of turning points under randomness
α = significance level for the rejection of H0: accounting system has no systematic effect on the degree of deviation from randomness

B) Comparisons of the Numbers of Positive Differences

Number (percentage) of firms where:

Variables compared	‖A(c)-E(c)‖ > ‖C(c)-E(c)‖	‖A(c)-E(c)‖ < ‖C(c)-E(c)‖	‖A(c)-E(c)‖ = ‖C(c)-E(c)‖	α
ASA vs. CSA	22 (56.4%)	10 (25.6%)	7 (17.9%)	.025
AOI vs. COI	25 (64.1%)	8 (20.5%)	6 (15.4%)	.002
ANI vs. CNIA	21 (53.8%)	10 (25.6%)	8 (20.5%)	.035
ANI vs. CNIB	23 (59.0%)	9 (23.1%)	7 (17.9%)	.010

Legend: A(c) = observed number of positive differences in the time series of the accrual-based variable
C(c) = observed number of positive differences in the time series of the cash-based variable
E(c) = expected number of positive differences under randomness
α = (see legend in panel A)

On the whole, the findings from individual firms support the results from cross-sectional analysis presented above. In the analysis of turning points, panel A of table 6-2 indicates that the number of firms where the degree of deviation from randomness was higher in the accrual-based variable than in the corresponding cash flow, was much larger than the number of firms in which the opposite occurred. For example, in 23 firms (59.0 %) the deviation of the observed number of turning points from its expectation was larger in accrual sales (ASA) than in cash sales (CSA). Only 7 firms (17.9 %) showed the opposite, while in 9 firms (23.1 %) no difference could be found (see the first line in panel A of table 6-2).

Similar results were obtained across all other pairwise comparisons between the two accounting systems; in the vast majority of firms accrual operating income (AOI) as well as the accrual net income (ANI) behaved in a less random manner than their cash-based counterparts. Using the sign test based on the binomial distribution (Siegel, 1956, pp. 68-75), the differences between the numbers of firms in the two groups appeared to be very significant (see the column on the far right in panel A of table 6-2).

The test results with the numbers of positive differences (panel B) were consistent with those of turning points. Deviations from randomness were found to be larger in accrual variables than in their cash-based counterparts in the majority of firms across all four comparisons, although the difference in the numbers of firms in the two groups were not quite as large as in panel A. Nevertheless, the differences were found to be significant in all comparisons (see the column on the far right in panel B).

As the third and final test of randomness, an <u>autocorrelation analysis</u> was performed on the time series data. In brief, the autocorrelation coefficient $r(k)$ at lag k for a stationary time series is given by (see e.g. Kendall, 1973, p. 69; Nelson, 1973, pp. 23-27; Makridakis, 1974a, pp. 16-17; Anderson, 1976, p. 6; Box and Jenkins, 1976, pp. 26-28):

$$r(k) = c(k)/c(0) \tag{6-5}$$

where $c(k)$ = autocovariance of the series at lag k $(k = \pm 1, \pm 2, \ldots)$
$c(0)$ = autocovariance at lag 0, i.e. the variance of the series

For a completely random series, the expected value of $r(k)$ is zero and its variance is approximately (see e.g. Box and Jenkins, 1976, p. 35):

$$\mathrm{Var}[r(k)] \approx 1/N \tag{6-6}$$

The null hypothesis of randomness can therefore be tested by examining the observed values of $r(k)$ at various lags against its normal expectation of zero and standard deviation $1/\sqrt{N}$ under complete randomness.

Autocorrelations at the first six lags [1] were estimated from the time series data in the following forms: (i) levels of the original variables, (ii) detrended variables obtained from regressing the original variables on time, and (iii) first differences of the original variables.

Consideration of the levels of the original variables was evident not only because of our interest in the behavior of the original variables as such, but also because it was a logical extension of the above distribution-free tests of randomness where the data was analyzed in the levels form.

The detrended series were analyzed primarily because the results from the above tests of randomness (and the visual inspection) suggested that the variables (especially the sales variables) contained trends. In such cases the autocorrelations estimated from the levels of the original variables would be obscure because the estimation of autocorrelation (expression 6-5) is based on the assumption that the series is stationary.

Finally, the autocorrelations from the first differences of the original variables were estimated primarily for the following reasons. First, it gave us the opportunity to compare the theoretical autocorrelations of some of the competing models (e.g. submartingales and mean reverting models) with the empirical estimates in order to see which of the models might be the best (or least bad) approximation of the underlying stochastic process. The second reason relating to the former was that the autocorrelation function estimated from the first differences also enabled us to see whether first order differencing sufficed to eliminate the trend from the series as evidenced by the dampening of the autocorrelation function.

At this point it should also be noted that autocorrelations estimated from the first differences of the original variables are equal to the autocorrelations of the first differences of the residuals obtained from regressing the original variables on time. Therefore, the estimation of the latter autocorrelations was unnecessary [2]. Cross-sectional results from the autocorrelation analysis are presented separately for each of the variables in tables 6-3A through 6-3G below.

TABLE 6-3A: Distributions of Estimated Autocorrelations for Accrual Sales (ASA)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	.828	.686	.574	.507	.406	.280
Median	.893	.794	.699	.605	.527	.450
3. quartile	.903	.812	.731	.646	.568	.477
Mean	.856	.738	.641	.553	.472	.390
Std. dev.	.093	.130	.144	.141	.136	.130
α = .10	39	39	37	38	33	29
= .01	38	37	36	33	26	22
b) Detrended series:						
1. quartile	.483	.125	-.072	-.124	-.101	-.111
Median	.615	.313	.144	.133	.054	-.036
3. quartile	.766	.564	.359	.309	.174	.097
Mean	.606	.323	.156	.078	.026	-.026
Std. dev.	.181	.258	.276	.243	.201	.152
α = .10	36	21	14	14	7	2
= .01	32	15	7	1	2	0
c) Differenced series:						
1. quartile	-.197	-.223	-.258	-.126	-.103	-.075
Median	-.038	-.135	-.112	-.023	.005	.065
3. quartile	.127	-.019	.049	.079	.195	.166
Mean	-.036	-.102	-.086	-.028	.021	.041
Std. dev.	.210	.184	.211	.161	.211	.183
α = .10	10	6	9	2	9	4
= .01	0	0	1	2	0	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

The distributions of the estimated autocorrelations for the levels of ASA show that the autocorrelation functions fail to die out at the first six lags in most firms (see the quartiles in panel a). It can also be seen that in the vast majority of firms, the individual autocorrelations were significant; even at lag 6 significant coefficients were found in 22 firms (56.4 %) at the 1 % level. In all, the results for the original ASA series fall well in line with the above tests of turning points thereby showing serial dependence in the ASA series.

Panel b in the table shows that the elimination of linear trend from the series results in a substantial decrease in the estimated autocorrelations at lags 2-6, while the decrease is not so large at the first lag (see e.g. the medians). Thus, the autocorrelation functions now seem to die out fairly quickly. However, the variation of autocorrelations across firms (see the standard deviations) is relatively high; therefore individual autocorrelations remain significant in a number of firms after the first lag.

Differencing the original ASA-variable (panel c) leads to autocorrelations which lie around zero at all lags (see e.g. the medians). Also, the number of firms where significant autocorrelations could be found is not very large. On the whole, the results from the differenced series suggest that the behavior of ASA in many of the sample firms might not be far from a submartingale. This is supported by the results from the original and detrended series showing significant positive autocorrelation at the first lag. To put these findings in perspective, it can be stated that they are not at all inconsistent with the results from some prior studies (e.g. Kodde and Schreuder, 1984), suggesting that corporate sales may behave like a random walk with drift.

TABLE 6-3B: Distributions of Estimated Autocorrelations for Accrual Operating Income (AOI)

(n = 39) Lag k:	1	2	3	4	5	6
a) Original series:						
1. quartile	.562	.305	.243	.194	.196	.175
Median	.708	.494	.430	.388	.353	.250
3. quartile	.825	.723	.600	.494	.458	.364
Mean	.670	.481	.392	.333	.306	.234
Std. dev.	.186	.251	.269	.220	.176	.167
α = .10	37	31	26	25	23	18
= .01	33	24	19	15	11	1
b) Detrended series:						
1. quartile	.204	-.062	-.187	-.106	-.035	-.061
Median	.429	.126	.021	.007	.074	.029
3. quartile	.602	.301	.325	.165	.163	.111
Mean	.413	.123	.054	.019	.064	.022
Std. dev.	.242	.302	.293	.216	.161	.151
α = .10	27	14	13	6	5	2
= .01	18	8	4	2	0	1
c) Differenced series:						
1. quartile	-.341	-.337	-.223	-.167	-.069	-.087
Median	-.183	-.193	-.095	-.066	.086	.073
3. quartile	-.058	.012	.092	.127	.254	.166
Mean	-.191	-.158	-.059	-.038	.058	.059
Std. dev.	.202	.230	.263	.218	.214	.177
α = .10	13	14	11	5	11	3
= .01	6	4	5	2	0	1

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

The broad tenor of the results for the AOI variable is similar to that of ASA presented above. The distributions of the estimated autocorrelations from the original series (panel a) show that the autocorrelation functions for most firms vanish very slowly, while only a little autocorrelation could be found from the detrended series after the first lag (panel b). Also, the number of firms where significant autocorrelations were estimated was large for the original variable, whereas it was much smaller in the detrended series at lags other than one.

It should be noted, however, that the degree of autocorrelation in the AOI series is generally somewhat lower than it was in the ASA series. At lag one for example, the median autocorrelations in the original and detrended AOI-series are approximately .7 and .4, while they were around .9 and .6 for ASA, respectively.

As regards the differenced series (panel c), the distributions of estimated autocorrelations lie around zero except at lag one, where a marginal tendency towards negative serial dependence can be found, (see the signs which are negative at all quartiles). Nevertheless, it was not significant in a majority of firms.

As a tentative conclusion, the underlying mechanism describing the behavior of accrual operating income numbers over time may be very similar to the model for accrual sales. In other words, a random walk presumably with a positive drift might well be a good approximation of the underlying stochastic process.

TABLE 6-3C: Distributions of Estimated Autocorrelations for Accrual Net Income (ANI)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	.296	.116	-.017	-.061	-.042	-.070
Median	.569	.266	.154	.161	.084	.110
3. quartile	.712	.571	.459	.359	.283	.251
Mean	.485	.302	.199	.142	.116	.083
Std. dev.	.273	.269	.267	.243	.203	.209
α = .10	31	19	16	12	10	7
= .01	23	15	11	5	2	0
b) Detrended series:						
1. quartile	.112	-.067	-.124	-.115	-.171	-.218
Median	.328	.174	.008	-.055	-.070	-.049
3. quartile	.556	.276	.182	.113	.054	.069
Mean	.337	.128	.033	-.028	-.064	-.080
Std. dev.	.264	.231	.216	.169	.152	.185
α = .10	25	10	9	3	3	7
= .01	16	3	2	1	0	1
c) Differenced series:						
1. quartile	-.428	-.277	-.153	-.110	-.122	-.105
Median	-.203	-.103	-.019	-.020	.041	.003
3. quartile	-.080	.083	.091	.078	.130	.167
Mean	-.224	-.084	-.003	-.007	.001	.017
Std. dev.	.234	.210	.205	.153	.163	.176
α = .10	16	8	8	3	2	2
= .01	8	1	2	0	0	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

Results for the ANI variable show that the autocorrelation functions from the original series (panel a of table 6-3C) tend to die out after the first two lags in most firms. As an indication of this, the mean and median autocorrelations are below .2 at lags 3-6. However, firm-specific differences from the general tendency exist, which can be seen from the standard deviations and the numbers of firms where significant autocorrelations e.g. at lag three could be found.

For the detrended series (panel b), significant autocorrelations are not common after the first lag. At lag one, however, the average autocorrelation is above .3 (see the median and mean), and significant estimates could be found in a large number of firms (e.g. in 16 firms (41.0 %) even at 1 % level).

It is worthwhile to note that, compared with the previous variables ASA and AOI, the level of autocorrelation estimates from the original and detrended series of ANI are lower. E.g. at lag one in the detrended series, the means of the estimated coefficients are approximately .6, .4 and .3 for ASA, AOI and ANI, respectively. Thus, it seems that the serial dependence in income variables decreases as we proceed from the top of an income statement to the bottom.

Finally, it can be seen that the results from the differences of ANI (panel c) are essentially the same as for the above variables; although a slight tendency towards negative correlation exists at lag one, significant autocorrelation cannot, in general, be found. As a tentative conclusion, the findings from the autocorrelation analysis for ANI are quite consistent with prior literature; the random walk (possibly with a positive drift) might also be a good approximation of the behavior of net income in the present data.

TABLE 6-3D: Distributions of Estimated Autocorrelations for Cash Sales (CSA)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	.810	.714	.593	.509	.403	.272
Median	.882	.787	.689	.593	.516	.438
3. quartile	.897	.808	.727	.643	.556	.471
Mean	.845	.733	.637	.546	.471	.384
Std. dev.	.093	.125	.145	.146	.125	.120
α = .10	39	39	38	38	35	29
= .01	38	37	36	32	27	17
b) Detrended series:						
1. quartile	.449	.096	-.039	-.033	-.055	-.128
Median	.591	.264	.161	.103	.066	-.050
3. quartile	.748	.530	.343	.244	.172	.091
Mean	.566	.297	.153	.084	.045	-.043
Std. dev.	.207	.248	.265	.224	.197	.152
α = .10	35	19	18	11	5	3
= .01	30	13	6	1	1	0
c) Differenced series:						
1. quartile	-.256	-.276	-.230	-.118	-.077	-.127
Median	-.070	-.115	-.121	.006	.076	-.083
3. quartile	.074	-.018	.057	.128	.192	.134
Mean	-.090	-.123	-.075	-.000	.046	.001
Std. dev.	.195	.178	.198	.142	.193	.179
α = .10	7	10	8	0	5	5
= .01	1	0	1	0	0	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

Table 6-3D shows that the autocorrelation functions for the CSA variable are virtually the same as for its accrual counterpart in table 6-3A above. That is, the autocorrelation functions fail to die out in the first six lags (panel a), the elimination of linear trend from the original series (panel b) effectively kills most of the autocorrelation at lags two to six while a significant part of it survives at lag one. Furthermore, differencing the series (panel c) produces distributions which lie around zero, and, with a few exceptions, significant coefficients cannot be found in the sample firms.

Comparing the degree of estimated autocorrelation for CSA with its accrual counterpart ASA indicates, however, that a marginal, although certainly not significant, difference exists. At lag one for example, the medians for CSA are .882, .591 and -.070 for the original, detrended and differenced series, respectively, while the corresponding estimates for ASA were .893, .615 and -.038.

Nevertheless, the difference between the accrual vs. cash-basis is so small at the sales level that the underlying process describing the behavior of the two sales variables is quite obviously very similar; i.e. a random walk presumably with a positive drift might also be a good approximation of the behavior of cash sales.

TABLE 6-3E: Distributions of Estimated Autocorrelations for Cash Operating Income (COI)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	.057	-.020	.032	-.029	-.018	.010
Median	.242	.191	.183	.178	.143	.101
3. quartile	.526	.408	.342	.336	.295	.206
Mean	.256	.199	.183	.156	.142	.105
Std. dev.	.311	.257	.234	.219	.207	.163
α = .10	19	16	14	15	12	7
= .01	15	9	5	3	4	1
b) Detrended series:						
1. quartile	-.168	-.162	-.140	-.111	-.110	-.102
Median	.040	-.013	.025	-.015	-.019	-.000
3. quartile	.153	.109	.119	.143	.186	.053
Mean	.039	-.009	.012	.012	.005	-.010
Std. dev.	.224	.189	.184	.174	.199	.142
α = .10	7	7	4	4	4	2
= .01	2	0	1	0	2	0
c) Differenced series:						
1. quartile	-.520	-.195	-.193	-.142	-.117	-.172
Median	-.429	-.095	-.004	-.016	.005	-.051
3. quartile	-.352	.062	.141	.183	.200	.153
Mean	-.436	-.057	.003	.009	.005	-.013
Std. dev.	.122	.197	.200	.185	.226	.178
α = .10	35	5	6	5	4	4
= .01	15	1	0	1	2	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

Distributions of autocorrelation estimates for the original COI-series show that a slight tendency towards positive serial dependence exists at all lags (panel a). At lag one, where the average autocorrelation is not higher than .25 (see the median and mean), the cross-sectional variation is relatively high (see the standard deviation of .31), and therefore significant autocorrelations could be found in 15 firms (38.5 %) even at the 1 % level.

However, eliminating trend from the series seems to produce autocorrelations which lie around zero at all lags (see e.g. the medians in panel b), and with a few exceptions, significant coefficients cannot, in general, be found in individual firms.

As regards the differenced series in panel c, it can be seen that a clear-cut tendency towards negative autocorrelation exists at lag one, while after that the autocorrelation functions vanish in most firms. At lag one the coefficients are significant in 35 firms (89.7%) at the 10 % level and in 15 firms (38.5 %) at the 1 % level, although the variation across firms is relatively small as indicated by the standard deviation. It should also be noted that, on average, the estimated autocorrelation at the first lag is less than -.4, which is not very far from the theoretical autocorrelation (-.5) of the first differences of constant processes.

Compared with the accrual counterpart (AOI), the autocorrelation analysis for COI gives a different view of the underlying stochastic process; while a submartingale was suggested for AOI, quite obviously it would be a poor description for the behavior of the cash-based COI. The results in table 6-3E are much more indicative of a constant process such as a mean reverting or linear trend model.

TABLE 6-3F: Distributions of Estimated Autocorrelations for Cash Net Income A (CNIA)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	-.066	-.132	-.103	-.090	-.076	-.083
Median	.024	.027	.072	.040	.036	.031
3. quartile	.157	.110	.201	.163	.200	.141
Mean	.060	.029	.064	.036	.051	.041
Std. dev.	.222	.222	.235	.200	.201	.176
α = .10	8	8	11	5	6	6
= .01	3	3	2	1	2	1
b) Detrended series:						
1. quartile	-.176	-.184	-.110	-.133	-.129	-.099
Median	-.043	-.020	-.005	-.054	-.034	-.009
3. quartile	.061	.063	.104	.101	.167	.073
Mean	-.028	-.059	-.015	-.032	-.013	-.017
Std. dev.	.187	.173	.186	.162	.182	.145
α = .10	5	6	4	2	4	3
= .01	1	0	0	1	1	0
c) Differenced series:						
1. quartile	-.564	-.196	-.089	-.191	-.160	-.093
Median	-.459	-.075	-.010	-.028	.010	-.003
3. quartile	-.377	.122	.092	.095	.192	.148
Mean	-.443	-.051	.017	-.021	.013	.007
Std. dev.	.137	.191	.175	.182	.215	.170
α = .10	33	4	6	4	9	4
= .01	20	0	0	0	0	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

The results of autocorrelation analysis for the first version of cash net income (CNIA) in table 6-3F give very little support to the existence of serial dependence in the original or detrended variable (see panels a and b), a result which was already suggested by the above tests of turning points and difference-sign. In general, the autocorrelation functions seem to fluctuate near zero at all lags, and the firms in which significant estimates could be found are the exception rather than the rule.

With respect to the differenced series (panel c), it seems unambigious that the autocorrelation functions in the vast majority of firms are dead after the first lag. At lag one, however, significant autocorrelations can be found in most firms, and as indicated by the signs, the dependence tends to be negative. To be more precise, the quartiles indicate that the estimated autocorrelations in half of the firms are between -.56 and -.38, the average being around -.45.

On the whole, the autocorrelation results for CNIA therefore lend support to the contention that the underlying mechanism for the behavior of cash net income numbers (as presently defined) might well be characterized by the mean reverting or similar process. If this were the case, the stochastic process behind accrual vis-a-vis cash net income variables would, indeed, be very different from each other.

TABLE 6-3G: Distributions of Estimated Autocorrelations for Cash Net Income B (CNIB)

(n = 39)	Lag k: 1	2	3	4	5	6
a) Original series:						
1. quartile	-.018	-.124	-.132	-.128	-.130	-.125
Median	.130	-.015	.025	-.042	-.001	-.011
3. quartile	.309	.153	.164	.130	.097	.106
Mean	.135	-.007	.005	-.008	-.016	-.001
Std. dev.	.220	.176	.210	.159	.172	.148
α = .10	14	3	4	1	4	2
= .01	3	0	2	0	1	0
b) Detrended series:						
1. quartile	-.072	-.220	-.175	-.142	-.189	-.170
Median	.102	-.081	-.073	-.075	-.016	-.032
3. quartile	.229	.037	.118	.064	.056	.067
Mean	.081	-.074	-.050	-.061	-.056	-.045
Std. dev.	.211	.174	.209	.157	.167	.153
α = .10	9	7	7	2	5	3
= .01	2	0	2	1	0	0
c) Differenced series:						
1. quartile	-.462	-.240	-.150	-.144	-.115	-.105
Median	-.374	-.139	-.000	-.013	.024	-.043
3. quartile	-.250	.072	.160	.118	.152	.088
Mean	-.354	-.115	-.006	-.004	.005	-.012
Std. dev.	.164	.206	.226	.162	.191	.167
α = .10	27	8	11	2	8	4
= .01	12	3	3	0	0	0

(The bottom section of each panel in the table shows the number of firms where H0: r(k) = 0 could be rejected at 10 % and 1 % levels of significance)

Compared with the first variant (CNIA), the autocorrelation results for the second version of cash net income (CNIB) give a similar general picture. That is, in most firms the autocorrelation function is virtually dead at all lags in the original and detrended series (panels a and b of table 6-3G) as well as in the differenced series after the first lag (panel c). At lag one, significant autocorrelation from the differences of CNIB could be found in a number of firms (27 and 12 firms at the 10 % and 1 % level), although the number is not so large as for the first version, CNIA. Moreover, the negative autocorrelations at this lag (see the quartiles) are an indication of a tendency towards mean reverting behavior in CNIB.

In brief, the conclusion that can be drawn from the above results is that, in contrast with the accrual net income (ANI), the random walk-type model might be a poor description for the behavior of cash net income numbers. This is the inference from autocorrelation analysis, irrespective of whether cash net income is defined after replacements (as in CNIA) or after total investments (as in CNIB).

Analogously to the above tests of randomness, the degrees of autocorrelation in the accrual and cash-based variables were finally compared with each other in individual firms. This analysis was performed for the autocorrelation coefficients estimated at lag one from the detrended series (note that the tests presented in table 6-2 were based on original series). The numbers and percentages of firms where the estimated autocorrelation in the accrual variable was larger (smaller) than in its cash counterpart appear in the second (third) column of table 6-4 below.

TABLE 6-4: Pairwise Comparisons of the Autocorrelation Coefficients Estimated at Lag One from Detrended Series of the Accrual and Cash-based Variables

Variables compared	Number (percentage) of firms where R1(A) > R1(C)	R1(A) < R1(C)	α
ASA vs. CSA	26 (66.7%)	13 (33.3%)	.027
AOI vs. COI	37 (94.9%)	2 (5.1%)	<.001
ANI vs. CNIA	34 (87.2%)	5 (12.8%)	<.001
ANI vs. CNIB	28 (71.8%)	11 (28.2%)	.005

Legend: R1(A) = first order autocorrelation coefficient estimated from detrended accrual series (i.e. the residuals obtained from regressing the accrual variable on time)
R1(C) = as above but for the cash-based series
α = significance level for the rejection of H0: the accounting system has no systematic effect on the degree of the estimated autocorrelation (the binomial test)

In brief, the main message of the above table is not very surprising in light of the findings presented above in this chapter. Across all pairwise comparisons (i.e. across the three levels of the income statement), the accrual-based income variables contain higher serial correlation in a significantly larger number of firms than where the opposite occurs. Thus, the accounting system seems to have a systematic effect on the degree of autocorrelation (at lag one) in the income variables: as opposed to the cash accounting system, income smoothing in sense of increasing the serial correlation of income variables is an underlying characteristic of the accrual accounting system.

6.2. Cross-Sectional Dependences in the Degree of Randomness and Tests of the Theoretical Models

Further evidence for the effect of the accounting system on the serial dependence of income numbers can be obtained by examining the cross-sectional dependences of autocorrelations in the accrual vs. cash accounting variables. The rationale behind this analysis is as follows. According to the general model of the characteristics of the income numbers generating process, the underlying determinants may be grouped into economic factors and factors relating to the use of different accounting methods (see the omega-model in expression 1-1).

Now, if the underlying economic factors are of greater relative importance than the accounting method-based factors, then the variation of serial correlation in income numbers across firms is primarily caused by the economic factors relating to individual firms rather than by differences in the accounting methods used, and a high (or low) autocorrelation in an income variable of a particular firm can be observed independently of the accounting method in question. It may thus be hypothesized that the larger the relative importance of economic factors as opposed to accounting method-based factors, the higher the cross-sectional dependence between the autocorrelations from accrual and cash-based income numbers.

To that end, the cross-sectional correlations of the first order autocorrelations estimated from the original and detrended income variables appear in the following table 6-5A.

TABLE 6-5A: Cross-Sectional Correlations between the Autocorrelations of the Accrual and Cash-based Income Variables Estimated at Lag One from the Original and Detrended Data.

(n = 39)	Autocorrelations Estimated from: Original Data	Detrended Data
r[R(ASA),R(CSA)]	.977	.887
α	<.001	<.001
r[R(AOI),R(COI)]	.444	.394
α	.002	.007
r[R(ANI),R(CNIA)]	.076	-.136
α	>.100	>.100
r[R(ANI),R(CNIB)]	.070	-.084
α	>.100	>.100

Legend: r[ ] = cross-sectional correlation between the autocorrelations given in the square brackets
R( ) = first order autocorrelation estimated from the time series of the income variable given in the brackets
α = (one-tail) significance level for the rejection of H0: r[ ] = 0.

The results in the above table reveal that, quite obviously, the role of economic vs. accounting factors as determinants of serial correlation depends on the level of income measurement. This is indicated by the decrease in the estimated cross-sectional correlations as we move from the top of the income statement (i.e. the sales level) where very high and significant dependence exists, down to the operating income level with a moderate correlation, and further down to the net income level where the dependence is insignificant. The decrease in the cross-sectional correlations can be interpreted as a reflection of the change in the relative importance of the economic and accounting determinants: the lower the income is measured, the smaller the role of economic factors and the larger the role of the factors relating to accounting method as a determinant of the serial dependence in income variables. Such contention is also intuitively appealing because the lower income is measured, the greater the number of operating, investment and financing transactions processed by the accounting system which therefore makes its effects on the properties of the resulting income variable more apparent.

The theoretical analysis of cash sales and cash operating income presented in chapter 3 suggested that their serial correlations are certain functions of the parameter values relating these variables to accrual sales and of its variance and autocovariances (see expressions 3-5 and 3-15 for cash sales and cash operating income, respectively). A theoretical expression was also derived for the serial correlation of accrual operating income showing the mechanism of why a lower serial dependence can be expected in accrual operating income than in accrual sales (see 3-12). Having the empirical data at our disposal, we are now in the position of being able to test the descriptive validity of the theoretical expressions in (3-5), (3-12) and (3-15). This can be done by looking at the cross-sectional correlations between the autocorrelations predicted by those expressions and the actual autocorrelations estimated from the empirical time series.

For that purpose, the following linear regressions (corresponding to equations 3-2, 3-9 and 3-14) were first estimated with the ordinary least squares for each of the sample firms:

$$CSA(t) = (\alpha 1)ASA(t) + (\alpha 2)ASA(t-1) + a(t) \tag{6-7}$$

$$AOI(t) = (m)ASA(t) - F - z(t) \tag{6-8}$$

$$COI(t) = (\beta 1)ASA(t) + (\beta 2)ASA(t-1) - F + e(t) \tag{6-9}$$

where $\alpha 1$, $\alpha 2$, m, F, $\beta 1$ and $\beta 2$ = parameters to be estimated
a(t), z(t) and e(t) = error terms with usual assumptions

With respect to these models, two remarks should be made. First, the model for cash sales (6-7) does not include a constant term, so it was accordingly suppressed in the estimation. Second, the models for cash sales and cash operating income (6-7 and 6-9) include consecutive accrual sales as independent variables which obviously lead to the notorious problems arising from multicollinearity. To be more exact, the high intercorrelation between the independent variables increases the variances of the parameter estimates which, therefore, remain uncertain. This implied that, *a priori*, not too much could be expected from the descriptive validity of the theoretical autocorrelations.

The estimated autocovariances at lags 0 to 2 of accrual sales and the estimated parameter values and residual variances from equations (6-7) through (6-9) were then used to compute each firm's theoretical autocorrelations for cash sales, accrual operating income and cash operating income in expressions (3-5), (3-12) and (3-15), respectively. Finally, the cross-sectional correlations between the theoretical and empirical estimates were computed, which gave the correlation matrix appearing in table 6-5B below. For comparative purposes, it also includes a variable denoting empirical autocorrelations from the accrual sales. Note that according to the theoretical expressions, the autocorrelations are functions of the autocovariances and the variance of accrual sales, which are also the components of its autocorrelation. It was therefore advisable to check whether the direct correlation of the empirical autocorrelations of the examined variables with the autocorrelations of accrual sales is higher than with their theoretical values. If this were the case, it would be an indication of the poor descriptive validity of the theoretical expression, despite the size of the correlation between the theoretical and empirical autocorrelations.

TABLE 6-5B: Cross-Sectional Correlations between the Theoretical and Empirical Autocorrelations Estimated from Original Data at Lag One.

(n=39)	Re(ASA)	Re(CSA)	Re(AOI)	Re(COI)	Rt(CSA)	Rt(AOI)
Re(ASA)	1.000					
Re(CSA)	.977	1.000				
Re(AOI)	.652	.625	1.000			
Re(COI)	.265	.273	.444	1.000		
Rt(CSA)	.983	.985	.649	.309	1.000	
Rt(AOI)	.609	.589	.809	.410	.592	1.000
Rt(COI)	.236	.234	.424	.970	.282	.368

Legend: Re( ) = empirical autocorrelation at lag 1 for the variable given in brackets
Rt( ) = theoretical autocorrelation at lag 1 for the variable given in brackets

N.B. Any correlation coefficient above .268 in the above table is significant at the 5 % level (one-tail test).

Table 6-5B reveals the following. First, while a very high cross-sectional correlation exists between the empirical autocorrelations of ASA and CSA (.977), the correlation between the empirical autocorrelations and the theoretical values given by expression (3-5) for CSA is even higher (.985). Second, the correlation between the empirical and theoretical autocorrelation given by expression (3-12) for AOI is also high (.809), and it clearly exceeds the benchmark correlation between the empirical autocorrelations of ASA and AOI (.652). Third, while a relatively modest correlation was found between the empirical autocorrelations for ASA and COI (.265), the theoretical autocorrelations from expression (3-15) for COI are very highly correlated with the empirical values (.970). Compared with the benchmark, the theoretical expression for the autocorrelation of cash operating income thus performed much better than the other two expressions.

On the whole, the findings from table 6-5B support the contention that the theoretical models derived in chapter 3 may have some descriptive validity. In fact, the cross-sectional correlations between the predictions of the theoretical expressions and empirical estimates for autocorrelations of cash sales, accrual operating income and cash operating income were surprisingly high, especially when one takes into account the problems caused by multicollinearity in the estimation of equations 6-7 and 6-9.

Some further evidence in favor of the descriptive content of the theoretical autocorrelations of accrual and cash operating income can be obtained by computing the difference between the theoretical autocorrelations obtained from (3-12) for AOI and (3-15) for COI. As was stated in chapter 3, depending e.g. on the parameter values of the equations relating these variables to accrual sales, the autocorrelation of cash-based operating income may or may not be higher than that of its accrual counterpart. If this hypothesis has any validity, then the signs of the computed differences between the theoretical values should fall in line with the corresponding differences in the empirical estimates. That is, the theoretical expressions should be able to discriminate between the firms where the autocorrelation of accrual operating income is higher than that of cash operating income and the firms where the opposite occurs.

The analysis indicated that for 31 firms a higher autocorrelation in the accrual operating income than in the cash operating income was predicted, while for 8 firms the opposite predictions were made. When the empirical differences were examined, it was found that the accrual variable had a higher autocorrelation in all of the 39 firms in the original data and in 37 firms in the detrended data (see table 6-4). Thus, the theoretical expressions made correct predictions for the relative magnitudes of the autocorrelations in approximately 80 % of the firms, while they made mistakes in 20 % of the cases. In a binomial test, this result is very significant at a level under .1 %.

Finally, the empirical autocorrelations of accrual sales and accrual operating income were examined. This was done in order to see the validity of the hypothesis based on expression (3-12) according to which a higher autocorrelation should exist in accrual sales than in accrual operating income. The analysis showed that, with only one exception, this was indeed the case in all of the sample firms. (Of course, such a result is statistically very significant.) Expression (3-12) may thus provide a valid explanation for why lower serial dependence can be expected at the operating income level than at the sales level.

6.3. Tests of Stationarity

A basic assumption required by many time series models (e.g. the autoregressive - moving average models) is that of weak stationarity, implying that the first two moments of the time series, i.e. the mean and the variance, are time invariant (for the concept of stationarity, see e.g. Nelson, 1973, pp. 19-23; Anderson, 1976, pp. 3-4; Box and Jenkins, 1976, pp. 26, 30). If the existence of non-stationarity is suspected in time series analysis, it is common practice to transform the data, e.g. by differencing the series until stationarity is achieved [3].

Unfortunately, there is no unique, well-established method for evaluating stationarity in empirical time series. The time series literature suggests inspection of estimated autocorrelation function as the principal method for this purpose (Nelson, 1973, pp. 75-76; Box and Jenkins, 1976, p. 175), but other methods such as visual inspection of plotted data and certain statistical tests can also be used.

As regards the visual inspection, table 4-3 can be recollected here. The findings from the graphical plots of the <u>levels</u> of the variables indicated that, on the whole, the assumption of weak stationarity could be rejected approximately in one half of the sample time series. To be more precise, trend and an instability of variance were detected in 49.1 % and 46.2 % of the sample time series, respectively.

The autocorrelation analysis (tables 6-3A through 6-3G) gave support to the contention that the <u>levels</u> of some of the examined variables were, indeed, nonstationary. This was the case, especially with respect to accrual sales (ASA), accrual operating income (AOI) and cash sales (CSA), where the estimated autocorrelation functions tended to die out slowly (see e.g. the medians in panels (a) of tables 6-3A, 6-3B and 6-3D). However, differencing the series produced autocorrelations showing very little, if any, persistence.

However, there are at least three problems arising from the use of autocorrelation functions. The first relates to the ability of autocorrelation function to reveal non-stationarity in the variance, even if the series is stationary in the mean. One might argue that autocorrelation analysis is presumably not the best method for revealing such non-stationarity.

The second is the general problem caused by the absence of well-defined criteria showing when the autocorrelation function "dies out quickly". For example Nelson (1973, p. 76) notes that there is no precise answer available from sample autocorrelations to the question: "how slowly is slow?", and that the context or nature of the data should provide a tentative answer to the question.

The third problem arises when the observation series are relatively short (as is the case in our data), thereby making the statistical estimation of individual autocorrelation coefficients unreliable especially at larger lags (see note 1). In conclusion, not too much weight should be attached to the above finding in favour of stationarity in differenced series via inspection of the estimated autocorrelation functions alone.

Some simple tests were performed as a complementary method for analyzing stationarity. These tests were carried out with <u>differenced</u> data primarily because the above findings from visual inspection and autocorrelation analysis suggested that the levels of some variables (especially sales) were not stationary, and it was therefore desirable to see whether the first differences sufficed to produce stationarity (as noted above, this was suggested by the autocorrelation analysis). In brief, the tests included an analysis of the difference of the means and the variances estimated separately from the first and the second half of the sample period [4]. If the weak form stationarity holds true, then, by definition, no significant difference should exist between the estimates from the two halves of the sample period.

Assuming that the first differences of the data are normally distributed, the parametric F-test was used for testing the difference between the variances and the t-test for testing the difference between the means of the first differences. The numbers of firms where the null hypothesis of equal means and variances in the two subperiods could be rejected at various significance levels, appear in the table 6-6 below.

TABLE 6-6: Results from the Tests of Stationarity in Differenced Series

a) Numbers of Firms (n = 39) in which the Following Null Hypothesis Could Be Rejected (Two-tail t-test):

$$H0: \mu(1) = \mu(2)$$

where $\mu(1)$ = the mean of first differences in the first subperiod 1951-67 (N=16)
$\mu(2)$ = the mean of first differences in the second subperiod 1967-84 (N=17)

Signific. Level α	Variable: ASA	AOI	ANI	CSA	COI	CNIA	CNIB
.10	7	0	3	4	0	0	0
.05	4	0	3	3	0	0	0
.01	1	0	0	1	0	0	0

b) Numbers of Firms (n = 39) in which the Following Null Hypothesis Could Be Rejected (F-test):

$$H0: \sigma^2(1) = \sigma^2(2)$$

where $\sigma^2(1)$ = the variance of first differences in the first subperiod 1951-67 (N=16)
$\sigma^2(2)$ = the variance of first differences in the second subperiod 1967-84 (N=17)

Signific. Level α	Variable: ASA	AOI	ANI	CSA	COI	CNIA	CNIB
.10	30	39	32	30	34	33	32
.05	28	39	27	28	30	29	29
.01	23	36	24	22	20	18	27
.001	18	35	21	13	12	13	20

The upper panel (a) of table 6-6 indicates that, with a few exceptions in ASA, ANI and CSA, the null hypothesis of equal means of differenced series in the two subperiods could not be rejected in the vast majority of firms. Thus, it turned out that first order differencing was sufficient to produce time series which are stationary in the mean, a result consistent with the preceding findings from autocorrelation analysis.

It is also noteworthy that the equality of the estimated means of the first differences imply that the growth included in the (undifferenced) time series data is linear rather than non-linear, because insofar as the growth would be better characterized as being e.g. quadratic, it should have been reflected as a frequent rejection of the null hypothesis in panel (a) of the above table. Consequently, the current results provide an ex-post rationalization for the inclusion of the simple linear trend (see 5-4) instead of non-linear (e.g. quadratic) models into the set of competing models.

As regards the lower panel (b) of table 6-6, the null hypothesis of equal variances in the subperiods could be rejected in a large number of firms for all of the variables. It can also be seen that no remarkable differences exist between the numbers of firms for the accrual vs. cash-based variables; e.g. at the 5 % level of significance, the null was rejected in 28 firms for ASA and CSA, in 39 and 30 firms for AOI and COI, respectively, and in 27 and 29 firms for ANI and CNIA/CNIB, respectively.

In contrast with the findings in panel (a), these results suggest that, irrespective of the variable or accounting system in question, the differenced time series data tend to be heteroscedastic, i.e. non-stationary in variance. It should be noted that this finding from the differenced series can also be projected back to the <u>levels</u>

of the original variables; because the first differences were found to be non-stationary in variance, then quite obviously this is the case with the levels, too.

With respect to the underlying models inferred from the autocorrelation analysis, the following conclusions can be made: (i) the observed non-stationarity in variance is consistent with the submartingale models tentatively suggested in section 6.1 for ASA, AOI, ANI and CSA (c.f. expression A5-7); (ii) the observed non-stationarity in variance is inconsistent with the basic assumption of the noise term included in the constant processes (see expressions 5-3 and 5-4). Therefore, the underlying processes tentatively suggested by autocorrelation analysis for COI, CNIA and CNIB (see section 6.1) should allow for the heteroscedasticity in these variables.

The observed heteroscedasticity in the time series data also has some important methodological implications for subsequent model estimation. The conventional wisdom manifested in standard text books of time series modeling suggests that a logarithmic transformation should be applied to raw data if it is suspected to be heteroscedastic (see e.g. Nelson, 1973, pp. 58-59; Anderson, 1976, p. 45; see also Johnston, 1963, pp. 207-211 indicating that the use of the least squares estimators produce uncertain parameter estimates in regression analysis when applied to heteroscedastic data).

Despite such recommendations, the logarithmic transformation was, however, not applied to the data, primarily for the following reasons.

First, because the time series data of some variables (particularly the net income variables) contained frequent negative values, it was not possible to take logs of such values. (Note that the addition of a positive constant sufficiently large to eliminate the negative values would have resulted in arbitrary results depending on the choice of the constant.)

Second, prior experience obtained from applying logarithmic transformation to accounting earnings series indicates that such transformation might <u>not</u> be useful in increasing the predictive ability; in fact, it has been found that logarithmic transformation may even have a counter effect on the forecasting performance of identified and estimated time series models (see Hopwood, McKeown and Newbold, 1981).

Third, as regards the related literature in this area, it has quite obviously been common practice <u>not</u> to perform logarithmic transformations to the data (or if performed, it has not been reported). Therefore, the logarithmic transformation would have decreased the comparability of the findings of the current study with those provided in the prior literature.

Fourth, logarithmic transformation was not desirable because of our main interest in the underlying processes of the original income variables, not of their log transformations.

6.4. Estimation Results

This section reports on the estimation results of the time series models described in section 5.2. above. The results will be reported in three parts: in section 6.4.1. the distributions of the optimal smoothing coefficients of EWMA models are examined, thereafter the identified and estimated ARIMA models are discussed in section 6.4.2., and finally in section 6.4.3. the goodness of fit of all the estimated models will be analyzed in terms of the distributions of coefficients of determination and Durbin-Watson statistics.

6.4.1. Optimal Smoothing Coefficients

The optimal parameter values for the EWMA models (see section 5.3.) were determined separately for each of the sample time series (273) in each of the three estimation periods (1951-75, 1951-78 and 1951-81) thus producing 819 parameter estimates. The cross-sectional distributions of the estimates are given in table 6-7 below for each income variable and each estimation period.

As regards the effect of the length of the estimation period, the table shows that the optimal parameter estimates are very stable across different estimation bases: only marginal, if any, changes could be found in the distributions of the estimates as the length of the estimation period increased 24 % from 25 years (in the first estimation period) to 31 years (in the third period).

With respect to the variation across variables, it can be seen that very high coefficients were estimated for accrual and cash-based sales (see e.g. the medians of .95) and the cross-sectional

TABLE 6-7: Distributions of Optimal Smoothing Coefficients by Income Variable and Estimation Period (n = 39)

Estimation period	Variable: ASA	AOI	ANI	CSA	COI	CNIA	CNIB
1. 1951-75:							
1. quart.	.85	.50	.30	.70	.10	.05	.05
Median	.95	.65	.60	.95	.20	.15	.20
3. quart.	.95	.95	.95	.95	.30	.25	.30
Mean	.90	.69	.60	.84	.24	.19	.24
Std. dev.	.08	.24	.32	.13	.17	.15	.22
2. 1951-78:							
1. quart.	.85	.40	.25	.75	.10	.10	.05
Median	.95	.70	.55	.95	.20	.15	.15
3. quart.	.95	.95	.95	.95	.30	.25	.30
Mean	.90	.65	.57	.87	.24	.18	.26
Std. dev.	.08	.25	.34	.13	.15	.15	.28
3. 1951-81:							
1. quart.	.90	.40	.30	.80	.10	.05	.05
Median	.95	.70	.65	.95	.25	.10	.10
3. quart.	.95	.95	.95	.95	.35	.25	.25
Mean	.91	.65	.59	.87	.25	.15	.22
Std. dev.	.09	.27	.33	.13	.15	.11	.25

variation as indicated by the standard deviations tended to be smaller than for any other variable. However, the tendency towards high smoothing coefficients in the sales variables is not very surprising, taking into account the trend component that is present in their time series. (The reader should recall that the parameter value of 1.00 was excluded from the feasible range, see section 5.3.. Quite obviously, if this value had been included, it would have been estimated for the two sales variables in a large number of firms.)

The average coefficients for the accrual operating income (AOI) were around .65 - .70 and similar results were also obtained on the net income level (ANI) where the medians .55 - .65 were slightly lower. These results are somewhat surprising, because they are inconsistent with the above findings in two ways. First, since the parameter estimates seem to fall far from unity in a large number of firms, the results are inconsistent with the autocorrelation analysis (see section 6.1.) which suggested submartingales for these variables. It should be noted, however, that estimates consistent with submartingales were also encountered in a number of firms (see the third quartiles of .95), a fact which mitigates the contradiction a little.

Second, when the average coefficients of the net income variable (ANI) are contrasted with the results obtained by Ball and Watts (1972, table 7, p. 677), a remarkable difference can be found because the optimal coefficient was as high as .95 in their data for a constant EWMA model not including trend. In addition to sample-related explanations for the difference between the present and Ball and Watts findings, one can speculate on a potential effect of the following methodological difference: Ball and Watts (1972) report results based on the sums (computed over 714 firms) of rank order numbers of individual coefficient values [5], while the current results were obtained directly from cross-sectional distributions of optimal smoothing coefficients.

Attempts to measure the relative power of the sample- vs. method-related explanations for the observed inconsistency were not, however, made. Instead, a 'final' answer of whether or not the accrual net income follows a process similar to a submartingale in the present data was left to be answered by predictive ability tests (to be reported in section 6.5.).

Finally, the medians and means of the distributions for the cash-based operating and net income variables (COI, CNIA and CNIB) indicate that, on average, the optimal smoothing coefficients tended to be substantially lower for these variables than for their accrual counterparts (the medians and means are around .20 for the former while they were around .60 for the latter). Interestingly, this finding falls well in line with the autocorrelation analysis above suggesting a constant process similar to the mean reverting or linear trend model for these variables. Moreover, although the average coefficients are clearly higher than the theoretical value of the pure mean reverting process (.00), the results are quite consistent with the simulation experiments performed by Ball and Watts (1972). They showed that a smoothing coefficient of around .20 can well be expected for time series actually generated by a simulated mean reverting process (ibid. p. 678).

6.4.2. <u>Identified and Estimated ARIMA Models</u>

The frequencies of the orders of identified ARIMA models obtained with employing the Schwarz criterion (see section 5.3.) appear in table 6-8 below. The table reports on the cross-sectional frequencies of different ARIMA models separately in each of the three estimation periods. It also gives parenthesized numbers of firms where ARIMA(0,0,0) and ARIMA(0,1,0), i.e. the mean reverting model and the submartingale, would have been selected if they were included in the feasible model set.

TABLE 6-8: Frequencies of the Identified ARIMA(p,d,q) Models in the Three Estimation Periods (n = 3 * 39 = 117)

Variable:

ARIMA p,d,q	Est. per.	ASA	AOI	ANI	CSA	COI	CNIA	CNIB	Σ
0,0,0	1		(1)	(10)		(21)	(26)	(16)	(74)
	2		(1)	(7)	(1)	(20)	(25)	(23)	(77)
	3		(3)	(5)		(18)	(23)	(24)	(73)
0,0,1	1		1	8		10	13	15	47
	2		3	6		11	16	16	52
	3		5	7		11	11	14	48
0,0,2	1	1	1	2		2	3	2	11
	2	1	1	3	1	1	2	3	12
	3	1	3	2		2	2	1	11
1,0,0	1		11	11	1	14	14	10	61
	2		7	11		14	9	12	53
	3		7	8	1	12	11	13	52
1,0,1	1			1				1	2
	2						1		1
	3								
1,0,2	1			4		3	5	5	17
	2		2	3		3	4	3	15
	3			2		3	7	7	19
2,0,0	1		1			2	2	2	7
	2			1		5	4	1	11
	3			3		3	3	2	11
2,0,1	1							1	1
	2		2						2
	3						1	1	2
2,0,2	1			2		3	1	1	7
	2		1	3		1	1	3	9
	3		2	3			1	1	7
Σ		3	47	80	3	100	111	114	458

(Continued on next page)

TABLE 6-8: (Continued)

Variable:

ARIMA p,d,q	Est. per.	ASA	AOI	ANI	CSA	COI	CNIA	CNIB	Σ
0,1,0	1	(18)	(6)	(4)	(17)	(1)			(46)
	2	(20)	(8)	(4)	(16)	(2)		(1)	(51)
	3	(18)	(4)	(4)	(19)				(45)
0,1,1	1	18	5	3	23	1			50
	2	16	6	3	9	2		1	37
	3	18	4	5	16	1	2		46
0,1,2	1	2	2		1			1	6
	2	2		2	6		1		11
	3	8	3		3	2			16
1,1,0	1	5	7	4	7	3	1		27
	2	7	2	5	5	1			20
	3	5	2	4	6	1	1		19
1,1,1	1								
	2		1						1
	3								
1,1,2	1	11	4	1	4				20
	2	9	4	1	10		1		25
	3	4	6	1	9	2			22
2,1,0	1	1	7	1	3	1		1	14
	2	2	5	1	2	1			11
	3	1	7	3	2	2			15
2,1,1	1								
	2		2						2
	3								
2,1,2	1	1		2					3
	2	2	3		6				11
	3	2		1	2				5
ΣΣ		117	117	117	117	117	117	117	819

(N.B. The totals on the bottom row do not include the parenthesized frequency numbers)

The following conclusions emerge from the frequency numbers in table 6-8. First, the frequencies of identified models seem to be relatively stable across the three estimation periods. This can be seen e.g. from the subtotals in the column on the far right which indicates that within each panel (i.e. for each (p,d,q)) the frequencies are relatively evenly distributed across the three estimation periods. The largest variation, however, can be found for ARIMA(0,1,1), which was identified from 50 time series in the first estimation period while the corresponding frequency was only 37 in the second period. (As can be seen, this variation is mainly due to the CSA variable, for which ARIMA(0,1,1) was identified in 23 and 9 firms in the first and the second estimation period, respectively.) Nevertheless, the general tendency of the table is that the length of the estimation period has an insignificant effect on the identified model structure (the computed chi-square for the dependence between the estimation period and model structure was not significant at any reasonable level). This finding is consistent with the results reported in the above section on optimal smoothing coefficients.

Second, in the unrestricted identification including models (0,0,0) and (0,1,0) in the feasible model range, the former (i.e. the mean reverting model) was commonly identified from the COI CNIA and CNIB series. E.g. from the CNIA series, this model was found in over half of the firms (in 26, 25 and 23 firms) in the three estimation periods. Although not quite so high, the frequencies for COI and CNIB were at about the same level. The submartingale model (0,1,0) was identified from the ASA series in approximately one half of the firms (18, 20 and 18 firms in the three estimation periods, respectively), and, not so surprisingly, it was also encountered with approximately the same frequency in the CSA series. On the whole, the results of the unrestricted identification thus lend support to the findings from autocorrelation analysis, suggesting submartingales for the sales variables and constant processes for the cash-based operating and net income variables.

Third, in the restricted identification from the model set with p+q > 0, the first order moving average of first differences (0,1,1) was most frequently (approximately in a half of the firms) identified for the two sales variables, ASA and CSA. Thus, the table shows that after (0,1,0) the second best model in the Schwarz criterion sense contained one additional parameter in the moving average part of the first differences. With respect to COI, CNIA and CNIB the restricted identification yielded either (1,0,0) or (0,0,1) models, as it can be seen from the concentrations of the frequencies to these models. Thus, after white noise (0,0,0) the behavior of these variables would be best described (in the Schwarz sense) in over half of the firms, either by a first order autoregressive or a moving average model in the levels of the original variable.

Fourth, any conclusions with respect to the other accrual variables, AOI and ANI, are difficult to draw from the table. As can be seen, the frequencies for these variables are scattered over a number of models so that no major concentrations can be observed in any particular model type. Even in the unrestricted identification, the submartingale (0,1,0) suggested by the above autocorrelation analysis seems to have frequency numbers that are no larger than 4 - 8 firms or 10% - 20% of the whole sample.

Fifth, as a general tendency, mixed models with p <u>and</u> q > 0 seem to be relatively uncommon in the sample. For example, (1,0,1) and (1,1,1) models were identified only three times and once, respectively, in the restricted identification. An exception however, is the mixed model (1,1,2) which was encountered with a frequency comparable to the (1,1,0) model (see the subtotals in the column on the far right).

When the present identification results are compared with those provided in prior studies, benchmarks can be found for the ANI and COI variables. The former has previously been modeled from annual data at least by Albrecht et al. (1977) and Watts and Leftwich (1977), and the latter by Adam (1984) (see the literature review). Despite certain differences between their methodology [7] as well as between their exact variable definitions [8], table 6-9 below suggests that the present identification results contain some common tendencies with these prior studies.

TABLE 6-9: A Comparison of the Frequency Distributions of Identified ARIMA Models for Accrual Net Income and Cash-Based Operating Income between Some Prior Studies and the Present Study

Studies on Accrual Net Income:

ARIMA p,d,q	(1) Albrecht et al. (1977) fr.	%	(2) Watts and Leftwich (1977) fr.	%	(3) Present study fr.	%
0,0,0	1	2.0	0	0.0	22	18.8
0,1,0	9	18.4	0	0.0	11	9.4
p,d,0	17	34.7	16	50.0	39	33.3
0,d,q	16	32.7	16	50.0	24	20.5
p,d,q	6	12.2	0	0.0	21	17.9
Σ	49	100.0	32	100.0	117	100.0

Studies on Cash Operating Income:

ARIMA p,d,q	(4) Adam (1984) Historical cost CF fr.	%	Constant dollar CF fr.	%	(5) Present study fr.	%
0,0,0	28	21.9	49	38.3	59	50.4
0,1,0	19	14.8	4	3.1	3	2.6
p,d,0	66	51.6	62	48.4	30	25.6
0,d,q	15	11.7	13	10.2	10	8.5
p,d,q	0	0.0	0	0.0	15	12.8
Σ	128	100.0	128	100.0	117	100.0

Notes:

(1) See Albrecht et al. (1977, table 1, pp. 230-231); the results are based on a sample of 49 firms and an estimation period of 26 years.
(2) See Watts and Leftwich (1977, table 3, p. 262); the results are based on a sample of 32 firms and an estimation period of 38 years.
(3) The results are based on the unrestricted identification from estimation periods of 25, 28 and 31 years.
(4) See Adam (1984, table 5.1, p. 82 and 5.2, p. 86); his results are based on a sample of 64 firms and estimation periods of 29 and 30 years. Constant dollar cash flows are based on financial statements restated at the 1981 price level.
(5) See note (3). As was explained in section 4.3., the cash flows in this study were computed from historical cost financial statements and the time series were then restated at the 1984 price level.

In regard to the models identified from accrual net income series, the upper panel of the table reveals some common tendencies towards autoregressive and moving average models in the studies compared. These models were encountered in approximately two thirds, all and over one half of the identifications performed in the three studies, respectively. Furthermore, although a number of mean revertings, random walks and mixed models were identified in the present study, they were nevertheless relatively infrequent in all of the studies compared above. Despite these similarities, however, it should be noted that the null hypothesis of identically distributed frequencies across the ARIMA classes can be rejected at significance levels of under 5 % in all of the three pairwise tests between the studies (the chi-square statistics are not reported here).

For the cash-based operating income variable (see the lower panel), similarities between Adam's study and the present one can be seen; both show a tendency towards mean reverting and autoregressive models. Approximately three fourths of all identifications performed by Adam for the historical cost cash flow variable fell into these model categories as was the case with this study, too. Adam identified even a higher proportion (38.3 % + 48.4 % = 86.7 %) of these models from constant dollar cash flow series. Interestingly, the frequency distribution of ARIMAs from the constant dollar series in Adam's study seems to be closer to that of the present study than the distribution of ARIMAs identified from historical cost series. Nevertheless, the distributions are not <u>identical</u>, because the chi-square tests (not reported) rejected the null hypothesis of identical distributions in all pairwise comparisons of the three distributions in the lower panel of table 6-9.

To complete this section, the estimation results of the identified ARIMA models will be briefly discussed below. For that purpose, the numbers and percentages of significant parameters (at 5 % level) in the models identified and estimated from the restricted model range are first reported in table 6-10. Thereafter, the results from the diagnostic checks of the estimated models are summarized in table 6-11.

The percentages of significant parameters appearing in table 6-10 below reveal that of all estimated parameters in all of the estimation periods, approximately one half (54.1 %) were significant at the 5 % level (see the bottom row of the lower panel of table 6-10), and this proportion seems to have remained stable across all three estimation periods (see the percentages 51.8 %, 51.1 % and 59.4 % in the three periods, respectively). This implies that because a large number (almost 50 %) of insignificant parameters were included in the estimated models, the use of the Schwarz criterion for model identification may have produced an overparameterized model set. However, this was not considered to be a serious problem for the study and the strategy of dropping the insignificant parameters from the estimated models was not selected for several reasons.

TABLE 6-10: Number of Estimated Parameters (NEP) and Number of Significant Parameters (NSP) at 5 % Level in ARIMA Models Identified and Estimated from the Three Estimation Periods

ARIMA p,d,q	First estimation period NEP	NSP	%	Second estimation period NEP	NSP	%
0,0,1	47	16	34.0	52	14	26.9
0,0,2	22	16	72.7	24	19	79.2
1,0,0	61	25	41.0	53	18	34.0
1,0,1	4	2	50.0	2	2	100.0
1,0,2	51	34	66.7	45	32	71.1
2,0,0	14	6	42.9	22	10	45.5
2,0,1	3	1	33.3	6	4	66.7
2,0,2	28	10	35.7	36	16	44.4
0,1,1	50	28	56.0	37	21	56.8
0,1,2	12	9	75.0	22	14	63.6
1,1,0	27	11	40.7	20	6	30.0
1,1,1	0	-	-	2	1	50.0
1,1,2	60	36	60.0	75	53	70.7
2,1,0	28	17	60.7	22	10	45.5
2,1,1	0	-	-	6	2	33.3
2,1,2	12	6	50.0	44	17	38.6
Σ	419	217	51.8	468	239	51.1

ARIMA p,d,q	Third estimation period NEP	NSP	%	All estimation periods NEP	NSP	%
0,0,1	48	21	43.8	147	51	34.7
0,0,2	22	18	81.8	68	53	77.9
1,0,0	52	17	32.7	166	60	36.1
1,0,1	0	-	-	6	4	66.7
1,0,2	57	44	77.2	153	110	71.9
2,0,0	22	17	77.3	58	33	56.9
2,0,1	6	4	66.7	15	9	60.0
2,0,2	28	17	60.7	92	43	46.7
0,1,1	46	25	54.3	133	74	55.6
0,1,2	32	19	59.4	66	42	63.6
1,1,0	19	6	31.6	66	23	34.8
1,1,1	0	-	-	2	1	50.0
1,1,2	66	47	71.2	201	136	67.7
2,1,0	30	23	76.7	80	50	62.5
2,1,1	0	-	-	6	2	33.3
2,1,2	20	8	40.0	76	31	40.8
Σ	448	266	59.4	1335	722	54.1

(i) First, the more parsimonious model set including only significant autoregressive and/or moving average parts would not have been optimal in the Schwarz sense. It was considered important to preserve this optimality throughout the study, implying that an overparameterized model with a better (lower) Schwarz criterion value would be preferable to a more parsimonious one with an inferior (higher) criterion value.

(ii) Second, as can be seen from table 6-10, the percentage of significant parameters was especially low for models (0,0,1), (1,0,0) and (1,1,0) which contain almost 30 percent (147 + 166 + 66 = 379) of the estimated parameters (1335). However, since each of these models already contains only a single parameter in autoregressive and moving average parts ($p + q = 1$), more parsimonious models did not exist in the admissible model range of the restricted identification. Thus, the dropping of the insignificant parameters from these models would not have been possible without violating the principle of restricted identification according to which $p + q \geq 1$.

(iii) Third, in the present research design the estimated ARIMA models are mainly used as more sophisticated alternatives of the naive models for predictive purposes. In that design the significance of individual parameters is irrelevant, because important conclusions are not drawn from their estimates at any stage. Unlike some causal models such as regression models, which are frequently used to test the descriptive validity of a priori causal hypotheses, the univariate ARIMA models are non-causal in that no such a priori hypotheses exist, for example with respect to the sign of individual parameter estimates. The significance of individual parameters thus remain relatively unimportant in the present research context.

Finally, it was necessary to perform ordinary diagnostic checking for the estimated ARIMAs in order to determine their feasibility and adequacy in the data. To that end, the number of parameter estimates outside the admissible region imposed by the stationarity and invertibility conditions of ARMA models was counted. In addition, the number of estimated ARIMAs with significant Ljung-Box Q-statistics for the residuals was counted [9]. When interpreting the results of these tests in the following table, it should be noted that the <u>insignificance</u> of the Ljung-Box statistic is indicative of model adequacy, because no significant autocorrelation can then be suspected in the residuals of the estimated model. (To save space and because the test results were very similar in the three estimation periods, table 6-11 below shows only aggregate results from the three periods.)

The test results presented in the table below indicate that 128 of the estimated 819 ARIMA models (15.6 %) did not meet the requirements imposed by stationarity or invertibilty conditions on stationary autoregressive-moving average processes (for a summary of these requirements, see e.g. Box and Jenkins, 1976, pp. 176-177). As can be seen from the table, the problem was most frequently encountered in models (0,0,2), (1,0,2), (2,0,2) and (1,1,2), i.e. in models containing two moving-average parameters [10]. However, inadmissible parameters were quite unusual in models with p + q = 1 (that is, in models (0,d,1) and (1,d,0)), which count for 512 (over 60 %) of all the models identified and estimated in the study; only 5 models (approximately 1 %) with inadmissible parameter values could be found from among them.

TABLE 6-11: Summary of the Diagnostic Checks of Estimated ARIMAs from All Estimation Periods

ARIMA p,d,q	NEM	Inadmissible fr.	Inadmissible %	Inadequate fr.	Inadequate %
0,0,1	147	0	0.0	4	2.7
0,0,2	34	20	58.8	0	0.0
1,0,0	166	5	3.0	5	3.0
1,0,1	3	2	66.7	0	0.0
1,0,2	51	25	49.0	7	13.7
2,0,0	29	2	6.9	1	3.4
2,0,1	5	4	80.0	0	0.0
2,0,2	23	15	65.2	3	13.0
0,1,1	133	0	0.0	5	3.8
0,1,2	33	9	27.3	1	3.0
1,1,0	66	0	0.0	4	6.1
1,1,1	1	0	0.0	0	0.0
1,1,2	67	33	49.3	8	11.9
2,1,0	40	2	5.0	2	5.0
2,1,1	2	1	50.0	0	0.0
2,1,2	19	10	52.6	1	5.3
Σ	819	128	15.6	41	5.0

Legend:

NEM: Number of estimated models

Inadmissible: Number of models with parameter estimates in inadmissible region

Inadequate: Number of models with significant Ljung-Box Q-statistic at the 10 % level (see note 9)

It is worthwhile to note that an analysis of the ARIMAs with inadmissible parameter estimates revealed that these models were evenly distributed across different estimation periods, income variables and firms (in the goodness of fit tests (not reported) the chi-square statistics were not significant). Consequently, the occurrence of inadmissible parameter estimates in ARIMA models cannot be attributed to any particular estimation period(s), income variable(s) or firm(s).

Indeed, the causes of the observed inadmissibility in the parameter estimates are difficult to identify precisely. Especially, it remains unclear whether the main source of the problem is attributable to the properties (e.g. the non-stationarity) of the data or to the (ineffective) estimation method used in this study (see note 4 to chapter 5). One can only assume that both of these factors may have a role to play in producing the inadmissible parameter estimates.

As regards the consequences of the inadmissible parameter estimates, what can be done at the very least is not to be overly optimistic about the predictive performance of the estimated ARIMA models because 16 % of them do no meet their underlying assumption. One must also be cautious in interpreting the results of the predictive ability tests for ARIMAs (to be reported in section 6.5.) because the inadmissible parameter estimates may decrease the relative predictive performance of these models. It will also be necessary to analyze the sensitiveness of the predictive ability results with respect to the ARIMA models including inadmissible parameter estimates (see <u>appendix 6-1</u> to this chapter). In order to put the problem into its proper perspective, it can also be seen the other way round; because 84 % of the ARIMA models had their parameter values in the admissible region, a vast majority of all the estimated models did not violate the underlying assumption.

Finally, it can be noted that very little, if any, attention has been paid to the problem in the prior studies of the area. There are at least the following explanations for this state of the art: (i) because the problem has not been encountered in prior studies, there has been no reason to comment on it; or (ii) the problem has been encountered but it has not been recognized. As examples from the former category, the studies by Watts and Leftwich (1977) and Adam (1984) can be mentioned; none of the parameter estimates reported in these studies were in the inadmissible region. As an example from the latter category, Albrecht et al. (1977) can be taken. They report detailed results for 49 ARIMA models (estimated from earnings available to common stockholders) and in 12 models (24 %) the parameter estimates can be found to be in the inadmissible region [11]. Thus, what can be concluded is that the current percentage (16 %) is far from being exceptionally high.

With respect to model inadequacy (see the column on the far right in table 6-11), the estimated ARIMAs did not show any noteworthy deficiencies; in only 5 % of all the models was the Ljung-Box Q-statistic significant at the 10 % level of significance [12]. Being such a small percentage, which is quite comparable with the prior studies referred to above, the problem of model inadequacy cannot thus be regarded as a serious problem in this study. Moreover, model 'inadequacy' per se only means that the model could perhaps be improved by additional parameters. The elimination of inadequacy from the models could therefore take place only at the cost of parsimony, a course of action that is inconsistent with the general philosophy of model building. Finally, it should also be noted that inclusion of additional parameters into the inadequate models would mean loss of the Schwarz optimality on which the model identification was based in this study.

6.4.3. Goodness of Fit of the Time Series Models

The goodness of fit of the competing time series models was examined in the three estimation periods with cross-sectional distributions of coefficients of determination (R^2) and Durbin-Watson (DW) statistics. In order to save space and because remarkable differences did not occur between individual estimation periods, only the pooled results from all three periods are presented in table 6-12.

With the remarks and reservations made in note [13], the following conclusions can be drawn from the table.

(i) For the accrual and cash-based sales (ASA and CSA) the best fitting model proved to be RWWD, as indicated by the quartiles of R^2. Although the differences in the distributions of R^2 are small between different models , it can be noted, however, that the low DW-statistics in constant models (such as LT) reveal significant autocorrelation in their residuals while no such problem can be found in submartingales (RW and RWWD). (For the reasons explained in note [13], the distributions of R^2 for ARIMAs should not be compared with other models for the ASA and CSA series.) Submartingales are thus clearly superior to constant processes, irrespective of whether sales are measured on the accrual or the cash basis.

TABLE 6-12: Quartiles of Coefficients of Determination (R^2) and Durbin-Watson (DW) Statistics for the Time Series Models from All Estimation Periods (n = 117)

Variable & Quartile	RW R^2	RW DW	RWWD R^2	RWWD DW	MR DW	LT R^2	LT DW	EWMA R^2	EWMA DW	ARIMA R^2	ARIMA DW
ASA:											
Q1	.809	1.38	.835	1.73	0.06	.763	0.51	.808	1.34	.079	1.74
Med	.883	1.69	*.899	2.01	0.10	.856	0.74	.873	1.58	.194	1.91
Q3	.924	2.09	.941	2.29	0.18	.915	0.99	.919	1.91	.327	2.00
AOI:											
Q1	.160	1.89	.173	1.96	0.26	.391	0.83	.276	1.59	.189	1.75
Med	.492	2.20	.498	2.26	0.49	*.584	1.10	.500	1.82	.321	1.92
Q3	.726	2.49	.732	2.59	0.80	.723	1.54	.730	1.97	.490	2.05
ANI:											
Q1	-.347	1.82	-.347	1.87	0.52	.047	0.84	-.042	1.57	.118	1.82
Med	.122	2.28	.131	2.28	0.86	.234	1.14	.213	1.84	*.304	1.97
Q3	.411	2.66	.417	2.66	1.22	.519	1.72	.502	2.02	.434	2.06
CSA:											
Q1	.752	1.62	.766	1.87	0.08	.755	0.59	.763	1.53	.039	1.87
Med	.849	1.86	*.857	2.14	0.14	.844	0.84	.843	1.76	.221	1.97
Q3	.914	2.34	.927	2.51	0.23	.901	1.15	.908	1.94	.363	2.03
COI:											
Q1	-1.09	2.62	-1.09	2.62	1.24	.039	1.72	-.132	1.85	.027	1.87
Med	-.659	2.85	-.657	2.84	1.65	*.146	2.03	-.046	2.05	.106	1.96
Q3	-.253	3.01	-.249	3.01	2.07	.350	2.38	.114	2.24	.302	2.06
CNIA:											
Q1	-1.24	2.65	-1.24	2.66	1.61	.017	1.80	-.118	1.87	.008	1.85
Med	-.913	2.84	-.912	2.85	1.88	.051	2.09	-.053	2.11	*.123	1.95
Q3	-.621	3.02	-.612	3.03	2.14	.170	2.35	-.006	2.26	.276	2.01
CNIB:											
Q1	-.988	2.33	-.983	2.34	1.22	.019	1.44	-.077	1.56	.037	1.85
Med	-.555	2.58	-.555	2.59	1.54	.066	1.73	-.048	1.84	*.124	1.95
Q3	-.224	2.88	-.224	2.88	1.90	.179	2.14	.050	2.12	.338	2.01

N.B. For each variable, the highest median R^2 across the models is preceded by an asterix (*)

(ii) At the operating income level (AOI and COI), the best fitting model in terms of least squared residuals is the simple linear trend (LT) whose R^2 tends to be higher than in any other model. Despite this similarity, the conclusion that the two variables behave in a similar manner is quite obviously unwarranted, at least for the following reasons.

First, the distribution of the DW-statistics in the LT models estimated from AOI series show that autocorrelated residuals can be suspected for a large number of series (the median DW is only 1.10, indicating that the null hypothesis of independent residuals can be rejected in at least half of the series). At the same time, while the median R^2 statistics of submartingales are almost as high as that of linear trend ($\approx$ .50 versus .58), their DW-statistics are much higher (see the medians around 2.2), implying that there is no reason to suspect autocorrelation in their residuals. To put it somewhat differently: although the LT model is able to fit the AOI data slightly better, the submartingales are more 'adequate' because their residuals are less autocorrelated.

Second, the different behavior of the accrual and cash-based operating income variables is perhaps even more apparent when one looks at the quartiles of the R^2-statistic of the submartingale models. The drastic difference in the coefficients of determination indicates unambigiously that while submartingales have a moderate fit in accrual operating income series, the fit is very poor in the cash-based series. (For example, while the median R^2 of RWWD is approximately .50 in AOI series, it is as low as -.66 in COI series.) Undoubtedly, such a large difference in the fit of the submartingale models would not be possible, if the underlying processes of these income variables were similar.

(iii) At the net income level (ANI, CNIA and CNIB), the best fitting models in terms of the R^2-statistic turned out to be ARIMAs. However, the median R^2 of these models is not very high; approximately .30 was obtained from the accrual series and only about .12 from the two cash-based series [14]. On the whole, the estimated ARIMA models thus explained an insignificant proportion of the total variance, at least in the cash-based net income series. It is also noteworthy that the performance of submartingales is also extremely poor in the cash-based net income series (see the negative quartiles of R^2) while their fit is not that bad in the accrual net income series (see the positive medians and third quartiles). Therefore, the conclusion which was drawn above for the operating income variables applies here as well; in terms of the goodness of fit, the underlying process of accrual versus cash-based net income can hardly be similar.

6.5. Predictive Ability Results

The results obtained from the analysis of the forecasting performance of the estimated time series models will be reported in three parts. First, the existence of overall differences in the predictive abilities among the time series models are examined in section 6.5.1.. Thereafter, the predictive abilities of the best performing models are tested pairwise with each of their rivals in order to determine the significance of their superiority. The results from these pairwise tests are reported in section 6.5.2.. Finally, in section 6.5.3. the intertemporal correlations of predictive abilities are analyzed in individual firms in order to determine the persistence of the relative performance of the models over time.

6.5.1. Overall Differences in the Predictive Abilities of the Time Series Models

For the reasons explained in chapter 5, the existence of overall differencies in the forecasting performance of the time series models was tested with the non-parametric Friedman two-way analysis of variance (for details of this test, see Siegel, 1956, pp. 166-173).

In order to carry out those tests, a rank order number was first assigned to each of the six time series models according to its relative forecasting performance so that number 1 was assigned to the model with the highest forecasting performance, number 2 to the second best model etc., and finally number 6 to the model with the least accurate forecasts. In all, these rank order numbers were assigned to the models 7371 times, because they were determined separately in each firm (39), for each variable (7), with each accuracy measure (3), on each forecasting horizon (3), and in each prediction period (3). The outcome was a multidimensional rank order matrix where each element can be denoted with the following variable containing subscripts for each of the six dimensions:

$$\text{RANK}(m,f,v,a,h,p) \tag{6-10}$$

where m = time series model (1, ..., 6)
f = firm (1, ..., 39)
v = income variable (1, ..., 7)
a = accuracy measure (1, 2, 3)
h = forecast horizon (1, 2, 3)
p = prediction period (1, 2, 3)

As was already noted in chapter 5, the ranking of the time series model is identical across different accuracy measures with one-period-ahead forecasts, i.e. for each m, f, v and p

$$\text{RANK}(m,f,v,1,1,p) = \text{RANK}(m,f,v,2,1,p) = \text{RANK}(m,f,v,3,1,p) \tag{6-11}$$

Consequently, a part of the rank order matrix (22.2 %) was redundant and was therefore not used in subsequent analysis.

At the next stage, the following sums of rank order numbers were computed over the sample firms separately for each m, v, a, h and p:

$$\text{RANKSUM}(m,v,a,h,p) = \sum_{f=1}^{39} \text{RANK}(m,f,v,a,h,p) \tag{6-12}$$

Now, the existence of differences in the forecasting performance of the time series models could be tested separately for each v, a, h and p by computing the following test statistic [15]:

$$CHI^2(v,a,h,p) = \frac{12}{nk(k+1)} \sum_{m=1}^{6} RANKSUM(m,v,a,h,p)^2 - 3n(k+1) \tag{6-13}$$

where $CHI^2(v,a,h,p)$ = the test statistic approximately distributed as chi-square with (5) degrees of freedom
n = number of firms = 39 ('number of rows')
k = number of models = 6 ('number of columns')

Of course, the same tests could be performed simultaneously from all three prediction periods (p) by pooling them together. In that case, the dimensions of the rank order sums reduce to m, v, a, and h:

$$RANKSUM(m,v,a,h) = \sum_{p=1}^{3} RANKSUM(m,v,a,h,p) \tag{6-14}$$

while the corresponding test statistic $CHI^2(v,a,h)$ becomes three-dimensional.

The chi-square statistic can easily be scaled to the size of the rank order matrix (i.e. the 'number of rows' times 'number of columns') with the following Kendall coefficient of concordance (Siegel, 1956, p. 236):

$$W(v,a,h(,p)) = CHI^2(v,a,h(,p))/[n(k-1)] \tag{6-15}$$

This coefficient can be shown to vary between zero and one depending on the degree of consistence across the 'rows'. In the current setting, the coefficient would be equal to one only if the ranking of the time series models were exactly the same in all of the sample firms (and prediction periods). On the other hand, if there were no consistence among the firms at all, the coefficient would be near zero, implying that there are no significant differences between the predictive abilities of the models.

The empirical results from the predictive ability analysis using the tests briefly described above are summarized separately for each income variable (v) in tables 6-13A through 6-13G below. The tables contain the average rank order numbers of each time series model (m), obtained with each accuracy measure (a), on each forecast horizon (h) and in each prediction period (p). These average rank orders were computed simply by dividing the respective rank order sums (see expression 6-12) by the number of addends (39) in them.

In order to increase readability, the average rank order of the best performing model is preceded by an asterix (*) in each prediction period and for each accuracy measure if the null hypothesis of no differences in the predictive abilities between the models could be rejected at a significance level of under 5 %.

Besides the results from each prediction period, the tables also give corresponding results from the tests where the periods were pooled together. In addition to an asterix (*) having been appended to the average rankings of best performing models whenever the null hypothesis was rejected, the tables also give the marginal significance levels (α) associated with the rejection of the null, as well as the Kendall coefficients of concordance (W) from the pooled tests. (To save space, the marginal significance levels and the coefficients of concordance in individual prediction periods were suppressed from the tables.)

Finally, it should also be noted that the test results reported in the tables below are based on a sample which includes forecasts from ARIMA models containing inadmissible parameter estimates (see table 6-11 in section 6.4.2. showing that these models account for approximately 16 % of the total number of ARIMAs used in the predictive ability tests). In order to determine the marginal effect of these ARIMA models on the overall predictive ability results, the Friedman analysis of variance reported below was repeated (in the pooled periods) excluding the cases of inadmissible ARIMAs from the tests. These results are reported in appendix 6-1 to this chapter. In brief, they show that the proportion of ARIMAs with inadmissible parameter estimates was so small that these models had only a marginal (if any) effect on the overall predictive ability results.

TABLE 6-13A: Average Predictive Ability Ranks for Accrual Sales (ASA)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	2.667	3.282	2.769	2.906	.304	<.001
		RWWD	*2.615	*2.385	*2.718	*2.573		
		MR	5.641	5.410	5.385	5.479		
		LT	3.564	3.487	3.897	3.650		
		EWMA	2.897	3.615	3.154	3.222		
		ARIMA	3.615	2.821	3.077	3.171		
2	MSE	RW	2.872	3.128	2.744	2.915	.294	<.001
		RWWD	*2.718	*2.385	*2.718	*2.607		
		MR	5.487	5.462	5.462	5.470		
		LT	3.205	3.410	3.846	3.487		
		EWMA	2.923	3.513	3.128	3.188		
		ARIMA	3.794	3.103	3.103	3.333		
2	MAE	RW	2.846	3.282	*2.795	2.974	.283	<.001
		RWWD	*2.821	*2.333	2.821	*2.658		
		MR	5.487	5.462	5.359	5.436		
		LT	3.282	3.410	4.000	3.564		
		EWMA	2.897	3.539	2.872	3.103		
		ARIMA	3.667	2.974	3.154	3.265		
2	ASDE	RW	2.923	3.231	*2.692	2.949	.292	<.001
		RWWD	*2.692	*2.308	2.795	*2.598		
		MR	5.512	5.462	5.436	5.470		
		LT	3.103	3.359	3.821	3.427		
		EWMA	3.000	3.615	3.180	3.265		
		ARIMA	3.769	3.026	3.077	3.291		
3	MSE	RW	3.205	3.231	2.897	3.111	.269	<.001
		RWWD	*2.846	*2.205	*2.667	*2.573		
		MR	4.974	5.539	5.641	5.385		
		LT	3.256	3.462	3.615	3.444		
		EWMA	3.102	3.564	3.282	3.316		
		ARIMA	3.615	3.000	2.897	3.171		
3	MAE	RW	3.154	3.231	2.846	3.077	.273	<.001
		RWWD	*2.846	*2.180	*2.590	*2.539		
		MR	5.077	5.462	5.590	5.376		
		LT	3.282	3.462	3.846	3.530		
		EWMA	3.077	3.590	3.282	3.316		
		ARIMA	3.564	3.077	2.846	3.162		
3	ASDE	RW	3.205	3.231	2.795	3.077	.277	<.001
		RWWD	*2.795	*2.180	*2.667	*2.547		
		MR	5.077	5.487	5.641	5.402		
		LT	3.180	3.539	3.795	3.504		
		EWMA	3.103	3.590	3.128	3.274		
		ARIMA	3.641	2.974	2.974	3.197		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

The predictive ability results for the ASA variable show the indisputable superiority of submartingales in predicting corporate sales. On all forecasting horizons, with each accuracy measure and in each prediction period significant differences could be found between the rankings of the time series models, and in each case, the submartingale models outperformed other models, as can be seen from the average rank order numbers. The results also show that, not so surprisingly, the best model tended to be a random walk with rather than without a drift term (the only exceptions to this general rule can be found in the third period, where the simple RW model had the best ranks on the two-year horizon with MAE and ASDE).

The coefficients of concordance (W) are around .27 - .30, which indicate that the ranking of the models is far from being identical in individual firms and prediction periods. Nevertheless, differences in the ranking totals obtained from pooling the prediction periods together are very significant ($\alpha < 0.1$ %) across all horizons and measures.

As a conclusion, the predictive ability results for the ASA variable fall well in line with the above results from the tests of randomness, autocorrelation analysis and estimation results of the time series models; the results consistently suggest that the underlying stochastic process of corporate sales could be characterized by a submartingale or similar process.

TABLE 6-13B: Average Predictive Ability Ranks for Accrual Operating Income (AOI)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.026	3.539	*2.872	*3.145	.050	<.001
		RWWD	3.359	3.077	3.077	3.171		
		MR	3.667	4.615	4.590	4.291		
		LT	3.846	*2.718	3.923	3.496		
		EWMA	3.487	3.308	3.308	3.368		
		ARIMA	3.615	3.744	3.231	3.530		
2	MSE	RW	3.000	3.462	3.026	3.162	.087	<.001
		RWWD	2.974	2.846	*2.974	*2.932		
		MR	3.846	4.794	4.897	4.513		
		LT	3.795	*2.692	3.410	3.299		
		EWMA	3.487	3.487	3.487	3.487		
		ARIMA	3.897	3.718	3.205	3.607		
2	MAE	RW	3.205	3.615	3.231	3.350	.081	<.001
		RWWD	*2.897	*2.744	3.205	*2.949		
		MR	3.795	4.872	4.821	4.496		
		LT	3.949	*2.744	3.410	3.368		
		EWMA	3.205	3.359	*3.154	3.239		
		ARIMA	3.949	3.667	3.180	3.598		
2	ASDE	RW	2.923	3.462	*3.000	3.128	.081	<.001
		RWWD	3.103	2.974	*3.000	*3.026		
		MR	3.846	4.821	4.872	4.513		
		LT	3.821	*2.795	3.436	3.350		
		EWMA	3.487	3.436	3.385	3.436		
		ARIMA	3.821	3.513	3.308	3.547		
3	MSE	RW	3.026	3.410	3.026	3.154	.148	<.001
		RWWD	*3.000	*2.744	*2.897	*2.880		
		MR	4.385	4.949	5.385	4.906		
		LT	3.821	2.769	3.205	3.265		
		EWMA	3.308	3.487	3.051	3.282		
		ARIMA	3.462	3.641	3.436	3.513		
3	MAE	RW	2.974	3.462	3.026	3.154	.153	<.001
		RWWD	*2.897	*2.744	*2.846	*2.829		
		MR	4.436	5.000	5.282	4.906		
		LT	3.769	2.795	3.282	3.282		
		EWMA	3.231	3.410	3.026	3.222		
		ARIMA	3.692	3.590	3.539	3.607		
3	ASDE	RW	*2.949	3.410	3.026	3.128	.145	<.001
		RWWD	3.026	*2.769	2.974	*2.923		
		MR	4.359	4.974	5.385	4.906		
		LT	3.949	2.872	3.333	3.385		
		EWMA	3.231	3.513	*2.923	3.222		
		ARIMA	3.487	3.462	3.359	3.436		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

The test results of the AOI variable from the pooled periods also reveal a tendency towards the superiority of submartingales; as the column on the far right indicates, very significant differences could be found in the predictive abilities of the models across all horizons and accuracy measures and in each case, a submartingale model produced the most accurate forecasts. However, the coefficients of concordance are much lower than with the ASA variable, indicating the existence of larger differences in the rankings between individual firms (and prediction periods).

With respect to individual prediction periods, the dominance of submartingales is consistent except in the second period, where the linear trend performed best with one- and two-year-ahead forecasts. On the three-year horizon, however, the best model once again turned out to be RWWD.

In brief, the predictive ability results of the AOI variable support the results from the above tests (e.g. autocorrelation analysis); a random walk with drift undoubtedly also provides a fairly good approximation of the underlying process for the accrual income variable at the operating income level.

TABLE 6-13C: Average Predictive Ability Ranks for Accrual Net Income (ANI)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.231	*2.692	3.026	*2.983	.111	<.001
		RWWD	3.205	2.846	*2.923	2.992		
		MR	4.256	4.641	5.026	4.641		
		LT	3.667	3.256	3.487	3.470		
		EWMA	3.410	3.282	3.000	3.231		
		ARIMA	3.231	4.282	3.539	3.684		
2	MSE	RW	3.051	2.974	3.180	3.068	.072	<.001
		RWWD	3.256	*2.821	*3.026	*3.034		
		MR	4.000	4.359	4.769	4.376		
		LT	3.641	3.128	3.205	3.325		
		EWMA	3.564	3.718	3.051	3.444		
		ARIMA	3.487	4.000	3.769	3.752		
2	MAE	RW	3.103	3.103	3.231	3.145	.063	<.001
		RWWD	3.333	*2.923	3.077	*3.111		
		MR	3.846	4.410	4.718	4.325		
		LT	4.026	3.051	3.410	3.496		
		EWMA	3.205	3.564	*2.795	3.188		
		ARIMA	3.487	3.949	3.769	3.735		
2	ASDE	RW	3.103	2.949	3.256	3.103	.071	<.001
		RWWD	3.256	*2.795	*2.923	*2.992		
		MR	4.051	4.359	4.795	4.402		
		LT	3.692	3.205	3.308	3.402		
		EWMA	3.641	3.692	3.205	3.513		
		ARIMA	3.256	4.000	3.513	3.590		
3	MSE	RW	3.077	3.103	3.256	3.145	.066	<.001
		RWWD	3.077	*2.872	*2.923	*2.957		
		MR	4.051	4.077	4.846	4.325		
		LT	3.897	3.180	3.128	3.402		
		EWMA	3.513	3.795	3.103	3.470		
		ARIMA	3.385	3.974	3.744	3.701		
3	MAE	RW	3.154	3.154	3.359	3.222	.055	<.001
		RWWD	3.026	*2.923	*2.949	*2.966		
		MR	4.026	4.205	4.539	4.256		
		LT	3.872	3.000	3.333	3.402		
		EWMA	3.590	3.795	3.154	3.513		
		ARIMA	3.333	3.923	3.667	3.641		
3	ASDE	RW	3.077	3.128	3.256	3.154	.070	<.001
		RWWD	3.000	*2.744	*2.949	*2.897		
		MR	4.000	4.077	4.923	4.333		
		LT	3.923	3.205	3.077	3.402		
		EWMA	3.539	3.821	3.128	3.496		
		ARIMA	3.462	4.026	3.667	3.718		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

The predictive ability results for accrual net income are very similar to those of the AOI variable above; very significant differences in the rankings of different models could be found from the pooled periods (see the α-column), coefficients of concordance (W) are at about the same low level and submartingales tended to outperform other models across all horizons and accuracy measures. Furthermore, the results from individual prediction periods indicate that in most cases the RWWD model produced the most accurate forecasts, the only exception being found in the third period where the EWMA models performed best on the two-year horizon according to the mean absolute error.

On the whole, the test results above are thus consistent with the findings from autocorrelation analysis, suggesting a model similar to random walk with drift for the behavior of accrual net income numbers. It is also evident that although the ARIMA models had, on average, the best fit in the estimation periods (see table 6-12), they were nevertheless unable to produce accrual net income forecasts that would have been any better than those given by the simple random walk with drift.

TABLE 6-13D: Average Predictive Ability Ranks for Cash Sales (CSA)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.051	3.231	2.923	3.068	.282	<.001
		RWWD	*2.667	*2.410	*2.872	*2.650		
		MR	5.513	5.641	5.180	5.444		
		LT	3.000	3.769	3.846	3.539		
		EWMA	3.026	3.333	2.923	3.094		
		ARIMA	3.744	2.615	3.256	3.205		
2	MSE	RW	*2.744	3.103	*2.667	*2.838	.274	<.001
		RWWD	2.923	*2.590	3.051	2.855		
		MR	5.410	5.539	5.333	5.427		
		LT	3.051	3.641	3.846	3.513		
		EWMA	2.923	3.436	2.897	3.086		
		ARIMA	3.949	2.692	3.205	3.282		
2	MAE	RW	*2.846	3.359	2.846	3.017	.265	<.001
		RWWD	2.923	*2.539	3.103	*2.855		
		MR	5.436	5.462	5.333	5.410		
		LT	2.974	3.564	3.846	3.461		
		EWMA	2.872	3.359	*2.667	2.966		
		ARIMA	3.949	2.718	3.205	3.291		
2	ASDE	RW	*2.718	3.103	*2.744	2.855	.272	<.001
		RWWD	2.897	*2.564	2.949	*2.803		
		MR	5.410	5.513	5.333	5.419		
		LT	3.103	3.564	3.821	3.496		
		EWMA	2.949	3.539	2.923	3.137		
		ARIMA	3.923	2.718	3.231	3.291		
3	MSE	RW	2.974	3.231	2.923	3.043	.275	<.001
		RWWD	*2.949	*2.308	*2.872	*2.709		
		MR	5.128	5.667	5.513	5.436		
		LT	3.205	3.462	3.692	3.453		
		EWMA	3.077	3.744	3.051	3.291		
		ARIMA	3.667	2.590	2.949	3.068		
3	MAE	RW	3.103	3.333	3.077	3.171	.273	<.001
		RWWD	*2.846	*2.333	*2.846	*2.675		
		MR	5.128	5.667	5.513	5.436		
		LT	3.128	3.359	3.590	3.359		
		EWMA	3.051	3.718	3.051	3.274		
		ARIMA	3.744	2.590	2.923	3.086		
3	ASDE	RW	*2.923	3.256	*2.692	2.957	.282	<.001
		RWWD	*2.923	*2.308	2.923	*2.718		
		MR	5.205	5.667	5.513	5.462		
		LT	3.154	3.436	3.744	3.444		
		EWMA	3.077	3.821	2.923	3.274		
		ARIMA	3.718	2.513	3.205	3.145		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

As one might expect on the basis of the preceding analysis, the main findings from the predictive ability tests for cash sales are very similar to those obtained for its accrual counterpart. In each individual prediction period as well as in the pooled tests, the submartingales were able to outperform other models across most forecast horizons and accuracy measures (the only exception to this general tendency can be found in the third period on the two-year horizon with MAE).

Also, the W-statistics are quite comparable to those of accrual sales: they are approximately .27 - .28 indicating that the degree of consistency across firms (and prediction periods) in the rankings of the models is about as high for the CSA variable as for its accrual counterpart. Moreover, the null hypothesis of non-existent differences in the rank order numbers between different time series models could once again be rejected at significance levels of under 0.1 % across all horizons and accuracy measures in the pooled tests.

Taking into account the similarities in the test results, the main conclusion that can be drawn from them for the CSA variable must, of course, be the same as for ASA. That is, submartingales (RWWD) quite obviously provide the most approximative model of the underlying process for cash-based sales, as they do for accrual sales, too.

TABLE 6-13E: Average Predictive Ability Ranks for Cash Operating Income (COI)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.564	3.385	3.410	3.453	.017	.076
		RWWD	3.872	3.513	3.692	3.692		
		MR	3.564	4.077	3.923	3.855		
		LT	3.615	3.077	3.333	3.342		
		EWMA	3.077	3.282	3.154	3.171		
		ARIMA	3.308	3.667	3.487	3.487		
2	MSE	RW	3.795	3.410	3.436	3.547	.039	<.001
		RWWD	3.846	4.051	3.231	3.709		
		MR	3.769	3.897	4.462	4.043		
		LT	3.000	3.205	*3.103	3.103		
		EWMA	3.026	3.077	3.128	*3.077		
		ARIMA	3.564	3.359	3.641	3.521		
2	MAE	RW	4.128	3.436	3.513	3.692	.054	<.001
		RWWD	3.769	4.308	*3.103	3.727		
		MR	3.795	3.821	4.462	4.026		
		LT	3.051	3.333	3.180	3.188		
		EWMA	*2.872	*2.513	3.128	*2.838		
		ARIMA	3.385	3.590	3.615	3.530		
2	ASDE	RW	3.795	3.462	3.359	3.539	.038	<.001
		RWWD	3.949	3.949	3.308	3.735		
		MR	3.718	3.949	4.462	4.043		
		LT	3.077	3.128	*3.077	*3.094		
		EWMA	3.051	3.231	*3.077	3.120		
		ARIMA	3.410	3.282	3.718	3.470		
3	MSE	RW	3.744	3.103	3.282	3.376	.050	<.001
		RWWD	3.590	3.897	3.180	3.556		
		MR	4.026	4.103	4.590	4.239		
		LT	2.872	3.282	*2.872	*3.009		
		EWMA	3.436	3.205	3.077	3.239		
		ARIMA	3.333	3.410	4.000	3.581		
3	MAE	RW	3.795	3.513	3.180	3.496	.059	<.001
		RWWD	3.692	3.692	*3.128	3.504		
		MR	3.974	4.231	4.718	4.308		
		LT	2.872	3.051	*3.128	*3.017		
		EWMA	3.256	*2.974	3.154	3.128		
		ARIMA	3.410	3.539	3.692	3.547		
3	ASDE	RW	3.487	3.103	3.308	3.299	.051	<.001
		RWWD	3.897	3.846	3.333	3.692		
		MR	4.051	4.128	4.513	4.231		
		LT	2.897	3.256	3.128	*3.094		
		EWMA	3.205	3.282	*2.974	3.154		
		ARIMA	3.462	3.385	3.744	3.530		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

The predictive ability ranks for cash operating income reveal remarkable differences from those of its accrual counterpart (AOI) examined above. In individual prediction periods, significant differences between the rankings of time series models were less frequent and, where such differences could be found, the best model proved to be either exponentially weighted moving average or linear trend (as an exception, RWWD performed best in the third period according to MAE). The superiority of these models could also be found in the tests from the pooled periods, where EWMA tended to produce the most accurate forecasts on one and two-year horizons, whereas LT performed best on three-year horizon.

It can also be noted that the coefficients of concordance (W) are very low (approximately .02 - .05), implying that large differences exist in the rankings of the models in individual firms (and prediction periods). Nevertheless, the null hypothesis of non-existent differences in the predictive abilities of the time series models could be rejected at significance levels of less than 0.1 % on two and three-year horizons and at 7.6 % on the one-year horizon.

In brief, the predictive ability results lend support to the existence of differences in the underlying processes of cash-based versus accrual operating income variable. While the predictive ability tests supported submartingale behavior for the AOI variable, the current results suggest a more constant process for COI.

TABLE 6-13F: Average Predictive Ability Ranks for Cash Net Income A (CNIA)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.667	3.615	3.641	3.641	.028	.005
		RWWD	4.205	4.154	3.795	4.051		
		MR	3.667	3.128	3.231	3.342		
		LT	3.282	3.487	3.744	3.504		
		EWMA	*2.846	3.410	3.308	*3.188		
		ARIMA	3.333	3.205	3.282	3.274		
2	MSE	RW	3.615	3.846	3.513	3.658	.036	<.001
		RWWD	4.205	4.590	3.667	4.154		
		MR	3.564	3.231	3.205	3.333		
		LT	3.077	3.180	3.897	3.385		
		EWMA	3.180	*3.077	3.410	*3.222		
		ARIMA	3.359	*3.077	3.308	3.248		
2	MAE	RW	3.744	4.103	3.615	3.821	.037	<.001
		RWWD	3.923	4.333	3.744	4.000		
		MR	3.769	*3.051	3.205	3.342		
		LT	3.180	3.180	4.077	3.479		
		EWMA	2.897	*3.051	3.000	*2.983		
		ARIMA	3.487	3.282	3.359	3.376		
2	ASDE	RW	3.667	3.923	3.462	3.684	.044	<.001
		RWWD	4.282	4.667	3.667	4.205		
		MR	3.641	3.154	3.205	3.333		
		LT	3.154	3.231	3.769	3.385		
		EWMA	3.231	3.180	3.385	3.265		
		ARIMA	*3.026	*2.846	3.513	*3.128		
3	MSE	RW	3.949	4.026	3.462	3.812	.080	<.001
		RWWD	4.564	4.487	4.231	4.427		
		MR	3.256	3.333	*3.026	3.205		
		LT	3.897	3.154	4.051	3.368		
		EWMA	*2.872	3.128	3.103	*3.034		
		ARIMA	3.462	*2.872	3.128	3.154		
3	MAE	RW	3.769	4.128	3.539	3.812	.064	<.001
		RWWD	4.256	4.590	4.026	4.291		
		MR	3.615	3.231	3.077	3.308		
		LT	*2.872	3.128	4.077	3.359		
		EWMA	*2.872	3.000	*3.051	*2.974		
		ARIMA	3.615	*2.923	3.231	3.256		
3	ASDE	RW	4.103	4.026	3.590	3.906	.097	<.001
		RWWD	4.821	4.513	4.154	4.496		
		MR	3.385	3.333	*2.974	3.231		
		LT	*2.795	3.180	3.923	3.299		
		EWMA	2.846	3.103	3.205	3.051		
		ARIMA	3.051	*2.846	3.154	*3.017		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

The average predictive ability ranks for the first cash net income variable (CNIA) are somewhat inconclusive because depending on the prediction period, forecast horizon and accuracy measure in question, the lowest ranks are scattered over four different models. For example, the MR model proves to be best in the third period and on the three-year horizon according to MSE and ASDE, the LT model in the first period on the three-year horizon according to MAE and ASDE, the EWMA model in the first period on the one-year horizon and on the three-year horizon according to MSE, and the individually identified and estimated ARIMA model in the second prediction period on the three-year horizon according to all accuracy measures. Despite these inconsistencies it can be noted, however, that submartingales (RW and RWWD) did not outperform other models in any prediction period, on any forecast horizon, or with any accuracy measure.

On the one hand, the test results obtained from the pooled prediction periods indicate that submartingales tend to provide the least accurate forecasts across all horizons and accuracy measures. On the other hand, the EWMA model performed best on all horizons according to MSE and MAE, whereas ASDE favored ARIMAs on the two- and three-year horizons. It can also be noted that very significant differences in the predictive abilities could be found in the pooled tests, while the coefficients of concordance remained low.

When the current results for CNIA are contrasted with those obtained for the accrual net income variable (ANI), it seems clear that the best predicting models for the two variables are different from each other; while submartingales do a very good job in predicting accrual numbers, they obviously fail to do so in predicting cash-based numbers (version A).

TABLE 6-13G: Average Predictive Ability Ranks for Cash Net Income B (CNIB)

(H)	(A)	(M)	(P) 1	2	3	1-3	W	α
1	ALL	RW	3.539	3.590	3.667	3.598	.030	.004
		RWWD	4.128	4.051	4.051	4.077		
		MR	3.154	2.872	3.282	*3.103		
		LT	3.282	3.872	3.103	3.419		
		EWMA	3.410	3.308	3.462	3.393		
		ARIMA	3.487	3.308	3.436	3.410		
2	MSE	RW	3.846	3.513	3.590	3.650	.052	<.001
		RWWD	4.615	4.026	4.026	4.222		
		MR	*2.821	3.128	2.846	*2.932		
		LT	3.385	3.436	3.462	3.427		
		EWMA	3.077	3.256	3.692	3.342		
		ARIMA	3.256	3.641	3.385	3.427		
2	MAE	RW	3.744	3.872	3.744	3.786	.042	<.001
		RWWD	4.462	4.026	3.744	4.077		
		MR	*2.923	3.231	3.077	*3.077		
		LT	3.590	3.103	3.744	3.479		
		EWMA	*2.923	3.205	3.256	3.128		
		ARIMA	3.359	3.564	3.436	3.453		
2	ASDE	RW	3.846	3.436	3.641	3.641	.052	<.001
		RWWD	4.692	3.974	4.051	4.239		
		MR	*2.821	3.308	2.744	*2.957		
		LT	3.410	3.641	3.436	3.496		
		EWMA	3.026	3.359	3.641	3.342		
		ARIMA	3.205	3.282	3.487	3.325		
3	MSE	RW	4.026	3.641	3.821	3.829	.093	<.001
		RWWD	4.897	4.231	4.282	4.470		
		MR	*2.410	3.231	*3.103	*2.915		
		LT	3.564	3.333	3.308	3.402		
		EWMA	2.795	3.000	3.385	3.060		
		ARIMA	3.308	3.564	*3.103	3.325		
3	MAE	RW	4.000	3.923	3.667	3.863	.068	<.001
		RWWD	4.615	4.205	3.872	4.231		
		MR	*2.436	*3.000	3.103	*2.846		
		LT	3.513	3.487	3.462	3.487		
		EWMA	3.103	3.026	3.539	3.222		
		ARIMA	3.333	3.359	3.359	3.350		
3	ASDE	RW	3.949	3.821	3.795	3.855	.103	<.001
		RWWD	5.000	4.308	4.333	4.547		
		MR	*2.436	3.256	3.103	*2.932		
		LT	3.487	3.205	3.385	3.359		
		EWMA	2.872	*3.103	3.410	3.128		
		ARIMA	3.256	3.308	*2.974	3.180		

Legend: H = the length of the forecast horizon; A = forecast accuracy measure (see section 5.4.); M = time series model (see section 5.2.); P = prediction period (see section 5.1.); W = Kendall coefficient of concordance; α = marginal significance level for rejecting H0

What was said above about the ability of submartingales to predict the first version of cash net income (CNIA) applies to a large extent for the second version (CNIB) as well; the test results from individual prediction periods and from the pooled periods clearly show the inferiority of RW(WD) models, irrespective of the forecast horizon or accuracy measure in question.

Compared with CNIA, the results for CNIB are more consistent because the lowest average ranks are less scattered over different models. For example, the results from the pooled periods consistently indicate the superiority of the MR model across all horizons and accuracy measures. This model also tended to have lowest ranks in individual periods where significant differences could be found (exceptions can be found, however, in the second and third period where EWMA and ARIMA, respectively, performed best on the three-year horizon according to ASDE).

As was the case with COI and CNIA, the coefficients of concordance computed from the pooled periods also remain low for CNIB. Nevertheless, the chi-square statistics are large enough so that the null hypothesis of equal rank order totals between different models could be rejected at significant levels across all horizons and accuracy measures.

Given these results for CNIB, it can be concluded that the exact definition of cash net income (i.e. whether it is calculated after total investments or after replacements only), does not play a crucial role in determining the relative predictive ability of submartingales. The current results clearly suggest that, contrary to accrual net income, the predictive ability of submartingales is very poor for cash-based net income variables, irrespective of the treatment of investment outlays in their definitions.

6.5.2. Pairwise Tests of Best Performing Models with Their Rivals

The Friedman two-way analysis of variance reported in the preceding section revealed significant differences between the predictive abilities of the tested time series models for all income variables, in most prediction periods, on most forecast horizons and with most forecast accuracy measures. Each time the null hypothesis of non-existent differences in the predictive abilities could be rejected, the average rank order number of the best performing model (in the sense of lowest average rank) was marked with an asterix (*) in tables 6-13A through 6-13G above. The rationale for interpreting the model with the lowest average rank being the 'best performing' model was based on the notion that should the chi-square statistic be large enough to warrant rejecting the null hypothesis, the rank order totals (on which the average ranks were based) would be the best indicators of the true relative performance of the objects analyzed, in this case the time series models (see Siegel 1956, p. 238).

It should be noted, however, that although significant differences could be found in the Friedman tests, they were in a sense 'overall' differences because all of the six models were tested simultaneously. Consequently, it remained unclear whether the 'best performing' model would also be significantly superior to each of its rivals when compared pairwise with them. (Note that in many cases the differences in the average rank orders of the best and the second best models in tables 6-13A through 6-13G were quite small, thus giving rise to suspicion that the differences between the models, when tested pairwise, might well be insignificant.)

In order to obtain some insight into this issue, the predictive abilities of the 'best performing' model achieving the lowest average rank across all firms and prediction periods (see the pooled column 1-3 in tables 6-13A through 6-13G above) were tested pairwise with each rival model, using the binomial test (for details of this test, see Siegel, 1956, p. 36-42). For that purpose, the following rank order differences were computed for each 'best' model (BM), with each of its rival model (RM $\neq$ BM), in each firm (f), for each income variable (v), with each accuracy measure (a), on each horizon (h) and in each prediction period (p):

$$\text{RANKDIF(RM-BM,f,v,a,h,p)} = \text{RANK(RM,f,v,a,h,p)} - \text{RANK(BM,f,v,a,h,p)} \tag{6-16}$$

Now, the sign of the RANKDIF(...) variable indicates the relative performance of the 'best' model vis-a-vis its rival: a positive sign indicates the superiority of BM over RM, while a negative sign indicates the opposite.

The numbers of positive and negative signs in the RANKDIF(...) variables were then computed across all firms (39) and prediction periods (3), thus giving a sample of 117 observations for each test. However, because the tests were performed separately for each rival model (5), for each variable (7), with each accuracy measure (3) and on each forecast horizon (3), the total number of binomial tests was 245 (note that the tests on the one-year horizon were performed with one accuracy measure only). The following tables 6-14A through 6-14G below report the results of these tests.

TABLE 6-14A: Pairwise Predictive Ability Tests for Accrual Sales (ASA)

(H)	(A)	(BM)	(RM)	(n = 117) +	-	α
1	ALL	RWWD	RW	74	43	.003
			MR	107	10	<.001
			LT	76	41	<.001
			EWMA	71	46	.013
			ARIMA	73	44	.005
2	MSE	RWWD	RW	70	47	.021
			MR	108	9	<.001
			LT	74	43	.003
			EWMA	70	47	.021
			ARIMA	75	42	.001
2	MAE	RWWD	RW	67	50	.069
			MR	106	11	<.001
			LT	76	41	<.001
			EWMA	70	47	.021
			ARIMA	72	45	.008
2	ASDE	RWWD	RW	70	47	.021
			MR	107	10	<.001
			LT	73	44	.005
			EWMA	73	44	.005
			ARIMA	75	42	.001
3	MSE	RWWD	RW	77	40	<.001
			MR	105	12	<.001
			LT	73	44	.005
			EWMA	76	41	<.001
			ARIMA	70	47	.021
3	MAE	RWWD	RW	78	39	<.001
			MR	103	14	<.001
			LT	74	43	.003
			EWMA	78	39	<.001
			ARIMA	72	45	.008
3	ASDE	RWWD	RW	77	40	<.001
			MR	106	11	<.001
			LT	74	43	.003
			EWMA	76	41	<.001
			ARIMA	71	46	.013

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
\+ = number of times 'best' model better
\- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

In brief, the test results for the ASA variable appearing in table 6-14A give strong support to the contention that the simple RWWD model is indeed able to outperform each of its rivals in terms of predictive ability; the null hypothesis of equal forecast accuracy between RWWD and other models could be rejected at (very) significant levels across all forecast horizons and accuracy measures in all of the pairwise tests. In particular, it can be noted that the RWWD model consistently proved to beat the constant process with drift (the LT model) implying that, according to the predictive ability criterion, the submartingale model undoubtedly provides a superior approximation of the underlying stochastic process for accrual sales.

TABLE 6-14B: Pairwise Predictive Ability Tests for Accrual Operating Income (AOI)

(n = 117)

(H)	(A)	(BM)	(RM)	+	-	α
1	ALL	RW	RWWD	62	55	>.10
			MR	76	41	<.001
			LT	64	53	>.10
			EWMA	65	52	>.10
			ARIMA	67	50	.069
2	MSE	RWWD	RW	64	53	>.10
			MR	85	32	<.001
			LT	66	51	.098
			EWMA	71	46	.013
			ARIMA	73	44	.005
2	MAE	RWWD	RW	66	51	.098
			MR	83	34	<.001
			LT	67	50	.069
			EWMA	69	48	.032
			ARIMA	72	45	.008
2	ASDE	RWWD	RW	61	56	>.10
			MR	82	35	<.001
			LT	65	52	>.10
			EWMA	68	49	.048
			ARIMA	70	47	.021
3	MSE	RWWD	RW	65	52	>.10
			MR	93	24	<.001
			LT	66	51	.098
			EWMA	70	47	.021
			ARIMA	71	46	.013
3	MAE	RWWD	RW	71	46	.013
			MR	94	23	<.001
			LT	66	51	.098
			EWMA	67	50	.069
			ARIMA	73	44	.005
3	ASDE	RWWD	RW	65	52	>.10
			MR	93	24	<.001
			LT	68	49	.048
			EWMA	64	53	>.10
			ARIMA	70	47	.021

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
\+ = number of times 'best' model better
\- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

The results for the AOI variable reveal that the submartingale models are able to generate more accurate operating income forecasts than most other models in a significantly large number of cases.

Anomalies to this general tendency can be found, however, with respect to the LT and EWMA models e.g. with one-year-ahead forecasts which were more accurately generated by the simple random walk in an insignificantly larger number of cases.

It can also be noted that the MSE and ASDE measures could not significantly discriminate between the submartingales (RW and RWWD) on any horizon. Therefore, in case these measures are the most valid surrogates of a decision maker's loss function, it remains unclear whether a random walk with or without drift provides a better model for predicting accrual operating income.

TABLE 6-14C: Pairwise Predictive Ability Tests for Accrual Net Income (ANI)

(H)	(A)	(BM)	(RM)	(n = 117) +	-	α
1	ALL	RW	RWWD	56	61	>.10
			MR	87	30	<.001
			LT	67	50	.069
			EWMA	69	48	.032
			ARIMA	74	43	.003
2	MSE	RWWD	RW	65	52	>.10
			MR	81	36	<.001
			LT	58	59	>.10
			EWMA	69	48	.032
			ARIMA	74	43	.003
2	MAE	RWWD	RW	58	59	>.10
			MR	78	39	<.001
			LT	63	54	>.10
			EWMA	66	51	.098
			ARIMA	73	44	.005
2	ASDE	RWWD	RW	64	53	>.10
			MR	83	34	<.001
			LT	61	56	>.10
			EWMA	71	46	.013
			ARIMA	73	44	.005
3	MSE	RWWD	RW	66	51	.098
			MR	81	36	<.001
			LT	63	54	>.10
			EWMA	71	46	.013
			ARIMA	75	42	.001
3	MAE	RWWD	RW	67	50	.069
			MR	80	37	<.001
			LT	63	54	>.10
			EWMA	72	45	.008
			ARIMA	73	44	.005
3	ASDE	RWWD	RW	68	49	.048
			MR	83	34	<.001
			LT	61	54	>.10
			EWMA	75	42	.001
			ARIMA	76	41	<.001

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
\+ = number of times 'best' model better
\- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

Test results for the accrual net income variable (ANI) reveal that the frequency of submartingales outperforming most of their rivals was significantly larger than could be expected under the null hypothesis.

An exception to this general finding was encountered in tests with the LT model on the two and three-year horizons, where the frequency of the superiority of submartingales was not large enough to allow rejection of the null with any accuracy measure (in fact, LT and RWWD performed equally well on the two-year horizon according to MSE). However, the previous year's accrual net income numbers tended to provide more accurate forecasts for the following year with significantly ($\alpha \approx 7$ %) larger frequency than the linear trend model.

Similarly to the AOI variable examined above, the tests were not able to discriminate between random walks with and without drift on one and two-year horizons with any accuracy measure. Contrary to AOI however, significant ($\alpha < 10$ %) test results favoring the performance of the drift version could be found at the net income level on the three-year horizon with all measures.

TABLE 6-14D: Pairwise Predictive Ability Tests for Cash Sales (CSA)

(H)	(A)	(BM)	(RM)	(n = 117) +	-	α
1	ALL	RWWD	RW	72	45	.008
			MR	107	10	<.001
			LT	72	45	.008
			EWMA	69	48	.032
			ARIMA	72	45	.008
2	MSE	RW	RWWD	53	64	>.10
			MR	108	9	<.001
			LT	68	49	.048
			EWMA	75	42	.001
			ARIMA	66	51	.098
2	MAE	RWWD	RW	63	54	>.10
			MR	107	10	<.001
			LT	69	48	.032
			EWMA	62	55	>.10
			ARIMA	67	50	.069
2	ASDE	RWWD	RW	64	53	>.10
			MR	107	10	<.001
			LT	69	48	.032
			EWMA	65	52	>.10
			ARIMA	69	48	.032
3	MSE	RWWD	RW	74	43	.003
			MR	104	13	<.001
			LT	72	45	.008
			EWMA	71	46	.013
			ARIMA	64	53	>.10
3	MAE	RWWD	RW	79	38	<.001
			MR	106	11	<.001
			LT	69	48	.032
			EWMA	71	46	.013
			ARIMA	64	53	>.10
3	ASDE	RWWD	RW	71	46	.013
			MR	107	10	<.001
			LT	70	47	.021
			EWMA	70	47	.021
			ARIMA	66	51	.098

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
+ = number of times 'best' model better
- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

Taking into account the similarities in the behavior of accrual and cash-based sales found in the tests that have been reported in preceding sections, it is not surprising that the current pairwise predictive ability tests also gave similar findings between the two variables. In other words, the RWWD model was once again able to beat most, if not all, of its rivals across all horizons and most accuracy measures.

Contrary to the findings for accrual sales, however, a few anomalies could be found for its cash-based counterpart. According to the MAE and ASDE measures, forecasts provided by EWMA were not significantly inferior to those of RWWD on the two-year horizon (note that very significant differences could be found with MSE), and on the three-year horizon ARIMA provided forecasts almost as accurate as RWWD according to the MSE and MAE criteria.

Another difference between the results for ASA and CSA can be found in tests on the two-year horizon. While the results for ASA revealed significant differences between the two versions of submartingales consistently across all horizons and measures (see table 6-14A), such differences could not be found for the CSA variable in table 6-14D on the two-year horizon. This is somewhat mysterious, because the null hypothesis could be rejected at (very) significant levels in tests performed both on the one and three-year horizons.

TABLE 6-14E: Pairwise Predictive Ability Tests for Cash Operating Income (COI)

(n = 117)

(H)	(A)	(BM)	(RM)	+	-	α
1	ALL	EWMA	RW	68	49	.048
			RWWD	70	47	.021
			MR	71	46	.013
			LT	57	60	>.10
			ARIMA	65	52	>.10
2	MSE	EWMA	RW	74	43	.003
			RWWD	70	47	.021
			MR	77	40	<.001
			LT	49	68	.048
			ARIMA	72	45	.008
2	MAE	EWMA	RW	85	32	<.001
			RWWD	72	45	.008
			MR	89	28	<.001
			LT	54	63	>.10
			ARIMA	70	47	.021
2	ASDE	LT	RW	66	51	.098
			RWWD	67	50	.069
			MR	77	40	<.001
			EWMA	67	50	.069
			ARIMA	63	54	>.10
3	MSE	LT	RW	62	55	>.10
			RWWD	63	54	>.10
			MR	82	35	<.001
			EWMA	73	44	.005
			ARIMA	70	47	.021
3	MAE	LT	RW	61	56	>.10
			RWWD	59	58	>.10
			MR	87	30	<.001
			EWMA	71	46	.013
			ARIMA	71	46	.013
3	ASDE	LT	RW	60	57	>.10
			RWWD	64	53	>.10
			MR	80	37	<.001
			EWMA	68	49	.048
			ARIMA	68	49	.048

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
+ = number of times 'best' model better
- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

Pairwise tests for the EWMA and LT models provided some inconclusive results with respect to their predictive superiority over rivals in predicting the COI variable. For example, EWMA was not able to significantly outperform ARIMA with one-year-ahead forecasts, nor did LT on the two-year horizon according to ASDE. Moreover, the three-year-ahead forecasts of the LT model were not significantly superior to those of submartingales with any accuracy measure.

However, when contrasted with corresponding results obtained for the accrual variable (see table 6-14B), the results fall well in line with the preceding analysis, suggesting that submartingales are much better descriptions for AOI than for COI.

This is because, e.g. on the one and two-year horizons submartingales were inferior to EWMA or LT with significant frequency in predicting COI (see table 6-14E), whereas the opposite tended to occur with AOI predictions (e.g. RWWD was significantly superior to LT and EWMA on the two-year horizon with MSE and ASDE when AOI was predicted, see table 6-14B). Furthermore, while RWWD also beat the LT model with significant frequency with the three-year-ahead forecasts for AOI (table 6-14B), LT showed a (insignificant) tendency to outperform submartingales with three-year-ahead forecasts of COI (table 6-14E). On the whole, the pairwise tests for COI are thus congruent with the preceding suggestions obtained in this study with respect to dissimilarities between the accrual and cash-based variables at the operating income level.

TABLE 6-14F: Pairwise Predictive Ability Tests for Cash Net Income A (CNIA)

(n = 117)

(H)	(A)	(BM)	(RM)	+	-	α
1	ALL	EWMA	RW	71	46	.013
			RWWD	72	45	.008
			MR	57	60	>.10
			LT	68	49	.048
			ARIMA	61	56	>.10
2	MSE	EWMA	RW	71	46	.013
			RWWD	75	42	.001
			MR	54	63	>.10
			LT	67	50	.069
			ARIMA	58	59	>.10
2	MAE	EWMA	RW	83	34	<.001
			RWWD	74	43	.003
			MR	65	52	>.10
			LT	70	47	.021
			ARIMA	61	56	>.10
2	ASDE	ARIMA	RW	72	45	.008
			RWWD	75	42	.001
			MR	67	50	.069
			LT	61	56	>.10
			EWMA	61	56	>.10
3	MSE	EWMA	RW	80	37	<.001
			RWWD	84	33	<.001
			MR	54	63	>.10
			LT	73	44	.005
			ARIMA	56	61	>.10
3	MAE	EWMA	RW	77	40	<.001
			RWWD	85	32	<.001
			MR	57	60	>.10
			LT	73	44	.005
			ARIMA	62	55	>.10
3	ASDE	ARIMA	RW	79	38	<.001
			RWWD	82	35	<.001
			MR	67	50	.069
			LT	62	55	>.10
			EWMA	59	58	>.10

Legend:
H = the length of the forecast horizon
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
\+ = number of times 'best' model better
\- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

The results of the pairwise tests for the first version of cash net income (CNIA) clearly show the poor ability of submartingales in predicting this variable; e.g. the EWMA model significantly outperformed RW and RWWD with the MSE and MAE measures across all forecasting horizons. Furthermore, the individually identified and estimated ARIMA models were able to provide more accurate CNIA forecasts than submartingales on the two and three-year horizons according to ASDE. These results are thus in sharp contrast with those obtained for the accrual counterpart (ANI), for which RW and RWWD models performed significantly better than EWMA and ARIMA (see table 6-14C).

Table 6-14F for CNIA also reveal that significant differences between EWMA and ARIMA could not be found on any horizon with any accuracy measure; neither could such differences be found between EWMA and MR with MSE and MAE on any horizon, nor between ARIMA and LT on two- and three year horizons according to ASDE. Therefore, the results with respect to the predictive performance of EWMA and ARIMA with each other as well as with constant processes (MR and LT) remain inconclusive.

TABLE 6-14G: Pairwise Predictive Ability Tests for Cash Net Income B (CNIB)

(n = 117)

(H)	(A)	(BM)	(RM)	+	-	α
1	ALL	MR	RW	69	48	.032
			RWWD	71	46	.013
			LT	63	54	>.10
			EWMA	71	46	.013
			ARIMA	65	52	>.10
2	MSE	MR	RW	70	47	.021
			RWWD	73	44	.005
			LT	71	46	.013
			EWMA	73	44	.005
			ARIMA	72	45	.008
2	MAE	MR	RW	79	38	<.001
			RWWD	68	49	.048
			LT	70	47	.021
			EWMA	59	58	>.10
			ARIMA	66	51	.098
2	ASDE	MR	RW	70	47	.021
			RWWD	72	45	.008
			LT	72	45	.008
			EWMA	73	44	.005
			ARIMA	69	48	.032
3	MSE	MR	RW	77	40	<.001
			RWWD	80	37	<.001
			LT	71	46	.013
			EWMA	67	50	.069
			ARIMA	66	51	.098
3	MAE	MR	RW	76	41	<.001
			RWWD	77	40	<.001
			LT	74	43	.003
			EWMA	76	41	<.001
			ARIMA	66	51	.098
3	ASDE	MR	RW	78	39	<.001
			RWWD	80	37	<.001
			LT	77	40	<.001
			EWMA	68	49	.048
			ARIMA	62	55	>.10

Legend:
H = the length of the forecast horizon;
A = forecast accuracy measure
BM = 'best' model with lowest average rank
RM = rival model
\+ = number of times 'best' model better
\- = number of times rival model better
α = marginal significance level for rejecting H0 (there is no difference in the forecasting ability of 'best' and rival models) in the binomial test

The results for the second version of cash net income (CNIB) confirm the preceding results for the first version (CNIA) in that submartingales are, indeed, very poor predictors of cash-based net income numbers, irrespective of the forecast horizon or accuracy measure in question, because the simple MR model was able to outperform (very) significantly the RW and RWWD models across all horizons and measures.

It can also be noted that the MR model also tended to outperform most of its other rivals in predicting the CNIB variable; this was the case e.g. with respect to two- and three-years-ahead forecasts when the MSE criterion was used as an accuracy measure.

However, the superiority of the MR model remains insignificant when tested e.g. against ARIMA with one-year-ahead forecasts, against EWMA on the two-year horizon with MAE, and against ARIMA on the three-year horizon according to ASDE. Nevertheless, on horizons longer than one year the MR model was significantly better than the other variant of constant process, viz. the linear trend model. This is somewhat surprising because one might expect a model including a drift to improve or at least to maintain its performance relative to a non-drift version as the length of the forecasting horizon increases. Contrary to that intuitively appealing expectation, however, the results in table 6-14G show that when tested against MR, the relative performance of the drift version (LT) was worse on longer horizons than on the one-year horizon.

6.5.3. Persistence of Relative Predictive Abilities in Individual Firms

The preceding analysis of the existence of overall differences between the predictive power of the time series models (see the Friedman tests reported in section 6.5.1.) revealed some common tendencies across all three prediction periods. For example, it was found that submartingale models tended to be superior predictors of accrual-based income at all income measurement levels (i.e. the sales, operating income and net income levels), irrespective of the particular prediction period in question (i.e. 1976-78, 1979-81, 1982-84), whereas models of a more constant type (EWMA, LT, MR) outperformed submartingales in predicting cash-based income at the operating and net income levels.

It should be recognized that the temporal persistence of the results noted above was based on cross-sectional evidence obtained from the average rank order numbers of the competing time series models computed over the sample firms. The purpose of this section is to provide additional insight into the persistence of relative predictive abilities of the time series models by examining the degree to which the rankings of the models in individual firms remained unchanged over time.

The motivation behind this analysis is two-fold. First, it may provide some evidence for the role firm-specific factors play as determinants of underlying processes. On the one hand, insofar as the $\alpha3$ and $\alpha4$ factors (see 1-1) are of the persistent type (i.e. they show only a little variation over time) and if they are at the same time of primary importance in determining the underlying process at the firm level, then the ranking of the models vis-a-vis each other should remain unchanged in consecutive periods. On the other hand, if the intertemporal correlation in the model ranking is low, it would be an indication either of the unimportance and/or temporal variation of the firm-specific $\alpha3$- and $\alpha4$-factors.

Another reason for analyzing the persistence of model ranking in individual firms is provided by more pragmatic motives. If there proved to exist a high dependence in the model ranking over time, then information of past relative performance of the models could be used to predict their forecasting performance in subsequent periods. Of course, such a finding would be valuable for managerial purposes aiming at forecasting income numbers in individual firms.

The persistence of relative predictive performance of the time series models was examined with the Spearman rank correlation analysis (for details of the computation and use of the Spearman rank correlation coefficient, see Siegel, 1956, pp. 202-213). For that purpose, the correlation coefficients of model rankings between prediction periods 1 and 2 as well as between periods 2 and 3 were computed in each firm (f), for each variable (v), with each accuracy measure (a) and on each forecast horizon (h):

$$\text{SPEARMAN}(f,v,a,h,p) = 1 - \frac{6 \sum_{m=1}^{k} \text{RANKDIF}(m,f,v,a,h,p)^2}{(k\ k\ k) - k} \qquad (6\text{-}17)$$

where

k = number of time series models (= 6)

RANKDIF(m,f,v,a,h,p) =

RANK(m,f,v,a,h,1) - RANK(m,f,v,a,h,2) for rank correlation between periods 1 and 2

RANK(m,f,v,a,h,2) - RANK(m,f,v,a,h,3) for rank correlation between periods 2 and 3

The results from the Spearman rank correlation analysis described above appear in the following tables 6-15A and 6-15B for correlations between the first and the second prediction period and between the second and the third period, respectively. For the sake of brevity, the table reports the distributions of the rank correlation coefficients estimated for the mean square error (MSE) only, because the results from using the other two measures (MAE and ASDE) proved to be very similar to those of MSE, and therefore gave little, if any, additional insight into the main issue regarding persistence of relative predictive abilities in individual firms [16].

Besides the information of the quartiles of rank order correlations for each income variable and each forecast horizon, the tables also give the number of firms (out of 39) in which the estimated correlation coefficient was significantly positive at the 5 % level. (Since six time series models were ranked, the estimated rank order correlation should be equal to or greater than +.829 in order to be significant at the 5 % level in a one-tail test.) Furthermore, for each variable and horizon the number of firms in which the estimated correlation was positive was counted. The null hypothesis of equal numbers of firms with positive and negative correlations was then tested with the binomial test and the marginal significance level for rejecting the null appears in the column on the far right in tables 6-15A and 6-15B.

TABLE 6-15A: Distributions of the Spearman Rank Correlation Coefficients between the Rankings of the Time Series Models in the First and the Second Prediction Period According to Mean Square Error (MSE)

(n = 39)

(V)	(H)	Q1	Med	Q3	Signif.	Posit.	α
ASA	1	.085	.371	.600	6	33	<.001
	2	-.028	.428	.771	6	29	.002
	3	.085	.542	.714	3	31	<.001
AOI	1	-.142	.085	.485	4	22	>.10
	2	-.257	.028	.600	4	21	>.10
	3	-.200	.085	.657	4	20	>.10
ANI	1	-.428	.142	.542	3	23	>.10
	2	-.371	.142	.542	0	21	>.10
	3	-.314	.314	.657	3	24	.100
CSA	1	.085	.257	.485	3	33	<.001
	2	-.028	.371	.771	4	29	.002
	3	.085	.428	.828	7	30	<.001
COI	1	-.485	.142	.600	3	24	.100
	2	-.485	.142	.771	6	20	>.10
	3	-.428	.085	.600	3	21	>.10
CNIA	1	-.600	.028	.657	5	20	>.10
	2	-.428	.142	.542	2	24	.100
	3	-.485	.371	.771	6	24	.100
CNIB	1	-.657	.085	.771	3	20	>.10
	2	-.371	.085	.600	2	21	>.10
	3	-.600	.142	.600	0	20	>.10

Legend:
V = variable
H = the length of the forecast horizon
Q1 = first quartile rank order correlation
Med = median rank order correlation
Q3 = third quartile rank order correlation
Signif. = number of significantly positive rank order correlations at 5 % level (one-tail test)
Posit. = number of positive rank order correlations
α = marginal significance level for rejecting H0 (there is no difference in the numbers of positive and negative rank correlations) in the binomial test

TABLE 6-15B: Distributions of the Spearman Rank Correlation Coefficients between the Rankings of the Time Series Models in the Second and the Third Prediction Period According to Mean Square Error (MSE)

(n = 39)

(V)	(H)	Q1	Med	Q3	Signif.	Posit.	α
ASA	1	-.085	.371	.600	7	29	.002
	2	.085	.314	.600	4	30	<.001
	3	.085	.314	.771	6	33	<.001
AOI	1	-.371	.142	.542	1	21	>.10
	2	-.142	.142	.600	5	26	.027
	3	-.085	.257	.771	5	28	.005
ANI	1	-.028	.314	.771	5	29	.002
	2	.028	.257	.600	3	30	<.001
	3	.142	.485	.657	5	32	<.001
CSA	1	.028	.371	.771	5	31	<.001
	2	.085	.485	.771	5	32	<.001
	3	.200	.485	.828	8	35	<.001
COI	1	-.428	.371	.600	4	25	.054
	2	-.428	.257	.600	3	23	>.10
	3	-.257	.085	.485	5	23	>.10
CNIA	1	-.771	-.085	.600	2	18	>.10
	2	-.600	-.085	.428	1	17	>.10
	3	-.600	-.142	.428	1	16	>.10
CNIB	1	-.657	-.200	.600	2	16	>.10
	2	-.657	-.371	.485	1	13	.027
	3	-.600	.314	.657	3	24	.100

Legend:
V = variable
H = the length of the forecast horizon
Q1 = first quartile rank order correlation
Med = median rank order correlation
Q3 = third quartile rank order correlation
Signif. = number of significantly positive rank order correlations at 5 % level (one-tail test)
Posit. = number of positive rank order correlations
α = marginal significance level for rejecting H0 (there is no difference in the numbers of positive and negative rank correlations) in the binomial test

The main findings from the test results appearing in the above tables are as follows.

First, the correlations of model rankings between consecutive prediction periods proved to be high neither in a large majority of individual firms (see the third quartiles which did not, in general, exceed .6 - .7 for most income variables and horizons) nor on average (see the medians around .1 - .3). Furthermore, the number of firms with significantly positive rank order correlations was rather small (approximately 3 - 4 firms or 10 % of the whole sample), showing that those cases in which the persistence of time series models was significant, are exceptions rather than a rule. On the whole, the low degree of correlation between model rankings over time suggests that there is not much to be gained from the information of past ranking of time series models in individual firms; it seems clear that it is very difficult to predict with high accuracy the future relative performance of time series models vis-a-vis each other with the knowledge of how they have performed in the past.

Another finding emerging from the tables is that, although the rank order correlations proved to be insignificant in most firms, the number of positive correlations was significantly greater than the number of negative correlations for some variables and horizons (see e.g. the results for ASA, AOI, ANI and CSA in table 6-15B). The conclusion from this would be that the firm-specific factors ($\alpha 3$ and $\alpha 4$) are indeed existent and play some role in determining the 'best' underlying processes in the predictive ability sense at the individual firm level. However, it should be noted that because the positiveness of the estimated correlations is not very high in the vast majority of firms, the role of the firm-specific determinants is far from being decisive, or if decisive, they exhibit considerable variation over time. Taken into account that the firm-specific factors may include e.g. firm size, growth, capital intensity, competitive capacity, cost structure, type of control, investment behavior etc. (see the general omega-model), the explanation that the low temporal persistence in the ranking of the models might be due to high variation in these factors, is not very obvious [17]. Consequently, the more likely explanation remains an indecisive (although existent) effect of those factors.

Interestingly, the current results of the importance of firm-specific determinants fall in line with the preceding results from an entirely different test design (see section 6.2., table 6-5A), where the relative importance of economic factors was found to be most prominent at the sales and operating income levels while they turned out to be insignificant at the net income level. In terms of the medians, tables 6-15A and 6-15B are congruent with that finding because higher correlation exists between model rankings at the sales than at the net income level. Moreover, for the cash-based variables, model rankings tended to be higher at the operating income level than at the net income level. The fact that this was not the case in ranking the models for the accrual operating and net income variables (i.e. the median rank correlation turned out to be higher for ANI than for AOI), is not so surprising because the role of the economic determinants relative to accounting determinants quite obviously is smaller under accrual accounting than under the cash accounting system.

Finally, as an interesting anomaly one can note the slight tendency towards negative rank correlations for the cash-based net income variables in table 6-15B. In particular, the significant number of firms with negative correlation in the model rankings for the CNIB variable on the two-year horizon is noteworthy; contrary to the general tendency, the ranking of the predictive abilities of time series models on this horizon in the third prediction period seem to be reverse of what it was in the second period. (A similar, although statistically insignificant result was also obtained for CNIA). Whether this anomaly is a reflection of 'true' reverse in the relative predictive abilities of the models or whether it is more attributable to a statistical sampling error remains, however, an unanswered question.

6.6. Summary of the Empirical Results

The main findings from the empirical inquiry reported in this chapter can be summarized as follows:

6.1. Tests of randomness: Results from the distribution-free tests with numbers of turning points and difference-signs revealed that the null hypothesis of randomness could be rejected in the vast majority of firms for the accrual and cash-based sales (ASA and CSA, respectively), and in approximately half of the firms for the accrual operating and net income variables (AOI and ANI, respectively). In contrast with these results, the tests of the cash-based operating and net income variables (COI, CNIA and CNIB) revealed that the null hypothesis of randomness could not be rejected in the vast majority of firms at any significant level. Furthermore, when the numbers of turning points and difference-signs of the accrual-based variables were compared with their cash-based counterparts in individual firms, it was found that the number of firms in which the deviation from randomness was larger for the accrual variable than for its cash-based counterpart, was significantly larger than the number of firms in which the behavior of the accrual variable was more random than its cash-based counterpart. This result was consistent across all levels of income measurement (i.e. sales, operating income and net income) in both of the distribution-free tests.

Besides the distribution-free tests, the degree of randomness in the income variables was further examined by autocorrelation analysis of original, detrended and differenced time series data. The broad tenor of these results supported the distribution-free tests because the accrual variables (ASA, AOI and ANI) and the cash-based sales (CSA) tended to be more autocorrelated than the cash-based operating and net income variables (COI, CNIA and CNIB). To be more exact, the estimated autocorrelation functions suggested that, on average, the underlying process of all accrual variables as well as cash-based sales might be something like a submartingale (random walk (with drift)), while the mechanism for the behavior of the cash-based operating income and especially the cash-based net income variables presumably might be much better described by a more constant process (a mean reverting or a linear trend model). Also, pairwise comparisons of first lag autocorrelation in the accrual vis-a-vis cash-based variables suggested that the number of firms with a higher autocorrelation in the former was significantly larger than the number of firms with a higher autocorrelation in the latter. Consistent with the distribution-free tests, this result was obtained across all income measurement levels.

In brief, the test results reported in section 6.1. suggest the following:

* Successive <u>changes</u> in the accrual income variables (sales, operating income and net income) as well as in the cash-based counterpart of accrual sales tend to be random, i.e. next year's growth (decline) cannot be predicted on the basis of the growth (decline) observed this year.

* As regards the behavior of cash-based operating and net income, successive <u>changes</u> in these variables tend to be negatively correlated, i.e. a large growth (decline) this year tends to be followed by a decline (growth) next year.

<u>6.2. Cross-sectional dependences in the degree of randomness and tests of the theoretical models:</u> Cross-sectional correlations between the (first order) autocorrelations of accrual and cash-based income variables turned out to be very high and very significant at the sales level, moderate and significant at the operating income level while insignificant correlations near zero were obtained at

the net income level. As a conclusion, the importance of economic factors versus accounting factors proved to be lower the lower income was measured, a finding that is consistent with the intuitively appealing expectation of more profound effect of the (accrual) accounting system on the bottom row than on the top row of an income statement.

The tests of the theoretical models of serial dependence (autocorrelation) in cash-based sales, accrual operating income and cash-based operating income indicated that the models might contain some descriptive validity. This was shown in three ways: first, the cross-sectional correlations between the autocorrelations predicted by the theoretical models and the empirical estimates turned out to be significantly positive (.8 - .9); second, the theoretical models quite correctly predicted a larger autocorrelation for accrual operating income than for its cash-based counterpart in the vast majority (79 %) of the sample firms; and third, the prediction of the theoretical models that a lower autocorrelation might be expected for accrual operating income than for accrual sales turned out to be descriptively valid in virtually all (97 %) of the sample firms.

In brief, the test results of section 6.2. suggest the following:

* If accrual sales are highly (lowly) autocorrelated in a particular firm, then it is <u>very likely</u> that its cash-based counterpart is also highly (lowly) autocorrelated.

* If accrual operating income is highly (lowly) autocorrelated in a particular firm, then it is <u>likely</u> that its cash-based counterpart is also highly (lowly) autocorrelated.

* If accrual net income is highly (lowly) autocorrelated in a particular firm, then it remains <u>uncertain</u> whether its cash-based counterpart is highly (lowly) autocorrelated.

* The effect of the accrual accounting system on the autocorrelation of income variables is more profound the lower the income is measured vertically in the income statement.

* The theoretical models for autocorrelation in income variables at sales and operating income levels turned out to contain some descriptive validity.

<u>6.3. Tests of stationarity:</u> The tests of the equality of the means and variances estimated separately from the first and the second half of the differenced time series data showed that while the null hypothesis of equal means could not be rejected in most firms, the behavior of all income variables turned out to be heteroscedastic in a majority of the firms.

These findings have at least the following implications. First, the equality of means of the first differences provide an ex-post rationalization for the inclusion of linear trend models instead of non-linear (e.g. quadratic) trends into the competing model set. Second, the inequality of variances fall in line with the findings from autocorrelation analysis suggesting submartingale-type models for the accrual-based variables as well as for cash-based sales. On the other hand, the observed heteroscedasticity was inconsistent with the basic assumption of constant processes suggested by autocorrelation analysis for the cash-based operating and net income variables. Furthermore, from a methodological point of view the observed heteroscedasticity suggested that a logarithmic transformation rather than the original form of the time series data should be used for model estimation purposes. However, such a transformation was not applied in subsequent model estimation, primarily because of the frequent negative observations in the data and because prior empirical evidence in the literature shows that logarithmic transformation applied to accounting earnings time series has not been able to increase the predictive ability of estimated time series models.

In brief, the test results reported in section 6.3. suggest the following:

* While <u>average differences</u> observed in the income variables do not increase or decrease significantly over time, the <u>dispersion of differences</u> tends to increase over time. This finding was obtained at all income measurement levels for both the accrual and cash-based variables (expressed at a uniform purchasing power of money).

<u>6.4. Estimation results:</u> The distributions of the optimal smoothing coefficients of the exponentially weighted moving average models (EWMA) showed that, as could be expected from the results of the preceding sections, the median coefficients estimated for the ASA, AOI, ANI and CSA variables were clearly higher (around .60 - .95) than those obtained for COI CNIA and CNIB (approximately .15). Although the broad tenor of these results falls in line with the tentative suggestions provided in preceding sections, some inconsistency was found in the parameter estimates of the AOI and ANI variables; higher values would have been expected insofar as the underlying process of these variables were of a pure submartingale type.

The identification results of the ARIMA models revealed that in the unrestricted identification where submartingales and mean reverting (white noise) processes were included in the feasible model range, the former were identified from the time series of the accrual and cash-based sales and the latter from the time series of cash-based operating and net income in approximately one half of the firms. In the restricted identification, excluding the submartingale and white noise processes, first order moving average models in first differences (0,1,1) were most frequently identified for the sales variables (ASA and CSA), and first order autoregressive models in the levels (1,0,0) for the accrual operating and net income variables (AOI and ANI). For the cash-based operating and net income variables (COI, CNIA and CNIB) the most frequently identified models (restricted identification) turned out to be first order moving averages (0,0,1) and autoregressives (1,0,0) in the levels. It was also found that the (unrestricted) identification results for the ANI and COI variables showed some tendencies common with prior results in the literature. Finally, while on average one half of all estimated parameters of the ARIMA models proved to be insignificant at the 5 % level, the diagnostic checks of the residuals revealed that for 15 % of all ARIMA models estimated in the study inadmissible parameter estimates were obtained and for 5 % of the models inadequacy could be suspected. Being such small percentages, the inadmissibility of parameter estimates and the inadequacy of the identified model structures were not considered to be an overly serious problem in the study.

When the goodness of fit of the competing time series models was examined in the estimation periods, submartingales (random walk with drift) showed superior fit in the ASA and CSA series, the linear trend models in the AOI and COI series, and individually identified ARIMAs in the ANI, CNIA and CNIB series. Consistently with the results of the preceding sections, it was also found that the fit of submartingales in the cash-based operating and net income series (COI, CNIA and CNIB) was very poor, indeed.

In brief, the test results provided in section 6.4. give the following suggestions:

* Random walk models (with drift) had a superior fit in the accrual and cash-based sales series, a linear trend in the accrual and cash-based operating income series, and individually identified ARIMA models in the accrual and cash-based net income series.

* Random walk models (with or without drift) had an extremely poor fit in the cash-based operating and net income series.

<u>6.5. Predictive ability results:</u> The tests of the existence of overall differences between the predictive abilities of different time series models gave positive results; the null hypothesis of non-existent differences among the competing models could be rejected for most variables, in most prediction periods, with most forecast accuracy measures and on most lengths of forecast horizons. The average rank order numbers computed across the sample firms and across the prediction periods revealed that submartingales (RWWD) did the best job of predicting all accrual variables (ASA, AOI and ANI) as well as cash-based sales (CSA) on all forecast horizons irrespective of the accuracy measure in question. However, time series models of the more constant type such as mean reverting, the linear trend and exponentially weighted moving average models were able to generate more accurate forecasts of the cash-based operating and net income variables (COI, CNIA and CNIB) than the submartingale models. Since the pairwise tests of the competing models also gave support to the general finding noted above, it can be concluded that the broad tenor of the predictive ability tests was quite consistent with the tentative suggestions provided in the early sections of the chapter.

Consistently with the findings of prior studies, the predictive ability results provided here lend little support to the usefulness of the univariate Box-Jenkins approach in forecasting income variables, irrespective of the income measurement level and of the accounting system. Presumably, the main reasons for the inefficiency of the Box-Jenkins methodology are attributable to the problems relating to the time series data; at the same time it was too short (to enable reliable estimation of the parameters), and too long (to avoid structural changes). Although a number of adjustments was applied to the data in order to mitigate the problems of structural changes, it turned out, however, that they were inadequate to improve the usefulness of the Box-Jenkins methodology.

Finally, the low persistence in the rankings of the time series models in individual firms revealed that the relative forecasting ability of the models in future prediction periods cannot, in general, be accurately predicted by analyzing their past performance. Nevertheless, the slight tendency towards positive rank correlations observed between consecutive prediction periods can be explained by the existence of firm-specific determinants of the underlying processes.

In brief, the predictive ability tests reported in section 6.5. suggested the following:

* A random walk (with drift) model provides the best predictions for the accrual sales, operating income and net income variables as well as for cash-based sales.

* Random walk models (with or without drift) were clearly outperformed by mean reverting, linear trend or exponentially weighted moving average models in predicting the cash-based operating and net income variables.

* The Box-Jenkins approach to forecasting income variables remains a futile exercise in terms of predictive ability.

* The best forecasting model in an individual firm cannot be determined by observing the performance of the model candidates in the past.

NOTES TO CHAPTER 6:

[1] See Anderson (1976, p. 6) who notes that, in practice, autocovariances and hence autocorrelation coefficients should not be computed for lags greater than N/4. Since the length of the time series data used in this study is over 30 observations (years), the estimation of the autocorrelation function at the first six lags seemed justified.

[2] The proof that autocorrelations estimated from the first differences of original variables are equal to the autocorrelations estimated from the first differences of the residuals obtained from regressing the original variables on time (years) is straightforward. Assume that the following linear trend is estimated for an original variable X(t):

$$X(t) = \beta 0 + \beta 1\ t + e(t)$$

where $\beta 0$ and $\beta 1$ = constant parameters
e(t) = residual from the linear trend

Since $e(t) = X(t) - \beta 0 - \beta 1\ t$ and $e(t+1) = X(t+1) - \beta 0 - \beta 1\ (t+1)$, then the first difference of the residual is:

$$e(t+1) - e(t) = X(t+1) - X(t) - \beta 1$$

Because this holds true with all t, it can be seen that the series of the first differences of the residuals is equal to the series of the first differences of the original variable <u>minus a constant</u> ($\beta 1$). Of course, autocorrelations estimated from the two series are identical.

[3] However, it may be argued that differencing alone is not sufficient to remove non-stationarity in the variance (heteroscedasticity) of a series (see Nelson 1973, p. 58; Asp 1979, p. 260). Note also that when applying (4-2) we have already used a particular transformation which has removed a major part of the non-stationarity from the raw (nominal) time series data. Nevertheless, it is necessary to examine the extent of remaining non-stationarity in the transformed data.

[4] This approach has been suggested by Makridakis (1974b) who recommends its use for analyzing stationarity in the variance. See also Watts and Leftwich (1977) who examined the stationarity of residuals of estimated ARIMA models with this method.

[5] Ball and Watts (1972) assigned the rank orders to different coefficient values according to mean absolute error computed over the estimation period. They note, however, (on p. 675) that "mean absolute error gives almost identical results to those of mean square error (unreported)".

[6] For example, the effect of the methodological differences between the studies could have been controlled by repeating the preceding analysis of optimal smoothing coefficients following the procedures of Ball and Watts (1972) in every single detail.

[7] For example, although not exactly reported, the prior studies compared here presumably employed the original Box-Jenkins

methodology for model identification. As was stated in section 5.3., the Schwarz criterion was used in this study for that purpose.

[8] For example, the operating cash flow analyzed by Adam (1984) was defined after tax, while the current COI variable has been defined before tax because taxes are regarded as financing rather than operating flows in this study. The primary reason for this interpretation is that the final tax amount is basically determined by the profitability of business operations, not vice versa (c.f. the costs of e.g. raw materials, which affect the profitability of operations). Note also that dividends are comparable to taxes in this sense because they undoubtedly are financing rather than operating outflows and are jointly determined by the profitability of the firm and its dividend policy. One can also argue that taxes are not operating outflows because they are not costs relating to the use of production factors (raw materials, work, energy) and are therefore not related to the production function of a firm, nor to any other functional area of business operations (e.g. marketing and administration).

[9] The Ljung-Box Q-statistic is computed as follows (Ljung and Box, 1978, p. 298):

$$Q = N(N+2)\left[\sum_{j=1}^{M} 1/(N-j)\, r(j)^2\right]$$

where N = the number of observations used to estimate the model
r(j) = the jth lag autocorrelation of the residual series
M = the number of lags used to compute Q, for example $M = \min\,[N/2; 3\sqrt{N}]$

As can be seen from the above expression, Q is a summary measure of the first M residual autocorrelations indicating the degree to which the estimated model has been succesful in absorbing the serial dependence from the time series data. Consequently, if the Q-statistic is <u>not</u> significant the estimated model is adequate in the sense that there is no significant serial dependence in the residuals. It can also be noted that the Ljung-Box Q statistic is a modified version (for small samples) of the original portmanteau test statistic, the Box-Pierce Q (see Box and Jenkins, 1976, p. 291). Saikkonen (1985) has compared the properties of time domain tests (such as the preceding one) with some frequency domain tests also applicable for diagnostic checking of time series models. He showed that the former (time domain tests) are superior to the latter because the frequency domain tests "have extremely poor asymptotic properties; their asymptotic relative efficiency (ARE) with respect to the Box-Pierce test turns out to be zero" (ibid., pp. 3-4).

[10] As shown by Box and Jenkins (1976, p. 70), the invertibility conditions for the second order moving average process are

(i) $-1 < \theta 2 < 1$
(ii) $\theta 2 + \theta 1 < 1$
(iii) $\theta 2 - \theta 1 < 1$

It may be worthwhile to note here that, in the current data, the violation of admissible region typically occurred with respect to the third condition (iii). The typical case was that the estimate of θ1 was significantly negative and smaller than -1, while the estimate of θ2 was insignificant and near zero.

[11] For the numbers of inadmissible parameter estimates in the studies referred, see Albrecht et al. (1977, table 1, pp. 230-231), Watts and Leftwich (1977, table 3, p. 262) and Adam (1984, tables A1-A9, pp. 140-159).

[12] Note that the significance level of 10 % was selected for the adequacy tests in order to preserve "conservatism" in these tests.

[13] With respect to table 6-12, the following remarks should be made:

First, for each series and each model, the coefficient of determination (R^2) was computed with the conventional formula (1 - sum of squared residuals/total sum of squares), which gives rise to a few notes: (i) In case of the mean reverting model (MR), the coefficient is, of course, equal to zero and the R^2-column has therefore been suppressed from the table for that model. (ii) If the fit of a model is extremely bad, the sum of squared residuals may exceed the total sum of squares, and hence the coefficient of determination can take negative values. (See e.g. the distribution of R^2 of the RW model for COI, CNIA and CNIB.) The use of the symbol R^2 may seem somewhat misleading in these cases but, nevertheless, it was used in the table, because it is the standard symbol for the purpose. (iii) Because the ARIMA models for ASA and CSA were estimated from the first differences in most firms (97 %), the coefficients of determination of these models are not comparable to to other models for these variables.

Second, the Durbin-Watson statistics of different models are not, strictly speaking, comparable to each other because the number of "explanatory variables" (k) varies across the models. Also, the DW-statistic has not been tabulated for $k = 0$, and therefore exact critical values for the MR model were not available. Nevertheless, as an approximate benchmark at the 5 % level, the following critical values for $k = 1$ and $n = 25$ can be used: $d(L) = 1.29$ and $d(U) = 1.45$. These critical values also serve as useful benchmarks for the ARIMA models, because in a majority of these models (62.5 %) the number of "explanatory variables" was equal to one.

[14] Note that for the ANI variable the distribution of the R^2-statistic of ARIMA models are based on a sample containing 80 (68 %) series estimated from the levels and 37 (32 %) series estimated from the first differences, see table 6-8. The first, second and third quartiles of R^2 from the levels series only were .124, .349 and .465, respectively. The quartiles shown in table 6-12 are thus biased downwards due to the effect of differencing. Similar problem does not occur, however, in the quartiles for CNIA and CNIB, because virtually all ARIMAs (95 - 97 %) were estimated from the levels of these variables.

[15] Strictly speaking, the null hypothesis underlying the Friedman test is that the rank order numbers of different 'columns' come from the same population (Siegel, 1956, p. 166). Since the time series models are in different 'columns' in the current test design, the null hypothesis that there is no difference in the rank orders across 'columns' is equivalent to saying that there is no difference in the predictive abilities of the time series models.

[16] The test results from using the MAE and ASDE measures are available from the author by request.

[17] For example, it is unlikely that any of the sample firms was able to duplicate or triplicate its size or essentially change its capital intensity, cost structure, type of control, or any other firm-specific factor within <u>three</u> years.

APPENDIX 6-1: An Analysis of the Effect of Inadmissible Parameter Estimates in ARIMA Models on the Overall Predictive Ability Results

As was reported in section 6.4.2. (see table 6-11), the Gauss-Newton algorithm used in this study for estimating the final parameter values for ARIMA models produced 128 models (15.6 %) in which the parameter estimates did not meet the stationarity and invertibility requirements of linear autoregressive-moving average processes.

In order to see the marginal effect of these ARIMA models on the overall predictive ability results, the Friedman analysis of variance for overall differences in the predictive abilities of the time series models (see section 6.5.1., tables 6-13A through 6-13G) was repeated, <u>excluding</u> the cases in which the ARIMA models had inadmissible parameter estimates. The results from these tests are reported separately for each variable, for each forecasting horizon and for each forecast accuracy measure in tables APP6-1A through APP6-1G below. For comparative purposes, the tables also give the respective results <u>including</u> the inadmissible cases.

The legend of the symbols used in the tables below are as follows:

- H = the length of the forecast horizon (years)
- A = forecast accuracy measure
- M = time series model
- APAR = average predictive ability rank (computed across firms and prediction periods)
- R = rank of the time series model according to APAR
- W = Kendall coefficient of concordance
- α = marginal significance levels for rejecting H0: there is no overall difference between the predictive abilities of the time series models

In brief, the broad tenor of the test results supports the contention that the inclusion of the ARIMA models with inadmissible parameter estimates has an insignificant effect on the overall predictive ability tests. This can be seen in the marginal difference which the inclusion of those models has (i) on the average predictive ability ranks; (ii) on the ranking of the time series models on the basis of average predictive ability ranks; (iii) on the Kendall coefficient of concordance; and (iv) on the marginal significance level for rejecting H0, all of which remain virtually unchanged between inclusion and exclusion of inadmissible ARIMAs. However, it can be seen from the direction of the change in the APAR statistics that the relative predictive performance of the ARIMA models with inadmissible parameter estimates is inferior to the performance of the models with admissible parameter estimates. This is because the APAR statistics turned out to be consistently slightly better when inadmissible ARIMAs were excluded than when they were included. Nevertheless, the marginal changes in the test statistics remain negligible for each variable, on each forecasting horizon and with each accuracy measure.

TABLE APP6-1A: Average Predictive Ability Ranks (APAR) for Accrual Sales (ASA) Excluding and Including Cases (17) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 100)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	2.920	2	.316	<.001	2.906	2	.304	<.001
		RWWD	2.520	1			2.573	1		
		MR	5.480	6			5.479	6		
		LT	3.760	5			3.650	5		
		EWMA	3.250	4			3.222	4		
		ARIMA	3.070	3			3.171	3		
2	MSE	RW	2.890	2	.298	<.001	2.915	2	.294	<.001
		RWWD	2.590	1			2.607	1		
		MR	5.460	6			5.470	6		
		LT	3.620	5			3.487	5		
		EWMA	3.180	3			3.188	3		
		ARIMA	3.260	4			3.333	4		
2	MAE	RW	2.970	2	.291	<.001	2.974	2	.283	<.001
		RWWD	2.640	1			2.658	1		
		MR	5.450	6			5.436	6		
		LT	3.640	5			3.564	5		
		EWMA	3.090	3			3.103	3		
		ARIMA	3.210	4			3.265	4		
2	ASDE	RW	2.920	2	.294	<.001	2.949	2	.292	<.001
		RWWD	2.590	1			2.598	1		
		MR	5.460	6			5.470	6		
		LT	3.550	5			3.427	5		
		EWMA	3.250	4			3.265	3		
		ARIMA	3.230	3			3.291	4		
3	MSE	RW	3.160	3	.273	<.001	3.111	2	.269	<.001
		RWWD	2.550	1			2.573	1		
		MR	5.390	6			5.385	6		
		LT	3.430	5			3.444	5		
		EWMA	3.380	4			3.316	4		
		ARIMA	3.090	2			3.171	3		
3	MAE	RW	3.140	3	.277	<.001	3.077	2	.273	<.001
		RWWD	2.520	1			2.539	1		
		MR	5.390	6			5.376	6		
		LT	3.480	5			3.530	5		
		EWMA	3.380	4			3.316	4		
		ARIMA	3.090	2			3.162	3		
3	ASDE	RW	3.110	2	.279	<.001	3.077	2	.277	<.001
		RWWD	2.550	1			2.547	1		
		MR	5.410	6			5.402	6		
		LT	3.510	5			3.504	5		
		EWMA	3.300	4			3.274	4		
		ARIMA	3.120	3			3.197	3		

TABLE APP6-1B: Average Predictive Ability Ranks (APAR) for Accrual Operating Income (AOI) Excluding and Including Cases (26) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 91)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	3.044	1	.060	<.001	3.145	1	.050	<.001
		RWWD	3.121	2			3.171	2		
		MR	4.319	6			4.291	6		
		LT	3.637	5			3.496	4		
		EWMA	3.418	3			3.368	3		
		ARIMA	3.462	4			3.530	5		
2	MSE	RW	3.110	2	.095	<.001	3.162	2	.087	<.001
		RWWD	2.868	1			2.932	1		
		MR	4.550	6			4.513	6		
		LT	3.429	3			3.299	3		
		EWMA	3.495	4			3.487	4		
		ARIMA	3.550	5			3.607	5		
2	MAE	RW	3.275	3	.088	<.001	3.350	3	.081	<.001
		RWWD	2.890	1			2.949	1		
		MR	4.528	6			4.496	6		
		LT	3.517	4			3.368	4		
		EWMA	3.242	2			3.239	2		
		ARIMA	3.550	5			3.598	5		
2	ASDE	RW	3.033	2	.093	<.001	3.128	2	.081	<.001
		RWWD	2.956	1			3.026	1		
		MR	4.550	6			4.513	6		
		LT	3.484	4			3.350	3		
		EWMA	3.407	3			3.436	4		
		ARIMA	3.571	5			3.547	5		
3	MSE	RW	3.132	2	.158	<.001	3.154	2	.148	<.001
		RWWD	2.879	1			2.880	1		
		MR	4.967	6			4.906	6		
		LT	3.734	5			3.265	3		
		EWMA	3.231	3			3.282	4		
		ARIMA	3.418	4			3.513	5		
3	MAE	RW	3.143	2	.155	<.001	3.154	2	.153	<.001
		RWWD	2.857	1			2.829	1		
		MR	4.934	6			4.906	6		
		LT	3.385	4			3.282	4		
		EWMA	3.176	3			3.222	3		
		ARIMA	3.506	5			3.607	5		
3	ASDE	RW	3.055	2	.160	<.001	3.128	2	.145	<.001
		RWWD	2.912	1			2.923	1		
		MR	4.956	6			4.906	6		
		LT	3.528	5			3.385	4		
		EWMA	3.154	3			3.222	3		
		ARIMA	3.396	4			3.436	5		

TABLE APP6-1C: Average Predictive Ability Ranks (APAR) for Accrual Net Income (ANI) Excluding and Including Cases (22) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 95)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	2.990	1	.113	<.001	2.983	1	.111	<.001
		RWWD	3.053	2			2.992	2		
		MR	4.705	6			4.641	6		
		LT	3.411	4			3.470	4		
		EWMA	3.263	3			3.231	3		
		ARIMA	3.579	5			3.684	5		
2	MSE	RW	3.095	1	.073	<.001	3.068	1	.072	<.001
		RWWD	3.105	2			3.034	2		
		MR	4.453	6			4.376	6		
		LT	3.295	3			3.325	3		
		EWMA	3.495	4			3.444	4		
		ARIMA	3.558	5			3.752	5		
2	MAE	RW	3.179	1	.062	<.001	3.145	2	.063	<.001
		RWWD	3.190	2			3.111	1		
		MR	4.400	6			4.325	6		
		LT	3.453	4			3.496	4		
		EWMA	3.242	3			3.188	3		
		ARIMA	3.537	5			3.735	5		
2	ASDE	RW	3.105	2	.076	<.001	3.103	2	.071	<.001
		RWWD	3.042	1			2.992	1		
		MR	4.474	6			4.402	6		
		LT	3.379	3			3.402	3		
		EWMA	3.558	5			3.513	4		
		ARIMA	3.442	4			3.590	5		
3	MSE	RW	3.232	2	.066	<.001	3.145	2	.066	<.001
		RWWD	3.042	1			2.957	1		
		MR	4.400	6			4.325	6		
		LT	3.284	3			3.402	3		
		EWMA	3.590	5			3.470	4		
		ARIMA	3.453	4			3.701	5		
3	MAE	RW	3.253	2	.059	<.001	3.222	2	.055	<.001
		RWWD	3.074	1			2.966	1		
		MR	4.347	6			4.256	6		
		LT	3.284	3			3.402	3		
		EWMA	3.611	5			3.513	4		
		ARIMA	3.432	4			3.641	5		
3	ASDE	RW	3.221	2	.071	<.001	3.154	2	.070	<.001
		RWWD	2.968	1			2.897	1		
		MR	4.400	6			4.333	6		
		LT	3.274	3			3.402	3		
		EWMA	3.611	5			3.496	4		
		ARIMA	3.526	4			3.718	5		

TABLE APP6-1D: Average Predictive Ability Ranks (APAR) for Cash Sales (CSA) Excluding and Including Cases (19) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 98)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	3.082	2	.284	<.001	3.068	2	.282	<.001
		RWWD	2.561	1			2.650	1		
		MR	5.408	6			5.444	6		
		LT	3.653	5			3.539	5		
		EWMA	3.153	4			3.094	3		
		ARIMA	3.143	3			3.205	4		
2	MSE	RW	2.857	2	.271	<.001	2.838	2	.274	<.001
		RWWD	2.837	1			2.855	1		
		MR	5.418	6			5.427	6		
		LT	3.531	5			3.513	5		
		EWMA	3.163	3			3.086	3		
		ARIMA	3.194	4			3.282	4		
2	MAE	RW	3.020	2	.258	<.001	3.017	3	.265	<.001
		RWWD	2.847	1			2.855	1		
		MR	5.388	6			5.410	6		
		LT	3.500	5			3.461	5		
		EWMA	3.031	3			2.966	2		
		ARIMA	3.214	4			3.291	4		
2	ASDE	RW	2.878	2	.267	<.001	2.855	2	.272	<.001
		RWWD	2.786	1			2.803	1		
		MR	5.398	6			5.419	6		
		LT	3.520	5			3.496	5		
		EWMA	3.214	4			3.137	3		
		ARIMA	3.204	3			3.291	4		
3	MSE	RW	3.071	3	.272	<.001	3.043	2	.275	<.001
		RWWD	2.765	1			2.709	1		
		MR	5.418	6			5.436	6		
		LT	3.459	5			3.453	5		
		EWMA	3.357	4			3.291	4		
		ARIMA	2.929	2			3.068	3		
3	MAE	RW	3.163	3	.270	<.001	3.171	3	.273	<.001
		RWWD	2.704	1			2.675	1		
		MR	5.418	6			5.436	6		
		LT	3.408	5			3.359	5		
		EWMA	3.296	4			3.274	4		
		ARIMA	3.010	2			3.086	2		
3	ASDE	RW	2.990	2	.278	<.001	2.957	2	.282	<.001
		RWWD	2.755	1			2.718	1		
		MR	5.449	6			5.462	6		
		LT	3.449	5			3.444	5		
		EWMA	3.316	4			3.274	4		
		ARIMA	3.041	3			3.145	3		

TABLE APP6-1E: Average Predictive Ability Ranks (APAR) for Cash Operating Income (COI) Excluding and Including Cases (14) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 103)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	3.447		.015	>.100	3.453		.017	.076
		RWWD	3.680				3.692			
		MR	3.874				3.855			
		LT	3.388				3.342			
		EWMA	3.243				3.171			
		ARIMA	3.369				3.487			
2	MSE	RW	3.515	4	.036	.002	3.547	4	.039	<.001
		RWWD	3.670	5			3.709	5		
		MR	4.078	6			4.043	6		
		LT	3.155	2			3.103	2		
		EWMA	3.107	1			3.077	1		
		ARIMA	3.476	3			3.521	3		
2	MAE	RW	3.680	4	.049	<.001	3.692	4	.054	<.001
		RWWD	3.680	4			3.727	5		
		MR	4.039	6			4.026	6		
		LT	3.272	2			3.188	2		
		EWMA	2.825	1			2.838	1		
		ARIMA	3.495	3			3.530	3		
2	ASDE	RW	3.495	4	.036	.002	3.539	4	.038	<.001
		RWWD	3.718	5			3.735	5		
		MR	4.078	6			4.043	6		
		LT	3.146	1			3.094	1		
		EWMA	3.155	2			3.120	2		
		ARIMA	3.408	3			3.470	3		
3	MSE	RW	3.320	3	.050	<.001	3.376	3	.050	<.001
		RWWD	3.524	4			3.556	4		
		MR	4.272	6			4.239	6		
		LT	3.087	1			3.009	1		
		EWMA	3.243	2			3.239	2		
		ARIMA	3.553	5			3.581	5		
3	MAE	RW	3.447	3	.056	<.001	3.496	3	.059	<.001
		RWWD	3.466	4			3.504	4		
		MR	4.311	6			4.308	6		
		LT	3.058	1			3.017	1		
		EWMA	3.155	2			3.128	2		
		ARIMA	3.563	5			3.547	5		
3	ASDE	RW	3.252	3	.051	<.001	3.299	3	.051	<.001
		RWWD	3.670	5			3.692	5		
		MR	4.262	6			4.231	6		
		LT	3.175	2			3.094	1		
		EWMA	3.155	1			3.154	2		
		ARIMA	3.485	4			3.530	4		

TABLE APP6-1F: Average Predictive Ability Ranks (APAR) for Cash Net Income A (CNIA) Excluding and Including Cases (10) with Inadmissible Parameter Estimates in ARIMAs

(H)	(A)	(M)	Inadmissible ARIMAs excluded (n = 107) APAR	(R)	W	α	Inadmissible ARIMAs included (n = 117) APAR	(R)	W	α
1	ALL	RW	3.636	5	.026	.018	3.641	5	.028	.005
		RWWD	4.000	6			4.051	6		
		MR	3.383	3			3.342	3		
		LT	3.551	4			3.504	4		
		EWMA	3.187	1			3.188	1		
		ARIMA	3.243	2			3.274	2		
2	MSE	RW	3.654	5	.033	.003	3.658	5	.036	<.001
		RWWD	4.122	6			4.154	6		
		MR	3.393	4			3.333	3		
		LT	3.365	3			3.385	4		
		EWMA	3.224	1			3.222	1		
		ARIMA	3.243	2			3.248	2		
2	MAE	RW	3.813	5	.035	.002	3.821	5	.037	<.001
		RWWD	3.963	6			4.000	6		
		MR	3.365	2			3.342	2		
		LT	3.495	4			3.479	4		
		EWMA	2.972	1			2.983	1		
		ARIMA	3.393	3			3.376	3		
2	ASDE	RW	3.673	5	.038	<.001	3.684	5	.044	<.001
		RWWD	4.159	6			4.205	6		
		MR	3.383	4			3.333	3		
		LT	3.365	3			3.385	4		
		EWMA	3.271	2			3.265	2		
		ARIMA	3.150	1			3.128	1		
3	MSE	RW	3.785	5	.079	<.001	3.812	5	.080	<.001
		RWWD	4.439	6			4.427	6		
		MR	3.215	3			3.205	3		
		LT	3.346	4			3.368	4		
		EWMA	3.065	1			3.034	1		
		ARIMA	3.150	2			3.154	2		
3	MAE	RW	3.766	5	.058	<.001	3.812	5	.064	<.001
		RWWD	4.262	6			4.291	6		
		MR	3.308	3			3.308	3		
		LT	3.393	4			3.359	4		
		EWMA	2.991	1			2.974	1		
		ARIMA	3.280	2			3.256	2		
3	ASDE	RW	3.888	5	.093	<.001	3.906	5	.097	<.001
		RWWD	4.477	6			4.496	6		
		MR	3.243	3			3.231	3		
		LT	3.299	4			3.299	4		
		EWMA	3.084	2			3.051	2		
		ARIMA	3.009	1			3.017	1		

TABLE APP6-1G: Average Predictive Ability Ranks (APAR) for Cash Net Income B (CNIB) Excluding and Including Cases (20) with Inadmissible Parameter Estimates in ARIMAs

			Inadmissible ARIMAs excluded (n = 97)				Inadmissible ARIMAs included (n = 117)			
(H)	(A)	(M)	APAR	(R)	W	α	APAR	(R)	W	α
1	ALL	RW	3.619	5	.033	.007	3.598	5	.030	.004
		RWWD	4.103	6			4.077	6		
		MR	3.134	1			3.103	1		
		LT	3.485	4			3.419	4		
		EWMA	3.361	3			3.393	2		
		ARIMA	3.299	2			3.410	3		
2	MSE	RW	3.691	5	.046	<.001	3.650	5	.052	<.001
		RWWD	4.165	6			4.222	6		
		MR	2.979	1			2.932	1		
		LT	3.485	4			3.427	3		
		EWMA	3.381	3			3.342	2		
		ARIMA	3.299	2			3.427	3		
2	MAE	RW	3.845	5	.036	.004	3.786	5	.042	<.001
		RWWD	4.031	6			4.077	6		
		MR	3.186	1			3.077	1		
		LT	3.423	4			3.479	4		
		EWMA	3.237	2			3.128	2		
		ARIMA	3.278	3			3.453	3		
2	ASDE	RW	3.629	5	.049	<.001	3.641	5	.052	<.001
		RWWD	4.196	6			4.239	6		
		MR	2.969	1			2.957	1		
		LT	3.567	4			3.496	4		
		EWMA	3.351	3			3.342	3		
		ARIMA	3.289	2			3.325	2		
3	MSE	RW	3.814	5	.080	<.001	3.829	5	.093	<.001
		RWWD	4.402	6			4.470	6		
		MR	3.000	1			2.915	1		
		LT	3.454	4			3.402	4		
		EWMA	3.103	2			3.060	2		
		ARIMA	3.227	3			3.325	3		
3	MAE	RW	3.928	5	.072	<.001	3.863	5	.068	<.001
		RWWD	4.247	6			4.231	6		
		MR	2.897	1			2.846	1		
		LT	3.495	4			3.487	4		
		EWMA	3.196	2			3.222	2		
		ARIMA	3.237	3			3.350	3		
3	ASDE	RW	3.814	5	.090	<.001	3.855	5	.103	<.001
		RWWD	4.474	6			4.547	6		
		MR	2.929	1			2.932	1		
		LT	3.423	4			3.359	4		
		EWMA	3.155	2			3.128	2		
		ARIMA	3.165	3			3.180	3		

7. SUMMARY AND CONCLUSIONS

As stated in chapter 1, the main objective of this study was to compare the time series properties of accrual and cash-based income variables in order to determine the basic (dis)similarities in the underlying mechanisms of their behavior over time. The main motives for this reseach objective were as follows:

(i) Knowledge of the (dis)similarities between the underlying processes of accrual and cash-based income variables is relevant because it increases our understanding of the effects of the prevailing accrual accounting process on resulting income numbers.

The review of the literature on the time series behavior of financial statement numbers (chapter 2) revealed that the bulk of prior studies have analyzed accounting net income, earnings per share, or rate of return variables from financial statements based on the accruals principle and historical costs. Empirical results obtained from annual data have almost consistently indicated that, on average, accrual accounting earnings tend to behave like a submartingale process (random walk with or without a drift). However, the literature has so far provided neither theoretical nor empirical explanations for the observed tendency towards submartingales. Even the basic question of whether the random walk-type behavior of accrual accounting income is an outcome of the economic factors and transactions underlying the income numbers or whether it is just a product of the accrual accounting system processing those transactions to the income numbers appearing in financial statements, has remained unanswered in the literature.

Consequently, this study was motivated by the aim to probe the relative strength of the industrial-organization-based explanation vis-a-vis the accounting-method-based explanation for the submartingale behavior in accrual income variables. It was assumed that an approach to such a probe might be provided by an analysis of the degree to which the underlying processes of accrual accounting and non-accrual accounting (i.e. cash-based) income variables are similar. To that end, the following alternative hypotheses were defined for the study:

> H0: If the economic factors relating to the <u>industrial-organization-based</u> explanation are of primary importance as determinants of the underlying processes of accrual-based income variables, then <u>similar</u> processes underlie the accrual-based variables and their cash-based (non-accrual) counterparts.
>
> H1: If the accounting choices relating to the <u>accounting-method-based</u> explanation are of primary importance as determinants of the underlying processes of accrual-based income variables, then <u>different</u> processes underlie the accrual-based variables vis-a-vis their cash-based counterparts.

(ii) Other motives for a time series analysis of accrual vis-a-vis cash-based income variables were provided by the implications the underlying mechanisms have for future income expectations. Such expectations are needed in at least the following contexts.

First, tests of the information content of income numbers through measuring market reactions to unexpected income require specificating some kind of expectation model. Therefore, if the information content of accrual and cash-based income variables is to be measured and if market expectations are approximated by models based on past observed behavior of income, then the knowledge of the (dis)similarities in the underlying processes is a prerequisite for those information content tests.

Second, income expectations are also needed for tests and applications of valuation models for corporate shares. For example, the application of the well-known capital asset pricing model (CAPM) developed in the 1960s for the valuation of a firm's securities requires specification of future cash flow expectations in one way or another. Knowledge of the time series behavior of cash flows (or accrual earnings) may provide a starting point for specifying such expectations.

<u>In chapter 3</u>, theoretical models were derived for cash-based sales, accrual operating income and cash-based operating income describing their autocorrelations (at lag one) as functions of the autocovariance and variance of accrual sales. Although these models produced inconclusive results with respect to the equality of the degree of serial dependence in accrual sales and operating income with their cash-based counterparts, the models showed how the answer to the question of whether the accrual variables contain a higher (or lower) autocorrelation than their cash-based counterparts is dependent on the particular parameter values relating these variables to accrual sales and what is the descriptive content of those parameters. Furthermore, the theoretical model for the serial dependence in the accrual operating income indicated why a higher autocorrelation can be expected at the sales level than at the operating income level under the accrual accounting system.

<u>In chapter 4</u>, the following accrual income variables (as reported by the firms) were selected for empirical analysis:

1. Accrual Sales (ASA),
2. Accrual Operating Income (AOI), and
3. Accrual Net Income (ANI)

For the cash-based counterparts, the following variables were defined (in respective order):

4. Cash Sales (CSA),
5. Cash Operating Income (COI),
6. Cash Net Income A (CNIA), and
7. Cash Net Income B (CNIB)

The main reason for the inclusion of two versions of cash net income (CNIA and CNIB) was in the conceptual difficulties encountered in defining a valid counterpart for the investment flows deducted as depreciation in accrual accounting. The first version (CNIA) was defined as cash net income after outlays for replacements only in order to follow the matching principle of the accrual accounting system. The second version (CNIB) was defined after total cash outflows for investments in fixed assets (net of any proceeds from divestitures) in order to follow the line of reasoning in financial theory according to which long-term investments should be deducted in their entirety in the period they realize as cash outflows.

It should be noted that all cash-based variables in the study were computed with the direct method of adjusting the accrual variables with respective changes in the accruals and deferrals relating to them. As an outcome, descriptively valid cash-based counterparts for the accrual-based income variables were obtained in the sense that, for each income measurement level, the inclusion of operating, investment and financing flows was consistent across the two accounting systems.

The empirical time series data describing the behavior of the above variables was obtained from the financial statements of 39 firms listed on the Helsinki Stock Exchange at the end of 1982. The sample of firms used in this study comprised almost 93 % of all manufacturing and trade firms listed on the Helsinki Stock Exchange at that time; only 3 firms had to be omitted from the sample, mainly because complete financial statements were not available from them for the whole time period covered.

Each of the 273 time series (= 39 firms * 7 variables per firm) analyzed in this study covered the 34-year period 1951 - 1984. (As an exception, because one of the sample firms was founded in 1952, the income series of this firm comprised only the 32-year period 1953 - 1984).

The following adjustments were made to the original raw data in order to make them more appropriate for time series analysis: (i) an adjustment for exceptional fiscal years, (ii) an adjustment for the growth pattern in nominal income numbers caused by inflation, and (iii) adjustments for individual outliers and sudden shifts in the level of series. While the inflation adjustment was applied to all the data, adjustments for exceptional fiscal years were needed for only 1.7 % of the total number of firm-years, adjustments for individual outliers for only 0.4 % of the total number of annual observations, and adjustments for sudden shifts in levels for only 0.1 % of the total number of differences in the data.

As the literature review indicated, a lack of well-defined theoretical frameworks guiding empirical inquiries has been typical of this research area. This state of the art was also reflected in the design of the empirical analysis of the present study. Consequently, the general design of the study defined <u>in chapter 5</u> took the form of a comparative empirical inquiry into the time series behavior of the selected income variables. This inquiry involved the following phases:

(i) First, the degree of randomness in the time series data was analyzed with distribution-free tests of the numbers of turning points and difference signs in order to obtain a preliminary picture of the (dis)similarities between the income variables. These tests were further complemented by autocorrelation analysis, which is the standard method in time series analysis. It is worthwhile to note that the autocorrelation analysis was performed not only with the levels of the income variables, but also with detrended and differenced series.

(ii) At the second stage, the following parsimonious univariate time series models were estimated from the data:

A. Submartingale Processes including:
   1. Random Walk (RW)
   2. Random Walk With Drift (RWWD)

B. Constant Processes including:
   3. White Noise or Mean Reverting Process (MR)
   4. Linear Trend (with noise) (LT)

C. Autoregressive and Moving Average Processes including:
   5. Exponentially Weighted Moving Average (EWMA)
   6. (Individually identified) Autoregressive Integrated Moving Average Processes (ARIMA)

Besides parsimony, these models were selected because of their popularity in related prior studies and because they covered a wide range of different stochastic processes in terms of serial correlation and the relevance of the most recent income observations for future expectations.

For estimation purposes, the following three periods were defined:

1. First estimation period: 1951 - 1975 (25 years)
2. Second estimation period: 1951 - 1978 (28 years)
3. Third estimation period: 1951 - 1981 (31 years)

The goodness of fit of the time series models estimated from these periods was examined with such standard statistics as the coefficient of determination and the Durbin-Watson statistic.

(iii) In accordance with the spirit of the predictive ability criterion, the third stage of the empirical analysis consisted of the tests of the predictive powers of the estimated time series models. For that purpose, the following non-overlapping prediction periods consisting of three consecutive years were used:

1. First prediction period: 1976 - 1978
2. Second prediction period: 1979 - 1981
3. Third prediction period: 1982 - 1984

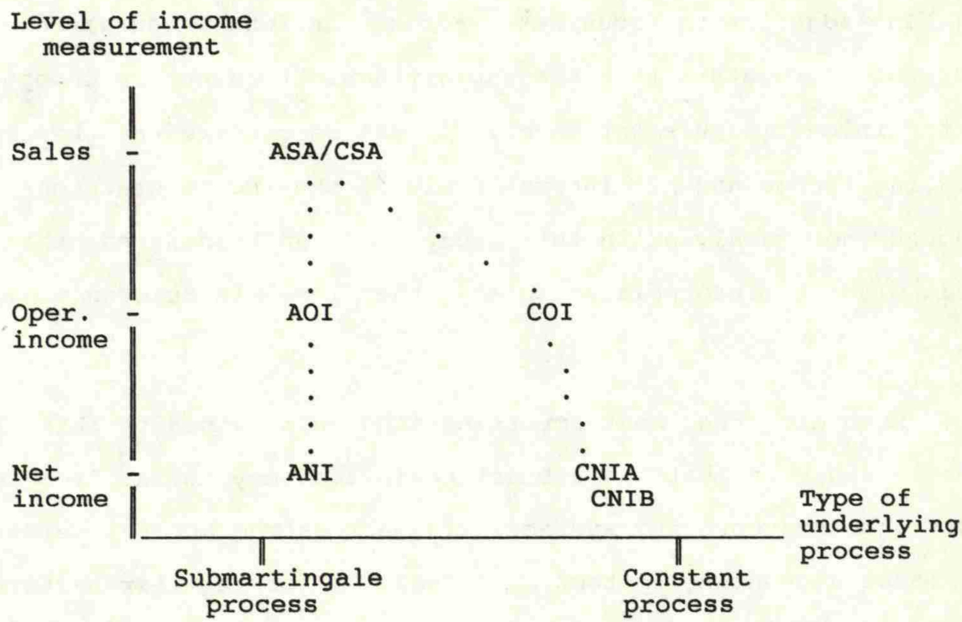
Of course, the models estimated from the first estimation period were tested in the first prediction period etc., so that the same annual income observations were not used for both estimation purposes and for predictive ability analysis.

The predictive performances of the time series models were measured with three different criteria: (i) the Mean Square (Prediction) Error (MSE); (ii) the Mean Absolute (Prediction) Error (MAE); and (iii) the Absolute Sum of Discounted (Prediction) Errors (ASDE). The first two measures (MSE and MAE) were selected because of their wide-spread use and acceptance among researches and practioners, while the third measure (ASDE) was used primarily because of its potential relevance in a valuation context. On the whole, the set of forecast accuracy measures employed in this study covers a wide range of assumptions about the form of the theoretical loss function, which is the ultimate criterion for forecast evaluation. It can also be noted that because each prediction period covered three consecutive years, the forecast performance of the estimated models could be measured with one-year-ahead, two-year-ahead and three-year-ahead forecasts. Thus, the predictive abilities of the models could be analyzed not only across different accuracy measures, but also across three different forecast horizons.

Finally, because the distributional properties of the selected forecast accuracy measures were unknown, the non-parametric Friedman two-way analysis of variance was used as the main method of statistical analysis in the predictive ability tests. By the same reasoning, the Binomial test and the Spearman rank correlation analysis were used, respectively, in pairwise tests of the time series models and in the analysis of the persistence of their predictive performance over time.

The empirical results reported in <u>chapter 6</u> will not be repeated in detail in this concluding chapter. (The reader is referred to section 6.6. for a summary of the test results.) However, the main research findings can be briefly summarized in the following figure:

FIGURE 7-1: Summary of Main Research Findings



(i) First, this study confirmed with data from Finnish firms the prior results obtained elsewhere (e.g. in the U.K., the Netherlands, the U.S.A., Australia and New Zealand) that, on average, the underlying mechanism of the accrual accounting income variables is close to a submartingale or similar process. Because the tendency towards submartingale behavior thus seems to be undisputedly robust across many different countries, it can be concluded that, quite obviously,

* the economy-wide factors varying from country to country, and
* the details of the accrual accounting system (the specific valuation and allocation rules) which also vary to some extent between different countries

play a limited role as determinants of the underlying processes of the accrual accounting income variables.

(ii) In addition to robustness across national boundaries, the figure above suggests that the submartingale tendency is independent of the income measurement level; it can be observed at the sales, operating income and net income levels of the income statement, and, although not analyzed in this study, it can be assumed that the result might be interpolated to any other level in between them, as well.

(iii) However, the most important finding provided by this study strongly suggests that the submartingale tendency is far from being robust across accounting systems, i.e. across the accrual versus the cash-based accounting systems. Although a very similar pattern was observed in the behavior of accrual and cash-based sales, it became obvious that the cash-based variable (COI) already showed markedly different behavior at the operating income level, suggesting that the underlying process might be something like a constant or similar process rather than a submartingale. At the net income level, the deviation from submartingales was even more clear-cut; the underlying processes turned out to be very near pure constant processes such as white noise, presumably without a deterministic trend. Interestingly, this result was obtained irrespective of whether investment outflows for fixed assets were deducted on a replacement basis (as in CNIA) or in their entirety (as in CNIB).

As a conclusion, the main research question motivating this study can be answered as follows:

* As opposed to the industrial-organization-based explanation, the relative strength of the accounting-method-based explanation for the observed (submartingale) patterns in the time series of accrual accounting income numbers is much stronger.

(iv) Although no formal theoretical model completely describing the relationship noted above was presented in this study, the empirical tests of the tentative theoretical models derived for serial dependence in sales and operating income variables showed that they may contain some descriptive validity. The theoretical analysis also provided a descriptively valid explanation for reported sales being more autocorrelated than operating income under the accrual accounting system. On the whole, the theoretical analysis may thus serve as a useful starting point for further elaborations of the causal relationship between the accrual accounting system and the time series properties of the income variables it produces.

Among other implications of the basic research findings described in figure 7-1 above are the following:

(v) Insofar as the time series behavior of corporate cash flows at the net income level is something like a constant process, and if share values are a function of the future expected net cash flows of the firm (as financial theory suggests), then the information content of cash flows can be expected to be much smaller than would be the case if cash flows behaved like a submartingale process. Of course, this is due to the fact that, under a constant process, the most recent cash flow observation is of little importance as a determinant of future cash flow expectations.

(vi) From a purely pragmatical point of view, the research findings imply that, on average, the most accurate univariate forecasts for corporate accrual income at sales, operating as well as net income levels can be obtained simply by looking at the respective number disclosed in the most recent income statement and then adding an appropriate drift to it. However, if corporate cash flows are to be predicted at the operating income level or below it, then the above rule of thumb is far from being optimal. Instead, much more accurate forecasts are provided by simple arithmetic means of past cash flow observations computed over a longer period of time.

Moreover, consistent with prior findings in the area, the predictive ability tests performed in this study showed that, compared with simple rules of thumb, the more sophisticated forecasting approach suggested by Box and Jenkins (1976) may be of limited usefulness, irrespective of whether accrual or cash-based income variables are forecasted. Because the building of ARIMA models for these series seems to remain a futile exercise in terms of forecast accuracy, and because the costs of building such models are much higher than the costs of using the rules of thumb, then the application of the Box-Jenkins approach is certainly not worth the money.

It is important to note the following assumptions and limitations behind the normative suggestions stated above:

First, they concern only the variables examined in this study and therefore may not apply to all variables appearing in financial statements.

Second, they are average results obtained in a sample of firms and therefore may not apply in every individual firm. Moreover, the test results indicated that, in general, one cannot determine the best forecasting model in an individual firm by looking at the past performance of model candidates.

Third, only univariate models were examined in this study. Therefore, it remains unclear whether multivariate models using larger information sets than those included in past time series of the income variables alone, might be more useful.

REFERENCES

Abdel-khalik A.R. and El-sheshai K.M., "Sales Revenues: Time-series Properties and Predictions", Journal of Forecasting (Vol. 2, Iss. 4, 1983), pp. 351-362.

Abdel-khalik A.R. and Thompson R.B., "Research on Earnings Forecasts: The State of The Art", The Accounting Journal (Winter 1977-78), pp. 180-209.

Adam S.T.N., Predictive Ability of Annual Cash Flow Under Historical Cost and Constant Dollar Accounting. Ph.D. Dissertation (Simon Fraser University, 1984).

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

Anderson O.D., Time Series Analysis and Forecasting. The Box-Jenkins approach. (Butterworth & Co Ltd, London 1976).

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

Armstrong J.S., "Relative Accuracy of Judgemental and Extrapolative Methods in Forecasting Annual Earnings", Journal of Forecasting (Vol. 2, Iss. 4, 1983), pp. 437-447.

Artto E., "Money Flow Analyses", Journal of Business Finance & Accounting (Vol. 5, No. 1, 1978), pp. 27-37.

Artto E., "Comparison of the Competitive Capacity of Finnish, Swedish and West German Metal Industry Enterprises 1971-1978", Zeitschrift Für Betriebswirtschaft (August 1982), pp. 754-765.

Artto E., Paperiteollisuuden kansainvälinen kilpailukyky (International competitiveness of the paper industry). (Oy Gaudeamus Ab, Helsinki 1985).

Artto E.W., "Relative Total Costs - An Approach to Competitiveness Measurement of Industries", Management International Review (No. 2, 1987), pp. 47-58.

Asp K., "Cross-Correlations of Cash Flows and Investments in Fixed Assets. Time Series Analysis of Cash Flows of Certain Finnish Companies", The Finnish Journal of Business Economics (No. 3, 1979), pp. 259-270.

Ball R. and Brown P., "An Empirical Evaluation of Accounting Income Numbers", Journal of Accounting Research (Autumn 1968), (In: Lorie, J. and Brealey R., eds., Modern Developments in Investment Management, Praeger 1972, pp. 610-629).

Ball R. and Foster G., "Corporate Financial Reporting: A Methodological Review of Empirical Research", Journal of Accounting Research (Supplement 1982), pp. 161-234.

Ball R. and Watts R., "Some Time Series Properties of Accounting Income", The Journal of Finance (June 1972), pp. 663-682.

Ball R. and Watts R., "Some Additional Evidence on Survival Biases", The Journal of Finance (March 1979), pp. 197-206.

Bao D.H., Lewis M.T., Lin W.T. and Manegold J.G., "Applications of Time-series Analysis in Accounting: A Review", Journal of Forecasting (Vol. 2, Iss. 4, 1983), pp. 405-423.

Barefield R.M. and Comiskey E.E., "The Accuracy of Bank Earnings Forecasts", Business Economics (May 1976), pp. 59-63.

Barnea A. and Lakonishok J., "An Analysis of the Usefulness of Disaggregated Accounting Data for Forecasts of Corporate Performance", Decision Sciences (January 1980), pp. 17-26.

Basi B.A., Carey K.J. and Twark R.D., "A Comparison of the Accuracy of Corporate and Security Analysts' Forecasts of Earnings", The Accounting Review (April 1976), pp. 244-254.

Beaver W.H., "The Time Series Behavior of Earnings", Journal of Accounting Research (Supplement 1970), pp. 62-99.

Beaver W.H. and Dukes R.E., "Interperiod Tax Allocation, Earnings Expectations and the Behavior of Security Prices", The Accounting Review (April 1972), pp. 320-332.

Beaver W.H., Griffin P.A. and Landsman W.R., "The Incremental Information Content of Replacement Cost Earnings", Journal of Accounting and Economics (November 1982), pp. 15-35.

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

Beidleman C.R., "Income Smoothing: The Role of Management", The Accounting Review (October 1973), pp. 653-667.

Bowen R.M., Burgstahler D. and Daley L.A., "Evidence on the Relationships Between Earnings and Various Measures of Cash Flow", The Accounting Review (October 1986), pp. 713-725.

Bowen R.M., Burgstahler D. and Daley L.A., "The Incremental Information Content of Accrual Versus Cash Flows", The Accounting Review (October 1987), pp. 723-747.

Box G.E.P. and Jenkins G.M., Time Series Analysis: Forecasting and Control. Revised Edition. (Holden-Day, San Francisco 1976).

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

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

Brown L.D. and Griffin P.A., "Perspectives on Forecasting Research in Accounting and Finance", Journal of Forecasting (Vol. 2, Iss. 4, 1983), pp. 325-330.

Brown L.D., Hagerman R.L., Griffin P.A. and Zmijewski M.E., "Security Analyst Superiority Relative to Univariate Time-Series Models in Forecasting Quarterly Earnings", Journal of Accounting and Economics (9, 1987), pp. 61-87.

Brown L.D., Richardson G.D. and Schwager S.J., "An Information Interpretation of Financial Analyst Superiority in Forecasting Earnings", Journal of Accounting Research (Spring 1987), pp. 49-67.

Brown L.D. and Rozeff M.S., "The Superiority of Analyst Forecasts as Measures of Expectations: Evidence from Earnings", The Journal of Finance (March 1978), pp. 1-16.

Brown L.D. and Rozeff M.S., "Univariate Time-Series Models of Quarterly Accounting Earnings per Share: A Proposed Model", Journal of Accounting Research (Spring 1979), pp. 179-189.

Brown P. and Ball R., "Some Preliminary Findings on the Association Between the Earnings of a Firm, Its Industry and the Economy", Journal of Accounting Research (Supplement 1967), pp. 1-14.

Brown P., Foster G. and Noreen E., Security Analyst Multi-Year Earnings Forecasts and the Capital Market. Accounting Research Study Series of the American Accounting Association #21 (1985).

Brown P. and Niederhoffer V., "The Predictive Content of Quarterly Earnings", Journal of Business (October 1968), pp. 488-497.

Buzzel R.D., Gale B.T. and Sultan R.G.M., "Market Share - A Key to Profitability", Harvard Business Review (January-February 1975), pp. 97-106.

Carbone R. and Armstrong J.S., "Evaluation of Extrapolative Forecasting Methods: Results of a Survey of Academicians and Practioners", Journal of Forecasting (Vol. 1, Iss. 2, 1982), pp. 215-217.

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

Cheung J.K., The Predictive Relevance of Accounting Income Numbers. Ph.D. Dissertation (University of Michigan, 1977).

Coates R., "The Predictive Content of Interim Reports - A Time Series Analysis", Journal of Accounting Research (Supplement 1972), pp. 132-144.

Cogger K.O., "A Time-Series Analytic Approach to Aggregation Issues in Accounting Data", Journal of Accounting Research (Autumn 1981), pp. 285-298.

Collins D.W., "Predicting Earnings with Sub-Entity Data: Some Further Evidence", Journal of Accounting Research (Spring 1976), pp. 163-177.

Collins W.A. and Hopwood W.S., "A Multivariate Analysis of Annual Earnings Forecasts Generated from Quarterly Forecasts of Financial Analysts and Univariate Time-Series Models", Journal of Accounting Research (Autumn 1980), pp. 390-406.

Conroy R. and Harris R., "Consensus Forecasts of Corporate Earnings: Analysts' Forecasts and Time Series Methods", Management Science (June 1987), pp. 725-738.

Copeland R.M. and Marioni R.J., "Executives' Forecasts of Earnings per Share versus Forecasts of Naive Models", Journal of Business (October 1972), pp. 497-512.

Cragg J.G. and Malkiel B.G., "The Consensus and Accuracy of Some Predictions of the Growth of Corporate Earnings", The Journal of Finance (March 1968), pp. 67-84.

Demski J.S. and Feltman G.A., "Forecast Evaluation", The Accounting Review (July 1972), pp. 533-548.

Deschamps B. and Mehta D.R., "Predictive Ability and Descriptive Validity of Earnings Forecast Models", The Journal of Finance (September 1980), pp. 933-949.

Dharan B.G., "Identification and Estimation Issues for a Causal Earnings Model", Journal of Accounting Research (Spring 1983), pp. 18-41. (1983a)

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

Dharan B.G., "Cash Flow Forecasting and Income Smoothing with Accrual and Cash Flow Accounting", Paper presented at the Annual Meeting of the American Accounting Association (Reno, August 1985).

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

Drtina R.E. and Largay III J.A., "Pitfalls in Calculating Cash Flow from Operations", The Accounting Review (April 1985), pp. 314-326.

Elliot J.W. and Uphoff H.L., "Predicting the Near Term Profit and Loss Statement with an Econometric Model: A Feasibility Study", Journal of Accounting Research (Autumn 1972), pp. 259-274.

Elton E.J. and Gruber M.J., "Earnings Estimates and the Accuracy of Expectational Data", Management Science (April 1972), pp. 409-424.

Fama E.F. and Miller M.H., The Theory of Finance. (Holt, Rinehart and Winston, Inc., 1972)

Fama E.F. and Babiak H., "Dividend Policy: An Empirical Analysis", Journal of The American Statistical Association LXIII (December 1968), pp. 1132-1161.

Foster G., "Quarterly Accounting Data: Time-Series Properties and and Predictive-Ability Results", The Accounting Review (January 1977), pp. 1-21.

Foster G., Financial Statement Analysis. Second Edition (Prentice-Hall, Inc., Englewood Cliffs, New Jersey, 1986)

Freeman R.N., Ohlson J.A. and Penman S.H., "Book Rate-of-Return and Prediction of Earnings Changes: An Empirical Investigation", Journal of Accounting Research (Autumn 1982, Pt. II), pp. 639-653.

Fried D. and Givoly D., "Financial Analysts' Forecasts of Earnings. A Better Surrogate for Market Expectations", Journal of Accounting and Economics (October 1982), pp. 85-108.

Garrod N.W. and Emmanuel C.R., "An Empirical Analysis of the Usefulness of Disaggregated Accounting Data for Forecasts of Corporate Performance", Omega (No. 5, 1987), pp. 371-382.

Gombola M.J. and Ketz E., "A Note on Cash Flow and Classification Patterns of Financial Ratios", The Accounting Review (January 1983), pp. 105-114.

Gonedes N.J., "Income-Smoothing Behavior under Selected Stochastic Processes", Journal of Business (October 1972), pp. 570-584.

Gonedes N.J., "Properties of Accounting Numbers: Models and Tests", Journal of Accounting Research (Autumn 1973), pp. 212-237.

Gonedes N.J. and Dopuch N., "Economic Analyses and Accounting Techniques: Perspectives and Proposals", Report 7644, Center for Mathematical Studies in Business and Economics (University of Chicago, October 1976).

Gonedes N.J. and Roberts H.V., "Statistical Analysis of Random Walks and Near Random Walks", Report 7606, Center for Mathematical Studies in Business and Economics (University of Chicago, February 1976)

Gooijer J.G. de, Abraham B., Gould A. and Robinson L., "Methods for Determining the Order of an Autoregressive-Moving Average Process: A Survey", International Statistical Review (53, 3, 1985), pp. 301-329.

Green D. Jr. and Segall J., "The Predictive Power of First Quarter Earnings Reports", Journal of Business (January 1967), pp. 44-55.

Griffin P.A., "The Time-Series Behavior of Quarterly Earnings: Preliminary Evidence", Journal of Accounting Research (Spring 1977), pp. 71-83.

Haley C.W. and Schall L.D., The Theory of Financial Decisions. Second Edition. (Mc-Graw-Hill, Inc., Tokyo 1979)

Hassel J.M. and Jennings R.H., "Relative Forecast Accuracy and the Timing of Earnings Forecast Announcements", The Accounting Review (January 1986), pp. 58-75.

Hawkins D.F., "Toward An Old Theory Of Equity Valuation", Financial Analysts Journal (November-December 1977), pp. 48-53.

Hendriksen E.S., Accounting Theory. Third Edition. (Richard D. Irwin, Inc., Homewood, Illinois 1977)

Hillmer J.C., Larcker D.F. and Schroeder D.A., "Forecasting Accounting Data: A Multiple Time-series Analysis", Journal of Forecasting (Vol. 2, Iss. 4, 1983), pp. 389-404.

Hopwood W.S., "The Transfer Function Relationship Between Earnings and Market-Industry Indices: An Empirical Study", Journal of Accounting Research (Spring 1980), pp. 77-90. (1980a)

Hopwood W.S., "On the Automation of the Box-Jenkins Modeling Procedures: An Algorithm with an Empirical Test", Journal of Accounting Research (Spring 1980), pp. 289-296. (1980b)

Hopwood W.S. and McKeown J.C., "An Evaluation of Univariate Time-Series Earnings Models and Their Generalization to a Single Input Transfer Function", Journal of Accounting Research (Autumn 1981), pp. 313-322.

Hopwood W.S. and Newbold P., "Time Series Analysis in Accounting: A Survey and Analysis of Recent Issues", Journal of Time Series Analysis (Vol. 1, No. 2, 1980), pp. 135-144.

Hopwood W.S., McKeown J.C. and Newbold P., "Power Transformations in Time-Series Models of Quarterly Earnings per Share", The Accounting Review (October 1981), pp. 927-933.

Hopwood W.S., McKeown J.C. and Newbold P., "The Additional Information Content of Quarterly Earnings Reports: Intertemporal Disaggregation", Journal of Accounting Research (Autumn 1982, Pt.I), pp. 343-349.

Hopwood W.S., Newbold P. and Silhan P.A., "The Potential for Gains in Predictive Ability Through Disaggregation: Segmented Annual Earnings", Journal of Accounting Research (Autumn 1982, Pt.II), pp. 724-732.

Icerman J.D., The Prediction of Corporate Cash Flows: An Analysis of Relevant Models and Presently Available Financial Statement Information. Ph.D. Dissertation (University of North Carolina, Chapel Hill 1977).

Ijiri Y., "Cash-Flow Accounting and Its Structure", Journal of Accounting, Auditing & Finance (1(4), 1978), pp. 331-348.

Imhoff E.A. and Pare D.V., "Analysis and Comparisons of Earnings Forecast Agents", Journal of Accounting Research (Autumn 1982, Pt.I), pp. 429-439.

Jaggi B., "Further Evidence on the Accuracy of Management Forecasts Vis-a-Vis Analysts' Forecasts", The Accounting Review (January 1980), pp. 96-101.

Johnston J., Econometric Methods. (McGraw-Hill Book Company, Inc., Tokyo 1963)

Kendall M.G., Time-Series. (Charles Griffin & Company Limited, London 1973)

Khumawala S.B., Time Series Properties and Predictive Ability of Quarterly Cash Flows: An Empirical Investigation. Ph.D. Dissertation (University of North Carolina, Chapel Hill 1978).

Kinney W.R., "Predicting Earnings: Entity vs. Subentity Data", Journal of Accounting Research (Spring 1971), pp. 127-136.

Kinney W.R., "ARIMA and Regression in Analytical Review: An Empirical Test", The Accounting Review (January 1978), pp. 48-60.

Kinnunen J., "Inflaation huomioonottaminen aikasarja-analyysiin perustuvassa yrityksen tuottoarvon määrityksessä", Helsingin kauppakorkeakoulun työpapereita F-47 (Tammikuu 1983).

Kinnunen J., The Time Series Properties of Corporate Cash Flows: Preliminary Evidence from Some Finnish Firms. Licentiate Thesis (Helsinki School of Economics Publications B-69, Helsinki 1984).

Klaassen J. and Schreuder H., "Confidential Revenue and Profit Forecasts by Management and Financial Analysts: Some First Results", Paper presented to the 5th Congress of The European Accounting Association (Århus, April 1982).

Kodde D.A. and Schreuder H., "Forecasting Corporate Revenue and Profit: Time-Series Models versus Management and Analysts", Journal of Business Finance & Accounting (Autumn 1984), pp. 381-395. (1984a)

Kodde D.A. and Schreuder H., "Optimal Composite Forecasts: A Cross-Sectional Method and an Application", Working Paper (July 1984). (1984b)

Koskela M., Yrityksen tulorahoituksen heilahtelu (The Volatility of Corporate Operating Income). Licentiate Thesis (Helsinki School of Economics Publications B-34, Helsinki 1978).

Koskela M., Osakkeen kassaperusteinen arvonmääritys (Summary: The Market Price of the Share: a Cash Based Approach). Ph.D. Dissertation (Helsinki School of Economics Publications A:43, Helsinki 1984).

Lawson G.H., "The Measurement of Corporate Profitability on a Cash-Flow Basis", The International Journal of Accounting Education and Research (Fall 1980), pp. 11-46.

Lee, T., Cash Flow Accounting. (Van Norstrand Reinhold (UK) Co. Ltd, Great Britain 1984)

Leskinen E., Aika-alueen keinoista mallien rakentamisessa: auto- ja ristikorrelaatioanalyysista. Teoksessa: Aikasarja-analyysin menetelmiä, Suomen Tilastoseuran julkaisuja 4 (Helsinki 1977), s. 78-116.

Lev B., "Industry Averages as Targets for Financial Ratios", Journal of Accounting Research (Autumn 1969), pp. 290-299.

Lev B., "Economic Determinants of Some Time-Series Properties of Earnings", Report 7705, Center for Mathematical Studies in Business and Economics (University of Chicago, January 1977).

Lev B., "Some Economic Determinants of Time-Series Properties of Earnings", Journal of Accounting and Economics (April 1983), pp. 31-48.

Lintner J. and Glauber R., "Higgledy Piggledy Growth in America?" Paper presented to the Seminar on the Analysis of Security Prices (University of Chicago, May 1967). In: Lorie J. and Brealey R., eds., Modern Developments in Investment Management (Praeger 1972), pp. 645-662.

Little I.M.D., "Higgledy Piggledy Growth", Bulletin of The Oxford University Institute of Statistics (November 1962), pp. 387-412.

Ljung G.M. and Box G.E.P., "On a measure of lack of fit in time series models", Biometrika (1978, 65, 2), pp. 297-303.

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., "A Commentary on Research on Earnings Forecasts: The State of the Art", The Accounting Journal (Winter 1977-78), pp. 210-217.

Lorek K.S., "Predicting Annual Net Earnings with Quarterly Earnings Time-Series Models", Journal of Accounting Research (Spring 1979), pp. 190-204.

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

Mabert V.A. and Radcliffe R.C., "A Forecasting Methodology as Applied to Financial Time Series", The Accounting Review (January 1974), pp. 61-75.

Manegold J.G., "Time-Series Properties of Earnings: A Comparison of Extrapolative and Component Models", Journal of Accounting Research (Autumn 1981), pp. 360-373.

Makridakis S., "A Survey of Time Series", INSEAD Research Papers Series 131 (Fontainebleau 1974). (1974a)

Makridakis S., "Tests for Non-Stationarity in Time Series", INSEAD Research Papers Series 133 (Fontainebleau 1974). (1974b)

Makridakis S. and Wheelwright S.C., Interactive Forecasting. Univariate and Multivariate Methods. Second Edition. (Holden-Day, Inc., San Francisco 1978)

Nelson C.R., Applied Time Series Analysis for Managerial Forecasting. (Holden-Day, Inc., San Francisco 1973)

Niskanen J., Ulkoisten ja yrityskohtaisten tekijöiden vaikutus metsäteollisuusyritysten kannattavuuteen (The Effect of External and Firm-Specific Determinants on the Profitability of Wood-Processing Firms). Licentiate Thesis (Helsinki School of Economics Publications B-81, Helsinki 1986).

Patell J.M. and Kaplan R.S., "The Information Content of Cash Flow Relative to Annual Earnings: Preliminary Tests", Working Paper presented at Stanford Accounting Research Seminar (August 1977).

RATS (Regression Analysis of Time Series), User's Manual, Version 2.00 by T.A. Doan and R.B. Litterman (VAR Econometrics, Minneapolis 1986)

Rayburn J., "The Association of Operating Cash Flow and Accruals with Security Returns", Journal of Accounting Research (Supplement 1986), pp. 112-133.

Rayner A.C. and Little I.M.D., Higgledy Piggledy Growth Again. (Oxford, Basil Blackwell, 1966)

Richards R.M. "Analysts' Performance and the Accuracy of Corporate Earnings Forecasts", Journal of Business (July 1976), pp. 350-357.

Richards R.M. and Fraser D.R., "The Predictability of Corporate Earnings", Atlanta Economic Review (March/April 1978), pp. 43-47.

Ronen J. and Sadan S., Smoothing Income Numbers: Objectives, Means and Implications. (Addison-Wesley Publishing Company, Inc., 1981)

Saikkonen P., Comparing Asymptotic Properties of Some Tests Used in the Specification of Time Series Models. (Statistical Studies No. 6 Published by the Finnish Statistical Society, Helsinki 1985).

Salamon G.L. and Smith E.D., "Additional Evidence on the Time Series Properties of Reported Earnings per Share: Comment", The Journal of Finance (December 1977), pp. 1795-1808.

Salmi T., "A Comparative Review of the Finnish Expenditure-Revenue Accounting", EIASM Working Paper 78-2 (Brussels 1978).

Samuelson P.A., "Proof That Properly Anticipated Prices Fluctuate Randomly", Industrial Management Review (Spring 1965), pp. 41 49.

Siegel S., Nonparametric Statistics for the Behavioral Sciences. (McGraw-Hill Book Company, Inc., New York 1956)

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

Schreuder H. and Klaassen J., "Confidential Revenue and Profit Forecasts by Management and Financial Analysts: Evidence from The Netherlands", The Accounting Review (January 1984), pp. 64-77.

Schwarz G., "Estimating the Dimension of a Model", The Annals of Statistics (Vol. 6, No. 2, 1978), pp. 461-464.

Staubus G.J., "The Association of Financial Accounting Variables with Common Stock Values", The Accounting Review (January 1965), pp. 119-134.

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

Watts R.L. and Zimmerman J.L., Positive Accounting Theory. (Prentice-Hall, Inc., Englewood Cliffs, New Jersey 1986)

Waymire G., "Additional Evidence on the Accuracy of Analyst Forecasts Before and After Voluntary Management Earnings Forecasts", The Accounting Review (January 1986), pp. 129-142.

Wilson G.P., "The Relative Information Content of Accruals and Cash Flows: Combined Evidence at the Earnings Announcement and Annual Report Release Date", Journal of Accounting Research (Supplement 1986), pp. 165-200.

Wilson G.P., "The Incremental Information Content of the Accrual and Funds Components of Earnings After Controlling for Earnings", The Accounting Review (April 1987), pp. 293-322.

Yli-Olli P., "Tilinpäätösanalyysissä käytettävien tunnuslukujen luokittelu ja luokittelun stabiilisuus (Summary: The empirical classification of financial ratios and the stability of the classification)", Proceedings of The University of Vaasa (Research Papers No. 95, Vaasa 1983).

HELSINGIN KAUPPAKORKEAKOULUN JULKAISUJA
Publications of the Helsinki School of Economies

A-sarja: väitöskirjoja – doctoral dissertations

A:1. EERO ARTTO: Yrityksen rahoitus – systematiikka ja mukauttamistavat. The Financing of the Firm. – Conceptual Framework for Adaptions of the Monetary Financial Process. Helsinki 1968.

A:2. RAIMO KELOHARJU: Markkinointiin orientoitunut tuotannonsuunnittelu monituoteyrityksessä. – Informaatiotarpeiltaan erilaisen malliparin vertailu. Marketing Oriented Production Planning in a Multiproduct Firm. – A Comparison of Two Models with Different Requirements for Input Information. Summary. Helsinki 1968.

A:3. EERO PITKÄNEN: Tuotostavoitteiden operationaalisuus julkisessa hallinnossa. Operational output Objectives in Public Administration. Summary. Helsinki 1968.

A:4. PERTTI KETTUNEN: Anniskeluravintoloiden kannattavuus 1965–67. Profitability of Licensed Restaurants 1965–67. Summary. Helsinki 1970.

A:5. RISTO LAULAJAINEN: The Base Location as a Factor of Efficiency for Mobile Activity. Helsinki 1970.

A:6. MEERI SAARSALMI: Consumer Purchases of Major Durables. Helsinki 1972.

A:7. OIVA LAAKSONEN: Yrityskuva ja työpaikan valinta. The Image of an Organisation and Job Selection. Helsinki 1972.

A:8. REIJO RUUHELA: Yrityksen kasvu ja kannattavuus. A Capital Investment Model of the Growth and Profitability of the Firm. Helsinki 1972.

A:9. JOUKO LEHTOVUORI: Kirjanpidon perusteet yrityksen tiedotuspolitiikan kannalta. The Foundations of Accounting from the Viewpoint of the Information Policy of an Enterprise. Helsinki 1972.

A:10. JAAKKO KETO: Elokuvalippujen kysyntä ja siihen vaikuttaneet tekijät Suomessa 1915–72. – Demand for Cinema Tickets and Factors Affecting it in Finland, 1915–72. Helsinki 1974.

A:11. TIMO SALMI: Joint Determination of Trade, Production, and Financial Flows in the Multinational Firm Assuming Risky Currency Exchange Rates. Helsinki 1975.

A:12. HEIKKI URMAS: Työrauhajärjestelmä yhteiskunnan osajärjestelmänä. Helsinki 1975.

A:13. AATTO PRIHTI: Konkurssin ennustaminen taseinformaation avulla. – The Prediction of Bankrupty with published Financial Data. Helsinki 1975.

A:14. JYRKI WALLENIUS: Interactive Multiple Criteria Decision Methods: an Investigation and an Approach. Helsinki 1975.

A:15. UOLEVI LEHTINEN: Merkinvalintamalli. Mallin muodostaminen sekä sen selityskyvyn ja sovellutusmahdollisuuksien tarkastelu. – A Brand Choice Model. The Formulation of Model and an Analysis of its Explanatory Power and Potential for Applications. Helsinki 1975.

A:16. JAAKKO HONKO & KALERVO VIRTANEN: The Investment Process in Finnish Industrial Enterprises. Helsinki 1975.

A:17. KYÖSTI PULKKINEN: Instituutiot ja virallistaminen organisaation rakennetta ja toimintaa säätelevässä hallintoprosessissa. Institutionalization and Formalization in the Administrative Process Controlling the Structure and the Process of Organization. Helsinki 1976.

A:18. JOUKO YLÄ-LIEDENPOHJA: On Optimal Financing Dividends, and Investment of the Firm. Helsinki 1976.

A:19. PEKKA LEHTONEN: On the Estimation of Statistical Cost Functions: An Empirical Study of Production and Cost Functions of Finnish Restaurants. Helsinki 1976.

A:20. TIMO AIRAKSINEN: A Dynamic Model of Interrelated Demand for Capital and Labour. A Theoretical Model with an Application to Timo-series Cross-section Data of Finnish Breweries in 1954–72. Helsinki 1977.

A:21. RISTO TAINIO: Determinants of Labour Turnover in a Firm. Helsinki 1977.

A:22. MARKKU LAHDENPÄÄ: Multiple Criteria Decision Making. With Empirical Study on Choice of Marketing Strategies. Helsinki 1977.

A:23. ANTTI KORHONEN: Stock Prices, Information and the Efficiency of the Finnish Stock Market: Empirical Tests. Helsinki 1977.

A:24. VEIJO RIISTAMA: Inflaatiovaraus. Tutkimus inflaation vaikutuksesta ansaintataloudellisen yrityksen jakokelpoiseen voittoon. Helsinki 1978.

A:25. LEO AHLSTEDT: Erikoistuminen ja liikkuvuus liikkeenjohtajan urakehitystekijöinä. Helsinki 1978.

A:26. TUOMAS LARJAVAARA: Suomen metalliteollisuuden kansainvälinen erikoistuminen. Helsinki 1978.

A:27. LIISA UUSITALO: Consumption Style and Way of Life. An Empirical Indentification and Explanation of Consumption Style Dimensions. Helsinki 1979.

A:28. PEKKA OLLONQVIST: Optimal Investment Behaviour in Putty-Clay-Clay Technology. Helsinki 1979.

A:29. KRISTIAN MÖLLER: Perceived Uncertainty and Consumer Characteristics in Brand Choice. Investigation with Durable and Nondurable Products. Helsinki 1979.

A:30. REIJO LUOSTARINEN: Internationalization of the Firm. An Empirical Study of the Internationalization of Firms with Small and Open Domestic Markets with special Emphasis on Lateral Rigidy as a Behavioral Characteristics in Strategic Decision Making. Helsinki 1979.

A:31. KALERVO VIRTANEN: Yritysoston suunnittelu prosessina. Helsinki 1979.

A:32. ROY DAHLSTEDT: Cyclical Fluctuation under Central Planning. An Inquiry into the Nature and Causes of Cyclical Fluctuation in the Soviet Economy. Helsinki 1980.

A:33. KALEVI KYLÄKOSKI: Yrityksen strategiasuunnittelu systeeminä ja prosessina. Helsinki 1980.

A:34. SAKARI KOROLAINEN: On the Conceptual and Logical Foundations of the General Theory of Human Organizations. A Cybernetic Approach. Helsinki 1981.

A:35. TAPANI LEHTONEN: Stochastic Comparisons for Many Server Queues. Helsinki 1981.

A:36. ASKO KORPELA: Ajka an Econometric model for Finland. Helsinki 1982.

A:37. SEPPO ALALUUSUA: Structural Determinants of the Budgeting Process: An Approach with Application to Finnish Firms. Helsinki 1982.

A:38. JUHA KÄHKÖNEN: Credit Rationing, Unemployment and Economic Policies: Disequilibrium Models of Industrialized Economies with Underdeveloped Financial Markets. Helsinki 1982.

A:39. KARI LILJA: Workers' Workplace Organisations. Helsinki 1983.

A:40. RAIMO KELOHARJU: Relativity Dynamics. Helsinki 1983.

A:41. ARTO LAHTI: Strategy and Performance of a Firm. An Empirical Investigation in the Knitwear Industry in Finland in 1969–81. Helsinki 1983.

A:42. JARMO ERONEN: Location Strategy and Patterns. An empirical Investigation of the Soviet Pulp and Paper Industry. Helsinki 1984.

A:43. MARKKU KOSKELA: Osakkeen kassaperusteinen arvonmääritys. Helsinki 1984

A:44. JARMO LEPPINIEMI: Rahoituspäätösten markkinaperusteinen informaatiomekanismi. Helsinki 1985.

A:45. KEIJO RÄSÄNEN: Tensions in Management. Helsinki 1985.

A:46. TUIRE SANTAMÄKI-VUORI: Cyclical Adjustment of Hours and Employment. Helsinki 1986.

A:47. HENRIK GAHMBERG: Symbols and Values of Strategic Managers. Helsinki 1986.

A:48. A Tribute to Arvi Leponiemi on his 60th Birthday. Ed. by Juha Kähkönen and Jouko Ylä-Liedenpohja. Helsinki 1986.

A:49. LIISA UUSITALO: Suomalaiset ja ympäristö. Helsinki 1986.

A:50. REIJA LILJA: Econometric Analyses of Family Labour Supply over the Life Cycle using U.S. Panel Data. Helsinki 1986.

A:51. PEKKA T. HIETALA: Essays on financial Economics. Helsinki 1987.

A:52. A Tribute to Aarni Nyberg on his 60th Birthday. Helsinki 1987.

A:53. HANNU KIVIJÄRVI: Implementing Model-Oriented Decision Support Systems. Helsinki 1987.

A:54. JYRKI VERANEN: The Ownership Function and the Performance of the Film. Helsinki 1987.

A:55. SUZANNE DE TREVILLE: Disruption, Learning, and System Improvement in Just-In-Time Manufacturing. Helsinki 1987.

A:56. ANNAMARIA RAPAKKO: Base Companies in Multinational Corporate Structures. Helsinki 1987.

A:57. TIMO RAPAKKO: Corporate Control and Parent Firms' Liability for their Controlled Foreign Subsidiaries: A Study on the Regulation of Corporate Conduct. Helsinki 1988.

A:58. JUHA KINNUNEN: The Time Series Properties of Accrual Versus Cash-Based Income Variables: Empirical Evidence from Listed Finnish Firms. Helsinki 1988.

B-sarja – studies

B:1. RISTO LAULAJAINEN: On the Classification of Centers. Helsinki 1968. (ennen C:II:2. before)

B:2. RISTO LAULAJAINEN: Store Size and Central Place Hierarcy. Helsinki 1968. (ennen C:II:3. before)

B:3. RAIMO KELOHARJU: Idealisoituun konfliktiasetelmaan perustuvan oligopolitilanteen stabiliteetti. – Stability of an Oligopoly which is Based on an Idealized Conflict Situation. Helsinki 1969. (ennen C:II:4. before)

B:4. KAI-VEIKKO VUORISTO: Foreign Tourist in Finland. Helsinki 1970. (ennen C:II:5. before)

B:5. PENTTI WOIVALIN: Yleisen Chance Constrained Programming -probleeman tarkastelua. Helsinki 1971. (ennen C:II:7. before)

B:6. LAURI ROSSI: Notes on the Syntax and Semantics of Probability Logic. Helsinki 1971. (ennen C:II:9. before)

B:7. KAI-VEIKKO VUORISTO: Talviulkoilualueet, niiden edellytykset ja käyttö erityisesti Etelä-Suomen olosuhteissa. – Winter Recreation Areas, Conditions for and Use of Them Especially in Southern Finland. Helsinki 1971. (ennen C:II:10. before)

B:8. ASKO KORPELA: Effects of Tariffs on Import to Finland. Helsinki 1971. (ennen C:II:11 before)

B:9. KAI-VEIKKO VUORISTO: Periferia-alue linja-autoliikennetiheyden ja toiminnallisten aluejakojen valossa. The Relation of a Periphelar Area to the Volume of Bus Traffic and Regional Division. Helsinki 1972. (ennen C:II:13. before)

B:10. KAI-VEIKKO VUORISTO: Virolahden matkailu ja sen kehittäminen. Tutkimus matkailun kansainvälisen liikennereitin merkityksestä rajaseudun kunnalle. Tourism in Virolahti. Southeastern Finland. A Study of the Effect of Tourism and an International Traffic Route on a Frontier Commune. Helsinki 1974. (ennen C:II:17. before)

B:11. JAAKKO HAVUKKALA & KAI-VEIKKO VUORISTO: Kahden eteläsuomalaisen kylän talousmaantieteellinen rakenne. Helsinki 1975.

B:12. KYÖSTI PULKKINEN: Tutkimus eriytymisestä organisaation rakenne-, viestintä- ja päätöksentekojärjestelmissä. Helsinki 1975.

B:13. TIMO SALMI: Ulkomaan rahan määräisten tase- ja tulostietojen kääntämisestä ja valuutta-aseman määrittelystä yrityksen laskentatoimessa. Helsinki 1976.

B:14. RAIMO KELOHARJU: Tuotannon resurssien ja niiden käytön suunnittelu. Helsinki 1976.

B:15. RISTO LAULAJAINEN: The Kokkola Sulphur Plant of Outokumpu Oy. Helsinki 1976.

B:16. JAAKKO VOIPIO: Valittamisesta yliopistojen ja korkeakoulujen hallinnossa. Helsinki 1977.

B:17. KYÖSTI PULKKINEN: Staff Unit. Helsinki 1977.

B:18. RISTO TAINIO: Research on the Factors Associated with the Propensity to Stay in Organization. Helsinki 1977.

B:19. KARI ASP: Yrityksen sisäisten suoritteiden arvostusongelma. Helsinki 1977.

B:20. JARMO LEPPINIEMI: Pankin taloudelliset toimintaedellytykset ja sidosryhmäjoustavuus. Helsinki 1977.

B:21. LIISA UUSITALO: Consumer Perception and Preferences of Message Structure. Helsinki 1977.

B:22. KARI LILJA: Työntekijöiden osallistuminen hallintoon teollisuusyrityksissä. Helsinki 1977.

B:23. ERKKI PIHKALA: Valtion tulojen ja menojen rakenne 1800-luvun jälkipuoliskolla. Helsinki 1977.

B:24. ARVI LEPONIEMI: Taneli-talouspolitiikan neljännesvuosimalli. Helsinki 1977.

B:25. KRISTIAN MÖLLER: Brand Choice under Perceived Uncertainty Development and Testing of a Multiattribute Choice Model. Helsinki 1977.

B:26. MAI ANTTILA: Consumer Price perception. Helsinki 1977.

B:27. EERO VOUTILAINEN: Hallinnon muodollinen kehittyneisyys suomalaisissa yrityksissä. Helsinki 1978.

B:28. JUHA NISSILÄ: Diversifioitumisen vaikutus yrityksen kannattavuuden ja tulorahoituksen vaihteluun. Helsinki 1978.

B:29. MATTI KOIRANEN: Tietojenkäsittelytoiminta ja sen johtaminen. Helsinki 1978.

B:30. OSMO A. WIIO: Contigencies of Organizational Communication. Helsinki 1978.

B:31. RAIMO KELOHARJU: Elintarviketalous systeeminäkökulmasta. Helsinki 1978.

B:32. TAPIO RIIKONEN: Rationalismipohjaisen suunnittelukäsityksen soveltaminen kuntasuunnittelussa. Helsinki 1978.

B:33. SEPPO I. ALALUUSUA: Budjetointiprosessin rakenne ja ohjaus. Helsinki 1978.

B:34. MARKKU KOSKELA: Yrityksen tulorahoituksen heilahtelu. Helsinki 1978.

B:35. IIRO JAHNUKAINEN: Henkilöstövoimavarojen ohjauksen organisaatio suomalaisissa keskisuurissa ja suurissa yrityksissä. Helsinki 1979.

B:36. KIRSTI PÄÄKKÖNEN: Pakkausmateriaalin vaikutus jäähileen muodostumiseen pakasteessa. Helsinki 1979.

B:37. ARVI LEPONIEMI – JUHA KÄHKÖNEN – MIKKO PUHAKKA – PERTTI SAVAJA – JUKKA TUOVILA: TANELI II – A Quarterly Model for Evaluating Economic Policy in Finland. Helsinki 1979.

B:38. ERKKI MATTILA: Polluting Firm and Environmental Policy. Helsinki 1979.

B:39. RISTO HÖLTTÄ: Innovaatioiden omaksuminen ja leviäminen alueellisena tapahtumana. Helsinki 1979.

B:40. LEIF ÅBERG: Organisaatioviestinnän kanavat, tietojen riittävyys ja työtyytyväisyys. Helsinki 1979.

B:41. OIVA LAAKSONEN – JUHANI KAUHANEN – SIRKKU KIVISAARI – SINIKKA VANHALA: Päätöksentekoon osallistuminen, arvot ja tyytyväisyys yrityksissä. Helsinki 1979.

B:42. TUIRE SANTAMÄKI: Potentiaalisen tuotannon estimointi Suomen kansantaloudessa. Helsinki 1980.

B:43. KARI HIETALA: De direkta investeringarna mellan de nordiska länderna. En teoretisk och empirisk analys. NORDARB-projektet. Helsinki 1980.

B:44. NIILO PÖYHÖNEN – FEDI VAIVIO: Projektexport utförd av nordiska företag. Problem, kartläggning och data angående åren 1973–75. NORDARB-projektet. Helsinki 1980.

B:45. KARI HIETALA: De direkta investeringarnas sysselsättnings- och migrations verkan. En teorisk och empirisk analys av svenska investeringars verkningar i Finland. NORDARB-projektet. Helsinki 1980.

B:46. KARI HIETALA: Företagssamarbete mellan industriföretag i Norden särskilt från sysselsättningseffektens synvinkel. En teoretisk och empirisk analys. NORDARB-projektet. Helsinki 1980.

B:47. MEERI SAARSALMI – SAARA HYVÖNEN – EIJA RAHIKAINEN: Markkinoinnin toimivuusselvitys. Summary: Marketing Audit. Helsinki 1980.

B:48. HENRIK GAHMBERG: Contact Patterns and Learning in Organizations. Helsinki 1980.

B:49. AIMO PENTINSAARI: Osakeyhtiön toimitusjohtajan liiketaloudellisesta, yhteiskunnallisesta ja oikeudellisesta vastuusta. Helsinki 1980.

B:50. JARMO ERONEN: Neuvostoliiton massa- ja paperiteollisuuden alueellinen ekspansio. Helsinki 1981.

B:51. SINIKKA VANHALA: Henkilöstön vaihtoalttiutta säätelevät tekijät yrityksessä. Helsinki 1981.

B:52. KYÖSTI PULKKINEN: Development of Structure and Communication in the Organization. Helsinki 1981.

B:53. ARTO LAHTI: Liiketoimintatason strateginen malli. Empiirinen testaus trikootoimialalla. Helsinki 1981.

B:54. KRISTIAN MÖLLER: Industrial Buying Behavior of Production Materials: A Conceptual Model and Analysis. Helsinki 1981.

B:55. KYÖSTI PULKKINEN: The Premises for Decision Support Systems. Helsinki 1981.

B:56. RISTO TAINIO: Internal Strategy of Management in Industrial Organizations. Helsinki 1982.

B:57. JAAKKO HONKO - AATTO PRIHTI - KALERVO VIRTANEN: Critical Areas in the Capital Investment Process of Enterprises. Helsinki 1982.

B:58. PEKKA AKKANEN: Budjettivalvontajärjestelmän rakenne ja muotoutuminen. Helsinki 1982.

B:59. REIJA LILJA: Leisure Time and Consumption. An Explorative Study of the Finnish Wage Earner Families in 1971. Helsinki 1982.

B:60. KRISTIAN MÖLLER - JUKKA ALLOS: Tuotannollisten komponenttien ostopäätösprosessi. Helsinki 1983.

B:61. PROCEEDINGS: Research Seminar on Strategy 1982. Helsinki 1983.

B:62. SIRKKU KIVISAARI: Välineellinen suhtautuminen työhön yritysorganisaatiossa. Helsinki 1983.

B:63. SAARA HYVÖNEN: Coordination and Cooperation in Vertical Marketing Systems: A Model Vertification. Helsinki 1983.

B:64. MAURI LAUKKANEN: Yritysjohtajien tilannemallit päätöksenteossa. Helsinki 1983.

B:65. HANNU KIVIJÄRVI: An Assessment of Modeling Activities. Helsinki 1983.

B:66. LEENA YLÄ-ANTTILA: Organisaatiorakenne ja sen selittyminen. Helsinki 1983.

B:67. MARGARETA SOISMAA (ed.): Proceedings: Seminar on Methodology in Management and Business Research, August 21 to 24, 1983. Helsinki 1984.

B:68. TIMO AIRAKSINEN: A Study of the Export Behaviour of the Firm Under Uncertainty. Helsinki 1984.

B:69. JUHA KINNUNEN: The Time Series Properties of Corporate Cash Flows: Preliminary Evidence from Some Finnish Firms. Helsinki 1984.

B:70. ANTTI JUHANI HAAHTI: An Empirical Study into Tourists' Cognitive Choice Structure. Helsinki 1984.

B:71. HILPPA SORJONEN: Sinfoniaorkesterin markkinoinnin suunnittelu. Helsinki 1985.

B:72. JUKKA LAAKSO: Interaction between Energy Supply and Long-term Development of the Finnish Economy. Helsinki 1985.

B:73. Problems in the Redescription of Business Enterprises. Proceedings of the first Summer Seminar of the Group on the Theory of the Firm. 7–8 August 1984, Espoo Finland. Helsinki 1985.

B:74. Report of the seventh Scandinavian Research Seminar on Systemeering. Helsinki Aug. 26–29 1984. I. Helsinki 1985.

B:75. Report of the seventh Scandinavian Research Seminar on Systemeering. Helsinki Aug. 26–29 1984. II. Helsinki 1985.

B:76. JAN-PETER PAUL: Ekonomiska sanktioner som politisk instrument i internationell politik. Helsinki 1985.

B:77. RIITTA AVIKAINEN: Benennungen im Rechnungswesen. Helsinki 1985.

B:78. HANNELE KUOSMANEN: Työllisyys, vaihtotase ja tarjonnan rakenne. Helsinki 1985.

B:79. LIISA TIITTULA: Vuoron vaihtuminen keskustelussa. Helsinki 1985.

B:80. Research Approaches on Business Enterprises. Ed. Kari Lilja, Keijo Räsänen, Risto Tainio. Helsinki 1985.

B:81. JYRKI NISKANEN: Ulkoisten ja yrityskohtaisten tekijöiden vaikutus metsäteollisuusyritysten kannattavuuteen. Helsinki 1986.

B:82. ANSSI HYVÄRINEN: Ekonomit työmarkkinoilla. Helsinki 1986.

B:83. SATU KÄHKÖNEN: Keskuspankkipolitiikka ja ulkoiset häiriöt pienessä avotaloudessa. Helsinki 1986.

B:84. Proceedings of the International Symposium on recent Developmnets in Business Management Research. Ed. Juha Kinnunen. Helsinki 1987.

B:85. MIRJALIISA LAMPI: Linguistic Components of Strategy in Business negotiations. Helsinki 1987.

B:86. MIKA PANTZAR: Rakenteita muuttava rakenteissa muuttuva taloussubjekti. Helsinki 1987.

B:87. TIMO SAARINEN: Essays on the Progress of Computer-based Information Systems in Organizations. Helsinki 1987.

C-sarja: oppikirjoja – textbooks

C:1. MIKKO TAMMINEN: Kotitalouksien tulonkäyttö: Kulutus ja säästäminen. 2. p. Helsinki 1973.

C:2. ASKO SAVIAHO – RAIMO SAILAS – TAUNO YLINEN: Julkisen talouden suunnittelu ja budjetointi. 2. p. Helsinki 1977. Teos korvaa entisen C:2:n (Asko Saviaho: Julkisen talouden budjettijärjestelmät).

C:3. JOUKO MANNINEN: Matematiikkaa taloustieteilijöille. 4. p. Helsinki 1974.

C:4. DOROTHEA VON VOLBORTH: Venäjänkielen johdantokurssi. 2. uud. p. Helsinki 1976.

C:5. VEIKKO JÄÄSKELÄINEN: Liiketaloustiede I, osa A, III jakso (osittain). Helsinki 1967.

C:6. REIJO LUOSTARINEN: Yrityksen toiminnan integroitu kokonaissuunnittelu. 10. p. Helsinki 1978.

C:7. HANNU TERÄS: Sihteerisaksaa. 4. p. Helsinki 1974.

C:8. TAUNO NURMELA – REINO HAKAMIES: Manuel de francais commecial à l'usage des finlandais. Helsinki 1968.

C:9. HENRIK VIRKKUNEN: Teollisen kustannuslaskennan perusteet ja hyväksikäyttö I–II. 3. p. Helsinki 1973.

C:10. PEKKA HEINÄNEN – JUKKA JUTILA: Tavaraoppi I. Helsinki 1968.

C:11. JOUKO LEHTOVUORI – KALERVO VIRTANEN: Kirjanpidon esikurssi. 11. uud. p. Helsinki 1981.

C:12. EERO ARTTO: Laskentatoimi, lyhyt oppijakso. 4. p. Helsinki 1977.

C:13. DOROTHEA VON VOLBORTH: Venäläisen kauppakirjeenvaihdon harjoitustehtäviä. 2. p. Helsinki 1973.

C:14. LEENA PORKO: Ajankohtainen sihteerin perussanasto suomi–englanti–suomi. 5. p. Helsinki 1977.

C:15. Ruotsin kielen pikakirjoitus. Nevanlinnan järjestelmän sovite. Helsinki 1972.

C:16. LEENA PORKO: Kauppakirjeenvaihdon sanontoja suomi–englanti. 3. p. Helsinki 1976.

C:17. KARI ASP – SEPPO ALALUUSUA – JUHA NISSILÄ: Laskentatoimi: Talouden hallinnon harjoitus- ja oppikirja. 5. uud. p. Helsinki 1981.

C:18 ARVI LEPONIEMI: Johdatus makrotaloustieteeseen. 3. korj. p. Helsinki 1974.

C:19. RAIJA KONTTINEN: Talouselämän viestintä. 5. uud. p. Helsinki 1981.

C:20. LEENA PORKO: Talouselämän lyhenteitä englanti–suomi. 3. p. Helsinki 1975.

C:21. SEPPO ALALUUSUA – KAIJU KALLIO – PAULI TORKKO: Kirjanpidon ja tuloslaskennan ongelmia harjoitustehtävineen. 5. uud. p. Helsinki 1981.

C:22. RAIJA KONTTINEN: Kielenkäytön opas. Helsinki 1973.

C:23. KYÖSTI PULKKINEN: Yrityksen organisaation rakenne, miehitys ja toiminta. 4. uud. p. Helsinki 1974.

C:24. JOUKO MANNINEN: Lineaarialgebraa taloustieteilijälle. 2. p. Helsinki 1974.

C:25. JOUKO MANNINEN – TIMO SALMI: Matemaattinen optimointi, teoriaa ja tekniikkaa. 3. korj. p. Helsinki 1975.

C:26. TIMO SALMI: Monikansallinen yritys ja lineaarinen optimointi. Helsinki 1975.

C:27. JOUKO MANNINEN: Lineaarisen optimoinnin matematiikkaa. Helsinki 1975.

C:28. REIJO LUOSTARINEN: Ulkomaisen tytäryhtiön perustaminen. Helsinki 1968. (ennen C:II:1 before)

C:29. EERO PITKÄNEN: Kustannus-hyötyanalyysi – yhteiskunnalliset ja liiketaloudelliset näkökohdat päätöksenteossa. 3. korj. p. Helsinki 1974. (ennen C:II:8 before)

C:30. JARL LOUHIJA ja tutkijaryhmä: Mainosteksti luettavuustutkimuksen kohteena. Helsinki 1972. (ennen C:II:14 before)

C:31. VESA SEPPÄLÄ: Johdatus sosiologian tutkimusmenetelmiin. 3. p. Helsinki 1976.

C:32. STIG JAATINEN – JAAKKO HAVUKKALA (toim.): Talousmaantieteellisiä artikkeleita. Helsinki 1967. (ennen C:III:1 before)

C:33. MARTTI SAARIO (toim.): Yrityksen tulos, rahoitus ja verotus, I. Artikkelikokoelma. 4. p. Helsinki 1974. (ennen C:III:1 before)

C:34. MARTTI SAARIO (toim.): Yrityksen tulos, rahoitus ja verotus, II. Artikkelikokoelma. 3. p. Helsinki 1975. (ennen C:III:3 before)

C:35. EERO ARTTO (toim.): Laskentatoimi, rahoitus I. Artikkelikokoelma. 4. p. Helsinki 1980.

C:36. EERO ARTTO (toim.): Laskentatoimi, rahoitus II. Artikkelikokoelma. 4. täys. uud. p. Helsinki 1981.

C:37. EERO PITKÄNEN: Ohjelmaperusteinen suunnittelu julkishallinnossa. Helsinki 1975.

C:38. JAAKKO VOIPIO: Liikeverotuksen ongelmia. Artikkelikokoelma. 2. p. Helsinki 1976.

C:39. HILKKA SAARIO: Timber Trade Terminology. 2. p. Helsinki 1975.

C:40. LEENA PORKO – HELMI JUTILA – KAARINA VAHERI (toim.): English Usage, Revised edition, Fourth print. Helsinki 1978.

C:41. JAAKKO HAVUKKALA: Kartografia. 6. p. Helsinki 1977.

C:42. CURT OLSSON: Yhtiöoikeus. 6. p. Helsinki 1978.

C:43. TIMO SALMI: Liiketaloudellisia Basic-ohjelmointikielen harjoitustehtäviä ratkaisuineen. Helsinki 1976.

C:44. JORMA PASANEN: Tavarakaupan yleiset kauppatavarat ja toimituslausekkeet. 2. p. Helsinki 1978.

C:45. KALERVO VIRTANEN (toim.): Laskentatoimi: Talouden hallinnon artikkelikokoelma. 2. laaj. p. Helsinki 1980.

C:46. NIILO HOME: Kyläkaupasta supermarketiin. Vähittäiskaupan sopeutuminen yhteiskunnan rakennemuutokseen vuosina 1952–1972. Helsinki 1977.

C:47. KAI-VEIKKO VUORISTO: Poliittiset ja taloudelliset alueet. Helsinki 1978.

C:48. JAAKKO VOIPIO: Lisää liikeverotuksesta. Liikeverotuksen ongelmia. II. Helsinki 1979.

C:49. JUHA NISSILÄ: Finanssi-investoinnit. Arvopaperisijoitusten perustiedot. Helsinki 1980.

C:50. MEERI SAARSALMI: Miten laadin tutkielman? Helsinki 1980.

C:51. YRJÖ WASILJEFF: Tietokoneohjelmoinnin perusteet 24Y4. Helsinki 1982.

C:52. MEERI SAARSALMI: Liiketaloustiede: Markkinoinnin harjoitus ja pienryhmätehtäviä. Helsinki 1982.

C:53. HENRI BROMS – HENRIK GAHMBERG: Semiotics of Management. Helsinki 1987.

D-sarja: laitosjulkaisuja, research reports

D:1. ERKKI VAISTO: Markkinoinnin kommunikaation kirjallisuus Suomessa vuosilta 1945–1969. Bibliography of Marketing Communications in Finland 1945–1969. 2. p. Helsinki 1972. (ennen C:II:6 before)

D:2. ERKKI VAISTO: Organisaatio-opin ja yrityksen hallinnon kirjallisuus Suomessa vuosilta 1945–1970. Bibliography of Organization and Administration in Finland 1945–1970. Helsinki 1972. (ennen C:II:12 before)

D:3. ERKKI VAISTO: Laskentatoimen kirjallisuus Suomessa vuosilta 1945–1971. Bibliography of Accountancy in Finland 1945–1971. Helsinki 1973. (ennen C:II:15 before)

D:4. HENRI BROMS – KYLLIKKI RUOKONEN: Sources of Company Information. Helsinki 1975.

D:5. MARTTI HELSILÄ: Käytännön huomioita yrityksen organisaation tutkimuksesta. Helsinki 1975.

D:6. MEERI SAARSALMI: Miten laadin laudatur-tutkielman? Helsinki 1978.

D:7. RAIMO KELOHARJU: Struktuurivaihtoehdot ja liiketaloustieteellinen tutkimus. Helsinki 1975.

D:8. MARJA PIRILÄ: Kansantaloustieteellinen kirjallisuus Suomessa 1974. Helsinki 1976.

D:9. MARJA PIRILÄ: Liiketaloustieteellinen kirjallisuus Suomessa 1974. Helsinki 1976.

D:10. RAIMO KELOHARJU: Simulation Models of Firm Growth. Helsinki 1976.

D:11. TIMO AIRAKSINEN: A Dynamic Disequilibrium Model of the Firm for Substitable Factors of Production. Helsinki 1976.

D:12. KYLLIKKI RUOKONEN: Directory of Economic Libraries in Scandinavia. Helsinki 1976.

D:13. RAIMO KELOHARJU: Four Papers in System Dynamics. Helsinki 1976.

D:14. RAIMO KELOHARJU: Corporate Modelling in System Dynamics. Helsinki 1977.

D:15. MARKKU KALLIO – ERKKI MATTILA: On the Efficiency of Some Control Policies for Industrial Pollution. Helsinki 1977.

D:16. MARKKU KALLIO: Production Planning in a Paper Mill. Helsinki 1977.

D:17. MARKKU KALLIO: A Corporate Planning Model. Helsinki 1977.

D:18. MARJA PIRILÄ: Kansantaloustieteen kirjallisuus Suomessa 1975. Helsinki 1977.

D:19. MARJA PIRILÄ: Liiketaloustieteellinen kirjallisuus Suomessa 1975. Helsinki 1977.

D:20. KYLLIKKI RUOKONEN: Taloustieteellisiä aikakauslehtiä 1977. Helsinki 1977.

D:21. EIJA ARJAS – TAPANI LEHTONEN: Approximating Many Server Queues by Means of Single Server Queues. Helsinki 1977.

D:22. LIISA UUSITALO: Konsumtionsstilen som en del av levnadssättet. Helsinki 1977.

D:23. TERO ANSIO – MARKKU KALLIO: Operaatiotutkimuksen hyväksikäyttö Suomessa. Helsinki 1977.

D:24. SEPPO SALO: On Optimal Control in Restricted State Space, I. Helsinki 1977.

D:25. JOUKO YLÄ-LIEDENPOHJA: On Growth, Dividends and Capital Gains in the Adjustment Cost Model of the Firm. Helsinki 1977.

D:26. KRISTIAN MÖLLER: Monidimensioiset valintamallit kuluttajan merkinvalintakäyttäytymisen tutkimuksessa. Helsinki 1977.

D:27. KYLLIKKI RUOKONEN: ATK-kirjallisuutta. Yhteisluettelo 1973–1976. Helsinki 1978.

D:28. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1976. Helsinki 1978.

D:29. JUHA KÄHKÖNEN – TUIRE SANTAMÄKI: Työttömyyden ennustaminen Boxin ja Jenkinsin menetelmillä. Helsinki 1978.

D:30. ERKKI VAISTO – TIMO RAUNIO: Taloustieteellinen tutkimus Suomessa 1976. Aikakauslehtiartikkeleita. Helsinki 1978.

D:31. JUHA KÄHKÖNEN – TUIRE SANTAMÄKI: On Instrument Costs in Decentralized Macroecenomic Decision Making. Helsinki 1978.

D:32. KRISTIAN MÖLLER: Managerial Application Potential of Multiattribute Choice Models. Helsinki 1978.

D:33. TAPANI LEHTONEN – EIJA ARJAS: Approximating Many Server Queues by Means of Single Server Queues II: Simulation Experiments. Helsinki 1978.

D:34. RISTO TAINIO: Henkilöstöhallinnon tutkimusasetelmat. Helsinki 1979.

D:35. SEPPO SALO: On Optimal Control in Restricted State Space II. Helsinki 1979.

D:36. TIMO AIRAKSINEN: Inflation and the User Cost of Capital. Helsinki 1979.

D:37. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1977. Tutkimuksia. Helsinki 1979.

D:38. ERKKI VAISTO – ARI LUOSTARINEN: Taloustieteellinen tutkimus Suomessa 1977. Aikakauslehtiartikkeleita. Helsinki 1979.

D:39. KYLLIKKI RUOKONEN – ERKKI VAISTO: Finland. Sources of Information. Helsinki 1979.

D:40. MARKKU SÄÄKSJÄRVI: Towards Cooperative Optimization. Working Paper. Helsinki 1979.

D:41. ROY DAHLSTEDT: Cyclical Fluctuation under Central Planning. Helsinki 1979.

D:42. MAI ANTTILA: Price Image Versus Price Reality. Helsinki 1979.

D:43. EERO ARTTO: Die Möglichkeiten der Kapitalflussrechnungen als Hilfe der Unternehmensanalysen. Helsinki 1979.

D:44. EERO ARTTO: Profitability and Cash Stream Analysis. Helsinki 1980.

D:45. ERKKI VAISTO – ARI LUOSTARINEN: Taloustieteellinen tutkimus Suomessa 1978. Aikakauslehtiartikkeleita. Helsinki 1980.

D:46. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1978. Tutkimuksia. Helsinki 1980.

D:47. ROY DAHLSTEDT: A Multiperiod Mixed-Integer Optimization Model of the Soviet Type Industrial Enterprise. Helsinki 1980.

D:48. TUOMO VESANEN – SEPPO SALO – EERO ARTTO: Metalliteollisuusyritysten kilpailukykyvertailu 1971–1978, Suomi–Ruotsi–Saksan Liittotasavalta. Helsinki 1980.

D:49. TUOMO VESANEN – SEPPO SALO – EERO ARTTO: Rakennuspuusepänteollisuusyritysten kilpailukykyvertailu 1971–1978, Suomi–Ruotsi. Helsinki 1980.

D:50. EERO ARTTO: Teollisuuden toimialojen kassaperusteinen kannattavuus ja rahoitus, Suomi 1961–1973, Ruotsi 1966–1974. Helsinki 1980.

D:51. EERO ARTTO: Cash-based Profilitability and Financing of Industries. Helsinki 1981.

D:52. TAPANI LEHTONEN: On the Optimality of The Shortest Line Discipline. Helsinki 1981.

D:53. TAPANI LEHTONEN: Stochastic Comparisons of Nonhomogenous Queueing Systems with Exponential Servers. Helsinki 1981.

D:54. ARTO LAHTI: Trikooyritysten strategiat vuosina 1969–1978. Helsinki 1981.

D:55. ARTO LAHTI: A Model of Business Strategy. Empirical Testing on the Knitwear Industry. Helsinki 1981.

D:56. LASSE SIURALA: Youth Attitudes towards Work. Helsinki 1982.

D:57. LASSE SIURALA: Effects of Youth Unemployment. Helsinki 1982.

D:58. HENRI BROMS – HENRIK GAHMBERG: Mythology in Management Culture. Helsinki 1982.

D:59. RISTO HÖLTTÄ: Innovaation monideminsioinen diffuusio. Helsinki 1982.

D:60. JAAKKO HAVUKKALA – KAI-VEIKKO VUORISTO: Kahden eteläsuomalaisen kylän talousmaantieteellinen rakenne. Helsinki 1982.

D:61. ARTO LAHTI: Historia-analyysi viidestä trikooyrityksestä. Helsinki 1983.

D:62. MEERI SAARSALMI: Incorporation of Resource Recycling in Marketing Model. Helsinki 1983.

D:63. ULLA AITTA: Uusi naisekonomi – haaste vanhalle työelämälle. Helsinki 1983.

D:64. EERO ARTTO: Teollisuuden toimialojen ja yritysten kannattavuus- ja rahoitusvertailu 1974–1980 Suomi–Ruotsi. Helsinki 1983.

D:65. LASSE SIURALA: Koulutuksellinen tasa-arvoisuus. Helsinki 1983.

D:66. LASSE SIURALA: Educational Equality. Helsinki 1983.

D:67. TAPANI LEHTONEN: A Note on the Proofs of Hall and Heyde for the Invariance Principles in the Martingale Limit Theory. Helsinki 1984.

D:68. RISTO HÖLTTÄ: Innovaatioiden tutkiminen 1980-luvulla. Helsinki 1985.

D:69. ARTO LAHTI: Yrityksen strategia ja menestyksellisyys. Helsinki 1985.

D:70. ARTO LAHTI: Teva-alan kansainvälinen kilpailutilanne. Helsinki 1985.

D:71. ARTO LAHTI: Pankkien kilpailustrategia. Helsinki 1985.

D:72. Pääkaupunkiseudun kaupan keskukset. Työryhmä Reijo Helle ym. Helsinki 1985.

D:73. ANNE af URSIN: Monetary, Fiscal and Exhange Rate Policy. Helsinki 1985.

D:74. TUOMO TEVAJÄRVI: Ongelmista Suomen ja Tanskan kaupallisessa kanssakäymisessä. Helsinki 1986.

D:75. KAI-VEIKKO VUORISTO: Suomalaisten seuramatkat Etelä- ja Kaakkois-Eurooppaan. Helsinki 1986.

D:76. ARTO LAHTI: Pienyritysten menestyminen kilpailussa avoimilla toimialoilla. Helsinki 1986.

D:77. PÄIVI AALTO: Kuluttajien ympäristöä koskevat asenteet. Helsinki 1986.

D:78. SATU PAULAHARJU: Central Bank Policy and External Disturbances in a Small Open Economy under Rational Expectations, Wage Rigidity, and Imperfect Capital Mobility. Helsinki 1986.

D:79. MARJA KORHONEN: Teatterin johtaminen Suomessa. Helsinki 1986.

D:80. SINIKKA VANHALA: Liikkeenjohtajien uraan vaikuttavat tekijät. Helsinki 1986.

D:81. SINIKKA VANHALA: Ekonomikunnan segmentoituneet työmarkkinat. Helsinki 1986.

D:82. ARTO LAHTI: Pankkien kilpailu ja yhteistyö pienyritysten kanssa. Helsinki 1986.

D:83. ARTO LAHTI: Entrepreneurship – an Economic Perspective. Helsinki 1986.

D:84. OLLI KANGAS: Luokkaintressit ja hyvinvointivaltio. Helsinki 1986.

D:85. TIMO JALAMO: Korkotulojen verotuksen vaikutuksia kotitalouksien sijoituskäyttäytymiseen. Helsinki 1986.

D:86. ANU SAARINEN: Korkojen verotuksen vaikutus investointeihin. Helsinki 1987.

D:87. HARRIET WAHLBERG: Korkojen verotuksen vaikutus kotitalouksien hyvinvointiin. Helsinki 1987.

D:88. JARMO LEPPINIEMI: Kansainvälinen tilinpäätösinformaatio. Sijoittajan näkökulma. Helsinki 1987.

D:89. HEIKKI NISKAKANGAS: Konsernivero-oikeutta. Helsinki 1987.

D:90. MARKKU TYKKYLÄINEN: Aloittavat pienyritykset maaseudulla. New small Enterprises in rural Areas. Helsinki 1987.

D:91. ANTTI HAAHTI: Imatran pienyritystutkimus. Helsinki 1987.

D:92. JARMO ERONEN: Teknologian siirto Neuvostoliiton metsäteollisuuteen. Helsinki 1987

D:93. ELINA KAARTINEN: Rahoitusmarkkinoiden muutoksen vaikutus yritysten investointikannustimiin. Helsinki 1987

D:94. ARJA GILLBERG: Tutkimus Helsingin kauppakorkeakouluun vuosina 1977–1979 sisäänpäässeiden opiskelijoiden opintomenestykseen vaikuttaneista tekijöistä. Helsinki 1987

D:95. KRISTIAN MÖLLER – MAI ANTTILA – PÄIVI VIRTANEN: Markkinointiosaaminen. Vertaileva tutkimus suomalaisissa ja ruotsalaisissa pienyrityksissä. Helsinki 1987.

D:96. PASI SORJONEN: The Relative Valuation of Dividends and Capital Gains in Finland. Helsinki 1987.

D:97. SATU KÄHKÖNEN: Central Bank Policy and External Disturbances under Fixed Exchange Rates. Helsinki 1987.

D:98. LASSE SIURALA: Nuorten työasenteet – Muuttuvatko iän mukana vai jäävätkö sukupolvea leimaamaan. Helsinki 1987.

D:99. SATU KÄHKÖNEN: Demand and Supply Shocks and Endogenous Government and Union Behavior. Helsinki 1987.

D:100. TAPANI LEHTONEN: A Note on the Comparison of two Sums of Exponentially Distributed Random Variables. Helsinki 1987.

D:101. ARTO LAHTI: Vaatetusalan rakennemuutos, protektionismi ja suomalaisten pienyritysten strategiavalinnat tärkeimmillä läntisillä vientimarkkinoilla. Helsinki 1987.

D:102. JOUKO YLÄ-LIEDENPOHJA: Effective marginal Tax Rates on Investment in Finland. Helsinki 1987.

D:103. The Department of Basic Research at the Helsinki School of Economics: Working Progress 1987. Helsinki 1987.

D:104. Pääkaupunkiseudun kulutusrahavirrat. Helsinki 1988.

E-sarja: selvityksiä:

E:1. Suomalaisen ja ruotsalaisen ekonomitutkinnon vertailu. Helsinki 1980.

E:2. En jämförelse av ekonomexamen i Finland och i Sverige. Helsinki 1980.

E:3. KALEVI SARVIKIVI – RISTO TAINIO: Tutkinnonuudistuksen seuranta Helsingin kauppakorkeakoulussa. Helsinki 1980.

E:4. Helsingin kauppakorkeakoulu. Tutkimusluettelo 1980. Helsinki 1980.

E:5. JAAKKO HONKO: Ehdotus Helsingin kauppakorkeakoulun kehittämiseksi 1980–1982. Helsinki 1980.

E:6. LASSE LEHMAN: Taloustieteen tesaurukset BILD/FINP ja SCANP/SCIMP. Suomenkielisen ja englanninkielisen terminologian vertailu. Helsinki 1980.

E:7. PIRJO LAAKSONEN: Informaatiopalvelutoiminnan nykytila Helsingin kauppakorkeakoulun kirjastossa ja suuntaviivoja sen kehittämiseksi suunnittelukaudella 1982–1986. Helsinki 1980.

E:8. Helsingin kauppakorkeakoulu. Tilastokirja vuodelta 1979. Helsinki 1980.

E:9. KYLLIKKI RUOKONEN: Tiedonlähteitä ja tiedonlähteillä. USAn tietopankkeihin tutustumassa. Helsinki 1980.

E:10. Tutkimuksen kehittämispäivä 21.11.1980. Helsinki 1981.

E:11. TUULA RATILAINEN – KAI-VEIKKO VUORISTO: EEC-projekti. Keski-Euroopan opintoretkeilyn raportit. Helsinki 1981.

E:12. ERKKI VAISTO – JUKKA EKLIN: Taloustieteellinen tutkimus Suomessa 1979. Aikakauslehtiartikkeleita. Helsinki 1981.

E:13. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1979. Tutkimuksia. Helsinki 1981.

E:14. Tutkimusluettelo 1981. Helsinki 1981.

E:15. Helsingin kauppakorkeakoulu. Tilastokirja vuodelta 1980. Helsinki 1981.

E:16. ERKKI VAISTO – TARU NUMMINEN: Taloustieteellinen tutkimus Suomessa 1980. Aikakauslehtiartikkeleita. Helsinki 1981.

E:17. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1980. Tutkimuksia. Helsinki 1982.

E:18. KYLLIKKI RUOKONEN: ATK-kirjallisuutta. Yhteisluettelo 1977–1981. ADP-literature. A Union Catalogue 1977–1981. Helsinki 1982.

E:19. KYLLIKKI RUOKONEN: Pakkausalan tietolähteet. Helsinki 1982.

E:20. Research Catalogue 1982. Helsinki 1982.

E:21. ERKKI VAISTO – TARU NUMMINEN: Taloustieteellinen tutkimus Suomessa 1980. Aikakauslehtiartikkeleita. Helsinki 1982.

E:22. EEVA-LIISA LEHTONEN: Helsingin kauppakorkeakoulun kirjaston kausijulkaisutiedosto. Helsinki 1982.

E:23. Helsingin kauppakorkeakoulu, tilastokirja vuodelta 1981. Helsinki 1982.

E:24. KYLLIKKI RUOKONEN – BENITA RINNE: Economic and Business Libraries in Scandinavia. Helsinki 1982.

E:25. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1981. Tutkimuksia. Helsinki 1983.

E:26. KAI-VEIKKO VUORISTO – TUULA RATILAINEN: Omnes viae roman ducunt! Italian opintomatkan raportit. Helsinki 1981.

E:27. ERKKI VAISTO – MATTI YRJÖLÄ: Taloustieteellinen tutkimus Suomessa 1982. Aikakauslehtiartikkeleita. Helsinki 1983.

E:28. Research Catalogue 1983. Helsinki 1983.

E:29. JAAKKO HONKO – JOUNI LÄTTI – MAINI MANNERKOSKI – MATTI SARAKONTU – KALEVI SARVIKIVI: Kauppakorkeakoulu – Helsingin kauppakorkeakoulu 1961–1981. Helsinki 1983.

E:30. Helsingin kauppakorkeakoulu, tilastokirja vuodelta 1982. Helsinki 1983.

E:31. ARVI LEPONIEMI: Korkeakoulujen toiminnan arviointi. Helsinki 1984.

E:32. KYLLIKKI RUOKONEN: Finnland: Wirtschaftswissenschaftliche Literatur 1960–1983. Helsinki 1984.

E:33. Research Catalogue 1984. Helsinki 1984.

E:34. ERKKI VAISTO – REIJO MANNINEN: Taloustieteellinen tutkimus Suomessa 1983. Aikakauslehtiartikkeleita. Helsinki 1984.

E:35. Miten johdan ja kehitän organisaatiotani. Studia-generalia luentosarja. Helsinki 1984.

E:36. Helsingin kauppakorkeakoulu, tilastokirja vuodelta 1983. Helsinki 1984.

E:37. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1982. Tutkimuksia. Helsinki 1984.

E:38. KAI-VEIKKO VUORISTO – RUULA RATILAINEN: Magyarorszag. Unkarin opintomatkan raportit. Helsinki 1985.

E:39. Research Catalogue 1985. Helsinki 1985.

E:40. ERKKI VAISTO – REIJO MANNINEN: Taloustieteellinen tutkimus Suomessa 1984. Aikakauslehtiartikkeleita. Helsinki 1985.

E:41. Helsingin kauppakorkeakoulu, tilastokirja vuodelta 1984. Helsinki 1985.

E:42. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1983. Tutkimuksia. Helsinki 1986.

E:43. MARJA PIRILÄ: Taloustieteellinen tutkimus Suomessa 1985. Aikakauslehtiartikkeleita. Helsinki 1986.

E:44. Research Catalogue 1986. Helsinki 1986.

E:45. VEIKKO LEIVO – AHTI LEHTOMAA: Pk-yritysten johtamisen runko-ohjelma Helsingin kauppakorkeakoulussa v. 1982–86. Helsinki 1986.

E:46. MARJA PIRILÄ – TUULA MÄLKÖNEN: Taloustieteellinen tutkimus Suomessa 1986. Aikakauslehtiartikkeleita. Helsinki 1987.

E:47. Research Catalogue 1987. Helsinki 1987.

E:48. Tilastokirja 1985–1986. Helsinki 1987.

E:49. KYLLIKKI RUOKONEN – BENITA RINNE: Economic Libraries. Helsinki 1987.

E:50. VEIKKO LEIVO-AHTI LEHTOMAA: Yrittäjyyden ja pienyritysten johtamisen opetus ja tutkimus Länsi-Euroopassa. Helsinki 1987.

E:51. ERKKI KOMULAINEN: Helsingin kauppakorkeakoulun opiskelijavalinnan toimivuuden tarkastelua kesän 1987 valinnan ylioppilasaineistolla. Valintaa kehittävän työryhmän muistio. Helsinki 1987.

F-sarja: työpapereita – working papers

F:1. TUIRE SANTAMÄKI: Työttömyysaste työmarkkinoiden kireyden mittarina. Helsinki 1980.

F:2. JUHA KÄHKÖNEN – ARVI LEPONIEMI – MIKKO PUHAKKA: Economic Policy in Finland 1974–1976: an Econometric Evaluation Using the Optimal Control Approach. Helsinki 1980.

F:3. TOMI DAHLBERG: Tietokone yritysjohdon päätöksenteon apuvälineenä – mahdollisuudet ja ongelmat. Helsinki 1980.

F:4. MARKKU SÄÄKSJÄRVI: Vaihejako vai superiointi tietosysteemien kehittämisessä – työmäärään vaikuttavien tekijöiden analyysi. Helsinki 1980.

F:5. MARKKU SÄÄKSJÄRVI: Tietojenkäsittelyn kokonaistutkimuksen työmenetelmät. METO 2. Helsinki 1980.

F:6. RISTO TAINIO: Structural Realism – an Alternative Approach for the Development of Organizational Theory. Helsinki 1980.

F:7. ANTTI HAAHTI: Palvelualalla toimivien pienyritysten johtamisen ongelmia. Helsinki 1981.

F:8. PEKKA AKKANEN: Yritysten budjetoinnin tutkimus – suuntaukset ja teoreettiset lähtökohdat. Helsinki 1981.

F:9. MARKKU KOSKELA: Osakkeen arvonmääritysteoriat. Helsinki 1981.

F:10. TUIRE SANTAMÄKI: Labour Hoarding. Käsite ja sen mittaaminen. Helsinki 1981.

F:11. MARKKU SÄÄKSJÄRVI – TOMI DAHLBERG – ERJA FAGERLUND – SIRPA HONKANEN – RAIMO JOKINEN: Tietokoneen opetuskäytön kehittäminen systeemiekonomin koulutusohjelmassa. Helsinki 1981.

F:12. MATTI TUOMALA – JOUKO YLÄ-LIEDENPOHJA: Shifts between direct and indirect Taxation: A Framework for the Evaluation of their Effects. Helsinki 1981.

F:13. ARVI LEPONIEMI: Wage Drift and the Exess Demand for Labour: The Case of Finland 1965–1976. Helsinki 1981.

F:14. KRISTIAN MÖLLER: TV-mainossanoman rakenne ja vaikutus – tutkimussuunnitelma. Helsinki 1981.

F:15. PEKKA KORHONEN – JYRKI WALLENIUS – STANLEY ZIONTS: Some Theory and a Method for Solving the Discrete Multiple Criteria Problem. Helsinki 1981.

F:16. SAARA HYVÖNEN: Markkinointijärjestelmän yhteistoiminta ja siihen vaikuttavat tekijät – tutkimussuunnitelma. Helsinki 1981.

F:17. PEKKA KORHONEN – EERO BLÅFILD: A Comparative Study of the Clustering Approaches by Day and Scott & Symons. Helsinki 1981.

F:18. RAIMO KELOHARJU: Relativity Dynamics. Helsinki 1981.

F:19. MAI ANTTILA – KRISTIAN MÖLLER: An Application of Additive and Multiplicative Conjoint Analysis Models in Explaining Consumer Price Utility Structures. Helsinki 1981.

F:20. RISTO TAINIO – JYRKI UUSITALO: On the Possibilities of Scientific Progress in Management and Organization Research. Helsinki 1981.

F:21. MARKKU KALLIO – MARGARETA SOISMAA: Some Improvements to the Reference Point Approach for Dynamic MCLP. Helsinki 1981.

F:22. PEKKA AKKANEN: Avointen järjestelmien teoria budjettivalvontajärjestelmän rakennetutkimuksen teoreettisena lähtökohtana. Helsinki 1981.

F:23. SINIKKA VANHALA: Työvoiman vaihtuvuuden mittaamisesta. Helsinki 1981.

F:24. TUIRE SANTAMÄKI: Työpanoksen sopeuttamiserojen selittäminen disaggregoidussa tarkastelussa. Helsinki 1981.

F:25. SINIKKA VANHALA: Voluntary Turnover in a Worsening Employment Situation. Helsinki 1982.

F:26. JAAKKO HAVUKKALA – KEIJO KAPULAINEN – TUOMAS SANTASALO: MAPS-kartanpiirtämisohjelma. Helsinki 1982.

F:27. TIMO AIRAKSINEN: Export Behavior of the Firm under Uncertainty. Helsinki 1982.

F:28. HENRI BROMS: The Middle Eastern Thinking as Expressed in Language and Style. Helsinki 1982.

F:29. MARKKU KOSKELA: Rahoituksen tasapainottaminen optimointimallin avulla. Helsinki 1982.

F:30. HENRIK GAHMBERG: "Analytic" Structuralism and Systems Theory as Potential Methodologies in Organizational Communication Research. Helsinki 1982.

F:31. HENRIK GAHMBERG: Communication, Language and Learning in Organizations. Helsinki 1982.

F:32. KRISTIAN MÖLLER – LEIF ÅBERG: Liikkeenjohdollisten käsitteiden hahmottaminen: pitkittäistutkimus Oy Karl Fazer Ab:ssa. Helsinki 1982.

F:33. RAIMO KELOHARJU: Relativity Dynamics. Helsinki 1982.

F:34. MARKKU SÄÄKSJÄRVI: Valmistautuminen toimistoautomaatioon Koulutuksen näkökulma. Helsinki 1982.

F:35. LEENA YLÄ-ANTTILA: Organisaatiorakenteen tutkimuksen suuntauksista, saavutuksista ja mahdollisuuksista. Helsinki 1982.

F:36. MARKKU KOSKELA: Kassavirta-analyysin soveltaminen kunnalliseen tilinpäätökseen. Helsinki 1982.

F:37. TIMO AIRAKSINEN: Export Performance of the Firms in the Finnish Engineering Industry. Helsinki 1982.

F:38. PEKKA KORHONEN – LIISA UUSITALO: A Visual Approach to Identifying Leisure Patterns. Helsinki 1982.

F:39. TIMO SANTANEN – RISTO TAINIO: Factors and Mechanisms Affecting Business Performance of Banks. Helsinki 1982.

F:40. MARKKU KOSKELA: Kunnallisen kassavirta-analyysin hyväksikäyttö. Helsinki 1982.

F:41. SEPPO ALALUUSUA: Determinants of the Structure and Control of Budgetary Processing in a Firm. Helsinki 1982.

F:42. ANSSI HYVÄRINEN: Organisaatiotutkimuksen kriisi – näkemyksiä ja ratkaisuehdotuksia. Helsinki 1982.

F:43. SEPPO ALALUUSUA: Information Economics and Budgetee Behavior. Helsinki 1982.

F:44. GEORGE A. MATTER – HENRI BROMS: The Myth of Garfield and Citation Indexing. Helsinki 1982.

F:45. JUHA KINNUNEN: Yritysten tilinpäätöstulosten aikasarja-analyyttisesta tutkimuksesta: The State of the Art 1982. Helsinki 1982.

F:46. MARKKU SÄÄKSJÄRVI: Cost Allocation in Cooperative Wood Procurement – A Game Theoretical Approach. Helsinki 1982.

F:47. JUHA KINNUNEN: Inflaation huomioonottaminen aikasarja-analyysiin perustuvassa yrityksen tuottoarvon määrityksessä. Helsinki 1983.

F:48. LIISA UUSITALO – KARI DJERF: Determinants of Gasoline Consumption. Helsinki 1982.

F:49. SEPPO ALALUUSUA: Kannattaako suunnittelu? Osa 1. Helsinki 1983.

F:50. LIISA UUSITALO: Naisten aseman kehityksestä kauppatieteellisellä alalla. Helsinki 1983.

F:51. OSMO KUUSI – RAIMO KELOHARJU: Internationality in System Dynamics: The Future of Time-use as an Illustration. Helsinki 1983.

F:52. LIISA UUSITALO – JYRKI UUSITALO: Paradigms in Scientific Development: the Example of Marketing. Helsinki 1983.

F:53. ANTTI HAAHTI: Values, Objectives, Stratecig Behavior and Performance in Small and Medium Sized Firms. Helsinki 1983.

F:54. KARI PAASONEN: Mittakaavaedut ja yrityksen pääomarahoitus. Helsinki 1983.

F:55. RITVA ALTONEN: On the Export Behavior of Firms. Helsinki 1983.

F:56. SEPPO LINDEMAN: Markkinoinnin didaktiikasta kaupallisissa oppilaitoksissa. Helsinki 1983.

F:57. PEKKA KORHONEN – JUKKA LAAKSO: A Visual Interactive Method for Solving the Multiple Criteria Problem. Helsinki 1983.

F:58. KRISTIAN MÖLLER: Research Paradigms in Analyzing Organizational Buying Process. Helsinki 1983.

F:59. ARTO LAHTI: Kilpailustrategia, strateginen ryhmä ja toimialan kilpailu toimialan kehitysprosessissa. Kirjallisuusanalyysi ja teorialähtökohdat elektroniikkatoimialan tutkimusprojektille. Helsinki 1983.

F:60 ARTO LAHTI: Kilpailustrategia, strateginen ryhmä ja toimialan kilpailu toimialan kehitysprosessissa. Empiirinen tutkimus trikootoimialan menestyksellisyydestä (väitöskirjan lyhennelmä). Helsinki 1983.

F:61. ARTO LAHTI: Kaupan neuvotteluvoiman kasvu ja tevanaketoimialojen strategiavaihtoehdot 1980-luvulla. Teorialähtökohdat tutkimusprojektille. Helsinki 1983.

F:62. SEPPO ALALUUSUA – LEIF ÅBERG: A Multi-Contingency Model for Managerial Control: Structure and Dynamics. Helsinki 1983.

F:63. MEERI SAARSALMI: Impact of Recource Recycling on Product Development in Marketing. Helsinki 1983.

F:64. KALERVO VIRTANEN: Yritysostojen epäonnistumisen syistä. Helsinki 1983.

F:65. MARKKU KOSKELA: The Marketing Price of Equity: a Cash Flow Based Approach. Helsinki 1983.

F:66. JAANA KUJALA: Technology-Structure Research: the State of the Art and Reorientation Possibilities. Helsinki 1983.

F:67. RISTO TAINIO – KARI LILJA – KEIJO RÄSÄNEN: Managerial "Arenas" of the Firm. Helsinki 1983.

F:68. LASSE SIURALA: Helsingin kauppakorkeakoulun opiskelijoiden käsityksiä korkeakouluun hakeutumisesta, opiskelusta ja työelämästä. Helsinki 1983.

F:69. SIRKKU KIVISAARI – SINIKKA VANHALA: Instrumental Work Orientation and Labour Stability. Helsinki 1983.

F:70. PEKKA KORHONEN – HERBERT MOSKOWITSZ – JYRKI WALLENIUS: A Sequential Approach to Modelling and Solving Multiple Criteria Decision Problems. Helsinki 1983.

F:71. PEKKA KORHONEN: A Case Study on Implementation of an Interactive Bargaining Model in Fortran by Stepwise Refining Control, Precedural and Data-Abstractions. Helsinki 1983.

F:72. PEKKA KORHONEN: The Ratio of the Absolute values of two Normal Variables. Helsinki 1983.

F:73. SEPPO LINDEMAN: Cross-Cultural Consumer Behavior and Stereotype Attitudes. Helsinki 1983.

F:74. JYRKI LIGNELL – MARKKU TUOMINEN: An Advertising Control Model of two State Variables. Helsinki 1983.

F:75. TUIRE SANTAMÄKI: The Overtime Pay Premium, Hours of Work, and Employment. Helsinki 1983.

F:76. PEKKA J. KORHONEN: A Hierarchial Interactive Method for Ranking Alternatives with Multiple Qualitative Criteria. Helsinki 1983.

F:77. PEKKA J. KORHONEN: Subjective Principal Component Analysis. Helsinki 1984.

F:78. PEKKA KORHONEN: Ordinal Principal Component Analysis. Helsinki 1984.

F:79. PEKKA KORHONEN – MARGARETA SOISMAA: Monitavoitteinen alkoholijuomien hinnoittelumalli. Helsinki 1984.

F:80. HANNU KIVIJÄRVI – PEKKA KORHONEN – JYRKI WALLENIUS: A Synthetic Approach to the Implementation Problems. Helsinki 1984.

F:81. MARKKU TUOMINEN: Eräs päätöksenteon tukijärjestelmä: Kassabudjettisimulaattori. Helsinki 1984.

F:82. MARKKU TUOMINEN – HANNU KIVIJÄRVI: Systeemidynamiikan ja optimikontrolliteorian välinen yhteys: DYSMAP-simultointikielen käyttö optimikontrollitehtävän ratkaisussa. Helsinki 1984.

F:83. ARTO LAHTI: Lähtökohtia TEVANAKE-toimialojen strategiavaihtoehdoille 1980-luvulla. Helsinki 1984.

F:84. URHO PAAKKUNAINEN: Yritysyhteistyötutkimuksesta. Helsinki 1984.

F:85. MARKKU VIRTANEN: The Core Rate of Inflation in the Buiter-Miller Model. Helsinki 1984.

F:86. TUIRE SANTAMÄKI: Employment and Hours Decisions, and the Willingness to Work Overtime Hours. Helsinki 1984.

F:87. TUOMAS SANTASALO: HP 125B käyttöohjekirja. Helsinki 1984.

F:88. MARKKU SÄÄKSJÄRVI: Selvitys liikkeenjohdon ja atk-osaston suhteista ja niiden kehittymisestä. Helsinki 1984.

F:89. TOMI DAHLBERG: Työasemat johdon työssä. Helsinki 1984.

F:90. TIMO SAARINEN: Johdon raportoinnin apuvälineitä. Helsinki 1984.

F:91. ARTO LAHTI: Strategic Management: A Theory of the Firm for Marketing Management. Helsinki 1984.

F:92. RITVA RAUTKYLÄ: Developing an Empirically Derived Index Measure for Enviromental Turbulence. Helsinki 1984.

F:93. RITVA RAUTKYLÄ: Assessing Organizational Performance: A Multicriteria Problem Involving the Business and Social Achievment of an Organization. Helsinki 1984.

F:94. ANNE OKSANEN: Adjustment and Structural Change Under Energy Price Increase. Helsinki 1984.

F:95. SEPPO LINDEMAN: The Case Method as a Teaching and Learning Tool in Marketing Education. Helsinki 1984.

F:96. TAPANI KYKKÄNEN: Divestointitutkimuksesta. Helsinki 1984.

F:97. JUHA VILJARANTA: Käyttö-, suorite- ja kassaperusteisten tilinpäätöstunnuslukujen ominaisuuksista ja suhteista. Helsinki 1984.

F:98. RISTO TAINIO – KARI LILJA – KEIJO RÄSÄNEN: Management and Modern Corporation in Society: How are They Interrelated? Helsinki 1984.

F:99. MARKKU KOSKELA: The Market Price of Equity: Some Empirical Results of the Finnish Stock Markets. Helsinki 1984.

F:100. ARTO LAHTI: Business Strategy, Strategic Groups and Industry Evolution, A View to the Finnish Knitwear Industry in 1969–1981. Helsinki 1984.

F:101. ARTO LAHTI: Strategic Models of the Finnish Knitwear Industry, 1969–1978. Helsinki 1984.

F:102. ARTO LAHTI: Strategy-Making, Performance Achievment and Industry Evolution, an Empirical Investigation in the Finnish Knitwear Industry in 1969–1981. Helsinki 1984.

F:103. JUHA VILJARANTA: Edustaako kassaperusteinen kannattavuus käyttöperusteista kannattavuutta? Helsinki 1984.

F:104. JYRKI NISKANEN: Indeksimalleista. Helsinki 1984.

F:105. HANNU KIVIJÄRVI – JUKKA LAAKSO – MARGARETA SOISMAA: Visual Aid for Investment Analysis. A Corporate Modelling Approach. Helsinki 1984.

F:106. KARI DJERF: Katsaus liikenteen suoritteiden, ajoneuvojen määrän ja liikenteen energiankulutuksen kehitykseen Suomessa. Helsinki 1984.

F:107. LIISA UUSITALO: The Symbolic Dynamics of TV-Viewing. Helsinki 1984.

F:108. JYRKI NISKANEN: Suhdannevaiheen ja tilinpäätöskäytännön vaikutus faktorianalyysin avulla suoritettavassa tilinpäätöstunnuslukujen luokittelussa. Helsinki 1984.

F:109. JUHA KINNUNEN: Enumeraation tehokkuus ARIMA-mallien identifioinnissa. Helsinki 1984.

F:110. SEPPO LINDEMAN: Schema Theoretical Approach to Stereotyping Products Made in Different Countries. Helsinki 1984.

F:111. KARI KOIVISTOINEN: Ulkomainen yritysosto kansainvälistymisvaihtoehtona. Helsinki 1984.

F:112. HANNU KIVIJÄRVI – JUKKA LAAKSO – MARGARETA SOISMAA: Budget Planning and Control as a Multiple Criteria Problem. A visual Approach. Helsinki 1985.

F:113. TIMO AIRAKSINEN: Profitability, Financial Position and R&D Expenditure of large Finnish Industrial Companies. Helsinki 1985.

F:114. ARTO LAHTI: Strateginen markkinointi markkinointitutkimuksen haasteena. Helsinki 1985.

F:115. RAIMO KELOHARJU – OSMO KUUSI: Evolving Future and the Choice. Helsinki 1985.

F:116. LASSE SIURALA: Työttömyys ja sen hoitokeinoja: tulevaisuuden näkymiä. Helsinki 1985.

F:117. JUHA VILJARANTA: Tulosyksikköorganisaation ohjaus empiiristen tutkimusten valossa. Helsinki 1985.

F:118. Johdon työasematietokoneet ja niiden hyväksikäyttö. Markku Sääksjärvi ym. Helsinki 1985.

F:119. TAPANI KYKKÄNEN: Divestoinnin käsite ja divestointien luokittelu. Helsinki 1985.

F:120. JUHA VILJARANTA: Suorituksen arviointi yrityksen ja sen tulosyksikköjen toiminnan ohjauksessa. Helsinki 1985.

F:121. KARI DJERF – LIISA UUSITALO: Autojen kysyntä – ekonometrisiä mallikokeita. Helsinki 1985.

F:122. JUHA VILJARANTA: Agenttiteoria yrityksen johdon laskentatoimen teoriana. Helsinki 1985.

F:123. VELI VIRKKUNEN: Yrityksen ulkoinen analyysi Saksan Liittotasavallassa. Helsinki 1985.

F:124. KARI KOIVISTOINEN: Tuottovaatimuksen vaikutus avioeroon yritysoston yhteydessä. Helsinki 1985.

F:125. SINIKKA VANHALA: Strategic Management of Human Resources. Helsinki 1985.

F:126. JAAKKO HONKO: From Manufacturing to Service-Based Economies. Helsinki 1985.

F:127. TIMO SAARINEN: Selecting a Strategy for an Information System Development Project to Support User Participation. Helsinki 1985.

F:128. HANNU KIVIJÄRVI – MARKKU TUOMINEN: A Visual Conceptualization and Optimization Approach to Dynamic Economic Problems. Helsinki 1985.

F:129. HANNU KIVIJÄRVI – MARKKU TUOMINEN: The Value of Information and Corporate Financial, Marketing and Production Planning. Helsinki 1985.

F:130. LASSE SIURALA: Nuorisotyöttömyyden tutkimus Suomessa. Helsinki 1985.

F:131. SEPPO I. SUOMINEN: The Prediction of Bankruptcy. Helsinki 1985.

F:132. JUHA KINNUNEN: A Proposition of the Serial Correlation of Income Numbers under Accrual and Cash Flow Accounting. Helsinki 1985.

F:133. SIRPA HAJBA: Mies- ja naisyrittäjien persoonallisuus. Helsinki 1985.

F:134. PEKKA KORHONEN: A Visual Reference Direction Approaches to Solving Discrete Multiple Criteria Problems. Helsinki 1986.

F:135. SINIKKA VANHALA: Needed a Reorientation in Labour Turnover Research. Helsinki 1986.

F:136. RAIMO KELOHARJU – OSMO KUUSI: On Extending O.R. Boundaries. Helsinki 1986.

F:137. SINIKKA VANHALA: Yritysympäristö, yrityksen toiminta ja työvoiman käyttö. Case: Valtionjohtoinen voimayhtiö. Helsinki 1986.

F:138. KARI TOIVIAINEN: Toimistoautomaation vaikutukset laskentatoimeen. Helsinki 1986.

F:139. MARKKU SÄÄKSJÄRVI: Peruskäyttäjien luokittelu sovellutuskehittimien käytön näkökulmasta. Helsinki 1986.

F:140. VEIKKO JÄÄSKELÄINEN: Negotiation of International Contracts. Helsinki 1986.

F:141. ARTO LAHTI: Strategic Marketing as the Key Concept of Success of Small Firms Competing in the Open Industries. Helsinki 1986.

F:142. PEKKA KORHONEN – OUTI LANTTO: An Experimental Comparison of Some Reference Direction Techniques for MCDM-Problems. Helsinki 1986.

F:143. TIIT ELENURM: Managerial Performance and Innovations in Organizations. Helsinki 1986.

F:144. KARI LILJA – KEIJO RÄSÄNEN – RISTO TAINIO: Towards Period Specific Theories of Management. Helsinki 1986.

F:145. JAAKKO HAVUKKALA: Esimerkkejä graafisen viestinnän esitystavoista. Helsinki 1986.

F:146. TIMO SAARINEN: State of Nolan's Stage Model. Helsinki 1986.

F:147. LIISA UUSITALO: On the Consumption of Pictorial Art. Helsinki 1986.

F:148. SIRKKU KIVISAARI – SINIKKA VANHALA: Psychophysical Strain in Office Work. Helsinki 1986.

F:149. KALERVO VIRTANEN: Pääomien allokointi monialaisessa tulosyksikköorganisaatiossa. Helsinki 1986.

F:150. JAAKKO HONKO: Developing Economic Strategies for Small Countries. Helsinki 1986.

F:151. SEPPO I. SUOMINEN: Katsaus vertikaaliseen yhdentymiseen. Helsinki 1986.

F:152. VEIKKO JÄÄSKELÄINEN: Financial Management of Commercial Banks, Part I. Helsinki 1986.

F:153. PEKKA J. KORHONEN: The Specification of a Reference Direction Using the AHP. Helsinki 1986.

F:154. MARKKU SÄÄKSJÄRVI: Tietokoneiden itsenäiskäyttö. Helsinki 1986.

F:155. URHO PAAKKUNAINEN: Approaches to Study Joint Venture as an economic Decision. Helsinki 1986.

F:156. PEKKA J. KORHONEN: VIS – A visual interactive Support System for multiple Criteria Decision Making. Helsinki 1986.

F:157. LIISA UUSITALO – MARJA KORHONEN: Management of Cultural Organizations. Helsinki 1986.

F:158. MARJA-LIISA PARJANNE: Determinants of Intra-Industry Trade: A theoretical and empirical Framework. Helsinki 1986.

F:159. SOILE TUORINSUO: Yhteistoiminnan säännöt sovellettuna yrityksen päätöstilanteisiin. Helsinki 1986.

F:160. MERJA PURHONEN: Osallistuvan johtamistyylin vaikutuksista toimihenkilöiden työtyytyväisyyteen. Helsinki 1986.

F:161. TINA REIJONEN: Yhteistoimintalaki ja koettu osallistuminen eri henkilöstöryhmien välillä Suomessa ja Ruotsissa. Helsinki 1986.

F:162. JOUKO YLÄ-LIEDENPOHJA: Kohti kulutetun tulonosan verottamista. Helsinki 1986.

F:163. JOUKO YLÄ-LIEDENPOHJA: Korkojen verotuskohtelun muutosvaihtoehdot. Helsinki 1987.

F:164. TIMO SANTALAINEN – B.R. BALIGA: Results Management (ReMa) Designing for Performance. Helsinki 1987.

F:165. ANNE OKSANEN: Dominant Firms, competitive Fringe and Entry: a Case of Book Publishing Industry. Helsinki 1987.

F:166. JOUKO YLÄ-LIEDENPOHJA: Taxing Real Investment. Helsinki 1987.

F:167. JOUKO YLÄ-LIEDENPOHJA: Perspectives on the Tax Base of the Finnish Economy. Helsinki 1987.

F:168. PEKKA KORHONEN – TIMO SANTALAINEN – RISTO TAINIO: Explaining Variations in Bank Performance. Helsinki 1987.

F:169. ANTTI J. HAAHTI: Product-Market Strategies of Small and Medium-Sized European Industrial Firms. Helsinki 1987.

F:170. ANTTI J. HAAHTI: A Word on Theories of Entrepreneurship and Theories of Small Business Interface. A few Comments. Helsinki 1987.

F:171. TIMO SAARINEN: Case Studies on Using the Contigency Approach for Selecting a System Development Strategy. Helsinki 1987.

F:172. TIMO SAARINEN–MARKKU SÄÄKSJÄRVI–JUKKA HEIKKILÄ: Itsenäiskäyttö ja sen johtaminen Suomessa. Helsinki 1987

F:173. PENTTI MIKKONEN: Virkamiehet ja liike-elämään osallistuminen. Helsinki 1987

F:174. IVAN GEORGIEV – MARKKU VIRTANEN: The Conceptual Approach to the Financing of Investments in an Industrial Enterprise. Helsinki 1987.

F:175. PEKKA KORHONEN – HERBERT MOSKOWITZ – JYRKI WALLENIUS: Choice Behavior in Interactive Multiple Criteria Decision-Making. Helsinki 1987.

F:176. LUCIEN DUCKSTEIN – PEKKA KORHONEN: A Visual and Interactive Fuzzy Multicriterion Approach to Forest Management. Helsinki 1987.

F:177. LIISA TIITTULA: apropos Oulainen, da fällt mir grad eine Anekdote ein... Überlegungen zu Metatext, Gliederungssignalen und discourse markers im Gespräch und zu ihrer Rolle als Planungsindikatoren. Helsinki 1987.

F:178. SEPPO I. SUOMINEN: Kuorma-autojen kysynnästä. Helsinki 1987.

F:179. PEKKA J. KORHONEN – SUBHAS C. NARULA: An Evolutionary Approach to Solving Linear Decision Models. Helsinki 1987.

F:180. PEKKA KORHONEN – JYRKI WALLENIUS: A Pareto Race. Helsinki 1987.

F:181. MARKKU KOSKELA: Suomalainen ja kansainvälinen tilinpäätöskäytäntö pörssiyritysten tilinpäätöksissä 1986. Helsinki 1987.

F:182. RITVA RAUTKYLÄ: Research Perspectives in Strategic Management. Helsinki 1987.

F:183. PIRJO VUOKKO: An Examination of Advertising Repetition Effects by Means of Learning Theory. Helsinki 1987.

F:184. OLLI TAHVONEN: Interaction of renewable Resource Exploitation and Pollution Control. Helsinki 1987.

F:185. SEPPO I SUOMINEN: Dynaaminen malli vertikaalisesta yhdentymisestä. Helsinki 1987.

F:186. PENTTI MIKKONEN: Virkamiesten liiketoimet ja esteellisyys. Helsinki 1987.

F:187. LIISA UUSITALO: Dilemma between Individual Utility and Collective Welfare. Helsinki 1987.

F:188. RITVA RAUTKYLÄ: Contributions and Challenges in Strategic Marketing Research. Helsinki 1987.

F:189. MARKKU SÄÄKSJÄRVI – JUKKA HEIKKILÄ – TIMO SAARINEN: Dual Role of Information Centers. Helsinki 1987.

M-sarja: Mikkelin Pienyrityskeskuksen julkaisuja

M:1. ANTERO KOSKINEN: Ristiinan kunnan elinkeinopoliittinen kartoitus ja toimenpideohjelma. Helsinki 1984.

M:2. TIMO NUUJA; TUTPRO: Tutkimusaiheita Mikkelin läänin parhaaksi ja kehittämiseksi. Helsinki 1984.

M:3. TUULI TUKIAINEN: Mikkelin läänin kommentoiva bibliografia. Helsinki 1985.

M:4. LAURI VALKONEN: Energiatiedotusprojekti: tehostettua energiatiedotusta Mikkelin läänissä. Helsinki 1985.

M:5. Hyvä koulutuskäytäntö I. Yritysjohdon koulutuksen laatukysymyksiä. Toim. Hilkka Kuisma. Helsinki 1985.

M:6. Viisi lukuvuotta Mikkelissä. Katsaus HKKK:n toimintaan Mikkelissä vuosina 1980–1985. Toim. Antero Koskinen. Helsinki 1985.

M:7. Pienyritykset. Tiedonhaku, pienyrityskirjallisuus ja pienyritystutkimukset. Helsinki 1985.

M:8. TUULA FOSSI – ANTERO KOSKINEN: Telepalvelut ja pk-yritykset. Helsinki 1985.

M:9. TIMO NUUJA: Yrityskohtaiset energiapalaverit – toiminnan arviointia. Helsinki 1985.

M:10. ANTERO KOSKINEN – PIRKKO SUOKAS: Yrittäjä- ja yritysjohdon koulutus. Helsinki 1986.

M:11. Pienyritykset – Small Business. Helsinki 1986.

M:12. Konsultointi PK-yrityksissä. Toim. Heikki Torniainen. Helsinki 1986.

M:13. VILHO MÄKELÄ – MARKKU VIRTANEN: Mikkelin läänin rahavirrat. Helsinki 1986.

M:14. MARKKU VIRTANEN: TUTPRO, Tutkimusaiheita Mikkelin läänin kehittämiseksi. Mikkeli 1986.

M:15. MARKKU VIRTANEN: An empirical Study of Interest Rate Differencies and Price Discrimination in the Finnish Business Loan Market. Helsinki 1987.

M:16. Mikkelin läänin osavalmistuspörssi. Puu- ja metalliteollisuus. Mikkeli 1987.

M:17. EEVA-LIISA LEHTONEN – ERKKI VAISTO: Kauppa. Tiedonhaku, ulkomainen kirjallisuus ja tutkimukset. Helsinki 1987.

M:18. MARKKU TYKKYLÄINEN: Teollisuuden työllistävyys 1980-luvulla. Mikkelin läänin asema valtakunnallisessa kehityksessä. Mikkeli 1987.

M:19. EEVA-LIISA LEHTONEN – ERKKI VAISTO: Koulutus ja työelämä. Opas tutkimuksen tiedonlähteille. Helsinki 1987.

M:20. ANTERO KOSKINEN: Oman yrityksen perustaminen. Teemapäiväosallistujat ja yritysideoiden kehitys 1980–1986. Mikkeli 1987.

M:21. ANTTI HAAHTI – RISTO RITALA – UNTO PALMINKOSKI: Maatilamatkailun edellytykset. Mikkeli 1987.

M:22. HEIMO KANNUS: Vähittäiskauppa Mikkelin läänissä. Helsinki 1987.

M:23. MARJA PIRILÄ – TUULA SEPPÄLÄ: Pienyritykset – Small Business II. Koti- ja ulkomaista kirjallisuutta vuonna 1986. Helsinki 1987.

M:24. TUULA SEPPÄLÄ – PIRKKO SUOKAS (toim.): Hyvä konsultointikäytäntö. Seminaarialustuksia. Konsulttirekisteri II. Helsinki 1987.

M:25. IVAN GEORGIEV – MARKKU VIRTANEN: Financing of Replacement and Innovation of Fixed Assets of a Socialist Enterprise. Helsinki 1987.

M:26. ANTERO KOSKINEN: Yrityksen perustamisjärjestelmä. Kurssilaiset ja kurssiarvioinnit. Mikkeli 1987.

M:27. JARI VARTIAINEN: Varastopalvelujen tarve Mikkelin talousalueella. Helsinki 1987.

M:28. Tutpro 1987. Tutkimusaiheita Mikkelin läänin kehittämiseksi. Mikkeli 1987.

M:29. MARKKU VIRTANEN: Mikkelin läänin elinkeinoelämän tutkimuspoliittinen ohjelma ja tutkimusohjelma 1987. Mikkeli 1987.

ISSN 0356-9969
ISBN 951-700-390-0
1988

KYRIIRI OY 1988