1

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS
STANDARD REFERENCE MATERIAL 1010a
(ANSI and ISO TEST CHART No. 2)

National Library
of Canada

Acquisitions and
Bibliographic Services Branch

395 Wellington Street
Ottawa, Ontario
K1A 0N4

Bibliothèque nationale
du Canada

Direction des acquisitions et
des services bibliographiques

395, rue Wellington
Ottawa (Ontario)
K1A 0N4

Votre file - Votre référence

Cher file - Notre référence

NOTICE

The quality of this microform is heavily dependent upon the quality of the original thesis submitted for microfilming. Every effort has been made to ensure the highest quality of reproduction possible.

If pages are missing, contact the university which granted the degree.

Some pages may have indistinct print especially if the original pages were typed with a poor typewriter ribbon or if the university sent us an inferior photocopy.

Reproduction in full or in part of this microform is governed by the Canadian Copyright Act, R.S.C. 1970, c. C-30, and subsequent amendments.

AVIS

La qualité de cette microforme dépend grandement de la qualité de la thèse soumise au microfilmage. Nous avons tout fait pour assurer une qualité supérieure de reproduction.

S'il manque des pages, veuillez communiquer avec l'université qui a conféré le grade.

La qualité d'impression de certaines pages peut laisser à désirer, surtout si les pages originales ont été dactylographiées à l'aide d'un ruban usé ou si l'université nous a fait parvenir une photocopie de qualité inférieure.

La reproduction, même partielle, de cette microforme est soumise à la Loi canadienne sur le droit d'auteur, SRC 1970, c. C-30, et ses amendements subséquents.

Canada

**A COMPARATIVE STUDY ON
NEW PRODUCT DIFFUSION MODELS:
A SCANNER DATA BASED STUDY**

by

**Andreas F. Mayer
Diplom-Betriebswirt (BA)**

**A thesis submitted to
the Faculty of Graduate Studies and Research
in partial fulfilment of
the requirements for the Degree of**

Master in Management Studies

School of Business

**Carleton University
Ottawa, Ontario**

August 18, 1993

© copyright

1993, Andreas F. Mayer

National Library
of Canada

Acquisitions and
Bibliographic Services Branch

395 Wellington Street
Ottawa, Ontario
K1A 0N4

Bibliothèque nationale
du Canada

Direction des acquisitions et
des services bibliographiques

395, rue Wellington
Ottawa (Ontario)
K1A 0N4

Votre copie - Votre référence

Quel que - Notre référence

The author has granted an irrevocable non-exclusive licence allowing the National Library of Canada to reproduce, loan, distribute or sell copies of his/her thesis by any means and in any form or format, making this thesis available to interested persons.

L'auteur a accordé une licence irrévocable et non exclusive permettant à la Bibliothèque nationale du Canada de reproduire, prêter, distribuer ou vendre des copies de sa thèse de quelque manière et sous quelque forme que ce soit pour mettre des exemplaires de cette thèse à la disposition des personnes intéressées.

The author retains ownership of the copyright in his/her thesis. Neither the thesis nor substantial extracts from it may be printed or otherwise reproduced without his/her permission.

L'auteur conserve la propriété du droit d'auteur qui protège sa thèse. Ni la thèse ni des extraits substantiels de celle-ci ne doivent être imprimés ou autrement reproduits sans son autorisation.

ISBN 0-315-89729-5

Canada

Name _____

Dissertation Abstracts International is arranged by broad, general subject categories. Please select the one subject which most nearly describes the content of your dissertation. Enter the corresponding four-digit code in the spaces provided.

--	--	--	--

U·M·I

SUBJECT TERM

SUBJECT CODE

Subject Categories

THE HUMANITIES AND SOCIAL SCIENCES

COMMUNICATIONS AND THE ARTS

Architecture 0729
Art History 0377
Cinema 0900
Dance 0378
Fine Arts 0357
Information Science 0723
Journalism 0391
Library Science 0399
Mass Communications 0708
Music 0413
Speech Communication 0459
Theater 0465

EDUCATION

General 0515
Administration 0514
Adult and Continuing 0516
Agricultural 0517
Art 0273
Bilingual and Multicultural 0282
Business 0688
Community College 0275
Curriculum and Instruction 0727
Early Childhood 0518
Elementary 0524
Finance 0277
Guidance and Counseling 0519
Health 0680
Higher 0745
History of 0520
Home Economics 0278
Industrial 0521
Language and Literature 0279
Mathematics 0280
Music 0522
Philosophy of 0998
Physical 0523

Psychology 0525
Reading 0535
Religious 0527
Sciences 0714
Secondary 0533
Social Sciences 0534
Sociology of 0340
Special 0529
Teacher Training 0530
Technology 0710
Tests and Measurements 0288
Vocational 0747

LANGUAGE, LITERATURE AND LINGUISTICS

Language
 General 0679
 Ancient 0289
 Linguistics 0290
 Modern 0291
Literature
 General 0401
 Classical 0294
 Comparative 0295
 Medieval 0297
 Modern 0298
 African 0316
 American 0591
 Asian 0305
 Canadian (English) 0352
 Canadian (French) 0355
 English 0593
 Germanic 0311
 Latin American 0312
 Middle Eastern 0315
 Romance 0313
 Slavic and East European 0314

PHILOSOPHY, RELIGION AND THEOLOGY

Philosophy 0422
Religion
 General 0318
 Biblical Studies 0321
 Clergy 0319
 History of 0320
 Philosophy of 0322
Theology 0469

SOCIAL SCIENCES

American Studies 0323
Anthropology
 Archaeology 0324
 Cultural 0326
 Physical 0327
Business Administration
 General 0310
 Accounting 0272
 Banking 0770
 Management 0454
 Marketing 0338
Canadian Studies 0385
Economics
 General 0501
 Agricultural 0503
 Commerce-Business 0505
 Finance 0508
 History 0509
 Labor 0510
 Theory 0511
Folklore 0358
Geography 0366
Gerontology 0351
History
 General 0578

Ancient 0579
Medieval 0581
Modern 0582
Black 0328
African 0331
Asia, Australia and Oceania 0332
Canadian 0334
European 0335
Latin American 0336
Middle Eastern 0333
United States 0337
History of Science 0585
Law 0398
Political Science
 General 0615
 International Law and Relations 0616
 Public Administration 0617
Recreation 0814
Social Work 0452
Sociology
 General 0626
 Criminology and Penology 0627
 Demography 0938
 Ethnic and Racial Studies 0631
 Individual and Family Studies 0628
 Industrial and Labor Relations 0629
 Public and Social Welfare 0630
 Social Structure and Development 0700
 Theory and Methods 0344
Transportation 0709
Urban and Regional Planning 0999
Women's Studies 0453

THE SCIENCES AND ENGINEERING

BIOLOGICAL SCIENCES

Agriculture
 General 0473
 Agronomy 0285
 Animal Culture and Nutrition 0475
 Animal Pathology 0476
 Food Science and Technology 0359
 Forestry and Wildlife 0478
 Plant Culture 0479
 Plant Pathology 0480
 Plant Physiology 0817
 Range Management 0777
 Wood Technology 0746
Biology
 General 0306
 Anatomy 0287
 Biostatistics 0308
 Botany 0309
 Cell 0379
 Ecology 0329
 Entomology 0353
 Genetics 0369
 Limnology 0793
 Microbiology 0410
 Molecular 0307
 Neuroscience 0317
 Oceanography 0416
 Physiology 0433
 Radiation 0821
 Veterinary Science 0778
 Zoology 0472
Biophysics
 General 0786
 Medical 0760
EARTH SCIENCES
Biogeochemistry 0425
Geochemistry 0996

Geodesy 0370
Geology 0372
Geophysics 0373
Hydrology 0388
Mineralogy 0411
Paleobotany 0345
Paleoecology 0426
Paleontology 0418
Paleozoology 0985
Palynology 0427
Physical Geography 0368
Physical Oceanography 0415

HEALTH AND ENVIRONMENTAL SCIENCES

Environmental Sciences 0768
Health Sciences
 General 0566
 Audiology 0300
 Chemotherapy 0992
 Dentistry 0567
 Education 0350
 Hospital Management 0769
 Human Development 0758
 Immunology 0982
 Medicine and Surgery 0564
 Mental Health 0347
 Nursing 0569
 Nutrition 0570
 Obstetrics and Gynecology 0380
 Occupational Health and Therapy 0354
 Ophthalmology 0381
 Pathology 0571
 Pharmacology 0419
 Pharmacy 0572
 Physical Therapy 0382
 Public Health 0573
 Radiology 0574
 Recreation 0575

Speech Pathology 0460
Toxicology 0383
Home Economics 0386

PHYSICAL SCIENCES

Pure Sciences
Chemistry
 General 0485
 Agricultural 0749
 Analytical 0486
 Biochemistry 0487
 Inorganic 0488
 Nuclear 0738
 Organic 0490
 Pharmaceutical 0491
 Physical 0494
 Polymer 0495
 Radiation 0754
Mathematics 0405
Physics
 General 0605
 Acoustics 0986
 Astronomy and Astrophysics 0606
 Atmospheric Science 0608
 Atomic 0748
 Electronics and Electricity 0607
 Elementary Particles and High Energy 0798
 Fluid and Plasma 0759
 Molecular 0609
 Nuclear 0610
 Optics 0752
 Radiation 0756
 Solid State 0611
Statistics 0463
Applied Sciences
Applied Mechanics 0346
Computer Science 0984

Engineering
 General 0537
 Aerospace 0538
 Agricultural 0539
 Automotive 0540
 Biomedical 0541
 Chemical 0542
 Civil 0543
 Electronics and Electrical 0544
 Heat and Thermodynamics 0348
 Hydraulic 0545
 Industrial 0546
 Marine 0547
 Materials Science 0794
 Mechanical 0548
 Metallurgy 0743
 Mining 0551
 Nuclear 0552
 Packaging 0549
 Petroleum 0765
 Sanitary and Municipal System Science 0554
 Geotechnical Research 0428
 Plastics Technology 0796
 Textile Technology 0994

PSYCHOLOGY

General 0621
Behavioral 0384
Clinical 0622
Developmental 0620
Experimental 0623
Industrial 0624
Personality 0625
Physiological 0989
Psychobiology 0349
Psychometrics 0632
Social 0451

Carleton
UNIVERSITY

Notice :

This thesis includes
2 disks. In addition,
the thesis can be
copied on microfilm,
even without the
disks.

A. Meyer

The undersigned recommend to
the Faculty of Graduate Studies and Research
acceptance of the thesis,

A COMPARATIVE STUDY ON
NEW PRODUCT DIFFUSION MODELS:
A SCANNER DATA BASED STUDY

submitted by

Andreas F. Mayer
Diplom-Betriebswirt (BA)

in partial fulfilment of the requirements
for the degree of Master of Management Studies

Thesis Co-Supervisor

Thesis Co-Supervisor

Director, School of Business

Carleton University

September 20, 1993

ABSTRACT

The prediction of success or failure of a new product is a critical - and difficult - management task. This thesis empirically tests whether 10 selected forecasting models can be employed to describe (ex post) and predict (ex ante) sales of a low involvement non-durable consumer product.

The descriptive analysis reveals that the models work well in some cases but not in others. There are significant differences in the performance of the individual models. Some give rather poor results, while the Bass model, the von Bertalanffy model, and especially the Brockhoff model describe the data at least reasonably well in the majority of cases.

The predictive analysis reveals an extremely poor accuracy of all models. Even though there are some differences in the performance, none of the models yields satisfactory results.

Apparently - at least for the available data - diffusion models can describe the past development of sales, but they cannot predict the future development of sales.

ACKNOWLEDGEMENTS

I am indebted to several people for their ongoing support and advice. First, I would like to thank Professor George Haines Jr. and Professor Uma Kumar for their willingness to meet and discuss my research whenever necessary - as well as for some joyful conversations. I would also like to express my gratitude to Professor Judith Marshall for providing helpful comments and directions. At this point I want to mention Douglas Henko whose previous work on the IRI database allowed me to extract the necessary data for this research.

I would also like to take the time to thank Jean Blair for taking care of all the administrative problems and thus letting me concentrate on my research. Although it is impossible to mention everyone, I would like to acknowledge the support from my fellow students who provided me with an environment that enabled me to work a lot as well as enjoy my stay in Canada.

Special gratitude is owed to some special people in my life. This includes in particular my parents who gave me constant encouragement and support throughout my education and in everything I have ever done.

THANK YOU!

TABLE OF CONTENTS

	PAGE
ACCEPTANCE SHEET	ii
ABSTRACT	iii
ACKNOWLEDGEMENTS	iv
TABLE OF CONTENTS	v
LIST OF TABLES	viii
LIST OF FIGURES	xii
LIST OF APPENDICES	xiii
1. INTRODUCTION	1
1.1 RESEARCH PROBLEM	6
1.2 RESEARCH OBJECTIVES AND ORGANIZATION OF THE THESIS	11
2. LITERATURE REVIEW	14
2.1 THE DIFFUSION PROCESS	14
2.1.1 THE INNOVATION	15
2.1.2 COMMUNICATION CHANNELS	18
2.1.3 TIME	21
2.1.4 THE SOCIAL SYSTEM	25
2.2 DIFFUSION MODELS	27
2.2.1 EXTERNAL INFLUENCE MODELS	30
2.2.2 INTERNAL INFLUENCE MODELS	32
2.2.3 THE BASS MODEL	34
2.2.4 FLEXIBLE MODELS	36
2.2.5 MODELS INCORPORATING ELEMENTS OF THE MARKETING MIX	53

	PAGE
3. METHODOLOGY	56
3.1 BEHAVIORSCAN	56
3.2 THE AVAILABLE DATA	61
3.3 DATA ANALYSIS	64
4. FINDINGS	72
4.1 DESCRIPTIVE VALUE OF THE MODELS	72
4.1.1 THE FISHER-PRY MODEL	73
4.1.2 THE BASS MODEL	76
4.1.3 THE SHARIF-KABIR MODEL	80
4.1.4 THE JEULAND MODEL	83
4.1.5 THE NUI MODEL	86
4.1.6 THE VON BERTALANFFY MODEL	89
4.1.7 THE GENERALIZED MODEL	91
4.1.8 THE KKK I MODEL	94
4.1.9 THE KKK II MODEL	97
4.1.10 THE BROCKHOFF MODEL	99
4.1.11 SUMMARY	103
4.2 PREDICTIVE VALUE OF THE MODELS	108
4.2.1 THE FISHER-PRY MODEL	109
4.2.2 THE BASS MODEL	112
4.2.3 THE SHARIF-KABIR MODEL	116
4.2.4 THE JEULAND MODEL	119
4.2.5 THE NUI MODEL	122
4.2.6 THE VON BERTALANFFY MODEL	124
4.2.7 THE GENERALIZED MODEL	127
4.2.8 THE KKK I MODEL	130
4.2.9 THE KKK II MODEL	133
4.2.10 THE BROCKHOFF MODEL	136
4.2.11 SUMMARY	140

	PAGE
5. CONCLUSION	146
5.1 IMPLICATIONS OF THIS STUDY	146
5.2 LIMITATIONS	149
5.3 FUTURE RESEARCH	152
BIBLIOGRAPHY	154

LIST OF TABLES

TABLE	DESCRIPTION	PAGE
1	CHARACTERISTICS OF THE SELECTED DIFFUSION MODELS	52
2	PRODUCT DATA SUMMARY	62
3	SUMMARY FISHER-PRY MODEL FIRST PURCHASE SALES - DESCRIPTION	74
4	SUMMARY FISHER-PRY MODEL TOTAL SALES - DESCRIPTION	75
5	SUMMARY BASS MODEL FIRST PURCHASE OCCASIONS - DESCRIPTION	77
6	SUMMARY BASS MODEL FIRST PURCHASE SALES - DESCRIPTION	78
7	SUMMARY BASS MODEL TOTAL SALES - DESCRIPTION	79
8	SUMMARY SHARIF-KABIR MODEL FIRST PURCHASE SALES - DESCRIPTION	81
9	SUMMARY SHARIF-KABIR MODEL TOTAL SALES - DESCRIPTION	82
10	SUMMARY JEULAND MODEL FIRST PURCHASE SALES - DESCRIPTION	84
11	SUMMARY JEULAND MODEL TOTAL SALES - DESCRIPTION	84
12	SUMMARY NUI MODEL FIRST PURCHASE SALES - DESCRIPTION	86
13	SUMMARY NUI MODEL TOTAL SALES - DESCRIPTION	87
14	SUMMARY VON BERTALANFFY MODEL FIRST PURCHASE SALES - DESCRIPTION	89
15	SUMMARY VON BERTALANFFY MODEL TOTAL SALES - DESCRIPTION	90

TABLE	DESCRIPTION	PAGE
16	SUMMARY GENERALIZED MODEL FIRST PURCHASE SALES - DESCRIPTION	92
17	SUMMARY GENERALIZED MODEL TOTAL SALES - DESCRIPTION	93
18	SUMMARY KKK I MODEL FIRST PURCHASE SALES - DESCRIPTION	95
19	SUMMARY KKK I MODEL TOTAL SALES - DESCRIPTION	96
20	SUMMARY KKK II MODEL FIRST PURCHASE SALES - DESCRIPTION	97
21	SUMMARY KKK II MODEL TOTAL SALES - DESCRIPTION	98
22	SUMMARY BROCKHOFF MODEL FIRST PURCHASE OCCASIONS - DESCRIPTION	100
23	SUMMARY BROCKHOFF MODEL FIRST PURCHASE SALES - DESCRIPTION	101
24	SUMMARY BROCKHOFF MODEL TOTAL SALES - DESCRIPTION	102
25	SUBJECTIVE RANKING BY THE AUTHOR OF THE MODELS FOR DESCRIPTIVE ANALYSIS OF NEW PRODUCT INTRODUCTION	106
26	SUMMARY FISHER-PRY MODEL FIRST PURCHASE SALES - PREDICTION	110
27	SUMMARY FISHER-PRY MODEL TOTAL SALES - PREDICTION	111
28	SUMMARY BASS MODEL FIRST PURCHASE OCCASIONS - PREDICTION	113
29	SUMMARY BASS MODEL FIRST PURCHASE SALES - PREDICTION	114
30	SUMMARY BASS MODEL TOTAL SALES - PREDICTION	115

TABLE	DESCRIPTION	PAGE
31	SUMMARY SHARIF-KABIR MODEL FIRST PURCHASE SALES - PREDICTION	117
32	SUMMARY SHARIF-KABIR MODEL TOTAL SALES - PREDICTION	118
33	SUMMARY JEULAND MODEL FIRST PURCHASE SALES - PREDICTION	120
34	SUMMARY JEULAND MODEL TOTAL SALES - PREDICTION	121
35	SUMMARY NUI MODEL FIRST PURCHASE SALES - PREDICTION	122
36	SUMMARY NUI MODEL TOTAL SALES - PREDICTION	123
37	SUMMARY VON BERTALANFFY MODEL FIRST PURCHASE SALES - PREDICTION	125
38	SUMMARY VON BERTALANFFY MODEL TOTAL SALES - PREDICTION	126
39	SUMMARY GENERALIZED MODEL FIRST PURCHASE SALES - PREDICTION	128
40	SUMMARY GENERALIZED MODEL TOTAL SALES - PREDICTION	129
41	SUMMARY KKK I MODEL FIRST PURCHASE SALES - PREDICTION	131
42	SUMMARY KKK I MODEL TOTAL SALES - PREDICTION	132
43	SUMMARY KKK II MODEL FIRST PURCHASE SALES - PREDICTION	134
44	SUMMARY KKK II MODEL TOTAL SALES - PREDICTION	135

TABLE	DESCRIPTION	PAGE
45	SUMMARY BROCKHOFF MODEL FIRST PURCHASE OCCASIONS - PREDICTION	137
46	SUMMARY BROCKHOFF MODEL FIRST PURCHASE SALES -- PREDICTION	138
47	SUMMARY BROCKHOFF MODEL TOTAL SALES - PREDICTION	139
48	EXAMPLE OF THE ACCURACY OF THE "AVERAGE" FORECAST	141

LIST OF FIGURES

FIGURE	DESCRIPTION	PAGE
1	DESCRIPTION OF INDIVIDUAL RECORDS (U < 0.7)	104
2	DESCRIPTION OF INDIVIDUAL RECORDS (U < 0.5)	105
3	PREDICTION OF INDIVIDUAL RECORDS (U < 0.7)	142
4	PREDICTION OF INDIVIDUAL RECORDS (U < 0.5)	143

LIST OF APPENDICES

APPENDIX	DESCRIPTION	PAGE
1	SAMPLE TSP PROGRAM USED FOR DESCRIPTIVE ANALYSIS	162
2	SAMPLE TSP PROGRAM USED FOR PREDICTIVE ANALYSIS	163
3	SAMPLE DATASET YIELDING GOOD DESCRIPTIVE AND PREDICTIVE RESULTS FOR MOST MODELS . . .	164
4	SAMPLE DATASET YIELDING GOOD DESCRIPTIVE AND SOMETIMES GOOD PREDICTIVE RESULTS FOR THE VARIOUS MODELS	165
5	SAMPLE DATASET YIELDING NEITHER GOOD DESCRIPTIVE NOR GOOD PREDICTIVE RESULTS FOR ANY MODEL	166
6	SAMPLE DATASET SOMETIMES YIELDING GOOD DESCRIPTIVE BUT NEVER GOOD PREDICTIVE RESULTS FOR THE VARIOUS MODELS	167
7	INDEX TO THE CONTENTS OF THE ATTACHED DISK INCORPORATING THE RESULTS OF THE ANALYSES	168
8	DEMONSTRATION OF RESULTS WITH U (1966) < 0.1	173
9	DEMONSTRATION OF RESULTS WITH U (1966) < 0.5	174
10	DEMONSTRATION OF RESULTS WITH U (1966) < 0.7	175

1. INTRODUCTION

The introduction of a new product to the marketplace confronts a firm with a high degree of uncertainty as well as a high degree of financial commitment - resulting in a high level of risk. At the same time new products usually account for a considerable percentage of a firm's total profits (Booz, Allen, and Hamilton, 1982), and are "expected to play a key strategic role in the marketplace - either to defend ... or to gain and maintain a marketshare" (Mahajan and Wind, 1988, p.356).

Consequently, the prediction of success or failure of a new product is a critical - and difficult - management task. The increasing complexity of the environment has made it even more difficult for management to consider all relevant factors in the decision process. Furthermore, the number and importance of decisions related to the introduction of new products has grown substantially with the increasing size of organizations (Makridakis, Wheelwright, and McGee, 1983).

The significance of accurate forecasting on the future performance of new products is illustrated by the high failure rate of such products. Conner (1964) estimates that roughly 92 percent of the approximately 6000 products introduced every year (data of 1964) fail. Similarly

Crawford (1977) quotes several sources indicating failure rates between 43 percent and 80 percent for new food and drug items. A study by Nielsen even suggests that failure rates have been increasing over time, while a more recent study by Booz, Allen, and Hamilton (1982) indicates that failure rates have at least not been decreasing between 1960 and 1980. This seems plausible as the variety of and competition among products - especially in the non-durable consumer product segment - is immense and has grown substantially since the mid 1960s, when most of the quoted studies were conducted.

Parallel to these high failure rates, there is some indication that the rate of adoption of new products is increasing and that similarly the product life cycle is shortening (Olshavsky, 1980). While the empirical support for this suggestion is limited, intuitive approval appears to be widespread among scholars. The combination of a shorter product life cycle and the high failure rate of new products emphasize the need to identify successful products early on, so that a firm can focus its financial and human resources on the products generating profits. Fourt and Woodlock (1960) point out that due to these environmental conditions, even modest improvements in the area of forecasting are important.

Forecasting models have been proposed as a useful decision support tool describing and predicting the development of sales for a new product. Makridakis (1988) remarks that one prerequisite for successful forecasting is the existence and subsequently the correct identification of a pattern or relationship concerning a certain event. Moreover, that pattern has to be consistent over the forecasting period for the statistical model to be able to forecast accurately. Often new developments in the external environment change that pattern, thus making forecasting more complex and difficult. This problem is intensified through actions taken by management which are aimed at changing the predicted future (e.g. promotion, advertising). Nevertheless, Mahajan and Wind (1988) argue that - if applied consciously - diffusion models can serve a big need, and reduce the risk of market failure, or at least reduce the cost of market failure by giving an early indication of potential problems. The present study concentrates on the performance of already (but newly) introduced products. Hence, the latter benefit (early indication) seems more applicable to this work.

Mahajan and Muller (1979) have stated that diffusion models intend to depict the spread of an innovation (a new product) among a set of potential adopters in terms of a simple mathematical function of time. It appears important

to emphasize the term "simple", as ideally, the simplest possible suitable model should be used. The issue is how to judge whether a model is suitable. According to Mahajan and Muller's statement, diffusion models serve two purposes: 1) to describe the increase in the number of adopters, and 2) to forecast the development of an ongoing diffusion process.

Research on the adoption process has revealed that the prevalent cumulative distribution can best be described by an S-curve. Consequently, most diffusion models give rise to some form of S-curve. This is also true for the models to be analyzed in this thesis. However, the specific shape of the S-curve (point of inflection, asymptote, symmetry) varies widely from model to model and is defined by the individual mathematical form and the parameters of the respective model. The problem the practitioner faces is deciding which model - if any - most accurately fits the current problem.

Evidently, epidemic models (Bailey, 1957) used for describing the spread of contagious diseases through personal contact can be considered the origin for many of the innovation diffusion models (Midgley, 1976). The behavioral rationale for these diffusion models is that a new product is first adopted by - a relatively small number of - innovators, who are then followed by an increasing number of imitators (Rogers and Shoemaker, 1971). According

to Mahajan and Wind (1986), these imitators are to a large extent influenced by word of mouth. However, imitation may also occur without word of mouth communication (Whyte, 1956).

Diffusion theory incorporates nearly two dozen different academic disciplines and includes several thousand publications, thus making it one of the most researched social phenomena (Mahajan and Peterson, 1985). Yet, it has often been criticized as not being applicable in real world situations - especially for ex-ante research. In light of the ongoing criticism towards this field of research, Makridakis, Wheelwright, and McGee (1983, p.9) remark that describing the future based on the past may seem questionable to people "unfamiliar with quantitative methods", since the environment is constantly changing. However, they point out that after becoming familiar with data and forecasting techniques, one realizes that history does repeat itself to some degree, thus validating the - conscious - application of diffusion models. Similarly, Makridakis (1988, p.474) points to empirical evidence gathered by Armstrong (1985), Dawes (1986), Goldberg (1970), Hogarth and Makridakis (1981), and Makridakis (1986) which indicates "that the accuracy of intuitive, judgemental approaches (to forecasting) is not any better than that of statistical models in the great majority of cases".

Furthermore, he remarks that such intuitive forecasts are significantly more expensive than the statistical forecasts, thus making the latter the better alternative. Yet, Makridakis (1991) concedes that there exist big impediments to forecasting on the theoretical and practical side and that consequently forecasting will sometimes be off the mark. Nevertheless, he claims that statistical forecasting measures can provide some help to managers and, moreover, there has not been developed a superior alternative that addresses the needs of decision makers.

1.1 RESEARCH PROBLEM

There exist many different models trying to give an accurate forecast or description of the diffusion process. Many authors felt a need to develop new (and often more complex) models. The approach often seems to have been to find data sets which fit the new model and then to report these results.

Mahajan and Wind (1988) summarize the current status of work on new product forecasting models as follows. Firstly, there is no overall agreement on the criteria to be used to evaluate the models. Secondly, there has not been identified a single best model. Thirdly, most papers concentrate on the

structural characteristics of the models and subsequently neglect analyzing their external validity and predictive accuracy. Fourthly, many researchers have for a long time not taken advantage of the findings in other fields (e.g. geography, technological innovation etc.). Finally, most applications of the models occur under very restrictive conditions, thus obviously limiting the external validity of the results.

In this context, Bernhardt and MacKenzie (1972, p.187) point out that simple models work well in some cases but not in others and that "the successes have been due to judicious choices of situation, population, innovation, and time frame". As a result Mahajan and Wind (1986) propose the development of further, extended diffusion models, implying that more complexity and flexibility will increase the models' accuracy. However, "there is absolutely no evidence that complicated mathematical models provide more accurate forecasts than much simpler models" (Schnaars, 1989, p.54). Schnaars even includes simple rules of thumb in this argument. Complex models might in some cases be able to generate a better ex-post fit to the data, as more parameters can be employed to describe the data. At the same time though, a model with many parameters requires substantially more data points to estimate - or efforts to guess - these parameters, thus reducing the model's

applicability in a forecasting context. Kumar and Kumar (1992a, p.160) argue that "from a forecasting viewpoint, models with omitted variables often are superior to complete models in the sense that a forecast need not be required of exogenous variables in developing a forecast of an endogenous variable". Nevertheless, the trend to develop more complex models is actively supported by the leading journals. Simon (1992) indicates that mathematical elegance consistently beats applicability when it comes to publishing in one of these journals. According to him, this development will eventually lead diffusion research into an ivory tower.

In contrast to Mahajan and Wind, however, some authors emphasize the need for simplicity and applicability of models. It is suggested that simpler models capture the essence of the diffusion process and that complex models reduce the likelihood of application by practitioners (Bass, 1986). Bass (1986, p.30) also observes that with more complex models, the range of guesses has to be augmented and that at the extremes "one might as well guess sales as parameters".

In terms of applicability, the models should be based on assumptions the practitioner can understand as well as interpret, and that can not be tampered with - consciously or unconsciously - in an attempt to create a forecast that

supports the forecaster's initial expectations (Fisher and Pry, 1971). Complex models often violate this criteria, as it is rarely possible to properly interpret their parameters and even less to explain the derived estimates for these parameters. "No theoretical rationale underlies various (more flexible) models as to why a particular diffusion pattern should follow one of these asymmetrical models or what the (economic or behavioral) explanation of the additional model parameters (... e.g. delay coefficients ...) might be" (Gruebler, 1991, p.164). Consequently, Makridakis, Wheelwright, and McGee (1983) call for the development of models that are not targeted exclusively at expert technicians, but rather at practitioners. The same authors indicate that before decisions will be based upon forecasts derived from quantitative models, the end user must understand and agree with the underlying conceptual construct of the model.

"A diffusion model's applied value is (thus) determined by its ability to help managers analyze, plan, and control the process of introducing and managing a new product" (Kalish and Lilien, 1986, p.277). Yet, such models are not supposed to provide a substitute for management judgement and are not intended to make the decisions for the manager. Especially in situations when the external conditions change, the initial forecasts presented by the models have

to be adjusted through management judgement. The models are clearly not capable of anticipating such changes. Rather they are intended to provide some support in the decision process related to new products. In order to be accepted as such by management, they need to be easy to understand and implement - as well as reasonably accurate (Kalish and Lilien, 1986).

Consequently one should not expect any model to give a 100 percent accurate forecast - especially not in every situation - as no model will be able to capture all factors influencing the performance of a new product. Rather it seems important to select and apply various models in order to get an indication of future developments. Which (if any) model eventually is applicable depends on the individual product/market combination. Up to now little empirical evidence has been gathered to help decide in which situation which model yields reasonable results. Considerable research is needed in order to provide practitioners with a framework for that decision.

In light of the above discussion, Schnaars' (1988) call for extensive testing of the existing models prior to developing new models seems appropriate. Considering the importance of practicability, the emphasis of this thesis is on testing relatively simple models - models with relatively

few parameters. This thesis can only be a first step in the process of testing a subset of models under various product/market situations. Obviously this leaves plenty of room for further research.

1.2 RESEARCH OBJECTIVES AND ORGANIZATION OF THE THESIS

As indicated previously, there is no single best model that can be applied in every situation. Rather it is necessary to select an applicable model for the respective situation. Following this argument, this thesis evaluates the applicability of a subset of models to a non-durable consumer product category, namely crackers. Despite the fact that probably the most new product introductions occur in the non-durable consumer product segment, little empirical research has been published in this area after Fourt and Woodlock's (1960) study on new grocery products.

This thesis relies on relatively simple models in light of the arguments presented in the previous section. The subset of models to be tested incorporates some findings from various research fields, namely technological innovation (substitution), biology, and marketing. Following Mahajan and Wind's (1988) call for more studies using richer data bases in order to evaluate the forecasting efficacy of

various models, this study employs scanner data, which provides more as well as more accurate information than traditional diary panels.

The applicability of the various models is tested in two contexts. Firstly, it is analyzed how well these models can describe (ex post) the sales pattern of each product. Secondly, it is examined how well the models are able to predict "future" sales. This distinction is very important, since several authors provide or point to empirical evidence showing that a good ex post fit does not necessarily imply good ex ante forecasting capabilities of a model (Dijkstra 1992, Mayer 1975, Gardner and Makridakis 1988, Makridakis 1988). Mayer (1975) indicates that out of the selected equations in his research, the best fitting ex post equation only yields the best prediction in roughly one third of the cases. Nevertheless, he concedes that selecting a model based on its performance in a sample period (the past) is still better than just random selection.

Five chapters comprise the remainder of this thesis. The literature review deals with the theory of the diffusion process underlying most diffusion models and discusses various quantitative models that have been developed and appear relevant. The next chapter depicts the methodology employed in the given thesis. Firstly, scanner technology

and respective consumer panels are discussed. Then the available product data and the statistical measures used for the data analysis are discussed. Ensuing the findings are discussed for each model and each type of data individually, so that the external validity of the models can be assessed. Finally, the limitations of this research as well as areas of future research are presented along with the implications of this study.

2. LITERATURE REVIEW

2.1 THE DIFFUSION PROCESS

Most of the diffusion models in the literature have their behavioral rationale in diffusion theory. This chapter presents a discussion of that underlying conceptual framework. In his overview of the history of diffusion research, Rogers (1976) points out that its conceptual foundations were created mainly by researchers in the field of anthropology as well as the French sociologist Gabriel Tarde (1903), who first suggested the S-curve for describing the diffusion process and who first pointed to the importance of opinion leaders in that process. One of the most influential works in this field was a study by Ryan and Gross (1943) on the diffusion of hybrid corn seed among farmers in Iowa. Through their study the authors introduced a new approach to the field of communication and change, which was 'adopted' by many researchers after them (Rogers, 1983).

Rogers (1983, p.5) defines diffusion as "the process by which an innovation is communicated through certain channels over time among the members of a social system". Based on these four variables - innovation, communication channels,

time, and social system - the following section presents a discussion of the diffusion process.

2.1.1 THE INNOVATION

Innovation can be defined in various ways, but the most widespread definition in marketing appears to be that an innovation describes a product perceived as new by a potential adopter (Engel, Blackwell, and Miniard, 1990). Robertson (1971) classifies innovations based on their impact on established patterns of consumption as being either continuous, dynamically continuous, or discontinuous. A continuous innovation presents the least disruption of current affairs as it depicts the modification of an existing product rather than the development of a really new one. At the other extreme, a discontinuous innovation depicts the development of a previously unknown product and often involves a serious disruption of existing consumption patterns. In light of these definitions, new non-durable consumer products can generally be classified as continuous innovations, since they normally do not represent a major change for the consumer. This is especially true for grocery products and thus for crackers.

However, not all products are equally likely to be adopted. Successful products have some common characteristics that influence their rate of adoption (Robertson, 1971). As Rogers (1983) points out, the important factor is how the five following characteristics are perceived by the consumer:

- a) Relative advantage describes the degree to which a new product is perceived as being superior to preceding and competing products (Robertson, 1971). This superiority can be based on many factors such as economic factors, increased social prestige, or simply convenience (Rogers, 1983). The larger the perceived relative advantage of a new product over competing products is, the faster it is likely to be adopted.
- b) Compatibility describes the degree to which a new product is perceived to be consistent with the existing set of norms (Rogers, 1983). The less compatible a new product is with existing values and beliefs, the slower the rate of adoption will be.
- c) Complexity describes the degree of difficulty a potential adopter expects in understanding and using the new product (Robertson, 1971). Obviously, a high degree of complexity will impede the adoption of a new product.

- d) Trialability describes the degree to which a new product may be used on a limited basis (Rogers, 1983). The ability to purchase small (sample) packages may encourage diffusion. Reversibility seems to be related to trialability, as it describes how easily the use of a new product can be suspended (Robertson, 1971). The higher perceived trialability and reversibility are, the faster adoption is likely to occur.
- e) Observability describes the degree to which a new product and the results of its use are visible to others (Rogers, 1983). The importance of observability in the adoption process is correlated with the social relevance of the product. Only if the relevance of the new product is perceived to be high, will observability influence the adoption process. Otherwise it is unlikely to accelerate the rate of adoption.

Another seemingly important characteristic is mentioned by Sheth (1968). He concludes that the perceived risk connected to the purchase of a new product also significantly inhibits the diffusion process. While the mentioned characteristics of an innovation are not the only factors influencing the rate of adoption, research indicates that they explain the single largest portion of the process (Rogers, 1983).

2.1.2 COMMUNICATION CHANNELS

Communication is defined as the "process by which consumers and marketing organizations share (and spread) information" (Engel, Blackwell, and Miniard, 1990, p. 695). As such, Rogers (1983) considers the exchange of information through which a new idea/product is communicated to other members of the social system, to be the essence of the diffusion process. The two communication channels that have been identified as exerting the most influence during the introduction of a new product are mass media and personal influence (word of mouth).

Research evidence suggests that these two communication channels vary in their effectiveness to influence potential adopters depending on the respective stage of the adoption process (see 2.1.3) the individual is in (Robertson, 1971). The mass media appears to have its largest effect in the earlier stages, whereas personal influence becomes dominant in the final stages (Gatignon and Robertson, 1985). Thus mass media is especially useful as a source of initial information and as a method creating awareness to a new product. Even though it may have some effect in the later stages of the adoption process as well, its importance decreases significantly (Lionberger, 1960).

At the same time empirical evidence shows that most potential adopters rely on the opinion of previous adopters when making their decision to purchase a new product (Rogers, 1983). The level of influence previous adopters possess depends largely on the degree to which potential adopters can relate to them or, in other words, how homophilous they are. The effect of word of mouth emphasizes the importance of imitation in the diffusion process. Consequently, most models that will be introduced later in this thesis, incorporate an 'imitation coefficient' - as Bass (1969) defined it - as a key parameter for describing the speed of diffusion.

Robertson (1971, p. 170) refers to personal influence as "a change in an individual's attitude or behavior as a result of interpersonal communication". However, not all consumers exert the same amount of influence on other consumers. Those that wield the most influence are called 'opinion leaders'. It is a crucial but difficult marketing task to identify and target these opinion leaders, so that they can contribute to the diffusion of a new product through word of mouth. In light of the previously mentioned high failure rates, it is, however, also important to note that negative personal influence seems to be a common phenomenon (Midgley, 1976).

Overall, the impact of personal influence appears to be larger than the impact of mass media. This is supported by Sheth's (1971) statement that most buyers do not react to mass media - especially in the segment of low risk frequently purchased supermarket products. According to Sheth, consumers consider the presented information exaggerated and not helpful, so that they instead rely on personal influence for information and evaluation of a new product. Engel, Blackwell, and Miniard (1990) further emphasize the importance of word of mouth for products like grocery products by indicating that it seems especially relevant when the choice between products is ambiguous. The ambiguity for these products is not created through complexity though, but rather through variety.

In contrast, Gatignon and Robertson (1985) suggest that personal influence is mainly relevant under high involvement situations - this obviously is not likely to be the case for the purchase of grocery products. There appears to be no need for social acceptance or for the collection of further information in low involvement situations, since the products do not have conceivable differentiating attributes (Robertson, 1976). In conclusion it can be stated that there exists some contradiction in the argument for a large effect of personal influence in the case of low involvement products.

2.1.3 TIME

Adoption of a new product is considered to be a process over time. According to Nicosia (1966) there appears to be widespread agreement among researchers that consumer behavior is indeed the outcome of a decision process. Over the last few decades researchers have proposed a variety of models describing the adoption process. These models incorporate a varying number of stages a consumer moves through before adopting a product. Indication for the existence of such stages - and thus the decision process - can be found in some early psychology literature (Lionberger, 1960).

The 'Adoption Process Model', developed by rural sociologists, is one of the earliest such models and can serve as an initial reference. It identifies five sequential stages: awareness, interest, evaluation, trial, and adoption (Lionberger, 1960). Awareness is the stage in which the individual is exposed to the new idea/product for the first time. Interest describes the process of searching for additional information on the idea/product. This is followed by an evaluation of the collected information in order to decide whether the product is beneficial in the current situation. Trial depicts the provisional testing of the product with the intention of gathering some practical

information. The final stage is the continued use - adoption - of the product.

Engel, Blackwell, and Miniard (1990) identify four other popular models that have been developed by researchers (the various stages are listed in brackets) - the AIDA Model [Attention --> Interest --> Desire --> Action], the Hierarchy of Effects Model [Awareness --> Knowledge --> Liking --> Preference --> Conviction --> Adoption], Robertson's model [Problem Recognition --> Awareness --> Comprehension --> Attitude --> Legitimization --> Trial --> Adoption --> Dissonance], and Roger's model [Knowledge --> Persuasion --> Decision --> Implementation --> Confirmation]. Consumer behaviour is a very complex subject and none of the above models can claim that it is the ultimate model describing the structure of the adoption process. Yet, they can still serve as an illustration for the existence of various stages.

Progressing from one stage to the next requires the collection of information and subsequently a decision, which implies that the elapsed time between awareness and adoption can vary widely (Bernhardt and McKenzie, 1972). For a low involvement product - like the one researched in this thesis - cognitive dissonance connected to such a decision can be expected to be rather small (Festinger, 1957). Similarly,

the amount of information needed to arrive at a decision is probably relatively small as well, so that the time span between awareness and adoption (or rejection) is likely to be reduced significantly for these products.

Furthermore, Krugmann (1965) indicates that models like the Hierarchy of Effects model can not be applied in low involvement situations. Since the "purchase (of a low involvement product) is not closely tied to a belief system" (Robertson, 1976, p.20), we can assume a simpler attitude structure than the one implied by the models mentioned above. This argument does not deny the existence of the proposed stages, but it suggests that the decision process can be summarized in substantially fewer steps.

In that context Ray (1973) suggests the stages Awareness --> Minimal Comprehension --> Trial --> Attitude, while Gatignon and Robertson (1985) identify the stages Awareness --> Trial --> Attitude Formation --> Adoption. In a dissertation related to the present thesis, Nakanishi (1968) developed a structure supposedly applicable to grocery products: Awareness --> Trial <--> Evaluation --> Adoption. Since trial is the method to gather information about the product, the consumer can always move back from the evaluation stage to the trial stage in order to gain additional information. Interpretation of this model signals

that personal influence is not of primary importance in this product category, since information and evaluation occur through trial of the product and not necessarily through consultation with other individuals.

These models illustrate that for low involvement products there are not only fewer stages than for high involvement products, but the sequence of these stages can also be different. Furthermore, they demonstrate that even though the process from awareness to trial might only take a few seconds, it is still a - probably much less conscious - decision process involving time.

In summary it can be concluded that the proposed stages can not be clearly identified and as a result there are a wide range of stages that have been proposed. In addition, the sequence of those stages can vary from product to product. Due to the resulting vastness of possible models, all presented models have to be examined with caution. Consequently, their primary benefit is to present a general framework instead of an explicit model. The main conclusion drawn from this discussion is, that adoption of a new product is not immediate, but involves a decision process with various stages.

2.1.4 THE SOCIAL SYSTEM

The social system defines the boundaries within which an innovation can diffuse. Its social structure (e.g. age, income, social class, etc.) can have a significant effect on the rate of adoption. The system itself is comprised of many individuals with varying characteristics that influence the probability and the timing of the adoption of a new product for every individual.

Rogers (1962) attempted to classify individuals into groups according to their propensity to adopt new ideas/products. Within the groups he created, the potential adopters are supposed to have a similar degree of innovativeness. Rogers (1983) defines the first 2.5 percent of adopters to be innovators. The following 13.5 percent are named early adopters. Next are two groups of 34 percent each, called early majority and late majority. The final 16 percent of adopters are identified as laggards. Even though this model is widely cited and often used as a basis, there is some criticism. For example, some laggards could be rejectors, thus resulting in less than 100 percent adoption. Furthermore, the stages are obviously arbitrarily defined and there are no clear cut boundaries between them. Consequently, the model's primary value lies in providing a

conceptual framework that indicates the existence of different adopter classes.

Innovators have been identified as the initial adopters of a new product. As such they are an important part of the diffusion process, since they are the ones who start it. However, there exist different views in the literature on their subsequent role in the diffusion process. Lionberger (1960) for example, points out that innovators are considered different by their neighbours and are not very well integrated in their community. He concludes that there often exists a difference between opinion leaders (also called influentials or key communicators) and innovators. As mentioned before, the influence of previous adopters on potential adopters depends on their similarity. Lionberger's argument indicates that innovators do not fulfil this requirement. Opinion leaders are usually well integrated and share the same values as the community, while being slightly more progressive than others.

In contrast Gatignon and Robertson (1985) characterize innovators as possessing higher opinion leadership and greater social participation among other traits. However, there exists some evidence that opinion leaders are primarily found in the early adopter/majority groups - supporting Lionberger's argument.

After reviewing the literature on diffusion theory, it becomes apparent that there still is a wide variance in concepts. The basic underlying construct appears to be understood to some extent, but the exact process of consumer behaviour remains open for further research. Yet, the theoretical construct can be employed in the analysis and development of diffusion models, as they give some indication on whether the assumptions underlying those models are reasonable.

2.2 DIFFUSION MODELS

All of the factors mentioned in the previous four sections have some influence on the rate of adoption and the pattern of the diffusion process. Consequently, the analysis of these characteristics is an elementary step for the practitioner or researcher involved in the introduction of a new product. The results of that analysis combined with empirical evidence should then be employed to decide which if any diffusion model most accurately reflects the situation at hand.

After a review of the literature, Gatignon and Robertson (1985) conclude that the expected pattern for a diffusion process can be derived from certain situational

variables, such as the ones discussed in the previous sections. They propose either a sigmoid or exponential pattern depending on the product-market situation:

- * Application of a model giving rise to S-shaped curve when
 - personal influence is important
 - Hierarchy of Effect Model describes adoption process
 - there is high innovation cost
 - there is high uncertainty

- * Application of model giving rise to exponential curve when
 - relative lack of personal influence
 - low social imitation (low degree of social relevance)
 - low involvement model of adoption describes process
 - low uncertainty
 - low innovation cost

This framework indicates that for the analysis of cracker sales, an exponential model would be most applicable, as the present situation can best be described by the latter of the two scenarios presented by Gatignon and Robertson. However, the only empirical support for this assumption seems to be the study on grocery products conducted by Fourt and Woodlock (1960). They argue that in this situation direct marketing effects outweigh personal influence. Yet, the overwhelming majority of models in the

literature give rise to S-shaped curves. Consequently, this thesis will examine a variety of S-shaped models as well as models representing exponential shape.

In terms of models giving rise to S-shaped curves, Kumar and Kumar (1992b) present the following desirable characteristics of such a model, which will subsequently be used to describe the various models.

- * availability of one or more parameters that can increase the goodness of fit (flexibility).
- * existence of a point of inflection that can occur at any adoption level. (Point of inflection denotes the time of maximum rate of diffusion).
- * possibility of symmetric as well as nonsymmetric behaviour patterns.
- * existence of a closed form solution.
- * inclusion of as few parameters as possible while remaining consistent with the previous points.

The most well known diffusion model in marketing is the one developed by Bass (1969). This model can be attributed with having popularized mathematical diffusion literature in the field of marketing. Many models that have been developed thereafter are directly or indirectly related to the Bass model (Kalish and Sen, 1986). Since the model subsumes an

external influence model as well as an internal influence model, external and internal influence models will be discussed first. Then the Bass model will be examined, followed by more flexible models. Finally, research on models incorporating various elements of the marketing mix will be briefly mentioned.

2.2.1 EXTERNAL INFLUENCE MODELS

External influence models assume that the diffusion process is only influenced by sources outside of the social system. Frequently this external source is designated to be mass media. However, it can also be interpreted as reflecting promotion or activities by government agencies, interest groups, and sales people. These models generally have the form

$$\frac{dF(t)}{dt} = p[L - F(t)]$$

(Mahajan and Peterson, 1985)

where p represents the effect of the mentioned external sources. L represents the upper limit of the diffusion. In many models L is set equal to 1, representing an eventual 100 percent diffusion of the new product. $F(t)$ indicates the

percentage of potential adopters that have adopted up to time t . Consequently, $dF(t)/dt$ describes the increase in adoption during period t . This terminology will be used throughout this paper.

External influence models give rise to an exponential diffusion curve, as the number of adopters increases at a constantly decreasing rate. The model assumes that the rate of adoption depends solely on the effect of external sources and the number of potential adopters remaining in the system. Personal interaction - word of mouth - is not considered to have any effect on the diffusion process.

This type of diffusion model was used in a modified form by Fourt and Woodlock (1960). They attempted to predict sales for grocery products by estimating a maximum market penetration for the products and a repurchase ratio based on data from diary panel. Their underlying model has the form

$$\frac{dF(t)}{dt} = pL[1 - p]^{t-1}$$

where L denotes the ceiling for penetration (e.g. 40%) and p is a constant of proportionality which describes the external effects. With their model Fourt and Woodlock imply that for the products they investigated, marketing efforts -

e.g. mass media - remain constant and are solely responsible for the increase in market penetration. The model yielded reasonable results when applied to the data of seven grocery products.

2.2.2 INTERNAL INFLUENCE MODELS

In contrast to the external influence models, internal influence models attribute the increase in adoption solely to interpersonal communication between previous and potential adopters. Thus these models neglect any external factors such as mass media, but they account for the importance of personal influence that was illustrated in earlier sections. In general, they have the following form

$$\frac{dF(t)}{dt} = qF(t)[L - F(t)]$$

where q represents the effect of interpersonal communication on adoption. This kind of model results in a logistic diffusion curve in contrast to the previously described exponential curve. The point of inflection which has been illustrated by Kumar and Kumar (1992a) as an important property, always occurs at $L/2$ for these models, thus limiting their flexibility.

The most prominent internal influence models are those by Mansfield (1961), Blackman (1971), and Fisher and Pry (1971) who developed alternate forms of the above model. Their biggest difference lies in the fact that Blackman allowed for a maximum penetration lower than 100 percent, while the other authors presented models with a ceiling of 100 percent ($L = 1$).

Even though the allowance for a maximum penetration rate of less than 100 percent seems plausible, Blackman (1974) concedes in a later paper that a 100 percent diffusion is highly probable. Fisher and Pry (1971) suggest in this context that if a technological innovation has captured a few percent of the market it will proceed to complete substitution of the old technology. This argument was however related to technological substitution. It can be argued that while a superior technological innovation might eventually fully replace an older technology, total diffusion of a consumer product is highly unlikely. Especially in terms of grocery products it is not conceivable that one product can capture the entire market. In this segment superiority is described through personal taste and other personal factors that vary from individual to individual. Thus it is difficult to present a product that will be conceived superior by all consumers.

While the Fisher-Pry, Mansfield, and Blackman models have been applied primarily in a technology context, a related model, the Gompertz-curve (1828), has also been applied to consumer products with some success. The Gompertz-curve can be expressed by the following equation

$$\frac{dF(t)}{dt} = qF(t)[\ln(L) - \ln(F(t))]$$

2.2.3 THE BASS MODEL

The Bass model (1969) serves as a prime example for mixed influence models. It reflects both the effect of external influence and the effect of internal influence, as it denotes an additive connection of the exponential and logistic model. The model follows the conceptual framework of the adoption process that was presented earlier, by assuming that potential adopters are influenced through two mediums, namely mass media and word of mouth.

The presented conceptual framework also proposes five adopter classes - innovators, early adopters, early majority, late majority, and laggards. Bass reduces this classification by summarizing the latter four groups as imitators. In his mathematical model innovators react solely

to mass media or other external factors. They are not influenced by the actions of other members of the social system and are generally the first to adopt a new product. In contrast, imitators are largely affected by the actions of the individuals around them. Their propensity to adopt increases with the number of previous adopters, since word of mouth makes the product more well known and the social pressure to "conform" increases over time.

The mathematical model representing these assumptions is given by the following equation

$$\frac{dF(t)}{dt} = [p + qF(t)][1 - F(t)]$$

where p indicates the coefficient of innovation (or external influence) and q indicates the coefficient of imitation (or internal influence). The model could be extended by following Blackman's example of replacing 1 with L to allow for a diffusion of less than 100 percent.

The equation implies that external influence will have its largest effect in the beginning, while the effect of internal influence will increase over time. This complies with the proposed influence of mass media and word of mouth presented in the previous chapter.

The Bass model creates a "generalized logistic curve" (Mahajan and Peterson, 1985, p.21) which is nonsymmetric. Its point of inflection can occur anywhere between 0 and 0.5, thus allowing some flexibility. Furthermore, the model offers a closed form solution which has been termed desirable for long range forecasting by Mahajan, Muller, and Bass (1990).

Empirical testing of the model revealed very good results initially, but subsequent research indicates that the model consistently underpredicts sales and the peak time of sales (Kalish and Sen, 1986). Due to the model's initial success and its consistency with diffusion theory, many researchers have attempted to overcome its limitations by modifying and extending the Bass model to some degree. This is also true for many of the models presented in the next section.

2.2.4 FLEXIBLE MODELS

In light of Kumar and Kumar's (1992b) comments on desired properties of diffusion models, it can be noted that the previously introduced models lack some of them. This led many researchers to develop more flexible models. However, it should be noted that large scale comparisons indicate

that flexible models often result in less accuracy or at least do not improve it (Schnaars, 1987). In the following section some of these models are discussed, namely the Floyd model, the Sharif-Kabir model, the Jeuland model, the NSRL model, the NUI model, the Von Bertalanffy model, the GRM I and GRM II models, the Generalized model, the KKK I and KKK II models, and the Brockhoff model. A summary of the individual characteristics of these models and of the previously mentioned models are presented in Table 1.

THE FLOYD MODEL

Floyd's model (1968) does not prove to be very flexible. It represents an attempt to describe growth approaching an upper limit based on expended effort and is given by the following equation:

$$\frac{dF(t)}{dt} = qF(t)[1 - F(t)]^2$$

The model gives rise to a nonsymmetric S-shaped curve that has its point of inflection fixed at 0.33. Floyd's model does not give a closed form solution for $F(t)$. Furthermore, it implies a decrease in the importance of internal influence.

Such a decrease is supported by Kotler (1971) who argues that late potential adopters are less responsive to an innovation. However, this is contradictory to the suggestion that social pressure (and thus personal influence) on not-adopting individuals increases over time. Some of the models presented below allow for internal influence to increase or decrease depending on the product-market situation.

THE SHARIF-KABIR MODEL

Sharif and Kabir (1976) developed a model based on Blackman's model and Floyd's model. The authors state that Floyd's model usually creates an underestimation and Blackman's model an overestimation of the forecast. According to their findings, the realistic forecast usually lies between these two extremes. As a result they developed a model that is bounded by the Blackman and Floyd curves.

$$\frac{dF(t)}{dt} = q \frac{F(t)[1 - F(t)]^2}{1 - F(t)[1 - \sigma]}$$

The variable σ is dimensionless and is interpreted as a delay coefficient that can range between 0 and 1. In this context 0 represents an optimistic forecast - little delay

in adoption - while 1 represents a pessimistic forecast - considerable delay in adoption. Sharif and Kabir define the delay coefficient as a function of data scatterness, data extent, market share at the time of forecast, and the time required for $F(t)$ to move from 0.1 to 0.9. The model reduces to the Floyd model for $\sigma = 1$. A new paper by Kumar and Kumar (1993) indicates however, that the model remains valid for σ ranging from 0 to ∞ . Thus the initial restriction is not put on the model in this thesis.

In terms of flexibility, the model allows for symmetric and nonsymmetric diffusion curves. Internal influence can be either constant or decreasing over time. However, the point of inflection is restricted to the narrow area between $F(t)$ equal to 0.33 and 0.5. Similar to Floyd's model, this model does not offer a closed form solution for $F(t)$.

THE JEULAND MODEL

Jeuland (1981) analyzed Bass' model and generalized it in order to allow for differences in the propensity to adopt among potential adopters. He argued that the remaining potential adopters have different characteristics which will make their probability to adopt vary across the population. He presumed that the propensity to adopt varies according to a gamma distribution. This led to the following model:

$$\frac{dF(t)}{dt} = [p + qF(t)][1 - F(t)]^{1+\gamma}$$

The model reduces to the Bass model for $\gamma = 0$. It is required that γ is larger than -1. The larger γ is, the smaller the propensity of the remaining individuals to adopt the new product.

The Jeuland model allows symmetric as well as nonsymmetric diffusion curves. The importance of internal influence can either remain constant or decrease over time. Nevertheless, it does not accommodate a point of inflection beyond 0.5 and it does not provide a closed form solution to its differential equation.

THE NSRL MODEL

Easingwood, Mahajan, and Muller (1981) introduced a nonsymmetric responding logistic model which denotes a flexible extension to the basic internal influence models presented by Mansfield (1961) and Blackman (1971). The flexibility in the model stems from a time varying coefficient of imitation. The resulting model is given by the equation

$$\frac{dF(t)}{dt} = qF(t)^{\delta}[1 - F(t)]$$

The parameter δ has been defined as the internal influence factor and is supposed to capture the changes in internal influence over time. It can range between 0 and 1 or be larger than 1. If δ is larger than 1, then the importance of internal influence increases over time; if it is less, then internal influence will decrease over time. Thus this model allows for both increasing or decreasing effects of word of mouth. The model also allows for symmetric and nonsymmetric shapes of diffusion curves. Furthermore, the point of inflection can be located anywhere during the diffusion process, i.e. range between 0 and 1. However, it does not offer a closed form solution to its differential equation either.

THE NUI MODEL

The non-uniform-influence model is a direct extension of the Bass model. Easingwood et. al. (1983) developed this second flexible model with the intention of incorporating external influence.

$$\frac{dF(t)}{dt} = [p + qF(t)^\delta][1 - F(t)]$$

δ again indicates the non uniform internal influence factor ranging between 0 and 1 or beyond 1. For $\delta = 1$ the model reduces to the basic Bass model and it assumes uniform internal influence. For $p = 0$ the model reduces to the NSRL model. The authors point out that when δ ranges between 0 and 1, internal influence decreases over time, so that the peak in the level of adoption will be reached earlier and will be higher. When δ is greater than 1, internal influence is delayed, so that the peak will be reached later and will be smaller.

The NUI model incorporates the same level of flexibility as the NSRL model. It allows for symmetry as well as nonsymmetry and the point of inflection can occur anywhere between 0 and 1. However, the model also does not offer a closed form solution.

THE VON BERTALANFFY MODEL

Von Bertalanffy's model (1957) originates in biology and represents an effort to describe the growth of an organism in terms of its metabolic rate. Richards (1959) elaborated on the model in the field of botany. The model incorporates a factor increasing body weight (enhancing diffusion) and a parameter decreasing body weight (inhibiting diffusion). The overall change in body weight is merely the difference between these two influences and is given by

$$\frac{dW}{dt} = \eta W^a - \kappa W^a$$

where η indicates anabolism and κ indicates catabolism.

Like the previous models, the transformed model gives rise to an S-shaped curve. Its equation is given by

$$\frac{dF(t)}{dt} = \frac{q}{1 - \theta} F(t)^\theta [1 - F(t)^{(1-\theta)}]$$

θ can be interpreted as a coefficient describing the importance of personal influence. The larger θ is, the larger the initial influence of word of mouth will be. For θ

equal to 0 the von Bertalanffy model reduces to the basic external influence model. For θ equal to 2 the model reduces to the basic internal influence model.

Even though the model breaks down at θ equal to 1, it allows for considerable flexibility. It can be symmetric as well as nonsymmetric and its point of inflection can range between 0 and 1. Personal influence decreases over time. Yet, in contrast to all flexible models examined so far, this model offers a closed form solution.

THE GRM I MODEL AND THE GRM II MODEL

Due to their similarity these two models are presented together. The GRM I model was motivated by the NSRL model. Skiadas (1985) intended to develop a model covering basically the same region as the NSRL model, but at the same time offering a closed form solution. The resulting model has the following form:

$$\frac{dF(t)}{dt} = q \frac{[1 - F(t)]^n}{1 - [1 - \sigma]F(t)} F(t)$$

σ serves the same purpose as δ in the NSRL model. It ranges between 0 and 1. n is an integer varying from 0 to ∞ .

An interpretation of this parameter is not offered by the author. Setting $n = 1$ and $\sigma = 1$ yields the Fisher-Pry model and by setting $n = 2$ and $\sigma = 1$ we get the Floyd model.

The model fulfils the requirements set by Skiadas in the beginning. It provides a closed form solution and covers the same region as the NSRL model. Furthermore, the model can give rise to a symmetric and a nonsymmetric shaped diffusion curve. The point of inflection depends on the value of n . For $n = 1$ the point of inflection can occur between 0.5 and 1, while for $n = 2$ the point of inflection is confined to the region between 0.33 and 0.5.

The GRM II model arises from the NSRL model (Skiadas, 1985). It incorporates the same parameters as the GRM I model and is given by the equation

$$\frac{dF(t)}{dt} = q \frac{F(t)^n [1 - F(t)]}{1 - [1 - \sigma][1 - F(t)]}$$

For $n = 1$ and $\sigma = 0$ the model reduces to an exponential model. Setting $n = 1$ and $\sigma = 1$ or $n = 2$ and $\sigma = 0$, yields the Fisher-Pry model. For $n = 2$ and $\sigma = 1$ the model becomes a special case of the NSRL model. The GRM II model has the same properties as the GRM I model, including the difficulty in interpreting n and thus in interpreting the entire model.

THE GENERALIZED MODEL

Skiadas (1986) presents a generalized model, slightly modified in respect to the original model introduced by Lawrence and Lawton (1981). The model is expressed by the equation

$$\frac{dF(t)}{dt} = q \frac{F(t) + g}{1 + g} [1 - F(t)]$$

The new parameter in this model is g . It summarizes the positive and negative effects of prior product users on potential adopters. Those prior product users are not always adopters, since some of them might not have been satisfied with the product. These prior product users can be expected to spread negative word of mouth and could thus be defined as active rejectors [see Midgley's (1976) classification scheme]. If these negative impressions among prior product users predominate, g could become smaller than 0 and thus represent an overall negative influence of word of mouth. In addition, g can be interpreted as a variable representing efforts by various external sources, such as government agencies, sales force, etc. However, this makes the parameter relatively complex and thus difficult to estimate and interpret.

The generalized model is an exclusively symmetric model, but its point of inflection can occur anywhere between 0 and 1. Furthermore, the model does have a closed form solution. Through manipulation of the parameters, the model can be reduced to the Bass model (Kumar and Kumar, 1992a). Lawrence and Lawton (1981) indicate that the model can provide reasonably accurate a priori estimates by setting q equal to 0.66 for industrial products and q equal to 0.5 for consumer products. They also suggest that g can be estimated by solving the differential equation for t equal to 1.

THE KKK I MODEL

The KKK I model has its origin in population dynamics. Kumar and Kumar (1992b) based their model on a model developed by Smith (1963). It is expressed by the equation

$$\frac{dF(t)}{dt} = \frac{[p + qF(t)][1 - F(t)]}{1 + bF(t)}$$

The parameter b can either have a positive or inhibiting effect on the diffusion rate, depending on whether it is smaller than 0 or larger than 0 respectively. This effect can be due to word of mouth or external factors. Thus this

factor can be interpreted similar to the parameter g in the Generalized model, as summarizing the positive and negative effects in the environment.

The KKK I model can be either symmetric or nonsymmetric. Its point of inflection can occur anywhere during the diffusion process. In addition, the model offers a closed form solution. It can be shown that the GRM II model is basically a special case of the KKK I model. Furthermore, Kumar and Kumar (1992a, p.161) point out that their model covers the same region as the NSRL model "but has the advantage of also accounting for external influences".

The model proposed by Kumar and Kumar has been developed primarily for the use in technological substitution. However, it can be noted here, that the introduction of a new consumer product can be interpreted in a similar context. It can be argued that a new consumer product often merely substitutes an existing consumer product of a similar kind. Thus it seems reasonable to attempt to apply technological substitution models in the given context.

THE KKK II MODEL

This model has its origin in population dynamics as well. Kumar and Kumar (1992b) also borrowed from Von Bertalanffy (1957) in the development of their technological substitution model. According to their argument, the adoption of an innovation is influenced by two contradictory forces, one enhancing the process, the other one impeding it. This is similar to Bertalanffy's discussion of anabolism and catabolism in an organism. Positive influences could result from the superiority of the product compared to existing products, while negative influences could be due to competition or poor market conditions. The KKK II model is given by the equation

$$\frac{dF(t)}{dt} = q \frac{F(t)[1 - F(t)^\alpha]}{\alpha}$$

The parameter α represents the counteraction between the positive and negative forces. In their interpretation of α the authors suggest that it accounts for the varying propensity to adopt among the potential adopters. The larger α is, the lower the propensity to adopt becomes.

The model has the same properties in terms of flexibility as the KKK I model. It can be symmetric as well

as nonsymmetric and the point of inflection can range between 0 and 1. Furthermore, the model offers a closed form solution. Through the substitution of parameters, the model can be transformed to the Fisher-Pry or Mansfield model.

THE BROCKHOFF MODEL

The final model to be reviewed is the one developed by Brockhoff (1967). Brockhoff based his model on the product life cycle and implied a substitution process as the cause for declining sales in the latter stages of the PLC. The model he proposed reflects the influence of related products sold by the same firm on the diffusion of a new product. The corresponding model is given by the equation

$$S(t) = at^qe^{-ct} + kR(t)$$

In this model $S(t)$ represents the sales in period t , while $dS(t)/dt$ describes the increase from the previous period. a is an indicator of the general adoption attitude. The larger it is, the higher total adoption will be. q can be interpreted as the factor of imitation, while c is the factor of substitution. Thus q is responsible for the increase in sales, while c reflects the inhibiting factor which is becoming more important over time, as other

products start replacing the formerly new product. R is a factor reflecting the sales of related products from the same company. The influence these sales have on the diffusion of the new product can be either complementary or detractory. k is the parameter indicating the direction of this influence by being either positive or negative, respectively. The model does not have an underlying behavioral explanation, since Brockhoff derived it more from a mathematical perspective.

However, this function incorporates many parameters, and especially estimates for k and R are difficult (and time consuming) to derive due to the required extensive data collection on additional products. Nevertheless, their estimation is conceptually straight forward. The analysis (inclusion) of R and hence the estimation of k goes beyond the scope of this thesis and the parameters are thus neglected here. Furthermore, the sales of products from the same manufacturer are hypothesized to be of minor relevance to the diffusion of new cracker products. This implies that k should be set equal to 0, so that the model can be simplified to

$$S(t) = at^q e^{-at}$$

The model can result in a symmetric as well as a nonsymmetric diffusion curve. In contrast to the previous models, this model does not require the estimation of an upper asymptote, thus increasing the model's flexibility. Furthermore, the model provides a closed form solution for the differential equation.

Table 1: Characteristics of the selected Diffusion Models

Model	Model Equation (dF/dt=)	Location of Point of Inflection	Symmetry	# of Param.
Logistic	$qF[1-F]$	0.5	S	1
Gompertz	$qF \ln(1/F)$	0.37	NS	1
Bass	$[p+qF][1-F]$	0-0.5	S	2
Floyd	$qF[1-F]^2$	0.33	S or NS	1
Sharif Kabir	$q \frac{F(1-F)^2}{1-F[1-\sigma]}$	0.33-0.5	S or NS	2
Jeuland	$[p+qF][1-F]^{1+\gamma}$	0-0.5	S or NS	3
NSRL	$qF^b[1-F]$	0-1.0	S or NS	2
NUI	$[p+qF^b][1-F]$	0-1.0	S or NS	3
Bertalanffy	$\frac{q}{1-\sigma} F^b[1-F^{1-\sigma}]$	0-1.0	S or NS	2
GRM I	$q \frac{[1-F]^n}{1-[1-\sigma]F} F$	0.5-1.0 0.33-0.5 for n=1,2	S or NS	3

Model	Model Equation (dF/dt=)	Location of Point of Inflection	Symmetry	# of Param.
GRM II	$q \frac{F^n[1-F]}{1-[1-\sigma][1-F]}$	0.5-1.0 0.33-0.5 for n=1,2	S or NS	3
Generalized	$q \frac{F+g}{1+g} [1-F]$	0-1.0	S	2
KKKI	$\frac{[p+qF][1-F]}{1+bF}$	0-1.0	S or NS	3
KKKII	$q \frac{F[1-F]^a}{a}$	0-1.0	S or NS	2
Brockhoff	$S(t) = at^a e^{-at}$	*	S or NS	3

Source: adapted from Easingwood et.al. (1983) and Kumar and Kumar (1992a)

2.2.5 MODELS INCORPORATING ELEMENTS OF THE MARKETING MIX

There have been considerable efforts to study the impact of marketing variables on diffusion. It has been argued that such variables must be included in diffusion models to account for the reactivity of the diffusion process to changes in the marketing environment. The marketing mix elements investigated the most in this context are price and advertising. Those models try, for example, to represent market potential as a function of time, or they modify the coefficients of external and internal influence to be a function of marketing variables (Mahajan, Muller,

and Bass, 1990). Researchers have started early to include the effects of marketing actions in their models - explicitly or implicitly. One example of such a model and its testing is the work done by Haines (1964) who included the variables promotion, advertising, concurrent and prior product availability.

Kalish and Sen (1986) provide an extensive review on the work done in this field. One of the first widely recognized models considering the influence of price on the diffusion process presented an extension of the Bass model and was developed by Robinson and Lakhani (1975).

$$\frac{dF(t)}{dt} = [p + qF(t)][1 - F(t)]G(P)$$

However, similar to most models of this kind, no empirical evidence is provided to support the model. The attractiveness of these models lies more in their mathematical elegance and the possibility to express the hypothesized impact of marketing mix variables on the diffusion process, than in their actual applicability.

Empirical studies on the impact of advertising on diffusion were conducted by Horsky and Simon (1983) as well as Simon and Sebastian (1982). While advertising was found

to have an (cumulative) effect, Simon and Sebastian (1982) indicate that models incorporating marketing mix elements are difficult to test empirically. Most available data bases do not provide rich enough data to differentiate between the various effects of factors in the environment.

In summary it can be stated that these models pose significant problems in terms of application and interpretation. The number of factors possibly influencing the diffusion process is vast and the inclusion of some parameters often requires the consideration of other related factors (e.g. if advertising is incorporated, advertising by the competition should also be reflected, as the relative level of advertising seems to be at least as important as absolute advertising). This however makes the models extremely complex as many parameters need to be added, so that the practical value will be reduced significantly.

3. METHODOLOGY

It was indicated above that one objective of this thesis is to empirically test the applicability of some of the discussed models for describing and predicting the development of sales of new cracker products. In order to accomplish this task, these models are applied to sales data for that product category obtained from Information Resources Inc. (IRI). The focus of this thesis is on products that have just been introduced, so that there is some initial sales data available to estimate the parameters of the respective models. IRI collected this data through a method called BehaviorScan which relies on household panels and scanner technology.

This chapter gives a detailed outline of the research methodology used in this study. Firstly, BehaviorScan is discussed, followed by a description of the available data. Finally, the data analysis - including parameter estimation considerations - is discussed.

3.1 BEHAVIORSCAN

Behavior Scan denotes a new, and at the time of its introduction, revolutionary method of collecting data on

consumers' purchase patterns. It was implemented by Information Resources Inc. in 1980 and covered initially 2 then 6 and now 8 mini test markets (small cities). In these cities consumer panels, each incorporating 2500 supposedly representative households were established. Each member of these households receives an ID card that is to be presented at the checkstand on every shopping trip. To encourage participation and the use of the ID cards, the panel households receive an annual gift and they participate in a monthly prize drawing. The chances to win in the drawing increase with every time the ID card is presented. Furthermore, all supermarkets in these locations were supplied - free of charge - with laser scanners for every checkstand in order to be able to accurately collect purchase data and to obtain maximum participation from the stores. This setup allows BehaviorScan to track 130,000 different items and to monitor over 95 percent of the all commodity volume in the test markets (Clarke, 1993).

The scanners rely on information contained in the Universal Product Codes (UPC's). At the checkout, the consumer presents his ID card which is read by the computer. Then every single product is pulled across a small window on the counter, where a laser reads the information on item, size, price, and manufacturer encoded in the barcode. If there is no UPC code on the product or the size of the

product prohibits the use of the scanner, the code is supposed to be entered manually. The information about the purchase is stored in the minicomputer together with the information on the respective household.

BehaviorScan offers an additional opportunity. Through patented technology it is possible to broadcast testcommercials to either the complete testmarket or to selected subgroups, so that the effects of new campaigns can be tested. Furthermore, BehaviorScan can supply information on promotional activities, features, coupons, and display, thus providing rich marketing data that can be evaluated. Clarke (1993) identifies the following information IRI records for one purchase:

- * the store where the purchase occurred
- * the price of the product
- * promotional activities
 - coupons (amount)
 - point of sale display
 - price reductions (amount)
- * location of product in store
- * price and sales volume of competing products
- * promotion for these products
- * advertising
- * advertising for competing products
- * other products purchased on the same occasion
- * extensive demographic information on the household
- * which TV advertisement the household had seen
- * which coupons the household could have used
- * history of purchases by household for past 2 years
- * which stores the household frequented

This rich marketing info opens new possibilities for data analysis. Individual effects of marketing mix variables can be identified more easily. Unfortunately, academic research has only limited access to this data. So far only - some - data on coffee and cracker products has been made available by IRI for institutions other than the firms paying for information on their products. Currently Nielsen, which is also generating Scanner Data, is increasing its efforts to work with universities, thus providing better access to such rich marketing data for some researchers.

The test markets had to fulfil certain requirements before BehaviorScan could be implemented. The following 6 criteria were summarized by Clarke (1993):

- 1) The cities had to be relatively small, so that supplying every supermarket with scanners did not become overly expensive. Yet, they had to be large enough to provide meaningful results (--> 75.000 - 100.000 people).
- 2) Residents have to do at least 95 percent of their shopping in the town.
- 3) The cities must have one main newspaper, so that the effects of newspaper advertising can be monitored and controlled.
- 4) The residents must have access to cable TV, so that TV advertising effects can be identified.

- 5) The minimarkets should be demographically representative of the U.S.
- 6) They must have clear boundaries.

So far eight markets have been identified by IRI:

Pittsfield, Ma., Marion, In., Eau Claire, Wi., Midland, Tx., Rome, Ga., Visalia, Ca., Grand Junction, Co., and Williamsport, Pa.

There are several advantages to the use of scanners for the collection of purchase data. IRI maintains that BehaviorScan provides a more representative and unbiased sample of consumers, as 70 percent of all households are willing to participate in this panel compared to only 5 percent in diary panels. Another advantage is related to the "instantaneous computerized data generation" (McCloughlin, 1983, p.25). This eliminates the memory bias frequently found in diary data and decreases the time gap between data collection and data availability. Furthermore, complete product category coverage occurs with exact brand, item, product information. This test market design leads to increased reliability and increased external validity of the data (Gabler Wirtschaftslexikon, 1988). Yet, the overall cost for a participating firm is lower than a conventional test market, as the initial production quantity and media cost can be reduced, due to the limited target area.

Nevertheless, there are also some disadvantages to scanner data that should be mentioned here. The occasional breakdown of the equipment and store irregularities can lead to loss of data. Incomplete data can also be generated through the misuse of barcodes. Another disadvantage is pointed out by Du Wors and Haines (1990). They remind that scanners can only record purchases within stores equipped with the technology, while diary panels can also record sales made at other locations. Finally, McCloughlin (1983) indicates that so far the panels are not truly representative of the U.S. or even the respective region.

3.2 THE AVAILABLE DATA

The data used in this thesis covers cracker products. It was obtained through the previously described BehaviorScan. This specific survey included three of the eight cities, namely Williamsport, Pa., Rome, Ga., and Midland, Tx. The total number of stores in these three cities is 31, incorporating national chains, regional chains, independent stores, and coop stores. In each city the panel consisted of 2500 households which are supposedly representative (according to IRI). The survey officially started on 29.08.1983. However, the actually available sales data covers the two year period from 02.01.1984 until

29.12.1985. Due to this long survey duration, a substantial number of new products can be examined.

During the two year period 729 new products were identified. However, the available data only provided the complete sales history for 641 products. 487 of these products did not record any sales during the examined time interval. Several other products did not record more than a few sales. This observation supports the initial statements on high failure rates of new products.

Table 2: Product Data Summary

Product Characteristics	Number of Records
Records with no sales data introduced after 1.02.84	487
Records with 8 or more data points first sales after 1.02.84	82
Records with 12 or more data points to be used for prediction	53
Records with less than 8 data points introduced after 1.02.84 (27.06.84)	72 (97)

Eventually 82 products have been selected for further analysis. The selection of these products occurred according to the following two criteria:

- * the product has to be positively identified as a new product
- * the product has to provide a minimum of 8 data points (periods with sales)

The latter criteria was chosen arbitrarily and is introduced to create a minimum in robustness of the parameter estimates that are based on that data.

One data point is a summary of the sales of one specific product (specific size, flavor, etc.) over a two week period. The data are split into initial purchases, repeat purchases, and total purchases (sum of the former two). Initial purchases indicate the purchase by a consumer who has never purchased the product before. Repeat purchases denote the purchase by a consumer who has previously tried the product.

Among the selected products are a few that are exposed to factors that might affect the statistical results. Some products were identified as having been introduced in some or all of the three markets at different points in time. Thus, there could be a jump in the diffusion process when the product is introduced in the next market. In addition,

there exist different sizes of the same product in some instances. It is indicated in the tables of the appendix which records are exposed to these factors and it is reported in the section "Limitations" whether this affected the overall results.

3.3 DATA ANALYSIS

As indicated in the discussion of the various models, not all of them are independent and they often are special cases of each other. The models to be applied in this study were selected on the basis that they be relatively independent and contain few parameters. The subsequently selected models are the Bass model, the Fisher-Pry model, the Sharif-Kabir model, the Jeuland model, the NUI model, the Von Bertalanffy model, the Generalized model, the KKK I and KKK II models, and the Brockhoff model. The Bass model was included because of its undisputed influence on diffusion research and the fact that it is the underlying model for many of the more complex models. The Fisher-Pry model was included because of its general popularity and simplicity. Instead of the GRM I model, the Generalized model was selected because Skiadas (1986) suggested that it yields better results than the GRM I model.

These models are subjected to testing on two types of data: initial purchase data and total sales data. Many models (e.g. Bass, 1969) were originally developed to represent initial purchase data. The same equation can however also be derived from a learning theory perspective, which offers the opportunity to interpret it as a total sales model. Hence, this thesis attempts to clarify empirically whether these models can be used to describe and predict initial sales as well as whether they can describe and predict total sales. In addition, the Bass model and the Brockhoff model are tested on initial purchasers data (number of people initially buying instead of the number of products initial purchasers buy), since both models were originally developed to explicitly describe that kind of data.

Before the various models can be applied, their respective parameters have to be estimated. This thesis relies on some sales data for estimating those parameters instead of deriving estimates without any quantitative data at hand. For describing the development of sales all available data points of each product are used for the estimation procedure. When 'predicting' the 'future' development of sales, the initial data of each product are used for the estimation procedure. The number of readings employed for the estimation of model parameters is adjusted

for every model, so that there are 5 degrees of freedom in each case. The latter procedure is only used for the 53 products that provide 12 or more data points.

The decision to employ initial data yielding 5 degrees of freedom was arbitrary but the rationale behind it is the goal to provide some stability and robustness to the estimates, while sustaining some predictive value of the results. The latter goal is overriding in this research. Heeler and Hustad (1980) suggest that stability and robustness for the estimates can only be achieved if the underlying data goes beyond the peak in first purchase sales. However, in that case substantial predictive value of the model would be lost. The analysis of the predictive value is restricted to products providing 12 or more data points because it is anticipated that a product failure within the following few weeks (which would be indicated by less than 3 to 5 additional sales occasions) can be foreseen better by management than by any model. Hence, in that case the use of a model is rather unlikely and its value for predictions very limited.

For the estimation of the respective parameters in the models, various estimation procedures are available. Basically there exist three alternatives in the present situation: ordinary least squares (OLS), maximum likelihood,

or non-linear least squares estimation procedures. A sometimes mentioned fourth method, algebraic estimation, proves primarily useful in situations where no time series data is available (Mahajan, Muller, and Bass, 1990). Bass (1986) even suggests that due to the extensive management guesses on parameters necessary for this method, sales could be guessed as well instead of putting the 'derived' parameters in complicated models.

The OLS procedure is the simplest and easiest to implement among the three methods. However, Schmittlein and Mahajan (1982) point to the following disadvantages of this estimation procedure. First of all, it may result in unstable parameter estimates because of possible multicollinearity between the independent variables. Furthermore, it does not readily provide standard errors for the estimated parameters, so that their statistical significance can not be evaluated. Finally the OLS procedure introduces a time interval bias because "this approach uses a discrete time model to approximate a continuous time model" (Mahajan, Mason, and Srinivasan, 1986, p.212).

The maximum likelihood method overcomes these shortcomings, as the time interval bias is eliminated and standard errors for the parameters are provided. Nevertheless, it also has some drawbacks as indicated by

Srinivasan and Mason (1986). They find that this approach allows only for sampling errors, neglecting other possible sources of error.

Mahajan, Mason, and Srinivasan (1986, p.213) conclude that the non-linear least squares estimation procedure yields the best results among the three methods. The authors point out though, that this method - similar to the maximum likelihood procedure - "may be slow to converge (or may not converge), may be sensitive to starting values, or yield local optimum results". Sensitivity analysis is conducted to overcome the problem of local optima. Considering these findings and the fact that a non-linear regression package (TSP Version 4.2B on UNIX) is readily available, a non-linear regression procedure is employed for the estimation of parameters.

One of the estimated parameters is the market potential L (or N --> see below) - the upper limit of the diffusion process. This approach may cause an error when predicting future sales. Martino (1972) indicates that we may get an underestimate of the upper limit of the diffusion process when the underlying data represents the early stage of the process. The prediction of future sales relies on only the first eight to ten data points, so that such a bias is possible in one of the two present applications.

For the analysis and parameter estimation, the selected models are rewritten in terms of N and $N(t)$, where N denotes the upper limit of diffusion in absolute numbers and $N(t)$ denotes the absolute sales in period t . Thus the number of parameters to be estimated increases by 1. This does not apply to Brockhoff's model, since it is already expressed in terms of sales in period t . Furthermore, for the purpose of comparison, the NUI, the Jeuland and the KKK I models are divided by $(p + q)$ (Kumar and Kumar, 1992a). This is done for all models that present extensions of the Bass model.

Various statistical measures are computed in order to evaluate the models. Often goodness of fit (accuracy) is considered the most important criterion. However, goodness of fit does not necessarily imply forecasting accuracy as well. The Root Mean Squared Error (RMSE) and the Standard Deviation of the Error (SDE) are other alternatives and are calculated by the employed statistical package. The RMSE is difficult to interpret though, as it is an absolute measure (Makridakis, Wheelwright, and McGee, 1983). For that reason it seems reasonable to include a relative measure such as the Mean Absolute Percentage Error (MAPE) in the analysis. However, the mentioned measures all emphasize large errors. As Makridakis, Wheelwright and McGee (1983, p.50) point out, "it would be helpful to have a measure that considers both the disproportionate cost of large errors and provides a

relative basis for comparison with naive (forecasting) methods". They propose the use of the U-statistic developed by Theil (1961 and 1966). This statistic is similar to the MAPE and the Naive Forecast NF1 (see Makridakis, Wheelwright, and McGee) and consequently used instead of the MAPE.

Naive Forecasting relies primarily on the value in period $t-1$ for the forecast in period t . Theil's U indicates whether it is reasonable to use a formal forecasting method or whether naive forecasting gives equally good (or better) results. The closer the 1966 U is to 0 the more advantageous the formal method is over naive forecasting. For a 1966 U equal to 1, both methods are equally good. However, if a 1966 U is greater than 1, the naive forecast yields better results than the formal method. In addition to the 1966 U , the 1961 U and its breakdown is computed. This U is confined to the region between 0 and 1, with 0 representing a high forecasting value of the model and 1 representing a low value. Its breakdown gives an indication whether the error is due to systematic or unsystematic errors. The three components of the breakdown are 1) U^m = inequality due to unequal central tendency, 2) U^s = inequality due to unequal variation, and 3) U^c = inequality due to unequal covariation (Theil 1961, p.33). If the forecaster does not get a total U equal to 0, it is desirable to attribute inequality mainly

to unsystematic errors, namely U^c (unsystematic error) equal to 1 and U^m and U^s (systematic errors) equal to 0.

Another useful statistical measure, the Coefficient of Determination (R^2), gives an indication of the explained and unexplained variance due to the regression line. However, the evaluation relies primarily upon Theil's U , since a "good" correlation coefficient "does not imply perfect forecasting, but only the existence of an exact linear relation" between predicted and actual values (Theil, 1961, p.31).

4. FINDINGS

4.1 DESCRIPTIVE VALUE OF THE MODELS

The following sections present a summary of the ex post findings for each model. The main points are illustrated by Theil's U (1966), the decomposition of Theil's U (1961), and the adjusted R^2 . For Theil's U (1966) two cutoff points were arbitrarily selected for reporting the results. It is anticipated that a U (1966) of less than 0.7 is a reasonably good result, while a U (1966) of less than 0.5 can be considered to be a rather good result. In contrast, a U (1966) beyond or equal to 1.0 is considered a very poor result, as naive forecasting is at least as successful as the model in predicting the outcome. The decomposition of Theil's 1961 U will concentrate on the portion of non-systematic error, since a large systematic error can be taken as an indication for built in bias in the forecasting technique (Haines, Alexis, and Simon, 1972). Consequently, a high percentage of non-systematic errors compared to systematic errors is desirable. U^c (1961) > 0.5 will be taken as the lower limit of reasonably good results, while good results start at 0.8. Finally a good adjusted R^2 will be reported for values greater than 0.8.

In addition it would be beneficial for research in this field, if it were possible to identify a range in which some of the parameters of the respective models fall most often. In that case the forecasting task could be simplified to a certain degree for the practitioner, as the number of parameters to be estimated could be reduced. For this reason frequency tables for the parameter values are presented in the appendix and briefly discussed in the following sections. Furthermore, it will be stated whether the parameter estimates are significant or not, since this is another indicator of the success of the regression analysis. In this context only the results for parameters other than NBAR (the upper limit of the diffusion process) will be discussed. NBAR is more often significant and close to the "real" value than the remaining parameter estimates, since the initial estimate used for the regression analysis was made with knowledge of the actual diffusion value. This introduced a positive bias and most likely resulted in a better than usual initial and final estimate for that parameter.

4.1.1 THE FISHER-PRY MODEL

The logistic model is the simplest of the models tested, as only two parameters, q and NBAR have to be

estimated. It describes first purchase sales well in only some cases. Theil's U (1966) is less than 0.7 in 42.0% of the cases and less than 0.5 in 14.8 % of the cases. However, Theil's U (1966) never is equal to or exceeds 1, which implies that this model gives constantly better results than naive extrapolation of last period's data - when describing first purchase sales data. In addition, the decomposition of the 1961 U reveals that a large portion of the error is due to inequality in covariation, thus indicating a predominant nonsystematic error. In 76.5% of the cases this non-systematic error accounts for more than 50% of total inequality and in 37.0% this error is even responsible for more than 80% of the total error. Yet, the adjusted R^2 which has often been reported in related studies (sometimes R^2 has been used) does not advocate the use of this model for first purchase sales either. Hardly any time series provides an adjusted R^2 greater than 0.8.

Table 3: Summary Fisher-Pry Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	42.0%
	< 0.5	14.8%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	76.5%
	> 0.8	37.0%

The results are slightly better for total sales data. Here Theil's U (1966) is less than 0.7 in 55.6% of the cases and less than 0.5 in 24.7% of the cases. Again there is no case where the inequality coefficient is equal to or exceeds 1. The portion of inequality due to difference in covariation is larger than 50% in 84.1% and larger than 80% in 36.6% of the cases. As can be seen later, only one other model - the one by Brockhoff - approaches such high percentages for the non-systematic error. Similar to first purchase sales data, the adjusted R^2 is usually very low with only a few exceptions yielding an R^2 larger than 0.8.

Table 4: Summary Fisher-Pry Model Total Sales
- Description -

Theil's U (1966)	< 0.7	55.6%
	< 0.5	24.7%
	≥ 1.0	0.0%
Theil's U^c (1961)	> 0.5	84.1%
	> 0.8	36.6%

The frequency tables for the parameter estimates show a considerable concentration of the parameter q in this model. For first purchase sales q ranges between 0.1 and 0.4 in 62.2% of the cases. For total sales this percentage increases to 68.3%. The vast majority of these parameter

estimates are significant at a significance level of 0.05 and even 0.01. This denotes a rather large concentration, but leaves too wide a margin within which these values fluctuate for proposing a specific value for q .

Overall it can be stated that the logistic model does not describe the available data sufficiently well - even though the model is superior to naive forecasting. In addition, it yields slightly better results for total sales than for first purchase sales.

4.1.2 THE BASS MODEL

The Bass model was tested on three data sets: first purchase occasions, first purchase sales, and total sales. First purchase occasions are described well in many but not all cases. Theil's U (1966) is less than 0.7 in 61.7% and less than 0.5 in 32.1% of all cases. In contrast to the logistic model there are a few - 3.7% - cases with a U (1966) ≥ 1 . In general, the model thus outperforms naive forecasting. The decomposition of the 1961 U shows a relatively large portion of error due to non-systematic error. This portion is more than 50% in 58.0% of the cases and more than 80% in 25.9% of the cases.

Table 5: Summary Bass Model First Purchase Occasions
- Description -

Theil's U (1966)	< 0.7	61.7%
	< 0.5	32.1%
	≥ 1.0	3.7%
Theil's U ^c (1961)	> 0.5	58.0%
	> 0.8	25.9%

Most adjusted R^2 in this context are relatively small, but 12.3% are larger than 0.8. Throughout the entire analysis it is apparent, however, that a high R^2 does not imply a low U and thus good forecasting. Neither is a high adjusted R^2 a requirement for a low U. As mentioned previously, this study puts its emphasis on Theil's U, since the correlation coefficient merely indicates whether a relationship exists between the predicted and actual sales.

The results are very similar for first purchase sales with some measures yielding better and some yielding worse results. Theil's U (1966) turns out to be less than 0.7 in 63.0% and less than 0.5 in 28.4% of the analyzed data sets. However, there are a substantial number of instances (9.9%) where $U \geq 1.0$. Thus some good results are mixed with some rather poor results. Non-systematic errors outweigh systematic errors by some margin. In 60.5% of the cases non-

systematic error accounts for more than 50% and in 19.8% of the cases it accounts for more than 80% of the total error. The adjusted R^2 again usually is relatively small with 11.1% being larger than 0.8.

Table 6: Summary Bass Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	63.0%
	< 0.5	28.4%
	≥ 1.0	9.9%
Theil's U^c (1961)	> 0.5	60.5%
	> 0.8	19.8%

The results improve a little for total sales. Here, U (1966) is less than 0.7 for 69.1% and less than 0.5 for 33.3% of the analyses. A negligible number of cases (1.7%) yield a description worse than naive extrapolation. Yet, the portion of error due to non-systematic error decreases a little compared to the previous cases, as only 54.3% of U^c are larger than 0.5 and 19.8% larger than 0.8. Most adjusted R^2 are relatively small as only 9.9% exceed 0.8.

Table 7: Summary Bass Model Total Sales

- Description -

Theil's U (1966)	< 0.7	69.1%
	< 0.5	33.3%
	≥ 1.0	1.2%
Theil's U ^c (1961)	> 0.5	54.3%
	> 0.8	19.8%

The Bass model incorporates the parameters p and q . While there is a strong concentration of estimated values for p , the concentration of q is much weaker. 54.0% of the estimated p -values range between 0 and 0.1 for first purchase sales, which increases to 68.6% for the range between 0 and 0.2. For total sales these percentages are 63.4% and 75.6% respectively. This is a good basis for suggesting a value of p between 0 and 0.1 - which also presents a reasonably narrow margin - in this market situation. q on the other hand, shows a concentration between -0.2 and 0. For first purchase sales this concentration amounts to 46.4%, for total sales to 43.9%. In both instances the values vary widely outside of this range. Thus the evidence is considered to be too weak for a reliable suggestion. Furthermore, the large majority of those parameter estimates are not significant at a level of

0.05. When significance is achieved, however, Theil's U often is reasonably good.

Overall, the model appears to outperform naive forecasting and the logistic model. Similar to the logistic model, the results are slightly better for total sales than for first purchase sales. In addition, first purchase sales are described better than first purchase occasions, even though the model was originally designed for the latter.

4.1.3 THE SHARIF-KABIR MODEL

The Sharif-Kabir model provides rather unsatisfactory results for both first purchase sales and total sales. Theil's U (1966) remains below 0.7 in only 30.9% of all first purchase sales time series. The second marker of 0.5 is only satisfied by 14.8%. Nevertheless, no inequality coefficient is equal to or exceeds 1, so that even this model is better than naive forecasting when describing the sales data at hand. Decomposition of Theil's 1961 U reveals that in barely more than 50% of the cases, non-systematic error accounts for more than 50% of total inequality. This figure is reduced to 16% when the cutoff point is a minimum of 80% non-systematic error.

2 of / de 2

MICROCOPY RESOLUTION TEST CHART
NATIONAL BUREAU OF STANDARDS
STANDARD REFERENCE MATERIAL 1010a
(ANSI and ISO TEST CHART No. 2)

Table 8: Summary Sharif-Kabir Model First Purchase Sales

- Description -

Theil's U (1966)	< 0.7	30.9%
	< 0.5	14.8%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	53.1%
	> 0.8	16.0%

Like the previous models, the Sharif-Kabir model provides a relatively small adjusted R^2 , with 8.6% being larger than 0.8.

The picture is similar but somewhat better for total sales. 39.5% of the time series yield a U (1966) < 0.7 and 17.3% yield a U (1966) < 0.5. Again no case is reported where naive forecasting outperforms the model. Non-systematic error accounts for more than 50% of total error in 53.1% of the cases and for more than 80% in 18.5% of the cases. Even though more of the adjusted R^2 are larger than 0.8 (12.3%) compared to first purchase sales, the remaining coefficients are also very small.

Table 9: Summary Sharif-Kabir Model Total Sales
- Description -

Theil's U (1966)	< 0.7	39.5%
	< 0.5	17.3%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	53.1%
	> 0.8	18.5%

The parameters in the Sharif-Kabir model that have to be estimated are q and σ . For neither of the two a reasonable suggestion about a likely parameter range can be formed based upon the results in this study. q appears to be concentrated in the range between 0 and 0.4. However, a concentration of 59.3% for first purchase sales and 48.9% for total sales does not provide sufficient indication, especially when considering this relatively wide margin. The parameter σ fluctuates even more widely, with less than 50% of its values falling between 0 and 100. In addition, hardly any of the parameter estimates - for both first purchase sales and total sales - are significant at a significance level of 0.05. On the contrary, many are highly insignificant with t-tests below 0.1. Similar to the previous cases, the overall results usually become rather good, when the parameter estimates are significant.

In summary, the model appears to be inferior to the previous two models in this context, even though it is still superior to naive no-change extrapolation. The model supports the trend established by the logistic and Bass models that total sales can be described somewhat better than first purchase sales.

4.1.4 THE JEULAND MODEL

The Jeuland model posed significant problems for the regression algorithm in the case of first purchase sales and total sales. 18.5% and 11.1% respectively of the regression procedures were aborted because of too many computational errors occurring. Unsurprisingly the results of the model are not very impressive either. For first purchase sales Theil's U (1966) is below 0.7 in 34.6% and below 0.5 in 16.0% of the cases. In addition to these rather low percentages of good results, 25.9% of the results turn out to be inferior to naive forecasting. Similarly, systematic error slightly outweighs non-systematic error. Inequality due to differences in covariation accounts for more than 80% of total inequality in 23.5% of the cases. As would be expected, the adjusted R^2 generally are extremely low, even though 12.3% exceed 0.8.

Table 10: Summary Jeuland Model First Purchase Sales

- Description -

Theil's U (1966)	< 0.7	34.6%
	< 0.5	16.0%
	≥ 1.0	25.9%
Theil's U ^c (1961)	> 0.5	48.1%
	> 0.8	23.5%

The results improve somewhat for total sales. Here U (1966) is below 0.7 in 42.0% and below 0.5 in 18.5% of the analyses. Again however, a large portion (21.5%) exceeds or is equal to 1, so that the model is often outperformed by naive no-change extrapolation. The percentage of cases where non-systematic error incorporates more than 50% of the total error increases to 59.3%, but the percentage where it incorporates more than 80% decreases to 22.2%.

Table 11: Summary Jeuland Model Total Sales

- Description -

Theil's U (1966)	< 0.7	42.0%
	< 0.5	18.5%
	≥ 1.0	21.0%
Theil's U ^c (1961)	> 0.5	59.3%
	> 0.8	22.2%

The majority of adjusted R^2 are extremely low and only 9.9% exceed 0.8.

The Jeuland model incorporates three parameters: p , q , and γ . While the latter two fluctuate widely and thus do not allow any suggestion about a specific range they would usually fall in, the parameter p shows considerable concentration. For first purchase sales 70.8% of the estimates range between -0.1 and 0.05 with the largest portion falling between 0 and 0.02. For total sales 74.0% range between -0.02 and 0.05, again with the largest portion between 0 and 0.02. This could serve as a basis for suggesting a value of p between 0 and 0.02, which represents a sufficiently narrow range. However, it has to be stressed that such a suggestion only applies to the given product market combination. Furthermore, it has to be treated with some caution as the Jeuland model hardly yields any significant parameter estimates at a level of 0.05. In the case of first purchase sales a mere 3.2% are significant; in the case of total sales it is 5.3%.

Overall, it can be stated that the Jeuland model yields rather unsatisfactory results, both from an evaluation point of view and from a regression execution point of view. While the results for total sales again are superior to first

purchase sales in this case, they still do not offer acceptable descriptive accuracy.

4.1.5 THE NUI MODEL

The results obtained by the non-uniform-influence model are disappointing as well - both for first purchase sales and for total sales. Only 28.4% of Theil's 1966 inequality coefficients remain below 0.7 for first purchase sales. A mere 8.6% remain below 0.5. On the other hand, more than half of the cases (53.1%) would be predicted better through naive forecasting, implying that the NUI model in this context is inferior to naive no-change extrapolation. Similarly, systematic errors dominate non-systematic errors in 72.8% of the cases. Non-systematic error accounts for more than 80% of total error in only 6.2% of the cases.

Table 12: Summary NUI Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	28.4%
	< 0.5	8.6%
	≥ 1.0	53.1%
Theil's U^c (1961)	> 0.5	27.2%
	> 0.8	6.2%

The adjusted R^2 also reports extremely unsatisfactory results, even though 11.1% surpass 0.8.

In the case of total sales, the results get somewhat better, though they can still be classified as rather poor. Theil's U (1966) is below 0.7 for 33.3% and below 0.5 for 21.0% of the analyzed time series. Similar to first purchase sales, there is a high percentage (39.5%) of inequality coefficients equal to or exceeding 1.0. In addition to these findings, decomposition of Theil's U (1961) again reveals a large portion of systematic error. Only in 35.8% of the analyses is non-systematic error dominant and only in 16.0% it accounts for more than 80% of the total error. Again, most adjusted R^2 are extremely low and less than 10% exceed 0.8.

Table 13: Summary NUI Model Total Sales

- Description -

Theil's U (1966)	< 0.7	33.3%
	< 0.5	21.0%
	≥ 1.0	39.5%
Theil's U^c (1961)	> 0.5	35.8%
	> 0.8	16.0%

The frequency tables for the model's parameters p , q , and δ present a mixed picture. p ranges between 0 and 0.2 in 65.1% for first purchase sales and 64.7% for total sales, with the majority falling between 0 and 0.1. This seems to suggest a value of p close to 0.1. The parameter q is concentrated in the same area. For first purchase sales 58.8% of the estimates fall between 0 and 0.2 with 42.5% ranging between 0.1 and 0.2. For total sales 41.5% fall between 0.1 and 0.2. Otherwise there is wide variation. Thus there is only weak evidence for suggesting a range between 0.1 and 0.2 for the parameter q . δ on the other hand, fluctuates very widely and does not allow a reasonable suggestion for either first purchase sales or total sales. These parameter estimates are again hampered by a very high percentage of extremely insignificant estimates. Only 6.2% of the estimates for first purchases sales and 10.3% of the estimates for total sales are significant at a significance level of 0.05. In light of these and the overall results, the value of a parameter suggestion for this model is questionable.

Thus the NUI model is not perceived as very useful in describing sales in this market. Nevertheless, the model supports the trend that total sales are described better than first purchase sales by the given models in this situation.

4.1.6 THE VON BERTALANFFY MODEL

The von Bertalanffy model yields reasonably good results for both first purchase and total sales. 58.0% of Theil's U (1966) range below 0.7 and 28.4% range below 0.5 for first purchase sales. A small amount (1.2%) report results inferior to naive no-change extrapolation. When looking at the components of the error, it becomes apparent that systematic error is slightly dominant, with 45.7% of the cases reporting the portion of non-systematic error to be larger than the systematic error. In 24.7% of the cases the inequality due to difference in covariation incorporates more than 80% of total inequality. The adjusted R^2 usually turns out to be rather low, but 11.1% of these measure exceed 0.8.

Table 14: Summary von Bertalanffy Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	58.0%
	< 0.5	28.4%
	≥ 1.0	1.2%
Theil's U^c (1961)	> 0.5	45.7%
	> 0.8	24.7%

Total Sales are described somewhat better by this model. Here U (1966) is less than 0.7 and less than 0.5 more often than for first purchase sales, 65.4% and 32.1% respectively. Furthermore, no cases with U (1966) ≥ 1.0 are reported. However, the percentage of non-systematic error decreases slightly in comparison to first purchase sales. It is dominant only in 42.0% and exceeds 80% of total error only in 21.0% of the cases. Most adjusted R^2 are rather low for this model. Again, 11.1% of the R^2 exceed the arbitrary mark of 0.8.

Table 15: Summary von Bertalanffy Model Total Sales
- Description -

Theil's U (1966)	< 0.7	65.4%
	< 0.5	32.1%
	≥ 1.0	0.0%
Theil's U^c (1961)	> 0.5	42.0%
	> 0.8	21.0%

For the von Bertalanffy model the parameters q and θ have to be estimated. Most of q 's values - 56.0% and 54.8% - can be found between 0 and 0.1 for first purchase sales and total sales respectively. However, the parameter fluctuates widely outside of this range, thus making a confident suggestion rather difficult. The parameter θ does not show

any concentration, so that a suggestion for a common range seems impossible. These difficulties are furthermore illustrated by the fact that only 13.0% and 11.7% of the parameter estimates for first purchase and total sales are significant at a significance level of 0.05.

Overall it can be stated that the model yields results that are reasonably good in several cases, but obviously not all cases. In the given context it seems to be superior to all previously discussed models except the Bass model. Again, total sales can be better described than first purchase sales.

4.1.7 THE GENERALIZED MODEL

The generalized model by Skiadas reports considerably better results for total sales than for first purchase sales. The latter are described well in some but not the majority of cases, as U (1966) remains below 0.7 in 44.4% and below 0.5 in 13.6% of the analyzed cases. While these percentages do not compare to the results achieved by the Bass and von Bertalanffy models, there is - like in those models - only a negligible amount of cases (2.5%) where U (1966) ≥ 1.0 . The portion of non-systematic error is rather low as it exceeds systematic error only in 28.4% of the time

series. It accounts for more than 80% of total inequality in 12.3%. The adjusted R^2 are usually extremely low and a mere 8.6% are larger than 0.8.

Table 16: Summary Generalized Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	44.4%
	< 0.5	13.6%
	≥ 1.0	2.5%
Theil's U^c (1961)	> 0.5	28.4%
	> 0.8	12.3%

For total sales the percentage of cases with an inequality coefficient below 0.7 and 0.5 increases to 58.0% and 30.9% respectively. This is a substantial change in comparison to first purchase sales. Naive extrapolation yields better results than Skiadas' model in only 1.2% of the cases, thus clearly demonstrating the model's superiority in this situation. The decomposition of the error term reveals that again systematic error is prevalent in most cases (65.4%). Non-systematic error exceeds 80% of total error in only 13.6%. Similar to first purchase sales, most adjusted R^2 reported for this model are rather low. Roughly 10% exceed the chosen cutoff point of 0.8.

Table 17: Summary Generalized Model Total Sales
- Description -

Theil's U (1966)	< 0.7	58.0%
	< 0.5	30.9%
	≥ 1.0	1.2%
Theil's U ^c (1961)	> 0.5	34.6%
	> 0.8	13.6%

Frequency tables for the model's parameters q and g display a relatively strong concentration for q . 53.7% of the parameter estimates for first purchase sales range between -0.05 and 0.05. This percentage increases to 83% if the interval is expanded to 0.2. For total sales the respective figures are 59.0% and 76.8%. This indicates a slight tendency for q to be larger than 0 instead of smaller than 0, so that a reasonable suggestion for q appears to be a value between 0 and 0.05. The parameter g on the other hand fluctuates widely and does not give any indication of a possible range it would usually fall in for the present product market combination. The parameter estimates are significant in 13.0% and 16.7% for first purchase and total sales respectively.

In summary, it can be stated that the model provides good results in some cases - especially for total sales -

but often it is considerably off target. While it provides somewhat better results than the Jeuland and NUI models, it does not perform as well as the Bass and von Bertalanffy models.

4.1.8 THE KKK I MODEL

The first model by Kumar and Kumar reports rather mixed results for both kinds of data. First purchase sales are described well in a number of instances, as Theil's U (1966) is below 0.7 for 42.0% and below 0.5 for 16.0% of the time series. However, there is a substantial portion of cases that are described rather poorly. This is demonstrated by the fact that 25.9% report a U (1966) ≥ 1.0 . In addition, systematic error is slightly dominant, since only in 46.9% of the time series, non-systematic error incorporates more than 50 % of the total error. In roughly 15% of the cases non-systematic error makes up more than 80% of the total error. The adjusted R^2 is larger than 0.8 in 11.1% of the analyzed cases. In most remaining instances it is, however, very low.

Table 18: Summary KKK I Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	42.0%
	< 0.5	16.0%
	≥ 1.0	25.9%
Theil's U ^c (1961)	> 0.5	46.9%
	> 0.8	14.8%

Similar to the previous findings, the results improve somewhat for total sales. Theil's 1966 inequality coefficient remains below 0.7 in nearly half of the cases. This model yields good results ($U < 0.5$) for 27.2% of the data sets. Yet, there is again a high percentage of unsatisfactory results, as U (1966) exceeds or is equal to 1.0 in 23.5% of the cases. Thus the model is superior to naive forecasting in the majority of cases, but not consistently. Analyzing the components of the inequality coefficient (1961) shows that non-systematic error is slightly dominant, as a little more than half of the cases report systematic error of less than 50%. Non-systematic error accounts for more than 80% of total error in 16.0%. As in the case of first purchase sales - and most previous models - the adjusted R^2 is usually very low, but 12.3% are larger than 0.8.

Table 19: Summary KKK I Model Total Sales

- Description -

Theil's U (1966)	< 0.7	49.5%
	< 0.5	27.2%
	≥ 1.0	23.5%
Theil's U ^c (1961)	> 0.5	53.1%
	> 0.8	16.0%

The KKK I model incorporates the parameters p , q , and b . There is a little concentration of p between 0 and 0.1, but it is not sufficient for drawing sustainable conclusions about its range. The parameters q and b show no concentration for either data set and thus make a range suggestion implausible. These findings are further strengthened by the fact that only 14.4% of the first purchase sales parameter estimates are significant at a level of 0.05. This figure decreases to 9.5% for total sales.

Overall it appears that the model suits this situation only in some cases, but proves to be unsuitable in several other instances. Again total sales yield better results than first purchase sales.

4.1.9 THE KKK II MODEL

The second model by Kumar and Kumar proves to be superior to the KKK I model in the given context. For first purchase sales, Theil's U (1966) ranges below 0.7 for nearly half of the cases and below 0.5 for roughly on fourth of the cases. Furthermore, only a small number of time series (4.9%) yield results with U (1966) ≥ 1.0 . The decomposition of Theil's U (1961) reveals that nearly half of the times non-systematic error outweighs systematic error. It accounts for more than 80% of total inequality in a little less than one fourth of the cases. However, most adjusted R^2 are usually very low, with only 8.6% being larger than 0.8.

Table 20: Summary KKK II Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	48.1%
	< 0.5	24.7%
	≥ 1.0	4.9%
Theil's U ^c (1961)	> 0.5	48.1%
	> 0.8	23.5%

The picture improves further for total sales, with more than half of the cases reporting a U (1966) below 0.7. 28.4% yield a U (1966) below 0.5 and only 3.7% yield a U (1966) $\geq$

1.0, thus implying that the model consistently outperforms naive no-change extrapolation. Nevertheless, systematic error remains slightly prevalent in this analysis, as 54.3% of the cases report inequality due to difference in covariation below 50% of total inequality. The portion of cases where non-systematic error makes up more than 80% of total error is roughly one fifth. Most adjusted R^2 are very low for this model and only 8.6% surpass 0.8.

Table 21: Summary KKK II Model Total Sales
- Description -

Theil's U (1966)	< 0.7	55.6%
	< 0.5	28.4%
	≥ 1.0	3.7%
Theil's U^c (1961)	> 0.5	45.7%
	> 0.8	19.6%

The parameters of the model, q and α show some concentration around certain values, but not enough for a specific suggestion. 40.5% of q 's estimates for first purchase sales range between 0 and 0.1 and nearly 90% range between -0.05 and 0.4. For total sales these percentages change to 13.0% and 85.0% respectively. α on the other hand ranges between -2 and 0 in 58.2% for both first purchase and total sales. These margins do not allow for a very useful

suggestion. The regression analysis provides significant parameter estimates in roughly one fourth of the cases for both kinds of data sets.

In summary it can be stated, that the model provides similar statistical results as the Generalized model, while being slightly superior to Skiadas' model. It continues the trend of describing total sales better than first purchase sales.

4.1.10 THE BROCKHOFF MODEL

The Brockhoff model, like the Bass model, was tested on first purchase occasions, first purchase sales, and total sales. It provides rather satisfactory results for describing all three kinds of data. For first purchase occasions more than three quarter (76.5%) of the cases reported a U (1966) of less than 0.7 and 39.5% reported a U (1966) smaller than 0.5. Moreover, there are no instances where the model does not outperform naive forecasting. Furthermore, non-systematic error is clearly dominant. In 79.0% non-systematic error is larger than systematic error and in 37.0% the ratio exceeds 80:20. Nevertheless, most adjusted R^2 remain relatively small, even though 19.8% are larger than 0.8.

Table 22: Summary Brockhoff Model First Purchase Occasions
- Description -

Theil's U (1966)	< 0.7	76.5%
	< 0.5	39.5%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	79.0%
	> 0.8	37.0%

The results are very similar for first purchase sales, though not quite as good. Slightly fewer cases report Theil's inequality coefficient (1966) to be smaller than 0.7. However, there are as many cases as for first purchase occasions with a coefficient smaller than 0.5 and also no cases with U (1966) ≥ 1.0 . Non-systematic error is again clearly dominant as it outweighs systematic errors in 74.1%. It makes up more than 80% of the total error in 35.8% of the cases. Most adjusted R² remain relatively low, even though several (18.5%) surpass 0.8.

Table 23: Summary Brockhoff Model First Purchase Sales
- Description -

Theil's U (1966)	< 0.7	74.1%
	< 0.5	39.5%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	74.1%
	> 0.8	35.8%

The results improve to the highest level achieved in this entire research for total sales. 79.0% of all total sales time series report a U (1966) lower than 0.7 for the Brockhoff model. 42.0% report a U (1966) lower than 0.5. At the same time, no case is reported where naive forecasting yields superior or even equivalent results. The decomposition of the error term shows, however, a somewhat smaller prevalence of non-systematic error than for the other two kinds of data. It is dominant in 67.9% of the cases. Similarly, the number of cases where inequality due to difference in covariation accounts for more than 80% is reduced to 28.4%. As would be expected in light of the previous results, the adjusted R^2 is usually relatively low, while 12.3% exceed 0.8.

Table 24: Summary Brockhoff Model Total Sales
- Description -

Theil's U (1966)	< 0.7	79.0%
	< 0.5	42.0%
	≥ 1.0	0.0%
Theil's U ^c (1961)	> 0.5	67.9%
	> 0.8	28.4%

The Brockhoff model requires the parameters a , q , and c to be estimated. While there appears to be considerable concentration for the parameters q and c , there is no particular range the parameter a points to, as it fluctuates widely. q varies primarily between -2 and 1 (~ 75%) for both first purchase sales and total sales. The parameter c on the other hand, ranges between -0.2 and 1.0 (76.8%) for first purchase sales and -0.05 and 1.0 (70.1%) for total sales. These margins still do not allow for a reasonably specific suggestion as to where the parameter value would usually fall. Contrary to the previous models though, the regression procedure yielded significant parameter estimates at a significance level of 0.05 in nearly half of the cases for both first purchase sales and total sales.

In summary, it is apparent that this model provides a rather good description for first purchase occasions, first

purchase sales, and total sales. Furthermore, the model outperforms all of the previous models. Finally, it also provides better statistical results for total sales than for first purchase sales. In contrast to the Bass model, however, it yields better statistical results for first purchase occasions than for first purchase sales.

4.1.11 SUMMARY

The results of the descriptive analysis can be summarized by Bernhardt and Mac Kenzie's (1972) statement. The models work well in some cases but not in others. There are significant differences, however, in the performance of the individual models. The NUI and Sharif-Kabir models describe the data at hand rather poorly in the large majority of cases. To a slightly lesser extent the same holds true for the Jeuland and KKK I models. The Bass and von Bertalanffy models on the other hand, describe the time series at least reasonably well in considerably more than half of all cases. However, it is the Brockhoff model that delivers by far the best results, as approximately three quarter of all cases are described at least reasonably well and nearly half are described well according to the proclaimed standards. Most models nearly always outperform naive forecasting when describing the data. This is not true

only for the Jeuland and KKK I models, for which roughly 25% of the time series achieve a U (1966) larger than or equal to 1.0 and especially the NUI model for which more than half of the time series are described very poorly.

Figure 1: Description of individual records ($U < 0.7$)

Figures 1 and 2 illustrate the fact that the models work well for some time series but not at all for other time series. It is apparent that 18.5% of first purchase sales time series are not even described reasonably well by any model and another 11.1% are described reasonably well by

Figure 2: Description of Individual Records ($U < 0.5$)

just one or two models. At the same time though, there are 12.3% of the time series that achieve a $U(1966) < 0.7$ with all or all but one models. In addition, there are a number of cases that are described reasonably well by 3-8 models. These percentages change if we look at time series described by a $U(1966)$ below 0.5. 55.6% of the records do not report such a value for even one model. 13.6% achieve it for one or two models. There remain 17.2% that are described well by 7 or more models. This mixed picture also applies for total sales. 19.8% of the records never report a value for U

(1966) below 0.7 and 50.6% never go below 0.5. The overall picture is however, visibly better for total sales, as 22.2% of the time series report an inequality coefficient (1966) below 0.7 for 9 or 10 models and still 9.8% report it below 0.5 for 9 to 10 models. This demonstrates that some diffusion processes can be described very well by some - or even all - models, but some give rise to a curve that can not be fitted to any of the tested models.

Table 25: Subjective Ranking by the Author of the Models for Descriptive Analysis of New Product Introduction

Ranking	First Purchase Sales	Total Sales	First Purchase Occasions
1	Brockhoff	Brockhoff	Brockhoff
2	Bass	Bass	Bass
3	v. Bertalanffy	v. Bertalanffy	-
4	KKK II	Generalized	-
5	Logistic	Logistic	-
6	Generalized	KKK II	-
7	Sharif-Kabir	Sharif-Kabir	-
8	KKK I	KKK I	-
9	Jeuland	Jeuland	-
10	NUI	NUI	-

Table 25 presents a subjective ranking of the models analyzed in this research. The Sharif-Kabir model is ranked better than the KKK I model for both total sales and first purchase sales, even though it yields good or reasonably good results in fewer occasions. This is due to the fact that the Sharif-Kabir model always yields predictions superior to naive forecasting, while the KKK I model results in a U (1966) greater or equal to 1 in several instances. The NUI model is ranked last. Yet, it has to be mentioned that the few times the model achieves a good fit ($U < 0.5$), the fit is commonly superior to that of the Brockhoff model.

Systematic error is significant in most models and usually is the dominant source of error in approximately 50% of the records. Exceptions to this rule are the NUI model, where systematic error is dominant considerably more often and the Brockhoff model, where it is prevalent in just 25% of the records. This suggests that in many cases the forecasting techniques seems to be inappropriate.

It is furthermore apparent - as was pointed out above - that the adjusted R^2 is not always a good measure for evaluating the forecasts. In several cases the adjusted R^2 is rather large, but the forecasting accuracy remains low. This indicates a relationship between the actual and

"predicted" (described) values, but not an actual proximity between those values.

The attempt to define specific intervals for the models' parameters was futile. For most models the reported parameter estimates cover too wide an area for any useful suggestions. The few cases where such a suggestion is possible are not very helpful in light of the remaining results.

4.2 PREDICTIVE VALUE OF THE MODELS

The following sections present a summary of the ex ante prediction findings for each model. The same statistical measures as for the descriptive part are employed to evaluate the results. While the adjusted R^2 is used to describe the regression procedure, the correlation coefficient R^2 is an additional measure describing the fit between predicted and actual values. In this analysis between 8 and 10 datapoints (each representing 2 week periods) - depending on the specific model - are used for parameter estimation.

For each model - except the Jeuland model - sensitivity analysis for a subset of records is presented. Its detailed

results can be found in the appendix. The Jeuland model was excluded because of its problematic results in the descriptive analysis and the original predictive analysis. In the sensitivity analyses 12, 15, 20, and 25 datapoints are employed for the parameter estimation procedure. This should show whether the predictive accuracy improves significantly with more underlying datapoints for estimation, and whether the arbitrary selection of five degrees of freedom for the regression analysis introduces a strong bias. It should be pointed out here that 25 datapoints cover nearly one year of sales, so that even if the results are better, a manager would have to wait longer than a reasonable time to get this benefit. The records for the sensitivity analysis are selected so that there are some time series covering a long time span as well as some covering a short time span. Furthermore, some generally yield rather good results in the descriptive analysis, while others do not yield that good results. This should provide a somewhat balanced mix.

4.2.1 THE FISHER-PRY MODEL

The parameter estimation procedure for the logistic model is based on eight datapoints. The results for first purchase sales and total sales are highly unsatisfactory, as

there are hardly any records for which good or even reasonably good results are obtained. Just 3.8% of the cases for first purchase sales report Theil's U (1966) to be smaller than 0.7 and a mere 1.9% report it to be smaller than 0.5. This picture is worsened by the fact that U (1966) is larger than or equal to 1.0 for 54.7% of the records, with the majority of the remaining records showing a U (1966) between 0.95 and 1.0. Thus naive forecasting appears to outperform this model for predictive purposes. Similarly, the proportion of non-systematic error is rather small, as systematic error is dominant in nearly 85% of the cases. The portion of non-systematic error exceeds 80% in 5.7%.

Table 26: Summary Fisher-Pry Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	3.8%
	< 0.5	1.9%
	≥ 1.0	54.7%
Theil's U ^c (1961)	> 0.5	15.1%
	> 0.8	5.7%

Most adjusted R^2 for the regression procedure remain very low and none are larger than 0.8. Yet, roughly 90% of the derived parameter estimates are significant at a significance level of 0.05. The correlation coefficient R^2

for the fitting of prediction and actual usually is extremely low (< 0.1) and only 1.9% are larger than 0.8.

The results are very similar for total sales. While slightly more cases (7.5%) report a U (1966) of less than 0.7, none report a U (1966) of less than 0.5. The proportion of inequality coefficients (1966) larger than or equal to 1.0 is also very high at 52.8%. The decomposition of the error term reveals a prevalence of systematic error in 83% of the cases. In a mere 1.9% non-systematic error accounts for more than 80% of total error.

Table 27: Summary Fisher-Pry Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	7.5%
	< 0.5	0.0%
	≥ 1.0	52.8%
Theil's U^c (1961)	> 0.5	17.0%
	> 0.8	1.9%

Most adjusted R^2 for the regression results are very low, with none being larger than 0.8. Nevertheless, there is again a large portion (80%) of significant parameter estimates. The majority of the correlation coefficients'

describing the fit between actual and predicted sales are smaller than 0.1 and none are larger than 0.8.

The sensitivity analysis for first purchase sales and for total sales shows no improvements in the results when more datapoints are used in the estimation procedure. Actually the results get worse in several cases.

Overall it is apparent that the logistic model is not suited for ex ante forecasting in this context - even if substantially more data points (covering up to nearly one year) are employed for parameter estimation. As far as one can distinguish "better" results, total sales provide slightly lower and thus better inequality coefficients.

4.2.2 THE BASS MODEL

The parameter estimation process for the Bass model is based on 9 datapoints. The model is used to analyze for first purchase occasions data, first purchase sales data, and for total sales data. It only yields somewhat better results than the logistic model for each of those categories. For first purchase occasion data, there are no instances where Theil's U (1966) is smaller than 0.5. 7.5% of the cases report U (1966) to be smaller than 0.7 and

22.6% report it to be larger than or equal to 1.0. Thus the Bass model usually, but not consistently, outperforms naive forecasting - though only by a narrow margin in several instances. Nevertheless, systematic error is still prevalent in the vast majority of cases (88.7%) and for none of the records does non-systematic error incorporate more than 80% of the total error.

The adjusted R^2 for the regression procedure are usually rather small, even though 11.3% exceed 0.8. In addition, a high R^2 does not appear to lead to a better predictive result. On the contrary, the few good results are usually obtained after a low adjusted R^2 in the regression. Unlike the results for the logistic model, only 20.8% of the parameter estimates are significant at 0.05. The resulting R^2 are generally extremely low, none exceeding 0.8.

Table 28: Summary Bass Model First Purchase Occasions
- Prediction -

Theil's U (1966)	< 0.7	7.5%
	< 0.5	0.0%
	≥ 1.0	22.6%
Theil's U^c (1961)	> 0.5	11.3%
	> 0.8	0.0%

This picture does not improve for first purchase sales. Theil's U (1966) remains below 0.7 for 11.3% and below 0.5 for 7.5% of the analyzed records. The percentage of records where predictive accuracy is worse than or equivalent to naive forecasting increases to 34%, implying that the model yields better results in just two thirds of the cases. Systematic error remains clearly dominant and there are only a few instances where non-systematic error accounts for more than 80% of total inequality.

Table 29: Summary Bass Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	11.3%
	< 0.5	7.5%
	≥ 1.0	34.0%
Theil's U ^c (1961)	> 0.5	15.1%
	> 0.8	3.8%

Similar to first purchase sales, most adjusted R^2 are relatively low, even though 13.2% exceed 0.8. Meanwhile the portion of significant parameter estimates decreases to 15.1%. The correlation coefficient R^2 again is below 0.1 in most cases and at no time exceeds 0.8.

The third type of data, total sales, is not predicted distinctly better by the Bass model either. While there are some cases (13.2%) with an inequality coefficient (1966) of less than 0.7, there are again no cases with a coefficient of less than 0.5. Furthermore, 28.3% report a U (1966) ≥ 1.0 . Systematic error is even more prevalent than for the two previous data sets. Inequality due to difference in covariation accounts for more than 80% of total inequality in only 3.8% of the cases.

Table 30: Summary Bass Model Total Sales

- Prediction -

Theil's U (1966)	< 0.7	13.2%
	< 0.5	0.0%
	≥ 1.0	28.3%
Theil's U^c (1961)	> 0.5	9.4%
	> 0.8	3.8%

The adjusted R^2 is usually rather low, with 9.4% exceeding the mark of 0.8. Parameter estimates for the model are significant in barely 16.0% of the regressions. Most R^2 are again extremely small at less than 0.1. None of these measures describing the relation between actual and predicted sales exceeds 0.8.

Sensitivity analysis does not provide better statistical results for first purchase occasions and first purchase sales when the estimation procedure is based on a longer time period. The predictive accuracy throughout the analysis remains very unsatisfactory. It does show some rather slight improvements for total sales. However, these improvements are not consistent, neither within the individual records nor across them.

In general, the Bass model does not provide a satisfactory instrument for predicting future sales in this context. Even though the model is slightly superior to the logistic model and to naive forecasting, it does not supply the practitioner with a useful tool. Total sales are somewhat better predicted than first purchase occasions and sales.

4.2.3 THE SHARIF-KABIR MODEL

The regression process employs 9 datapoints to estimate the parameters of the Sharif-Kabir model. The predictive accuracy of the model is similar to that of the Fisher-Pry model. For first purchase sales, 3.8% of Theil's U (1966) range below 0.7 and 1.9% range below 0.5. At the same time nearly 68% exceed or are equal to 1.0, demonstrating the

model's inferiority to naive no-change extrapolation. Moreover, systematic error is prevalent for all records.

The regression procedure usually yields relatively small adjusted R^2 , but 18.9% surpass 0.8. Only a negligible amount (1.9%) of the parameter estimates derived through the regression analysis are significant at a significance level of 0.05. Similarly most correlation coefficients R^2 , describing the fit between the actual and predicted values are below 0.1, while none exceed 0.8. Some yield between 0.7 and 0.8, but those generally result in a very high inequality coefficient.

Table 31: Summary Sharif-Kabir Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	3.8%
	< 0.5	1.9%
	≥ 1.0	67.9%
Theil's U^c (1961)	> 0.5	0.0%
	> 0.8	0.0%

For total sales the results become - unsubstantially - better. Theil's U (1966) ranges between 0.5 and 0.7 in 7.5% of the cases, but never goes below 0.5. Meanwhile, more than 60% of the inequality coefficients are equal to or exceed

1.0. There is again no instance where non-systematic error outweighs systematic error. This indicates a slight superiority of naive forecasting to this model in the given context.

Most reported adjusted R^2 are low, with 7.5% exceeding 0.8. Merely 1.9% of the parameter estimates are significant at 0.05. In conjunction with this trend, most R^2 range below 0.1 and none range above 0.8.

Table 32: Summary Sharif-Kabir Model Total Sales

- Prediction -

Theil's U (1966)	< 0.7	7.5%
	< 0.5	0.0%
	≥ 1.0	60.4%
Theil's U^c (1961)	> 0.5	0.0%
	> 0.8	0.0%

The sensitivity analysis reveals improvements in some instances for both types of data when the estimates are based on more initial datapoints. Yet, these improvements are not consistent within or across the various records for which the analysis was performed.

4.2.4 THE JEULAND MODEL

The estimation procedure for the Jeuland model requires 10 datapoints to meet the limit of five degrees of freedom. In several instances statistical measures could not be computed for this model. For first purchase sales nearly 25% of the procedures were terminated without reporting the statistical measures, either because the predictions trailed out of the computer's mathematical range or because of too many computational errors in the regression process. The former obviously implies extremely low forecasting accuracy. For total sales this percentage increases to 34%. The results for the remaining records are not very good either. It is necessary to note that the following percentages reflect the proportions on the basis of all records and not on the basis of the remaining records. For first purchase sales Theil's U (1966) ranges below 0.7 for 5.7% and below 0.5 for 1.9% of the records. It exceeds or is equal to 1.0 in the majority of cases. Systematic error again dominates non-systematic error clearly and only in 1.9% of the cases does the latter account for more than 80% of the total error.

Table 33: Summary Jeuland Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	5.7%
	< 0.5	1.9%
	≥ 1.0	52.8%
Theil's U ^c (1961)	> 0.5	13.2%
	> 0.8	1.9%

The adjusted R^2 exceeds 0.8 in 11.3% of the cases, but usually remains rather low. It is an interesting point that less than 1% of the parameter estimates are significant at a significance level of 0.05. Moreover, the predictions derived by the model result in usually very low correlation coefficients R^2 .

The statistical results improve somewhat for total sales, but still can not be considered acceptable. Theil's inequality coefficient (1966) is reported below 0.7 for nearly 10% and below 0.5 for 3.8% of the analyzed cases. The most visible change is the decrease to 30.2% in cases with U (1966) ≥ 1.0 . However, it has to be kept in mind that there are substantially more cases for total sales data where no results could be computed, so that the number of poor forecasts might be higher than indicated. Systematic error again dominates in roughly 85% of the cases and the portion

of non-systematic error surpasses 80% in a mere 1.9% of the cases.

Table 34: Summary Jeuland Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	9.4%
	< 0.5	3.8%
	≥ 1.0	30.2%
Theil's U ^c (1961)	> 0.5	15.1%
	> 0.8	1.9%

Just 7.5% of the adjusted R^2 exceed 0.8, while most others remain rather low. These results are further emphasized by the fact that only 1.3% of the parameter estimates are significant at 0.05. None of the R^2 are larger than 0.8, most being extremely small (< 0.1).

The Jeuland model again poses substantial problems in its application. In addition to its computational difficulties, it does not provide good predictions of sales in the given situation. The model often is inferior to naive forecasting and is thus not considered to be a useful tool for ex ante forecasting. Total sales are slightly better predicted than first purchase sales.

4.2.5 THE NUI MODEL

The NUI model incorporates the parameters p , q , and δ , so that 10 datapoints are employed for parameter estimation. The predictive accuracy achieved by the model is nevertheless very disappointing. More than 75% of the first purchase sales records can be predicted better through naive forecasting. Hardly any cases (1.9%) achieve good results with $U(1966) < 0.5$ and unsubstantially more (5.7%) remain below 0.7. Similar to the previous models, systematic error is extremely dominant. Non-systematic error outweighs systematic error in barely 15% and accounts for more than 80% of total error in just 5.7%.

Table 35: Summary NUI Model First Purchase Sales
- Prediction -

Theil's $U(1966)$	< 0.7	5.7%
	< 0.5	1.9%
	≥ 1.0	77.4%
Theil's $U^c(1961)$	> 0.5	15.1%
	> 0.8	5.7%

Accordingly, most adjusted R^2 for the regression procedure are relatively low, with only 7.5% surpassing 0.8. The parameter estimates resulting from the regression are

insignificant in nearly 95% of the cases. The low resulting fit between predicted sales and actual sales is demonstrated by extremely low correlation coefficients R^2 in nearly all cases.

The overall picture hardly improves for total sales. The amount of records with an inequality coefficient (1966) below 0.7 and 0.5 remains the same at 5.7% and 1.9%, respectively. The percentage of cases with U (1966) ≥ 1.0 decreases to a still overwhelming 62.3%. At the same time the dominance of systematic error increases slightly and there are no cases where non-systematic error incorporates more than 80% of the total error.

Table 36: Summary NUI Model Total Sales

- Prediction -

Theil's U (1966)	< 0.7	5.7%
	< 0.5	1.9%
	≥ 1.0	62.3%
Theil's U^c (1961)	> 0.5	13.2%
	> 0.8	0.0%

Most adjusted R^2 remain very low, just 5.7% being larger than 0.8. The obtained parameter estimates are insignificant at a significance level of 0.05 in more than

90% of the cases. Again the reported correlation coefficients R^2 are extremely low, none being larger than 0.8.

There are some improvements in the predictive accuracy of the NUI model when more datapoints are employed for the estimation of the model's parameters. This applies for both first purchase sales and total sales. However, these improvements do not occur in all cases and usually are not substantial enough to present reasonably good predictions.

In summary it can be stated that the NUI model - like in the descriptive analysis - provides the least satisfactory results so far. It is often outperformed by naive extrapolation and incorporates substantial portions of systematic error. There is hardly any difference between its statistical performance for first purchase and total sales.

4.2.6 THE VON BERTALANFFY MODEL

For the estimation of this model's parameters, the data from the initial 9 two week periods are employed. Von Bertalanffy's model achieves the best prediction results of all the models analyzed up to this point, though they are not very good either. For first purchase sales Theil's U

(1966) is reported below 0.7 in 13.2% and below 0.5 in 5.7% of the cases. The major improvement in comparison to most previously mentioned models is the low rate (17%) of inequality coefficients (1966) that exceed or are equal to 1.0. However, most of the figures ranging between 0.7 and 1.0 end up being only slightly less than 1.0, so that the model's advantage over naive forecasting is actually smaller than indicated by this percentage figure. Systematic error is dominating non-systematic error in 86.8% of the cases. The latter accounts for more than 80% of the total error in just 5.7% of the cases.

Table 37: Summary von Bertalanffy Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	13.2%
	< 0.5	5.7%
	≥ 1.0	17.0%
Theil's U ^c (1961)	> 0.5	13.2%
	> 0.8	5.7%

The regression procedure yields 15.1% adjusted R^2 exceeding 0.8, but most others are relatively low. This is accompanied by just 12.3% significant parameter estimates. Among the R^2 there are no instances where it exceeds 0.8, most being extremely small.

The results improve somewhat for total sales, but still do not denote not acceptable predictions. 20.8% of the records - the largest percentage in the predictive analysis so far - report Theil's U (1966) to be smaller than 0.7. The portion reporting a U (1966) below 0.5 also increases a notch to 7.5%. However, the number of cases reporting worse than or equivalent results to naive forecasting increases to 22.6%. Similarly, systematic error is even more prevalent and outweighs non-systematic error in more than 90%. There are no records where the latter accounts for more than 80% of the total error.

Table 38: Summary von Bertalanffy Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	13.2%
	< 0.5	7.5%
	≥ 1.0	22.6%
Theil's U ^c (1961)	> 0.5	7.5%
	> 0.8	0.0%

The regression yields adjusted R^2 that are generally rather low, but 11.3% exceed 0.8. Roughly one tenth of all resulting parameter estimates are significant at 0.05. The poor fit between predicted and actual values is further illustrated by extremely low R^2 s, none exceeding 0.8.

The ensuing sensitivity analysis reveals no consistent improvements in the reported results for the selected records of first purchase sales when more datapoints are employed during the estimation procedure. While there occur a few statistical improvements for predicting total sales, they do not indicate substantial and continuing effects.

The von Bertalanffy model provides better results than the previous models, even though the results are still far from being adequate. In contrast to several of the other models, it does - in the vast majority of cases - outperform naive forecasting. This indicates that this model might be useful to some extent in providing some decision support. Nevertheless, it still incorporates an overwhelming portion of systematic error. In addition, this model again predicts total sales somewhat more successfully than first purchase sales.

4.2.7 THE GENERALIZED MODEL

The generalized model contains two parameters besides the upper limit $NBAR$ and thus requires 9 datapoints for the estimation procedure. The model by Skiadas obtains inequality coefficients for first purchase sales that are somewhat poorer than the ones for von Bertalanffy's model.

Theil's U (1966) ranges between 0 and 0.7 in 7.5% of the analyses. The majority of these cases (5.7% overall) actually range between 0 and 0.5. For approximately one third of the records the reported U (1966) exceeds or is equal to 1.0. Thus a considerable number of records, though not the majority, are predicted better by naive extrapolation. The systematic error is dominating non-systematic error in 86.8% of the cases and non-systematic error never accounts for more than 80% of the total error.

Table 39: Summary Generalized Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	7.5%
	< 0.5	5.7%
	≥ 1.0	37.7%
Theil's U ^c (1961)	> 0.5	13.2%
	> 0.8	0.0%

The regression procedure leads to usually rather low adjusted R^2 , even though 11.3% surpass 0.8. Roughly one fifth of the emerging parameter estimates are significant at a level of 0.05. Similarly, most correlation coefficients R^2 remain extremely low.

Total sales are predicted distinctly better. Yet, the improvements are again by no means sufficient. Theil's U (1966) ranges below 0.7 in 20.8% and below 0.5 in 3.8%. At the same time the portion of cases with an inequality coefficient larger than or equal to 1.0 decreases to 20.8%. Nevertheless, non-systematic error still is not able to outweigh systematic error in more than 13.2% of the analyzed cases. In 1.9% it accounts for more than 80% of the total error.

Table 40: Summary Generalized Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	20.8%
	< 0.5	3.8%
	≥ 1.0	20.8%
Theil's U ^c (1961)	> 0.5	13.2%
	> 0.8	1.9%

Most of the reported adjusted R^2 are rather low and just 5.7% exceed 0.8. The portion of significant estimates does, however, increase to more than one third. Despite some improvements, most correlation coefficients remain very low, even though 1.9% exceed 0.8.

The sensitivity analysis presents mixed results for first purchase sales and total sales data. Some of the records show improvements, but for most of them the statistical results do not change substantially and sometimes even get worse.

Overall, the generalized model proves to be ineffective for predicting sales in the given context, even though its results are usually superior to those of several of the earlier models as well as to those of naive extrapolation. It incorporates - not unlike the other models - a very large portion of systematic error in its forecast, which again illustrates the poor prediction results. The model yields better results for the prediction of total sales than for first purchase sales.

4.2.8 THE KKK I MODEL

This model's parameters are estimated using the 10 initial datapoints. It yields rather poor predictions, especially for first purchase sales. Here 66.0% of the predictions compare unfavourably to naive extrapolation predictions. Just 5.7% of the predictions lead to a U (1966) below 0.7 and none allow for a U (1966) below 0.5. At the same time systematic error is prevalent for more than 90% of

the records. At no point is the proportion of non-systematic error encompassing more than 80% of total error.

Table 41: Summary KKK I Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	5.7%
	< 0.5	0.0%
	≥ 1.0	66.0%
Theil's U ^c (1961)	> 0.5	7.5%
	> 0.8	0.0%

Even though 13.2% of the adjusted R^2 exceed 0.8, they are generally very low. This scenario is accompanied by just a few (8.8%) significant parameter estimates. Accordingly, most of the R^2 describing the fit between actual and predicted remain very low, with not one exceeding 0.8.

These figures change slightly for total sales. Theil's inequality coefficient (1966) indicates reasonably good results (< 0.7) for 15.1%, while 3.8% of the cases yield good results (< 0.5). The number of cases with U (1966) being equal to or larger than 1.0 decrease a little, but still make up more than 50%. The dominance of systematic error also decreases slightly. Non-systematic error

outweighs systematic error in 13.2% and accounts for more than 80% of total error in 3.8% of the analyzed cases.

Table 42: Summary KKK I Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	15.1%
	< 0.5	3.8%
	≥ 1.0	50.9%
Theil's U ^c (1961)	> 0.5	13.2%
	> 0.8	3.8%

The regression procedure yields adjusted R²s that are normally rather low. Just 5.7% of the parameter estimates are significant at a significance level of 0.05. The poor fit between the predictions and actual sales is again illustrated by very low R²s.

The sensitivity analysis for both first purchase sales and total sales reveals that there are improvements in some cases when more datapoints are employed during the estimation process. However, these improvements are not consistent across or within the individual records.

The KKK I model yields generally very poor results for both types of data, even though total sales again are

predicted somewhat better than first purchase sales. The model is apparently not suited for predicting sales in this situation.

4.2.9 THE KKK II MODEL

The parameters for the second model by Kumar and Kumar are estimated based on 9 initial data points. While this model yields somewhat better predictions than the authors' first model, its accuracy is still poor for the vast majority of records. Theil's U (1966) remains below 0.7 in less than 10% of the analyses and below 0.5 in just 7.5% of the analyses. Meanwhile, nearly one third of the predictions result in a U (1966) ≥ 1.0 . The systematic error in those predictions is prevalent in roughly 90% and inequality due to difference in covariation only accounts for more than 80% of total inequality in 1.9%.

Table 43: Summary KKK II Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	9.4%
	< 0.5	7.5%
	≥ 1.0	30.2%
Theil's U ^c (1961)	> 0.5	11.3%
	> 0.8	1.9%

The parameter estimation procedure yields an adjusted R^2 that normally stays relatively low, except for 11.3% where it exceeds 0.8. 22.6% of the derived parameter estimates are significant at 0.05. Similarly most correlation coefficients R^2 remain very low. One record reports this measure to be larger than 0.8, but the respective inequality coefficient (1966) is very high.

The figures don't present a much different, though slightly worse, picture for total sales. 7.5% of Theil's U (1966) range below 0.7 and a mere 1.9% below 0.5. The percentage of cases with U (1966) being equal to or exceeding 1.0 decreases slightly to 28.3%. At the same time, nearly all records (98.1%) report a dominant systematic error. As would be expected in such a situation, there is no instance where non-systematic error accounts for more than 80% of total error.

Table 44: Summary KKK II Model Total Sales

- Prediction -

Theil's U (1966)	< 0.7	7.5%
	< 0.5	1.9%
	≥ 1.0	28.3%
Theil's U ^c (1961)	> 0.5	1.9%
	> 0.8	0.0%

The regression yields an adjusted R^2 that is larger than 0.8 for roughly 10% of the analyses, but the majority of adjusted R^2 s are relatively low. The amount of significant parameter estimates decreases to 17.0%. Parallel to these developments, most correlation coefficients R^2 stay very low, none exceeding 0.8.

Employing more data points during the parameter estimation process yields some but not consistent improvements for first purchase sales. For total sales, however, the improvements are relatively consistent. Nevertheless, Theil's inequality coefficient (1966) does not go below 0.5 even if nearly one year's data are employed.

Overall the KKK II model continues the trend of poor predictions established by the other models. It does outperform naive forecasting in the majority of cases, but

incorporates a dominant systematic error in its forecasts. The KKK II model marks the first time in this analysis that first purchase sales are predicted - or described - better than total sales.

4.2.10 THE BROCKHOFF MODEL

This model incorporates the parameters a , q , and c . Since the model does not require an estimate for the upper limit of the diffusion process, 9 datapoints are sufficient to fulfil the set requirements for the estimation process. While the model yields rather good descriptive results, its performance in the prediction of first purchase occasions, first purchase sales, and total sales is very poor. Merely 5.7% of the first purchase occasions are predicted such that U (1966) remains below 0.7. This figure decreases to 1.9% when the cutoff point is set to 0.5. At the same time, 45.3% of the records yield an inequality coefficient (1966) larger than or equal to 1.0. Nearly half of those cases record U (1966) equal to 1.0, implying a forecast that is as "accurate" as naive extrapolation would be. Likewise, systematic error is prevalent for 92.5% of the records. The ratio between non-systematic and systematic error exceeds 80:20 in just 1.9%.

Table 45: Summary Brockhoff Model First Purchase Occasions
- Prediction -

Theil's U (1966)	< 0.7	5.7%
	< 0.5	1.9%
	≥ 1.0	45.3%
Theil's U ^c (1961)	> 0.5	7.5%
	> 0.8	1.9%

Nevertheless, a considerable portion (22.6%) of adjusted R^2 exceed 0.8, even though most remain relatively small. Furthermore, 36.5% of the parameter estimates are significant at a significance level of 0.05. Despite these sometimes good regression results, most correlation coefficients R^2 describing the fit between predicted and actual sales stay very low, none exceeding 0.8.

The overall results deteriorate further for first purchase sales. Just 3.8% of Theil's inequality coefficients (1966) record a value below 0.7. Actually all of these are below 0.5. The percentage of cases not predicting better than naive extrapolation increases to 50.9%, half of which designate cases with U (1966) equal to 1.0. Meanwhile, the dominance of systematic error increases further to 98.1%. The remaining 1.9% denote a case where non-systematic error accounts for more than 80% of the total error.

Table 46: Summary Brockhoff Model First Purchase Sales
- Prediction -

Theil's U (1966)	< 0.7	3.8%
	< 0.5	3.8%
	≥ 1.0	50.9%
Theil's U ^c (1961)	> 0.5	1.9%
	> 0.8	1.9%

The portion of regression procedures leading to an adjusted R^2 larger than 0.8 increases to 28.3%, but the majority remains relatively low. The number of significant parameter estimates stays the same at 36.5%. While there is one case with a R^2 exceeding 0.8, most others again are very low.

There are some minor improvements for total sales. Theil's U (1966) is less than 0.7 in 11.3% and less than 0.5 in 7.5% of the analyzed cases. Yet, there remain 50.9% where the model does not outperform naive forecasting. Even though the prevalence of systematic error decreases slightly, it still outweighs non-systematic error in an overwhelming 90.6%. For just 3.8% of the records, non-systematic error accounts for more than 80% of total error.

Table 47: Summary Brockhoff Model Total Sales
- Prediction -

Theil's U (1966)	< 0.7	11.3%
	< 0.5	7.5%
	≥ 1.0	50.9%
Theil's U ^c (1961)	> 0.5	9.4%
	> 0.8	3.8%

The percentage of adjusted R^2 exceeding 0.8 decreases to 11.3% and most of the remaining coefficients are relatively low. Roughly 30% of the parameter estimates are significant at 0.05. The fit is described by generally very low correlation coefficients R^2 . Just one case - which also yields a good U (1966) - exceeds 0.8.

The sensitivity analysis reveals some but no consistent improvements for first purchase occasions and first purchase sales. For total sales these improvements become even considerable, though they also are not consistent across or within the individual cases.

The Brockhoff model does not repeat its good results obtained in the descriptive analysis during the predictive analysis. It provides forecasts that are in roughly half of the cases not superior to naive forecasting and incorporates

a very large portion of systematic error in its predictions. Total sales are, like for nearly all other models, predicted slightly better than first purchase sales.

4.2.11 SUMMARY

The predictive accuracy of all analyzed models is extremely poor. Even though there are some differences in the performance, none of the models yields satisfactory results. The logistic model, the Sharif-Kabir model, the Jeuland model, the NUI model, the KKK I model, and the Brockhoff model all report results that are no better than those achieved by naive forecasting in at least half of the cases. The remaining models - the Bass model, the Generalized model, the KKK II model and especially the von Bertalanffy model - yield results that are in the majority of cases superior to naive forecasting. In conjunction with Makridakis' (1991) argument, the practitioner might be best off by taking the average of these four models as the most likely forecast. However, the statistical results of these models usually compare only slightly favourably to naive forecasting. Moreover, all models incorporate large amounts of systematic error, indicating a built-in bias in the forecasting method. When tested, Makridakis' argument was only partially supported by the findings of this study, as

can be seen in table 45. This table reports the statistical value of U (1966) for a subset of 10 new products. It incorporates the forecasts created by the four mentioned models as well as the arithmetic average of those four forecasts. The results for the first four products support Makridakis' hypothesis. The results for the last six products do not. For these cases, there is always at least one individual model that yields a better forecast than the average forecast.

Table 48: Example for the Accuracy of the "Average" Forecast

All entries are Theil (1966) U statistics for predictions between 8 and 10 periods forward.

No.	KKK II	GENERALIZED	BERTALANFFY	BASS	AVERAGE
1	0.738	0.819	0.738	3.286	0.574
2	0.657	0.768	0.546	0.672	0.536
3	0.749	0.751	0.749	0.933	0.717
4	0.847	0.570	0.849	0.528	0.675
5	0.998	0.930	0.998	0.930	0.963
6	0.981	0.954	0.981	0.954	0.965
7	0.911	0.889	0.910	0.889	0.899
8	0.930	0.885	0.732	0.885	0.851
9	0.924	0.830	0.923	0.830	0.874
10	0.952	0.894	0.951	0.874	0.908

Figure 3: Prediction of Individual Records ($U < 0.7$)

Figures 3 and 4 illustrate the results obtained by the individual records. It can be seen that 82.7% of first purchase sales are not predicted well enough by any model to achieve a $U(1966)$ below 0.7. Another 11.1% are described reasonably well by just one or two models. A mere two time series are predicted reasonably well by 6 or more models. These figures change for records with $U(1966) < 0.5$. 92.6% of the time series do not achieve this requirement with any model and another 3.7% achieve it only with one or two

Figure 4: Prediction of individual records ($U < 0.5$)

models. Just two records obtain good predictions from 5 or 6 models.

Those numbers improve a little for total sales, but still present a dismal picture. 67.9% of the time series are not predicted even reasonably well by any model. Nearly 20% achieve that goal with one or two models. Finally, there is one record that is predicted reasonably well by all but one model. The results deteriorate further when examining the number of cases with $U (1966) < 0.5$. More than 90% are not

predicted well by any of the analyzed models. 8.6% obtain such a low U (1966) just with one or two of the tested models. One time series however, is predicted well by 7 of the 10 models.

The presented picture contrasts sharply with the results obtained in the descriptive analysis, where the portion of cases with a good or reasonably good fit is considerably larger. The overall picture also does not seem to change when more datapoints are employed during the estimation procedure. Even if up to 50 weeks of sales are used to predict the following 10 - 20 weeks, the results do not consistently improve. Only for some isolated cases are improvements in the predictive accuracy reported. Whenever such improvements occur, they are not consistent within or across the records as can be seen in the appendix. Even though the sensitivity analysis does not present results for all records, it does give some credence to the conclusion that the models can usually not be used successfully for predictive purposes.

The results also show that a high adjusted R^2 for the regression procedure does not imply high forecasting accuracy. On the contrary, good results for the estimation process often appear to lead to especially poor forecasts. The same is true for those instances where significant

parameter estimates are achieved. There seems to be no relation between a good fit for the estimation period and the resulting fit of the predictions to the actual values. This is contrary to the results achieved during the descriptive analysis, where a high adjusted R^2 combined with significant parameter estimates usually resulted in high descriptive accuracy. Moreover, good predictions are mostly achieved after poor regression results. This introduces the question whether those few good results are obtained purely by chance. Similarly it shows that the researcher or practitioner can not confidently "predict" based on the estimation period whether good predictions will be achieved.

5. CONCLUSION

5.1 IMPLICATIONS OF THIS STUDY

This study has demonstrated that many of the existing diffusion models have considerable value in describing (ex post) sales data for a non-durable consumer product. This finding differs in two ways compared to most prior research in this field. First of all, non-durable consumer products have previously been widely neglected when testing diffusion models, even though this is probably the area with the most new ideas (products). Most research either concentrated on durable consumer products or on technological innovation. Secondly, this research concentrates on sales data, which is substantially different from traditional diffusion research. In the given context more than one purchase by each panel member is possible and consequently included in the data. Commonly diffusion models have been used and developed to describe/predict initial purchase occasions, thus limiting each panel member to just one recorded purchase. Despite these differences it appears that some of the models can be applied in this environment as well - for descriptive purposes.

The statistical results for the various models furthermore indicate that simpler models outperform models with more parameters. The Jeuland model, the NUI model, and the KKK I model all required the estimation of four parameters. One assumption of proponents of more complex models is that with more parameters a model can fit the diffusion curve better, since it is more flexible. This research does not support that assumption. The mentioned three models - especially the NUI model and Jeuland model - are consistently outperformed by the less complex models in both the descriptive and predictive analysis. This supports Schnaars' (1989) argument that complex models do not yield better results than simple models.

The major implication of this research relates however, to the second part of the analysis. It becomes apparent that, while the models often can describe the sales data after the fact, they are not - except in a few isolated cases - capable of predicting the sales with adequate accuracy. The combination of these two findings indicates that the actual value of diffusion models is limited and not exactly what their developers hoped it to be. Instead of being able to serve managers as a decision support tool for handling innovations (new products), they can serve primarily as a mathematical instrument explaining the past. While some conclusions might be drawn from the past to

direct future actions, the direct decision support value of the models seems to be reduced significantly.

Furthermore, even this explanatory value is questioned by authors like Simon (1992), who argues that the coefficients in the models may have no construct validity and may have been introduced solely to achieve a fit to a certain diffusion pattern. He concludes that "the models may be useful for pedagogical purposes in helping students to understand how a diffusion process may develop", but no more (Simon, 1992, p.11). This argument is supported by the fact that many of the derived parameter estimates in this research do not make much sense when interpreted according to the models' original specifications and behavioral rationale.

Consequently, the given findings support Schnaars', Simon's, and even Makridakis' (1991) sceptical evaluation on the ability of diffusion models to predict the future. As Makridakis - commonly a fervent supporter of diffusion research - put it in one of his most recent publications on this subject: "the real world behaves in a way that does not fit the idealized assumptions of statistical theory" (Makridakis 1991, p.123).

The resulting implications for the practitioner are disillusioning, as this research has presented further evidence that the future can not be predicted safely or even remotely well by looking at the past. While the analyzed models might yield reasonable projections if the internal and external factors remain constant, they simply can not anticipate changes in the environment that substantially alter the diffusion curve. Thus the practitioner should use considerable caution when interpreting forecasts derived by a diffusion model. Decision makers should not expect the forecasts to be accurate every time - in light of this research not even more than a few times. They should also realize that their actions taken after evaluating such a forecast will ultimately affect the outcome and might be another reason for substantial differences between forecasts and actual results.

5.2 LIMITATIONS

There are a number of limitations to the outlined research that should be addressed. These limitations apply especially to the generalizability of the findings. First of all, the analysis employed sales data, which is uncommon compared to other diffusion research. Thus it is difficult

to extend these findings for general applicability in diffusion research.

In addition, the findings are confined to the area of cracker products for sales outside of large North American urban areas, even though some implications outside of this field have been hinted. Yet, there is no indication at this point how valid the cracker results are for other non-durable consumer products (not to mention durables). As pointed out initially, there is a general need to test more data (product categories) against the existing models before reasonable generalizations can be made. Furthermore, the above discussion of diffusion models does not provide a complete list, so that the analysis is merely an attempt to evaluate a subset of existing models.

Further limitations are related to the available (scanner) data. Some disadvantages have already been pointed out. In particular there might be some lost data due to electronic failures, due to customers forgetting their I.D. cards, or due to store irregularities. Another small problem is presented by some minor inconsistencies in the available data with respect to the recorded product introduction dates. The six products that showed these inconsistencies were not included in the analysis. As a result some new product data might have been neglected.

In addition, it was examined whether the existence of other product sizes influenced the statistical results. Nine products in the dataset were identified where another size of the same product existed in the market. Apparently there is no negative influence, since most of the resulting time series are described well or even very well. However, there is not enough evidence to evaluate a possible positive influence. Further problems related to the data stem from the fact that some products were introduced in the three markets at different points in time. Since the reported data is aggregated over the three markets, the resulting diffusion curve would be unusual. The products where this occurred were identified and examined. It appears that in most cases the introduction was simultaneous or occurred only in one market at all. The few records where this caused visible problems - identified through the descriptive analysis - do not change the overall picture presented in this research.

Finally, there might be some error introduced due to the manual entering of the data into the statistical program. This procedure was necessary since the data was only available in hardcopy form. To minimize this error, regular crosschecks were performed after the data was entered.

5.3 FUTURE RESEARCH

Areas of future research have already been outlined during this thesis. It would be beneficial if additional research could be performed using data from different product categories - durable and non-durable. That should indicate whether the results found here can be generalized outside of the given limitations and whether the models achieve higher predictive accuracy for other products. If the models perform better in other research areas, it would also be beneficial to derive parameter suggestions for specific product market situations, thus reducing the amount of parameters a practitioner has to estimate.

With access to richer databases like the ones by IRI and Nielsen, it should also be possible to evaluate the impact of marketing variables describing price, promotion, advertising, etc. Consequently, models incorporating such parameters could be tested to find out whether they yield more predictive accuracy or whether they face the same problems as the more complex models in the given analysis.

Finally, future research could evaluate the predictive accuracy of dynamic forecasts - forecasts that incorporate the newest sales data and update the forecasts accordingly. It is anticipated that the predictive accuracy would improve

in that case. However, the practical purpose of such forecasts is considerably different to the forecasts evaluated in this research.

BIBLIOGRAPHY

- Armstrong, John C., Long Range Forecasting: From Crystal Ball to Computer, 2nd ed., New York: Wiley Interscience, 1985.
- Bailey, N.T.J., The Mathematics of Epidemics, New York: Hafner, 1957.
- Bass, Frank M., A New Product Growth Model for Consumer Durables", Management Science, 15, January 1969, p.215-227.
- _____, The Adoption of a Marketing Model: Comments and Observations", in Innovation Diffusion Models, Vijay Mahajan and Yoram Wind, eds., Cambridge: Ballinger Publishing Company, 1986.
- Bernhardt, Irwin and Kenneth D. MacKenzie, "Some Problems in Using Diffusion Models for New Products", Management Science, 19, October 1972, p.187-200.
- Blackman, A.W., "The Rate of Innovation in the Commercial Aircraft Jet Engine Market", Technological Forecasting and Social Change, 3, 1971, p.441-452.
- _____, "A Mathematical Model for Trend Forecasts", Technological Forecasting and Social Change, 3, 1972, p.441-452.
- _____, "The Market Dynamics of Technological Substitutions", Technological Forecasting and Social Change, 6, p.41-63.
- Booz-Allen and Hamilton, New Product Management for the 1980's, Chicago: Booz-Allen and Hamilton, Inc., 1982.
- Brockhoff, Klaus, "A Test for the Product Life Cycle", Econometrica, 35, July-October 1967, p.472-484.
- Clarke, D., Marketing Analysis and Decision Making: Text and Cases with Spreadsheets, 2nd edition, San Francisco: The Scientific Press, 1993.
- Conner, John T., "Progress Reshapes Competition", Printers Ink, (287), 1964, p.36.
- Crawford, C. Merle, "Marketing Research and the New Product Failure Rate", Journal of Marketing, 41, April 1977, p.51-61.

- Goldberg, L.R., "Man Versus Model of Man: A Rational Plus Some Evidence for a Method of Improving on Clinical Inferences", Psychological Bulletin, 73, (6) 1970, p.422-432.
- Gompertz, B., "On the Science Connected with Human Mortality", Phil. Trans. Roy. Soc., 115, 1828, p.513.
- Gruebler, Arnulf, "Long-Term Patterns and Discontinuities", Technological Forecasting and Social Change, 39, 1991, p.159-180.
- Haines Jr., George H., "A Theory of Marketing Behavior After Innovation", Management Sciences, 10, July 1964, p.634-658.
- Haines, Jr., George H., Leonard S. Simon, and Marcus Alexis, "Consumption Behavior of Prisoners: The Case of the Inner City Shopper", in Improving Inner City Marketing, Alan R. Andreasen, ed., Chicago: American Marketing Association, 1972, p.25-59.
- Heeler, Roger M. and Thomas P. Hustad, "Problems in Predicting New Product Growth for Consumer Durables", Management Science, 26, October 1980, p.1007-1020.
- Hogarth, R.M. and Spyros Makridakis, "Forecasting and Planning: An Evaluation", Management Science, 27, (2) 1981, p.115-138.
- Horsky, Dan and Leonard S. Simon, "Advertising and the Diffusion of New Products" Marketing Science, 2, Winter 1983, p.1-18.
- Jeuland, Abel P., "Parsimonious Models of Diffusion of Innovation: Part A, Derivations and Comparisons", Working Paper, Graduate School of Business, University of Chicago, 1981.
- Kalish, Shlomo and Gary L. Lilien, "Applications of Innovation Diffusion Models in Marketing", in Innovation Diffusion Models, Vijay Mahajan and Yoram Wind, eds., Cambridge: Ballinger Publishing Company, 1986.
- _____ and Subrata K. Sen, "Diffusion Models and the Marketing Mix for Single Products" in Innovation Diffusion Models, Vijay Mahajan and Yoram Wind, eds., Cambridge: Ballinger Publishing Company, 1986.
- Kotler, Philip, Marketing Decision Making: A Model Building Approach, New York: Holt, Rinehart and Winston, 1971.

Krugmann, Herbert E., "The Impact of Television Advertising: Learning Without Involvement", Public Opinion Quarterly, 29, 1965, p.349-356.

Kumar, Uma and Vinod Kumar, "Technological Innovation Diffusion: The Proliferation of Substitution Models and Easing the User's Dilemma", IEEE Transactions on Engineering Management, 39, May 1992a, p.158-168.

Kumar, Vinod and Uma Kumar, "Innovation Diffusion: Some New Technological Substitution Models", Journal of Mathematical Sociology, 17, (2-3) 1992b, p.174-194.

_____ and _____, "Technological Substitution Models of Innovation Diffusion: Analysis of The Parameter Ranges", Working Paper, Carleton University, School of Business, 1993.

Lawrence, Kenneth D. and William H. Lawton, "Applications of Diffusion Models: Some Empirical Results, in New Product Forecasting: Models and Applications, Yoram Wind, Vijay Mahajan, and Richard Cardozo, eds., Lexington: Lexington Books, 1981.

Lionberger, Herbert F., Adoption of New Ideas, Ames: The Iowa State University Press, 1960.

Mahajan, Vijay, Charlotte H. Mason, and V. Srinivasan, "An Evaluation of Estimation Procedures for New Product Diffusion Models", in Innovation Diffusion Models, Vijay Mahajan and Yoram Wind, eds., Cambridge: Ballinger Publishing Company, 1986.

_____ and Eitan Muller, "Innovation Diffusion and New Product Growth Models in Marketing", Journal of Marketing, 43, Fall 1979, p.55-68.

_____, _____, and Frank M. Bass, "New Product Diffusion Models in Marketing: A Review and Directions for Research", Journal of Marketing, 54, January 1990, p.1-26.

_____ and Robert A. Peterson, Models for Innovation Diffusion, Beverly Hills: Sage Publications Inc., 1985.

_____ and Yoram Wind, "Innovation Diffusion Models of New Product Acceptance", in Innovation Diffusion Models, Vijay Mahajan and Yoram Wind, eds., Cambridge: Ballinger Publishing Company, 1986.

- _____ and _____, "New Product Forecasting Models: Directions for Research and Implementation", International Journal of Forecasting, 4, (3) 1988, p.341-358.
- Makridakis, Spyros, "The Art and Science of Forecasting", International Journal of Forecasting, 2, 1986, p.15-39.
- _____, "Metaforecasting", International Journal of Forecasting, 4, (3) 1988, p.467-491.
- _____, "Forecasting in the 21st Century", International Journal of Forecasting, 7, (2) 1991, p.123-126.
- _____, Steven C. Wheelwright, and Victor E. McGee, Forecasting Methods and Applications, New York: John Wiley & Sons, Inc., 1983.
- Mansfield, Edwin, "Technical Change and the Rate of Imitation", Econometrica, 29, October 1961, p.741-766.
- Martino, J.P., "The Effects of Error in Estimating the Upper Limit of a Growth Curve", Technological Forecasting and Social Change, 4, p.77-84.
- Mayer, Thomas, "Selecting Economic Hypotheses By Goodness of Fit", The Economic Journal, 85, December 1975, p.877-883.
- Mc Cloughlin, Ivor, "The Scanner Revolution: Collection of Purchasing Data from Consumer Panel Households", PMRS Journal, 2, 1983, p.24-27.
- Midgley, David E., "A Simple Mathematical Theory of Innovative Behavior", Journal of Consumer Research, 3, June 1976, p.31-41.
- Nakanishi, Masao, "A Model of Market Reactions to New Products", unpublished doctoral dissertation, Graduate School of Business Administration, University of California, Los Angeles, 1968.
- Nicosia, Francesco M., Consumer Decision Processes, Englewood Cliffs: Prentice Hall, Inc., 1966.
- Olshavsky, Richard W., "Time and the Rate of Adoption of Innovations", Journal of Consumer Research, 6, March 1980, p.425-428.

- Pearl, Raymond and Lowell J. Reed, "On the Mathematical Theory of Population Growth", Metron, 3, (1),, 1923, p.6-19.
- Ray, Michael L., "Marketing Communication and the Hierarchy of Effects" in New Models for Mass Communication Research, Vol.2, P. Clarke, ed., Beverly Hills: Sage Publications Inc., 1973.
- Richards, F.J., "A Flexible Growth Function for Empirical Use", Journal of Experimental Botany, 10, p.290-300.
- Robertson, Thomas S., Innovative Behavior and Communication, New York: Holt, Rinehart and Winston, 1971.
- _____, "Low Commitment Consumer Behavior", Journal of Advertising Research, 16, April 1976, p.19-24.
- Robinson, Bruce and U. Lakhani, "Dynamic Price Models for New Product Planning", Management Science, 10, June 1975, p.1113-1122.
- Rogers, Everett M., "New Product Adoption and Diffusion", Journal of Consumer Research, 2, March 1976, p.290-301.
- _____, Diffusion of Innovations, New York: The Free Press, 1983.
- _____ and Floyd Shoemaker, The Communication of Innovations: A Cross-Cultural Approach, New York: The Free Press, 1971.
- Ryan, Bryce and Neal C. Gross, "The Diffusion of Hybrid Seed Corn in Two Iowa Communities", Rural Sociology, 8, March 1943, p.15-24.
- Schmittlein, David C. and Vijay Mahajan, "Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance", Marketing Science, 1, Winter 1982, p.57-78.
- Schnaars, Steven P., Book Review on "Innovation Diffusion Models of New Product Acceptance", Vijay Mahajan and Yoram Wind, International Journal of Forecasting, 3, (3-4) 1987, p.531-532.
- _____, Megamistakes: Forecasting and the Myth of Rapid Technological Change, New York: The Free Press, 1989.

Sharif, M. Nawaz and Chowdhury Kabir, "A Generalized Model for Forecasting Technological Substitution", Technological Forecasting and Social Change, 8, p.353-364.

Sheth, Jagdish N., "Perceived Risk and Diffusion of Innovations" in Insights Into Consumer Behavior, Johan Arndt, ed., Boston: Allyn and Bacon, Inc., 1968.

_____, "Word of Mouth in Low Risk Innovations", Journal of Advertising Research, 11, June 1971, p.15-18.

Simon, Hermann and Karl-Heinz Sebastian, "Diffusion and Advertising: The German Telephone Company", Management Science, 33, April 1987, p.451-466.

_____, "Marketing Science's Pilgrimage to the Ivory Tower", Working Paper, School of Business, Johannes Gutenberg-Universitaet Mainz, April 1992.

Skiadas, Christos H., "Two Generalized Rational Models for Forecasting Innovation Diffusion", Technological Forecasting and Social Change, 27, p.39-62.

_____, "Innovation Diffusion Models Expressing Asymmetry and/or Positively or Negatively Influencing Forces", Technological Forecasting and Social Change, 30, p.313-330.

Smith, F.E., "Population Dynamics in Daphnia Magna and a New Model for Population Growth", Ecology, 44, p.651-663.

Srinivasan, V. and Charlotte H. Mason, "Nonlinear Least Squares Estimation of New Product Diffusion Models", Marketing Science, 5, Spring 1986, p.169-178.

Tarde, Gabriel, "The Laws of Imitation", translated by E.C. Parsons, New York: Holt, 1903.

Theil, Henri, Economic Forecasts and Policy, Amsterdam: North Holland Publishing Company, 1961.

_____, Applied Economic Forecasting, Amsterdam: North Holland Publishing Company, 1966.

von Bertalanffy, Ludwig, "Quantitative Laws in Metabolism and Growth", Quarterly Review of Biology, 32, September 1957, p.217-231.

Wind, Yoram, "A Framework for Classifying New Product Forecasting Models", in New Product Forecasting: Models and Applications, Yoram Wind, Vijay Mahajan, and Richard Cardozo, eds., Lexington: Lexington Books, 1981.

Whyte, William H., The Organization Man, New York: Simon and Schuster, 1956.

APPENDIX 1:

SAMPLE TSP PROGRAM USED FOR DESCRIPTIVE ANALYSIS

BASS MODEL

#556 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- DESCRIPTION -

```
OPTIONS CRT;
SMPL 1 13;
LOAD Y;
49 19 7 19 17 28 14 25 13 18 25 24 27;

LOAD X;
64 113 132 139 158 175 203 217 242 255 273 298 322;

FRML EQ Y=(A*NBAR+B*X)*(NBAR-X)/NBAR;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
GENR EQ YHAT ;
ACTFIT Y YHAT;
PRINT Y YHAT;
END;
END;
```

APPENDIX 2:

SAMPLE TSP PROGRAM USED FOR PREDICTIVE ANALYSIS

BASS MODEL

#556 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- PREDICTION -

```

OPTIONS CRT;
SMPL 1 13;
LOAD Y;
49 19 7 19 17 28 14 25 13 18 25 24 27;

LOAD X;
64 113 132 139 158 175 203 217 242 255 273 298 322;

SMPL 1 9;
FRML EQ Y=(A*NBAR+B*X)*(NBAR-X)/NBAR;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
SET Z(1)=X(1);
GENR EQ YHAT;
DO I=2 TO 9;
SET F=I-1;
SET Z(I)=X(I);
ENDD;
DO I=10 TO 13;
SET F=I-1;
SET YHAT(I)=(A*NBAR+B*Z(F))*(NBAR-Z(F))/NBAR;
SET Z(I)=YHAT(I)+Z(F);
ENDD;
SMPL 10 13;
ACTFIT Y YHAT;
PRINT Y YHAT;
END;
END;

```

APPENDIX 3:

**SAMPLE DATASET YIELDING GOOD
DESCRIPTIVE AND PREDICTIVE RESULTS
FOR MOST MODELS**

BASS MODEL

#556 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- DESCRIPTION -

OPTIONS CRT;
SMPL 1 13; 13 2-week periods of data

- Y denotes the sales per period -

LOAD Y;
49 19 7 19 17 28 14 25 13 18 25 24 27;

- X denotes cumulative sales per period -

LOAD X;
64 113 132 139 158 175 203 217 242 255 273 298 322;

FRML EQ $Y = (A * NBAR + B * X) * (NBAR - X) / NBAR$;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
GENR EQ YHAT ;
ACFIT Y YHAT;
PRINT Y YHAT;
END;
END;

APPENDIX 4:

**SAMPLE DATASET YIELDING GOOD DESCRIPTIVE
AND SOMETIMES GOOD PREDICTIVE RESULTS
FOR THE VARIOUS MODELS**

BASS MODEL

#295 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- DESCRIPTION -

OPTIONS CRT;
SMPL 1 36; 36 2-week periods of data

- Y denotes the sales per period -

LOAD Y;
6 16 20 3 17 9 13 9 12 8 10 7 7 5 8 7 7 4 4 5 3 8 4 1 1 4 1 3
5 0 0 1 1 0 0 3;

- X denotes cumulative sales per period -

LOAD X;
1 7 23 43 46 63 72 85 94 106 114 124 131 138 143 151 158 165
169 173 178 181 189 193 194 195 199 200 203 208 208 208 209
210 210 210;

FRML EQ $Y = (A * NBAR + B * X) * (NBAR - X) / NBAR$;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
GENR EQ YHAT ;
ACTFIT Y YHAT;
PRINT Y YHAT;
END;
END;

APPENDIX 5:

SAMPLE DATASET YIELDING NEITHER GOOD
DESCRIPTIVE NOR GOOD PREDICTIVE RESULTS
FOR ANY MODEL

BASS MODEL

#36 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- DESCRIPTION -

OPTIONS CRT;
SMPL 1 29; 29 2-week periods of data

- Y denotes the sales per period -

LOAD Y;
1 0 2 1 0 0 0 0 1 0 0 1 0 0 2 0 0 0 0 0 0 1 1 2 2 0 1 1 1;

- X denotes cumulative sales per period -

LOAD X;
1 2 2 4 5 5 5 5 5 6 6 6 7 7 7 9 9 9 9 9 9 9 10 11 13 15 15 16
17;

FRML EQ $Y = (A * NBAR + B * X) * (NBAR - X) / NBAR$;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
GENR EQ YHAT ;
ACTFIT Y YHAT;
PRINT Y YHAT;
END;
END;

APPENDIX 6:

SAMPLE DATASET SOMETIMES YIELDING GOOD
DESCRIPTIVE BUT NEVER GOOD PREDICTIVE RESULTS
FOR THE VARIOUS MODELS

BASS MODEL

#611 FIRST PURCHASE SALES

NONLINEAR LEAST SQUARES ESTIMATION

FOR CRACKERS

- DESCRIPTION -

OPTIONS CRT;
SMPL 1 18; 18 2-week periods of data

- Y denotes the sales per period -

LOAD Y;
54 28 11 12 11 27 6 8 8 6 4 4 2 2 7 7 12 31;

- X denotes cumulative sales per period -

LOAD X;
12 66 94 105 117 128 155 161 169 177 183 187 191 193 195 202
209 221;

FRML EQ $Y = (A * NBAR + B * X) * (NBAR - X) / NBAR$;
PARAM A .1 NBAR 500 B .1;
LSQ (MAXIT=50) EQ;
GENR EQ YHAT ;
ACTFIT Y YHAT;
PRINT Y YHAT;
END;
END;

APPENDIX 7:**INDEX TO THE CONTENTS OF THE ATTACHED DISK
INCORPORATING THE RESULTS OF THE ANALYSES**

Due to the extensive data analysis, there is a large amount of statistical results available. Out of space considerations these results are available on the two attached disks. These disks can be obtained from Professor George Haines Jr. or Professor Uma Kumar at reproduction cost.

Write to:

Carleton University
School of Business
Ottawa, Ontario
K1S 5B6
Canada

On the following pages the directory of the disks is reproduced with a short explanation of the file contents.

UNABLE TO FILM MATERIAL ACCOMPANYING THIS THESIS (I.E.
DISKETTE(S), SLIDES, MICROFICHE, ETC...).

PLEASE CONTACT THE UNIVERSITY LIBRARY.

INCAPABLE DE MICROFILMER LE MATERIEL QUI ACCOMPAGNE CETTE THESE
(EX. DISQUETTES, DIAPOSITIVES, MICROFICHE (S), ETC...).

VEUILLEZ CONTACTER LA BIBLIOTHEQUE DE L'UNIVERSITE.

NATIONAL LIBRARY OF CANADA
CANADIAN THESES SERVICE

BIBLIOTHEQUE NATIONALE DU CANADA
LE SERVICE DES THESES CANADIENNES

RESULTS OF DESCRIPTIVE ANALYSIS

<u>FILENAME</u>	<u>CONTENTS</u>
ABASSFIR.THS	First Purchase Occasions - Bass Model
ABASSNEW.THS	First Purchase Sales - Bass Model
ABASSTOT.THS	Total Sales - Bass Model
ABERTNEW.THS	First Purchase Sales - von Bertalanffy Model
ABERTTOT.THS	Total Sales - von Bertalanffy Model
ABROCFIR.THS	First Purchase Occasions - Brockhoff Model
ABROCNEW.THS	First Purchase Sales - Brockhoff Model
ABROCTOT.THS	Total Sales - Brockhoff Model
AFISHNEW.THS	First Purchase Sales - Fisher-Pry Model
AFISHTOT.THS	Total Sales - Fisher-Pry Model
AGENNEW.THS	First Purchase Sales - Generalized Model
AGENTOT.THS	Total Sales - Generalized Model
AJEUNEW.THS	First Purchase Sales - Jeuland Model
AJEUTOT.THS	Total Sales - Jeuland Model
AKKK1NEW.THS	First Purchase Sales - KKK I Model
AKKK1TOT.THS	Total Sales - KKK I Model
AKKK2NEW.THS	First Purchase Sales - KKK II Model
AKKK2TOT.THS	Total Sales - KKK II Model
ANUINew.THS	First Purchase Sales - NUI Model
ANUITOT.THS	Total Sales - NUI Model
ASKABNEW.THS	First Purchase Sales - Sharif-Kabir Model
ASKABTOT.THS	Total Sales - Sharif Kabir Model

RESULTS OF PREDICTIVE ANALYSIS

<u>FILENAME</u>	<u>CONTENTS</u>
PBASSFIR.THS	First Purchase Occasions - Bass Model
PBASSNEW.THS	First Purchase Sales - Bass Model
PBASSTOT.THS	Total Sales - Bass Model
PBERTNEW.THS	First Purchase Sales - von Bertalanffy Model
PBERTTOT.THS	Total Sales - von Bertalanffy Model
PBROCFIR.THS	First Purchase Occasions - Brockhoff Model
PBROCNNEW.THS	First Purchase Sales - Brockhoff Model
PBROCTOT.THS	Total Sales - Brockhoff Model
PFISHNEW.THS	First Purchase Sales - Fisher-Pry Model
PFISHTOT.THS	Total Sales - Fisher-Pry Model
PGENNEW.THS	First Purchase Sales - Generalized Model
PGENTOT.THS	Total Sales - Generalized Model
PJEUNNEW.THS	First Purchase Sales - Jeuland Model
PJEUTOT.THS	Total Sales - Jeuland Model
PKKK1NEW.THS	First Purchase Sales - KKK I Model
PKKK1TOT.THS	Total Sales - KKK I Model
PKKK2NEW.THS	First Purchase Sales - KKK II Model
PKKK2TOT.THS	Total Sales - KKK II Model
PNUINNEW.THS	First Purchase Sales - NUI Model
PNUITOT.THS	Total Sales - NUI Model
PSKABNEW.THS	First Purchase Sales - Sharif-Kabir Model
PSKABTOT.THS	Total Sales - Sharif Kabir Model

RESULTS OF SENSITIVITY ANALYSIS

<u>FILENAME</u>	<u>CONTENTS</u>
PBAS1FIR.THS	First Purchase Occasions - Bass Model
PBAS1NEW.THS	First Purchase Sales - Bass Model
PBAS1TOT.THS	Total Sales - Bass Model
PBER1NEW.THS	First Purchase Sales - von Bertalanffy Model
PBER1TOT.THS	Total Sales - von Bertalanffy Model
PBRO1FIR.THS	First Purchase Occasions - Brockhoff Model
PBRO1NEW.THS	First Purchase Sales - Brockhoff Model
PBRO1TOT.THS	Total Sales - Brockhoff Model
PFIS1NEW.THS	First Purchase Sales - Fisher-Pry Model
PFIS1TOT.THS	Total Sales - Fisher-Pry Model
PGEN1NEW.THS	First Purchase Sales - Generalized Model
PGEN1TOT.THS	Total Sales - Generalized Model
PKI1NEW.THS	First Purchase Sales - KKK I Model
PKI1TOT.THS	Total Sales - KKK I Model
PKI11NEW.THS	First Purchase Sales - KKK II Model
PKI11TOT.THS	Total Sales - KKK II Model
PNUI1NEW.THS	First Purchase Sales - NUI Model
PNUI1TOT.THS	Total Sales - NUI Model
PSKB1NEW.THS	First Purchase Sales - Sharif-Kabir Model
PSKB1TOT.THS	Total Sales - Sharif Kabir Model

FREQUENCY TABLES FOR RANGE OF MODEL PARAMETERS

<u>FILENAME</u>	<u>CONTENTS</u>
FRQBANEW.THS	First Purchase Sales - Bass Model
FRQBATOT.THS	Total Sales - Bass Model
FRQBENEW.THS	First Purchase Sales - von Bertalanffy Model
FRQBETOT.THS	Total Sales - von Bertalanffy Model
FRQBRNEW.THS	First Purchase Sales - Brockhoff Model
FRQBRTOT.THS	Total Sales - Brockhoff Model
FRQFINEW.THS	First Purchase Sales - Fisher-Pry Model
FRQFITOT.THS	Total Sales - Fisher-Pry Model
FRQGENEW.THS	First Purchase Sales - Generalized Model
FRQGETOT.THS	Total Sales - Generalized Model
FRQJENEW.THS	First Purchase Sales - Jeuland Model
FRQJETOT.THS	Total Sales - Jeuland Model
FRQK1NEW.THS	First Purchase Sales - KKK I Model
FRQK1TOT.THS	Total Sales - KKK I Model
FRQK2NEW.THS	First Purchase Sales - KKK II Model
FRQK2TOT.THS	Total Sales - KKK II Model
FRQNUNEW.THS	First Purchase Sales - NUI Model
FRQNUTOT.THS	Total Sales - NUI Model
FRQSKNEW.THS	First Purchase Sales - Sharif-Kabir Model
FRQSKTOT.THS	Total Sales - Sharif Kabir Model
BACKGRD.THS	<p>Table with background information on records with special circumstances:</p> <ol style="list-style-type: none"> 1) existence of another size of same product 2) introduction dates in various markets differ by more than four weeks 3) product only introduced in one market

APPENDIX 8:

DEMONSTRATION OF RESULTS WITH U (1966) < 0.1

APPENDIX 9:

DEMONSTRATION OF RESULTS WITH U (1966) < 0.5

APPENDIX 10:

DEMONSTRATION OF RESULTS WITH $U (1966) < 0.7$

END

1 | 8-07-94

FIN