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PIMS

Profit Impact of Marketing Strategy Project: Retrospect and Prospects

Edited by

Paul W. Farris and Michael J. Moore

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The Profit Impact of Marketing Strategy Project: Retrospect and Prospects

New developments in strategic thinking and econometric methods, along-side fundamental changes in technology and in the nature of competition, argue the need for an in-depth but accessible assessment of the Profit Impact of Marketing Strategy project. Here, Paul Farris and Michael Moore gather together contributions from experts across the United States and Europe to offer a retrospective analysis alongside innovative perspectives on future marketing strategy and performance assessment methods. Appealing to scholars and reflective practitioners interested in fostering new practical knowledge about business innovation and changes, this book explores not only new ways of thinking about and working with PIMS but also the unresolved issues arising from the original data. As the business community renews its attempts to recreate the kind of interfirm cooperation that produced the PIMS project, sharing many of the ideals, this timely volume will broadly appeal.

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Keith Roberts is Managing Director of PIMS Europe. He first joined the company in its US office in 1979 and was responsible for the development of many of the benchmarking models used by PIMS consultants. In 1981 he moved to London to set up PIMS Europe. His consulting experience has encompassed a wide range of industries: publishing, engineering, chemicals, paper, oil, pharmaceuticals, metals, minerals, packaging, consumer goods, and financial services. As well as coordinating the new product activities of PIMS, he currently works with leading international FMCG and oil companies. Keith had experience as a PIMS client while working in two major companies. From 1976 to 1979 he was a strategic planner, evaluating the corporate portfolio, at Reed (now Reed Elsevier), where PIMS played a major part in the transformation of Reed from a paper/packaging-based conglomerate to a successful publishing company. Prior to that he was one of the first UK participants in the PIMS program, in the marketing department of Tioxide (now part of ICI). From 1970 to 1973 he was in OR consultancy for local government. Keith has a degree in mathematics and an advanced degree in statistics from Cambridge University.

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We would like to acknowledge certain key individuals, without whom this project to honor Bob Buzzell's work could not have been completed. Professor Robert Bruner and Elizabeth O'Halloran of the Batten Institute at the Darden School of Business were uncommonly generous in providing financial and logistical support for the project. The early and enthusiastic commitment of Professors George Day and David Reibstein of Wharton, and the endorsement of Professor Don Lehman of the Marketing Science Institute gave the undertaking critical mass. Professor Stephen Greyser of Harvard also generated early momentum for us. Lutz Hildebrandt not only traveled from Berlin, but suggested the conference to celebrate Bob Buzzell's PIMS contributions many years ago. Dr. Katy Plowright of Cambridge University Press encouraged us to undertake this book. Jackie Warren, Production Editor, kept us moving in the right direction and Chris Doubleday's careful reading of the manuscripts improved them all. Of course, we take responsibility for whatever errors might remain. Finally, we would like to thank each conference participant for their efforts, not only in preparing the manuscripts contained in this volume, but also for making the trip to Charlottesville.

Introduction

PAUL W. FARRIS AND
MICHAEL J. MOORE

This volume contains essays that revisit the ideals of the PIMS (Profit Impact of Marketing Strategy) project. They are collected and published here in honor of Robert D. Buzzell's contributions to marketing research in general and the PIMS project in particular. The impetus for these essays originated from a conference held in October 2002. A group of scholars and researchers gathered at the University of Virginia's Darden School to honor Bob Buzzell and exchange ideas and papers reflecting on the achievements and recent advances relating to the PIMS program of research on marketing strategy. What did we learn and what should we have learned from the PIMS project concerning the economic causes and consequences of marketing decisions?

The following people attended the conference:

- Kusum Ailawadi, Tuck School, Dartmouth College
- Jay Bourgeois, The Darden School, University of Virginia
- Eric Boyd, The Darden School, University of Virginia
- Robert Buzzell, Georgetown University
- Markus Christen, INSEAD
- George Day, The Wharton School, University of Pennsylvania
- Paul Farris, The Darden School, University of Virginia
- Bradley Gale, Customer Value, Inc.
- Hubert Gatignon, INSEAD
- Lutz Hildebrandt, Humboldt University, Berlin
- William Kehoe, McIntire School of Commerce, University of Virginia
- Trey Maxham, McIntire School of Commerce, University of Virginia
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- Michael Moore, The Darden School, University of Virginia
- Russ Morgan, University of Utah
- Bill Moult, Marketing Science Institute
- Mark Parry, The Darden School, University of Virginia

- Jack Pendray, retired
- David Reibstein, The Wharton School, University of Pennsylvania
- Keith Roberts, PIMS Europe Ltd.
- William Robinson, Purdue University
- Paul Simko, The Darden School, University of Virginia
- Robert Spekman, The Darden School, University of Virginia
- David Szymanski, Mays School of Business, Texas A&M University
- Ron Wilcox, The Darden School, University of Virginia

The time is right to revisit some of the ideals and achievements of the PIMS project. Sufficient time has elapsed to review critically the observations, views, and unresolved issues from PIMS research. New developments in strategic thinking, econometric methods, and fundamental changes in technology and the nature of competition also make this exercise important. Further, we know that there are periodic attempts to regenerate the kind of interfirm cooperation that produced the PIMS data. Most of these attempts are relatively modest in scope compared to the original PIMS project. Still, they share many of the ideals: generating practical business insights and cross-firm learning that are based in the rigorous analysis of a shared database, and producing findings that are replicable and open to scholarly debate. It is our hope that such projects will benefit from the essays in this volume.

Batten Institute

The initial support for the conference to honor Bob Buzzell and the PIMS project came from the Batten Institute. This institute is a foundation within the Darden Graduate School of Business Administration at the University of Virginia. It invests in applied research and knowledge transfer programs at the frontiers of change in organizations, markets, and technologies. Certainly the PIMS project is an example of applied research that pushed the frontiers of organizational change and strategy formulation. The institute is a nexus of practitioners and scholars interested in fostering new practical knowledge about business innovation and change.

The Darden School was founded as the Virginia Business School in 1954 and its first classes in entrepreneurship and small business were offered in 1961. In early 1996, Darden created the Batten Center for Entrepreneurial Leadership with a generous gift from the Batten family of Norfolk, Virginia, and its Landmark Foundation. The Batten Institute, which succeeded the Batten Center on January 1, 2000, was made possible through a subsequent gift from University of Virginia alumnus Frank Batten, Sr.

Marketing Science Institute

This book and the PIMS project owe a debt of gratitude to the Marketing Science Institute (MSI) and Don Lehmann, who, as executive director in 2002, agreed to co-sponsor the conference that led to this book. MSI is a unique, not-for-profit institute that was established in 1961 as a bridge between business and academia. Its mission is to initiate, support, and disseminate leading-edge studies by academics that address research issues specified by member companies. MSI functions as a working sponsorship and brings together executives with leading researchers from approximately a hundred universities worldwide. Bob Buzzell was executive director of MSI when the PIMS project was launched under the auspices of MSI.

Overview

We have organized the chapters in this volume around four themes. A brief summary of each theme follows.

PIMS in retrospect: achievements, context, and calibration (Chapters 1–3)

What are the strategic questions we hoped to answer and what did PIMS accomplish? Three chapters address PIMS achievements. The first, by Paul Farris, details the richness of the database, the number of journal articles published, and the debates inspired around the questions raised. An additional contribution to Chapter 1 is John Farley's description of how comparative international research has benefited from the performance measures pioneered by PIMS. George Day's chapter then laces PIMS' contributions to the field of marketing strategy into the context of the growth and maturation of the field. He shows how PIMS anticipated many of the developments in strategy through the phases of sources, positional advantage, and performance. The third chapter, by Eric Boyd, Paul Farris, and Lutz Hildebrandt, provides some needed calibration of PIMS against the corporate universe as captured by COMPUSTAT data.

Major dimensions of marketing strategy (Chapters 4–7)

The strategic decision to enter a market is arguably the most important one that a business will face. In developing an understanding of the causes and consequences of entry timing, the expected reaction by competitors to entry must first be modeled, and its role then evaluated. Then the newness and quality of the offerings relative to the competitors are inevitably evoked as explanations for greater or lesser success. Decisions on pricing, marketing investments, and sustainable levels of product quality quickly follow, however. The four chapters in this section address these issues in turn. William Robinson and Mark Parry survey what we have learned on early entry. David Szymanski, Michael Kroff, and Lisa Troy review assembled evidence to question whether innovativeness really enhances new product success. The subsequent two chapters focus on marketing, prices, and product quality. David Reibstein and his co-authors review PIMS-based and other studies of advertising and prices. They argue that marketing spending should include sales-force spending and expand earlier work on advertising, prices, and profitability to include investments in the sales force. Lutz Hildebrandt and Dirk Temme revisit a classic study of the influence of product quality, using now state-of-the-art econometric techniques to control unobserved variables. This chapter, with its heavy emphasis on methodology, sets the stage for the next section.

Methodological questions and answers for panel data (Chapters 8–10)

What have we learned about modeling causal relationships among systems of variables, adjusting for scale differences, levels versus differences, specification involving identities, and the role of cross-sectional versus time-series or meta-analyses? Problems with strictly cross-sectional data are well known, as are the shortcomings of inappropriately pooled data (including time series). Can new approaches and methodologies produce analyses of PIMS-type data to overcome some of these limitations? We think so, and the three methodologically oriented chapters contained here highlight this potential. In Chapter 8, Kusum Ailawadi and Paul Farris argue that the role of components and identities is a special problem and opportunity as concerns the specification of causal models. In Chapter 9, Michael Moore, Russ Morgan, and Judith Roberts show how PIMS data *should* be used in conjunction with standard specification tests to shed insight into the correct specification of simultaneous equation marketing models. In Chapter 10, Marcus Christen and Hubert Gatignon address what is perhaps the most controversial issue resulting from the PIMS database – the relationship between market share and profitability. Through the use of simulation where the underlying relationship is known, they demonstrate that the first-differencing methods commonly used by other researchers underestimate the true relationship between market share and profits.

PIMS in prospect (Chapter 11)

Becoming data-driven is a current business mantra, but it is not always clear what kinds of data are appropriate to address various decisions. In this final section we take on the task of speculating how PIMS might be different if we were launching it today. First, what are the newer metrics for describing marketing strategy and evaluating business performance that a revised PIMS would probably include? Second, what have the methodological debates taught us about how to approach research in this field? Finally, how would a dataset like PIMS be constructed to reflect developments in the industrial organization literature, particularly regarding the measurement of market power and the implications for policy, particularly antitrust? Paul Farris and Michael Moore explore each of these questions in turn in the final chapter.

1 *The PIMS project: vision, achievements, and scope of the data*

PAUL W. FARRIS
WITH JOHN U. FARLEY

The Profit Impact of Marketing Strategy (PIMS) project, which began in 1972, was one of the most successful and influential partnerships between marketing academics and the private sector. Robert Buzzell, as Executive Director of the Marketing Science Institute, was one of a small group of people who made the PIMS project possible. The program resulted in a unique dataset used to investigate the links among marketing strategy, market structure, and performance. The Marketing Science Institute was a near-perfect organizational platform from which to launch a project that had the ambitious goal of understanding how and why some marketing strategies were more profitable than others. To enable this investigation, PIMS, from the beginning, set a new standard of depth and breadth for panel data collected from operating business units. In this book we have collected a set of original essays that revisit the ideals of the PIMS project. Our purpose is to explore what we learned and, perhaps, what we should or still might learn about researching the connections between marketing strategy and profits.

This does not mean that we are finished with the questions that PIMS helped the field of marketing strategy pose. However, enough time has passed and enough additional evidence has been accumulated that we believe it is appropriate to appraise what was accomplished. Some of the essays will help put the achievement of PIMS into the context of the times (both then and now). Others will provide additional insights, evidence, and reflections on the important questions that were raised by PIMS research. Lastly, we believe this book contains ideas for shaping the future of the questions and methodologies of marketing strategy research.

Since many readers may have little familiarity with PIMS, we first describe the PIMS data and offer some observations on what made these data unique, including the historical context, the central role of market share in strategy research, and a brief description of the methodological debates that the PIMS data inspired and enabled. Finally, this chapter will summarize some of the major accomplishments of the PIMS project.

1.1 What was unique about the PIMS data?

The PIMS data were exceptional for four reasons. First, the extensive questionnaire collected an unprecedented number of descriptors of business strategy and market structure, and financial performance. Many of these variables were innovative ways of characterizing differences among businesses. Second, the strategic business unit (SBU) as the unit of observation was uniquely suited for strategy research in terms of organizational disaggregation. (Diversified businesses were allocating resources with the help of share-growth matrices that steered more funds towards "business units" that had strong competitive positions.) Third, because of both the number and variety of businesses in the database, more sophisticated analyses that required more observations (degrees of freedom) became possible. PIMS, from the very beginning, augmented a primarily cross-sectional database with a time series (four years of data) on each business. The availability of both time-series and cross-sectional data was a key asset. Fourth, PIMS asked for information in what now seems to be an amazingly rich variety of different formats and scales (log-scales, percentage of totals, five-point scales, three-point scales – to name just a few). As Kusum Ailawadi pointed out to me, this avoids the "methods bias" that plagues many questionnaires and reduces the respondent fatigue that leads to less thought and more automation in responses. John Farley explores the influence of the PIMS questionnaire in an appendix to this chapter.

1.1.1 Design and scope of the questionnaire

Since the full PIMS questionnaire has been reproduced elsewhere (Buzzell and Gale 1987), we offer a more compact overview of the data here. The design of the questionnaire was a major achievement. Tables 1.1a–1.1c provide a summary of the data collected by the PIMS questionnaire. The list of "variables" available for analysis is

Table 1.1a. *A summary of data collected by PIMS: I*

Most PIMS variables are categorical variables with the number of discrete values indicated (e.g. C-8 refers to the eight different classifications for Type of Business. Other types of variables include undisguised number (UD), disguised dollar figure (D$), and undisguised percentage (%).) Most financial measures are useful only as ratios to other measures with the same disguise factor.

Data on products, customers, end user, channels, competitors	*Type of variable*	*Data on products, customers, end user, channels, competitors*	*Type of variable*
Type of business	C-8	Change in customer concentration	C-3
Year category/market established	C-5	Above relative to competitors	C-3
Year of firm entry into market	C-5	Purchase frequency end users	C-7
Life-cycle stage	C-4	Purchase frequency customers	C-7
Order of entry (Pioneer – Laggard)	C-3	Purchase amount end users	C-9
Sig. patents products/processes	C-4	Purchase amount customers	C-9
Standardized/customized products	C-2	% annual purchases	C-5
Frequency of product-line changes	C-4	Importance of products' customers	C-5
Major technology changes last five years	C-2	Importance of auxiliary services	C-3
New product development time	C-5	Reliance on advisers for purchase	C-3
% sales to: hhs., mfs., instit., gov. & contractors	5×%	% sales: direct, through own channels, to wholesale, to retail	4×%
Number end users	C-9	Gross margins earned by channels	%
Number immediate customers	C-8	SIC code	UD
End user concen. (% = 50% sales)	%	Geographic scope market	C-5
Change in user concentration	C-3	Number of competitors	C-5
Above relative to competitors	C-3	Entry major competitors	C-2
Customer concen. (% = 50% sales)	%	Exit major competitors	C-2

Table 1.1b. ***A summary of data collected by PIMS: II***
See note at head of Table 1.1a

Vertical/horizontal integration	*Type of variable*	*Relative measures (versus three leading competitors)*	*Type of variable*
SBU vertical integration	C-3	Shares of three largest competitors	3×%
Company vertical integration	C-3	Market share rank	UD
SBU purchases within company	%	% superior, equivalent, inferior quality	3×%
Common reports f/suppliers SBU	C-2	Relative prices vs. competitors	Index
Sales to other SBUs same company	%	Relative costs (non-marketing)	Index
Common reports for above	C-2	Relative wages	Index
Shared facilities other SBUs	C-3	Relative salaries	Index
Shared customers other SBUs	C-4	% new products for SBU	%
Shared marketing (e.g. SF, ad prog.)	C-3	% sales f/new product for three leading competitors	%
% purchases f/three largest suppliers	%	Breadth of line	C-3
Above as % supplier sales	%	Breadth served market, type customers	C-3
Alternative sources supply	C-3	Breadth served market, no. customers	C-3
Compete with suppliers	C-3	Breadth served market, size customers	C-3
Possible supplier forward integration	C-2	Relative sales force % sales	C-5
Compete w/other SBUs in company?	C-2	Relative media	C-5
		Relative sales promotion	C-5
		Quality of services	C-5
		Relative image	C-5

Table 1.1c. ***A summary of data collected by PIMS: III***
See note at head of Table 1.1a.

Financial measures and productivity ratios	*Type of variable*	*Financial measures and productivity ratios*	*Type of variable*
Size of served market	D$	Gross book value P&E	D$
Sales/lease revenue	D$	Net book value P&E	D$
Order backlog >50% sales	C-2	Average investment (including cap. leases)	D$
Purchases (value added)	D$	Average current liabilities	D$
Manufacturing and distribution expense	D$	Total assets	D$
Product/process R&D	D$	Sales value of capacity	D$
Sales force	D$	Capacity utilization	%
Advertising and promotion	D$	Sales/employee (UD)	UD
Media	D$	Sales/salesman (UD)	UD
Other marketing expense	D$	Employee unionization	%
Total marketing expense	D$	Four-year price growth	UD
Depreciation	D$	Four-year material costs growth	UD
Net income	D$	Four-year wage cost growth	UD
Average receivables	D$	Production input shortages	4×2
Average finished goods inventory	D$	Price controls	C-2
Average inventory inputs & WIP	D$		

considerably longer than appears in these three tables. Mathematical transformations and combinations of the raw data created many additional variables. Examples of variables resulting from such transformations are three-firm concentration indices, return on investment, volatility of market share, and dummy variables representing high purchase-amount and high purchase-frequency.

Each table lists a code for the type of variable collected. Of particular note is the code D$, indicating that the variable is recorded as a dollar figure but that the actual amount has been disguised. In the process of creating the questionnaire that captured the PIMS data, the corporate and academic sponsors confronted the conflicting demands for precision and confidentiality. A "disguise" factor, known only to the respondents, was used to preserve the confidentiality and the research value of most ratios. Perhaps because the companies and SBUs were anonymous, the PIMS questionnaire requested a great deal of information on marketing strategy, customers and end users, and competitors. The percentage of sales from new products, typical purchase amounts and frequency, relative price, and perceptions of quality are just some examples of the measures that PIMS pioneered and that others subsequently adopted. The result, although then more of a means to an end than an end itself, was that the PIMS project enriched the language and vocabulary used to differentiate marketing strategy.

1.1.2 SBU as unit of analysis

The PIMS unit of analysis, the strategic business unit (SBU), reflected a view of where operating managers had the most influence and of the dividing line between corporate and business/marketing strategy. There was also a heavy emphasis on businesses manufacturing consumer or industrial (B2B) products. SBUs are generally the smallest unit of the firm for which a complete operating income statement might be available. For some consumer-products companies an SBU might include more than one brand in a single category, while a company such as General Electric would have divided the GE brand into many operating units.

1.1.3 Variety and number of variables and businesses in PIMS database

Ultimately, more than 400 firms contributed, on average, six years of data on over 2,600 separate SBUs (Marshall and Buzzell 1990). Those companies covered eight different business types (consumer non-durables and durables, industrial raw materials, components, capital equipment, supplies, services, and wholesale/retail businesses). Although there was a definite concentration among manufacturing businesses, as we will show in Chapter 3, the data on services and wholesale/retail businesses were substantial.

It is remarkable that so many different variables were collected from so many businesses. Of course, this raises the question of how so many managers were convinced of the potential usefulness of this project and thereby motivated to complete the questionnaire that generated such a rich database. The Marketing Science Institute, as an organization, promoted the kind of dialogue needed to help motivate managers and recruit the academic and analytical talent to produce the research results to fulfill the promises made. PIMS is a testimony to the importance and possibilities of this kind of dialogue between managers and academics.

The best affirmation that managers were convinced of the ongoing utility of PIMS research was the continued support the database received for many years. The research outgrew the original partnership with MSI, requiring separate facilities, and, ultimately, achieving the freedom to do more consulting-oriented projects that were incompatible with the mission of MSI. The PIMS project was spun off under the auspices of the Strategic Planning Institute (SPI), where it continued to accumulate additional data on the businesses that remained and to recruit new businesses until just before 2000. PIMS is now headquartered in the United Kingdom (see Chapter 11 for more details on the current PIMS operation).

1.1.4 A retrospective view of the role and importance of market share measures

It is important to emphasize that PIMS' scope and vision were not limited to what we have undoubtedly stereotyped below as the 1970s' world-view of strategy. The PIMS questionnaire included variables that reflected that growth–share matrix view. But, as George Day explains in Chapter 2, PIMS also explored questions about quality, new products, rates of technological change, relative marketing and pricing levels, and market entry and exit. All of this was done with a keen awareness of what might make one business situation different from another in terms of customer behavior and cost, relative measures of SBU resources, strategy, and performance. Having said this, market share, perhaps, inevitably occupied center stage.

Market share was a central concept and measure for both the PIMS project and then-current views of marketing strategy. Two measures of share were available. Both were dollar-based measures (where relevant, measured in manufacturer, not retailer, prices). The first share measure was calculated as sales revenue divided by served market size. The second, a measure of relative share, was obtained by dividing the first share measure by the share of the largest competitor. Although defining sales revenue is never easy, the difficulties of revenue definition pale in comparison to those that surround market definition. The PIMS approach to this problem of market definition was a creatively simple way to cut the Gordian knot of potential complexities relating to market definition. PIMS asked managers to consider the "served market," thus tying the definition of market as much to the managerial ambition and scope of vision as to any particular conceptual anchor.

Market definitions will always retain some degree of subjectivity. Managers were forced to make multiple assessments about their own definitions. For example, they were asked to estimate the number of end users and the number of immediate customers separately. For each of these groups, purchase amount and purchase frequency had to be estimated. Numerous other variables reinforced the view of "served market." So while the definition of "served market" may have relied on managerial judgment, it was clearly a considered judgment and one that had to be revisited several times to complete the questionnaire.

Served-market definitions were required to calculate both market share and market growth. These two variables were central to a "portfolio" approach to allocating funds among separate business units. Generally, high-share businesses were expected to have a combination of higher prices and lower costs. Small-share businesses were thought to be viable only in high-growth markets. The Boston Consulting Group's (BCG) famous 2×2 matrix used relative market share and market growth to classify strategic business units into four groups. High-share/high-growth businesses were "stars" and high-share/low-growth business were "cows." Low-share businesses in high-growth markets were designated "question marks," while low-share/low-growth businesses were termed "dogs." The growth–share matrix appealed to managers who needed a system and rationale for requesting/allocating limited funds for the investment needs of multiple business units. The logic was that cows should be "milked" for funds to support the future growth of stars and, perhaps, to attempt to improve the competitive prospects of a few question marks. Dogs were put on a short cash leash and instructed to find new owners.

Why the emphasis on relative share? The logic was simple and compelling. If a business unit's share was lower than that of its competitors, the chances were good that its costs were higher. If its costs were higher, that business unit would not be able to lower prices or invest in marketing at the same rates as the market leader. If market growth was slowing, the chances were slim that a follower could justify the investment to gain share, accumulate the production experience to lower cost, and therefore become generally competitive with the market leaders.

Market share was widely regarded as a potentially good indicator of a business unit's relative cost and market power (prices). Relative market share (usually compared to the largest competitor) was a refinement of the basic measure. It seems clear that the very notion of market share is meant to provide a benchmark for businesses to assess where the business stands with respect to competitors.[1]

1.1.5 Windows of strategic opportunity and the rule of three

The BCG matrix and related portfolio analyses shared a common assumption. That assumption was that only a few companies would survive and prosper in a given market (maybe as few as three or four). Further, the assumption was made that the winners would have lower costs, higher prices, and better utilization of fixed investments. The result would be higher returns on investments. Jack Welch, longtime CEO of GE, one of the original founders and supporters of the PIMS project, famously required divisions to be number 1 or 2, or else face the auction block. At certain critical phases of product market lifecycles (shakeouts), it was expected that intense competition would force some firms to exit. Immediately prior to shakeouts, competitors were required to invest in programs enabling them to keep pace with rapid market growth, or face declining market shares and diminished competitive viability. Seeing the future clearly enough to make invest/divest decisions was a critical part of marketing strategy as practiced in multidivisional companies of the 1970s. Relative market share and market growth were the most important metrics in determining whether SBUs were good bets for the future. PIMS and the associated

[1] This raises the question of whether various definitions of the market would provide equally valid insights into the relative competitiveness of a business with respect to costs and prices. Relative costs, one presumes, might be more related to a market definition that is biased toward the factors of production. Market power with customers and end users, on the other hand, might have a stronger relationship with a demand-oriented market definition.

models (as, for example, the PAR model of profitability) provided benchmarks for evaluating historical managerial performance, suggestions for improving results, and a basis for sorting the attractiveness of different businesses.

Table 1.1b shows that the PIMS questionnaire asked managers to rate their SBU relative to the leading competitors (often the three leading competitors) on several dimensions. The measures, like the definition of served market, cut through the conceptual complexities that plague any attempt to produce precise definitions of variables such as relative quality, prices, and product-line breadth. Most simply ask managers for their best estimates, although, as is clear from reading through the questionnaire, managers were forced to think, estimate, and corroborate – not just "guess." Among others, PIMS collected relative measures of

- entry order
- breadth of served market definition (number and size of customers)
- breadth of product line
- customer and supplier concentration/leverage
- new products as percentage of sales
- selling prices
- product/service quality
- marketing costs (including advertising, promotion, and sales force)
- manufacturing and distribution costs (including wages and salaries)

These relative measures were thought to be antecedents, consequences, or both, of SBU market share compared to the leading competitors. Often, the three largest competitors were specified. Why three? In part, we may trace the answer to Bruce Henderson's then well-known article, "The Rule of Three and Four." Henderson claimed that "a stable competitive market never has more than three significant competitors, the largest of which has no more than four times the share of the smallest." He also argued that, "It depends on an accurate definition of relevant market. *However, the rule appears to be inexorable*" (Henderson 1976). Although Henderson's article was published after PIMS was well under way, the thinking that underlies the article appears to have been prevalent in strategic planning circles. Even before this, however, economists had calculated "three- and four-firm concentration ratios" to assess concentration. More recently, Sheth and Sisodia (2002) echoed this observation, writing, "With startling regularity, we have found that the number of dominant players in each industry is confined to three. Any other number, greater or smaller, is usually a temporary aberration."

Table 1.1c offers a summary of the financial performance variables collected by PIMS. These basic measures may be used to calculate other summary measures and transformations such as ROI, cash flow, and investment intensity (investment/sales ratios).

If the prevailing view of strategy is that only three or four businesses are likely to survive a critical period (shakeout) in the evolution of a market, it is very important to assess whether a particular SBU is likely to be among the winners. Two measures of market share and a number of other variables that capture multiple dimensions of competitive strengths and weaknesses were designed to help managers make the decision to invest or withdraw.

1.2 What did PIMS accomplish?

We choose to address this question from a series of different perspectives. First, we will present some numbers: companies, business units, journal articles, and authors provide one impression of PIMS' influence. Second, we will summarize some of the major findings or foci of research conducted – the questions PIMS raised. Finally, we argue that PIMS first reflected and then anticipated and shaped the language of research into marketing strategy. The appendix to this chapter by John Farley shows how the PIMS questionnaire uniquely combined and validated both objective and subjective measures of marketing strategy and business unit performance.

We believe it is also important to address the controversy, passion, and visibility of reactions to PIMS-based research. The importance of the questions that PIMS posed and the power of the evidence to lead and shape our thinking (or, in the view of critics, to mislead) is, we believe, an important part of assessing and understanding PIMS' impact. Finally, if imitation is the best compliment, PIMS can point to ongoing attempts to duplicate the original approach and success.

A select bibliography of PIMS-based research was compiled in October 2002 and is presented at the end of this volume. It contains 176 entries. Numerous academics have published research that is based on analysis of PIMS data, and it is not an exaggeration to say that the analyses and critiques that PIMS data made possible helped to launch several academic careers. Industry and trade associations have initiated numerous efforts (not all successful) to create similar databases for "benchmarking." We believe that PIMS was influential in motivating many of these efforts.

A wide variety of topics have been studied using PIMS data. Some of the more intensely researched topics include the effect on profitability of

- market share, relative market share, and market structure (concentration)
- relative marketing costs and relative prices
- relative product quality
- vertical integration and capital intensity
- unionization
- new products, innovation in product line, and new ventures
- R&D investments
- shared programs

These topics motivated a large number of articles that have been published in virtually every major marketing and general business journal. Table 1.2 provides a partial listing of the journals in which PIMS-based articles have appeared.

1.2.1 Substantive questions addressed and methodological debates inspired/enabled

In addition to the impact on profits of relative quality, market share, investment intensity, and vertical integration, PIMS has been cited as providing evidence for the importance of new products, the influence of advertising and pricing strategies on ROI, and the determinants of marketing cost/sales. Clearly the relationship between market share and ROI garnered the most attention and controversy. Table 1.3 shows, briefly and without statistical elaboration, the cross-sectional relationship among market share, ROI, and selected variables reported by PIMS.

Much has changed since the mid-1970s, when the PIMS project began to produce evidence on marketing strategy and profitability. Shifts from manufacturing to services are part of the change. And we can find businesses in retailing, services, and manufacturing to illustrate the issues. Wal-Mart, Southwest Airlines, and Dell Computer are examples of companies (disruptive business models?) that initially had little to offer except low costs to their customers and high profits to

Table 1.2. ***A partial list of journals in which PIMS-based articles have appeared***

1	Academy of Management Journal	17	International Marketing Review	33	Marketing
2	Antitrust Bulletin	18	International Studies of Management and Organization	34	Marketing Science
3	Applied Economics	19	Journal of the Academy of Marketing Science	35	Oxford Economic Papers
4	British Brands	20	Journal of Advertising Research	36	Planning Review
5	Business and Finance	21	Journal of Business Research	37	Quality Progress
6	California Management Review	22	Journal of Business Strategy	38	Quarterly Journal of Economics
7	Chief Executive	23	Journal of Economic Studies	39	Quarterly Review of Economics and Business
8	CMA Magazine	24	Journal of Industrial Economics	40	Quarterly Review of Marketing
9	Economic Journal	25	Journal of Marketing	41	Research Management
10	European Journal of Management	26	Journal of Marketing Research	42	Sales and Marketing Management in Canada
11	Financial Executive	27	Keio Business Forum	43	Sloan Management Review
12	Financial Management	28	Long Range Planning	44	Southern Economic Journal
13	Harvard Business Review	29	Management Science	45	Strategic Management journal
14	Information and Software Technology	30	Management Today		
15	International Journal of Operations and Production Management	31	Managerial Planning		
16	International Journal of Research in Marketing	32	Market Leader		

Table 1.3. ***Market share and ROI***

PIMS SBUs with market share (%)	*Reported an average ROI (%)*
0–10	11
11–20	14
21–30	17
31–40	21
41–50	29
51–60	31
60+	44

Source: Buzzell and Gale, 1987.

investors. In these three cases, while there may be some scale effects, it is also true that the firms started with (or very quickly achieved) relatively low costs. In other words, they competed as small-share competitors with lower costs and used the low costs to offer lower prices to gain share. Do these companies stand on its head the notion of high share leading to low costs? Or will scale effects make them even more dangerous competitors? These questions are typical of the methodological debates that early PIMS publications inspired.

The importance of the questions addressed increased the visibility of findings and fueled the intensity of the subsequent debate on the validity of the findings and interpretations. Methodological questions that PIMS raised concerned the ability to derive prescriptions from descriptive (generally, cross-sectional) data. The debates around the interpretations of patterns in the PIMS data also generated a (generally) fruitful discourse on how to model causal relationships with panel data. This debate spawned a number of opinions and exchanges concerning how to account for the potential effects of unobserved variables, such as management skill, luck, or other resources. The trail of the original theses and antitheses can be found in a series of articles:

1. Buzzell, Gale, and Sultan (1975), "Market Share – A Key to Profitability."
2. Rumelt and Wensley (1981), "In Search of the Market Share Effect."
3. Jacobson (1990), "Unobservable Effects and Business Performance."

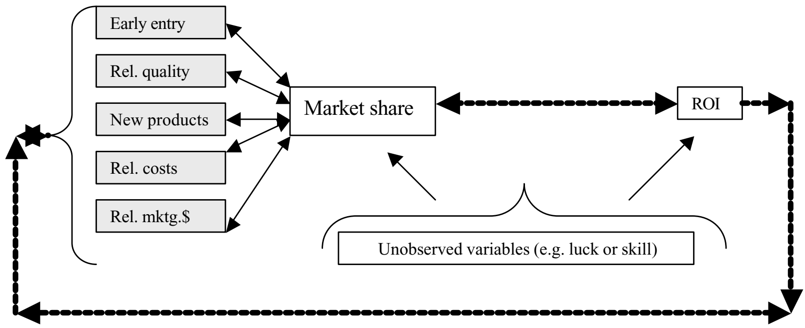

Figure 1.1. The share–ROI debate: does share cause ROI? Or, does ROI cause share? How do businesses gain share? Might "unobserved variables" (e.g. luck or skill) cause both? What causes share?

4. Phillips, Chang, and Buzzell (1983), "Product Quality, Cost Position and Business Performance: A Test of Some Key Hypotheses."
5. Jacobson and Aaker (1985), "Is Market Share All That It's Cracked Up To Be?"

There was some tendency toward polarization of positions, and more advanced econometric techniques often did not settle disagreements on how to interpret the analyses. Figure 1.1 depicts the debate that pitted various econometric attempts to isolate the influences of controllable variables such as quality versus "unobservables." Inevitably, some businesses left for various reasons, and even after recruiting new businesses, the result was that PIMS analyses had only limited time-series data available. On the other hand, published research increasingly pitted time-series advocates against those who favored cross-sectional studies. Occupying center-stage in these debates was the role of market share and profitability as well as the inevitable disputes concerning the leads and lags characterizing the relationship.

Because the PIMS data became available (eventually) to critics and supporters alike, the same data have been analyzed (and reanalyzed) with many different models developed by researchers with different perspectives and modeling philosophies. This availability has fostered a continuing dialogue that has often been frustratingly impossible with other databases. It was not only the availability but also the quality of the data that enabled a series of researchers to replicate and extend earlier published analyses. As we show in Chapter 3, compared to COMPUSTAT, which had a similarly large number of observations

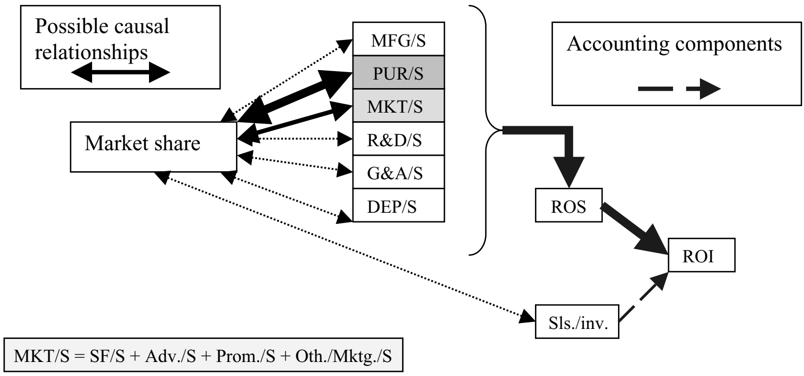

Figure 1.2. A view of the accounting components of ROI. Disaggregation of the ROI measures into the accounting components may shed light on the likely empirical causes of the covariance between market share and ROI. The size of the arrows represents the extent to which differences in these accounting components explain the empirical covariance of share and ROI. Purchases and marketing/sales are dominant.

and even fewer variables, the extent of missing variables in PIMS data is relatively small.

Further, the sheer number of variables that PIMS collected and the large number of observations provided degrees of freedom that, in turn, enabled ever more complex analyses. These were not only of the "What will happen if we account for . . . ?" type of extension, but also included totally different perspectives on the same questions. For example, developing a parallel accounting-components view of the structural share–ROI relationship provided new insights. Figure 1.2 and Table 1.4 show how ROI can break down into different categories of costs and investment intensity.

These alternative views of the share–ROI relationship do not represent causal paths in the usual sense of the word. However, accounting components provide a relatively "error-free" lens for viewing alternative causal explanations of the share–ROI relationship. First, this view suggests that high-share businesses do not have higher ROIs because of a greater sales/assets ratio, but because of a higher ROS. (ROI = ROS * sales/assets). Further, we can see that although purchases would normally be considered a "variable" expense (meaning it is relatively constant as a percentage of sales as sales increase), differences in the

Table 1.4. ***Low-, average-, and high-share businesses: a comparison of ROI and accounting-components means (Standard deviations in parentheses)***

	SBU share		
	0–14.6%	*14.61–31.0%*	*31.0%+*
Share	7.97 (3.79)	22.26 (4.85)	48.94 (12.58)
ROI	8.3 (25.2)	17.1 (26.7)	29.8 (37.0)
S/I (sales/investment)	2.02 (1.26)	2.01 (1.64)	2.16 (1.13)
ROS (return on sales)	2.6 (16.2)	8.1 (10.1)	13.2 (12.6)
Purchases/sales	48.9 (17.5)	45.9 (16.2)	42.7 (16.1)
Manuf./sales	24.8 (13.0)	26.6 (12.0)	25.0 (12.0)
Depreciation/Sales	2.6 (3.0)	2.4 (1.9)	2.2 (1.5)
Marketing/sales	11.2 (9.9)	9.2 (8.2)	8.6 (7.5)
R&D/sales	2.1 (7.3)	2.0 (2.7)	2.0 (2.8)
Other admin./sales	6.9 (5.2)	6.0 (4.4)	6.3 (5.4)
Rel. price	1.04 (9.3)	1.05 (8.9)	1.06 (8.8)
Number of observations	934	950	902

Note: ROI = S/I * ROS; ROS = 100 – purchases/sales – manuf./sales – depreciation/sales – marketing/sales – R&D/sales – other admin./sales.

purchases/sales ratio "explain" in an accounting sense most of the covariance between share and ROS. While vertical integration is a possibility, spreading fixed cost over a larger volume of production is less likely to be consistent with these patterns.

As we show in Chapter 3, PIMS data were unique in providing the detailed pictures of accounting components with a minimum of missing variables. Such detailed data made it possible for researchers to conduct increasingly sophisticated analyses and replications of PIMS-based research. Only the FTC's Line-of-Business (LOB) data are comparable with regard to the detail of the financial variables reported, and PIMS can claim the lion's share of credit for inspiring the creation of those data.

Other projects inspired by PIMS include the ADVISOR project, which focused on industrial advertising. The questionnaires of both the ADVISOR and the LOB show the strong imprint of the PIMS project. Although marketing has a long history of databases that have been shared among researchers to enable replications and comparisons of methodologies (e.g. Lydia Pynkham data), the visibility and success of PIMS, we believe, encouraged the practice of sharing data among wider communities of researchers.

Appendix: The use of PIMS-based performance measures in international research on organizational culture and climate, innovativeness, and market orientation (John U. Farley)

The motivations for the use of subjective performance measures are multiple, but they include a number of the known benefits of one of the PIMS system's approaches – comparative self-reports of performance. PIMS developed these measures in part to create a system that focuses on individual lines of business, rather than aggregates of highly diverse multiproduct, multimarket businesses that characterize many large corporations. (One major contribution of the PIMS project was to calibrate the importance of the line-of-business data and corresponding corporate aggregates.) PIMS developed these comparative performance measures in part because of considerations of confidentiality. We have found that the comparative performance measures impart additional benefits in comparative international research.

1.A.1 PIMS-like comparative self-evaluations of performance

One contribution of PIMS was the developing and testing of a series of performance measures in which respondents were asked to compare their firm with other firms that are well known, in competition, or both (Buzzell and Gale 1987). These comparisons are generally made on five-point scale items centered at 3, which indicates about the same level in the item under study. The values of 1 and 2 on the scales indicate "much lower" and "lower," respectively. Values of 4 and 5 similarly indicate "higher" or "much higher," respectively.

Use of self-reported performance measures internationally

These types of performance measures were used in a series of international studies involving personal interviews with managers of business-to-business firms in seventeen cities located in eleven countries (Deshpandé and Farley 2004). Four such items were used to construct a performance scale: profits, growth, size, and relative market share.

In the questionnaire, two items were reversed to check calibration of responses.

The explanatory variables of performance were established measures of organizational culture and climate, innovativeness, and market orientation drawn from literatures in organizational behavior, performance, and marketing.

The entire questionnaire is contained in an appendix to an article by Deshpandé, Farley, and Webster (1993).

Reliability and validity of self-reported comparative performance measures

The reliabilities of the performance scale constructed from the self-reported comparative performance items were remarkably consistent over the six published studies summarized by Deshpandé and Farley (1999, 2004). The respective Cronbach α's were: Japan .78, five industrial countries .71, six Asian countries .80, China and Vietnam .71, Hong Kong .80, and six cities of the People's Republic of China .68. Among the eight scales used in these studies, the performance measure was the most reliable. Various researchers who use reliability as a major criterion in development created the other seven scales.

One measure of validity was the significant positive correlation between the subjective performance measures reported by a sample of US companies and corporate performance measures derived from public sources. (It is important to interpret this result in the light of level-of-aggregation differences of the business-level subjective measures from the corporate aggregates of multiproduct, multimarket firms; this problem tends to reduce the correlations.)

Another measure of validity is in the consistency of relationships with the hypotheses about how the subjective performance measurements should relate to other scales measuring organizational culture and climate, innovativeness, and market orientation (Deshpandé and Farley 2004). Of 41 regression coefficients from the countries listed above in the discussion of reliability, 40 had the hypothesized signs and 26 of these were statistically significant.

1.A.2 Why are comparative self-reports of performance useful?

We do not question the desirability and usefulness of objective measures of performance, and they should certainly be used when they are available. Whenever possible, subjective measures should be validated with objective measures, and we have done so in certain cases. But the subjective performance comparisons also have certain advantages.

Line-of-business focus of the PIMS measures

As mentioned above, PIMS brought attention to the fact that complex multiproduct, multimarket firms are typically in many businesses, each of which has special characteristics. This is of particular importance in trying to assess the impact of marketing, as marketing activities are generally managed at a product-market level, where accounting practices may be highly variable.

Objective measurement highly variable outside the industrial world

Accounting and reporting standards in the economies in transition from central economic planning are highly variable. More broadly, lack of transparency and reluctance to release figures in any kind of research also make objective measures rare and hard to compare internationally. Similarly, stock exchanges outside the industrial world do not necessarily reflect the real market values of firms, although this is taken as routine in the industrial world.

Ability and willingness to answer

We found that the fractions of individual items in comparative performance scales that respondents completed were not significantly different from those of other measures used in the series of studies discussed in this appendix. This indicates both an ability and a willingness to answer self-reporting performance measures of this type in many industrial settings. In pretests of questionnaires that attempted to collect numerical values for performance measures, the majority of subjects were either unable or unwilling to respond.

Cross-study comparability

The studies mentioned above were done serially over a period of some years. A specific benefit of using the comparative measures in this setting is the high degree of cross-study comparability. Of course, all methods also have disadvantages, which are discussed in some detail by Deshpandé and Farley (2004).

1.A.3 Conclusions

Subjective performance measures of the type used in parts of the PIMS studies have had a high degree of reliability in the international research settings discussed here. They have some advantages in organizational research related to marketing, in that they measure at the appropriate point in the organization, as opposed to at the level of the total multiproduct, multimarket corporation. Managers in many countries have been found to understand the concepts, and they are generally willing to answer the questions structured as comparisons – certainly more than they are willing to answer inquiries about numerical values of profits, market shares, etc. Based on substantive results of the studies, the subjective performance measures also seem to have at least an adequate level of substantive validity.

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2 Putting PIMS into perspective: enduring contributions to strategic questions

GEORGE S. DAY

This is an opportune time to put the PIMS program into an historical perspective. Not because it is yesterday's news, but in recognition of its continuing relevance. Indeed, it is striking how well the PIMS framework complements contemporary thinking on strategy-making.

This retrospective view also reveals some continuing dilemmas the field of strategy is struggling to address. While PIMS may not resolve these issues, the framework and the cumulative research using the database help to highlight and properly frame the questions.

The sources → positions → performance framework for assessing the competitive advantages (Day and Wensley 1988) of businesses will guide our exploration of the contributions of PIMS and the evolution of the field of strategy. The *sources* are the resources the firm deploys – their capabilities, assets, and controls – and the strategic choices of markets to serve and competitive positions to pursue. What one sees in the market, from the vantage point of a customer or competitor, is a *positional advantage*. These advantages can be achieved in a myriad of ways through some combination of lower costs and superior customer value (Markides 2001). These positional advantages should translate into superior *performance* (growth, profitability, and economic value creation).

2.1 The evolution of strategy

Firms have always had strategies, whether strategy is viewed as a choice of competitive position; as a collection of rules; as stretch and leverage; as intent; as the embodiment of a firm's values, or in other ways (Markides 2001). The resulting integrated pattern of activities may have been arrived at self-consciously through a logical planning

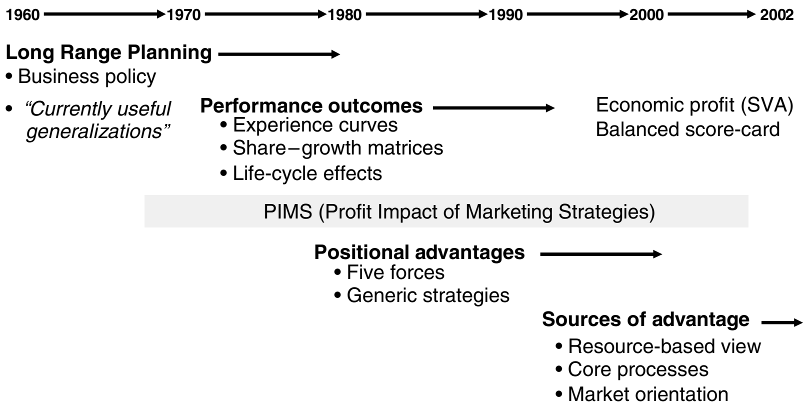

Figure 2.1. The evolution of strategy from a marketing perspective.

process, or as the final outcome of trial and error, learning, and adaptation – or more likely through both these processes.

The field of strategy – as seen in academic writing, consulting practices, and a plethora of books for practitioners – can be traced to the work of military strategists and historians. The most obvious roots are in the loosely coupled frameworks that appeared in the 1960s under the rubric of "Long Range Planning." There is still a significant legacy to be found in the various sequential planning frameworks, typically initiated by the familiar SWOT analysis with considerable emphasis on setting goals and objectives. Analyses were rudimentary, being restricted mostly to cost, revenue, and investments, and to linear forecasting. There were no discernible theoretical frameworks to guide the planning process. Instead, the emphasis was on heuristics and "currently useful generalizations" that were abstracted from rich case studies.

The inadequacies of Long Range Planning set the stage for the field of strategy. This field has evolved through three overlapping phases to arrive at the currently nuanced and deep understanding of strategy. These phases appeared in the reverse order of the sources → positions → performances framework and are schematically shown in Figure 2.1. In effect, the field evolved by working backward along a (presumptively) causal chain to understand better the underlying reasons for observed performance differences.

2.1.1 Phase 1: performance outcomes

This was the era of experience curves, share–growth matrices, and PIMS. Managers greeted each of these warmly because they were rigorous, conceptually appealing, and held out the promise of deeper insights into market mechanisms with clear-cut (albeit simplistic and frequently misleading) prescriptions for resource allocation and strategic action.

During this period, the PIMS program offered the most complete understanding of the consequences of strategy. That story was somewhat obscured during this period by the attention the Boston Consulting Group attracted with its advocacy of strategies for building, maintaining, and harvesting share (Buzzell 2004). This left the impression that market share was a performance outcome, with standing equivalent to growth and profit.

Important contingencies were increasingly considered – notably the growth rate or stage of product life-cycle. In reaction to the simplification of the share–growth matrix, there was development of multifactor business strength–market attractiveness matrices for displaying product-market positions and business units.

Toward the end of this first phase, industry structure analysis became influential through Michael Porter's work (Porter 1980). His model of the "Five Forces" of competition built on the structure → conduct → performance paradigm of industrial organization economics, and received important validation from the PIMS program, which drew on the same theoretical foundation.

2.1.2 Phase 2: positional advantage

During this phase, attention shifted to understanding the industry context and finding an attractive competitive position within an industry that minimized direct rivalry by achieving lower delivered costs or superior customer value through differentiation.

This phase peaked in the mid-to-late 1980s and was marked by active interest in strategic typologies, generic strategies, and the attributes of advantage such as superior perceived quality, and channel relations. The PIMS program was influential in clarifying the importance of relative quality as a measure of differentiation, and demonstrated there was not a cost penalty to higher quality levels.

Also during this phase there was increasing use of economic theory to explore strategic issues, ranging from transaction cost analysis to game-theoretic studies of entry and exit strategies, and the influence of producer reputations. Academic usage of the PIMS database was especially high because the dual roots in industrial organization economics and marketing fitted well with the research interests of this period.

2.1.3 Phase 3: sources of advantage

This phase shifted the center of gravity of the field from outside to inside the firm. The central question was how positional advantages and performance outcomes derived from relative superiority in the skills, assets, collective learning, and prevailing values and culture that were embedded in the firm, and the ability of management to align and marshal these resources (Amit and Schoemaker 1993; Barney 1991). In effect, we had a belated recognition that what really matters is the specific actions that management takes to innovate with products and processes, enhance product and service quality, shorten the time-to-market, and build strong customer and channel relationships.

The transition to phase three was signaled by the enthusiastic reception given to the concepts of core competence and competing on capabilities. Because capabilities proved so difficult to identify, most of the attention was on self-contained aspects such as coordinating diverse production skills, harmonizing streams of technology, and organizing work processes. This proved to be a very internal view of competencies, potentially subject to a circular logic that dealt with only a part of the chain of causality. The early work stopped at the point of observing that successful businesses outperform their rivals because they have superior resources. Hardly a solid base for prescription! These problems are being addressed by specifying the conditions under which capabilities are valuable, such as scarcity (is it imitable or substitutable, and is it durable?) and appropriability (who owns the profits?). This has led to a significant stream of research on the sustainability of competitive advantages.

The interest in capabilities exercised within processes, and the associated resource-based view of the firm, fitted well with the emphasis of the early 1990s on delayering, restructuring, and reengineering, since they required a reconception of the firm as a collection of linked processes. This phase ran its course by the mid-1990s as the strategic priorities moved from reducing costs and cutting assets to achieving growth and renewal.

This "capsule" history has highlighted the mainstream work on the *content* of strategies. Valuable parallel work also was progressing on the *process* of making strategies. According to this point of view, strategies are more likely to emerge from piecemeal, interim responses to events over which management has little control, than through the analytical planning methods of matching opportunities with capabilities. Work by Quinn, Mintzberg, and others has attempted to gain insights into the organizational processes, which yield a strategy as a somewhat unintended consequence. Mintzberg summed up this perspective by arguing that "strategy making requires insight, creativity and integration, whereas planning is about analysis and decomposition." This leads him to conclude that the term strategic planning is an oxymoron. While this is surely an overstatement, all researchers should be sympathetic to his viewpoint.

Each succeeding phase has left its legacy, even as new insights into the nature and origins of strategy have moved into the foreground. Thus, economic profit and the balanced score-card have respectable roots in the prior work on performance outcomes. Indeed, the balanced score-card owes a major debt to the indicators and measures that were first developed for the PIMS program.

2.2 A resource–based view of PIMS

Although the conceptual and empirical foundations for the PIMS program were laid fifteen years before the resource-based view of the firm was rigorously specified, Bob Buzzell and his colleagues anticipated the inherent distinctions between the sources and positions of competitive advantage that account for sustained differences in firm performance.

The essence of the resource-based view is that when a firm's resources are valuable, durable, superior to those of rivals, and difficult to imitate or substitute, they are the basis for a sustainable competitive advantage. A key premise of the resource-based view is that resource and capability development is a selective and path-dependent process (Dierckx and Cool 1989).[1] The development process is selective in that firms choose

[1] The resource-based view is usually traced back to Wernerfelt (1984), although a good case could be made that Edith Penrose was the first to articulate the core ideas.

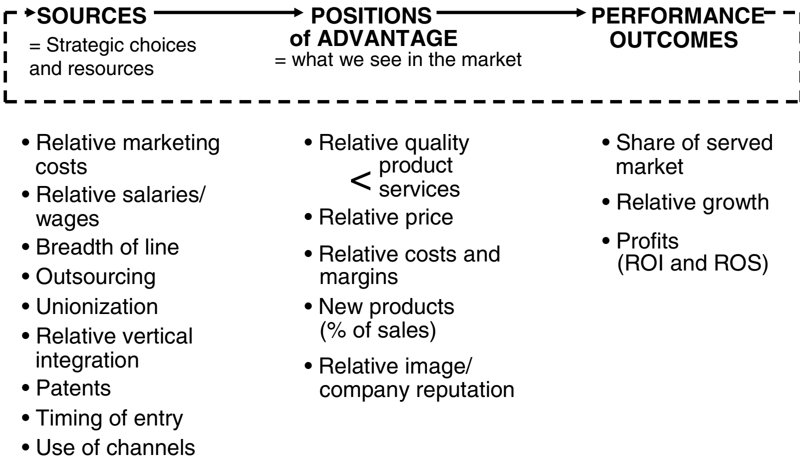

Figure 2.2. A framework for value creation: recasting the PIMS variables.

whether to make a capability the central thrust of their strategy or a subordinate element. The process exhibits path dependency in that firms build on what they know and on their past successes. Behind the immediate strategic choices are prior choices that sensitize the firms to certain possibilities and create a knowledge platform on which they can keep building. Thus, we expect that firms that are demonstrably superior in managing customer relationships will have both a strategy thrust that emphasizes relational value through superior service quality, and a superior customer-relating capability.

It does not take too much imagination or force-fitting to recast the PIMS variables into the sources → positions → performance framework as I have done in Figure 2.2. This is instructive for two reasons. First, it shows that PIMS was indeed ahead of its time. But it also shows how PIMS would have benefited if it were being developed today with the guidance of the work of the strategy field over the past thirty years.

2.2.1 *Sources of advantages*

For some years there has been a debate about whether strategy-making is an *outside-in* process (starting with the market and seeking attractive positions to occupy) or an *inside-out* one (starting with existing capabilities and searching for opportunities to use them). The answer is surely that both processes are operating iteratively as strategies evolve and adapt. This also means that a superior resource, whether a patent, a customer-relating capability, or a manufacturing process, is unlikely to be a productive source of advantage unless it supports and is guided by a competitive strategy.

The PIMS variables that seem to capture the sources of advantage are generally better at representing strategic choices than assets or capabilities. Indeed, PIMS is mute on the three main capabilities that are exercised through the core customer relationship management (CRM), supply chain management (SCM), and innovation management (IM) processes (Srivastava, Shervani, and Fahey 1999). This is not surprising, as this trichotomy has been accepted only recently and the capabilities exercised through these core processes have proven difficult to measure.

While we would classify only patents and timing of entry as assets that can be leveraged with capabilities, a case could be made for also including relative brand image/reputation as an asset rather than a positional advantage. Brand image/reputation is a tradeable asset that can be valued as brand equity. It also reflects the positive associations that target customers have of the brand, based on their experience, and thus reflects what the business has achieved in the market, which is the defining feature of a positional advantage.

2.2.2 Positional advantages

The nature of the positional advantage one pursues is the defining feature of most classifications of competitive strategy, including Porter's (1980) differentiation versus lowest delivered cost, Treacy and Wiersema's (1995) customer intimacy versus operational excellence versus performance superiority, and Mittal and Sheth's (2001) performance, price, and personalization components in the customer value space. The latter two classifications distinguish product advantages – reflecting superior value through quality, performance, and price of the core offering – from relational advantages, which imply that customers get superior value through better service, responsiveness to their individual problems and needs, and ease of collaboration.

The distinction between product and relational advantages adheres closely to what Coviello *et al.* (2002) call transactional versus relational marketing. They argue that most successful strategies are a hybrid of the two types of marketing. Relationships cannot be developed and sustained if product quality is unacceptable, the underlying technology is out of date, or the product is persistently unavailable. Similarly, we do not preclude the possibility that firms enjoy both product and relational advantages.

In my view, the path-breaking aspect of the PIMS database was the inclusion of the relative quality measure. As Buzzell (2004) notes, the findings on the role of quality changed the prevailing conversation about strategy. Not only did PIMS researchers demonstrate that superior quality (appropriately accounting for the market share effects) had a strong, positive association with profitability, but they also showed how important it was to encompass holistically both the core product and the service augmentation.

It is a moot point whether the percentage of sales from new products reflects a positional advantage, due to the customer benefits that innovation offers, or should be a source of advantage because it is both a strategic choice and a measure of the innovation management capability. I classify it as a positional advantage here because the sales from new products are an outcome of the innovation processes rather than an input.

2.2.3 Performance outcomes

Neither relative growth nor profitability is a controversial measure, although the way PIMS measures ROI does not fully capture economic profit, since there is no way to recognize the cost of capital. If PIMS were being developed today, it would surely include relative rates of customer retention and perhaps customer satisfaction.

Whether share of market is a performance outcome is more controversial. Some would argue it is simply a proxy for scale and thus is a positional advantage. I am following Buzzell (2004) here in treating market share as an outcome that reflects the relative ability of a business unit to satisfy customer requirements.

2.3 Enduring questions for strategy

C. K. Prahalad (1995) once described the state of research in management as a silent, ongoing battle between weak signals from the realm of management practice, and strong well-developed paradigms in the established fields of scholarly inquiry. Often the early signals of a major shift in substantive areas of interest of management practice are either ignored or misinterpreted with existing academic tools and established paradigms.

Research in strategic marketing is not immune to this problem. We would have to plead guilty to developing theories based on the assumption that market structures are stable and market boundaries are clear and static, despite the reality that boundaries are blurring and competition and cooperation exist side-by-side in many markets. However, there are many other dilemmas that create pulls on the field from seemingly opposite directions. The resolution of these dilemmas, or the ability to address several seemingly contradictory things at the same time, will influence the next stage of evolution (Day 1998) in the field of strategy.

2.3.1 Theories versus concepts

Practitioners frequently ignore academic research because it focuses on theories that specify the relationships between constructs and then tests the relationships between the variables that operationalize these constructs. While those tests are essential to the cumulation of scientific knowledge, the necessary abstractions are far removed from the context of these managers. What is often more valuable to managers are the conceptual frameworks, typologies, and metaphors that are the precursors to the actual theory-building. Managers absorb this language into the mental models that guide their actions.

The complexity of many theories further limits their managerial value. There is a paradox in the strategy and organization literatures between the espoused view of managerial behavior as boundedly rational, constrained by rules and procedures, and continually satisfying, and the complexity of the world that is implied by the measures and methods applied to these behaviors. The continuing challenge will be to find simpler, yet robust models for describing important phenomena.

2.3.2 Strategy content versus process

Another dilemma for strategy research is the division of research into two distinct camps based on different assumptions about the rationality of decision-making. The strategy content camp is populated with management scientists and economists using rigorous models and large databases to study well-defined choices and observable outcomes. By contrast, the process camp sees strategy-making as a complex stream of trial-and-error moves, reactions, and reflections, rather than discrete choices. Communication between the two camps is impeded by the use of different vocabularies, methods, and theories. To borrow a metaphor, strategy process research is full-color cinematography, whereas strategy content research is more like a black-and-white freeze-frame photograph.

This is something of a false dichotomy, for the approaches are increasingly complementary. For example, it would appear that content researchers are concerned with the links of competitive position and resource superiority to performance, while process researchers seem less concerned with performance linkages. Yet, if the structure is incorrect and the process of decision-making is dysfunctional, performance will suffer because the strategy cannot be implemented. It is both ironic and encouraging that the resource-based view of strategy, with its origins in the content camp, is turning its attention to capabilities that derive from the superiority of organizational processes. Since capabilities incorporate routines, skills, cumulative learning, systems, values, and norms, this shift in emphasis will encourage more convergence.

2.3.3 Rules versus exceptions

Here the enduring question is how to interpret and use empirical regularities. The first difficulty is that the observed results of strategic moves reflect behaviors constrained by industry rules, norms, and conventional wisdom, and that are susceptible to a survivor bias. We are usually unable to observe the results of either failed processes or strategies. Not only are we mostly studying organizations that survive, but the resulting theories are based on those that survive and are willing to be studied.

A more profound problem is that any first-order economic law, such as "invest to increase market share in rapid growth markets," cannot be acted on because it contradicts the economic principle of rational expectations. Since everyone can be expected to use such a general rule in the same way, it does not offer a basis for differentiation. This is leading scholars and insightful practitioners to seek exceptions to the general rules.

Consider how companies such as CNN in broadcasting, Virgin in airlines, and Samsung in semiconductors have been able to surmount traditional barriers to entry. By exploiting technology and offering a superior value proposition, they created an exception to the rule. Often it was the incumbents who had difficulty adjusting because the commitments that were supposed to protect them actually constrained them.

2.3.4 Objective versus enacted reality

The normative strategy literature implicitly assumes that market environments are objective and independent entities waiting to be discovered, and that managers are rational and well-informed information processors, using their conceptual frameworks to formulate and choose strategies. A revisionist view is challenging this assumption and stating that what matters is how managers enact this environment in the mental models they use to simplify and make sense of their environment. Proponents argue that such constructs as markets, segments, competitive forces, and entry barriers are abstractions given meaning through processes of selective perception and simplification. These processes are learned through experience, shared through industry conventional wisdom, warped by functional biases, and tempered by the ready availability of data. Thus far, this competing view has little influence on research in strategic marketing despite persuasive evidence that these enactments matter.

2.4 Summary

The field of strategy has evolved continually over the past forty years. Our retrospective view sections this evolutionary path into three overlapping phases to demonstrate that PIMS has contributed to these advances during each stage. Indeed, the underlying theoretical framework on which PIMS was originally built over thirty years ago anticipated some of the important developments such as the resource-based view of the firm. Familiar concepts that are embedded in the received wisdom of the field of strategy, such as the contribution of perceived quality to positional advantages, or the desirability of a diverse array of metrics in a balanced score-card, have their genesis in PIMS findings.

But during that forty years, the strategy environment has changed – sometimes out of recognition – as market boundaries have blurred, competition and collaboration increasingly coexist, durable relationships transcend transactional activities, and incumbent advantages are under siege. While PIMS can speak to some of these issues, we are still left with some real and durable dilemmas whose resolution will influence the next stage of evolution. It will require initiatives with the scale and imagination of PIMS to address these issues.

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3 *PIMS and COMPUSTAT data: different horses for the same course?*

D. ERIC BOYD, PAUL W. FARRIS, AND LUTZ HILDEBRANDT

FOR researchers investigating questions related to marketing strategy and financial performance, there are few databases that are, in any way, comparable to PIMS. However, COMPUSTAT is one database that researchers have used frequently to address such questions. Other databases that provide limited additional points of comparison are that of the Inland Revenue Service (IRS) and the Federal Trade Commission (FTC) Line of Business data. In this chapter we will provide some comparisons between PIMS and COMPUSTAT data.

From the beginning, researchers were impressed by the "overwhelming superiority of PIMS data to other sources in quantity, number of measured variables, timeliness, [and the] conscientious attempt to minimize potential sources of input error" (Anderson and Paine 1978). Of course, the "timeliness" of the PIMS data is no longer a strong point and, since 1990 or so, publications of empirical findings based on the PIMS data have appeared far less frequently in major marketing and strategy journals – published articles have declined along with the size and currency of the data.

On the other hand, publications based on COMPUSTAT data are appearing with increasing frequency in marketing journals. Further, many of the issues addressed by researchers using COMPUSTAT are similar to those addressed with analyses of the PIMS data. For example, both COMPUSTAT and PIMS data have been used to study: relationships of market share, firm size, and power to profits; determinants of marketing cost ratios and media budgets; and returns from R&D and new products activities, and patents.[1]

The authors are grateful to Kusum Ailawadi and Michael Moore for helpful comments in developing the material for this chapter.

[1] Some examples of PIMS-based research include Ramaswamy, Gatignon, and Reibstein (1994) and their examination of competitive marketing

It is important to know whether PIMS and COMPUSTAT simply provide different perspectives on the same fundamental economic activity or whether these two databases describe quite different samples of firms and businesses. Determining the similarity between PIMS and COMPUSTAT will help researchers answer several important questions, including:

1. Is PIMS still viable as a data source for studying marketing strategy?
2. Are PIMS-based findings applicable in building hypotheses for testing using COMPUSTAT data?
3. Can research from these two datasets be combined in a way that enhances both?

In order to address these questions, this chapter compares key financial ratios of firms in the COMPUSTAT data with the same ratios for strategic business units (SBUs) reporting PIMS data. These comparisons will help determine whether the financial profiles of PIMS SBUs were similar to the "average" firm in the COMPUSTAT data in the late 1970s. Further, we are interested in how these variables may have changed over time. Analyses based on PIMS data have been used to benchmark marketing costs, profit rates, and asset intensity. Are the PIMS financial ratios still valid bases of comparison?

The chapter is organized as follows. Section 3.1 summarizes research published in selected marketing journals that has relied on COMPUSTAT data. This section also contrasts the construction of key financial ratios in COMPUSTAT with similar ratios in the PIMS data. While profits and aggregate performance variables are similar, there are differences in how gross margins and marketing costs are constructed and defined. In Section 3.2 we use COMPUSTAT data to document the shift in economic activity from manufacturing to services. We then discuss differences in selected financial ratios reported by PIMS SBUs with similar ratios reported by COMPUSTAT samples. This comparison is based on a subset of firms identified by COMPUSTAT in manufacturing SICs in order to accommodate the acknowledged skew of PIMS toward manufacturing businesses. IRS data from a much broader sample of US businesses are used to benchmark both COMPUSTAT and PIMS data on manufacturers. Section 3.3 identifies changes in financial ratios reported by manufacturing firms in 2000 COMPUSTAT data.

behavior; Jacobson and Aaker (1988) and their examination of product quality's contribution to financial performance. Table 3.1 provides an extensive list of references for COMPUSTAT.

Large increases in gross margins, R&D/sales, and depreciation/sales are found. Further, the ratio of sales/assets has declined almost 50 percent. Section 3.4 discusses the definitions of "market share" available in COMPUSTAT and PIMS. We also provide a new test of the potential bias of the PIMS market share measures by using PIMS data to construct an estimate of "served market" size and comparing this to reported market share. The same process serves as a test of the consistency of the data and points to some opportunities for improving these measures. The final section, 3.5, evaluates the potential of COMPUSTAT to provide a database for time-series analyses. Unlike PIMS, which has very little missing data, COMPUSTAT data are shown to be plagued by missing data that will make time-series analyses difficult for studying marketing strategy. We also compute the relative extent of time-series and cross-sectional variance in COMPUSTAT and PIMS.

3.1 Growing reliance of marketing strategy research on COMPUSTAT data

Increasingly, researchers have turned to the COMPUSTAT database for empirical evidence on research questions that are similar to those addressed with the PIMS data. Table 3.1 is a partial listing of studies and questions that have been addressed with COMPUSTAT and published in mainstream marketing journals.

PIMS data were designed and collected with the specific objective of addressing research questions in marketing strategy. COMPUSTAT data were assembled for other purposes, probably for financial analysis. Therefore, from a marketing research point of view, COMPUSTAT statistics are a database of convenience. However, marketers have become more concerned with the ability to relate marketing strategies to shareholder value and COMPUSTAT data can be linked to stock returns, patent data, merger-acquisition activities, and other public data sources. Some relevant differences between the two datasets are these:

- COMPUSTAT is based on publicly traded corporate entities. PIMS is based on SBUs of companies that are very likely contained in COMPUSTAT data. Certainly, COMPUSTAT and PIMS are both far less representative of the smaller firms that, in the aggregate, play an important role in the US and world economies.

Table 3.1. ***Selected COMPUSTAT-based research in marketing journals***

Author(s)	*Sample*	*COMPUSTAT variables*	*Key finding(s)*
Aaker and Jacobson (2003)	Nine high-technology firms, 1988–96	Firm level (quarterly): stock price, dividends, shares outstanding	Changes in consumers' brand attitudes toward a firm related to a firm's market value.
Rust, Moorman, and Dickson (2002)	100 Fortune 500 firms, 1997–98.	Firm level: net income, total assets, number of employees	Strategies based on revenue expansion positively related to ROA while cost and dual emphasis strategies not significantly related to ROA.
Bloom and Perry (2001)	Selected suppliers to Wal-Mart, 1988–94	Firm level (annual): sales, net profit Industry level (annual): sales, net profit by SIC	Large-share firms benefited from being a Wal-Mart supplier while small-share firms did not.
Houston and Johnson (2000)	Suppliers in joint ventures and contracts with buyers during the years, 1993–94.	Firm level (annual): sales, R&D, book value of assets, stock price, shares outstanding	Suppliers' assets specificity and performance ambiguity related to formation of joint ventures. Suppliers' market value increased with joint ventures while buyers did not.
Dutta, Narasimhan, and Rajiv (1999)	Semiconductor manufacturers, SIC 3674, 1985–94	Firm level (annual): advertising, SG&A, receivables, R&D, employees, wages	SG&A, unlike advertising, contributes positively to marketing capability. Marketing capability positively related to R&D and operational capabilities.

Armstrong and Collopy (1996)	100 large firms, 1974–82	Firm level (annual): total assets, net income	Competitor-oriented strategies negatively related to ROI.
Ailawadi, Borin, and Farris (1995)	Manufacturers and retailers, 1982–92	Firm level (annual): sales, cost of goods sold, SG&A, advertising, inventory, total assets, SIC	Retailers' EVA and MVA increased at a significantly lower rate than manufacturers' during study period.
Farris and Ailawadi (1992)	Food manufacturers and retailers, 1971–90	Firm level (annual): sales, cost of goods sold, net profit after depreciation, interest and extraordinary items, net profits before and after taxes, total assets	Food manufacturers' margins, ROSs, and ROAs increased faster than retailers' margins during the study period.
Kumar, Kerin, and Pereira (1991)	Retailers, 1970–85	Firm level (annual): sales, cash flow, total assets, book value, debt, retained earnings Industry level: sales by SIC	Likelihood of retailer being a bidder in acquisition positively related to firm market share and the ratio of cash flow to total assets.
Balasubramanian and Kumar (1990)	Firms from various SICs, 1975–84	Firm level (annual): sales, advertising, profit margin Industry level (annual): sales	Market growth is negatively related, while market share is positively related to marketing communication intensity.

- COMPUSTAT data are undisguised and may be verified and augmented with other documents such as annual reports; PIMS data cannot be attributed to a specific company or industry and the data offer no means for independent verification of individual values. However, comparison of aggregate statistics may confirm general validity.
- COMPUSTAT data, compared to PIMS, are relatively inconsistent with respect to what is reported (quite often, advertising and R&D are not reported separately), with much less emphasis on marketing variables of interest.
- COMPUSTAT data are available for longer periods of time, more than thirty years in many cases. PIMS collected data on an annual basis beginning in 1970 and ending, in the United States, in 1987. At its peak in 1976, PIMS collected data from 1728 SBUs. As of 2003, PIMS data are still collected for European businesses, but are no longer collected in the United States (Buzzell 2004).

COMPUSTAT does have a section of the database that provides a limited amount of financial data at a business segment level, but attempts to calibrate the distribution of sales from the corporate to business segments proved unsuccessful. Communication with staff at Wharton Research Data Services, the organization responsible for managing and maintaining COMPUSTAT, indicated that firms have wide discretion in distributing sales across business segments. Beginning in 1997, under the newer SFAS 131, a "management approach" is taken, in which information on business segments is reported based on how management internally evaluates the operating performance of its business units (Berger and Hahn 2003).

Financial variables that have similar names in both databases are not always comparable in construction. Table 3.2 illustrates the differences in definitions for key financial variables available in COMPUSTAT.

From Table 3.2, we conclude that COMPUSTAT does not offer the same conceptually valid definitions of two key ratios: gross margins and marketing spending. COMPUSTAT includes physical distribution expenses in SG&A (although there appears to be a wide degree of latitude in what may or may not be reported as part of SG&A).[2]

[2] According to the definition of SG&A outlined in the COMPUSTAT Data Guide, SG&A includes the following items when not broken out separately: accounting expense, advertising expense, amortization of R&D, bad debt,

Table 3.2. ***Comparison of COMPUSTAT and PIMS variable compositions***

COMPUSTAT variables include these accounting items	*Accounting items*[2]	*PIMS variables include these accounting items*
cost of goods sold (a + b)	a. purchases	purchases costs (a)
	b. manufacturing expense	manufacturing & distribution costs (b + c)
sales, general & administrative expense (c + d + e + f + g + [sometimes] h[1])	c. distribution expense	
	d. promotional costs	promotion costs (d)
	e. other marketing	other marketing (e)
	f. sales force	sales force expense (f)
	g. other administration	other administration (g)
advertising[1] (h)	h. media costs	media costs (h)
depreciation expense (i)	i. depreciation expense	depreciation expense (i)
R&D expense (j)	j. R&D expense	R&D expense (j)
net income (k)	k. net income = 1 – sum(a–j)	net income (k) = l – sum(a–j)
sales (l)	l. sales	sales (l)
assets (m)	m. assets	assets (m)

Notes: [1] Compared to PIMS, COMPUSTAT probably overstates margins by excluding variable costs of distribution. SG&A for COMPUSTAT should be larger than PIMS' total marketing (d + e + f + h) plus other administration (g).
[2] Advertising in COMPUSTAT is reported separately when broken out from SG&A by the reporting firm.

Neither COMPUSTAT nor PIMS attempts to separate fixed from variable costs in order to compute what marketers often refer to as contribution margin, or economists as marginal costs. Hence we believe that either database can provide approximately similar margins "before marketing, depreciation, R&D, and some (ill-specified) administrative costs." However, COMPUSTAT does not report a separate item for

> commissions, corporate expense, delivery expense, director's fees, engineering expense, foreign currency adjustments, freight-out expense, labor and related expenses, legal expense, marketing expense, patent company charges for administrative expenses, recovery of allowances for losses, company-sponsored R&D, research and development expense, severance pay, state income tax, strike expense, and stock-based compensation.

marketing expenses, but lumps these together with other administrative expenses. Marketing spending in COMPUSTAT will likely be overstated because of the inclusion of administrative expenses that are not directly associated with marketing activities. On the other hand, advertising costs in COMPUSTAT, which are (sometimes) included as a separate item, understate total marketing costs significantly. (See Chapter 8 for a discussion of advertising as a percentage of total marketing costs.) Because of these differences between the two databases in how important variables are defined, comparisons of gross margins and value-added will be somewhat problematic and comparisons of marketing expenses should be made with extreme caution.

Other important variables that are often linked with marketing strategy choices or outcomes include R&D intensity, asset intensity, and profitability. Specific ratios calculated from COMPUSTAT and PIMS data include: R&D/sales, depreciation/sales, ROA (return on assets), and ROS (net profit/sales). As Table 3.2 illustrates, there appear to be relatively few differences in how PIMS and COMPUSTAT define these variables.

Even for variables that are defined similarly, there are likely to be differences in average values of financial ratios resulting from the PIMS' SBU unit of observation compared to COMPUSTAT's firm-level aggregation of SBUs. The process of creating SBU statements for operating income and balance sheets inevitably involves somewhat arbitrary allocations of shared costs and assets. Income statements constructed at the SBU level are likely to be "purer"[3] reflections of the business unit strategies and cost structures, but there are nagging questions about whether all costs and assets are accounted for in the process of disaggregating multidivisional firms into such SBUs. If all costs and assets are completely, even if arbitrarily, allocated to SBUs, then we believe that financial averages should be comparable for large samples of PIMS SBU and COMPUSTAT firms. Comparison of sales/assets and depreciation/sales ratios may show differences in corporate and SBU ratios if not all

[3] Of all firms reporting data in Compustat for 2000, 48 percent (1008/2097), those with a primary SIC in manufacturing report sales in a business segment outside of manufacturing according to the business segment level data available from COMPUSTAT. Analysis of COMPUSTAT segment level data also shows that 39 percent (813/2097) of firms with a primary SIC in manufacturing operate in a single manufacturing SIC.

Table 3.3. ***Distribution of selected types of businesses in COMPUSTAT data, 1980 and 2000***

	1980			*2000*		
	Number of firms	*Percentage of firms*	*Percentage of total sales*	*Number of firms*	*Percentage of firms*	*Percentage of total sales*
Manufacturing	2707	43	58	3690	36	43
Services	2262	36	27	5140	50	42
Retail/Wholesale	711	11	12	855	8	12
Other	570	9	4	568	6	3
Total	6250	100	100	10,253	100	100

Notes: Distribution of business types based on standard industry classifications (SIC) reported in the Industrial COMPUSTAT database for the year of analysis. The SICs included in the classifications were: manufacturing, 2000–3999; services, 4000–4999 and 6000+; retail/wholesale, 5000–5999; other, 0–1999.

corporate assets are allocated to SBUs. Also, net profits as a percentage of sales may be lower at the corporate level when there are costs associated with managing multiple SBUs or shared resources that are not completely allocated. Finally, since the launch of the PIMS research program, there have been speculations on whether companies participating in PIMS might be larger than the COMPUSTAT average and whether those companies might have selected SBUs for inclusion in PIMS that disproportionately represent strategic successes (Ramanujam and Venkatraman 1984).

3.2 COMPUSTAT and PIMS: key financial variables for manufacturing SBUs/SICs

Our comparison of PIMS and COMPUSTAT focuses on manufacturing SBUs and SICs, respectively. PIMS data have an acknowledged skew toward manufacturing businesses and larger firms. There are only a few (less than a hundred in 1982) service and retail SBUs in the PIMS data. Table 3.3 compares the percentages of firms and sales reported by firms that COMPUSTAT classifies to selected sectors (based on SICs). The data are reported for 1980 and 2000. The table confirms the often-noted trend toward services, but, perhaps surprisingly, there are now more firms in each of the three major sectors: manufacturing, services, and retail/wholesale. Services have more than doubled the number of reporting firms, while sales have grown about 50 percent. Relatively (ratio of percentage of sales to percentage of firms), manufacturers are still larger than services. By this measure of concentration, however, retailers clearly dominate in 2000, in contrast to the position in 1980.

For further comparisons of COMPUSTAT and PIMS, we attempt to minimize sample differences by restricting our analysis to manufacturing businesses. As we show below, further restriction to larger firms is required to achieve ratios that are similar to the averages reported by PIMS.

Table 3.4 provides comparisons, for 1980, of selected financial ratios of companies with manufacturing SICs and PIMS SBUs identified as manufacturing businesses. In addition, a third reference point is provided by IRS data on manufacturing companies. IRS data provide a more comprehensive picture of the universe of all US businesses. Although not all ratios are available from each of the sources, when possible we report a nested group of ratios that have the following relationship to each other:

a. 100 – COGS/sales = margin/sales
b. margin/sales – SG&A/sales – R&D/sales = EBITDA/sales
c. EBITDA/sales – depreciation/sales = ROS
d. ROS * sales/assets = ROA

where COGS = cost of goods sold; SG&A = selling, general, and administrative costs; EBITDA = earnings before interest, taxes, depreciation, and amortization; ROS = return on sales; and ROA = return on assets. Tables 3.11 and 3.12 in Appendix 1 to this chapter provide the definitions for each variable analyzed, along with the actual data items pulled from PIMS and COMPUSTAT, respectively, in constructing the variables above.

Tables 3.4 and 3.5 provide a separate set of statistics for the firms in the COMPUSTAT and IRS data that reported assets greater than $250 million in 1980 and 2000. In addition, for COMPUSTAT, the averages are calculated in two ways. “Total” ratios are the ratios of the sums of all items. For example, the sum of sales, general & administrative (SG&A) expenses for all firms in the sample is divided by the sum of sales for all firms to calculate the total SG&A/sales ratio. Companies with missing values for any of the variables listed in Tables 3.4 and 3.5 are excluded in order to report averages that are less likely to be inflated with unreported items in other categories.[4] "Firm" ratios are first calculated for each company, and averages are then computed for the sample with no weighting for different sales levels.

A further, interesting difference relates to the gross margins and SG&A figures for the total and firm averages. For both 2000 and 1980, the pattern is the same: total margins are higher and SG&A is lower by roughly the same amount. For the sample of larger businesses, this pattern hold true. PIMS values for margins and SG&A are much closer to the firm averages in COMPUSTAT than to the total averages.

In addition, we can see in Table 3.4 that there are significant differences between the total and firm ratios for the sample of all manufacturing firms with no filtering for minimum sales. Applying a filter of \$250 million assets substantially reduces the differences between total ratios and firm ratios, primarily by making firm ratios more comparable to aggregate ratios. It appears that if researchers are interested in studying companies that might be considered representative of total sales and expense patterns, the PIMS data are closer to the mark than an unfiltered COMPUSTAT database.

Notable differences in COMPUSTAT data and PIMS data include the higher return on assets that appears to be primarily attributable to higher sales/assets ratios reported for PIMS SBUs. The higher ratios are accompanied by lower depreciation/sales, and somewhat higher R&D/sales and SG&A/sales for PIMS. We speculate, but cannot demonstrate, that the higher sales/assets and lower depreciation/sales ratios for PIMS are due to some depreciable assets not being allocated to the individual SBUs reported in PIMS data.

We have not attempted to compare standard deviations, because, as Marshall and Buzzell (1990) noted, the PIMS data "have been audited and cleaned, and extreme values suppressed . . . to the value represented by 2.75 standard deviations above or below the same mean for a given variable." However, those who do wish to compare these standard deviations should see Tables 3.13 and 3.14 in Appendix 1 to this chapter.

Tables 3.4 and 3.5 also show that unless one screens the COMPUSTAT data for companies above a certain level of sales, the

[4] For example, if we included companies that did not report R&D, the averages for SG & A or COGS are more likely to be inflated with the addition of some aspects of R&D to one or both of these categories.

Table 3.4. *Financial ratios for manufacturing businesses/firms, 1980*

	All firms			*$250 million + assets*			*All*
	Total IRS	*Firm COMPUSTAT*	*Total COMPUSTAT*	*Total IRS*	*Firm COMPUSTAT*	*Total COMPUSTAT*	*SBU PIMS 1979–82*
ROA%	6.77	8.37	11.67	7.38	12.19	11.62	18.25
Sales/assets	1.41	1.44	1.38	1.16	1.39	1.38	2.06
ROS%	10.23	−22.39	8.44	8.05	9.48	8.43	7.89
Depreciation/sales	–	4.51	3.52	–	3.15	3.57	2.35
EBITDA/sales	–	−17.88	11.96	–	12.63	12.00	10.25
R&D/sales	–	7.86	1.97	–	2.19	1.95	2.03
SG&A/sales	–	36.38	10.62	–	15.38	10.26	16.33
Margin	–	26.36	24.54	–	30.20	24.21	28.59
COGS/sales	70.11	73.64	75.46	68.45	69.80	75.79	71.41
Observations	233K	1484	1484	705	400	400	2786

Notes: 1 PIMS includes distribution costs in COGS; COMPUSTAT in SG&A.
2 Firm = unweighted averages of individual firm ratios; total = ratios of the sums of individual items.
3 IRS financial ratios based on average of SIC-level reporting of corporate IRS tax filings for the year of analysis.
4 PIMS and COMPUSTAT financial ratios based on methodology described in Tables 3.11 and 3.12, respectively.
5 Eliminating COMPUSTAT firms that do not report all of the financial ratios in Table 3.4 reduces the number of firms to 1783 from 6250. The remaining firms account for 80.1% of sales, 79.6% of assets, and 98% of R&D spending.
6 Tables 3.11–3.14 provide definitions and standard deviations for the variables reported in Tables 3.4 and 3.5.

sample will be skewed toward including many small companies whose activities may not be material for aggregate markets. Whether or not this skew should be interpreted as a "bias" probably depends on how the research will be interpreted. Regression based on unfiltered COMPUSTAT data would contain many extreme values and might not represent the companies or businesses that account for the majority of sales or assets in the COMPUSTAT data.

Another point of comparison is provided by the 1980 and 2000 IRS data. These IRS data include many of the small firms that, in aggregate, account for much activity in the economy. In the COMPUSTAT data, small firms do *not* account for a significant amount of economic activity. Future research might address the challenging issue of whether to include and how to weight the many small firms in the COMPUSTAT data to create averages that are typical of the economy as a whole.

3.3 COMPUSTAT: changes between 1980 and 2000

Table 3.5, reporting IRS and COMPUSTAT data for 2000, is similar in construction to Table 3.4. PIMS data are not available for 2000. An additional category for COMPUSTAT has been reported (firms with more than $500 million in assets). Comparing the ratios in Table 3.5 with the values in Table 3.4, we see some important differences. For the total averages, gross margins are in the range 35–40 percent in 2000. The values are approximately 10 percentage points (almost one-third) higher than the 24–30 percent range in the 1980 COMPUSTAT sample. We also see that firm average margins are still approximately 5 percentage points higher than the total averages for 2000. The overall increase in gross margins is offset by a four percentage point increase in SG&A, a two percentage point increase in R&D, and a two percentage point increase in depreciation/sales for 2000 data. In 2000, total averages of ROS for COMPUSTAT firms in manufacturing SICs increased by about two and one-half percentage points compared to 1980. For the firm averages, the filter of $250 million assets does not produce the same degree of similarity between the firm and total averages. R&D/sales and depreciation/sales are 2–6 times their 1980 values. Adjusting the filter to include only companies with more than $500 million in assets comes closer to reproducing the relative size of companies represented by the 1980 asset filter of $250 million (see Table 3.6). The higher

Table 3.5. *Financial ratios for manufacturing businesses/firms, 2000*

	All firms			*\$250 million + assets*			*\$500 million + assets*
	Total IRS	*Firm* COMPUSTAT	*Total* COMPUSTAT	*Total IRS*	*Firm* COMPUSTAT	*Total* COMPUSTAT	*Firm* COMPUSTAT
ROA%	5.99	−11.12	9.75	4.95	8.93	9.91	9.79
Sales/assets	9.12	1.00	.91	.70	.95	.91	.94
ROS%	7.17	−455.70	10.72	5.41	.48	10.90	8.97
Depreciation/sales	–	16.50	5.43	–	7.03	5.44	6.51
EBITDA/sales	–	−439.20	16.16	–	7.51	16.35	15.49
R&D/sales	–	186.10	4.43	–	13.37	4.35	7.14
SG&A/sales	–	291.87	14.50	–	19.09	14.31	17.19
Margin	–	38.75	35.09	–	39.97	35.02	39.82
COGS/sales	62.71	61.25	64.91	63.28	60.03	64.98	60.18
Observations	405K	2,097	2,097	1,975	862	862	647

Notes: 1 Firm = unweighted averages of individual firm ratios; total = ratios of the sums of individual items.
2 IRS financial ratios based on average of SIC-level corporate IRS tax filings for the year of analysis.
3 COMPUSTAT financial ratios based on methodology described in Table 3.12.
4 Eliminating COMPUSTAT firms that do not report all of the financial ratios in Table 3.5 reduces the number of firms to 2097 from 3685. The remaining firms account for 68.7% of sales, 70.9% of assets, and 86.8% of R&D spending.
5 The maximum (minimum) ratio values for COMPUSTAT all firms, firm-level ratios are: ROA 71.42 (−863.29); sales/assets 1972.84 (0.08); ROS 53.04 (−577,000); depreciation/sales 8500 (0.31); EBITDA/sales 63.55 (−568,500); R&D/sales 227,400 (0.02); SG&A/sales 341,100 (−6250); margin 99.25 (−600); COGS/sales 700 (0.75).

Table 3.6. ***Percentage of total value accounted for by COMPUSTAT firms exceeding $250 million or $500 million in assets: selected variables***

	1980 $250M+ assets – all firms with no missing data	*2000 $250M+ assets – all firms with no missing data*	*2000 $500M+ assets – all firms with no missing data*
Percent firms	27	41	31
Percent assets	96	99	97
Percent sales	96	99	97
Percent EBITDA	96	100	99
Percent depreciation	97	99	97
Percent COGS	96	99	97
Percent R&D	95	97	95
Percent operating income	93	100	99

Note: Values to be read as "firms listed in Industrial COMPUSTAT database in 1980 as having $250 million or more in total assets represented 96 percent of the total assets reported in COMPUSTAT for all firms with no missing data." Firms with no missing data represented on average approximately 82 percent and 74 percent of the aggregate sum for each variable listed above when compared with all firms listed in COMPUSTAT for 1980 and 2000, respectively.

filter produces ROS averages that are closer to the total, but R&D and depreciation/sales ratios are even higher.

As shown in Table 3.7, the distribution of increased ratios for SG&A, depreciation/sales, and R&D/sales appears fairly evenly distributed and not attributable to a few extreme values. We conclude, therefore, that a more general trend is operating to produce such long-term changes in these fundamental financial ratios.

In summary, we see from Tables 3.4 and 3.5 that the financial ratios of SBUs in PIMS were, in 1980, comparable to the same ratios for firms with assets greater than $250 million. As of 2000, however, the same larger firms have begun to report larger gross margin, higher R&D and depreciation/sales ratios, and sales/assets ratios that are almost 50 percent lower. Therefore, the original PIMS data appear to be no longer representative of even the larger firms in the US economy. However, the relations between some variables in the database may still be the same in 2000. Further, the definition of "larger" that is required to filter firms in order to produce averages that are comparable to the totals has changed. An asset filter of $500 million and higher produces

Table 3.7. ***Distribution of R&D/sales, depreciation/sales, and SG&A/sales ratios, 1980 and 2000, COMPUSTAT data***

Interval of ratios	*% firms with R&D/ sales in interval*		*% firms with depreciation/ sales in interval*		*% firms with SG&A/ sales in interval*	
COMPUSTAT	*1980*	*2000*	*1980*	*2000*	*1980*	*2000*
0–2.5%	69	46	11	9	1	3%
2.51–5.0%	20	18	49	44	7	9
5.1–10.0%	10	15	39	35	23	17
10.1–30.0%	1	18	1	10	60	31
30.1% +	0	3	0	2	9	40
Maximum value	16	231	11	87	45	131

Note: Firms in 1980 have $250 million in assets or more; firms in 2000 have $500 million in assets or more. Values based on data drawn from the Industrial COMPUSTAT database for the years of study.

approximately the same cumulative percentage of sales in 2000 as did a filter of $250 million in 1980.

3.4 Market share measures: served market versus SIC

Market share for both PIMS and COMPUSTAT is defined as revenue divided by the market size. For PIMS, managers are asked both to decide what the served-market limits are and to estimate the market size used to calculate market share. Research that used COMPUSTAT typically has divided firm revenue by the total revenue for all COMPUSTAT firms using the same primary SIC code. SIC codes represent a relatively arbitrary collection of firms, as the coding is typically more oriented toward the technology and production processes than toward markets and customer perceptions of substitutability. Of course, most, if not all, researchers are well aware of the differences and relative advantages and disadvantages of these two measures. These measures of share are quite different, and relatively little is known about how they compare.

One important comparison was published of analyses of market share using SIC codes and PIMS served-market measures. That particular study used FTC's Line of Business (LOB) data and the SIC approach to calculating market share (Marshall and Buzzell 1990). The emphasis was on comparing coefficients of share in the same regression model formulation explaining ROA. PIMS coefficients were in the range .284–.299, implying a 2.84–2.99 percentage point higher ROA for each 10 percentage point difference in share. The same regression equation applied to the LOB database produced quite similar estimates (.271). The average SIC-based share was slightly less than 4.0%. The average share for PIMS businesses was closer to 24%. A difference of 1 share point is associated with a difference in ROA of .28 or so for both the PIMS and LOB data. However, an increase of 1 share point would represent a 25% increase in sales for the average LOB business (average share 4%), but the same 1 share point difference would represent only a 4% difference in sales revenue for the average PIMS business (average share 24.7%). To our knowledge, it is not known whether the differences in PIMS and LOB average market shares are attributable to different estimates of market size (SIC versus served market) or whether PIMS has a disproportionate number of larger businesses. We are also not aware of any studies that compare regression coefficients of share from the same equations using COMPUSTAT and PIMS data. Hence, we must look to other methods for assessing the potential bias in served-market size.

3.4.1 Testing for potential bias in served-market definition and market share

This section presents some new evidence on the potential bias in the definition of PIMS' served-market variable using scaled measures reported in the PIMS database. This estimate compared PIMS' reported served-market shares to our estimate of served-market size to test for a potential negative bias.

"Business unit and the market in which the business participates are subjectively defined, and the definitions may lead businesses systematically to overstate their market shares by understating the scope of the markets in which they compete" (Marshall and Buzzell 1990). Similar speculations on the potential bias in served-market size have been advanced by others (Anderson and Paine 1978; Anterasian and Phillips 1988). Because PIMS reports revenues and estimates of served-market size as disguised numbers, it is not possible to obtain direct estimates of served-market size. Only the ratio of numbers using the same disguise factor is exact. However, we can calculate a very rough approximation of the served-market size with three other categorical PIMS variables:

average purchase frequency, average purchase amount, and number of end users (alternatively, number of customers). We use the midpoint of each interval and use these in place of the original numerical coding. This allows a rough calculation of served-market size as the product of average purchase dollar amount, average purchase frequency, and number of end users. This calculation also produces a number of estimates that have very low “face validity.” Less than 1 percent of observations were discarded as providing estimates out of a reasonable range (more than $100 billion or less than $10,000). These estimates were eliminated as probably reflecting some confusion among managers about a proper response to these questions.

In Table 3.8 we see that businesses reporting larger shares tend also to report values for purchase amount, purchase frequency, and number of end users that imply a small estimated size for their definition of served market. SBUs reporting shares above 50 percent have estimated served-market sizes between $740 million and $820 million. SBUs reporting lower shares report values for estimated market size that are about twice as large. Because there is almost as much variance within these share categories as across them, we cannot conclude that a major determinant of differences in market shares reported by PIMS is attributable to different estimates of market size. We can compare the four-digit SIC sales levels of the COMPUSTAT data with the served-market size estimates to make another comparison.

A review of 1980 COMPUSTAT firms by manufacturing SIC code reveals that the average firm size reported by PIMS and shown in Table 3.8 matches well with the average firm size based on sales data reported in manufacturing SIC codes in COMPUSTAT for 1980. The COMPUSTAT-based market size is $967 million on average for manufacturing firms during 1980. Comparing this figure with the market size reported in Table 3.8, we see a high degree of congruency between PIMS-reported market size and market size based on SIC data.

Another verification of the estimated market size reported by PIMS concerns the relationship between market share and ROA. PIMS analysis reveals a strong, positive relationship between these two variables. We tested the same relationships in COMPUSTAT using estimates of SIC market share and corporate ROAs. We first identified all firms reporting sales data for each year in the period 1980–2000. This filtering resulted in a sample of 250 firms. We calculated the market

Table 3.8. ***Comparison of PIMS reported market share with estimated market size***

PIMS SBUs reporting percentage market share in range	*n*	*Average – market size estimate ($ billion)*
0–10	4099	1.52
11–20	4037	1.55
21–30	2796	1.27
31–40	1751	1.32
41–50	1180	1.08
51–60	736	0.74
61–70	1058	0.82

A regression of market share on estimated market size produces an intercept of .248, a coefficient for market share of $-.29 * 10^{-8}$, and an R-square of .0036.

Note: Market size estimates for each firm in the database based onfirmresponses to questions in the PIMS study regarding end users. The three questions used in constructing the market estimates were the estimated number of end users (v1618), the average purchase amount for end users (v1628), and the purchase frequency of end users (v1626). The three end-user questions provide response ranges for respondents to answer each question. We calculate estimated market size by taking the midpoint of each response option for each question and multiply the midpoint of the responses for each respondent. Interpretation of the estimated average market size by industry for COMPUSTAT should bear in mind our sales filter and the fact that COMPUSTAT assigns all of a firm's sales to the SIC code for the part of the firm that generates the largest sales volume for the firm. The SIC-based market size estimate is underestimated to the extent it does not include sales of companies below our filter and sales from companies that have another SIC as their "main" SIC. Market size is overestimated to the extent it includes firms with sales in more than one SIC.

share for each firm in each year by dividing the firm's reported sales by the total reported sales in the SIC classification for the firm. We regressed ROA onto market share using a Fuller–Battese model since we had a full panel and in order to control for unobserved factors. The results reveal a positive and marginally significant (90 percent confidence level) link between market share and ROA. Compared to PIMS, the correlation of share and ROA in COMPUSTAT is relatively weak.

3.5 Time-series and cross-sectional analyses: PIMS versus COMPUSTAT

PIMS data were originally collected for the current year (1975) and the three preceding years, providing a set of time series as well as cross-sectional data. The first analyses were based on the four-year averages and changes within the four years. Later, more businesses were added to the data, and existing businesses either contributed additional years to the time series or dropped out. As the number of participating SBUs increased over the first few years, a database that was complete (very few missing variables) and extensive on both cross-sectional (number and variety of SBUs) and time-series dimensions was assembled. Gradually, SBUs began to drop out of the data at a faster rate than new SBUs were being added. Finally, shortly before 2000, the collection of original data ceased in the United States. The total number of observations, however, exceeded 3,000 SBU-years of observations. Over 1,000 businesses provided at least six years of data in the period between 1972 and 1987. Some businesses provided as many as thirteen years of data, and many as few as five.

COMPUSTAT, in contrast, contains a large number of companies and the number has increased steadily. COMPUSTAT history is also much longer (extending back to 1950). Of course, COMPUSTAT data also have difficulties with mergers, bankruptcies, and the willingness of companies to provide detailed data on their operations. In the case of mergers, COMPUSTAT combines the data from the two companies into one dataset at the time of the merger and the data are listed under the name used by the merged companies. The pre-merger data is still reported for both firms. For example, COMPUSTAT reports data for both Compaq and HP through the year 2001, but data are reported only for HP for 2002. New companies are also added, so COMPUSTAT suffers from missing companies as well as from missing variables for reporting companies.

Tables 3.9 and 3.10 provide two different views of the time series available from COMPUSTAT. Table 3.9 shows that even for "fundamental" variables such as sales and assets, as many as 40 percent of firms in any given year did not report. When we examine variables of particular interest to marketing, such as "advertising," the percentage sinks even lower, ranging in the 1982–83 interval from a low of 22.5 percent to a high of 43.2 percent.

Table 3.9. ***Percentage of COMPUSTAT firms reporting selected financial ratios***

	1972	*1973*	*1974*	*1975*	*1977*	*1978*	*1979*	*1980*	*1982*	*1983*
Inventory	55.8	65.7	90.5	91.9	86.5	85.0	83.6	84.7	59.1	73.9
Total assets	62.2	68.7	93.5	94.6	88.0	86.8	85.6	87.0	60.9	76.1
Sales	62.0	68.5	93.2	94.3	87.7	86.5	85.2	86.6	60.6	75.7
Advertising	25.9	33.0	43.2	42.6	37.6	36.2	35.3	33.9	22.5	28.7
R&D	29.5	33.6	46.9	46.8	40.3	38.4	37.3	36.6	25.6	32.8
Depreciation	47.4	54.9	78.3	80.3	75.4	73.4	71.6	71.7	38.8	47.2
Net income	62.2	68.6	93.2	94.4	87.6	86.4	85.2	86.7	60.7	75.7
Working capital	57.8	63.5	84.9	85.6	79.2	77.2	75.5	76.7	53.6	67.3

Notes: 1 Values to be read as "the percentage of firms listed in the Industrial COMPUSTAT database in 1972 reporting a value for inventory is 55.8 percent."
2 Percentages determined by dividing the total number of firms listed in the Industrial COMPUSTAT database for a given year into the number of firms reporting a value for the respective variable in the year of analysis.

Table 3.10. ***Percentage of COMPUSTAT firms reporting four consecutive years of variable in selected periods***

	1975	*1980*	*1985*	*1990*	*1995*	*2000*	*Average*
Inventory	18.2	16.9	9.1	2.8	26.6	33.7	17.9
Total assets	19.8	19.1	9.8	3.2	27.9	35.0	19.1
Sales	19.6	18.7	9.6	3.1	27.6	34.9	18.9
Advertising	1.4	0.7	0.3	0.1	0.0	0.4	0.5
R&D	1.9	1.0	1.1	0.3	3.6	5.9	2.3
Depreciation	13.5	9.6	1.7	0.4	0.0	0.0	4.2
Net income	19.6	18.8	9.6	3.2	27.6	34.7	18.9
Working capital	15.3	12.2	7.2	2.2	21.5	25.0	13.9

Notes: 1 Values to be read as "the percentage of firms listed in the Industrial COMPUSTAT database in 1975 reporting a value for inventory for 1975 and the immediately preceding three years is 18.2 percent."
2 Percentages determined by dividing the total number of firms listed in the Industrial COMPUSTAT database for a given year into the number of firms reporting a value for the respective variable during the year of analysis and the three immediately preceding years.

A more stringent criterion would be the percentage of firms reporting four consecutive years with no missing variables. Table 3.10 shows that for the six five-year intervals between 1975 and 2000, very few firms reported four consecutive years of data during these intervals. Therefore, an uninterrupted time series that is based on more than a very few variables will be difficult to assemble.

Although we have not attempted it here, research that models the missing values and tests whether these missing variables are non-random, but systematically related to firm and industry attributes or events, is sorely needed. Further, missing variables may not be "missing," but simply reported elsewhere. For example, if R&D or advertising are not reported as separate items, they may be reported as part of SG&A. In our earlier analyses we guarded against inflation of certain variables by analyzing only the sample of firms that report all of our variables for a given year. Extending this type of analysis over a longer time series will be very difficult because of the "Swiss cheese" nature of the database.

To get an overview of the time-series properties of the COMPUSTAT database, we selected all firms identified by SIC code as being manufacturers who reported sales data for the entire period 1980–2000 and calculated market share for each using the procedure discussed earlier. We then analyzed the firms to assess the extent to which variance in the COMPUSTAT data is time-series rather than cross-sectional in nature. Time-series variance was determined by calculating the variance in market share in the period 1980–2000 for each firm and summing the individual variances to arrive at a total time-series variance. Cross-sectional variance was calculated by finding the variance across firms for each year and then summing across years. The total variance for the 250 firms in the interval 1980–2000 is the sum of time-series and cross-sectional variance. The results show that 95 percent of the market share variance in the COMPUSTAT data is cross-sectional, leaving only 5 percent as time-series.

3.6 Conclusions: PIMS versus COMPUSTAT

We began this chapter by noting that many of the research questions that were addressed with PIMS data are now, increasingly, investigated through other datasets, in particular COMPUSTAT. By comparing aggregate financial ratios reported by PIMS and COMPUSTAT in

1980, we have attempted to assess the degree to which PIMS SBUs were drawn in an unbiased manner from firms that are representative of the US economy. Further, by looking at changes in the COMPUSTAT data, augmented with IRS data comparisons, this chapter has also provided evidence on whether PIMS analyses of twenty or more years ago are valid indicators for the current business environment. We offer the following conclusions.

1. At the time the PIMS data were collected and analyzed, the aggregate statistics on important variables were reasonably comparable to COMPUSTAT firms reporting assets of $250 million or more in 1980. Further, those firms with $250 million or more in assets are more representative of the economy as a whole than are unweighted averages of all firms in the data. The reason is that many of the smaller firms report extreme values for financial ratios. These extreme values bias the overall averages.[5]

2. Unless one screens the COMPUSTAT data for firms above a certain level of sales, the sample will be biased toward many relatively small firms whose financial ratios may not be material for markets as a whole. This means that regressions that do not apply size filters to the sample should be interpreted in quite a different way from those that do use such filters. We believe there is a fruitful avenue for further research on how one satisfies the desire to model the many small firms that contribute to the bulk of the economy, while at the same time avoiding contaminating estimates with extreme values that characterize these unweighted samples. Variance suppression through eliminating outliers is one way of treating firms with extreme values. Although this procedure has been criticized, effectively, it may not be that different from simply screening for larger businesses. Without some controls, it is not clear how we can have confidence in regression coefficients estimated from unweighted, unscreened samples of firms.

[5] For example, the firm average ROS for all COMPUSTAT firms with manufacturing SIC codes was −455 percent, while the ratio of total profits to total revenue is 10.7 percent. Similarly, the average of all manufacturing R&D/sales ratios was 186 percent. In the same year, the ratio of total R&D to total revenue was 4.43 percent. (Recall, the firm averages are unweighted, so a few small firms that lose a lot of money and have low sales can heavily skew the percentages in their direction.)

3. Over the period 1980–2000, potentially important changes in key financial ratios of manufacturing firms were observed. Over that time, the following significant changes occurred. R&D and depreciation/sales ratios increased substantially, perhaps by factors of 2–3. Gross margins and SG&A as ratios to sales also climbed by as much as five percentage points. Finally, we observed that sales/assets ratios decreased significantly. We are at a loss to explain these changes, but they remained even after applying a large-size filter.[6]

4. Many studies of marketing strategy and profitability rely heavily on measures of marketing, research development, asset intensity, gross margins, and profitability. All of these are potentially significant intervening variables for models of marketing strategy and profitability. Comparing regression coefficients in equations estimated on 1980 data with those estimated on 2000 data may have significant problems, because of these changes in key ratios.

5. Market share measures for PIMS were long suspected of a bias in the definition of served market. We provided a test of this bias and were pleased to find that while the bias appears to exist, it seems relatively weak and not a major cause for concern. In fact, the earlier discussion revealed that the reportings of market share from PIMS match closely with market share estimates based on SIC codes in COMPUSTAT.

6. Time series: PIMS versus COMPUSTAT. PIMS data are relatively complete for the time the SBUs are in the data. However, in general, the time series is not very long and, as Christen and Gatignon observe in Chapter 10, less than 5 percent of the total variance in key variables such as market share and ROI is due to variation over time. Almost all is due to cross-sectional differences between SBUs in the databases. COMPUSTAT is not plagued by missing firms, but by missing data for the firms reported. Longitudinal analysis is possible only if one accepts the methodologies for imputing missing values, uses relatively short time periods, and/or estimates models with very few variables.

[6] For example, a filter of $500 million in assets is required to capture the same degree of concentration in companies as captured by a filter of $250 million in 1980. Increasing the filter size, however, does not yield a sample with financial ratios comparable to the 1980 sample.

In conclusion, it is regrettable that the detail and completeness of the PIMS panel data are no longer available in a current form. Somewhat perversely, as the PIMS data declined in scope and currency, newer methods for analyzing time series data were made more widely available. At the time PIMS data were at their peak of timeliness, methods for controlling unobservable variables and tests of causal hypotheses were not nearly as developed as they are today. It is also easy to forget that when PIMS was started, in the early 1970s, even simple regressions typically required mainframe computer access and knowledge of special software. Software packages like SAS, SPSS, LISREL, and others were only a little more than ideas. SAS and LISREL became available in the mid-1970s; SPSS at the end of the 1960s. Even today, the data requirements for more advanced tests of causal hypotheses are formidable. As Moore, Morgan, and Roberts discuss in Chapter 9, these data hurdles are rarely cleared.

Appendix 1: Data and methodology

Our samples come from three sources. The first sample includes all firms filing a corporate tax return with the Internal Revenue Service (IRS) for the calendar years 1980 and 2000. Data based on IRS corporate filings come from the Almanac for Business and Industrial Financial Ratios. The Almanac collects aggregated data on several financial variables and ratios from corporate filings data provided by the IRS. The Almanac data is reported by industry SIC classification. The IRS's aggregated ratios analyzed in this chapter represent the average of the SIC reported financial variables and ratios for SIC codes falling between 2000 and 3999.

The second sample involves data from the Strategic Planning Institute's Profit Impact of Marketing Strategy (PIMS) database published in 1986. Table 3.11 shows the definitions and variables used in constructing the financial ratios based on the PIMS database.

The third sample is based on firm-level data retrieved from the COMPUSTAT database maintained by Wharton Research Data Services. COMPUSTAT reports yearly and quarterly firm-level data for over 300 financial variables. Data are available from COMPUSTAT from 1950 to the present. Table 3.12 reports the individual variables pulled from COMPUSTAT and the procedure used in constructing financial ratios based on COMPUSTAT data.

Table 3.11. *Variable definition and construction process for PIMS analysis*

PIMS variable	*Definitions*	*PIMS variable number*
ROA	Net income/total assets	v147/v158
Sales/assets	Sales/total assets	v131/v158
ROS	Net income/sales	v147/v131
Depreciation/sales	Depreciation/sales	v145/v131
EBITDA/sales	Net income/sales + depreciation/sales	v147/v131 + v145/v131
R&D/sales	Process R&D/sales + product R&D/sales	v138/v131+ v137/v131
SG&A/sales	Total marketing/sales + other exp./sales	v144/v131 + v146/v131
Margins	1− (mfg./sales + purchasing/sales)	1 − (v136/v131 + v134/v131)
COGS/sales	Mfg./sales + purchasing/sales	v136/v131 + v134/v131

Note: The variables listed were pulled for the year 1980 from the Strategic Planning Institute's Profit Impact of Marketing Strategy database, published in 1986. The table shows the definitions and variables used in constructing financial ratios. The SPSS syntax used in constructing the PIMS-based variables is available upon request from the authors.

Appendix 2: In-house research and development and COMPUSTAT

Several marketing papers use research and development expense reported in COMPUSTAT. Mizik and Jacobson (2003), for example, use these data in comparing how shareholders react to changes in a company's efforts in value creation (research and development expenditures reported in COMPUSTAT) versus how they react to value appropriation (advertising expenditures reported in COMPUSTAT). Similarly, Dutta, Narasimhan, and Rajiv (1999) use measures of research and development reported in COMPUSTAT in studying the importance of marketing capabilities in high-technology markets. One issue with COMPUSTAT's reporting of research and development expenses is the inclusion of in-house research and development expense; in-house research and development represents the research and development a

Table 3.12. ***Variable definition and construction process for COMPUSTAT analysis***

COMPUSTAT variable	*Definitions*	*COMPUSTAT variable number*
ROA	Operating income after depreciation/total assets	DATA178/DATA6
Sales/assets	Sales/total assets	DATA12/DATA6
ROS	Operating income after depreciation/sales	DATA178/DATA12
Depreciation/sales	Depreciation/sales	DATA14/DATA12
EBITDA/sales	Operating income before depreciation/sales	DATA13/DATA12
R&D/sales	R&D/sales	DATA46/DATA12
SG&A/sales	SG&A/sales – R&D/sales	DATA189/DATA12 – DATA46/ DATA12
Margins	(Sales – cost of goods sold)/sales	(DATA12 – DATA41)/DATA12
COGS/sales	(Cost of goods sold)/sales	DATA41/DATA12

Note: The variables listed were pulled from the Industrial COMPUSTAT tapes for years 1980 and 2000. Firms used in constructing the ratios represent those firms reporting no missing values for any of the financial variables listed above. Financial ratios are reported using three filters. The first involved analyzing all firms included in the year of study that reported a value for each of the financial variables regardless of the value of total assets reported for the firm. Alternative filters include selecting firms reporting a value in each financial variable *and* reporting total assets greater than $250 million and greater than $500 million, respectively. The SPSS syntax used in constructing the COMPUSTAT financial ratios is available upon request from the authors.

firm obtains in an acquisition or merger. Accounting Practices Board (APB) Opinion No. 16 directs firms to allocate the entire cost of acquiring a business to the firm's individual assets and liabilities based on their fair values. All assets acquired in a business combination are capitalized except for the amount allocated to purchased R&D, which must be written off immediately, pursuant to FASB Interpretation No. 4, unless it has a use other than in that R&D project.

The valuation of in-house research and development has come under scrutiny from both regulators and academic researchers. In remarks to the Software and Service Industry Analyst Group on February 10, 1999, Lynn E. Turner, Chief Accountant at the Securities and Exchange

Table 3.13. ***Financial ratio standard deviations for manufacturing businesses/firms, 1980***

	All firms			*$250 million + assets*			*All*
	Total IRS	*Firm COMPUSTAT*	*Total COMPUSTAT*	*Total IRS*	*Firm COMPUSTAT*	*Total COMPUSTAT*	*SBU PIMS 1979–82*
ROA%	3.31	23.14	n.a.	4.14	7.27	n.a.	31.25
Sales/assets	0.50	52.48	n.a.	0.42	41.91	n.a.	136.8
ROS	n.a.	569.81	n.a.	n.a.	6.07	n.a.	14.01
Depreciation/sales	–	50.78	n.a.	–	1.64	n.a.	2.23
EBITDA/sales	–	521.05	n.a.	–	6.43	n.a.	13.49
R&D/sales	–	52.82	n.a.	–	2.20	n.a.	4.78
SG&A/sales	–	254.51	n.a.	–	9.04	n.a.	12.61
Margin	–	244.45	n.a.	–	13.34	n.a.	16.59
COGS/sales	6.80	244.45	n.a.	8.22	13.34	n.a.	16.59
Observations	233K	1484	1484	705	400	400	2786

Table 3.14. ***Financial ratio standard deviations for manufacturing businesses/firms, 2000***

	All firms			*\$250 million + assets*			*All*
	Total IRS	*Firm* COMPUSTAT	*Total* COMPUSTAT	*Total IRS*	*Firm* COMPUSTAT	*Total* COMPUSTAT	*SBU PIMS 1979–82*
ROA%	n.a.	61.89	n.a.	3.17	10.53	n.a.	31.25
Sales/assets	0.45	73.27	n.a.	0.34	44.88	n.a.	136.8
ROS%	n.a.	12,896.13	n.a.	n.a.	117.47	n.a.	14.01
Depreciation/sales	–	196.21	n.a.	–	12.69	n.a.	2.23
EBITDA/sales	–	12,706.09	n.a.	–	113.45	n.a.	13.49
R&D/sales	–	5176.37	n.a.	–	120.37	n.a.	4.78
SG&A/sales	–	7668.87	n.a.	–	27.12	n.a.	12.61
Margin	–	33.37	n.a.	–	18.58	n.a.	16.59
COGS/sales	14.41	33.37	n.a.	15.36	18.58	n.a.	16.59
Observations	233K	1484	1,484	705	400	400	2786

Commission, addressed the issue of in-house research and development. Turner (1999) noted in his remarks that:

> Some in the financial community believe that unreasonably large write-offs of purchased R&D are being used to hype the company's stock price. Amounts paid in the business combination are written off immediately as purchased R&D when they should have been allocated to other, capitalized assets. The excessive up-front write-off avoids future amortization and depreciation expense. The misleading results in periods immediately after the acquisition are higher earnings, higher earnings per share, higher return on assets, and higher return on equity.

Pursuant to concerns in the financial community, the SEC undertook an investigation of several acquisitions during the 1990s and found three recurring flaws in how companies handled in-house research and development. The SEC found that "some companies were not rigorously isolating the R&D project from all other valuable assets acquired in the transaction." Second, the SEC found "appraisals often reflected little or no analysis of the project's stage of development or the complexity and uniqueness of the seller's achievements at the acquisition date relative to the complexity and uniqueness of efforts which the purchaser must undertake to complete it." Lastly, the investigation discovered that "some appraisals computed an 'investment value' for the R&D project, rather than its 'fair value.'"

Turner concluded his comments on the subject of in-house research and development by stating: "When the staff stepped back in 1998 and looked at the particular cases where we had dug the deepest into the support for the appraisal, we were struck most profoundly by the fact that many of the valuations of purchased R&D simply were not grounded in basic business sense."

The issue of in-house research and development has also drawn the interest of academic researchers. Zhen and Lev (1999: 10) studied the valuation of in-house research and development and found that "the valuation of R&D-in-process as part of corporate acquisitions is a recent and fast growing phenomenon. Despite the fact that our search spanned the years 1985–1996, eighty-five percent of the sample cases occurred during the period 1994–96, and the number of acquisitions per year is fast growing (note that the 147 acquisitions in 1996 occurred in the first half of the year)." Zhen and Lev also report regarding the value of in-house research and development. Their study finds that in-house research and development accounts for 72 percent of the acquisition price on average, making in-house research and development the single largest asset in the acquisition.

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4 Order of market entry: empirical results from the PIMS data and future research topics

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Over the past twenty years, numerous empirical research studies have examined the magnitude of market pioneer advantages and the associated sources of these advantages. Review articles by Kalyanaram, Robinson, and Urban (1995); VanderWerf and Mahon (1997); Kerin, Varadarajan, and Peterson (1992); Lieberman and Montgomery (1988, 1998); and Robinson, Kalyanaram, and Urban (1994) summarize these research studies.

The PIMS data played an important role in helping to start this research stream and advancing it over time. Because most of this empirical research has been done in marketing, Scherer (1994: 173) says, "we are in debt to business scholars for illuminating the relevant relationships." The following discussion summarizes the important role PIMS data played in examining order of market entry topics. These topics cover market share, return on investment, firm skills, and marketing strategy development. Future research topics are also discussed.

4.1 Order of market entry and market share

In the late 1970s, industry studies in the economics literature documented long-lived market share advantages for first entrants in two specific markets: pharmaceutical products (Bond and Lean 1977) and cigarettes (Whitten 1979). Still, because market pioneers in other markets such as ballpoint pens (Reynolds International Pen), hand-held electronic calculators (Bowmar Instruments), and diet colas (Royal Crown Cola) were quickly overtaken by later entrants, it was not clear whether market pioneer advantages typically surfaced in most North American markets.

Two key papers published during the mid-1980s supported the view that (1) market pioneers tend to have higher-than-average market shares, relative to later entrants, and (2) the share advantages enjoyed by early entrants tend to last for decades. Both studies examine the relationship between order of market entry and market share using samples of mature consumer goods. The first paper uses the PIMS data, while the second uses a broad cross-section of consumer packaged goods.

The first paper, by Robinson and Fornell (1985), analyzes 385 mature consumer goods businesses in the PIMS data. In the PIMS data, three self-reported categories assess order of market entry: a "market pioneer" was one of the first entrants into the market; an "early follower" entered a growing, dynamic market; and a "later entrant" entered a more established market situation. In Table 4.1, the average market share level is 29 percent for market pioneers, 17 percent for early followers, and 12 percent for later entrants. Because 80 percent of the market pioneers had been in their market for at least twenty years, these market share advantages are both substantial and sustainable.

Why do market pioneers tend to have higher market shares compared to later entrants? In the PIMS data, market pioneers who have been in the market less than twenty years tend to have higher perceived product quality. (Perceived product quality is based on customer perceptions of quality.) Pioneer product quality advantages deteriorate sharply, though, for pioneers who have been in the market for twenty years or more.

More important are product line breadth advantages, which show limited deterioration even after decades of competition. Product line breadth advantages can arise when a market pioneer launches products for the biggest and best market segments. When a late entrant attempts to satisfy an unmet need by targeting a market niche, its product line is often narrow.

These product line breadth conclusions are also supported by the empirical pooling approach of Ramaswamy *et al.* (1993). Across homogeneous groups of PIMS businesses, market pioneers are more likely to serve national or international markets. In contrast, late entrants are more likely to serve regional markets. The results indicate that broader target markets and the associated product line breadth tend to benefit the market pioneer and limit a later entrant's upside potential.

In the mid-1980s, the second key paper concerning order of market entry used an independent sample of mature consumer packaged goods. Urban *et al.* (1986) also conclude that market pioneers typically develop sustainable market share advantages. Holding positioning quality and advertising spending constant, their results estimate that the *n*th entrant's market share relative to the first entrant's share equals one divided by the square root of *n*. Thus, the fourth entrant's market share tends to equal one divided by the square root of four, or one-half of the first entrant's market share.

For Urban *et al.*'s (1986) sample of consumer packaged goods, the market pioneer's stronger brand name should help maintain its higher market share levels. This result is consistent with Schmalensee's (1982) model in which risk-averse consumers tend to buy the pioneering brand out of habit. It is also consistent with Carpenter and Nakamoto's (1989) conclusion that, when quality is subjective, first experiences help shape consumer tastes in favor of the pioneering brand.

Overall, the robust results across Robinson and Fornell's (1985) PIMS sample of mature consumer goods and the Urban *et al.* (1986) consumer packaged goods sample help support the validity of the PIMS data for order-of-entry research. This is an important conclusion because the PIMS data have been criticized for collapsing the order-of-entry measure into just three categories and comprising only relatively successful businesses.

4.1.1 Industrial markets

While Robinson and Fornell (1985) and Urban *et al.* (1986) examine consumer goods, do first-mover advantages also arise for industrial goods? Using the PIMS data, Robinson (1988) examines 1,218 mature industrial goods businesses. In Table 4.1, the average market share for market pioneers is 29 percent, for early followers 21 percent, and for later entrants 15 percent. These results indicate that market pioneers also tend to have sustainable market share advantages in industrial goods markets.

Similar to the PIMS consumer goods results, product line breadth advantages for market pioneers tend to be more sustainable than product quality advantages. Another similarity between the two studies is that product patent and trade secret protection does not play a

Table 4.1. ***Order of entry and market share: consumer goods vs. industrial goods***

	Consumer goods	*Industrial goods*
Market pioneers	29%	29%
Early followers	17%	21%
Later entrants	12%	15%
R^2	18%	8%

Source: Robinson (1988); Robinson and Fornell (1985).

significant role in explaining pioneer market share advantages. Thus, pioneer first-mover advantages tend to arise in the marketplace, not in the patent office.

The most important difference between consumer and industrial goods businesses is based on the product's purchase amount. For consumer goods, pioneers tend to have a higher market share when the product's typical purchase amount is less than $10. As mentioned above, this can arise when consumers buy the pioneering brand out of habit or when consumer tastes for packaged goods are shaped in favor of the pioneering brand. In contrast, market pioneers in industrial goods markets tend to have higher market shares when the product has a high purchase amount. For big-ticket items, this can arise from switching costs and a high level of perceived risk.

4.1.2 Concentrated versus fragmented markets

Parry and Bass (1990) provide additional PIMS data insights into the types of markets in which market pioneers tend to have the largest share point advantages. A key theoretical point is that barriers to entry can limit both the number of competitors in a market and the market share of later entrants. If so, then market pioneers should have the greatest market share rewards in concentrated rather than fragmented markets. This is because concentrated markets are more likely to surface when entry barriers are high.

In Table 4.2, Parry and Bass (1990) classify concentrated markets as arising when the market share level of the business plus that of the three leading competitors is at least 55 percent. Fragmented markets have a total market share that is less than 55 percent. As predicted, market pioneers have the highest absolute market share levels in concentrated

Table 4.2. *Order of entry and market share: concentrated vs. fragmented markets*

	Consumer goods		*Industrial goods*	
	Concentrated markets	*Fragmented markets*	*Concentrated markets*	*Fragmented markets*
Market pioneers	34%	12%	33%	14%
Early followers	24%	7%	26%	10%
Later entrants	17%	6%	20%	8%

Source: Parry and Bass (1990).

markets, equaling 34 percent in concentrated consumer goods markets and 33 percent in concentrated industrial goods markets. Market pioneers also have the greatest advantage in market share points in concentrated markets. For consumer goods, it is 17 share points versus 6 share points in fragmented markets. For industrial goods, it is 13 share points versus 6 share points in fragmented markets. These results consistently support the prediction that entry barriers help market pioneers maintain their relatively high market share levels.

In Table 4.2, it is important to note that market pioneers also have higher market share levels in fragmented markets. Thus, even in the absence of key entry barriers, market pioneers appear to be able to develop long-lived market share advantages over later entrants.

4.2 Order of market entry and return on investment

While market share is an important measure of marketplace performance, return on investment (ROI) is an important measure of financial performance. Similar to the research on order of market entry described above, studies of the relationship between entry strategy and ROI have focused on surviving businesses. To estimate how financial returns vary over the life of a business, start-up, adolescent, and mature businesses are all examined.

Start-up businesses are defined as being in their first four years of commercialization. Adolescent businesses are in their fifth to eighth years of commercialization. (The start-up and adolescent businesses come from the start-up business database, which is an offshoot of the PIMS data for start-up ventures.) Mature businesses are in the product

Table 4.3. *Order of entry and ROI*

	Start-up businesses (yrs. 1–4)	*Adolescent businesses (yrs.5–8)*	*Mature businesses*	
			Consumer goods	*Industrial goods*
Market pioneers	−23%	21%	25%	24%
Early followers	−17%	18%	19%	19%
Later entrants	−17%	9%	16%	15%

Note: The differences for the start-up business sample are not statistically significant at the 10 percent level. The differences across the other three samples are all significant at the 1 percent level.
Source: Lambkin (1988); Robinson, Kalyanaram, and Urban (1994).

life-cycle's maturity phase and have typically been in the market for at least twenty years.

Lambkin (1988) estimates financial returns for both start-up and adolescent businesses. While the start-up businesses in Table 4.3 consistently lose money, the market pioneer's financial losses are not significantly greater than those of early followers and later entrants. Adolescent businesses are making money, with market pioneers reporting significantly higher ROI than later entrants. Thus it appears that the higher costs and risks associated with a pioneering strategy do not start to pay off until the fifth to eighth years of commercialization.

Robinson, Kalyanaram, and Urban (1994) provide similar descriptive statistics for PIMS samples of mature consumer ($n = 593$) and industrial goods ($n = 1{,}287$) businesses. In both types of markets, pioneers have significantly higher ROI than that of early followers. And early followers have significantly higher ROI than that of later entrants. Overall, these results support the proposition that while a market pioneering strategy is both costly and risky, successful pioneers are often rewarded with higher market share levels and higher ROI. Because the pioneer market share advantages in Table 4.2 are greater than the ROI advantages in Table 4.3, it appears that higher pioneer dollar profits are influenced more by their market share advantages.

More recent PIMS research by Boulding and Christen (2003) concludes that market pioneers have a long-term profit disadvantage. This result holds consumer learning, market position, and patent protection constant. Because pioneers tend to benefit in each area relative to later entrants, the authors conclude, "These three moderating factors together can actually help pioneers achieve a sustainable profit advantage over later entrants" (Boulding and Christen 2003: 1). This is consistent with their descriptive statistics that report average ROI for market pioneers in consumer goods industries of 25 percent versus 19 percent for later entrants. The corresponding averages for industrial goods markets are 26 percent and 19 percent.

4.3 Alternative explanations

The research studies above conclude that market pioneering tends to lead to stronger business performance in terms of market share. Established market pioneers also tend to have higher ROI. Two alternative explanations question the causal nature of these relationships.

First, if market pioneers tend to have superior skills and resources compared to early followers and later entrants, then superior skills and resources can also explain why pioneers tend to have higher market share levels. (See PIMS data studies by Moore, Boulding, and Goodstein 1991; and Vanhonacker and Day 1987).

While the literature predicts skill and resource differences across market pioneers, early followers, and later entrants, it does not predict clear superiority for market pioneers. (See Lambkin and Day 1989; Lieberman and Montgomery 1988; Lilien and Yoon 1990; and Robinson, Fornell, and Sullivan 1992). In fact, Lambkin and Day (1989) suggest that, if any entrant type has superior skills and resources, it is early followers who are often established giants in related markets.

The second explanation is that market pioneers may not survive as often as early followers and later entrants. If so, once market pioneer share levels are adjusted for survival differences, market pioneer share advantages may disappear. Because the PIMS data cover only survivors, this important issue must be addressed using other databases.

Golder and Tellis (1993) highlight this possibility in their sample of thirty-six market pioneers whose long-term survival rates equaled 53 percent. This study, along with Tellis and Golder (1996), speculates that the first to market is often the first to fail. The conclusion is speculative because survival rates are not linked to order of market entry. This is because their data do not include survival rates for early followers and later entrants.

When survival rates are linked to order of market entry, Kalyanaram, Robinson, and Urban (1995) conclude that across eight industry studies, there is no relationship between order of market entry and survival. A more recent study by Robinson and Min (2002) compares survival rates across 167 market pioneers and 286 early followers. For these 167 new industrial goods markets, market pioneers tend to have significantly higher five- and ten-year survival rates. The authors conclude that first-mover advantages that help market pioneers maintain higher market share levels also increase the pioneer's chance of survival. In total, these empirical studies do not support the dire prediction that the "first to market is the first to fail."

4.4 Order of market entry and marketing strategy

Most research on order of market entry examines either (1) the impact on business performance in terms of market share, ROI, or survival; or (2) attempts to isolate the sources of first-mover advantages. In contrast, a few studies examine the impact of order of market entry on marketing strategy development.

To the best of the authors' knowledge, Buzzell and Farris (1977) was the first study utilizing the PIMS measure of order of market entry. Their cross-sectional study of consumer goods industries concludes that market pioneering in conjunction with a higher market share tends to yield cost savings in terms of lower advertising and promotion-to-sales ratios. Fornell, Robinson, and Wernerfelt (1985) reach a similar conclusion across a sample of 172 PIMS businesses that sell low-priced consumer goods.

While pioneers often start a new market with an innovative product, do they continue to invest in major innovations? Across a sample of 2,273 growing and mature PIMS businesses, Robinson and Chiang (2002) compare product development strategies for market pioneers to those for early followers and later entrants. They conclude that market pioneers are more likely to invest in new product R&D spending and to have positive sales of new products. Even so, pioneer product-development strategies tend to emphasize product improvements and line extensions. This is consistent with Apple Computer's product development strategy. CEO Steve Jobs says, "Don't try to start the next revolution, just crank out smart, affordable consumer products" (*Worth* 2000: 134).

In contrast, later entrants who invest in new product R&D and new product sales are more likely to emphasize major innovations. This can arise when a later entrant attempts to leapfrog its higher-share competitors. Because a market pioneer often starts a new market with a major innovation and a later entrant enters with a minor innovation, these results point to a role reversal in product development strategies. This is because established market pioneers typically emphasize minor product development projects, while later entrants often place the greatest emphasis on major projects.

4.5 Future research

While the empirical research studies described above yield many important order-of-entry insights, numerous opportunities exist to clarify and extend these findings. These research opportunities are organized below by data type. Some of the cross-sectional data topics can be addressed using the PIMS data. In contrast, the time-series and case-data projects will require different databases.

4.5.1 Cross-sectional studies

Some of the research findings described in Section 4.1 merit further investigation. For example, Robinson and Fornell (1985) find a strong relationship between relative product breadth and pioneer market share. This relationship would seem to reflect a "line extension" advantage, in that pioneers have the first opportunity to introduce minor extensions (sizes, packaging variety, flavors, designer colors, scents, etc.). However, the pioneer who capitalizes on this opportunity might benefit in several different ways. Urban *et al.* (1986) speculate that pioneers enjoy more shelf space (per SKU) than later entrants, and there is some evidence from a survey of reseller attitudes to support this speculation (Alpert, Kamins, and Graham 1992). Apart from the question of the amount of shelf space enjoyed by pioneers, Lieberman and Montgomery (1998) argue that pioneers enjoy a spatial-preemption advantage, meaning that pioneers have access to better (e.g. more noticeable) shelf space. Taken together, these observations suggest that the line extensions of pioneers might receive more and better shelf space.

In addition, the pioneer who takes advantage of line extension opportunities may have an attention advantage driven by (1) the total amount of shelf space devoted to the pioneer's product line, and (2) the fact that the firm with the widest product line is most likely to have the largest package sizes on the shelf. The breadth of the product line may also increase the productivity of other elements of the marketing mix. Line extensions may increase the productivity of in-aisle promotions (e.g. signs, shelf-talkers, coupons, etc.), because the whole product line benefits from promotions for individual items in the line. In essence, a wide product line permits the pioneer to better leverage a fixed expenditure on in-aisle promotions. Similarly, line extensions may increase the pioneer's advertising productivity, because the whole product line benefits from promotions for individual items in the line. In summary, there are a number of mechanisms that might explain the pioneer breadth advantage that Robinson and Fornell (1985) identified; the relative importance of these mechanisms is a topic for future research.

Other opportunities arise by taking the PIMS data in a different direction. For PIMS-based research projects, many studies have examined market pioneer advantages and early follower and later entrant disadvantages. Reversing the perspective to examine market pioneer disadvantages plus early follower and later entrant advantages could yield important research insights. This is because a number of empirical generalizations have been established, but exceptions to these empirical generalizations have received much less attention.

For example, an explicit comparison of high- and low-share later entrants might yield some valuable insights. In his book on imitation strategies, Schnaars (1994) argues that imitators follow one or more of three generic strategies: (1) lower prices (2) a superior product, or (3) the application of market power, which refers to some combination of marketing clout, access to existing distribution channels, and financial resources. The third generic strategy is illustrated by Microsoft's success in promoting its Web browser, word processing, and spreadsheet software. An explicit comparison of successful or unsuccessful later entrants might permit the identification of the relative frequency and relative success of these imitator strategies.

Section 4.2 reviewed the relationship between order of entry and ROI, while Section 4.4 examined the relationship between order entry and strategy. Similarly to the research described in Section 4.1, these studies focus on the differences between pioneers, early followers, and later entrants. Examining differences among pioneers can extend this research. Are there different kinds of pioneer entry strategies? If so, what is the expected ROI associated with each of those generic strategies? Are there unique skills and resources associated with each generic strategy (Section 4.3)? What is the expected survival rate for each strategy?

More international comparisons would also be useful. Song, di Benedetto, and Zhao (1999) surveyed manufacturing and service firms in nine countries around the world. While managers in these nations typically perceive that market pioneers have important long-lived advantages, the magnitude of these advantages has not been quantified. Moreover, there are sound reasons to think that the magnitude of pioneer advantages varies in different parts of the world. Some countries (e.g. Germany) have placed restrictions on advertising and promotion, which should benefit pioneers who establish a strong reputation early in the product life-cycle. However, if a pioneer fails to establish a strong reputation before the entry of competitors, advertising and promotion restrictions may benefit followers, because the restrictions limit the ability of pioneers to leverage scale-driven marketing economies.

Some countries (e.g. Japan) have distribution systems that are very different from those found in the United States. Third World countries often have relatively less-developed technological and economic infrastructures. All of these forces have the potential to affect the strength of the relationship between order of entry and market share. For this reason, documenting the different international sources of market pioneer advantages should yield important research insights.

Finally, given their economic importance, high-technology markets and services are underrepresented in empirical research on first-mover advantages. As a result, we do not know whether even the most fundamental results (e.g. the relationship between order of market entry and market share) hold in high-technology markets. Case studies have identified mechanisms (e.g. virtuous cycles, installed base effects, and bandwagon effects) that are likely to enhance pioneer advantages in high-technology markets, but the relative importance of these mechanisms has not been confirmed in large-sample studies. Moreover, the increased possibility of technological leap-frogging raises the possibility that current estimates of survival may not apply to high-technology markets. For example, Mitchell's (1991) study of five markets for medical diagnostic imaging concludes: "the later a firm entered relative to other entrants, the longer it survived" (Mitchell 1991: 95). This possibility seems even stronger when the high-technology market includes a player like Microsoft, which has significant financial assets and relevant skills that can be applied to new markets. Together, these considerations suggest that market pioneers may have greater survival risks in high-technology markets than in consumer and industrial goods markets.

Finally, recent discussions of the differences between sustaining and disruptive technologies (e.g. Christensen 1997) suggest that the magnitude of first-mover advantages in high-technology markets may depend on the potential for integrating new technologies with existing ones. A disruptive technology has the potential to create learning curve advantages for pioneers, as well as create free-rider opportunities for followers. In addition, we expect that the impact of a disruptive technology on the performance of a pioneer depends on the distribution of relevant skills and assets among the leaders and followers. If a pioneer has the necessary skills and assets to exploit a disruptive technology, the result may be significant performance advantages. In contrast, if the pioneer does not have the necessary skills and assets, but a follower does, a disruptive technology may not produce any performance advantage for the pioneer.

4.5.2 Time-series studies

Studies based on PIMS data indicate that mature pioneers generally experience a slow deterioration in market share – one or two share points per decade. However, case studies have identified pioneers who were initially successful but experienced dramatic losses of market share in the mature stage of the product life-cycle. For example, Pampers lost over 50 points of market share between 1970 and 2000 (Parry 2002). Possible explanations for the Pampers share loss include:

- The nature of the product category (the need for disposable diapers is easy to predict and the diapers themselves are expensive, they do not spoil, and their quality is easy to verify);
- Rapid technological innovation (for many years, a new generation of disposable diapers appeared every eighteen months);
- Aggressive branded and private-label competition;
- Broad demographic changes (more women working);
- Technological changes (scanners that increased the power of retailers and the fragmentation of communication channels);

- Incorrect market research (in the 1980s, P&G concluded that there was no market for training pants); and
- Questionable strategy (P&G's decision to introduce Luvs, which resulted in confusion about the proper positions for the two brands and a division of marketing efforts at a time when Kimberly-Clark was pouring all of its efforts into a single brand, Huggies).

To date, research has explained pioneer decline by highlighting (1) shifts in market tastes (2) shifts in market technology (3) incumbent inertia, and (4) the self-immolation that often results from internal strife (see Lieberman and Montgomery 1998, and Schnaars 1994). The Pampers case suggests that other factors might also be important, some of which can be properly evaluated only with time-series data.

Another topic requiring time-series data is the impact of the pioneer's launch strategy on market growth. There is a strategic tension between the desires to (1) develop a market alone in order to earn monopoly profits and (2) invite or wait for competitors who spur market expansion by legitimizing the market. In the case of radical innovations, sometimes the desire to spur rapid growth creates a backlash among consumers and special interest groups that undermines the marketing efforts of the pioneer. For example, Monsanto's aggressive launch strategy for genetically modified seeds resulted in a backlash that has slowed the spread of genetic crops (Parry 1999). Some experts believe that the market's development has been set back ten or twenty years. Dr. Henry Miller, a senior research fellow at the Hoover Institution, said simply, "Food biotech is dead . . . The potential now is an infinitesimal fraction of what most observers had hoped it would be." (Eichenwald 2001) From the perspective of market growth, when is an aggressive launch strategy appropriate? When can it backfire? When can the presence of a competitor spur market growth, and when is the cost for the pioneer (in terms of forgone profit) too high?

4.5.3 Case studies

In some cases, pioneers benefit from the use of a marketing innovation that is very effective when first introduced, in part because no one else is using that tool. However, when the pioneer is successful, others copy the marketing tool and its effectiveness declines. For example, Crest pioneered the fluoride toothpaste category. To market this innovation, Crest applied for and (after supplying extensive

Table 4.4. *Citations of empirical research on order of market entry*

Authors (date of publication)	*Citations*
Selected industry studies	
Bond and Lean (1977)	57
Whitten (1979)	35
Lilien and Yoon (1990)	57
Mitchell (1991)	57
TOTAL	**206**
PIMS data	
Robinson and Fornell (1985)	151
Van Honacker and Day (1987)	15
Lambkin (1988)	95
Robinson (1988)	87
Parry and Bass (1990)	12
Moore, Boulding, and Goodstein (1991)	22
Robinson, Fornell, and Sullivan (1992)	31
Ramaswamy, DeSarbo, and Robinson (1993)	13
Murthi, Srinivasan, and Kalyanaram (1996)	9
TOTAL	**435**
Consumer packaged goods	
Urban, Carter, Gaskin, and Mucha (1986)	139
Kalyanaram and Urban (1992)	32
Brown and Lattin (1994)	23
Huff and Robinson (1994)	22
Bowman and Gatignon (1996)	11
TOTAL	**227**
Behavioral data	
Carpenter and Nakamoto (1989)	119
Hauser and Wernerfelt (1990)	92
Kardes and Kalyanaram (1992)	37
Kardes, Kalyanaram, Chandrashekaran, and Dornoff (1993)	34
TOTAL	**282**
Survival data	
Golder and Tellis (1993)	82
Robinson and Min (2002)	1
TOTAL	**83**
Review articles	
Lieberman and Montgomery (1988)	273
Kerin, Varadarajan, and Peterson (1992)	97
Robinson, Kalyanaram, and Urban (1994)	26
Kalyanaram, Robinson, and Urban (1995)	22
Vander Werf and Mahon (1997)	10
TOTAL	**428**

documentation) received the American Dental Association's (ADA) endorsement, as well as permission to place the ADA label on its package. Many people believe that this endorsement was a primary reason why Crest's share went from about 10 percent in 1960 to 40 percent by 1970. Thus P&G's product innovation (fluoride toothpaste) accounted for some of Crest's success, but the marketing innovation (ADA endorsement) significantly bolstered Crest's share (Parry 2001). Are there other cases in which pioneers have used innovative marketing tactics to leverage product innovations? When have those marketing innovations been successful, and when have they failed? What guidelines might these case studies suggest for the future "marketing innovation" pioneers?

4.6 Conclusions

Over the past twenty years, empirical research on order of market entry has evolved from being an overlooked research area to its current status as a mature research area. In the 1980s, PIMS data research, along with the Urban *et al*. (1986) award-winning study, helped start this research area in marketing. After the mid-1980s, PIMS-based studies provided additional insights into the market share performance for market pioneers, their financial performance, advertising strategies, and product development strategies. Thus, the PIMS data helped provide many key research insights into the literature on order of market entry.

One way to quantify the influence of the PIMS data is through citation counts. Table 4.4 provides citation counts for empirical research on order of market entry. The citation counts were gathered in February 2003 from the online version of the Social Science Citation Index. In chronological order, Table 4.4 covers selected industry studies that helped motivate and develop research on order of market entry. Other empirical studies that address general tendencies arise from the PIMS data, research on consumer packaged goods, behavioral research, and survival studies. Table 4.4 also includes five review articles.

In Table 4.4, the PIMS studies have 435 research citations. The second most cited category is review articles, with 402 citations. Consistent with the importance of being first, it is interesting to note that the first paper in a given research topic area has the greatest number of citations in five out of six topic areas.

In conclusion, it is safe to say that the PIMS data have played a key role in starting and developing empirical research on order of market entry. While research in economics had long recognized the importance of entry barriers, order of entry "was not explicitly identified" (Scherer 1994: 175). With almost 300 citations, Lieberman and Montgomery's (1988) review article in the *Strategic Management Journal* indicates the importance of research on order of market entry in strategic management. This widely cited article has helped diffuse the PIMS order-of-entry insights into a number of disciplines, including economics, strategic management, and marketing.

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5 Does innovativeness enhance new product success? Insights from a meta-analysis of the evidence

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The field of product innovation has expanded rapidly, and insights regarding the relationship between product innovativeness and new product performance have become clouded, as findings are increasingly mixed. To address this issue and add clarity, the authors quantitatively analyze the extant product innovativeness–new product performance findings. They find that while the resulting relationship between innovativeness and performance is small on average, it lacks generalizability because of a number of measurement (e.g. definition of newness and nature of performance data) and contextual factors (e.g. goods versus services) that moderate the magnitude of the product innovativeness effect found. They subsequently discover that the magnitude of the relationship also has diminished over time as competitive conditions have unarguably intensified. The authors explore the implications of these findings and the revised contingency perspective for academic research and business practice.

As a research base expands, it becomes critical to take stock of extant findings to ensure that previous conclusions and perspectives remain valid and to further ensure that the proper approach to research is being pursued. This assessment becomes even more critical when an area is relevant to practitioners and is attracting a growing number of researchers. Such is the case with the literature focusing on the role of product innovativeness in the marketplace performance of new product offerings.

Because product innovativeness has long been viewed as a strategy of high risk yet potentially high returns, researchers have been expending significant effort in recent years (e.g. Ali, Krapfel, and LaBahn 1995; Atuahene-Gima 1996; Firth and Narayanan 1996; Gatignon and Xuereb 1997; Hultink and Robben 1995; Kuester, Homburg, and

Robertson 1999; Li and Calantone 1998; Madhavan and Grover 1998; Olson, Walker, and Ruekert 1995; Sethi 2000; Shankar, Carpenter, and Krishnamurthi 1998; Song and Parry 1997; Swink 2000) to understand the underlying forces behind the success or failure of highly innovative new products. However, as this empirical research base has expanded, the true relationship between product innovativeness and marketplace performance has become less, rather than more, apparent. While some studies continue to find a positive relationship between product innovativeness and new product success (e.g. Gatignon and Xuereb 1997; Li and Calantone 1998; Parry and Song 1994; Swink 2000), others report effects that are not significantly different from zero (e.g. Mukherjee 1998; Tatikonda and Rosenthal 2000), and still other studies report effects that are statistically significant and negative in direction (e.g. Atuahene-Gima 1996; Ryans 1988). As a consequence, the range in effect sizes reported in the literature is quite broad, and this invariably complicates the efforts of managers and researchers to develop a unified sense of the role of innovativeness in new product performance. These disparate research findings also raise three pertinent questions. One is whether product innovativeness can be characterized as a major driver of new product success (e.g. Crawford 1977; Cooper 1993, 1996; Lynn, Morone, and Paulson 1996). The second is whether the variance in the effect sizes is sufficient to conclude a lack of generalizability in the innovativeness–new product performance relationship. The third question is whether researcher decisions (i.e. study measurement and contextual issues and the timing of the research) play a moderating role in whether or not innovativeness emerges as a prominent predictor of the estimated level of the offering's commercial success.

It is against this backdrop of growing research relevancy, greater research attention, growing disparity in research findings, and mounting questions regarding the role of innovativeness in new product performance that we present the findings from our meta-analysis of the innovativeness–performance literature. Meta-analysis is an analytical tool typically used to address questions of central tendency, external validity, and contingency. It also is a tool that becomes more relevant as the number and disparity of findings reported in a literature increase. Our meta-analysis, therefore, focuses on providing insights into the expected size and direction of the growing number of disparate findings reported in the innovativeness literature; disentangling the variance across the reported effects; and identifying key moderators accounting for this disparity in effect sizes. To accomplish these objectives, we first discuss relevant definitions of innovativeness and performance and the reasons why greater innovativeness might translate into either superior or inferior marketplace performance. We then provide an overview of the methodology used in the meta-analysis, followed by the presentation of the findings. We close by discussing the implications of the findings, limitations of the investigation, and directions for future research.

5.1 Conceptual background for the study

5.1.1 Definition and operationalization of constructs

A cursory review of the product innovativeness literature suggests relative agreement among authors on how to define innovativeness and performance conceptually, but disagreement on how best to operationalize the constructs. For example, a classical definition of product innovativeness is the degree to which new products differ from existing alternatives (Zaltman, Duncan, and Holbek 1973). Although this definition has been broadened by some to include a meaningfulness dimension to innovativeness (e.g. Cooper and Kleinschmidt 1987; Sethi, Smith, and Park 2001), there seems to be general agreement that innovativeness is a difference characteristic inherent to varying degrees in new product offerings. Greater disagreement occurs, however, with respect to the most appropriate way to operationalize innovativeness (e.g. Garcia and Calantone 2002). In general, researchers have operationalized innovativeness with regard either to how new the product is (new to the world, new to the firm) or to what about the product is new (newness of technology utilized, newness of product attributes). We also find inconsistencies in innovativeness measures in regard to the use of single-item or multi-item scales and categorical or continuous measures for capturing innovativeness levels. These disparities have invariably contributed to the overall confusion as to what individual studies are capturing.

Likewise, we find relative agreement among authors on the conceptual definition of new product performance, but less agreement on how best to capture performance. Generally, performance is defined in terms of how well the offering does in the open market. Yet, when it comes to measuring performance, we find researchers once again adopting different measures (e.g. market share and profitability) and measurement approaches (e.g. relative versus absolute and subjective versus objective) for capturing marketplace performance. Because such disparities could account for the variance in innovativeness effect sizes found across studies, their role needs to be documented.

5.1.2 Competing perspectives on innovativeness and performance

In addition to differences in defining constructs, a review of the literature finds numerous firm-based and consumer-based perspectives being discussed that support either a positive or a negative effect of product innovativeness on new product performance levels. These opposing perspectives imply that the positive, negative, or nonsignificant effects found in the literature are likely to be nonspurious. They also accent the difficulties that managers and researchers likely face when trying to predict the performance outcome when marketing a highly innovative product.

To illustrate, positive *firm-based* effects are thought to result from highly innovative products fostering a spirit of innovation in the company that can help attract and retain highly creative employees and improve worker productivity. This can ultimately reduce costs, employee turnover, and discontinuities in idea generation (Urban, Weinberg, and Hauser 1996). Innovation can also create first-mover barriers (e.g. patents or preemption of competitive space) that can increase return on investment and cause competitors to invest in ventures where they have little expertise (Kerin, Varadarajan, and Peterson 1992; Szymanski, Troy, and Bharadwaj 1995). In addition, positive *consumer-based* effects are realized when the innovativeness of the offering leads consumers to greater product trial (Holak and Lehmann 1990) and creates greater customer value (Smith and Andrews 1995; Mukherjee 1998).

Concurrently, negative forces exist that must be considered when predicting whether innovativeness will emerge as a positive or negative factor in new product success. The mitigating *firm-based* factors include the possibility that (1) employee response may not be universally positive when new product fit with other units within an organization is poor (Bloch 1995); (2) team members can become overwhelmed with the greater diversity of new tasks (Sethi 2000);

(3) dominant product designs can be lacking, which can complicate the execution of innovative ideas (Song and Parry 1999); (4) new mental and physical skills, new equipment, and new organizational structures may be required but may not be easily obtainable or mastered (Atuahene-Gima 1995; Sethi 2000); and (5) competitors may innovate around the offering, capitalize on second-mover advantages, increase advertising, or sharply discount offerings (e.g., Kuester, Homburg, and Robertson 1999). Finally, negative *consumer-based* factors include the possibility that (1) consumers may resist learning about innovative new offerings (i.e. by being cognitive misers) or may be unable to process complex information when cognitive capabilities are limited (Herbig and Kramer 1994; Holak and Lehmann 1990); (2) acquiring new knowledge can render existing knowledge useless, further discouraging consumers from considering radical products (Song and Parry 1999); and (3) radical products can discourage customers by rendering current possessions obsolete, requiring the purchase of compatible items, and requiring new consumer behaviors (Urban, Weinberg, and Hauser 1996).

All told, a review of the innovativeness literature not only highlights the diverse nature of the reported effects, but also uncovers competing firm-based and consumer-based perspectives that support the reasonableness of finding conflicting innovativeness effects. In turn, these competing perspectives and diverse findings imply that a meta-analysis might add value by identifying meaningful explanations for the observed variance in effect sizes. It can also add value by identifying the most accurate description of the underlying relationship between product innovativeness and new product performance, namely, that innovativeness and performance are either (1) positively related, (2) negatively related, or (3) unrelated (i.e. offsetting positive and negative effects) on average. The methodology used to achieve these objectives follows.

5.2 Research design

5.2.1 Identification of relevant studies

We began the meta-analysis by identifying the empirical studies in which innovativeness is either a central focus of the empirical investigation or innovativeness is specified as one of the predictors in a multivariate model of new product performance. These studies were identified by (1) reviewing several electronic databases (e.g. ABI/Inform, ProQuest, and Ovid) using relevant keywords such as *product innovativeness, product newness, product novelty, product uniqueness, radical products,* and *discontinuous innovation*; (2) reviewing the citations in innovativeness studies; (3) hand-searching the leading journals most likely to publish articles on product innovativeness (*Academy of Management Journal, Journal of the Academy of Marketing Science*, *Journal of Marketing, Journal of Marketing Research, Journal of Product Innovation Management, Management Science,* and *Marketing Science*); and (4) writing directly to academic experts (twenty authors) and posting a request for relevant working papers on the Electronic List for Marketers (ELMAR, over 3,200 subscribers). We concluded our search in December 2002, when it became clear that additional efforts were not yielding additional studies. In total, we identified thirty-seven empirical studies (thirty-six published and one unpublished) capturing the relationship between product innovativeness and new product performance.

5.2.2 Unit of analysis

The next step in the meta-analysis focused on identifying the appropriate measure of association that would permit the largest number of studies and effects to be included in our review. Although analyzing either elasticities or correlations is appropriate, we discovered that only one of the thirty-seven studies on product innovativeness reported elasticities (Sethi 2000), while twenty-nine of the studies reported correlations (or data convertible to correlations [see Glass, McGaw, and Smith 1981]). Analyzing correlations therefore allows us to include data from 78% of the studies in our meta-analysis.[1] This inclusion rate is greater than the rate typically found for meta-analyses in marketing (e.g. Brown and Peterson [1993], 66%; Henard and Szymanski [2001], 68%; Szymanski, Bharadwaj, and Varadarajan [1993], 63%; and Szymanski, Troy, and Bharadwaj [1995], 70%). The twenty-nine

[1] A list of the twenty-nine studies whose findings are included in the meta-analysis is available from David M. Szymanski, along with a list of the eight studies reporting discriminant findings and the like, but not reporting correlations.

studies also compare favorably to the number of studies included in meta-analyses by Assmus, Farley, and Lehmann (1984; 28 studies), Sultan, Farley, and Lehmann (1990; 15 studies), and Szymanski and Busch (1987; 24 studies). Moreover, the eighty-nine correlations exceed the number of effects analyzed in several other meta-analyses in marketing (e.g. Brown and Stayman [1992; 47 effects]; Rao and Monroe [1989; 85 effects]; Szymanski, Troy, and Bharadwaj [1995; 64 effects]) and represent a fivefold increase over the number of innovativeness effects reported in Henard and Szymanski's (2001) meta-analysis of the drivers of new product performance. Finally, the eighty-nine correlations offer adequate power (.80) for detecting the significance ($\alpha = .05$, two-tailed) of medium ($r = .30$) and large ($r = .50$) effects, or all but the smallest effects, of product innovativeness on new product performance (Cohen 1988).

5.2.3 Level of analysis

Following the identification of relevant studies and the pertinent metric, we determined whether a model-level or study-level examination was more appropriate for our analysis. We did so by applying the Q test for homogeneity of effects within studies to the twenty-one studies reporting multiple innovativeness effects (Hedges and Olkin 1985). The Q test was rejected for ten of the twenty-one (47.6%) studies, or 35% of the twenty-nine studies in our database, implying that a model-level analysis (analyzing individual correlations for each model) is more appropriate than a study-level analysis (averaging the correlations of multiple models within a study) owing to excessive heterogeneity among correlations. Therefore, similarly to Assmus, Farley, and Lehmann (1984), Henard and Szymanski (2001), Sultan, Farley, and Lehmann (1990), Szymanski and Busch (1987), and Tellis (1988), we conduct our meta-analysis at the model level.

5.2.4 Potential moderators

As the final step leading up to data analysis, we identified potential moderators of the innovativeness–performance relationship that could be coded from the studies. These potential moderators are those that have been reported often enough in the literature (i.e. fifteen or more models) and that vary sufficiently in their levels or presence/absence across models to allow for reasonable statistical analysis. They also represent factors that in theory could moderate the estimated correlations.

As is typical in meta-analysis, the potential moderators fall into one of three classes: (1) omitted variables (i.e. factors correlated to both innovativeness and performance whose presence/absence varies across the models); (2) measurement factors (e.g. differences across innovativeness and performance measures); and (3) contextual elements (e.g. alternative product and industry settings). Ultimately, six omitted variables spanning product-related (product advantage), firm-specific (customer, competitor, and technological orientation of the firm, interfunctional coordination), and industry (competitive intensity) categories that in theory could bias the estimated correlation between innovativeness and performance were identified and coded from the extant studies.[2] Ten measurement and three contextual factors were also identified

[2] The direction of omitted variable bias is determined by the sign of the relationship between innovativeness and the omitted variable times the sign of the relationship between performance and the omitted variable. Omitted variables that could result in a positive bias of the innovativeness–performance correlation include: (1) *product advantage* – because offerings with a relative advantage are likely to be more successful (Gatignon and Xuereb 1997; Song and Parry 1997) and product innovativeness can be a component of product advantage (Li and Calantone 1998); (2) *technological orientation* – because both product innovativeness and product performance may increase as technically oriented firms anticipate trends in new technologies and develop better solutions to customer needs (Gatignon and Xuereb 1997); and (3) *interfunctional coordination* – because an emphasis on teamwork and managerial support can be conducive to superior performance and because interfunctional coordination can augment a firm's ability to develop highly innovative new products (Troy, Szymanski, and Varadarajan 2001). On the other hand, omitted variables that might negatively bias the innovativeness–performance correlations include: (1) *customer orientation* – because understanding customers can enhance marketplace performance (Gatignon and Xuereb 1997), but a focus on the salient needs of the consumer can have a detrimental effect on innovativeness when latent needs go unrecognized (Hamel and Prahalad 1991); (2) *competitor orientation* – because understanding competitors can have a positive effect on performance when it allows firms to generate new products according to their competitive advantages (Gatignon and Xuereb 1997), but also can have a detrimental effect on innovativeness when new products result from reactive rather than proactive strategies; and (3) *competitive intensity* – because competitive intensity can be associated with reduced performance

and coded along with information obtained from study authors on the year the innovativeness data were collected. Two researchers independently coded the complete set of correlations and potential moderators. Coding agreement was achieved in 95 percent of the instances, with the few discrepancies resolved through discussions with the researchers in reference to the coding scheme. The findings from an analysis of these coded variables and their associated effects follows.

5.3 Results

The presentation of findings proceeds with descriptive information on the innovativeness correlations. Our objective here is to offer insights into what the body of evidence looks like and whether much of the variance in the correlations is real as opposed to artificial (i.e. due to sampling and measurement error). The latter determination is important for documenting whether a subsequent search for moderators is justified from a statistical perspective.

5.3.1 Descriptive findings

As illustrated in Figure 5.1, the range of the 89 innovativeness correlations is quite broad, ranging from .69 to −.79. Most of these correlations are positive (70 of 89) and their distribution is negatively skewed (−1.16). As a consequence, the reliability-corrected mean (i.e. the mean adjusted for sample-size and reliability differences in the measures) of .26 ($p \leq .05$) is also positive. However, this point estimate must be interpreted with caution because it has not yet been corrected for bias due to omitted variables or measurement and contextual differences. The fact that the unexplained variance (i.e. not accounted for by sampling error and reliability differences) in the correlations of 94.4% is high compared to the 25% criterion outlined in Hunter and Schmidt (1990) indicates the necessity for identifying potential moderators and further correcting the estimate. We therefore turn our attention to the findings

(Cooper 1984) when market uncertainty (Gupta, Raj, and Wilemon 1986) and competitive information needs are high (Kohli and Jaworski 1990), but the relationship between competitive intensity and product innovativeness can be positive when firms take innovation risks to gain competitive advantages (Covin and Slevin 1989).

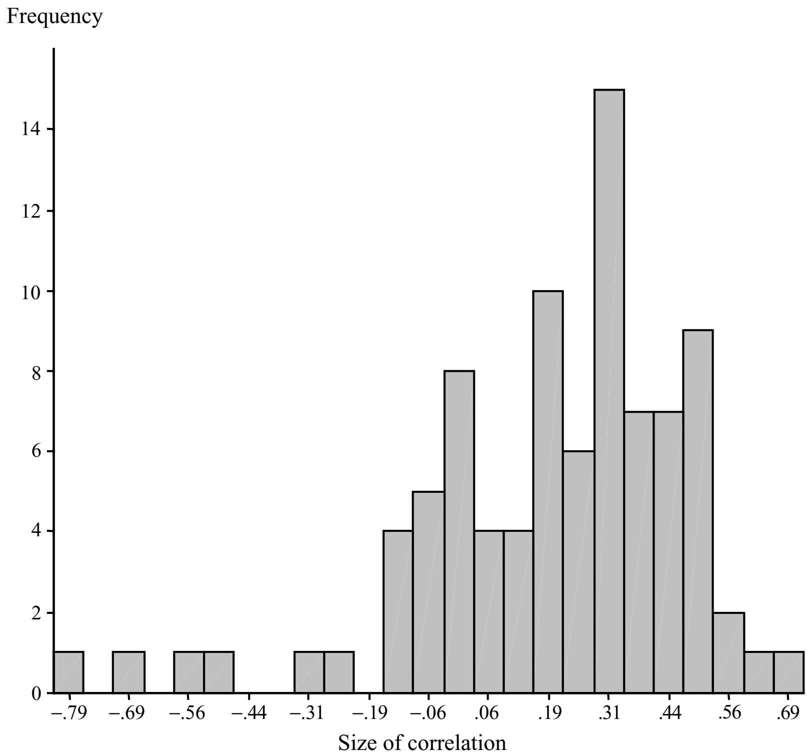

Figure 5.1. Distribution of innovativeness–performance correlations.

from this search for moderators and the corresponding corrections of the estimate of central tendency.

5.4 Moderator variable analysis

5.4.1 Role of omitted variables

To determine whether omitted variable bias is present to a significant degree, we estimated the partial correlation for innovativeness and performance, controlling for the product, firm, and marketplace factors whose correlations are listed in Table 5.1a. We find that the resulting partial correlation of .21 ($p = .06$) is smaller, but the difference relative to the reliability-corrected value of .26 is neither statistically ($p = .09$, one-tailed) nor practically significant ($\Delta R^2 = .0025$). This outcome is

Table 5.1a. ***Correlations among omitted variables, innovativeness, and performance***

Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*
1. Product advantage	1.00						
2. Customer orientation	.28*	1.00					
3. Competitive orientation	.31*	.81*	1.00				
4. Technological orientation	.50*	.49*	.52*	1.00			
5. Interfunctional orientation	.25*	.79*	.80*	.51*	1.00		
6. Innovativeness	.25*	.12	.16	.42*	.15	1.00	
7. Performance	.21*	.17	.23*	.20	.24*	.26*	1.00

Note: * Statistically significant at $\alpha \leq .05$, two-tailed.

also evidenced when the respective omitted variables and innovativeness are regressed on performance using the z-transformed values of the correlations from Table 5.1a as input. The overall model is not statistically significant ($F_{7,80} = 1.70$, $p = .12$), it explains little of the variance in new product performance ($R^2 = .13$), and the coefficient for innovativeness once again fails to achieve statistical significance. All told, these findings imply that omitted variable bias as it pertains to the variables captured here does not provide a meaningful explanation of the variance in the innovativeness correlations. Concentrating instead on the role contextual and measurement factors play in this regard might prove more revealing.

5.4.2 Role of contextual and measurement variables

As is common in meta-analysis, we used OLS regression to capture the variance in the correlations attributable to contextual and measurement characteristics (e.g. Sultan, Farley, and Lehmann 1990; Szymanski and Busch 1987; Szymanski and Henard 2001; Tellis 1988). Specifically, our model has the following form:

$$r_{I,P} = r_0 + B_1 Y_r + B_2 C_1 + B_3 C_2 + B_4 C_3 + B_5 M_1 + \cdots + B_{14} M_{10} + \cdots \quad (1)$$

where $r_{I,P}$ is the z-transformed value of the reliability-corrected correlation, r_0 is the grand mean correlation for innovativeness with performance, B_i are the unstandardized regression coefficients, Y_r is the year of data collection (continuous variable), and C_i and M_i are the dummy-coded contextual and measurement moderators, respectively.[3] The correlation matrix for the model is presented in Table 5.1b. The rationale behind the respective predictors is presented in Table 5.2. The findings from estimating model (1) are reported in Table 5.3.

5.4.3 Adequacy of the model

The descriptive data for the model offer evidence in support of its suitability. The model is statistically significant ($F_{14,72} = 3.26, p < .001$), captures a reasonable proportion of the variance ($R^2 = .39$) in the correlations, and is devoid of significant outliers (i.e. two outliers with standard deviations greater than three were withheld from the analysis). In addition, collinearity is not unduly influencing the estimated coefficients (i.e. the maximum variance inflation value [Max VIF] of 6.07 is below the critical value of 10 [Neter *et al.* 1996]), the model is reasonably valid as implied by the relatively low PRESS ratio (prediction sum of squares to the sum of squares error) of 1.52, and an analysis of the residual plots indicates the error variance is relatively constant over all cases partly because the time component of the database (Y_r) is specified as a predictor variable in the model (Cohen and Cohen 1983, p. 129).

5.4.4 Regression findings

From Table 5.3 we see that the grand mean (i.e. the model intercept) of .10 is not statistically significant ($p = .49$) and is much smaller ($\Delta r = .16, p = .035$, one-tailed) than the reliability-corrected estimate of .26. Because the grand mean is considered to be the more accurate

[3] While it may be desirable to include the omitted variables along with the measurement and contextual factors in a single regression model, the correlation matrix of omitted variables (Table 5.1a) cannot be merged with the correlation matrix of measurement and contextual variables (Table 5.1b). The former contains correlations for each of the omitted variables with innovativeness and performance separately, whereas the latter contains correlations for each of the measurement and contextual factors with the correlation *between* innovativeness and performance. As a consequence, separate analyses of omitted variable bias and contextual and measurement biases are conducted.

Table 5.1b. *Correlations of methodological and contextual factors with the reported innovativeness-performance effect*

Variables	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*13*	*14*
1. Innovativeness–performance effect	1.00													
2. Multi-item vs. single-item predictor[1]	−.04	1.00												
3. New-to-market vs. new-to-firm	.36*	−.27*	1.00											
4. Categorical vs. continuous predictor	.12	−.79*	.22*	1.00										
5. Newness of technology vs. product	−.17	.24*	−.50*	−.20	1.00									
6. Newness vs. meaningfulness	−.28*	−.45*	−.10	.48*	.09	1.00								
7. Multi-item vs. single-item criterion	−.22*	.50*	−.45*	−.38*	.03	−.10	1.00							
8. Subjective vs. objective criterion	−.11	.61*	−.34*	−.59*	.01	−.27*	.64*	1.00						
9. Relative vs. absolute criterion	−.05	.19	−.20	−.26*	−.06	.04	.42*	1.00	1.00					

10.	Financial vs. marketplace performance	.10	−.16	−.02	.20	.10	.14	.01	−.19	.00	1.00				
11.	Most knowledgeable vs. senior exec.	.13	.21*	−.06	−.25*	−.06	−.27*	−.07	.30*	.22*	−.35*	1.00			
12.	Year of data collection	−.28*	.44*	−.33*	−.41*	.07	−.04	.61*	.66*	.46*	−.29*	.38*	1.00		
13.	NewProd vs. non-NewProd data	.21*	.35*	.02	−.36*	−.02	−.32*	−.19	.27*	.10	−.04	.46*	−.19	1.00	
14.	Goods vs. goods and services	.08	.35*	−.21*	−.33*	.09	−.03	.12	.23*	.33*	−.15	.62*	.44*	.30*	1.00
15.	High-tech vs. low-tech industries	−.03	.37*	−.10	−.28*	.09	−.16	.37*	.40*	.09	−.28*	.15	.33*	.00	.09

Notes: [1] Predictor refers to product innovativeness and criterion refers to new product performance throughout the table.
* Statistically significant at $\alpha \leq .05$, two-tailed.

Table 5.2. ***Rationale behind selected moderators of the innovativeness–performance relationship***

Potential measurement moderators

Multiple-item vs. single-item measures of innovativeness and performance (+)[1]: The accuracy and effectiveness of single-item measures have been questioned in the psychometric and marketing literatures for several reasons (Churchill 1979; Nunnally and Bernstein 1994). Generally, single-item measures can produce lower correlations with the attribute being measured while also being correlated with other attributes; and single-item measures are often of more questionable reliability. In contrast, multi-item measures are thought to overcome these deficiencies by averaging out the specificity of items, distinguishing perceptions more finely among respondents, and increasing reliability while decreasing measurement error as the number of items in the scale increases; this implies that the innovativeness–performance correlation could be greater when using multi-item measures for capturing these constructs.

Categorical vs. continuous measure of innovativeness (+/−): Principles grounded in statistical and psychometric theory argue that using continuous measures for capturing the underlying nature of the relationship between continuous variables produces more accurate estimates of relationship strength (Cohen and Cohen 1983). Because both product innovativeness and performance are continuous measures, we would expect the correlations grounded in continuous measures to be the more accurate correlations, with the direction of the improved accuracy being an empirical issue.

New-to-the-market vs. new-to-the-firm innovations (+): A product that is perceived as new-to-the-market (i.e. its intended customer base) may perform better in the marketplace because consumers can distinguish the product and its benefits more effectively from existing offerings (Crawford 1992). In contrast, new-to-the-firm products can require changes in managerial activities, reduce synergies with existing firm knowledge and skills (Cooper and Kleinschmidt 1991), and represent offerings that are indistinguishable from other products on the market. Although they may be inherently more risky, new-to-the-market innovations have greater potential to capture customers' attention and outperform new-to-the-firm products, all else being equal.

Table 5.2. (*cont.*)

Newness of technology vs. product (+): Innovativeness is typically contrasted by researchers to the product itself or the product's underlying technology (e.g. Cooper et al. 1994; Sethi 2000; Swink 2000; Tatikonda and Rosenthal 2000). Newness of technology usually refers to novelty in product architecture, product parts, and modules (Tatikonda and Rosenthal 2000) as well as newness of technology in the product's features, functions, and manufacturing processes (Swink 2000). Newness of the product, on the other hand, refers to a more general or overall perception of innovativeness; for example, newness of the product to customers and firms (Atuahene-Gima 1995). Because innovativeness with respect to the product can be more relevant and easier for consumers to evaluate than innovativeness embedded in difficult-to-detect technological processes, the resulting innovativeness effect on performance may be stronger when scale items focus on newness of the product instead of newness of technology.

Newness vs. newness plus meaningfulness (−): As the traditional definition of product innovativeness as the degree of newness/difference from existing alternatives (e.g. Booz-Allen and Hamilton 1982, Song and Parry 1999; Zaltman, Duncan, and Holbek 1973) has been extended to include a usefulness or meaningfulness dimension (Crawford 1977; Cooper 1993, 1996; Sethi, Smith, and Park 2001), the documented effect on performance might also change. As the richness of the construct and the domain being sampled increases (Churchill 1979), a more accurate estimate should emerge; and as an important dimension of purchase is added to the definition, i.e. usefulness, we would expect a stronger association between innovativeness and performance to emerge.

Subjective vs. objective measure of performance (+): Whether performance is captured as an objective (e.g. return on investment, sales, market share, or profits) or subjective assessment (e.g. managers' perceptions of how well the new product performed relative to expectations) could further moderate the estimate of the innovativeness effect. *A priori*, associations grounded in subjective rather than accounting data can be less accurate as a result of demand artifacts (e.g. desires by managers to look good to researchers), managers' inability accurately to gauge consumers' assessments, and variation in the standards managers use for assessing success (e.g. Starbuck and Mezias 1996, Walsh 1988). Because issues of self-esteem and escalation of commitment indicate that managers are often unwilling to admit new product failure, especially when the new products are more innovative (Schmidt and Calantone 2002), it is likely that subjective measures portray innovative offerings as being more successful than they really are.

(*cont.*)

Table 5.2. (*cont.*)

Relative vs. absolute measure of performance (+/−): The appropriateness of a relative or absolute measure of product performance can depend on the context for the study. For example, using an absolute measure of market share can be appropriate in a single-industry study where the sum for the individual businesses in the industry would equal 100. In a cross-industry study, however, relative measures of market share would be more appropriate because single-industry constraints are not applicable (Szymanski, Troy, and Bharadwaj 1995). In addition, a relative measure can decrease the amount of noise in the data because a common reference across respondents (e.g. relative to the market leader or three major competitors) is now available for grounding performance estimates (cf. Nunnally and Bernstein 1994). Consequently, we might expect variance in the product innovativeness–new product performance correlations partly from new product performance being an absolute or relative measure, with ascertaining the direction and size of the difference being a component of our empirical examination.

Financial vs. marketplace performance (+/−): Marketplace performance consists of both sales and market share. These constructs are related mathematically; sales is central to market share estimations and market share takes into account performance relative to the entire market. In comparison, financial measures of new product performance (e.g. profits or ROI) focus on revenues and costs of the specific product, whereby performance relative to competitors is not always an explicit component in these calculations. Market and financial performance measures and the correlations grounded in the respective measures could therefore differ because of these disparities. This possibility is supported in Szymanski, Bharadwaj, and Varadarajan (1993), who document that market share and financial performance (ROI) are far from perfectly correlated (mean elasticity of .259). While proposing a directional hypothesis is difficult *a priori*, it is reasonable to propose that variance in the performance metric could contribute to the variance in the innovativeness correlations.

Person most knowledgeable vs. senior executive (+/−): Information reported by the senior executive may differ from the information reported by the person most intimate with the new product, such as a project manager (Griffin and Page 1996). Although a senior executive can be familiar with a new project, the project manager is likely to be closer to the project and likely to have more accurate information to provide researchers. In contrast, information passed up to the executive level could be distorted or otherwise inaccurate depending upon the breadth and depth of the communication

Table 5.2. (*cont.*)

channel – i.e. how second-hand the data turn out to be. The expectation, therefore, is that the product innovativeness–performance correlation would differ depending on whether the data were obtained from a senior executive or the new product manager. The nature of the difference will be documented in the meta-analysis.

Potential contextual moderators

Year of data collection (−): The argument could be made that over time, researchers become better at capturing the true, central properties of a phenomenon (e.g. Churchill et al. 1985). The refinement of research instruments, higher journal standards for excellence in measurement reliability and validity, and improved understanding of nomological validity are among the factors that could lead to better measures and better estimates of relationship strength reported in the innovativeness literature over time. The expectation, therefore, is that the year of data collection provides an indication of the level of accumulated knowledge and research standards at that point in time. A subsequent analysis of time can capture changed market conditions and the changing role of innovativeness in new product success. For example, the point is often made in the business press that markets are more competitive (i.e. more companies competing for consumer dollars) and cluttered (i.e. more new products in the marketplace), which can make it more difficult for highly innovative products to stand out and be successful (e.g. McKay 2000; Williams 2001). Consequently, the relationship reported between innovativeness and performance may be weaker in more recent studies of new product success.

NewProd vs. non-NewProd Data (+): The NewProd initiative in the late 1970s (Cooper 1979a, 1979b, 1982) and its replication in the mid-1980s (e.g. Cooper and Kleinschmidt 1987) are the primary large-scale empirical initiatives focusing on the antecedents of new product success. While these studies share characteristics in context and study design, e.g. exclusive focus on new products from Canadian firms, other research in product innovativeness not derived from the NewProd datasets is likely to have contextual and study design features that differ from the NewProd sets. For example, in contrast to Canadian markets, US markets can be portrayed as having more consumers, more manufacturers, more promotion and advertising, more consumer options, etc., which create a more competitive and noisier marketplace in which to innovate (Szymanski, Bharadwaj, and Varadarajan 1993). As a result, innovativeness may be less of a differentiating factor in US success, causing innovativeness and performance to emerge as more strongly (weakly) related in Canadian (US) markets.

(*cont.*)

Table 5.2. (***cont.***)

The resulting correlations grounded in NewProd data should therefore be stronger, all else equal.

Goods vs. goods and services (+): Well established are the notions that relative to goods, services are more intangible, inconsistent, inseparable in production and consumption, and more perishable; as well as more difficult for consumers to assess before purchase (Zeithaml, Parasuraman, and Berry 1985). Differences such as these imply that since highly innovative offerings are inherently more risky to buy (i.e. requiring greater change in adoption and usage behaviors), consumers may be even less willing to adopt innovative new services, services which by their nature are even harder for consumers to evaluate before purchase. As a result, the relationship between innovativeness and performance may be stronger for goods than for services. In our case, because innovativeness research focuses more on goods or a combination of goods and services (exceptions are Cooper and de Brentani 1991; Cooper et al. 1994; de Brentani 1989), we test for a positive contrast of goods relative to goods and services combined.

High-technology vs. low-technology industries (−): Compared to low-technology markets, high-technology markets are often more complex, information-intensive, turbulent, and uncertain owing to rapidly changing and heterogeneous technologies (Glazer 1991). Shorter product life-cycles and a situation where innovation is more common may also mean that innovativeness is simply necessary for survival among high-technology firms. However, in low-tech industries where product life-cycles are longer and innovativeness less frequent, greater innovativeness may translate into superior marketplace performance. For example, while innovativeness in consumer package goods can appear mundane when compared to high-tech innovations, the benefits derived from them can deviate from current products in a more meaningful way (Andrews and Smith 1996). Hence, we might expect to find weaker (stronger) product innovativeness–new product performance correlations in high-technology (low-technology) industries.

Note: [1] The parentheses contain the direction of the hypothesized moderating effect.

estimate of central tendency (Tellis 1988), its small size and lack of significance imply that innovativeness does not exert a substantial direct effect on new product performance when all else is held constant.

But herein lies the value of the moderator analysis as executed through the estimation of model (1). When the *ceteris paribus* condition is relaxed, we find that the strength of the innovativeness–performance relationship can be masked by the context in which it is examined and the method used for estimating the association. In fact, three measurement features of innovativeness emerge as significant moderators: innovativeness measured as new-to-the-market versus new-to-the-firm ($\beta = .35, t = 2.66$), innovativeness captured as a categorical versus a continuous variable ($\beta = .39, t = -2.32$), and innovativeness measured as including versus excluding a meaningfulness dimension ($\beta = .34, t = 2.71$). With regard to new product performance, one measurement factor significantly moderates the innovativeness effect: the use of subjective perceptions rather than objective measures of success ($\beta = .42, t = 2.07$). We also find that two contextual factors significantly moderate the innovativeness–performance relationship: year (recency) of data collection ($\beta = -.65, t = -2.88$) and the innovativeness present in goods versus goods and services ($\beta = .36, t = 2.46$).

In all, the significant findings from the moderator analysis are consistent with our hypothesized effects (see Table 5.3). They also indicate that the relationship between innovativeness and performance is stronger on average when the focus is on true innovativeness, i.e. goods that are new-to-the-market, and when using measures of innovativeness that incorporate meaningfulness items. Furthermore, in light of the fact that the better data are typically more contemporary data grounded in continuous and objective measures of innovativeness and performance respectively (Table 5.2), our findings argue for the better estimate of the innovativeness–performance relationship being the weaker rather than the stronger estimates. The insights generated from these and the other findings of the meta-analysis are discussed next.

5.5 Discussion of the findings

Our research findings, when cast against our three original research questions, highlight the fact that the average effect of product innovativeness on new product performance is relatively weak, the reported effects lack generalizability, and researcher decisions on methods and settings do have a direct bearing on the resulting estimates of the innovativeness–performance relationship. Not only do the latter findings partly explain the former two, they are consistent with the theory that researcher decisions and resulting estimates of relationship strength can be intertwined (Mir and Watson 2000). Moreover, the

Table 5.3. *Potential moderators regressed on the innovativeness–performance correlation*

Potential moderator	*Hypothesis*	*No. of* r's	β (B)[3]	t-*value*	p-*value*
Measurement factors					
Innovativeness construct					
Multi-item[1] vs. single-item	+/–	46, 41	.17 (.11)	.87	.39
Categorical vs. continuous	+/–	42, 45	.39 (.26)*	2.32	.02
New-to-market vs. new-to-firm	+	50, 30	.35 (.26)*	2.66	.01
New technology vs. product	+	16, 34	.08 (.08)	.66	.51
Newness vs. newness and meaningfulness	–	33, 27	−.34 (−.28)*	−2.71	.01
Product performance					
Multi-item vs. single-item	+/–	42, 45	−.05 (−.04)	−.29	.77
Subjective vs. objective	+	59, 27	.42 (.31)*	2.07	.04
Relative vs. absolute	+/–	42, 44	.15 (.10)	1.29	.20
Financial vs. marketplace	+/–	29, 16	.09 (.08)	.78	.44
Respondent					
Person most knowledgeable vs. senior executive	+/–	38, 24	.14 (.12)	.84	.41
Contextual factors					
Year of data collection[2]	–	87	−.65 (−.03)*	−2.88	.01
NewProd vs. non-NewProd data	+	17, 70	−.26 (−.22)	−1.40	.17
Goods vs. goods and services	+	55, 23	.36 (.28)*	2.46	.02
High-tech vs. low-tech	–	28, 15	.01 (.01)	.11	.91
Grand mean (intercept)	+		.10	.70	.49
R^2 (R^2 adjusted)			.39 (.27)		
Model p level ($F_{14,72}$)			$\leq$.01 (3.26)		
Max VIF			6.07		
PRESS ratio			1.52		

Notes: [1] The first predictor type listed represents the "1" dummy code, while the second predictor represents "0."

[2] Year of data collection is treated as a continuous variable coded with increasing whole numbers from earliest to most recent year.

[3] The unstandardized regression coefficients are in parentheses.

* Statistically significant at $\alpha \leq .05$, two-tailed.

moderator findings highlight that more accurate estimates of product innovativeness are likely to be easily within the researcher's and manager's domain and range of possibilities. In particular, our results emphasize the value of (1) having *sound measures* with *clear definitions*, (2) qualifying findings in their proper product and industry *contexts*, and (3) interpreting findings in their appropriate *time frame*. We elaborate on each of these three issues.

5.5.1 Which measures and definitions are better?

Arguably, one of the most important steps in studying any phenomena of interest is clearly defining and measuring the relevant constructs. Whereas previous studies call attention to the myriad of different definitions and categorizations for capturing the innovativeness construct (e.g. Garcia and Calantone 2002), our meta-analysis documents that the size of the innovativeness–performance effect actually depends on the way innovativeness is defined and measured. Specifically, performance estimates are higher when the definition of innovativeness includes a meaningfulness component along with a measure of newness. It is logical to expect new products that have more meaningful benefits to outperform products that are perceived as novel alone. However, researchers must be cognizant of issues associated with discriminant validity when defining and operationalizing constructs. When innovativeness incorporates a meaningfulness dimension, the potential for conceptual overlap with other drivers of new product success identified in the literature (e.g. product quality, relative advantage, product benefits) is greater. Researchers must also consider whether incorporating the meaningfulness dimension clouds the issue of the impact of newness on new product success.

Next, among the statistically significant moderators of innovativeness effects are several factors discussed in the psychometric, statistics, marketing, and management literatures as being characteristic of sound measures. They are multi-item rather than single-item scales (Churchill 1979; Nunnally and Bernstein 1994), continuous measures for capturing continuous variables (Cohen 1988) and objective data rather than managers' opinions when measuring business performance (Starbuck and Mezias 1996; Walsh 1988). We find the relationship between innovativeness and performance is weaker when innovation is measured as a continuous variable and when performance is measured objectively

(Table 5.3). Holding all else constant, model (1) predicts that scales possessing both characteristics yield more conservative estimates of relationship strength between innovativeness and product performance on average. This finding implies that developing sound measures is critical for producing accurate estimates of relationship strength, the very same estimates that likely factor into managers' new product development strategies.

5.5.2 Which contexts are more impactful?

Our meta-analysis further indicates that some forms of innovativeness are more strongly related to new product success than others. Innovations that are new-to-the-market instead of new-to-the-firm, and innovations that are grounded in goods rather than services exhibit a stronger relationship with expected levels of new product success. First, new-to-the-firm products may be less successful because they can require changes in managerial activities that may have little to do with existing firm skills and processes (Crawford 1992; Kleinschmidt and Cooper 1991). In contrast, new-to-the-market products may capitalize on company technologies found in other offerings and may serve distinct markets. Finally, consumers may perceive a new-to-the-market product as actually being innovative and as having significantly different benefits from a new-to-the-firm product. Hence, true innovativeness seems to be related to success.

Our findings further suggest that marketing highly innovative products is likely to yield greater returns to investment (whether operationalized as market share or financial performance) in goods rather than service industries, and, specifically, in industries offering both goods and services. It may be that service offerings are more susceptible to the inherent risks of innovativeness than goods offerings because consumers are less able to visualize, sample, or otherwise physically evaluate the service before actually purchasing it. Furthermore, research on service quality indicates that customers base service quality evaluations on their perceptions regarding the actual service compared to what they expected (Zeithaml, Berry, and Parasuraman 1993). Service quality evaluations would likely suffer when innovativeness in a service is unanticipated and unwanted. Research investigating the possible relationship between innovativeness and service quality evaluations could therefore prove insightful.

5.5.3 Is timing everything?

A particularly interesting finding in our meta-analysis that has not previously been documented in the literature is the role of timing. Undoubtedly, better measures for innovativeness and performance have evolved over time, implying that we are becoming more effective at capturing the true relationship between innovativeness and performance. However, unique variance between timing and the size of the innovativeness–performance relationship still remains after accounting for these better measures. An important question, therefore, is whether innovativeness today is more appropriately represented as a cost of doing business versus the competitive advantage it may have provided in earlier times. In situations of growing marketplace turbulence, greater competitive intensity, shorter product life-cycles, etc., managers and their firms may be facing a situation where being more innovative is simply a competitive imperative for surviving in a continually redefined competitive space. This would imply that product differentiation alone does not hold the key to marketplace success. Rather, offering unique products while also effectively executing the marketing and management functions likely holds the key to augmented marketplace performance. This perspective is echoed in the contingency research on first-mover advantage, which finds that being first to the market is less important than being first to the market armed with a proper marketing infrastructure and strategy (Szymanski, Troy, and Bharadwaj 1995). Likewise, it seems reasonable to conclude that innovativeness alone (i.e. without proper marketing and firm competencies) no longer can be viewed as effectively carrying the burden of superior new product performance.

5.6 Research directions

An empirical synthesis such as ours often concludes with, among other things, a call for improved measures for relevant constructs (e.g. Henard and Szymanski 2001; Szymanski, Troy, and Bharadwaj 1995). A positive outcome of this study is finding that research in product innovativeness does indeed appear to be improving over time as evidenced by the positive correlations between the year of study and what arguably are more technically correct methods of measuring and capturing constructs (Table 5.1b). As a result, the following research directions emphasize overcoming the literature's limitations that otherwise restrict the insights generated from a meta-analysis. They include the following:

- For one, the sampling frame in innovativeness studies includes firms having the necessary competencies to survive in the marketplace. A logical question is whether innovativeness effects generalize to start-up, resource-impoverished, and marketplace-challenged firms. These firms may be more innovative in a desperate attempt to survive in the marketplace. If so, then the range or frequency of innovativeness effects in the literature is underreported and needs to be expanded to include such effects.
- Second, studies on product innovativeness rely almost exclusively on managers' perceptions of consumers' views of innovativeness, including studies using new-to-the-market measures (e.g. Calantone and Cooper 1981; Cooper 1979a, 1979b). The absence of evidence to indicate that managers and consumers have similar perceptions of radical products calls for research to compare and contrast these perspectives.
- Third, critical insights can stem from modeling additional moderators of the innovativeness–performance relationship. They include industry (e.g. firm size and resource endowments, brand perceptions, turbulence, etc.), product (e.g. the specific nature of the good, its unique attributes, and characteristics such as complexity, divisibility, etc.), and consumer features (e.g. income, risk-taking behavior) that could account for the variance not explained by model (1). Our findings indicate that interesting results are in the interactions and contextual understanding of innovativeness effects. Future research yielding these results should therefore be encouraged and pursued.
- Finally, the possibility that innovativeness effects on performance may be *mediated* by selected firm, marketplace, or consumer factors also needs to be captured in future research. While studies have captured certain non-performance effects from greater innovativeness such as cycle time, manufacturer ability, managerial commitment, developmental processes, and coordination mechanisms (e.g. Olson, Walker, and Ruekert 1995; Schmidt and Calantone 1998), the subsequent indirect effects of innovativeness on performance have not yet been estimated, but should be. Hence, more rather than less complicated models and subsequent analyses are called for.

5.7 Summary

To effectively advance knowledge, the findings from our study argue for a changed perspective. Our findings document that adopting a contingency perspective grounded in conditional effects creates renewed opportunities for researchers and managers to uncover the true keys to new product success and discover the role that product innovativeness actually plays in that success. This meta-analysis accents the need periodically to step back and assess the field, as new and hidden insights might emerge that can have implications for future modeling efforts and approaches to capturing a phenomenon of interest such as product innovativeness. But, more to the point, the findings from our meta-analysis of product innovativeness effects demonstrate that things have changed over time and, indeed, may need to change further in order to properly expand researchers' and managers' understanding in this highly topical and relevant area to business success.

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6 *Marketing costs and prices: an expanded view*

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More than twenty years ago Farris and Reibstein (1979) published research that demonstrated a strong cross-sectional correlation between relative advertising expenditures and relative prices charged by manufacturers of non-durable consumer goods. Data for that research were taken from the PIMS database. The correlation was demonstrated to survive a number of controls for relative quality and market share. The correlation was also shown to be stronger for later stages in the product life-cycle and for products purchased in relatively small dollar amounts. The research made no claims about the direction of causality from advertising to prices or vice versa. Instead, the paper argued that from the management perspective "consistency" between advertising and pricing was important. In other words, businesses with high (or low) relative prices should generally also have high (or low) levels of relative advertising. The claim for the importance of consistency was buttressed by evidence in the paper that businesses with inconsistent pricing and advertising strategies earned lower ROIs.

In this chapter we first review and then extend the earlier Farris and Reibstein (1979) study with new analyses based on the PIMS data. The review is placed in the context of a broader managerial (not necessarily a public policy) concern with the relationship between total marketing costs (not just advertising) and prices. The expanded view of marketing costs includes salesforce and other marketing expenses – budget items with collective dollar values that are typically three to four times advertising budgets. The consistency index used in earlier research was based solely on relative prices and relative media expenditures. Herein, a similar index is developed that includes relative marketing of all kinds, including salesforce, given the broader inspection across a variety of industries beyond consumer non-durables.

We suggest that the question of marketing spending and prices is relevant to many industries beyond the consumer non-durable category.

These other industries include industrial (business-to-business) products and services as well as higher-ticket consumer durables. Using both a broader sample of businesses and an expanded definition of marketing expenditures, we show that businesses pursuing what we have called "consistent" pricing and marketing strategies are shown to earn higher ROIs than businesses with inconsistent combinations of marketing and pricing.

Our chapter is structured as follows. Section 6.1 provides a brief discussion of the marketing management research literature addressing marketing budgeting and prices. We focus especially on the management question of finding the right combination of marketing spending and relative prices. Sections 6.2 and 6.3 argue that both the public policy and management literature should adopt a broader definition of marketing costs and move beyond consumer non-durables as a focus. Our intent is not to develop a methodology or theory for optimizing marketing spending and pricing decisions; rather we seek to demonstrate that managers should pay more attention to sales force and other marketing spending and their impact on or influence by the relative prices a firm charges. Sections 6.4 and 6.5 present the hypotheses that we wished to test with the PIMS data and briefly describe the data used in this study. Next, the results of our analyses and hypothesis test are presented in Section 6.6. Finally, Section 6.7 summarizes our findings, discusses implications for marketing management, and suggests some directions for further research.

6.1 Marketing and pricing

In this section we will review the arguments for expecting marketing to affect price elasticities and price levels as well as the arguments for expecting the pricing decision to affect the advertising budgeting decisions. Many of these arguments are couched in "advertising" terms, but can readily be extended to other marketing efforts. Empirical evidence on prices and advertising is briefly summarized, emphasizing the differences between studies that used consumer (retail) prices and those that used manufacturer prices. Our focus is on the level of manufacturer selling prices. See Appendix to this chapter for a discussion of different pricing metrics.

6.1.1 Arguments that advertising affects prices

The belief that advertising causes higher prices is dominant, even among those who we might think are sympathetic toward advertising. Benham (1972) polled "several" of his colleagues in marketing and economics at the University of Chicago and reported:

> Approximately 50% of the economists and 100% of those in marketing expected prices to be the same or lower where advertising was prohibited .... it is, I think, the most common view to emphasize the costs of advertising, the demand inducing and product differentiating aspects, and to put relatively less emphasis on the information provided and the effects of this information on organization and efficiency in the market. (Benham 1972: 350)

We suspect that a more formal poll of marketers and economists might return the same result today. The belief that marketing spending increases prices is partially based on the still widely practiced "cost-plus" method of pricing and the view that "Advertising = Cost." Simply put, this argument states that as costs go higher, firms pass those costs onto their customers. This is obviously true at some extreme. As *variable costs* rise, margins shrink without a price increase. At some point margins will become negative and no amount of volume increase can compensate. While advertising is generally regarded as a *fixed cost* within the marketing community (one that does not change with sales volume), firms that closely monitor their advertising to sales ratios might be treating advertising as a variable cost.[1] For a given price–quantity demand function, the optimal price increases as variable costs increase, but is not affected by fixed costs. So, one neglected perspective on this debate is whether marketing managers consider advertising to be a variable or fixed cost.

When advertising is a fixed cost, it affects prices through increased demand. In economic terms, advertising shifts the demand curve outward, makes it less elastic, thereby allowing a firm to charge a higher price. The notion is that advertising generates greater demand by differentiating the product from its competition, thereby making the product less substitutable. This is generally known as the "Advertising = Market Power" argument. In the language of marketers, this allows the firm to charge a higher price; in the language of economists, it increases

[1] Further, as we discuss in Chapter 11, many price discounts have (improperly) been treated as marketing. Most of these are variable in nature.

the profit-maximizing price. Of course, if advertising merely convinces more people to buy the product, but does not change the distribution of individuals' willingness to pay, there is no demand-based or profit-maximizing reason for prices to increase. (The demand function shifts outward by rotating around the price intercept.)

Numerous studies have investigated the relationship between advertising and price. The managerial question has rested on whether advertising budgets can be justified not only by raising the unit sales volume for products, but by helping the product command higher selling prices at a given unit sales volume. If advertising shifts a demand curve outward, managers might decide to capitalize on this shift by some combination of higher selling prices or increased unit sales (Ailawadi, Lehmann, and Neslin 2003).

The "Advertising = Information" school of thought argues that advertising eases the entry of new products into markets, informs consumers of alternatives, thereby increasing their consideration set, and makes consumers more sensitive to price. For a review of these arguments, see, for example, Farris and Albion (1980) and Mitra and Lynch (1995). Another stream of research considers competitive reactions and whether advertising by one competitor causes a second competitor to lower its price. We believe these arguments should distinguish between the average level of market prices resulting from advertising (over time) and relative prices of competitors at any point in time. See Appendix 1 for a discussion of some of these issues.

6.1.2 Arguments that price affects advertising intensity

Advertising "intensity" is most often measured by the advertising to sales ratio. The economics view is that costs, prices, elasticities, and margins are determined simultaneously. For example, the price–costs margins as a percentage of sales for the profit-maximizing price are equal to the unsigned reciprocal of price elasticity. A price elasticity of −2.0 results in what marketers call a contribution margin of 50 percent. All else equal, higher prices will yield higher unit contribution margins. These higher margins will increase the optimal advertising to sales ratio for a given response function that exhibits diminishing returns; in other words, higher prices drive higher advertising, not the other way around (Farris and Albion 1981; Nerlove and Arrow 1962). Therefore, a correlation between advertising levels and price levels may result

Table 6.1. *Literature review*

Focus of study	*Study finding/interpretation*
Retail advertising of prices and service is associated with *lower average price* levels – and higher price elasticity	*Yes*: Benham (1972), Cady (1976), Moriarty (1983), Bemmaor and Mouchoux (1991) *No*: Maurizi (1972)
Higher manufacturer advertising associated with *higher retail price elasticity* and/or promotional price elasticity	*Yes*: Eskin (1975), Eskin and Baron (1977), Wittink (1977), Sethuraman and Tellis (2002), Bolton (1989) *Mixed*: Vanhonacker (1989), Mitra and Lynch (1995) *No*: Prasad and Ring (1976)
Higher manufacturer advertising associated with *higher relative manufacturer prices or manufacturer gross margins*.	*Yes*: Farris and Reibstein (1979), Comanor and Wilson (1974), Lambin (1976), Farris and Buzzell (1976) *No*: No studies found.
Higher manufacturer advertising associated with *lower retail margins*	*Yes*: Albion and Farris (1987), Reekie (1979), Steiner (1993) *No*: No studies found.

from a simple management decision to take higher prices and earn higher margins and to "sell harder" because the added margin justifies it. Also, as product or service quality improves and is more differentiated from the competition it may create both higher advertising elasticities, given there is something to say, and lower price elasticities (higher prices and margins). While the economists' view will almost always be that price, quality, and advertising should be "jointly optimized" (Dorfman and Steiner 1954), the managerial view may not be so elegant or simple.

6.1.3 Conflicting empirical evidence on advertising, prices, elasticities, and margin

As can be seen from the selected studies in Table 6.1, there have been numerous studies on various aspects of the advertising–price relationship. A notable difference is whether advertising and prices, elasticities, or margins were studied at the retail or manufacturer level. Most have modeled the "causal relationship"[2] between advertising and price, while relatively few have focused on the effect of price on advertising intensity.

Several researchers have attempted to reconcile the conflicting evidence in Table 6.1. Part of the answer must be found in the metric that was used (see Appendix 1 for a discussion of some of these metrics). Farris and Albion (1980) offered one of the first attempts to reconcile the conflicting evidence, using theories of advertising and retail gross margins advanced by Steiner (1973). Succinctly, Farris and Albion state that manufacturers may be able to extract higher prices from retailers by creating consumer demand, while retailers are willing to sell the products at lower margins; this results in lower retail prices because of the rapid turnover of the product. In addition, when advertising creates more demand, levels of distribution rise, leading to higher levels of inter-retailer competition and to prices being driven downward. Hence, the results that one would find about the relationship between advertising and prices would depend on whether the research was conducted at the manufacturer price level or the retail price level.

There have been many other arguments which attempt to reconcile the differences among these studies, including the following: examining the differences between local and national advertising; attracting price-sensitive rather than price-insensitive purchasers (Kaul and Wittink 1995); expanding the consideration set of brands; relying on consumer memory or point of purchase to determine brands in the consideration set (Mitra and Lynch 1995); and whether or not distribution has been considered as an intervening variable (Abela and Farris 2001; Farris and Reibstein 1979).

We have briefly reviewed the extensive and controversial evidence on advertising and price with two purposes. The first was to demonstrate that causality in this relationship is difficult to assess and the most elegant models view advertising, pricing, and quality levels as being simultaneously determined. However, this is not very satisfying from a management perspective. A second purpose of this review was to make

[2] Even when causality is not explicitly addressed, there is a frequent implication that advertising leads to higher prices, even for studies that are correlational in nature.

clear that this particular study should not be interpreted as addressing the complex topic of whether advertising increases the average level of market (absolute) prices that consumers pay for a given quality.

Having established what we are *not* investigating, we turn to what we are addressing, namely how *relative levels of marketing and prices*, measured at the *manufacturer level*, are correlated; and, further, whether this correlation helps explains differences in business profitability.

6.2 A broader view of marketing beyond advertising

While advertising has always received the most research attention, it is only one of several marketing instruments that might affect the prices that a firm can/should charge. As demonstrated in the next section, advertising is a relatively small part of most marketing budgets – especially in businesses selling industrial products, consumer durable goods, and services. The biggest single item in most marketing budgets[3] is the salesforce:

> the sales force is probably the single largest [marketing] cost to your company. Look at your P&L statement. Isn't sales force compensation the largest single line item? If you're like most distributors, your sales force costs range around 25–35% of gross profit. (Kahle 2003)

Salesforce and other marketing budgets are typically three or four times as large as advertising media expenditures. Further, for many companies, the purpose of advertising and promotional spending is not to substitute for salesforce expenditures, but to enhance their effectiveness. This includes products that are sold direct to consumers as well as those that are sold through salesforces and then resupplied through distributors or other resellers.

We have estimated the total amount spent on salesforces in the United States in three ways. These three estimates demonstrate a fair degree of convergence.

Method 1: Use PIMS data to estimate the ratio of salesforce to media spending. Multiply this ratio by public-source estimates of total

[3] Although many firms do not consider salesforce as part of the marketing budget, by the broader definition of marketing, it clearly is part of the communications function of the firm.

advertising spending in the US economy. Using the ratio of expenditures on salesforces to media expenditures in the PIMS data, the sample of consumer and industrial manufacturers, service providers, and retailers in the PIMS data spent approximately 2.0 percent of sales for media. Advertising spending in the United States has long been in the neighborhood of 1–2 percent of GDP, lending credence to the general applicability of this estimate. The same PIMS strategic business units that spent an average of 2 percent for media reported spending 6.5 percent of sales on salesforces. Thus, the ratio of salesforce to media expenditure is roughly 3.2:1. Total advertising expenditure in the United States in 2002 was reported as $247 billion by Abela and Farris (2002). Depending on what is included in advertising costs, total advertising estimates can range as low as $137 billion. Based on PIMS ratios of salesforce to advertising expenditures, and using public sources for total advertising expenditure, we conclude that salesforce spending may be slightly more than three times that for advertising, or between $500 and $700 billion for all types of businesses, including manufacturers, services, and retailers.

Method 2: Use the Labor Bureau (2003) statistics on the number of salespeople employed and their average earnings. That source reports that 13.4 million salespeople earn about $28,900 each per year. If benefits and non-salary costs of maintaining a salesforce are estimated as 50 percent of the salary (this may be conservative), then the total cost of each salesperson is approximately $44,000 per year, bringing the total cost of the 13.4 million salespeople in the United States to approximately $590 billion.

Method 3: From COMPUSTAT data, estimate the ratio of the average spending on sales, general, and administrative costs (SG&A) to sales revenue. COMPUSTAT data allow us to calculate the average for SG&A across retail, services, and manufacturing industries as 17.3 percent of sales. Since not all of SG&A can be considered marketing, we need to subtract non-marketing from this estimate. The PIMS data provide an estimate of this "other" category: approximately 6.24 percent of sales across all industries. Subtracting this category from SG&A leaves us with an estimate of 11.05 percent for total marketing spend/revenues. From the COMPUSTAT data, we also estimate the ratio for advertising and promotional spend (media/revenues) to be 2.75 percent. Assuming the rest of the marketing budget to be salesforce spending, our estimate for salesforce spending as a percentage of revenues from the COMPUSTAT data is 8.3 percent. Again, this indicates that the ratio of salesforce spending to advertising spending is approximately three to one.

Our purpose here was briefly to justify the assertion that salesforce spending exceeds advertising media spending by a factor of 2–3, or possibly more. These are necessarily rough estimates, because there is no general agreement on what constitutes advertising or selling expenses. Our second purpose was to point out how important it is not to focus solely on advertising's relationship on price, but to include salesforce and other marketing expenditures as well. Once we reach beyond consumer non-durables the role of these other variables are a much greater part of the firm's overall marketing budget, as seen in Appendix 2 to this chapter.

6.3 Marketing affects pricing strategy in the business-to-business sector too

In earlier sections we briefly reviewed the reasons for expecting higher marketing and advertising expenditures to be associated with higher selling prices. The same reasons increasingly apply to products that are sold for consumption, use, and resale by businesses. It is relatively easy to show that many business-to-business units have used advertising to build their brands. What is not clear, perhaps, is the role that salesforce spending is playing in allowing firms to command premium prices. For pharmaceutical programs, especially ethical drugs, the salesforce is a key leverage point for all communication with MDs and health maintenance organizations. Intel, Dell, Dupont (with Stainmaster, Lycra, Kevlar, and others), Goretex, and many other products are marketed with similar combinations of "push" and "pull" marketing. It is clear that the prevalent types of marketing spending differ by industry as shown in the Table 6.6 at the foot of Appendix 2, describing the PIMS data. While advertising is almost 50 percent greater than salesforce expenditures for consumer non-durables, for consumer durables it is just the reverse. For services and distribution businesses, the salesforce expenditure is nearly three times that invested in advertising, with an extreme difference of almost five times more spending for the salesforce than for advertising in industrial businesses.

6.4 Hypotheses

Farris and Reibstein (1979) showed a positive correlation between relative advertising levels and relative prices for consumer non-durables. Consistent with that research, the first question addressed was whether this positive correlation also held for other types of businesses. Our first hypothesis were:

H_1: The correlation between relative advertising levels and relative prices is positive.

Given that advertising is generally a higher percentage of the total marketing budget for consumer non-durables than for other types of businesses (see Table 6.6), we believed that the correlation between relative prices and advertising levels would be highest for consumer non-durables. Therefore,

H_2: The correlation is stronger for consumer non-durables than for other types of business.

As described above, advertising is just one component of the marketing budget that might affect prices charged. As such, our next set of hypotheses all refer to the entire marketing budget.

H_3: The correlation between relative marketing spending and relative price is positive.
H_4: The correlation between relative marketing spending and relative price is positive after controlling for market share and the quality of products and services.
H_{4a}: The correlation between relative marketing spending and relative price is positive for firms with both high and low market shares.
H_{4ab}: The correlation between relative marketing spending and relative price is positive for both high and low levels of product quality.

In line with our earlier findings on the relationship between relative advertising–pricing consistency and ROI for consumer non-durables, we expect that a positive correlation between relative marketing–pricing consistency and ROI will be found in other types of business.

H_5: Businesses that are consistent with their relative levels of marketing spending and relative price are more profitable than businesses with inconsistent relative marketing and pricing strategies.

6.5 Data

The data that will be used to test the study's hypotheses are taken from the PIMS database. These allow us to explore in a cross-sectional manner the levels of spending and the corresponding prices. We use the SPIYR dataset that has multiple observations for each firm in the PIMS database. The definition of the variables used in this study is shown in Appendix 2.

6.6 Results

The first step in the analysis was to look at the relationship between relative advertising and relative price. This is similar to the analysis that Farris and Reibstein (1979) reported, although here it is performed for all eight types of business reported by PIMS, not just for consumer non-durables.

Table 6.2 provides the average prices relative to competition for businesses reporting each level of relative advertising. A "1" for relative advertising means the business reports spending "much less, as a percentage of sales" than competitors. Values 2–5 are "somewhat less," "about the same," "somewhat more," and "much more," respectively. For relative prices, a value of 103.1 means the businesses averaged prices 3.1 percent greater than their most important competitors'. Based on Table 6.2 we observe that for all levels of advertising, the average price is at least 3 percent above average, meaning that most PIMS firms report prices that are on average higher than competitors'. We do not speculate whether this is a bias in the sample toward higher-priced business strategies or measurement error. While there are some (14.3 percent) observations that do have prices below average (below 100), the majority are clearly above average. Thus, the data must all be viewed with the understanding that we are dealing with a censored dataset. Interestingly, fewer firms report spending "much" or "somewhat" more on advertising as a percentage of sales than report spending "much" or "somewhat" less than their competitors.

Rows 3–5 of Table 6.2 provide corresponding values for advertising/sales, marketing/sales and market share for the five relative advertising levels. While these variables are correlated, the patterns show larger differences between values "4" and "5" than for any of the other

Table 6.2. ***Averages of relative prices, advertising and promotion/sales, marketing/sales, and market shares for levels of relative advertising (averages for all business types)***

	Relative advertising					
	Much less 1	*Somewhat less* 2	*About the same* 3	*Somewhat more* 4	*Much more* 5	*All firms*
Relative price*	103.1	104.1	103.9	105.4	110.9	104.4
Number of firms	3327	3855	6808	2084	1106	17,180
Advertising and promotion/ sales, %	2.3	1.9	1.6	2.7	4.6	2.1
Marketing/ sales, %	9.9	9.4	8.5	10.0	13.0	9.5
Market share, %	18.3	20.9	25.8	27.8	34.8	24.1

Note: * Significant at $p < 0.001$; multiple $r^2 = 0.023$.

intervals. The last row indicates the market share for each level of advertising spending. This row most clearly indicates the positive relationship between market share and spending, further complicating the interpretation of a simple causal relationship between advertising, marketing, market share, and prices. Certainly, the overall pattern is consistent with an interpretation that marketing spending shifts the demand curve outward as well as making some customers willing to pay more. This directly addresses H_1 and is consistent (at a significant level) with the direction of the hypothesis.

We see from Figure 6.1 that the pattern of relative prices is fairly flat until encountering SBUs with above-average expenditure levels. The upper levels of advertising spending coincide with higher relative prices. The patterns appear to be the same for most of the types of businesses, although distribution/retail, industrial supplies, and raw or semi-finished materials are "flatter" than the other five types of business represented in the PIMS data. Perhaps most surprising is how robust the general trend is across all eight industry categories. The second hypothesis, that the correlation between relative advertising and

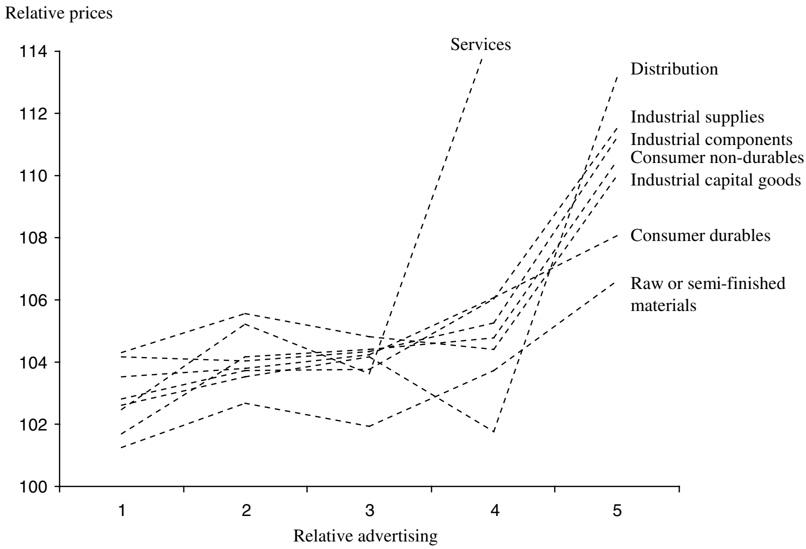

Figure 6.1. Relative prices vs. relative advertising for eight industry categories.

relative prices is strongest for consumer non-durables, is not consistent with the data, as there are several other industry categories where the relationship is just as strong. For services, the average relative price for the highest level of relative advertising spending even falls outside the range of the figure. The relative price for this level is 124.4, or a 24.4 percent price premium. Again, the advertising allows for the differentiation for services, such that a premium price can be charged; and/or, if the services price is at a premium relative to competition, it needs significant advertising to support it, and the margins allow for it.

In a similar manner, we next looked at the relationship between relative salesforce expenditure and relative prices across all eight industry categories, as shown in Figure 6.2 and Table 6.3. As can be seen, the same general relationship holds – relatively flat for the parity or lower levels of relative spending, but more pronounced differences in the higher levels of relative spending – with a six percentage point increase for higher levels of relative salesforce spending. Again, the same

Table 6.3. ***Averages of relative prices, salesforce/sales, marketing/sales, and market shares for levels of relative salesforce (averages for all business types)***

	Relative advertising					
	Much less	*Somewhat less*	*About the same*	*Somewhat more*	*Much more*	*All firms*
	1	*2*	*3*	*4*	*5*	
Relative advertising	1.7	2.3	2.7	2.9	3.5	2.6
Relative price*	103.7	103.9	103.5	105.2	109.7	104.4
Number of firms	1483	3879	6795	3842	1181	17,180
Salesforce/ sales, %	4.6	4.8	5.1	5.7	7.5	5.3
Marketing/ sales, %	8.1	8.3	9.4	10.1	13.3	9.5
Gross margin/ sales, %	23.7	24.6	25.5	27.2	31.6	25.9
Market share, %	20.5	22.2	24.0	24.5	33.2	24.1

Note: * Significant at $p < 0.001$; multiple $r^2 = 0.015$.

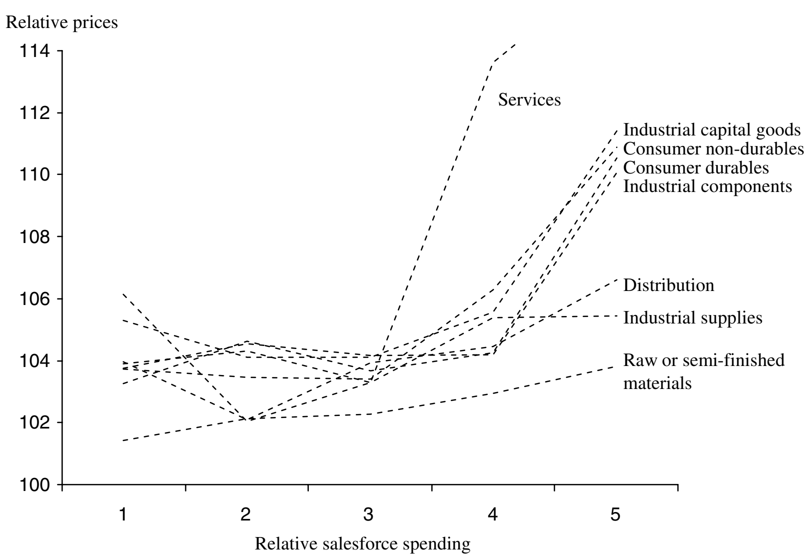

Figure 6.2. Relative prices vs. relative salesforce spending for eight industry categories.

general relationship holds in each of the eight industries.[4] This finding is consistent with our third hypothesis.

It is possible that companies use advertising as a substitute for salesforce expenditure. This would imply a negative correlation between the two forms of expenditure. The relationship shown in Table 6.3 between relative advertising and relative salesforce expenditure would imply that firms with greater levels of advertising also have greater levels of salesforce expenditure. A common antecedent of both advertising and salesforce spending may be relative gross margins. As argued earlier, firms with higher gross margins have greater incentive to spend to increase sales.

The PIMS index of relative advertising asks managers to compare their spending *as a percentage of sales* with that of competitors. As such, there should be no simple, "ratio" connection to market share. However, since optimal levels of both salesforce spending/sales and advertising spending/sales depend on gross margins (price elasticity), we suspect that businesses with low elasticities/high gross margins might tend to spend at higher relative levels of these ratios. Thus, the next step was to compare the correlation of relative advertising expenditure and relative salesforce expenditure with relative prices, controlling for market share. Table 6.3 shows that both relative advertising and relative salesforce expenditures function almost as effective surrogates for each other, but that each adds some additional explanatory power for prices.

By taking the population of firms in the PIMS database into two groups, those with low and high market shares respectively, we were able to take a simple look at the relationship between marketing spending (advertising and salesforce) and relative prices. The corresponding price premiums may be merely a reflection of the firms' market power. Figure 6.3 reflects the relative advertising and salesforce spending and its relationship to relative price for both low and high market share levels. The higher market share firms do command a higher price. Most interesting is the fact that the relationship between relative market spending and price holds up for both low and high market share firms. This is consistent with our fourth hypothesis. Again, it should

[4] Again, the impact for services was significantly higher than for the other industries with relative prices at 117 for the highest level of relative salesforce spending.

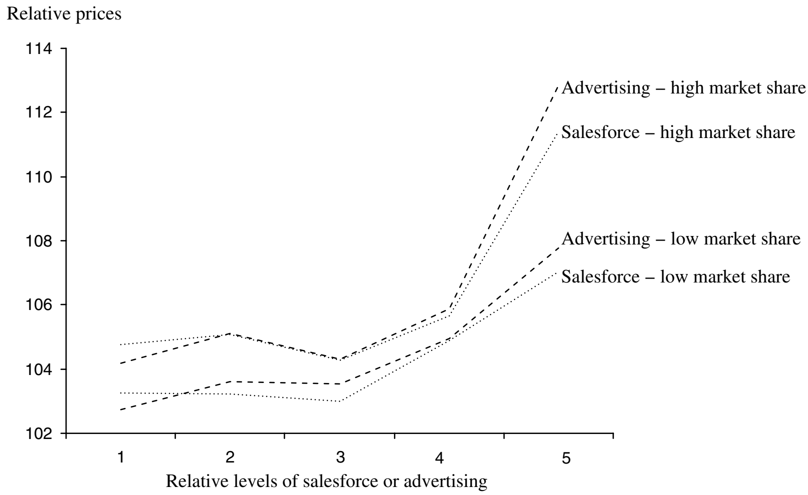

Figure 6.3. Relative prices vs. relative salesforce and advertising, controlling for market share (all eight industry categories).

be noted, that the greatest difference is only at the highest levels of spending.

A similar question should also be posed for the quality of the products being offered. Is it the case that the ability to charge a premium price is a function of the relative quality of the offering more than of the relative marketing spending levels for the firm? Shown in Figure 6.4 are the results by levels of relative product quality. As one might expect, there is a definite impact of relative price based on the relative quality of the product. Firms offering a higher quality to the competition are able to command a premium price. Of interest is that even when accounting for the difference in relative product quality, there is still a relationship between spending levels and price premium. This means that having a product of lesser quality than the competition can be compensated for by heavier levels of marketing spending. It is also the case that just having a superior product is not sufficient. To truly capitalize on this higher perceived quality, there is benefit in spending more on marketing. This also supports our fourth hypothesis.

We also wanted to look at all levels of marketing spending and relative prices. This result is shown in Table 6.4. Once again, we see the same general relationship – with greater spending we see higher relative prices being charged.

Table 6.4. ***Relative price vs. relative marketing spending***

Relative marketing spending = average of relative salesforce, relative advertising, relative promotion, and relative services

	Relative marketing spending					
	Much less	*Somewhat less*	*About the same*	*Somewhat more*	*Much more*	*All firms*
	1	*2*	*3*	*4*	*5*	
Relative price*	101.6	103.1	103.6	106.4	113.5	104.4
Number of firms	195	3294	9429	3717	545	17,180
Market share, %	12.8	17.5	23.3	29.8	40.3	24.1
Marketing/ sales, %	10.0	8.8	9.3	10.1	11.2	9.5

Note: * Significant at $p < 0.001$; multiple $r^2 = 0.038$.

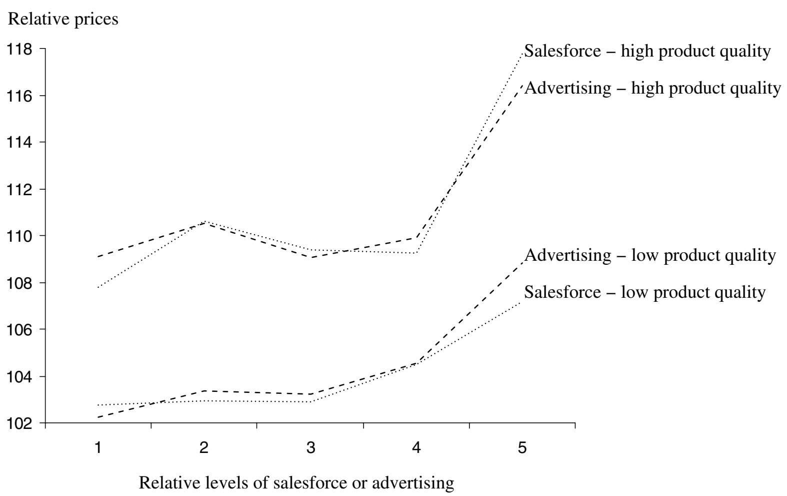

Figure 6.4. Relative prices vs. relative salesforce and advertising, controlling for quality (all eight industry categories).

Thus far our analysis has focused on descriptions of managerial pricing and marketing budgeting behavior. Normative analyses with prescriptive implications are considerably more difficult. Following the approach used by Farris and Reibstein (1979), we formed a consistency index, a measure of the degree to which a firm used marketing spending

Table 6.5. ***Regression results for ROI vs. consistency index (based on marketing spending and relative price)***

ROI = *f*(Marketing index, Relative product quality, Relative market share)

	Value	*Std. error*	t-value	*Pr(>|t|)*
(Intercept)	24.0884	0.8970	26.8534	0.0000
Consistency index	0.7417	0.2126	3.4894	0.0005
Relative product quality	4.5311	0.3015	15.0301	0.0000
Relative market share	6.7499	0.2078	32.4902	0.0000

Note: Multiple r^2: 0.0806.

(advertising, salesforce, and promotion) and prices consistently. Businesses were classified as consistent if relative marketing and relative prices had approximately the same value. In other words, low relative price and low relative marketing spending would be classified as consistent, as would a combination of high prices and high marketing. On the other hand, high prices and low marketing would be inconsistent.[5] We then regressed this index against ROI, controlling for other variables such as market share and relative product quality.

This regression of ROI on the consistency index yields a highly significant positive coefficient (0.7417, with $p < 0.001$). The regression results are summarized in Table 6.5. The relationship is positive and significant, albeit not overly predictive as there are numerous other factors that drive ROI.

6.7 Summary and implications for future research

The purpose of this chapter was to expand our view of marketing spending and prices. For marketing spending, we argued that salesforce spending, in particular, in dollar terms and as a percentage of sales is far more important than advertising for most business types. We also noted that the distinction between consumer and business-to-business markets is becoming increasingly blurred and that branding and the role of marketing in increasing price premiums is

[5] The computation of the consistency index is detailed in Appendix 3.

also a matter of concern for business-to-business marketers and high-ticket consumer durables that historically have not spent as much on advertising. We used three separate approaches to estimate the total spending on salesforces relative to advertising in the United States. Each of these approaches yielded results consistent with the assumption that salesforce spending is approximately three times advertising spending.

We pointed out that caution should be exercised in using the accumulated empirical evidence on advertising and prices to draw conclusions about whether advertising is "anti-competitive" or causes customers to pay more for equivalent quality products in the long term. The measurement of prices is complicated both by the need to specify the vertical (channel) level at which the price is captured and by the need to make reliable and valid adjustments for quality differences. Further, we have only a very limited ability to untangle the complicated causal relationships among advertising, demand elasticity, market share, cost, and margins. Therefore, without attempting to identify causal relationships, we examined the PIMS data for relative pricing patterns exhibited by businesses spending at higher and lower relative marketing levels.

The results confirm that relative levels of total marketing are correlated with relative pricing decisions. Further, businesses that show a high degree of consistency between these two decisions also report higher levels of profitability. We believe that our emphasis on total marketing spending is new to our field. Our analyses demonstrated that businesses in the PIMS dataset that spend at higher relative marketing levels also charge higher relative prices. The correlation was positive for each of the eight different types of businesses, but was more pronounced for some business types than others and for higher levels of relative marketing. This was true for high market share firms as well as low market share brands. It was also true across different levels of product quality. We observed that firms that do not follow this pattern have lower levels of profitability.

We hope that future research will develop new methods of explaining what seems to be an important paradox in marketing. The evidence and prevailing opinions among marketers are that higher marketing spending will help a firm command higher prices and shares than lower-spending competitors. At the same time, marketing has been associated with higher levels of price sensitivity at end user (consumer) levels and the general belief that it is pro-competitive. If we assume that unobserved differences in quality or other variables are not responsible for the covariance of advertising and prices, the question remains of how to explain this pattern. Do businesses with higher relative marketing have higher relative prices because (1) lower-advertising competitors reduce their prices (2) channels reduce their margins, or (3) customers pay more on both an absolute and relative basis?

Appendix 1: Conceptualizing, operationalizing, and interpreting measures of price differences

6.A1.1 Relative prices and "average prices"

To calculate relative prices requires a baseline for comparison. Some researchers use "average prices" as that baseline. However, calculating average prices requires the construction of "standard statistical units" to combine different "unit prices" (e.g. prices per ounce) across various stock-keeping units (SKUs). An average price per unit is typically calculated by weighting SKU unit prices by unit sales or, sometimes, "availability." Because unit sales or "availability" of different SKUs will also have non-price sources of variation, the weighting scheme will almost always be subject to variances in the average price that are not caused by actual price changes. For example, when a relatively lower-priced item is placed on display in a high-traffic location at regular selling prices, the relative unit sales of this item will increase, lowering the volume-weighted average price.

If researchers succeed in establishing a benchmark against which to measure the "relative" prices of various brands in the market, then they will have also created a good measure for evaluating how prices change over time. We believe that most public policy-makers are concerned (or should be concerned) about the effect of marketing on the increase or decrease in "average" market prices over time. If an acceptable quality-adjusted "market price" were available it could be used to determine how prices are changing over time. Without such quality and innovation adjustments, comparisons of prices over longer periods are problematic. Consider that a 5″ portable Motorola television sold in 1947 for $189 (the equivalent of $1,360 in 2001 dollars). In 2003, you could buy a 5″ portable television from Amazon.com for $39.94 (plus shipping).

6.A1.2 Vertical price differences: different levels in the distribution channel

It is only appropriate to compare prices among manufacturers if we capture those prices at the same level of the marketing channel or supply chain. Those concerned with consumer welfare are most likely to be concerned about the effects of marketing on the prices that end customers for industrial products and consumers pay. On the other hand, marketers and business managers will be concerned about their own selling prices as well as the "final" prices that consumers and end users pay.

Between retailer and manufacturer, there may (or may not) exist a variety of middlemen. Depending on the structure of the channel the margins earned by these middlemen may be accounted for in different ways. Wal-Mart is known for refusing to buy except direct from manufacturers. Depending on the channel, the item, and the region, the same brand may be sold directly to retailers for stocking in the chain warehouse and subsequent delivery to the stores in the retailer's trucks, with the assistance of brokers (who often do not take possession), through wholesalers or distributors who do take possession and break bulk, delivered directly to the store shelves by the manufacturer's salesforce, or some combination of the above. Often, where the manufacturer has a high share or strong brand franchise, direct distribution to the chain warehouse is the preferred option. Where the brand is weaker, distribution is indirect through wholesalers and/or with the assistance of brokers. Indirect distribution adds a substantial amount to the channel margins. The percentage of the final retail price captured by the manufacturer varies significantly. The president of P&G's largest global division stated that "most of our products are sold by retailers at a loss." This is clearly not true of most products, but is most likely to be true of those with dominant shares.

Even without the intervening margins of middlemen there are significant problems in establishing comparable selling prices across manufacturers. Rebates, trade promotions, cooperative advertising allowances, and other payments to the trade vary among manufacturers and across time. List price increases are often accompanied by higher promotion allowances and even relatively sophisticated retailers have difficulty allocating many of these payments to individual SKUs. These payments are not always reflected in the lowering of wholesale prices, but may be simply taken as lump sums and accounted for elsewhere in the income statement. For several years, many marketers were not recording the bulk of such discounts as reductions in price, but rather as increases to marketing budgets. Rulings by the Financial Accounting Standards Board in 2002 have changed this practice and many companies are restating prior income statements for prior years. Finally, retail prices may be calculated gross, or net of discounts such as coupons or rebates provided by the reseller as part of "loyalty" programs.

Researchers should consider how market power and strategic channel choices of different manufacturers may confound the comparison of prices by creating or reflecting vertical price differences. Consider, for example, that a major retailer's private label may often (although not always) involve no middlemen. For such a private label, is the difference between retail selling price and retail purchase price a reflection of retail margin, manufacturer margin, or a combination of the two? Much of the evidence cited on the effect of manufacturer marketing on prices fails to distinguish adequately among the vertical pricing issues discussed above, but simply compares "relative prices." Further, the measurement of prices has been greatly confounded by the various treatments of trade and consumer discounts.

It is possible to interpret the higher relative prices that are associated with higher marketing spending in at least two different ways. One interpretation is that higher marketing and advertising spending enables companies to charge prices that are higher than the market average that would prevail in the absence of marketing. A second, less common interpretation is that the companies spending more for marketing establish a ceiling under which other competitors are forced to price below the branded/advertised product (why pay *more* for an unadvertised product that is merely equal to an advertised product?). The good news for these brands is that they are able to "free ride" on the marketing of the leader through a "just as good as –, but cheaper" positioning.

Appendix 2: PIMS variables used in this study and their definitions

Name	*Description*
Total revenues	Reported net of returns, allowances, and bad debts. Lease revenues and progress payments received in a year are included in sales revenue. Temporary price reductions are treated as promotional expenses, but discounts and price concessions that continue for extended time periods are deducted from net sales.
Salesforce expenses	Include compensation and expenses of sales people, commissions paid to agents or brokers, and costs of salesforce administration. When two or more business units share a salesforce, the total cost is allocated amongst them.
Advertising & promotion expenses	Include costs of catalogs, exhibits, displays, premiums, samples, and revenue reductions associated with temporary price reductions.
Media advertising expenses	Covers only the costs of media time and space (including advertising agency commissions).
Other marketing expenses	Covers all marketing outlays not included in sales force, media advertising, and sales promotion. Marketing administration and research fall in this category.
Total marketing expenses	Sum of the four sub-categories listed above.
Other expenses	This residual category includes business unit general and administrative Expenses as well as allocated corporate or divisional overhead charges. It also includes depreciation or goodwill, if any.
Type of business	One of eight types (consumer durables, consumer non-durables, industrial capital goods, raw or semi-finished materials, industrial components, industrial supplies, services or retail & wholesale distribution).

Name	*Description*
Relative product quality	For each year, estimate the percentage of this business's sales volume accounted for by products and services that from the perspective of the customer are assessed as 'Superior', 'Equivalent' or 'Inferior' to those available from the three leading competitors. In assessing quality, the customer's perception of both the intrinsic characteristics of the product or service and any associated services (delivery time, warranties, application assistance, etc.) should be taken into account where these are important in decisions to purchase.
Salesforce/revenue	Salesforce spend as a percentage of revenue
Advertising & promotion/revenue	Advertising and promotional spend as a percentage of revenue
Media advertising/ revenue	Media advertising as a percentage of revenue
Marketing/revenue	Total marketing spend as a percentage of revenue
Gross margin/revenue	Gross margin as a percentage of revenue. Gross margin is defined as value added (actual, not adjusted) minus manufacturing & distribution and depreciation expenses. Gross margin defined this way is the amount available to cover discretionary expenses (R&D, marketing, and general & administrative expenses) and pre-tax profits.
ROI	Profits as a percentage of investment
Market share	Sales of a business as a percentage of the served market.
Relative prices	Average level of selling prices of this business's direct costs per unit of products and services, relative to the average level of the three largest competitors.
Relative salesforce expenditures	Relative to the three largest competitors, did this business spend "about the same" percentage of its sales on salesforce effort? Or "somewhat more" (or less)? Or "much more" (or less)?

(*cont.*)

Name	*Description*
Relative media advertising expenditures	Relative to the three largest competitors, did this business spend "about the same" percentage of its sales on media advertising? Or "somewhat more" (or less)? Or "much more" (or less)?
Relative sales promotion expenditures	Relative to the three largest competitors, did this business spend "about the same" percentage of its sales on sales promotion efforts? Or "somewhat more" (or less)? Or "much more" (or less)?
Relative quality of customer services	Customer services are the supporting services which accompany the primary products or services. Was the quality of the customer services this business provided to end users "about the same", "somewhat better (or worse)" or "much better (or worse)"? than that provided by the three largest competitors?

Table 6.6. ***Selected marketing ratios from PIMS data***

	Averages				
	Consumer durables	*Consumer non-durables*	*Industrial*	*Services & distribution*	*All firms*
Salesforce/ sales, %	5.2	6.0	6.9	8.4	6.5
Adv. & prom./sales, %	4.1	12.2	1.4	3.8	4.8
Media/sales, %	1.8	5.4	0.6	1.2	2.0
Marketing/ sales, %	11.8	20.2	11.1	14.2	13.7
Salesforce/ marketing, %	45.1	35.4	61.8	60.5	52.3
Advertising/ marketing, %	33.2	56.4	12.9	22.5	27.7
Media/ marketing, %	14.4	25.9	4.9	7.5	12.0
Number of firms	847	1676	3511	170	6204

Note: From eMarketer, annual US media spend for 2002 is ~ \$237 billion. From above, since media/sales ~2%, the annual US sales are estimated at \$11,850 billion. Salesforce/sales ~6.5%, thus estimated annual US salesforce spend is ~ \$770 billion.

Table 6.7. ***Computing the consistency index fractions***

	Relative salesforce				
Relative price	*1*	*2*	*3*	*4*	*5*
1	1	0.5	0.33	0.25	0.2
2	0.5	1	0.67	0.5	0.4
3	0.33	0.67	1	0.75	0.6
4	0.25	0.5	0.75	1	0.8
5	0.2	0.4	0.6	0.8	1

Table 6.8. ***Key to consistency index coding***

For fraction ≤ 0.2, index $=$ 1; for fraction < 0.4, index $=$ 2; for fraction < 0.6, index $=$ 3; for fraction < 0.8, index $=$ 4; else index $=$ 5

Fraction	*Index*
0.20	1
0.25	2
0.33	2
0.40	3
0.50	3
0.60	4
0.67	4
0.75	4
0.80	5
1.00	5

Table 6.9. ***Coding the consistency index***

	Relative salesforce				
Relative price	*1*	*2*	*3*	*4*	*5*
1	5	3	2	2	1
2	3	5	4	3	3
3	2	4	5	4	4
4	2	3	4	5	5
5	1	3	4	5	5

Appendix 3: Development of the consistency index

The consistency index was constructed to create a measure of consistency between a company's actions on marketing spend variables and observed pricing policy. We now illustrate the construction of the index based on relative salesforce spending. Relative prices are classified into the 1–5 range based on observed values. Then, as outlined in Table 6.7, we compute the ratio of relative price to relative salesforce spending.

Next, we code these fractions on a 1–5 scale, indicative of the consistency between marketing action and pricing policy. For example, a fraction equal to or very close to the value one means that a company that spends much more on sales force also charges prices that are much higher. These behaviors are highly consistent with the recommendations in the chapter and are coded as maximum consistency (5). Similarly, the rest of the fractions are coded as in Table 6.8. The final coding is as illustrated in Table 6.9.

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7 *The model by Phillips, Chang, and Buzzell revisited – the effects of unobservable variables*

LUTZ HILDEBRANDT AND
DIRK TEMME

This chapter reviews some key hypotheses from empirical research on success factors in marketing. These hypotheses on drivers of business profitability, in particular quality and market share, have been a major subject of critique, and these critiques have come primarily from the resource-based view in management research. According to this perspective, general laws of business success based on manageable strategic input factors do not exist. Instead, unobservable, firm-specific variables are regarded as the key drivers of profitability. However, only a few studies have been able to show that strong relations discovered in empirical success factor research disappear if unobservable variables are controlled in econometric models.

In this chapter, we show that some of these results may be methodological artifacts. Based on the hypotheses of Phillips, Chang, and Buzzell (1983) regarding the effects of quality and market share on profitability, we use PIMS data to replicate their study using a modified modeling approach. Whereas Phillips, Chang, and Buzzell use data taken at two points in time to investigate the relationships between some key variables, this chapter uses a six-year cross-section of time series and a panel modeling approach to estimate the parameters. This approach allows us to overcome some major objections to the traditional PIMS approach; key relations between observable success factors and profitability highlighted by the PIMS research can be estimated while simultaneously the effects of different types of unobservable firm-specific factors can be controlled. The empirical results in our study show that quality and market share still have a significant impact on profitability even if unobservables are controlled.

7.1 Introduction

For several decades, the PIMS project (Buzzell and Gale 1987) has been regarded as the most promising data source to determine key drivers of business profitability. Although the results of this project have served numerous practitioners and researchers in developing and implementing strategic planning instruments, some researchers have raised concerns regarding the interpretation of the PIMS findings, even if a powerful methodology has been applied. A good example of empirical research using a sophisticated approach is the study by Phillips, Chang, and Buzzell (1983; hereafter PCB) on the impact of product quality and market share on profitability. PCB build upon the classical IO-perspective of the PIMS project, but instead of using a simple linear regression as in earlier studies, they estimate a structural equation model ("LISREL" model) which makes it possible to decompose the influence of the variables into direct and indirect (mediating) effects. Simultaneously, measurement errors are controlled by using a test-retest approach. The structure of their model represents the key relations between product quality and profitability, including mediating factors – price, costs, and market share – as well as eight control variables. The analysis was carried out on six different types of business using data from two consecutive years. The main results of the study are: in general, a positive effect of product quality and market share on profitability exists; the effect of product quality on profitability is mediated by market share; and the impact of the key variables varies considerably across the analyzed business types.

Although the results on product quality and market share confirmed earlier findings on these key success factors, the research provoked many methodological as well as conceptual critiques. In a series of studies especially focusing on the influence of market share on profitability, other researchers were able to show that in particular the typically strong effect of market share disappears if unobservable, firm-specific factors are taken into account in the analysis (Jacobson 1988, 1990; Jacobson and Aaker 1985; Rumelt and Wensley 1980). On the basis of these results, the whole approach of empirically searching for law-like strategic success factors was called into question (Camerer and Fahey 1988; Ghemawat 1991; Rumelt, Schendel, and Teece 1991), although economic theory offered fundamental theoretical explanations for the causal impact of variables like market share.

The major critique came from scholars supporting the resource-based view (Barney 1986; Penrose 1959; Wernerfelt 1984) in strategic management research. The fundamental assumption of this theory is that firms differ (at least to some extent) in their resource endowments, and that in the end these differences result in differences in profitability. The strict advocates of this theory regard firm-specific resources and competencies as the fundamental causes of sustained competitive advantage (e.g. Barney 1991; Grant 1991; Peteraf 1993; Teece, Pisano, and Shuen 1997). Because not every resource is strategically relevant, general characteristics have been developed that qualify a resource (or a team of resources) as the basis for competitive advantage (e.g. Barney 1991; Peteraf 1993). Such resources should be valuable and rare and not easily transferred, reproduced, or substituted. If we accept this perspective, the resource-based view offers a theoretical foundation for the explanation of generally unobservable, firm-specific factors of success. Consequently, the approach can be regarded as an alternative or at least as a supplement to the classical, IO-based approaches used in PIMS research to explain a firm's success.

The problem, however, is that the resource-based view does not offer operational measurement models for its key concepts. Especially for the concepts that are related to knowledge, capabilities, or people, almost no satisfactory indicator is available. In addition, from a managerial perspective, frequently cited but unobservable variables such as "luck" or "management quality" do not provide an operational basis for strategic planning or control. Two ways may be used to fill this gap: the development and validatation of appropriate measurement models; or the use of econometric models to control unobservable, firm-specific effects statistically when the impact of variables supposed to drive profitability is estimated.

This chapter follows the second approach. First, we want to show that a structural equation approach to the analysis of panel data offers a capable methodology for estimating the impact of controllable and manageable input variables, thus taking strategic planning purposes into account, and simultaneously for controlling for unobservable variables. In contrast, existing studies controlling for unobservables are restricted to single-equation models. The structural equation approach starts with a cross-sectional model for pooled data, reflecting the long-term character of strategic variables. This model is extended stepwise to control for unobservable variables that can be distinguished according to their behavior over time. Second, we want to verify whether some of the main objections to the results of the study by PCB remain justified, if the same model is specified and estimated, but unobservable firm-specific factors are controlled. Earlier studies on market share and profitability have generally produced different results using the same data (Ailawadi, Farris, and Parry 1999; Boulding 1990; Boulding and Staelin 1990, 1993; Hildebrandt and Annacker 1996). Thus, the substantial results seem method-dependent to a certain degree.

The remainder of this chapter is organized as follows. First, we provide a brief, state-of-the-art overview of how to control for unobservable variables in business performance models. Second, we propose a structural equation approach to pooled time-series cross-sectional data in order to control for unobservable variables. Following the structure proposed by PCB for analyzing the impact of product quality on profitability, it will be shown how different types of unobservables can be taken into account by gradually extending a cross-sectional baseline model. Third, in order to demonstrate the capabilities of the structural equation approach in the analysis of panel data, we apply the methodology to three different samples from the PIMS database. The specified models are estimated using the maximum likelihood option in LISREL. Finally, we discuss the implications of our study.

7.2 Methods to control for unobservable variables

In order to control the influence of unobservable variables on the observed relationships between proposed key drivers of success and measures of firm performance, different methods may be used. For example, selected unobservable variables might be operationalized in terms of multiple observed indicators, or proxy variables for managerial efficiency can be created using data envelopment analysis (Charnes, Cooper, and Rhodes 1978). A more comprehensive approach rests on the availability of panel data and has already been applied in previous studies analyzing business performance (e.g. Ailawadi, Farris, and Parry 1999; Boulding and Staelin 1990, 1993, 1995; Jacobson 1990). The large number of unobserved as well as truly unobservable variables (Griliches 1974) that potentially are correlated with both the observed strategic factors and firm performance are classified according to the temporal characteristics of their influence. Customarily, three types of variables are distinguished and represented by specific components of an additive error term v_{it}:

$$v_{it} = \mu_i + u_{it}, \quad \text{where} \quad u_{it} = \rho u_{i,t-1} + \varepsilon_{it}. \tag{1}$$

(1) Firm-specific variables that have a stable effect over the period of analysis, for example corporate culture or management quality, are taken into account by the time-invariant component μ_i.
(2) Other variables whose influence is likewise persistent but dissipating over time (e.g. product innovations or technological know-how), are captured by the term $\rho u_{i,t-1}$ if a first-order autoregressive (AR1) process, as the most parsimonious representation, is supposed.
(3) Finally, temporary stochastic shocks (e.g. "luck") whose effects last only one period (e.g. one year) are modeled by the serially uncorrelated stochastic disturbance ϵ_{it}.

To control simultaneously for the different types of unobservable effects, for example in a linear, single-equation regression

$$y_{it} = \beta' x_{it} + v_{it}, \tag{2}$$

where x_{it} is a $(K \times 1)$ vector of exogenous variables and β is a $(K \times 1)$ vector of regression parameters, the following procedure (Boulding and Staelin 1993) has been proposed. First, a ρ-transformation followed by the taking of first differences eliminates both the serially correlated effects $\rho u_{i,t-1}$ and the time-invariant variables μ_i. This leads to the following autoregressive distributed lag (ARDL) model, where Δ denotes first differences:

$$\Delta y_{it} = \rho \Delta y_{i,t-1} + \beta_1' \Delta x_{it} + \beta_2' \Delta x_{i,t-1} + \Delta\varepsilon_{it}. \tag{3}$$

The first-order autocorrelation model imposes the restriction $\beta_2 = -\rho\beta_1$. Second, to control for a possible contemporaneous correlation between the moving-average error term $\Delta\epsilon_{it}$ and the explanatory variables, values lagged at least two periods (levels or differences) can be used as instruments in a 2SLS estimation of equation (3).

Although, formally, the described approach represents a valid method to control for unobservable variables, it should be pointed out that the required transformations fundamentally alter the model and its interpretation (e.g. Buzzell 1990). As can be seen from equation (3), year-to-year changes of strategic factors are related to year-to-year changes in performance (e.g. ROI). If one assumes that long-term and short-term effects differ, this means that in using difference data only short-term effects of strategic factors are examined. Only with respect to short-term effects, stochastic influences might play an important role in the relationships between key factors of success and firm performance. If the researcher is instead concerned with the strategic and therefore long-term implications of key success factors, temporary stochastic shocks might be neglected. From this perspective, it seems justified to focus on the control of time-invariant and serially correlated unobservable effects.

Meanwhile, a large body of econometric literature (e.g. Baltagi 2001; Hsiao 1986) exists to help researchers in specifying panel models, and major statistical software packages (e.g. SAS) provide special procedures for the estimation of such models. Alternatively, a structural equation approach (LISREL), whose application in econometric panel studies was already proposed in the late 1970s (Jöreskog 1978), can be used. This approach, however, has largely been ignored in economics and business research (for exceptions see Annacker and Hildebrandt 2004; Hildebrandt and Annacker 1996; Lillard and Willis 1978) although it offers much greater flexibility in the specification of panel models, including the integration of measurement models. We will now show how LISREL (Jöreskog and Sörbom 1996) can be specified to control for the biasing influence of different types of unobserved variables in a structural equation model.

7.3 The basic model and extensions controlling for unobservables

7.3.1 Baseline model

In order to examine how unobservable or simply unobserved variables influence the direct and indirect effects of perceived product quality on business units' profitability, we start with a baseline model that ignores the possibly distorting effects of unobservables. The overall structure of the cross-sectional simultaneous equation model closely resembles the one proposed by Phillips, Chang, and Buzzell (1983) and builds the core of all further models analysed in this study (see also Hildebrandt and Buzzell 1991). Return on investment (*ROI*) is specified as a function of product quality (*QUA*), market share (*MS*), relative prices

Table 7.1. ***Hypothesized effects of the exogenous control variables***

Exogenousvariables except relative product quality (control variables)	*Variable name*	*Endogenous variables*			
		Market share	*Relative direct costs*	*Relative prices*	*Return on investment*
Investment intensity of business	*INVINT*		x	x	x
Vertical integration of business	*VERTINT*		x	x	x
Real market growth in business's product market	*MKTGRW*		x	x	x
% Business's employees unionized	*UNION*		x	x	x
% Business's capacity utilization	*CAPAC*		x		x
% of Business's sales derived from new products	*NEWPROD*	x	x	x	x
Salesforce expenditures relative to competitors	*SLSFORCE*	x	x	x	x
Advertising/promotion expenditures relative to competitors	*ADVPROM*	x		x	x

(*PRICES*), and direct costs (*COSTS*). Although PCB found no significant effects of relative prices on ROI, prices were included in the ROI equation to determine if this result changes by controlling for unobservable variables. Direct costs are influenced by product quality and also by market share, which in turn is driven by product quality and relative prices. Relative prices depend on direct costs and on product quality. Thus, a nonrecursive model including a loop between market share, direct costs, and relative prices results. In addition to product quality, eight further exogenous variables are included in the model both as control variables and in order to make the model identifiable (for the hypothesized effects of these variables on the endogenous variables, see Table 7.1). We assume that the disturbances of the endogenous variables are uncorrelated both over time and across equations (note that specifying free contemporaneous correlations between the disturbances would make the model underidentified). The baseline model for business unit i at time t can be written as follows:

$$\begin{aligned}
COSTS_{it} &= \beta_1 MS_{it} + \gamma_1 QUA_{it} + \sum_{c\in C_1} \gamma_c^{(1)} CV_{cit} + \varepsilon_{1it}, \\
MS_{it} &= \beta_2 PRICES_{it} + \gamma_2 QUA_{it} + \sum_{c\in C_2} \gamma_c^{(2)} CV_{cit} + \varepsilon_{2it}, \\
PRICES_{it} &= \beta_3 COSTS_{it} + \gamma_3 QUA_{it} + \sum_{c\in C_3} \gamma_c^{(3)} CV_{cit} + \varepsilon_{3it}, \qquad (4) \\
ROI_{it} &= \beta_4 COSTS_{it} + \beta_5 MS_{it} + \beta_6 PRICES_{it} + \gamma_4 QUA_{it} \\
&\quad + \sum_{c\in C_4} \gamma_c^{(4)} CV_{cit} + \varepsilon_{4it},
\end{aligned}$$

$$i = 1, \ldots, N, \quad t = 1, \ldots, T,$$

where C_g is the set of control variables CV_c for equation g, $g = 1, \ldots, 4$, and

$$E(\varepsilon_{git}\varepsilon_{g'i't'}) = \begin{cases} \sigma_{\varepsilon_g}^2 & \text{if } g = g', i = i', t = t', \\ 0 & \text{else.} \end{cases}$$

To control for the persistent effects that can be attributed to unobservable variables, this baseline model is gradually extended by incorporating different error components.

7.3.2 Model extensions

Controlling for time-invariant effects

As a first step in investigating the role of unobservable variables in the relationship between quality and ROI, we control for unobserved persistent characteristics of the business units supposed to be invariant over time (e.g. management quality or customer-oriented culture). Although one can expect that product quality as well as some of the control variables are correlated with these individual effects, we initially specify a random-effects model (RE) under the assumption of no such correlation (see model (6) in the appendix to this chapter). Since the unobserved time-invariant effects which influence the endogenous variables might overlap, we assume that the random effects are correlated across equations. As is well known from the literature on econometric panel data analysis (e.g. Baltagi 2001; Hsiao 1986), the consistency of the parameter estimates in the RE model hinges on the fact that the exogenous variables are indeed uncorrelated with the individual effects (since we use a system estimator, the correlations between the endogenous variables, costs, prices, and market share, and the individual random effects of these three variables are properly taken into account; for a discussion of system estimators in the context of simultaneous equation models with random error components, see, for example, Baltagi 2001). If the assumption of no correlation between the individual effects and the exogenous variables does not hold, a fixed-effects specification is typically chosen (Hsiao 1986).

In previous studies on business performance, time-invariant effects were predominantly eliminated by taking first differences of the data (e.g. Ailawadi, Farris, and Parry 1999; Boulding and Staelin 1990). As an alternative specification, which likewise controls for a possible correlation between the individual effects μ_{gi} and the exogenous variables x_{it}, we propose a modified random-effects model, hereafter referred to as the RECEV (random effects correlated with exogenous variables) model (see model (8) in the appendix to this chapter).

The RECEV model has several advantages over the first-difference (FD) model. In contrast to the FD model, time-invariant observed variables can be included. In addition, the model allows a flexible specification of correlations between the individual effects and selected exogenous variables. Because the RE model is nested in the RECEV model, hypotheses about correlations between the individual effects and all or specific exogenous variables can be easily tested with likelihood ratio tests. Alternatively, a Hausman test can be performed that relies on the differences in the parameter estimates between the random- and the fixed-effects specification (Hausman 1978).

Controlling for autoregressive effects

As a further extension, we assume in addition to the time-invariant individual effects that persistent unobserved variables correlated over time are present and correlated with the explanatory variables. The latter effects can be eliminated by ρ-differencing the data (e.g. Boulding and Staelin 1993, 1995). This leads to the following autoregressive distributed lag (ARDL) specification of our simultaneous equation model:

$$
\begin{aligned}
COSTS_{it} &= \rho_1 COSTS_{i,t-1} + \beta_1 MS_{it} + \beta_2 MS_{i,t-1} + \gamma_1 QUA_{it} \\
&\quad + \gamma_2 QUA_{i,t-1} + \sum_{c\in C_1} \gamma_c^{(11)} CV_{cit} + \sum_{c\in C_1} \gamma_c^{(12)} CV_{ci,t-1} \\
&\quad + \mu_{1i}^* + \varepsilon_{1it}, \\
MS_{it} &= \rho_2 MS_{i,t-1} + \beta_3 PRICES_{it} + \beta_4 PRICES_{i,t-1} + \gamma_3 QUA_{it} \\
&\quad + \gamma_4 QUA_{i,t-1} + \sum_{c\in C_2} \gamma_c^{(21)} CV_{cit} + \sum_{c\in C_2} \gamma_c^{(22)} CV_{ci,t-1} \\
&\quad + \mu_{2i}^* + \varepsilon_{2it}, \\
PRICES_{it} &= \rho_3 PRICES_{i,t-1} + \beta_5 COSTS_{it} + \beta_6 COSTS_{i,t-1} \\
&\quad + \gamma_5 QUA_{it} + \gamma_6 QUA_{i,t-1} + \sum_{c\in C_3} \gamma_c^{(31)} CV_{cit} \\
&\quad + \sum_{c\in C_3} \gamma_c^{(32)} CV_{ci,t-1} + \mu_{3i}^* + \varepsilon_{3it}, \\
ROI_{it} &= \rho_4 ROI_{i,t-1} + \beta_7 COSTS_{it} + \beta_8 COSTS_{i,t-1} + \beta_9 MS_{it} \\
&\quad + \beta_{10} MS_{i,t-1} + \beta_{11} PRICES_{it} + \beta_{12} PRICES_{i,t-1} \\
&\quad + \gamma_7 QUA_{it} + \gamma_8 QUA_{i,t-1} + \sum_{c\in C_4} \gamma_c^{(41)} CV_{cit} \\
&\quad + \sum_{c\in C_4} \gamma_c^{(42)} CV_{ci,t-1} + \mu_{4i}^* + \varepsilon_{4it}, \\
\mu_{1i}^* &= \pi_1 COSTS_{i1} + \pi_2 MS_{i1} + \pi_3 PRICES_{i1} + \pi_4 ROI_{i1} \\
&\quad + \sum_{t=1}^{T} \pi_{5t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(1)} CV_{cit} + \omega_{1i}, \\
\mu_{2i}^* &= \pi_6 COSTS_{i1} + \pi_7 MS_{i1} + \pi_8 PRICES_{i1} + \pi_9 ROI_{i1} \\
&\quad + \sum_{t=1}^{T} \pi_{10t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(2)} CV_{cit} + \omega_{2i}, \\
\mu_{3i}^* &= \pi_{11} COSTS_{i1} + \pi_{12} MS_{i1} + \pi_{13} PRICES_{i1} + \pi_{14} ROI_{i1} \\
&\quad + \sum_{t=1}^{T} \pi_{15t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(3)} CV_{cit} + \omega_{3i}, \\
\mu_{4i}^* &= \pi_{16} COSTS_{i1} + \pi_{17} MS_{i1} + \pi_{18} PRICES_{i1} + \pi_{19} ROI_{i1} \\
&\quad + \sum_{t=1}^{T} \pi_{20t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(4)} CV_{cit} + \omega_{4i}, \qquad (5)
\end{aligned}
$$

$$
i = 1, \ldots, N, \quad t = 2, \ldots, T,
$$

where $\mu^*_{gi} = (1 - \rho_g)\mu_{gi}$, $C^* = C \setminus \{UNION_i\}$, and

$$E(\omega_{gi}\omega_{g'i'}) = \begin{cases} \sigma^2_{\omega_g} & \text{if } g = g', i = i', \\ \sigma_{\omega_{gg'}} & \text{if } g \neq g', i = i', \\ 0 & \text{else.} \end{cases}$$

$$E(\varepsilon_{git}\varepsilon_{g'i't'}) = \begin{cases} \sigma^2_{\varepsilon_g} & \text{if } g = g', i = i', t = t', \\ 0 & \text{else.} \end{cases}$$

The serial correlation hypothesis imposes nonlinear restrictions on the coefficients for the lagged explanatory variables (e.g. $\beta_2 = -\rho_1\beta_1$ or $\gamma_2 = -\rho_1\gamma_1$), since it is assumed that the explanatory variables have only a current effect on the dependent variables. The autoregressive effects of the lagged dependent variables in each equation therefore exclusively reflect the impact of serially correlated unobserved variables, which influence business performance and possibly also the explanatory variables. Because the autocorrelation model with individual effects (hereafter noted as AR1-RECEV) is nested in the unrestricted ARDL model (5), χ^2 difference tests (likelihood ratio tests) can be used to examine if the nonlinear restrictions of this model hold. A rival hypothesis states that the explanatory variables influence unobserved variables, for example "goodwill," which in turn affect the dependent variables, for example, profitability. In this state-dependence model, the indirect, lagged influence of strategic factors such as product quality via some unobserved state variables is reflected in the autoregression coefficient of the lagged dependent variable; this is a contrast to its interpretation in the autocorrelation model. It gives rise to the restriction that the coefficient for the lagged explanatory variable is zero in the ARDL model (5) (for a discussion of both the serial correlation and the state-dependence model, see Ailawadi, Farris, and Parry 1993; Jacobson 1990).

7.4 Empirical study

7.4.1 Data

The structural equation modeling approach to controlling for unobservable variables is applied in an empirical analysis of time-series/cross-sectional data from the PIMS SPIYR database. Our sample contains strategic business units (SBUs) which provide information for at least six consecutive years. This sampling scheme results in a total sample of 1141 SBUs. In order to control for differences due to the industry to which an SBU belongs, we additionally analyse the following two subsamples:

- (other) industrial goods ($n = 608$)
- consumer goods ($n = 311$)

The sample termed “industrial goods” consists of business units that produce raw and semi-finished materials, components, and industrial supplies; the sample does not include SBUs that manufacture capital goods. The latter ones, as well as service and distribution businesses, were excluded from separate analyses because sample sizes were too small given the model complexity that results from controlling unobservable variables. For the same reason, we do not follow PCB in subdividing the “industrial goods” and “consumer goods” samples into further subsamples.

7.4.2 Results

All models in our study have been estimated with LISREL 8.51 (Jöreskog and Sörbom 1996), using the maximum-likelihood (ML) estimation procedure. In line with PCB, we report only results for core variables in our model.

Baseline model

In order to establish a benchmark for analyzing the impact of unobservable variables on the quality effects on business profitability, we first report the results for the baseline model (see model (4) in Section 7.3.1). The measures of overall fit (Table 7.2) clearly indicate that this cross-sectional model is rejected both in the total sample and in the two subsamples. For example, the RMSEA is far above the conventional cut-off value of .05 used for this fit index (Browne and Cudeck 1993; Hu and Bentler 1999). Likewise, CFI and NFI are considerably below the threshold value of .95 (Hu and Bentler 1998; for an overview of fit measures and their interpretation in structural equation modelling, see Bagozzi and Baumgartner 1994). In light of the inadequate model fit, an interpretation of the parameters becomes meaningless. To allow for comparisons with the extended models, we will nevertheless briefly

Table 7.2. ***Parameter estimates and fit measures for the baseline model***

Parameter	*Total sample*	*Industrial goods*	*Consumer goods*
$\gamma_{ROI,QUA}$	.105*** (.009)	.090*** (.013)	.094*** (.018)
$\gamma_{MS,QUA}$	.170*** (.008)	.201*** (.011)	.146*** (.014)
$\gamma_{COSTS,QUA}$	.017*** (.003)	.006 (.005)	.018*** (.006)
$\gamma_{PRICES,QUA}$	.090*** (.003)	.086*** (.004)	.103*** (.006)
$\beta_{ROI,MS}$	.229*** (.014)	.217*** (.020)	.327*** (.030)
$\beta_{COSTS,MS}$	−.084*** (.006)	−.056*** (.008)	−.109*** (.010)
$\beta_{ROI,COSTS}$	−.344*** (.035)	−.383*** (.047)	−.311*** (.076)
$\beta_{PRICE,COSTS}$	.392*** (.011)	.404*** (.013)	.412*** (.030)
$\beta_{ROI,PRICES}$	.062* (.035)	.263*** (.052)	−.079 (.060)
$\beta_{MS,PRICES}$	.284*** (.031)	.104** (.044)	.520*** (.050)
Fit measures			
$\chi^2_{(df)}$	$47{,}121_{(1437)}$	$26{,}103_{(1437)}$	$15{,}167_{(1437)}$
RMSEA	.165	.163	.168
CFI	.640	.645	.620
NFI	.637	.638	.608
RMR^s	.118	.117	.126

Note: Standard errors are in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.

discuss the estimated direct and indirect effects of product quality in the baseline model.

The direct effects of product quality on market share, relative prices, and ROI are significantly positive in all samples (throughout the study we use a significance level of $\alpha = .05$). Since market share increases ROI both directly and indirectly (via reducing relative direct costs), the positive impact of quality on profitability is further enhanced by these indirect effects. For industrial goods only, another indirect effect of quality results from the positive impact of prices on ROI (higher quality seems to strengthen the capability of SBUs to charge higher prices than competitors both by a direct effect and by increasing market share). The positive market-side effects of quality on ROI are partly offset by higher direct costs accompanying higher product quality, although this effect is non-significant for industrial goods industries. Even though the different subsamples used in the Phillips, Chang, and Buzzell study prevent a direct comparison, overall our results correspond closely both with their findings and with general PIMS "wisdom" based on cross-sectional studies (Buzzell and Gale 1987).

Controlling for time-invariant effects

As a first step in controlling for unobservable firm effects, we extend the baseline model by considering the impact of time-invariant unobservables. In order to test the assumption that perceived product quality is correlated with these firm effects, we initially estimate a conventional random-effects (RE) model (see model (6) in the appendix). We thus assume that the individual effects μ_{ROI}, μ_{MS}, μ_{COSTS}, and μ_{PRICES} are correlated with each other but not with quality and the exogenous control variables. Despite a huge improvement in model fit, thus supporting the assumption that individual effects exist, the RE model is still rejected in all samples (see the measures of fit in Table 7.3). Part of this misfit might result from neglecting the potential correlations between the exogenous variables and the time-invariant effects.

Therefore, we estimate two alternative specifications that take such a correlation into account – the RECEV (see model (8) in the appendix) and the FD model. Although some of the fit indices for these models (Table 7.4) reach levels of acceptable fit (RMSEA for the FD model and RMR^s and CFI for the RECEV model), we finally conclude that the static models do not provide an adequate approximation of the underlying data-generating process.

Table 7.3. ***Parameter estimates and fit measures for the RE model***

Parameter	*Total sample*	*Industrial goods*	*Consumer goods*
$\gamma_{ROI,QUA}$	.078*** (.012)	.077*** (.017)	.098*** (.023)
$\gamma_{MS,QUA}$	.064*** (.004)	.063*** (.006)	.052*** (.008)
$\gamma_{COSTS,QUA}$	−.021*** (.003)	−.024*** (.004)	−.029*** (.006)
$\gamma_{PRICES,QUA}$	.028*** (.003)	.018*** (.004)	.062*** (.007)
$\beta_{ROI,MS}$	.240*** (.042)	.216*** (.058)	.387*** (.089)
$\beta_{COSTS,MS}$	−.010 (.010)	−.029** (.012)	−.026 (.020)
$\beta_{ROI,COSTS}$	−.323*** (.061)	−.248*** (.090)	−.412*** (.114)
$\beta_{PRICE,COSTS}$	.239*** (.015)	.250*** (.020)	.242*** (.034)
$\beta_{ROI,PRICES}$	−.050 (.052)	.059 (.080)	−.340*** (.084)
$\beta_{MS,PRICES}$	−.014 (.016)	.069*** (.025)	−.044* (.024)
Fit measures			
$\chi^2_{(df)}$	$12{,}889_{(1427)}$	$8084_{(1427)}$	$5255_{(1427)}$
RMSEA	.088	.090	.093
CFI	.910	.904	.894
NFI	.901	.888	.864
RMR^s	.070	.071	.083

Note: Standard errors are in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.

Table 7.4. ***Parameter estimates and fit measures for the RECEV and FD models***

	Total sample		*Industrial goods*		*Consumer goods*	
Parameter	*RECEV*	*FD*	*RECEV*	*FD*	*RECEV*	*FD*
$\gamma_{ROI,QUA}$	.061*** (.015)	.037** (.017)	.087*** (.021)	.059** (.025)	.077*** (.028)	.035 (.033)
$\gamma_{MS,QUA}$	.057*** (.005)	.037*** (.005)	.054*** (.007)	.025*** (.007)	.044*** (.008)	.031*** (.009)
$\gamma_{COSTS,QUA}$	−.025*** (.003)	−.022*** (.004)	−.025*** (.004)	−.020*** (.005)	−.034*** (.006)	−.039*** (.007)
$\gamma_{PRICES,QUA}$	.013*** (.004)	.009** (.004)	−.001 (.005)	.003 (.005)	.056*** (.008)	.044*** (.009)
$\beta_{ROI,MS}$	.231*** (.042)	.289*** (.046)	.206*** (.057)	.217*** (.065)	.374*** (.088)	.479*** (.098)
$\beta_{COSTS,MS}$	−.012 (.010)	−.004 (.009)	−.030** (.012)	−.014 (.012)	−.028 (.020)	−.021 (.020)
$\beta_{ROI,COSTS}$	−.316*** (.061)	−.276*** (.067)	−.251*** (.089)	−.271*** (.099)	−.391*** (.114)	−.341*** (.127)
$\beta_{PRICES,COSTS}$	.236*** (.015)	.191*** (.015)	.248*** (.020)	.217*** (.021)	.241*** (.034)	.177*** (.032)
$\beta_{ROI,PRICES}$	−.054 (.052)	−.025 (.059)	.072 (.079)	.001 (.086)	−.345*** (.084)	−.119 (.098)
$\beta_{MS,PRICES}$	−.018 (.016)	−.018 (.017)	−.063** (.025)	.051** (.023)	−.044* (.024)	−.035 (.026)
Fit measures						
$\chi^2_{(df)}$	$12{,}082_{(1235)}$	$2897_{(970)}$	$7529_{(1235)}$	$2344_{(970)}$	$4812_{(1235)}$	$2020_{(970)}$
RMSEA	.093	.040	.094	.047	.096	.053
CFI	.915	.805	.909	.772	.901	.696
NFI	.907	.752	.896	.699	.876	.614
RMR^s	.015	.037	.018	.045	.020	.060

Note: Standard errors are in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.

Despite this limitation, we tested the null hypothesis of no correlation between the exogenous variables and the individual effects. We first compared the RECEV model and the restrictive RE specification (Table 7.5). The likelihood ratio test statistics for the three samples are highly significant, leading to the conclusion that the RE model is indeed incorrect. In order to test whether the time-invariant effects are correlated with product quality in particular, we performed additional likelihood ratio tests based on appropriate restrictions of the RECEV model. An overall test results from fixing all regression coefficients for product quality in the reduced form equations of the individual effects to zero (reduced form parameters for the control variables are freely estimated). Again, we see a significant drop in fit for all samples (Table 7.5). Thus, the joint hypothesis that quality is uncorrelated with all time-invariant effects is rejected. Such a result could be due to the fact that, for example, either quality is moderately correlated with all individual effects or only highly correlated with a specific effect. Thus, we separately tested the independence hypothesis for each individual effect. In order to maintain an overall significance level of .05, we use a Bonferroni adjusted nominal test level of .05/6 = .008 for the individual tests in each sample.

Identical pictures emerge for the total sample and the industrial goods sample: quality seems to be consistently correlated with the individual effects for ROI, market share, and prices but uncorrelated with μ_{COSTS}. Divergent results, however, occur for the consumer goods sample. The most remarkable difference is that in this sample, product quality obviously is uncorrelated with the individual effect in the ROI equation.

Compared to the baseline model, the most striking result of the RECEV/FD specifications is a reversal in sign for the quality–cost link that already occurred in the RE model. Quality seems to reduce direct costs once unobserved individual effects have been taken into account. Cost reductions might result, for example, from lower failure rates, thus reducing defective goods and warranty expenses (Garvin 1988), or from a stronger decline in production costs along the quality-based learning curve (Fine 1986). However, the negative parameter for the quality's effect on costs has alternatively been reduced to the fact that, based on the PIMS quality assessment, management perception of quality might be inversely related to the customers' quality perceptions, thus creating an artifact regarding the quality–cost relationship (Boulding 1992; Boulding and Staelin 1993). Another interesting aspect is that

Table 7.5. ***Likelihood ratio tests on uncorrelation between product quality and individual effects***

Alternative models	χ^2	*df*	$\Delta\chi^2$	Δdf	*p*
Total sample					
RECEV	12,081.97	1235	—	—	—
RE	12,889.43	1427	807.46	192	.000
RECEV$_{\setminus(\mu-QUA)}$	12,296.83	1259	214.86	24	.000
RECEV$_{\setminus(\mu_{COSTS}-QUA)}$	12,097.24	1241	15.27	6	.018
RECEV$_{\setminus(\mu_{MS}-QUA)}$	12,148.80	1241	66.83	6	.000
RECEV$_{\setminus(\mu_{PRICES}-QUA)}$	12,207.01	1241	125.04	6	.000
RECEV$_{\setminus(\mu_{ROI}-QUA)}$	12,108.32	1241	26.35	6	.000
Industrial goods					
RECEV	7528.97	1235	—	—	—
RE	8084.09	1427	555.12	192	.000
RECEV$_{\setminus(\mu-QUA)}$	7687.19	1259	158.22	24	.000
RECEV$_{\setminus(\mu_{COSTS}-QUA)}$	7533.15	1241	4.18	6	.652
RECEV$_{\setminus(\mu_{MS}-QUA)}$	7575.63	1241	46.66	6	.000
RECEV$_{\setminus(\mu_{PRICES}-QUA)}$	7617.60	1241	88.63	6	.000
RECEV$_{\setminus(\mu_{ROI}-QUA)}$	7552.16	1241	23.19	6	.000
Consumer goods					
RECEV	4812.42	1235	—	—	—
RE	5254.95	1427	442.53	192	.000
RECEV$_{\setminus(\mu-QUA)}$	4894.51	1259	82.09	24	.000
RECEV$_{\setminus(\mu_{COSTS}-QUA)}$	4827.22	1241	14.80	6	.022
RECEV$_{\setminus(\mu_{MS}-QUA)}$	4857.30	1241	44.88	6	.000
RECEV$_{\setminus(\mu_{PRICES}-QUA)}$	4829.07	1241	16.65	6	.011
RECEV$_{\setminus(\mu_{ROI}-QUA)}$	4816.90	1241	4.48	6	.612

industrial goods businesses are no longer able to achieve higher prices than competitors offering lower perceived product quality. Even for consumer goods, the positive quality effect on prices is considerably smaller than in the baseline model.

If static models capturing time-invariant unobserved characteristics of the SBUs would indeed be good approximations of the underlying data-generating process, one would expect similar parameter estimates for the RECEV and the FD model (for two periods, a RECEV model without the time-invariant control variable "unionization" is equivalent to the FD model). However, there are a few noteworthy differences between the two specifications. For example, in the consumer goods sample, the quality impact on ROI remains significantly positive in the RECEV model, whereas this effect completely vanishes if first differences are analyzed. A further discrepancy exists regarding the direct costs–market share link in the industrial goods sample. In contrast to the FD model, the market share parameter is still significantly negative in the RECEV model. A possible explanation for these discrepancies is that differencing the data to a certain extent already eliminates the bias caused by autocorrelated unobservable variables (the higher the autocorrelation, the larger the effect). In a final step, we therefore control for both time-invariant and autocorrelated unobserved effects.

Controlling for autoregressive effects

As discussed in Section 7.3.2, the serially correlated unobserved variables in the autocorrelation model with individual effects (AR1-RECEV model) are eliminated by ρ-differencing the data. This transformation results in an autoregressive distributed lag model with time-invariant effects in which the coefficients of the lagged explanatory variables are subject to nonlinear constraints. Before actually testing the AR1-RECEV model, we first estimate an unconstrained ARDL model (see model (5) in Section 7.3.2). This model serves as a benchmark by which the performance of the AR1-RECEV model can be judged.

Unfortunately, the initial estimation of the unconstrained ARDL model led to improper solutions in all samples since some error variances of the individual effects were negative (so called Heywood cases; see, for example, Chen *et al.* 2001). Except for market share in the industrial goods sample, only the error variances for μ_{PRICES} and μ_{COSTS} were involved. Whereas for direct costs, where none of the negative variances was significantly different from zero (this is also true for market share in the industrial goods sample), we found significant error variances for μ_{PRICES} in the two subsamples "industrial goods" and "consumer goods." A possible explanation for these negative error variances might be that owing to the ρ-transformation, the variances of the individual effects reduce toward zero if autocorrelations increase toward one (for example, given an autocorrelation coefficient of $\rho = .85$, the original variance of the individual effect is multiplied by a factor $(1-\rho)^2 = .0225$). It is well known that in the PIMS database, the autocorrelation of the endogenous variables "direct prices" and "direct costs," as well as "market share," is rather high (e.g. Jacobson and Aaker 1987). Thus, it can be assumed that the population values of the error variances (i.e. that part of the variance of the individual effects that is not "explained" by the exogenous variables in the reduced form equations) are indeed very close to the boundary of the admissible interval. To cope with this problem, we imposed non-negative interval restrictions on these variances. Although the estimation of these modified models led to variances of zero for the restricted error terms in the reduced forms, the total variances of the individual effects were still positive. In order to assess the appropriateness of this procedure, we fixed the problematic error variances to zero (this resulted in results which were virtually identical to those for the models with interval restrictions), and performed likelihood ratio tests. None of these models showed a significant drop in fit compared to their unconstrained counterparts.

Judged by cut-off criteria common in structural equation modeling, the overall fit of the unrestricted ARDL specification is quite good (Table 7.6). For the total sample and the industrial goods businesses, the RMSEA, for example, is well below the critical value of .05 (the upper bound of the 95 percent confidence interval of the RMSEA does not even include this critical value). For consumer goods, the fit is only slightly worse. Since the confidence interval for the RMSEA captures .05, the model nevertheless provides an acceptable fit. This conclusion is further supported by the satisfactory levels of the remaining fit indices.

As already discussed, the AR1-RECEV model implies specific constraints for the parameters of the lagged explanatory variables. To gain a preliminary impression of the adequacy of this model, we calculated the corresponding parameter values to be expected under an autocorrelation model based on the estimated contemporaneous effects and the autocorrelation coefficients in the unconstrained ARDL model (see the second column for each sample in Table 7.6). A closer inspection of these figures shows that there are some noteworthy deviations between the calculated and the estimated unconstrained lagged effects. For example, in the total and the consumer goods sample, the

Table 7.6. *Parameter estimates and fit measures for the unconstrained ARDL and AR1-RECEV models*

	Total sample			*Industrial goods*			*Consumer goods*		
Parameter	*unconstrained*	*calc. val.*	*constrained*	*unconstrained*	*calc. val.*	*constrained*	*unconstrained*	*calc. val.*	*constrained*
$\gamma_{ROI,QUA}$	.027		.024	.054*		.050	.000		−.001
	(.021)		(.021)	(.031)		(.031)	(.039)		(.039)
γ_{ROI,QUA_1}	.019	−.017	−.015	.004	−.034	−.031	.032	.000	.000
	(.022)		(.013)	(.032)		(.019)	(.040)		(.020)
$\gamma_{MS,QUA}$	.034***		.026***	.015*		.012	.035***		.029***
	(.006)		(.006)	(.009)		(.008)	(.010)		(.010)
γ_{MS,QUA_1}	−.003	−.028	−.023***	−.005	−.014	−.011	−.001	−.027	−.022***
	(.006)		(.005)	(.009)		(.007)	(.011)		(.008)
$\gamma_{COSTS,QUA}$	−.028***		−.023***	−.026***		−.021***	−.046***		−.041***
	(.004)		(.004)	(.006)		(.005)	(.008)		(.008)
γ_{COSTS,QUA_1}	.014***	.027	.022***	.013**	.025	.020***	.027***	.040	.036***
	(.005)		(.004)	(.006)		(.005)	(.009)		(.007)
$\gamma_{PRICES,QUA}$	.007		.005	.005		.002	.038***		.041***
	(.005)		(.004)	(.007)		(.006)	(.010)		(.010)
γ_{PRICES,QUA_1}	.001	−.006	−.004	.005	−.004	−.001	−.041***	−.034	−.037***
	(.005)		(.004)	(.007)		(.005)	(.011)		(.009)
$\beta_{ROI,MS}$	.370***		.398***	.250***		.243***	.588***		.613***
	(.056)		(.054)	(.079)		(.079)	(.112)		(.111)

(*cont.*)

Table 7.6. (*cont.*)

	Total sample			*Industrial goods*			*Consumer goods*		
Parameter	*unconstrained*	*calc. val.*	*constrained*	*unconstrained*	*calc. val.*	*constrained*	*unconstrained*	*calc. val.*	*constrained*
$\beta_{ROI,MS_{-1}}$	−.406***	−.231	−.251***	−.331***	−.156	−.153***	−.409***	−.299	−.316***
	(.054)		(.036)	(.077)		(.050)	(.109)		(.063)
$\beta_{COSTS,MS}$	.019		.006	.019		.003	−.022		−.021
	(.012)		(.010)	(.015)		(.014)	(.024)		(.022)
$\beta_{COSTS,MS_{-1}}$	.007	−.018	−.006	.013	−.018	−.003	.014	.019	.018
	(.011)		(.010)	(.015)		(.013)	(.023)		(.019)
$\beta_{ROI,COSTS}$	−.272***		−.276***	−.296**		−.301**	−.456***		−.452***
	(.079)		(.079)	(.117)		(.118)	(.144)		(.144)
$\beta_{ROI,COSTS_{-1}}$	.181***	.170	.174***	.330***	.184	.189**	.093	.232	.233***
	(.078)		(.051)	(.116)		(.075)	(.142)		(.077)
$\beta_{PRICES,COSTS}$	.167***		.171***	.183***		.197***	.164***		.164***
	(.018)		(.017)	(.025)		(.024)	(.038)		(.035)
$\beta_{PRICES,COSTS_{-1}}$	−.162***	−.147	−.150***	−.201***	−.153	−.163***	−.143***	−.147	−.146***
	(.019)		(.016)	(.026)		(.022)	(.038)		(.033)
$\beta_{ROI,PRICES}$	.007		−.001	−.092		−.100	.062		.054
	(.069)		(.069)	(.098)		(.101)	(.114)		(.115)
$\beta_{ROI,PRICES_{-1}}$	.081	−.004	.001	.112	.057	.063	−.062	−.031	−.028
	(.068)		(.044)	(.102)		(.063)	(.112)		(.059)
$\beta_{MS,PRICES}$	−.036*		−.021	.023		.046*	−.025		−.019
	(.020)		(.019)	(.028)		(.025)	(.031)		(.030)

$\beta_{MS,PRICES_{-1}}$	−.003	.030	.019	−.061**	−.021	−.043*	−.016	.019	.015
	(.019)		(.017)	(.027)		(.023)	(.030)		(.023)
ρ_{ROI}	.624***		.631***	.622***		.628***	.508***		.516***
ρ_{MS}	.824***		.903***	.931***		.932***	.760***		.787***
ρ_{COSTS}	.951***		.947***	.959***		.955***	.871***		.871***
ρ_{PRICES}	.879***		.877***	.836***		.828***	.894***		.893***
Fit measures									
$\chi^2_{(df)}$	$2609_{(977)}$		$2669_{(987)}$	$2148_{(977)}$		$2184_{(987)}$	$1997_{(977)}$		$2012_{(987)}$
RMSEA	.036		.036	.042		.042	.050		.049
90% CI_{RMSEA}	.034/.045		.034/.038	.039/.044		.040/.045	.046/.053		.045/.053
P_{RMSEA}	1.0		1.0	1.0		1.0	.572		.640
CFI	.987		.987	.983		.983	.972		.972
NFI	.980		.979	.970		.970	.948		.948
RMR^s	.009		.009	.012		.012	.014		.015

Note: Standard errors are in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.

calculated values for the lagged effect of quality on market share are several times bigger (in absolute terms) than the estimated parameters (−.003 versus −.028 and −.001 versus −.027). Given the estimated standard errors, these calculated lagged effects would be significant. In the unconstrained ARDL model, however, the coefficients are not different from zero. Such a discrepancy raises the question of whether or not the autocorrelation hypothesis holds indeed for all relationships between the core variables in the model. A mere comparison between calculated and estimated values, though, is insufficient to decide on this matter. As a comprehensive test of the AR1-RECEV model, we therefore imposed the implied nonlinear restrictions on the parameters of the lagged explanatory variables in the ARDL specification (constraints are limited to the core variables of quality, market share, relative prices, and direct costs). In addition, non-negative error variances for the individual effects were again accomplished by appropriate interval restrictions.

A closer look at the overall fit measures (Table 7.6) shows that except for the χ^2 test statistic, the estimation of the AR1-RECEV model leads to almost the same fit as for the unconstrained ARDL model. Thus, at first glance it seems reasonable to assume that the autocorrelation model is completely corroborated by the results of our analysis. However, there are some aspects that deserve special attention.

First, for the total and the industrial goods sample, the problem of improper solutions is aggravated by imposing the constraints implied by the autocorrelation model. For both samples, we initially obtained significant negative error variances for the time-invariant individual effects of market share and prices (for direct costs the error variances were also negative, albeit not significant). A likelihood ratio test indicates that imposing interval restrictions led to a significant decrease in fit, at least for the total sample.

Second, likelihood ratio tests comparing the unrestricted ARDL model and the nested AR1-RECEV model result in significant test statistics for the total and the industrial goods sample (see rows marked by (a) in Table 7.7). In contrast, in line with the other fit indices, the χ^2 difference for consumer goods does not indicate a significant drop in model fit. Together with the identified deviations between some of the estimated and computed lagged effects as well as the inadmissible solutions, these results provide some indications that the null hypothesis of an autocorrelation model at least does not hold for all relationships in the model. Thus, the autoregressive coefficients of the endogenous variables cannot be completely reduced to the influence of serially correlated unobservable firm effects. Instead, they partially seem to reflect the effect of explanatory variables in previous periods as proposed by the state-dependence hypothesis.

Now we will explore further the issue of state dependence versus serial correlation. Since we do not pursue the aim to detect the "true" underlying model for the three samples, we especially focus on the impact of quality on market share, prices, costs, and ROI. As a first step, we tested the hypothesis of serially correlated disturbances separately for each endogenous variable (see the rows marked by (b) in Table 7.7). In order to assess to what extent quality is responsible for the results of this first step, we also tested models in which for each endogenous variable only quality's lagged parameter was restricted (see the rows marked by (c) in Table 7.7).

For the total sample, the null hypothesis of an autocorrelation model is rejected for market share, direct costs, and ROI (judged by a Bonferroni adjusted nominal test level for the likelihood ratio tests of .05/9 = .006). Given the significant drop in fit that results from constraining only the lagged quality coefficient, quality does not seem to influence market share and direct costs in accordance with the autocorrelation hypothesis. Thus, for example, given the nonsignificant lagged effect of quality on market share in the unconstrained estimation of the ARDL model (Table 7.6), the quality–share relationship instead complies with a state-dependence hypothesis. In addition to the positive contemporaneous quality effect, quality levels in previous periods indirectly influence current market share via unobservable variables like goodwill or brand strength; this indirect effect is reflected in part by the high autocorrelation of market share. To assess the total effect of quality, the long-run multiplier can be calculated.

Unlike the case of the overall sample, the autocorrelation hypothesis for the endogenous variables cannot be rejected for the industrial and consumer goods subsamples. It should be noted, however, that in contrast to consumer goods, this conclusion for industrial goods especially depends on the test level resulting from the Bonferroni adjustment (see rows marked by (b) in Table 7.7). Since the tests are not independent, the Bonferroni correction leads to a rather conservative significance level; at a conventional test level of .05, the null hypothesis would have been rejected for three of the four endogenous variables. Nevertheless,

Table 7.7. *Likelihood ratio tests of the autocorrelation hypothesis*

Alternative models	χ^2	*df*	$\Delta\chi^2$	Δdf	*p*
Total sample					
Unconstrained ARDL	2609.32	977	—	—	—
(a) AR1-RECEV	2668.77	987	59.45	10	.000
(b) AR1-RECEV$_{ROI}$	2630.04	981	20.72	4	.000
(c) AR1-RECEV$_{Q\rightarrow ROI}$	2613.22	978	3.90	1	.048
(b) AR1-RECEV$_{MS}$	2632.81	979	23.49	2	.000
(c) AR1-RECEV$_{Q\rightarrow MS}$	2630.13	978	20.81	1	.000
(b) AR1-RECEV$_{PRICES}$	2616.07	979	6.75	2	.034
(c) AR1-RECEV$_{Q\rightarrow PRICES}$	2611.77	978	2.45	1	.118
(b) AR1-RECEV$_{COSTS}$	2625.20	979	15.88	2	.000
(c) AR1-RECEV$_{Q\rightarrow COSTS}$	2618.51	978	9.19	1	.002
Industrial goods					
Unconstrained ARDL	2147.86	977	—	—	—
(a) AR1-RECEV	2183.64	987	35.78	10	.000
(b) AR1-RECEV$_{ROI}$	2159.80	981	11.94	4	.018
(c) AR1-RECEV$_{Q\rightarrow ROI}$	2149.97	978	2.11	1	.146
(b) AR1-RECEV$_{MS}$	2151.77	979	3.91	2	.142
(c) AR1-RECEV$_{Q\rightarrow MS}$	2149.31	978	1.45	1	.229
(b) AR1-RECEV$_{PRICES}$	2156.23	979	8.37	2	.015
(c) AR1-RECEV$_{Q\rightarrow PRICES}$	2150.09	978	2.23	1	.135
(b) AR1-RECEV$_{COSTS}$	2156.95	979	9.09	2	.011
(c) AR1-RECEV$_{Q\rightarrow COSTS}$	2152.77	978	4.91	1	.027
Consumer goods					
Unconstrained ARDL	1996.65	977	—	—	—
(a) AR1-RECEV	2012.23	987	15.58	10	.112
(b) AR1-RECEV$_{ROI}$	2000.06	981	3.41	4	.492
(c) AR1-RECEV$_{Q\rightarrow ROI}$	1997.56	978	0.91	1	.340
(b) AR1-RECEV$_{MS}$	2005.29	979	8.64	2	.013
(c) AR1-RECEV$_{Q\rightarrow MS}$	2004.60	978	7.95	1	.005
(b) AR1-RECEV$_{PRICES}$	1997.21	979	0.56	2	.756
(c) AR1-RECEV$_{Q\rightarrow PRICES}$	1997.17	978	0.52	1	.471
(b) AR1-RECEV$_{COSTS}$	1999.69	979	3.04	2	.219
(c) AR1-RECEV$_{Q\rightarrow COSTS}$	1999.49	978	2.84	1	.092

except for direct costs, it can safely be concluded that quality effects are not reflected in the autocorrelation coefficients (see rows marked by (c) in Table 7.7).

Although for consumer goods the hypothesis of an autocorrelation model was corroborated both for the overall model and separately for each endogenous variable, there exists a noticeable departure from this overall pattern. In line with the results of the total sample, the autocorrelation hypothesis is rejected with respect to the effect of quality on market share. Again, the nonsignificant coefficient for lagged quality supports the assumption of a state-dependence-like relationship.

Finally, we summarize the most important findings of our study. Although a direct comparison with Phillips, Chang, and Buzzell's study is difficult (because of the different subdivision into samples it is not a one-to-one replication of PCB), we relate our results to those of their study that belong to the business lines analysed in the present study (Table 7.8).

The fact that the strong positive effect of quality on ROI initially found in the baseline model vanishes consistently in all three samples, once time-invariant and autocorrelated unobservable variables are taken into account, is one of the most interesting findings (Table 7.6). It should be noted, however, that in the study by PCB a positive direct impact was revealed in their cross-sectional model only for consumer non-durables and components businesses. Thus, together with the non-significant effect of price on ROI, the "niche theory" connected with a direct quality effect is likewise rejected in our study.

With respect to the other effects of quality, major differences exist between the samples. For the total sample and consumer goods businesses, quality positively influences ROI through both market- and cost-side effects (Table 7.6). Looking first at the market-side effects, it is evident that quality remains a strong driver of market share. Since our empirical results supported the state-dependence hypothesis for the quality–market share relationship, the actual effect is even considerably higher than the estimated contemporaneous effect (we refrain from presenting a long-run multiplier in this case because of the loop between market share, direct costs, and prices). Although an advantageous quality position enables businesses in consumer goods industries to charge higher prices than their lower-quality rivals (in the total sample no such effect exists), these higher prices seem not to be detrimental to market share. In connection with the positive direct effect of market share on ROI, quality thus is a significant driver of profitability. Overall, these findings correspond well with the results of PCB (Table 7.8). Looking next at the cost side, we found that profitability is further enhanced by a cost-reducing effect of quality. Thus, judged by the present results, the way quality seems to influence the cost position of a business unit differs markedly from the pattern found by PCB. In their study, overall direct costs were found to be lowered only *indirectly* via the cost-reducing effect of market share (they at best were able to reject the hypothesis that higher quality always implies a higher cost level). In our study, quality instead exclusively reduces costs *directly*, since the market share effect has vanished by controlling for unobservable variables (for a detailed analysis of the role unobservables play in the relationship between market share and costs, see Ailawadi, Farris, and Parry 1999).

Likewise, in stark contrast to the PCB findings and also to the results for the other samples, we found virtually no market-side effect of quality in the industrial goods sample. The only way quality increases profitability is by reducing direct costs. Looking at the market share effect on profitability (Table 7.8), we can observe that the direct impact of this variable remains significant and positive in all analyzed samples. This finding confirms the importance of market share as a mediating factor for other variables investigated in the model even if unobservables are controlled.

7.5 Conclusion

Meanwhile, in strategy research some consensus exists that controlling for unobservable, firm-specific effects is of great relevance for empirical research on key success factors. Aside from determining the "causal," typically short-term effects of these strategic factors, observing the influence of unobservable variables can provide important insights into the processes that lead to observed long-term relationships between strategic factors and business performance.

In this study, we have proposed a structural equation approach to control for time-invariant and autocorrelated unobservable variables based on panel data. Gradually extending a cross-sectional, simultaneous equation model on the direct and indirect effects of

Table 7.8. *Comparison between the results of Phillips, Chang, and Buzzell (1983) and the present study*

	Total sample		*Consumer goods businesses*		*Industrial goods businesses*	
Effects	*This study*	*PCB*[1]	*This study*	*PCB*[2]	*This study*	*PCB*[3]
Product quality						
ROI	ns	+/ns	ns	+/ns	ns	ns
Costs	–	ns	–	ns	–	ns
Market share	+	+	+	+	ns	+
Prices	ns	+	+	+	ns	+
Market share						
Costs	ns	–	ns	–	ns	–
ROI	+	+	+	+/ns	+	+
Relative direct costs						
Prices	+	+	+	+/ns	+	+
ROI	–	–	–	–/ns	–	–
Relative prices						
Market share	ns	+/ns	ns	+/ns	ns	ns
ROI	ns	na	ns	na	ns	na

Notes: + significantly positive ($\alpha = .05$); – significantly negative ($\alpha = .05$); ns not significant; na not applicable.

[1] Results predominantly found in all six subsamples of the PCB study.

[2] Results predominantly found for consumer durables and non-durables businesses.

[3] Results predominantly found for raw & semi-finished materials, components and supplies businesses.

product quality on profitability has allowed us to assess how these different types of unobservables influence the relations in the model.

We have refrained from also controlling for transitory stochastic effects for several reasons. First, stochastic shocks, whose influence lasts only one period, seem relevant at most when the short-term "causal" effect of strategic factors is of interest. In contrast, we have focused on the effects that unobservable variables have on the long-term relationships between product quality, market share, and ROI; empirical evidence also supports this view. As Ailawadi, Farris, and Parry (1999) have shown, controlling exclusively for temporary stochastic shocks alters the estimated impact of market share on the different components of ROI only marginally compared to a cross-sectional regression.

Second, even if one is interested in the short-term effect of strategic factors, the use of lagged values as instruments in an IV estimation of a first-difference model like equation (3) might lead to some methodological problems. Ideally, the instruments should be uncorrelated with the disturbances but highly correlated with the explanatory variables. Although the autocorrelations for data in levels is very high for many PIMS variables (e.g. market share, relative direct cost, and product quality), this is not true for the time series of first differences. Likewise, the correlation between first differences and lagged levels is also rather low. For example, for a time series of market share from the PIMS SPIYR database covering a period of six years ($n = 1141$), we found correlations between first differences and levels lagged two and three periods in the range of −.033 and −.152. Under such conditions, IV estimates might be seriously biased and highly imprecise (e.g. Bound, Jaeger, and Baker 1995; Staiger and Stock 1997).

For our reanalysis of the Phillips, Chang, and Buzzell model, we used data from the PIMS annual database. Although the limited number of variables in the model must be taken into account, perceived product quality and market share, long emphasized by PIMS researchers as important drivers of profitability (Buzzell and Gale 1987), remain relevant despite the controlled influence of time-invariant and autoregressive firm-specific effects. For the three types of industry under analysis, quality drives ROI by increasing market share, which in turn has a positive direct effect on profitability. For industrial goods alone, the direct effect of product quality on profitability is still positive. This means that customers are willing to pay a price premium for higher quality in this industry. To further explore how product quality is linked to higher profitability in the cross-sectional models, a component-level analysis should be performed (Farris, Parry, and Ailawadi 1992).

An interesting result of our study concerns the relationship between product quality and market share. Whereas typically the control of autocorrelated unobservables has been identified with the serial correlation model, the empirical results for the market share equation favor the state-dependence hypothesis. Thus, unobservable variables like "goodwill" are positively influenced by product quality, which in turn improves the market share position.

Appendix

7.A.1 The random-effects (RE) model

For each equation g, the random individual effects are represented in the LISREL model by additional latent variables μ_{gi} without measurement relations (Jöreskog 1978). In contrast to the time-varying disturbances ε_{git}, we assume that the individual effects are correlated with each other. The model can be formulated as

$$\begin{aligned}
COSTS_{it} &= \beta_1 MS_{it} + \gamma_1 QUA_{it} + \sum_{c\in C_1} \gamma_c^{(1)} CV_{cit} + \mu_{1i} + \varepsilon_{1it},\\
MS_{it} &= \beta_2 PRICES_{it} + \gamma_2 QUA_{it} + \sum_{c\in C_2} \gamma_c^{(2)} CV_{cit} + \mu_{2i} + \varepsilon_{2it},\\
PRICES_{it} &= \beta_3 COSTS_{it} + \gamma_3 QUA_{it} + \sum_{c\in C_3} \gamma_c^{(3)} CV_{cit} + \mu_{3i} + \varepsilon_{3it}, \quad (6)\\
ROI_{it} &= \beta_4 COSTS_{it} + \beta_5 MS_{it} + \beta_6 PRICES_{it} + \gamma_4 QUA_{it}\\
&\quad + \sum_{c\in C_4} \gamma_c^{(4)} CV_{cit} + \mu_{4i} + \varepsilon_{4it},\\
i &= 1, \ldots, N, \quad t = 1, \ldots, T,
\end{aligned}$$

where

$$E(\mu_{gi}\mu_{g'i'}) = \begin{cases} \sigma^2_{\mu_g} & \text{if } g = g', i = i', \\ \sigma_{\mu_{gg'}} & \text{if } g \neq g', i = i', \\ 0 & \text{else.} \end{cases}$$

$$E(\varepsilon_{git}\varepsilon_{g'i't'}) = \begin{cases} \sigma^2_{\varepsilon_g} & \text{if } g = g', i = i', t = t', \\ 0 & \text{else.} \end{cases}$$

7.A.2 The random effects correlated with exogenous variables (RECEV) model

Following Mundlak (1978), we assume that the conditional expectation of the random effects $E(\mu_{gi}|x_{it})$ can be approximated by the following linear reduced form:

$$\mu_{gi} = \sum_{t=1}^{T} \pi'_{gt} x_{it} + \omega_{gi}, \tag{7}$$

where $\omega_{gi} \sim N(0, \sigma^2_{\varpi_g})$. Augmenting the RE model by the reduced form equations for the individual effects leads to the following model:

$$\begin{aligned}
COSTS_{it} &= \beta_1 MS_{it} + \gamma_1 QUA_{it} + \sum_{c\in C_1} \gamma_c^{(1)} CV_{cit} + \mu_{1i} + \varepsilon_{1it}, \\
MS_{it} &= \beta_2 PRICES_{it} + \gamma_2 QUA_{it} + \sum_{c\in C_2} \gamma_c^{(2)} CV_{cit} + \mu_{2i} \\
&\quad + \varepsilon_{2it}, \\
PRICES_{it} &= \beta_3 COSTS_{it} + \gamma_3 QUA_{it} + \sum_{c\in C_3} \gamma_c^{(3)} CV_{cit} + \mu_{3i} \\
&\quad + \varepsilon_{3it}, \\
ROI_{it} &= \beta_4 COSTS_{it} + \beta_5 MS_{it} + \beta_6 PRICES_{it} + \gamma_4 QUA_{it} \\
&\quad + \sum_{c\in C_4} \gamma_c^{(4)} CV_{cit} + \mu_{4i} + \varepsilon_{4it}, \\
\mu_{1i} &= \sum_{t=1}^{T} \pi_{1t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(1)} CV_{cit} + \omega_{1i}, \\
\mu_{2i} &= \sum_{t=1}^{T} \pi_{2t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(2)} CV_{cit} + \omega_{2i}, \qquad (8) \\
\mu_{3i} &= \sum_{t=1}^{T} \pi_{3t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(3)} CV_{cit} + \omega_{3i}, \\
\mu_{4i} &= \sum_{t=1}^{T} \pi_{3t} QUA_{it} + \sum_{c\in C^*} \sum_{t=1}^{T} \pi_{ct}^{(4)} CV_{cit} + \omega_{4i}, \\
& i = 1, \ldots, N, \quad t = 1, \ldots, T,
\end{aligned}$$

where $C^* = C \backslash \{UNION_i\}$ and

$$E(\omega_{gi}\omega_{g'i'}) = \begin{cases} \sigma^2_{\omega_g} & \text{if } g = g', i = i', \\ \sigma_{\omega_{gg'}} & \text{if } g \neq g', i = i', \\ 0 & \text{else.} \end{cases}$$

$$E(\varepsilon_{git}\varepsilon_{g'i't'}) = \begin{cases} \sigma^2_{\varepsilon_g} & \text{if } g = g', i = i', t = t', \\ 0 & \text{else.} \end{cases}$$

Since the percentage of unionized employees remains constant over time, it is not possible to control for a correlation with the individual effects. Therefore, the variable *UNION* is included in the structural equations but not in the reduced forms for the individual effects.

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8 Causation and components in market share–performance models: the role of identities

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The marketing literature contains several structural models, many of them based on the PIMS database, in which one variable is a definitional component of another, related to it through an identity. These definitional relationships have the potential for providing important insights into marketing phenomena, if they are appropriately modeled. On the other hand, they result in inconsistent parameter estimates if they are not separated from other, non-definitional, relationships in the model that need to be empirically estimated. This chapter first discusses the substantive information that can be obtained by studying the definitional components of a composite variable instead of the variable alone. Then, it examines each of the ways in which definitional relationships appear in marketing models, identifies those that are misspecified, analyzes the impact of the misspecification, and then provides the correct specification. It also disproves a commonly held belief that using instrumental variable estimation in a simultaneous equation system resolves the problems caused by mixing definitional relationships with structural ones. Thus, it provides a comprehensive view both of the potential benefits and of the pitfalls of definitional relationships in structural models. Much of the work reviewed in this chapter was inspired and enabled by the PIMS research database, which provides data not only on profitability, but also on each of its cost and revenue components for a variety of strategic business units over multiple years.

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8.1 Introduction

The PIMS research program, through the unique data it gathered, has made possible the development of a large body of substantive knowledge on the determinants of financial performance. In the three decades since it was initiated, the program has also inspired and enabled the use of rigorous econometric methods to study models of performance, particularly models of the association between ROI and market share, and refine some of the early findings on this subject. Of particular value in these advances is the availability of longitudinal data from a large cross-section of strategic business units, not only on profitability but on all its revenue and cost components. The purpose of this chapter is to highlight some of the methodological lessons from this research, particularly as they relate to the appropriate handling of definitional relationships in structural models.

Several of the constructs that are of interest to marketing researchers can be decomposed into two or more definitional components, and are called composite variables. The definitional components of a composite variable are an integral part of its conceptual identity. Their effect on the composite is known without error and does not require estimation with observational data. Thus, they are different from non-definitional determinants whose identity is conceptually distinct from the composite and whose relationship with it does require empirical estimation. A ubiquitous example in marketing and strategy research is the composite variable "profit," and its definitional components, revenue and various costs. The distinction between definitional components and other determinants has several important implications for the specification of structural models containing either the composite variable alone or the composite variable and one or more of its components. The relationship between a composite variable and its components presents the potential for improved understanding of the phenomenon being studied, if it is appropriately specified, and the danger of econometric bias and misinterpretation if it is not.

This chapter evaluates each of the ways in which definitional relationships are and should be incorporated in marketing models, thus presenting a comprehensive analysis of the application and misapplication of composite–component relationships. Our objective is threefold. First, we discuss the usefulness of the empirical information that can be obtained if the definitional relationship between a composite variable and its components is appropriately modeled. Second, we identify and resolve the problems that arise when it is not modeled appropriately, thus reducing the likelihood of such model misspecification in future research. Third, we aid researchers in correctly interpreting previous empirical research that suffers from misspecification, but offers other valuable insights that should not be dismissed.

The chapter is organized as follows. Section 8.2 identifies the various ways in which definitional relationships appear in the literature, providing examples of each type of model. It reviews research that has noted the problems associated with these models or attempted to address them, and provides closure on some debated issues. Section 8.3 examines an approach that is perceived as a solution to the problems associated with mixing definitional and structural relationships – the use of estimation procedures based on instrumental variables in simultaneous systems where a composite variable is specified to be a function of one of its components and vice versa. We first interpret the estimated coefficients in such systems, showing that simultaneous system estimation is not a solution to the problem, and then provide an appropriate specification for the system. Section 8.4 illustrates this process using Comanor and Wilson's (1974) widely cited model of the advertising–profit relationship. Finally, Section 8.5 concludes the chapter with a discussion of the role of PIMS and composite–component relationships in furthering the understanding of marketing phenomena, their limitations, and some implications for future research.

8.2 A review of definitional relationships in performance models

Duncan (1966) was perhaps the first researcher to note that the relationship of a composite variable with its definitional components is fundamentally different from its relationship with other determinants that may affect it but are not a definitional part of it. He pointed out the benefits of examining the components of a composite variable: "where such decomposition is available, it is of interest (1) to compute the relative contributions of the components to variation in the composite variable and (2) to ascertain how causes affecting the composite variable are transmitted via the respective components." At the same time he cautioned against treating components like other causes: "By this route one can arrive at the meaningless result that net migration is a more important 'cause' of population growth than is change in manufacturing output."

Philosophers of science draw a similar distinction between analytical and synthetic statements, as is clear from the following excerpt from Bagozzi (1980):

An analytic statement is one in which its predicate is "contained in" or is "part of" the concept of its subject . . . [It] can only be logically true or false, not factually so. A synthetic statement, in contrast, is one in which the meaning of the predicate is not contained in the concept of the subject . . . It is possible to subject the [synthetic] statement to empirical validation.

Bagozzi also notes that causality is synthetic in that the concept of a cause is independent of the concept of an event – any particular cause and effect contain distinct factual information. By this yardstick, therefore, the relationship of a composite variable with its components is analytic, and not causal in the same way as is its empirical relationship with a non-definitional determinant.

Despite this early distinction between components and non-definitional determinants of a composite variable, we, as researchers, continue to mix the two and treat them on the same footing in our models of marketing phenomena. Table 8.1 summarizes the various ways, both appropriate and inappropriate, in which composite variables and/or their definitional components appear in the literature, along with examples of each type of model. We briefly discuss them in this section, reviewing studies that have either used the correct specification or identified problems with the incorrect ones, and identifying issues that still remain unresolved.

8.2.1 The composite–component identity

There is no uncertainty associated with the coefficients of a composite–component relationship in a sample of empirical observations. Denoting the composite by Z and its components by z_i, we can write the identity for a two-component additive composite as:

$$Z \equiv a_1 z_1 + a_2 z_2 \tag{1}$$

and the expression for its variance as:

$$\sigma_Z^2 \equiv \left(a_1^2\,\sigma_{z_1}^2\right) + \left(a_2^2\,\sigma_{z_2}^2\right) + \left(2\,a_1\,a_2\,\sigma_{z_1 z_2}\right) \tag{2}$$

Table 8.1. ***Model specifications with composite variables in the literature***

Specification	*Examples of* Dependent variable	*Examples of* Explanatory variables	Representative studies
$Z = \gamma_0 + \gamma_1 X_1 + \varepsilon$	*ROS*	Market share	Farris *et al.* (1989, 1992); Boulding and Staelin (1993)
$Y = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* Z + \varepsilon^*$	Job satisfaction	Difference between (algebraic, absolute, squared) actual and desired job attributes	French *et al.* (1982); Chatman (1989, 1991)
$Z = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* z_1 + \varepsilon^*$	*ROS*	Marketing/sales	Porter (1976); Ravenscraft (1983); Buzzell and Gale (1987); Jacobson (1990)
$z_1 = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* Z + \varepsilon$	*A/S* ratio	*ROS*	Comanor and Wilson (1974)
$Z = \gamma_{10}^* + \gamma_{11}^* X_1 + \beta_{11}^* z_1 + \varepsilon_1$ $z_1 = \gamma_{20}^* + \gamma_{21}^* X_1 + \gamma_{22}^* X_2 + \beta_{21}^* Z + \varepsilon_2$	*ROS*, *A/S* ratio	*ROS*, *A/S* ratio	Comanor and Wilson (1974); Intriligator (1978); Chang and Choi (1988)

Notes: Z = composite variable; z_i = Component; Y = non-definitional dependent variable; X = non-definitional explanatory variable.

There is no error in either of these two equations and there are no unknown parameters that need to be empirically estimated. However, the degree to which variation in the composite variable (Z) is due to variation in a given component (z_1 or z_2) is an empirical question. For instance, variance in *ROI* for a firm over time might be due to variance in either *S/I* or *ROS*, or some combination, each possibility having its own set of implications for the management skills at work in the firm. Similarly, variation in sales over time may be due mainly to variation in the number of customers, their average purchase amount, or their average purchase frequency. Again, each of these possibilities implies a very different mechanism by which sales change. The extent to which two components covary also provides insights. Indeed, a composite variable Z might have very little variance in a given sample, even with substantial variation in both z_1 and z_2, if the covariance between the two components is negative. Which components contribute the most to variation in the composite variable, and which ones covary positively or negatively with one another? These are empirical questions, answers to which can provide important insights on the composite variable being studied. Thus, even though the definitional identity is known *a priori*, there is useful empirical information to be gleaned from the sources of variance in the composite. However, such analyses are underutilized in the marketing literature. One exception that we know of is in the work of Farris, Parry, and Webster (1989). These researchers use PIMS data to examine the extent to which each cost component of profitability contributes to its variance across businesses. Their primary findings are that most of the cross-sectional variance in ROI is due to variance in ROS, not in the S/I ratio. Further, a substantial portion of the variance in ROS is attributable to the purchases/sales ratio, with other cost components contributing much less.

8.2.2 Models for a composite dependent variable

Recognition of the components is also useful in a structural model that specifies a composite variable as function of only non-definitional explanatory variables:

$$Z = \gamma_0 + \gamma_1 X_1 + \varepsilon \tag{3}$$

This is a purely empirical model with no definitional relationships between variables on the two sides of the equation. Regressions of profit on market share and product quality, or sales on advertising are some examples of models with composite dependent variables. Although the components are not explicitly specified, the effect of the explanatory variables on the composite dependent variable must occur through its logically prior components. Therefore, decomposing the composite dependent variable into its various components and determining the impact of the explanatory variables on each component can provide useful information to the researcher. This strategy is used quite frequently in the sales promotion literature, where the effect of promotion on sales or share may be modeled through number of purchasers, purchase frequency and purchase amount; brand switching, purchase acceleration and primary demand; or penetration, share of requirements, and category usage (e.g. Ailawadi, Lehmann, and Neslin 2001; Bell, Chiang, and Padmanabhan 1999; Gupta 1988; Neslin and Shoemaker 1983). Doing so provides useful information about the mechanism by which sale promotion operates, and also helps to evaluate its profitability. Boulding and Staelin (1993) and Ailawadi, Farris, and Parry (1999) have also used such component-level analyses with PIMS data to better understand the effect of market share and unobserved management skill, respectively, on profitability.

8.2.3 Models with a composite independent variable

A composite variable often appears as an independent variable in marketing models:

$$Y = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* Z + \varepsilon^* \tag{4}$$

Difference scores and measures of congruence, widely used as explanatory variables in behavioral models of person–job fit, stress, satisfaction, etc. provide some different, nonfinancial examples of such specifications. In such models, recognition of the definitional components is not just desirable but necessary. To see why, consider the following form of equation (4):

$$Y = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* (a_1 z_1 + a_2 z_2) + \varepsilon^* \tag{5}$$

It shows that using the composite variable Z as an independent variable is mathematically equivalent to using both components, z_1 and z_2, as independent variables, but constraining their coefficients such that the ratio of the coefficients is equal to a_1/a_2. If the constraint is incorrect, it will result in biased estimates of all the coefficients in the model (Johnston 1984). Such constraints can and should be empirically tested by estimating the following unconstrained model:

$$Y = \gamma_0 + \gamma_1 X_1 + \gamma_2 z_1 + \gamma_3 z_2 + \varepsilon \tag{6}$$

Edwards (1994) and Peter, Churchill, and Brown (1993) provide a good review of these and other methodological issues in the use of congruence measures and difference scores.

8.2.4 Mixed models of a composite dependent variable

So far, we have discussed the definitional identity itself and the first two types of models listed in Table 8.1, where the components themselves are not explicitly included in the model. In such cases, it is always useful, though not always econometrically necessary, to decompose a composite variable into components. The remaining model specifications in Table 8.1 are more problematic – they include a composite variable and one of its components in a single model, one of them being an independent variable and the other the dependent variable. Thus, they mix *a priori* definitional relationships with empirical ones that need to be estimated with observational data, resulting in serious econometric problems. There are a host of mixed models in the literature. They have been used, quite often, in PIMS-based studies of the profit–market share relationship (e.g. Buzzell and Gale 1987; Jacobson and Aaker 1985; Prescott, Kohli, and Venkatraman 1986) and in industrial organization studies of the Structure–Conduct–Performance paradigm (e.g. Comanor and Wilson 1974; Porter 1976; Ravenscraft 1983). For instance, Comanor and Wilson specify a model where profitability is regressed on one of its components (advertising/sales) while Prescott, Kohli, and Venkatraman regress *ROI* on ratios of investment, manufacturing, marketing, and R&D to sales. These studies illustrate the following mixed specification:[1]

$$Z = \gamma_0^* + \gamma_1^* X_1 + \gamma_2^* z_1 + \varepsilon^* \tag{7}$$

Such mixing of known definitional relationships with structural relationships that must be empirically estimated has been a subject of concern among researchers for quite some time. This concern stems from two issues. The first questions the explanatory power of a model when a variable appears on both sides of the equation. For instance, Gale and Buzzell (1990), in their review of studies of profitability, note that the inclusion of several accounting variables in a regression model of *ROS*

[1] Throughout this chapter, we use an asterisk to depict parameters in mixed models.

or *ROI* results in a "virtual algebraic identity which does not explain anything," despite its high R^2. Zenor and Leone (1991) state that, in a series of empirical analyses, they obtain a much higher R^2 when dollar revenue is predicted by price and other variables than when unit sales is the dependent variable. Ailawadi and Farris (1993) quantify the inflation in R^2 that occurs when an additive component of a composite variable is included as an explanatory variable in a regression model of the composite. The inflation occurs due to the artificial "explanation" of the composite by the error term of the included component.

The second issue deals with the correlation between a composite and its component. For instance, Mahajan, Varadarajan, and Kerin (1987) note that the negative association of *ROI* with the investment/sales ratio may be partly or wholly an "artifact" of their definitional relationship. Similarly, the substantial literature on the analysis of ratio variables discusses the spurious correlation between two ratio variables with a common component (e.g. Bollen and Ward 1979; Pendleton, Warren, and Chang 1979; Schuessler 1974).

However, the regression of a composite variable on its own component also affects the estimated coefficients of all the other explanatory variables in the model. Farris, Parry, and Ailawadi (1992) quantify this econometric bias, showing that the estimated coefficients of the non-definitional antecedents in the model reflect their effect, not on the dependent variable but only on those of its definitional components that are excluded from the right-hand side of the model. They illustrate this bias with two PIMS-based models of the market share–ROI relationship, Jacobson and Aaker (1985; hereafter denoted JA) and Buzzell and Gale (1987). They replicate these mixed models by decomposing the dependent variable, *ROI*, into its definitional components, and estimating the effect of the variables on the right-hand side on each of the definitional components. By doing so, they illustrate the econometric result that the estimated coefficients of the variables in the mixed model reflect their effect not on *ROI* but only on its excluded components.

Jacobson and Aaker (1993) subsequently published a comment on this research. It is worth addressing the issue raised in that comment and clarifying its relevance to the primary message of the Farris, Parry, and Ailawadi (1992) work. We summarize the issue in the following statements of fact while making one simplification for expositional purposes – we use *ROS* instead of *ROI* as the dependent measure of profitability.[2]

(1) JA regress profitability on its own lagged values, current values of two of its definitional components, value added/sales and marketing/sales, and other explanatory variables. As they recognize in their 1993 comment, including the two definitional components on the right-hand side of their model biases all the estimated coefficients.

(2) The estimated coefficients of their model with *ROS* as the dependent variable are exactly equal to the algebraic combination of the estimated coefficients when each of the additive components of *ROS* (value added/sales, marketing/sales, and other costs/sales) is regressed on the same set of right-hand-side variables. To see this, consider the following:

$$\begin{aligned}
ROS &\equiv VA/S - Mktg/S - OtherCosts/S \\
ROS &= X\beta_{ROS} + \varepsilon \\
\hat{\beta}_{ROS} &= (X'X)^{-1}X'ROS \\
&\equiv (X'X)^{-1}X'(VA/S - Mktg/S - OtherCosts/S) \\
&\equiv (X'X)^{-1}X'(VA/S) - (X'X)^{-1}X'(Mktg/S) \\
&\quad - (X'X)^{-1}X'(OtherCosts/S) \\
&\equiv \hat{\beta}_{VA/S} - \hat{\beta}_{Mktg/S} - \hat{\beta}_{OtherCosts/S}
\end{aligned} \tag{8}$$

(3) Thus, in order to replicate JA's model at the component level, one must regress each component on the complete set of explanatory variables in their composite model, i.e. lagged profitability and the other variables in their model.

(4) Jacobson and Aaker (1993) argue that the JA model was not correctly replicated and that each component should have been regressed on the lagged value of that component to control for unobserved

[2] The definitional relationship of *ROS* with its cost components is additive, which makes the exposition simpler than the multiplicative relationship with *ROI*. The analysis can be extended to *ROI*, as shown in Farris, Parry, and Ailawadi (1992).

variables. They further note that a structural model that would lead to regressing each component on JA's set of explanatory variables is "not readily apparent."

(5) We make three points in this regard. First, the component-level models used by Farris, Parry, and Ailawadi (1992) do replicate JA's composite-level model, as the equations above show. Using lagged components instead of lagged profitability on the right-hand side would not replicate the composite model. Second, if the structural model underlying the component-level replication of JA's composite model is "not readily apparent," then the composite model may need to be reexamined. After all, algebraically combining the estimates from the component models yields the estimates from the composite model. Third, we fully agree with JA that unobserved variables should be properly controlled for. We might add, though, that the question of how best to control for them, be it in composite- or component-level models, remains an open one. It is not clear that first-differencing to control for fixed effects and/or ρ-differencing to control for autocorrelated unobserved variables is always ideal, as is evidenced by the work of Christen and Gatignon (this volume, Chapter 10).

8.2.5 Mixed simultaneous systems of a composite and its component

Several researchers have noted that including a component as an independent variable in the model for a composite variable violates the assumption of independence between the error term and the independent variables and biases the OLS estimates (e.g. Boulding 1990; Comanor and Wilson 1974; Farris, Parry, and Ailawadi 1992). Therefore, having regard to standard econometric treatments of simultaneous systems (e.g. Intriligator 1978; Johnston 1984), an estimation procedure based on instrumental variables is expected to solve the problem. In the next section, we show that this is, unfortunately, not true. Such an estimation procedure does not solve the problems associated with the mixing of definitional and structural relationships – the solution to the problem lies in appropriate model specification, not estimation. In doing so, we reveal some important issues relating to the identification of simultaneous systems that are unique to mixed composite–component systems, and we also examine another type of mixed model, the regression of a component on a composite variable.

8.3 Composite–component relationships in simultaneous systems

One often encounters simultaneous equation systems in the marketing literature where a composite variable is specified as a function of one of its components and vice versa. In fact, as noted earlier, it is believed that (i) the definitional relationship between a composite variable and its component causes the component to be endogenous in the system that determines the composite, and (ii) the use of an instrumental-variable-based estimation procedure in the simultaneous framework solves the problem. One important example lies in the advertising–profit relationship studied under the well-known Structure–Conduct–Performance (SCP) paradigm. Since advertising is one of the cost components that is deducted from gross profit to compute net profit, models using a net rate of return mix definitional relationships with structural parameters to be estimated from observational data. Comanor and Wilson (1974) were probably the first to suggest that the advertising–profit relationship should be estimated in the simultaneous equation framework, at least partly to address the definitional problem:

> A simultaneous-equation model is appropriate not only because of the possible presence of reverse causality in the profit rate equation but also because the error terms in the two structural equations are likely to be negatively correlated. Profits and advertising are linked by the identity that profits net of all deductions are derived from gross cash flow by deducting depreciation, income taxes and advertising.

Several other researchers use similar models in their studies of the SCP paradigm (e.g. Chang and Choi 1988; Intriligator 1978; Kumar 1990; Porter 1976; Ravenscraft 1983), showing that Comanor and Wilson's model was not an isolated case and making it especially important to determine whether such procedures are appropriate. Our analysis shows that simultaneous equation specification and estimation procedures do not solve the problem of separating the definitional relationship between the two endogenous variables from structural effects. We use the following mixed simultaneous system, to illustrate our analysis:

$$z_1 = \gamma_{10}^* + \gamma_{11}^* X_1 + \gamma_{12}^* X_2 + \beta_{12}^* Z + \varepsilon_1^* \tag{9}$$

$$Z = \gamma_{20}^* + \gamma_{21}^* X_1 + \gamma_{23}^* X_3 + \beta_{21}^* z_1 + \varepsilon_2^* \tag{10}$$

where $$Z \equiv z_1 + z_2 \tag{11}$$

Thus, the two endogenous variables in the system are Z and z_1, and, as is conventionally done, the system is identified by including at least one explanatory variable in each equation that does not appear in the other equation. We now evaluate the coefficients that are obtained when the above system is estimated using an instrumental variable technique, such as 2SLS. We begin with equation (10) for the composite, Z, where an instrument is used for z_1.

8.3.1 Interpreting coefficients of the composite equation

In the first step of the 2SLS procedure, z_1 is regressed on all the exogenous variables in the system:

$$z_1 = \alpha_{10} + \alpha_{11} X_1 + \alpha_{12} X_2 + \alpha_{13} X_3 + \mu_1 \tag{12}$$

Then, the predicted value of z_1 from the above equation is used as an instrument for z_1 in the Z equation:

$$Z = \gamma^*_{20} + \gamma^*_{21} X_1 + \gamma^*_{23} X_3 + \beta^*_{21} \hat{z}_1 + \varepsilon^*_2 \tag{13}$$

To interpret the second-stage regression estimates in (13), we substitute for Z using:

$$Z \equiv z_1 + z_2 \equiv \hat{z}_1 + \hat{\mu}_1 + z_2 \tag{14}$$

Equation (13) can then be written as:

$$\hat{z}_1 + \hat{\mu}_1 + z_2 = \gamma^*_{20} + \gamma^*_{21} X_1 + \gamma^*_{23} X_3 + \beta^*_{21} \hat{z}_1 + \varepsilon^*_2 \tag{15}$$

Equation (15) combines three regressions. Its coefficient estimates are given by the algebraic sum of the corresponding coefficient estimates when $\hat{z}_1$, z_2 and $\hat{\mu}_1$ are regressed on all the regressors in the equation:

$$\hat{z}_1 = \gamma^*_{\hat{z}_1 0} + \gamma^*_{\hat{z}_1 1} X_1 + \gamma^*_{\hat{z}_1 3} X_3 + \beta^*_{\hat{z}_1 1} \hat{z}_1 + \varepsilon^*_{\hat{z}_1} \tag{16}$$

$$\hat{\mu}_1 = \gamma^*_{\hat{\mu}_1 0} + \gamma^*_{\hat{\mu}_1 1} X_1 + \gamma^*_{\hat{\mu}_1 3} X_3 + \beta^*_{\hat{\mu}_1 1} \hat{z}_1 + \varepsilon^*_{\hat{\mu}_1} \tag{17}$$

$$\hat{z}_2 = \gamma^*_{\hat{z}_2 0} + \gamma^*_{\hat{z}_2 1} X_1 + \gamma^*_{\hat{z}_1 2} X_3 + \beta^*_{\hat{z}_2 1} \hat{z}_1 + \varepsilon^*_{\hat{z}_2} \tag{18}$$

and

$$\begin{aligned} \gamma^*_{2i} &= \gamma^*_{\hat{z}_1 i} + \gamma^*_{\hat{z}_2 i} + \gamma^*_{\hat{\mu}_l i} \quad \text{forall } i \text{, and} \\ \beta^*_{21} &= \beta^*_{\hat{z}_1 1} + \beta^*_{\hat{z}_2 1} + \beta^*_{\hat{\mu}_1 1} \end{aligned} \tag{19}$$

Note that a variable is a perfect predictor of itself. Therefore, when $\hat{z}_1$ is regressed on a set of variables including itself, the coefficient estimate of $\hat{z}_1$ is exactly one, with a standard error of zero, the coefficient estimates of all the other variables in the equation are zero, and the R^2 is exactly 1.0. Therefore, the estimates of equation (16) are:

$$\begin{aligned} &\hat{\gamma}^*_{\hat{z}_1 0} = \hat{\gamma}^*_{\hat{z}_1 1} = \hat{\gamma}^*_{\hat{z}_1 3} = 0, \text{ and} \\ &\hat{\beta}^*_{\hat{z}_1 1} = 1 \end{aligned} \tag{20}$$

Also note that the residual μ_1 is, by definition, uncorrelated with all of the exogenous variables in the system and with z_1. Therefore, R^2 is zero for equation (18) and the coefficient estimates are:

$$\hat{\gamma}^*_{\hat{\mu}_1 0} = \hat{\gamma}^*_{\hat{\mu}_1 1} = \hat{\gamma}^*_{\hat{\mu}_1 3} = \hat{\beta}^*_{\hat{\mu}_1 1} = 0 \tag{21}$$

Equations (19) through (21) show that the estimates of γ^*_{20} through γ^*_{23} represent the effects of the corresponding variables on z_2 alone. The estimate of β^*_{21} equals the structural effect of z_1 on z_2, plus the known definitional parameter 1. Thus, we find that, despite the instrumental variable estimation, the problem with coefficient estimates of the mixed composite model still remains. We now turn our attention to the equation for the component.

8.3.2 Interpreting coefficients of the component equation

In equation (9), a logically prior component (z_1) is regressed on its composite (Z). The same two-stage procedure is followed for the estimation of the z_1 equation. Z is regressed on all the exogenous variables in the system and its predicted value is used as an instrument for Z in the z_1 equation. To analyze the coefficients obtained by this process, consider the following identity:

$$Z \equiv z_1 + z_2 \equiv \hat{Z} + \hat{\mu} \equiv (\hat{z}_1 + \hat{z}_2) + (\hat{\mu}_1 + \hat{\mu}_2) \tag{22}$$

where μ_1 and μ_2 are residuals from the regression of z_1 and z_2 respectively, on all the exogenous variables in the system. Substituting in (9), i.e. the z_1 equation, we have:

$$(\hat{z}_1 + \hat{\mu}_1) = \gamma^*_{10} + \gamma^*_{11} X_1 + \gamma^*_{12} X_2 + \beta^*_{12}(\hat{z}_1 + \hat{z}_2) + \varepsilon^*_1 \tag{23}$$

Estimates of the γ^*_1 vector and β^*_1 in (23) are treated as consistent estimates of the coefficients in the z_1 equation. But, this equation is, in effect, a constrained regression where the coefficients of z_1 and z_2 are forced to be equal. Further, the coefficient estimates of the variables in equation (23) are simply the sum of the corresponding coefficient estimates when they are used as regressors for z_1 and μ_1. If the constraint on the coefficients were removed, as in:

$$(\hat{z}_1 + \hat{\mu}_1) = \gamma^*_{10} + \gamma^*_{11} X_1 + \gamma^*_{12} X_2 + \beta^*_{1\hat{z}_1} \hat{z}_1 + \beta^*_{1\hat{z}_2} \hat{z}_2 + \varepsilon^*_1 \quad (24)$$

we would have:

- A coefficient of 1 for $\hat{z}_1$, since all the other variables would drop out of the $\hat{z}_1$ equation and, by definition, the residual and predicted values are uncorrelated.
- Coefficient estimates with expected values of zero, for all the exogenous variables in the system, since they drop out of the $\hat{z}_1$ regression and are uncorrelated with the residual.
- A non-zero coefficient estimate for $\hat{z}_2$, which reflects its association with the residual, i.e. its effect on z_1 once all the other variables have been accounted for.

Thus, the constraint imposed in the z_1 equation only serves to disguise these *a priori* relationships. Since the only part of Z that remains to be defined once z_1 has been defined is the other component, z_2, it is this component that should be used in the z_1 equation. Such a specification is intuitively appealing and, at the same time, it separates the definitional relationship of z_1 with Z from any structural relationship between the two components, z_1 and z_2:

$$z_1 = \gamma_{10} + \gamma_{11} X_1 + \gamma_{12} X_2 + \beta_{12} z_2 + \varepsilon_1 \quad (25)$$

Once the equations for both components have been correctly specified, an appropriate procedure can be used to estimate their structural parameters. An instrumental-variable-based procedure like 2SLS is needed because the system is nonrecursive, not because of any definitional endogeneity. When z_1 is included in the equation for Z, the only error remaining in the Z equation is that due to z_2, i.e. ϵ_2. This error term in the mixed Z equation is not *definitionally* correlated with z_1. The OLS assumption of $E(X'^{\varepsilon}) = 0$, which researchers like Comanor and Wilson (1974), Boulding (1990), and Farris, Parry, and Ailawadi (1992) are concerned about, is defied if the two component errors, ϵ_1 and ϵ_2, are correlated, and not "by definition."

8.3.3 Implications of identifying restrictions in the equation for Z

From the above discussion, it would appear that 2SLS estimates of the mixed Z equation provide consistent estimates of the effect of non-definitional explanatory variables on z_2. Even this may not be true, however. It depends on whether the following equation for z_2 implied by (20) is correctly specified:

$$z_2 = \gamma_{20} + \gamma_{21} X_1 + \gamma_{23} X_3 + \beta_{21} \hat{z}_1 + \varepsilon_2 \tag{26}$$

To see if the specification in (26) is correct, we determine the implications of the mixed system for the z_2 equation, focusing specifically on the exclusion restrictions incorporated in the Z equation.

Recall that the effect of an antecedent on Z is the sum of its effects on z_1 and z_2. Therefore, the effect of a variable on Z can be zero (as is implied by an exclusion restriction) only if (i) it does not affect either component or (ii) the sum of its effects on z_1 and z_2 is zero. Keeping this fact in mind, consider the role of X_2 in the mixed simultaneous system. Since it is excluded from the researcher's equation for Z, he must believe that X_2 has no effect on Z. Given that X_2 does affect z_1, its effect on z_1 must be exactly offset by an effect on z_2, if the exclusion restriction is valid. The appropriate specification for z_2 should then be:

$$\begin{aligned} &z_2 = \gamma_{20} + \gamma_{21} X_1 + \gamma_{22} X_2 + \gamma_{23} X_3 + \beta_{21} z_1 + \varepsilon_2 \\ &\text{where} \quad \gamma_{22} = -\gamma_{12} \end{aligned} \tag{27}$$

This discussion reveals an important consideration. If the exclusion restriction is appropriate, a relevant variable, X_2, has been excluded from the z_2 equation in (25), rendering it misspecified. But, how reasonable is it to expect the exclusion restriction to be valid? The researcher must have very strong theoretical priors about the specific variable, X_3, to assume that its effect on z_2 is exactly equal in magnitude, and opposite in sign, to its effect on z_1. Although we have illustrated this problem with only exclusion restrictions for a single explanatory variable, it applies to other types of identifying restrictions as well (e.g. equality restrictions). Recognition of such implications of their identifying restrictions not only encourages researchers to ensure that their model specification accurately reflects the underlying theory, but, we hope, it may cause them to rethink their theory in a more complete and logically consistent manner. The work by Moore, Morgan, and Roberts (this volume, Chapter 9) provides important methodological guidelines for testing the validity of identifying restrictions in simultaneous systems in general, and would be particularly helpful in the context of such mixed models.

8.4 Simultaneous model of advertising–profit relationship

In this section, we use Comanor and Wilson's (1974) simultaneous model of the advertising–profit relationship as an illustration to summarize the key issues examined above. Their model is as follows:[3]

$$\begin{aligned}\frac{A}{S} &= \gamma_{10}^* + \gamma_{11}^* LGR + \gamma_{12}^* DUR + \gamma_{13}^* LCONC \\ &\quad + \gamma_{14}^* TECH + \beta_{12}^* ROS + \varepsilon_1^* \qquad (28)\\ ROS &= \gamma_{20}^* + \gamma_{21}^* LGR + \gamma_{25}^* LCAP + \gamma_{26}^* LOCAL \\ &\quad + \beta_{21}^* \frac{A}{S} + \varepsilon^* \qquad (29)\end{aligned}$$

where LGR is the natural log of demand growth rate, DUR is a dummy variable for durable goods industries, $LCONC$ is the natural log of industry concentration ratio, $TECH$ is a dummy variable for high technical barriers to entry, $LCAP$ is the natural log of volume of absolute capital requirement, $LOCAL$ is a dummy variable for local industry, ROS is the net return on sales, and A/S is the advertising/sales ratio.

8.4.1 *Problems with the mixed model*

Our analysis in the previous section leads us to note at least four important issues about this model. First, the coefficient of the included component, A/S, is equal to 1 plus the structural effect of A/S on the gross rate of return before advertising costs have been deducted (denoted as Π/S), and the corresponding t-statistic must be appropriately interpreted. Second, irrespective of the estimation procedure used, the coefficients of non-definitional explanatory variables in the ROS equation are effects *only* on Π/S, irrespective of whether or not advertising costs are deducted to compute the dependent profit rate measure. This finding renders almost irrelevant the discussion in the industrial organization literature about whether the profit measure should be gross or

[3] They use return on equity instead of ROS but note that different rates of return are highly correlated and lead to similar empirical results. We illustrate their model using ROS to avoid the additional complexity of a multiplicative identity.

net of advertising (see, for example, Sawyer 1982; Schumacher 1991). If the researcher is really interested in the effects of non-definitional variables (e.g. concentration) on profit *gross* of advertising there is no reason for using net profit as the dependent variable. If, on the other hand, the researcher wants to estimate the effects of these variables on profit *net* of advertising then, too, net *ROS* should not be used. Equations for both components, gross *ROS* and *A/S*, must be estimated, and total effects on net *ROS* computed from them.

Third, the specification of the *A/S* equation is incorrect, and its coefficients are biased and inconsistent. This is true for OLS as well as the 2SLS estimates analyzed above. Since *ROS* cannot be defined until *A/S* has been defined, at least contemporaneously, it is counterintuitive to use it to predict *A/S*. Just as *ROS* cannot be and is not used to contemporaneously predict one component, gross *ROS*, it cannot predict the other component, *A/S*. The *A/S* equation should be:

$$\frac{A}{S} = \gamma_{10} + \gamma_{11} LGR + \gamma_{12} DUR + \gamma_{13} LCONC + \gamma_{14} TECH + \beta_{12} \frac{\Pi}{S} + \varepsilon_1 \tag{30}$$

Fourth, the exclusion restrictions that are incorporated in mixed simultaneous equation models of *ROS* and *A/S*, in order to identify the equations, have very stringent underlying implications about the magnitude and direction of the effects of the antecedent variables on the components. Three exogenous variables, *DUR*, *LCONC*, and *TECH* are excluded from the *ROS* equation although they are included in the *A/S* equation, while two other variables, *LCAP* and *LOCAL*, are excluded from the *A/S* equation. Consider the implications. First, if an exogenous variable in the *ROS* equation is excluded from the *A/S* equation (e.g. *LCAP*), it must have an effect on the other component, Π/S. Furthermore, the effect of that variable on *ROS* is equal to its effect on Π/S, since Π/S is the only component through which it affects *ROS*. Although not particularly stringent, it is useful for the researcher to recognize this implication so as to ensure its consistency with theory. Second, if an exogenous variable affects *A/S* but is excluded from the *ROS* equation (e.g. *LCONC*), its effect on Π/S must be exactly equal to its effect on *A/S*. Thus, if the exclusion restrictions in the model are indeed valid, each of the three exogenous variables, *DUR*, *LCONC*, and *TECH*, must have an exactly equal effect on Π/S as on *A/S*,

Table 8.2. *Estimates of the Comanor and Wilson model*

Dep. var.	*Const.*	*LGR*	*DUR*	*LCONC*	*TECH*	*LCAP*	*LOCAL*	*A/S*	*ROS*	*Π/S*
Comanor and Wilson (replication): OLS				39 industries						
A/S	1.32	−0.21	1.90*	0.34	−1.21	—	—	—	0.74*	—
	(2.71)	(0.90)	(0.94)	(0.77)	(1.26)				(0.25)	
ROS	1.15*	0.43	—	—	—	0.49*	0.84	0.24*	—	—
	(0.45)	(0.52)				(0.17)	(0.97)	(0.08)		
Π/S	1.15*	0.43	—	—	—	0.49*	0.84	1.24*	—	—
	(0.45)	(0.52)				(0.17)	(0.96)	(0.08)	—	—
Comanor and Wilson (replication): 2SLS				39 industries						
A/S	2.18	0.20	−2.23*	0.38	−0.89	—	—	—	0.40	—
	(3.19)	(1.11)	(1.12)	(0.86)	(1.45)	—		—	(0.49)	—
ROS	1.15	0.43	—	—	—	0.49*	0.84	0.24	—	—
	(0.66)	(0.57)				(0.21)	(1.08)	(0.20)	—	—
Π/S	1.15	0.43	—	—	—	0.49*	0.84	1.24*	—	—
	(0.66)	(0.57)				(0.21)	(1.08)	(0.20)		

Note: Standard errors are in parentheses; * $p < 0.05$

leading to the following specification for Π/S:

$$\frac{\Pi}{S} = \gamma_{20} + \gamma_{21} LGR + \gamma_{22} DUR + \gamma_{23} LCONC + \gamma_{24} TECH + \gamma_{25} LCAP + \gamma_{26} LOCAL + \beta_{21} \frac{A}{S} + \varepsilon_2, \tag{31}$$

where $\gamma_{22} = \gamma_{12};\ \gamma_{23} = \gamma_{13};\ \gamma_{24} = \gamma_{14}.$

The theoretical justification required to support this specification is certainly not obvious, if at all possible. The researcher specifying these systems of equations should explicitly recognize these assumptions and evaluate their feasibility. Once suitable identifying constraints have been determined, the model can be respecified so as to separate any definitional parameters from structural effects that must be empirically estimated. In the advertising–profit framework, this implies that the effect of A/S on ROS basically occurs through Π/S, and vice versa. Both components are consequently endogenous, and the first part of the system should model the nonrecursive relationship between them. Therefore, we must write down structural equations for the two components, each containing only exogenous variables and a component as explanatory variables. Finally, the composite variable, ROS, must only appear in the second part of the model, comprising the definitional identity.

8.4.2 Empirical illustration

We replicated Comanor and Wilson's original dataset as closely as possible for thirty-nine of the forty-one industries analyzed by them. Data on several of the variables in their model are included in their book, and William Comanor kindly provided us with data on some of the other variables. Table 8.2 presents the OLS and 2SLS estimates of their A/S and ROS equations (28) and (29), obtained from this data. It also provides OLS and 2SLS estimates when ROS is replaced by Π/S as a dependent variable:

$$\Pi/S = \gamma^*_{30} + \gamma^*_{31} LGR + \gamma^*_{35} LCAP + \gamma^*_{36} LOCAL + \beta^*_{31} \frac{A}{S} + \varepsilon^*_3 \tag{32}$$

Note that the coefficient estimates of all the exogenous variables in the mixed ROS equation are exactly equal to the corresponding estimates for the Π/S equation. This is true of both OLS and 2SLS

Table 8.3. *Estimates of the respecified Comanor and Wilson model*

Dep. var.	*Const.*	*LGR*	*DUR*	*LCONC*	*TECH*	*LCAP*	*LOCAL*	*A/S*	*ROS*	*Π/S*
2SLS estimates of respecified Comanor and Wilson model										
$\Pi/S_{\text{constrain}}$	2.92	0.69	−1.51	0.26	−0.65	0.60	0.51	0.66	—	—
	(1.54)	(1.35)				(0.49)	(2.55)	(0.48)		
A/S	1.43	0.10	−1.51	0.26	−0.65	—	—	—	—	0.31
	(3.53)	(1.14)	(1.59)	(0.87)	(1.38)					(0.34)
Computed effect on *ROS*										
ROS_{compute1}	−0.28	0.33	1.51	−0.26	0.65	0.49	0.84	1.24	—	−0.31
ROS_{compute2}	1.49	0.59	0.00	0.00	0.00	0.60	0.51	0.66	—	−0.31

Notes: Standard errors are in parentheses; * $p < 0.05$.

estimates. Thus, although 2SLS does remove any inconsistency due to reverse causality in the advertising–profit relationship, it does not remove the definitional "inconsistency."

Next, we estimate the A/S and Π/S equations (30) and (31) implied by their model, and compute corresponding estimates for ROS. Note that 3SLS would provide more efficient estimates than 2SLS since these restrictions apply to structural coefficients across equations, and the error terms for the two components are probably correlated. To maintain comparability with Comanor and Wilson's 2SLS estimation procedure, however, we make use of the 2SLS procedure in two steps. First, we estimate the coefficients of equation (30) for A/S by 2SLS. These estimates are then used to constrain the required coefficients in equation (31) for Π/S and 2SLS is used to estimate the constrained version.

Table 8.3 depicts the impact of this respecification on the coefficient estimates. It also depicts the impact of the exclusion constraints imposed on the original model, by computing effects on ROS from both Π/S specifications, (32) and (31). These computed coefficients for ROS are labeled ROS_{compute1} and ROS_{compute2}, respectively. Note the difference between the A/S coefficients for the ROS_{compute1} and ROS_{compute2} equations, −1.24 versus 0.66. Thus, the constraints implied by Comanor and Wilson's exclusion restrictions substantially lower the A/S coefficient. The coefficients of all the other variables in the equation are also affected by these constraints although the differences are not statistically significant.[4] The same is true for estimates of the respecified A/S equation.

8.5 Conclusion

8.5.1 Summary of findings

As we noted in the beginning of this chapter, the definitional identity relating a composite variable to its components appears quite often in the literature, and in various model specifications. Table 8.4 summarizes our discussion of each, pointing out which models are misspecified and what the correct specification and analysis should be.

[4] Since the Comanor and Wilson model does not fit the data well, standard errors of the estimated coefficients are high.

Table 8.4. ***Model with composite variables: summary of appropriate analyses***

Specification in literature	*Appropriate specification and analyses*
$Z = \gamma_0 + \gamma_1 X_1 + \varepsilon$	• Analyze variances and covariances of components: $\sigma_Z^2 = \sigma_{z_1}^2 + \sigma_{z_2}^2 + 2\sigma_{z_1 z_2}$ • Regression of composite on X: $Z = \gamma_0 + \gamma_1 X_1 + \varepsilon$ • Regression of components on X: $z_1 = \gamma_{10} + \gamma_{11} X_1 + \varepsilon_1 \qquad z_2 = \gamma_{20} + \gamma_{21} X_1 + \varepsilon_2$
$Y = \gamma_0{}^* + \gamma_1{}^* X_1 + \gamma_2{}^* Z + \varepsilon^*$	• Use components (interactions and transformations, if necessary) as separate explanatory variables: $Y = \gamma_0 + \gamma_1 X_1 + \gamma_2 z_1 + \gamma_3 z_2 + \varepsilon$
$Z = \gamma_0{}^* + \gamma_1{}^* X_1 + \gamma_2^* z_1 + \varepsilon^*$	• Specify and estimate equations for each component, with included component affecting the excluded one(s): $z_1 = \gamma_{10} + \gamma_{11} X_1 + \varepsilon_1 \qquad z_2 = \gamma_{20} + \gamma_{21} X_1 + \beta_{21} z_1 + \varepsilon_2$
$z_1 = \gamma_0{}^* + \gamma_1{}^* X_1 + \gamma_2^* Z + \varepsilon^*$	• Specify and estimate equation with excluded components(s) as explanatory variable(s), not Z: $z_1 = \gamma_0 + \gamma_1 X_1 + \gamma_2 z_2 + \varepsilon_1$
$Z = \gamma_{10}{}^* + \gamma_{11}{}^* X_1 + \beta_{11}^* z_2 + \varepsilon_1^*$	• Specify equation for each component, with other component(s) as explanatory variables; impose suitable identifying constraints with caution.
$z_2 = \gamma_{20}{}^* + \gamma_{21}{}^* X_1 + \gamma_{22}{}^* X_2 + \beta_{21}{}^* Z + \varepsilon_2^*$	$z_1 = \gamma_{10} + \gamma_{11} X_1 + \beta_{11} z_2 + \varepsilon_1 \qquad z_2 = \gamma_{20} + \gamma_{21} X_1 + \gamma_{22} X_2 + \beta_{21} z_1 + \varepsilon_2$

Notes: $Z .. z_1 + z_2$; *signifies parameters of a misspecified model.

We have seen that, as long as it is appropriately incorporated in the model, recognition of definitional relationships between marketing constructs can be very useful, assuming, of course, that data are available on the components. In summary, we have found that:

- Valuable insights into the mechanism by which the composite variable changes can be obtained by determining the extent to which variance in each component and covariance between two components contributes to the total variance of the composite variable.
- Similarly, estimating the effect of non-definitional determinants on each component of the composite variable provides an empirical understanding of the mechanism by which these determinants affect the composite variable that is not available from analyses of the composite variable alone.
- Using a composite as an explanatory variable can lead to biased and inconsistent results if the constraint that is implicitly placed on the coefficients of the components is incorrect. The components should be used as separate explanatory variables so that the constraint can be empirically tested.
- Composite models that include a component as an explanatory variable not only have biased and inconsistent coefficients, but their explanatory power and tests of significance are also affected. Including a component always inflates the explanatory power of the model relative to the corresponding model without the component.
- Models of a component where the composite variable is used as an explanatory variable also produce biased and inconsistent results because of the imposition of an incorrect constraint.
- Finally, contrary to commonly held beliefs, these problems in a mixed composite or component model are not solved by the use of an instrumental variable estimator in the simultaneous equation framework. Further, identifying conditions such as exclusion and equality constraints, that are commonly imposed upon the mixed equation for a composite variable in order to identify the system, have very stringent theoretical implications for the effect of the excluded variables on the components.

The solution to these problems lies in appropriate model specification – a model that contains both a composite variable and one or more of its definitional components must be specified in two distinct parts. The first part models relationships between components and non-definitional antecedents, that must be empirically estimated. The second comprises the known definitional identity that has no impact on the estimation or interpretation of the first part. This two-part specification procedure makes the identity truly independent of the structural model.

The reasoning process by which the researcher makes the choice of composite and component variables is helpful in at least two ways. First, she is forced to think through the underlying theory in a more complete and logically consistent manner. And, second, she avoids both the misapplication of simultaneous equation procedures and misinterpretation of model estimates.

Of course, multiple schemes for defining and organizing these components may exist. For instance, return on investment (ROI) might be specified as the product of sales/investment (S/I) and return on sales (ROS) or as the difference between S/I and costs/investment. Mathematically, neither is superior – both are identities. However, one set of components might be more useful than another for a particular theory or from a managerial viewpoint.

8.5.2 Identifying definitional components

Some definitional relationships such as the one between profit and its components, or between incremental sales and its components (e.g. Neslin and Shoemaker 1983) are quite easy to identify. Others, such as the relationship between total passengers flown during a given period and the number of flights operating in that period in Gatignon's (1984) model of advertising reactivity in the airline industry, may not be as obvious. Even for a given identity, definitional relationships may be more obvious in the use of some components than in others. For instance, the use of gross profit, along with other strategic variables like market share and product quality, to predict net profit would likely be identified immediately as tautological; yet, the definitional relationship of R&D and value added (which is nothing but 1 minus purchases) with net profit is not as readily questioned (e.g. Phillips, Chang and Buzzell 1983; Prescott, Kohli and Venkatraman 1986). However, the consequences of mixing are the same, irrespective of which specific components are included in the mixed model.

Of course, all of this is under the assumption that it is possible to distinguish a composite variable from its components in an identity. In the case of definitional identities such as those relating advertising and profit, the distinction between components and the composite is quite unambiguous since net profit cannot be determined until all the costs have been determined. For other identities, the context in which the model is being developed may determine which is the composite and which are the components. Consider the identity that is implicit in Gatignon's (1984) model of airline passengers flown:

$$\text{Total passengers flown} \equiv \text{Number of flights} \times \text{Average passengers per Flight}$$

The model uses number of flights as an explanatory variable. One might argue that passengers per flight and number of flights are logically prior to the total passengers flown and, since the model does not attempt to model variations in number of passengers from flight to flight, number of flights and average passengers per flight should be considered components of total passengers flown. On the other hand, it may be argued that average passengers per flight is computed only after we have data on total passengers flown and therefore should not be considered a component of the latter.[5] Our view is that the context and the theory used by the researcher helps to distinguish the components from the composite variable. However, the fact remains that using number of flights to explain variations in total passengers flown automatically implies that the coefficients of the non-definitional variables in the model reflect their effect only on average passengers per flight, not total passengers flown. It is important for the researcher to recognize this fact and ensure that his/her theory is consistent with this implicit assumption.

The aim of research is to increase understanding (and to reduce error in our equations). Identities and tautologies may be useful ways to conceptualize some parts of the system that we seek to understand. The development of better and more complete theories can be encouraged by requiring them to be logically consistent with the existence of these unambiguous identities. A good description and understanding of a composite variable might use multiple decomposition schemes on a single dependent variable. Further, it may be that more complete and precise theories will enable us to express variables that were previously considered empirical causes, as components. It would be fruitful to

[5] We thank Hubert Gatignon for making this point.

attempt to extend the domain of "components" to include variables that were previously considered empirical causes.

As models become more complicated and statistical techniques less transparent, the potential for simple truths to become obscured will grow. Recognition of the relationship between composite variables and their definitional components may help us ensure that identities are separated from empirical investigations, yet contribute significantly to an overall understanding of the phenomenon that is being studied.

For some types of identities, it may not be possible or even meaningful to make such a differentiation between components and the composite, even in the specific context of the theoretical framework being modeled. Equilibrium identities, which only hold at optimal points (e.g. Supply $\equiv$ Demand), or synthetic relationships between ratios (e.g. US/UK exchange rate $\equiv$ US/French rate $\times$ French/UK rate) are examples of such identities. Our analysis in this chapter is clearly not relevant to these non-definitional identities.

Also, our analysis in this chapter has been limited to additive identities. Purely multiplicative identities can be analyzed similarly if the models are specified in log-linear form. It is equally incorrect to specify a mixed model for a composite variable that includes multiplicative components from one level of decomposition and additive components from another level as explanatory variables (e.g. models of *ROI* that contain both investment turnover and marketing/sales ratios) although interpreting the estimates of such a model is more difficult. We hope that our work serves to caution modelers against mixing any kind of definitional and structural relationships.

We conclude with a word of gratitude to Bob Buzzell and the other researchers who pioneered the PIMS program and have provided so much food for thought and material for research to empirical and methodological researchers alike, that issues raised by the early studies of PIMS data continue to be actively researched three decades after the program was launched.

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9 *Cargo cult econometrics: specification testing in simultaneous equation marketing models*

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An extensive empirical literature seeks to analyze the effects of strategic marketing choices on performance using non-experimentally generated, or "real-world," data. Research utilizing the PIMS database is an important example. Correct treatment of the strategic choices recognizes that they can be "endogenous" for a variety of reasons, including, but not limited to, reverse causation, simultaneity, omitted variables, sample selection, and measurement error. The standard approach for correcting this problem is to use instrumental variable techniques, such as two- and three-stage least squares, in an attempt to purge the endogenous variation from the strategic choice variables, when these variables are used as regressors in a structural equation.

In estimating simultaneous equation models, three important specification issues arise. First, which of the explanatory variables are potentially endogenous? Second, which of the exogenous variables can be excluded from each structural equation? Third, how important are these excluded exogenous variables as predictors of the included endogenous variables? Accompanying these three issues are three specification tests: the endogeneity tests of Wu (1973) and Hausman (1978), Basmann's (1960) test of overidentifying restrictions, and a simple *F*-test of the explanatory power of the excluded exogenous variables in the "first stage," or reduced form of the model. Surprisingly, these tests have not been implemented in tandem to any extent in the literature. As a result, many of the results in this literature should be viewed with caution at best, and skepticism at worst.

In this chapter, we discuss the implementation of these tests and problems associated with failure to do so. We provide an example of their implementation, and of the importance of performing these tests, in a replication of Robinson and Fornell's study of pioneering advantages in consumer goods industries.

Cargo cult science

In the South Seas there is a cargo cult of people. During the war they saw airplanes land with lots of good materials, and they want the same thing to happen now. So they've arranged to make things like runways, to put fires along the sides of the runways, to make a wooden hut for a man to sit in, with two wooden pieces on his head like headphones and bars of bamboo sticking out like antennas – he's the controller – and they wait for the airplanes to land. They're doing everything right. The form is perfect. It looks exactly the way it looked before. But it doesn't work. No airplanes land. So I call these things cargo cult science, because they follow all the apparent precepts and forms of scientific investigation, but they're missing something essential, because the planes don't land.

Now it behooves me, of course, to tell you what they're missing. But it would be just about as difficult to explain to the South Sea Islanders how they have to arrange things so that they get some wealth in their system. It is not something simple like telling them how to improve the shapes of the earphones. But there is *one* feature I notice that is generally missing in cargo cult science. That is the idea that we all hope you have learned in studying science in school – we never explicitly say what this *is*, but just hope that you catch on by all the examples of scientific investigation. It is interesting, therefore, to bring it out now and speak of it explicitly. It's a kind of scientific integrity, a principle of scientific thought that corresponds to a kind of utter honesty – a kind of leaning over backwards. For example, if you're doing an experiment, you should report everything that you think might make it invalid – not only what you think is right about it: other causes that could possibly explain your results; and things you thought of that you've eliminated by some other experiment, and how they worked – to make sure the other fellow can tell they have been eliminated.

. . . There is also a more subtle problem. When you have put a lot of ideas together to make an elaborate theory, you want to make sure, when explaining what it fits, that those things it fits are not just the things that gave you the idea for the theory; but that the finished theory makes something else come out right, in addition . . . If you've made up your mind to test a theory, or you want to explain some idea, you should always decide to publish it whichever way it comes out. If we only publish results of a certain kind, we can make the argument look good.[1]

[1] Feynman (1997).

9.1 Introduction

A curious transformation often takes place in moving from marketing strategy, as taught, to empirical marketing strategy research, as published. In this transformation, strategic marketing decisions are analyzed and presented in the classroom as the result of a rational optimization process, but appear in published research as randomly assigned treatments. In the extreme, strategic choice as taught is the equilibrium result of a complex dynamic interaction among sophisticated, forward-looking competitors. As published, strategic choice is implicitly treated as nothing more complicated than the result of a strategic dart-throwing exercise, with options arrayed on some type of "strategy dart board."

Within these extremes, much of the econometric research published in the marketing strategy literature consists of applications of simultaneous equation techniques, primarily linear two- and three-stage least squares, to model the effects of strategic marketing choices on outcomes such as market share, return on investment, returns to advertising, costs, and so forth. In these applications, the strategic choices are treated as endogenous variables, and rightly so, in principle. However, the treatment is often lacking in statistical rigor, on account of casual imposition of model specifications. More specifically, the failure to consistently apply three common, simply implemented statistical tests leads to conclusions and consequent recommendations that have little more substance than those of the dart-throwing exercise referred to above, and little more chance of generating the expected results than the efforts of Feynman's islanders.

This is the cargo cult of empirical marketing strategy. Identification of strategic effects in this research is often achieved via arbitrary restrictions, and can reflect more the effects of noise, dubious selection of instruments that either lack power or are endogenous themselves, or other misspecifications, than the actual results attributable to a particular strategic action. Aberrant results are interpreted as indicating "irrational" behavior. Even worse, they form the basis of policy and strategy recommendations to an unsuspecting public. The results of such a casual approach to estimation are of more than passing academic interest: to the extent that the results in this literature are used to inform practitioners, students, and other constituents of the academic enterprise, they (the results) are at best uninformative, and at worst destructive.

This chapter addresses three issues regarding the specification of linear simultaneous equation marketing models. These are (1) the decision on which exogenous variables to exclude from each structural equation (and, perhaps more fundamentally, which of these excluded instruments are truly exogenous), (2) the endogeneity of strategic choice variables as predictors of outcomes, and (3) the power that the excluded exogenous variables have to identify the structural effects of the strategic choices. The three corresponding tests at issue are Basmann's (1960) test of overidentifying restrictions, the endogeneity tests of Wu (1973) and Hausman (1978), and the test for the relevance (in the reduced form) of the excluded instruments.[2] These tests have been in the literature for some time: Basmann's original paper on overidentification was published over forty years ago, and the test of overidentifying restrictions has been a staple specification tool in applied micro- and macroeconomics for some time since then, particularly following the rational expectations revolution in macroeconomics. The Wu–Hausman test first appeared in the 1970s. While it too has been underutilized, there have been some applications in marketing.[3] These have been limited, perhaps because of issues related to the potential lack of statistical power of the test. This concern is well placed. However, the third test, the test of the relevance of excluded instrumental variables, gives some insight into the extent to which lack of power is, in fact, a problem, and therefore into whether the Wu–Hausman tests have any power to discriminate between null and alternative hypotheses. It also gives substantive insight into the identification and correct interpretation of the estimated effects of endogenous explanatory variables, as we describe below.

The remainder of this chapter proceeds as follows: Section 9.2 discusses the econometric issues and tests. Section 9.3 reviews the simultaneous equation literature in marketing, summarizing the extent to which these three tests have been implemented in published research. Section 9.4 presents empirical evidence on their application and

[2] See, for example, Staiger and Stock (1994).
[3] See, for example, Moore, Boulding, and Goodstein (1991).

relevance by revisiting some previously published research. Section 9.5 concludes the chapter.

9.2 Econometric background

Econometric marketing strategy research consists largely of the analysis of "third-party" or non-experimental data. There are a number of problems endemic to these data. The fundamental problem created by these data is that "treatment" effects, i.e. the effects of many of the key strategic choice variables in the empirical models, are not randomly assigned, giving rise to the endogeneity problem. Consequently, it is never clear whether an observed statistical association between the outcome of interest and the non-experimentally assigned treatment reflects a true causal relationship, or the effects of omitted variables, measurement error, reverse causality, self-selection, or some other misspecification.[4]

The most common occurrence of this problem arises when the treatment involves a choice by the observational unit, such as the choice of a particular marketing strategy. The overarching econometric solution to this problem is the technique known as instrumental variable regression, in which "instruments," which are variables thought to be related to the treatment, but not to the outcome, are used to project purely exogenous variation in the treatment via an auxiliary regression. In a sense, the instrumental variable estimator can be viewed as a two-step procedure, where the second step estimates a regression of the dependent variable on the predicted value of the treatment effect, and where the prediction is (usually) a linear combination of the instrumental variables from a first-stage regression. The instrumental variables are hypothesized, via economic intuition or institutional fact, some statistical tests, or arbitrary restrictions, to be independent of the outcome, conditional on the level of the treatment and the other explanatory variables that are included in the model.

[4] In the classical normal linear regression model $y = \alpha + \beta x + \epsilon$, the explanatory variable x is said to be *exogenous* if the condition $E[\epsilon \mid x] = 0$ holds. Each of the problems noted (self-selection, measurement error, omitted variables, etc.) leads to violation of this condition, and we will refer generally to violations due to any of them as *endogeneity*, regardless of the source of the problem.

We will briefly describe the endogeneity problem and its solution, for reference in what follows. Suppose we have a regression model

$$y = \beta x + \gamma s + \varepsilon, \tag{1}$$

where y is an outcome variable such as ROI, x represents exogenous factors, such as input costs, and s is a strategic choice, such as entry order, that satisfies all of the classical assumptions, with the possible exception of the assumed independence of s and ε.[5] In econometric parlance, s is "endogenous" when this assumption is invalid. This endogeneity can, in practice, arise from a number of causes: omitted variables that are correlated both with y and s, measurement error in s, simultaneity between y and s, reverse causality, and self-selection into the sample are some primary culprits.

To see how this can lead to problems, suppose there is an omitted variable in ε that causes both s and y to increase. A relevant example in the marketing literature is "managerial ability," which may be correlated with strategic choices (s), such as entry timing, that are difficult or costly to implement, and the consequences of those choices (y), such as costs or ROI. In this case, higher ability will lead to an observed association between s and y that is not causal, but rather that reflects in part the effects of ability on chosen entry time and on ROI.

The instrumental variable solution to this problem seeks to find some variables, w, that are correlated with s but not with y, as represented in the linear model

$$s = \phi x + \delta w + v. \tag{2}$$

Here, x represents the included instruments (i.e. included in the structural model given by (1)), and w the excluded instruments (i.e. those not included in (1)). Instrumental variable estimation of (1) then can be thought of as proceeding in two stages. In the first stage, estimate (2) using OLS, yielding the predicted values s^*. Note that these predicted values are an exact linear combination of x and w.

In the second stage, estimate the equation

$$y = \beta x + \gamma s^* + \varepsilon^*,$$

[5] For a discussion of the classical normal linear regression model, see Kmenta (1984).

where the * on the error term indicates that it differs from the structural error term in equation (1).[6] Note that, since s^* depends only on x and w and, since x and w are independent of ϵ (by assumption), the classical independence, now between s^* and ϵ^*, is restored, and the estimates of (1) can be interpreted as structural and causal.

Three recurring problems that arise in practice with this technique are:

1. Some of the variables in w, denoted by w_1, may be excluded from (1) inappropriately. That is, the "true" structural model is

$$y = \beta x + \gamma s + \theta w_1 + \varepsilon.$$

2. The variables in w may not cause any variation in s. That is, in the first-stage regression

$$s = \phi x + \delta w + \nu,$$

   the coefficient δ might not be significantly different from zero.
3. Some of the variables in w might not be exogenous. That is, $E[w|\epsilon] \neq 0$, so that the instruments are not valid, and the second-stage regression

$$y = \beta x + \gamma s^* + \varepsilon^*,$$

   is still plagued by endogeneity of s^*

Fortunately, a battery of tests is available to determine whether problems (1) and (2) exist. Also, the tests due to Wu (1973) and Hausman (1978) allow us to determine whether the strategy variables are endogenous, conditional on the quality of the instrumental variables.[7] It

[6] In particular, $\epsilon^* = \epsilon + \gamma(s - s^*)$. Note that this leads to heteroskedasticity, as is well known. Most, if not all, standard instrumental variables programs correct for this problem automatically. Two-step estimation of the type described here, while useful for expositional purposes, does not, and there is a tendency to find significant effects of s^* as a result, when these effects are not in fact significant. For extensive discussions of two-step estimation, see Pagan (1984, 1986) and Topel and Murphy (1985).

[7] Since the strategy variables are choice variables that, in principle, are the result of some optimizing process, they are arguably endogenous regardless of what the specification test results show. Failure to establish endogeneity via a statistical test in this light is no more than *prima facie* evidence that the specification test is flawed.

almost goes without saying that, if problems as outlined in (1) and (2) are present, the Wu–Hausman tests are invalid, or at least difficult to interpret owing to a lack of power. Also, to the extent that we are concerned about potential endogeneity of instrument candidates, we can test for their endogeneity using the Wu–Hausman tests as well, provided we have suitable instruments for these variables. While this places even greater demands on our ability to find suitable instruments, it is certainly preferred to arbitrarily assuming that variables are both exogenous and excludable, and thereby simply claiming, equally arbitrarily, that we have identified and estimated structural effects of interest.

For purposes of testing the validity of the exclusion restrictions, we utilize Basmann's test of overidentifying restrictions. This test essentially asks whether it is legitimate to exclude the variables w from the structural equation given by (1), and amounts to a test of whether the coefficient vector θ in

$$y = \beta x + \gamma s + \theta w + \varepsilon$$

differs from zero.[8]

Once we have arrived at a suitable (excludable) set of instruments, w_2, we can then proceed to estimate the first-stage, or reduced form, model given by

$$s = \phi x + \delta_1 w_1 + \delta_2 w_2 + \nu,$$

and use the prediction s^{**} in estimating the second stage equation

$$y = \beta x + \theta_1 w_1 + \gamma s^{**} + \varepsilon^{**}.$$

To have any faith in the estimates from this model, it must also be the

[8] It is possible, of course, to search possible subsets of w in order to find instruments that can be excluded legitimately. See Marshall and Zarkin (1987) for an application to identification of structural hedonic models. Data-mining exercises such as this create their own problems as well. Given the extent of data-mining typically conducted in the applied literature anyway, it is not clear how much is lost by searching instrument sets.

case that the variables in w_2 explain a significant amount of variation in s in the first-stage regression.[9] It is straightforward to examine the contribution of w_2 in the reduced form by an F-test of the significance of δ_2 in the model

$$s = \phi x + \delta_1 w_1 + \delta_2 w_2 + \nu.$$

Note that, if s^{**} varies only because of variation in x, w_1, and "noise," this induces an errors-in-variables problem in the second-stage estimate of (3), since the variation in s^{**} that is independent of x and w_1 is primarily noise. In the textbook case, the errors-in-variables problem leads to understated coefficient estimates of the coefficient γ, and overstated estimates of its standard error. To the extent that s^{**} is also correlated with x, w_1, and noise, which is true by construction via the first-stage regression, it also induces collinearity, which will be more severe, the lower the explanatory power of the excluded instruments. Collinearity will also inflate the standard errors of the coefficient estimates, and render the point estimates of the coefficients themselves unstable.

Once a set of instruments that is both legitimate to exclude and that explains significant variation in s has been identified, we can test the endogeneity of s in the structural model, as suggested by Hausman, by testing the significance of the coefficient(s) α in the equation

$$y = \beta x + \theta_1 w_1 + \gamma s + \alpha s^{**} + \varepsilon.$$

These tests have been available for some time, but they have not, as yet, been incorporated broadly in the econometric analysis of marketing strategies.[10] They are also very easy to implement, as will be illustrated below. It would certainly be useful to evaluate the previously published empirical marketing strategy research in light of these tests, and also to

[9] See, among others, Bound, Jaeger, and Baker (1995), Nelson and Startz (1990), Staiger and Stock (1994), and Stock and Wright (1996).

[10] We will also argue below that their implementation is often flawed because of problems of lack of power and/or endogeneity of excluded instruments.

make their use a required part of any simultaneous equation estimation exercise in future marketing applications.

9.3 Simultaneous equations in the marketing literature

A great deal of empirical research in marketing, as well as strategy and operations, has utilized some form of simultaneous equation technique to derive insight into important strategic issues. Much of this research utilized the PIMS database, in part because of the difficulty of obtaining anything comparable in scale or scope. While there are well-documented issues related to the use of PIMS data, there has been widespread use of the data and dissemination of results over the past two decades. A comprehensive summary of this research would be too extensive to present here, but we provide an analysis of a representative cross-section of recent research in Table 9.1. An extensive list of empirical research utilizing PIMS data was originally provided by Buzzell and Gale (1987). The list has been updated in the bibliography to this book.

The thirteen papers presented in Table 9.1 were published in a variety of journals by a number of authors prominent in the field. All of the papers utilized PIMS data and all but three were published in the 1990s. Our interest in these papers is in reporting the degree to which strategic choices were treated as endogenous and whether the three previously discussed statistical tests were performed. Two of the papers (Caves and Ghemawat 1992; Schwalbach 1991) failed to consider the endogeneity of the strategy variables. Of those that did in some way address the endogeneity, there was a pervasive failure to test for endogeneity, to test the validity of the exclusion restrictions, and to test the power or discriminatory ability of the excluded instruments in the endogeneity test and in the structural estimates. While four of the papers did perform a Hausman test for endogeneity, no faith can be placed in their findings in the absence of information on the other two tests.

The obvious question arising from this general failure adequately to test the specifications of these models is whether these tests would change the results and the strategic implications derived from those results. In the following empirical examples we illustrate the tests and provide a comparison of results from specifications that ignore the results of the three tests to specifications based on the three tests.

Table 9.1. *Sample of simultaneous equation models utilizing PIMS data*

Author(s)	Method	Key dependent variables	Key Explanatory variables	*Specification tests*		
				Over-ID	Relevance	Endogeneity
Ailawadi, Farris, and Parry (1999)	IV-FD	ROI, ROS	Market share (MS)			x
Boulding (1990)	GLS/LIV GLS/DIV	ROI	ROI_{t-1}, PARROI			
Boulding and Staelin (1995)	IV, differencing	Price, performance	R&D, factors affecting R&D and performance			x
Boulding and Staelin (1990)	2SLS	Price, cost	Market position, firm position, forces			
Boulding and Staelin (1993)	2SLS	Costs	MS			x
Caves and Ghemawat (1992)	OLS	RDIFF – difference in profits relative to industry average	Pioneer, patent, new products, services			

Fornell, Robinson, and Wernerfelt (1985)	Two-stage: PLS/OLS	Consumption experience	Advertising, sales promotion	
Jacobson (1990)	IV	ROI	ROI lagged, PARROI, quality, marketing	
Jacobson and Aaker (1985)	OLS	ROI, MS	Lagged ROI, MS	
Kekre and Srinivasan (1990)	W2SLS	MS, price, cost, inventory, ROI	Product-line breadth (PLB)	
Moore, Boulding, and Goodstein (1991)	2SLS	MS, PLB, product quality (PQ), relative price (RP), direct cost (DC)	Pioneering	x
Robinson and Fornell (1985)	2SLS/3SLS	MS, PQ, PLB, RP, DC	Pioneering	
Schwalbach (1991)	OLS	Profit	MS	

9.4 Empirical results

To illustrate the issues described above, in this section we will replicate and extend the market share–pioneering model developed by Robinson and Fornell (R-F). The results here can also be seen as an extension of the paper by Moore, Boulding, and Goodstein (1991), which tested the original R-F model for endogeneity using the Hausman test. In what follows, we will examine the validity of the exclusion restrictions in the original R-F model, select a set of instruments that is both exogenous and legitimately excluded (if the original exclusion restrictions are not valid), examine the power of both the R-F instruments and the alternative instruments chosen based on the overidentification tests, and once again examine the issue of exogeneity with respect to the order-of-entry variable.

Tables 9.2a–9.2b define the variables and provide descriptive characteristics. Table 9.3 presents estimates of four versions of the structural market share model estimated by R-F. There are five equations in the model, with equations for market share, relative product quality, relative product-line breadth, relative price, and relative direct costs. Estimates of the latter four equations are presented in Tables ??–??, and we focus on the market share equation and its specification in Tables 9.3 and 9.4. Column 1 of Table 9.3 reproduces the R-F results as reported in their paper, and column 2 the results of our similarly specified model.[11] Column 3 presents estimates of the model with pioneering treated as exogenous, but with exogenous variables included in each structural equation as indicated by the test of overidentifying restrictions. That is, in estimating the models in column 3, we searched possible instrument sets to identify those instruments that are legitimate to exclude, and included those that were not in each structural model. In column 4, we present estimates of the model with pioneering treated as endogenous, using only those instruments excluded on the basis of the test of overidentifying restrictions to identify the pioneering effect and to test its endogeneity.[12]

[11] The replication is not exact. However, as our purpose is not to test the R-F model explicity, an exact replication is of secondary importance. The more important comparisons for our purposes are those between our replication and the versions of the market share model that are correctly specified relative to our replication.

[12] Estimates of the first-stage equations for the models with pioneering endogenous are reported in Table 9.9a–9.9b.

Table 9.2a. *Variable definitions*[1]

Market share	Share of market accounted for by this firm
Relative product quality	Product quality relative to competition
Relative product-line breadth	Product line-breadth relative to competition
Relative price	Price relative to competition
Relative direct costs	Direct costs relative to competition
Pioneer	= 1 if firm was a pioneer when it first entered this business
# competitors	# of competing businesses in the served market
Relative advertising & promotion/sales	Advertising & promotion expenditure as a percentage of sales relative to competitors
Percentage new products	Percent of total sales accounted for by new products
Relative customer type	Breadth of customer type relative to competitors
Relative number of customers	Number of customers relative to competitors
Relative customer size	Customer size relative to competitors
# immediate customers	Number of immediate customers served by this business in the past year
Plant & equipment newness	Net book value of plant & equipment/gross book value
Capacity utilization	Percentage of capacity utilized on average during the year
Relative backward integration	Degree of backward integration of this business relative to its leading competitors
Employee productivity	Value added per employee
Percentage unionized	Percentage of employees in this business who are unionized
20 years	= 1 if the firm has been in business twenty years or more
Low price	= 1 if typical purchase by end-user costs less than $10
High purchase-frequency	= 1 if end-users typically purchase once per month or more frequently
Low customer service importance	= 1 if auxiliary services are of little or no importance to end-user
Low purchase-frequency	= 1 if end-users typically purchase once per year or less
Seasonal change	= 1 if product offering is typically changed seasonally
Annual/periodic change	= 1 if product offering is typically changed annually or periodically

Note: [1] See Robinson and Fornell (1985) for additional detail about variable definitions.

Table 9.2b. ***Descriptive statistics***

Variable	*Mean*	*Standard deviation*
Market share	22.80	17.83
Relative product quality	23.03	30.13
Relative product-line breadth	2.02	0.77
Relative price	104.38	10.26
Relative direct costs	102.02	7.08
Pioneer	0.51	0.50
Pioneer*20 years	0.43	0.49
Pioneer*low price	0.28	0.45
Pioneer*high purchase-frequency	0.18	0.38
Pioneer*low customer service importance	0.30	0.46
Pioneer*low purchase-frequency	0.14	0.35
Pioneer*seasonal change	0.04	0.20
Pioneer*annual/periodic change	0.13	0.33
# competitors	2.31	1.07
Relative advertising & promotion/sales	2.73	1.28
Percentage new products	7.31	14.63
Relative customer type	1.97	0.56
Relative number of customers	1.98	0.78
Relative customer size	2.04	0.60
# immediate customers	6.51	1.22
Plant & equipment newness	55.25	14.65
Capacity utilization	73.30	18.09
Relative backward integration	1.91	0.55
Employee productivity	37.25	29.86
Percentage unionized	44.43	34.06
Low price	0.49	0.50
High purchase-frequency	0.33	0.47
Low customer service importance	0.60	0.49
Low purchase-frequency	0.33	0.47
Seasonal change	0.08	0.27
Annual/periodic change	0.26	0.44

Table 9.3. *Market share equations: coefficient estimates and* t-*ratios*[1,2]

	R-F (1)	*Replicate R-F (2)*	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Relative product quality	0.14 (1.61)	0.16 (4.07)	0.18 (2.61)	0.30 (4.89)
Relative product-line breadth	13 (5.52)	14.00 (17.11)	−4.44 (−1.86)	−4.55 (−2.21)
Relative price	−0.25 (−0.71)	0.37 (2.42)	−0.98 (−3.52)	−1.13 (−4.44)
Pioneer	−2.11 (−0.47)	0.27 (0.2)	9.19 (5.17)	4.24 (1.19)
Pioneer*20 years	−2.03 (−0.67)	−0.16 (0.17)	−2.56 (−2.21)	4.22 (4.15)
Pioneer*low price	7.87 (2.8)	6.38 (6.64)	2.20 (1.89)	5.77 (4.94)
Pioneer*high purchase-frequency	2.29 (0.85)	−0.40 (−0.45)	−1.50 (−1.31)	0.11 (0.10)
Pioneer*low customer service importance	2.61 (0.97)	−0.01 (−0.01)	3.95 (3.73)	0.24 (0.24)
Pioneer*low purchase-frequency	5.01 (1.65)	1.00 (0.9)	0.89 (0.64)	2.12 (1.79)
Pioneer*seasonal change	−9.1 (−1.39)	1.49 (0.99)	−10.43 (−4.94)	−9.62 (−7.99)
Pioneer*annual/periodic change	−3.78 (−1.39)	−2.46 (−2.48)	−6.60 (−5.33)	−3.28 (−3.22)
# competitors	−6.63 (−9.28)	−7.07 (−30.99)	−6.82 (−26.79)	−6.83 (−26.02)
Relative advertising & promotion/sales	1.85 (1.7)	0.58 (1.83)	2.95 (6.65)	2.44 (5.24)
Relative number of customers			8.45 (8.21)	8.10 (7.33)
Relative customer size			4.04 (6.39)	3.43 (5.98)
Capacity utilization			−0.07 (−2.96)	−0.09 (−4.46)
Relative backward integration			1.64 (2.78)	1.56 (3.21)
Employee productivity			0.02 (2.1)	0.03 (2.50)
Constant	26.77 (0.74)	−37.68 (−2.44)	105.50 (3.54)	122.84 (4.56)

1 All standard errors corrected for heteroskedasticity.

2 All equations were estimated with year dummies to allow for time-specific effects.

Comparing columns 1 and 2, we see a close correspondence between our replication of the R-F model and their original results.[13] The only differences of note, where our results indicate the opposite finding in terms of statistical significance and/or direction of effect, are in the relative price variable, which in our model is positive and significant, but which had no effect in R-F, and in the pioneer × annual/periodic change variable, which is more precisely estimated in our results, but which had a fairly strong, albeit insignificant, effect in the R-F results.

Taking our replication as reference, the results in column 3 examine the effects of including in the market share equation all of the exogenous variables indicated by the overidentification test as important predictors. These include indicators of relative number of customers, relative customer size, capacity utilization, relative backward integration, and employee productivity. Each of these is individually statistically significant, so that their exclusion solely for purposes of identification creates the potential for omitted-variable bias problems.

Inclusion of these variables as regressors will have three distinct effects. First, it provides information on the predictive ability of the

[13] Differences between R-F and our replication are probably due to slight differences in variable definition, model specification, and sample selection. In some cases, R-F do not spell out the complete details of their model, and we have had to make some assumptions. For example, R-F include the *pioneer* variable interacted with a number of explanatory variables (*20 years, low price, high purchase-frequency, low customer service, low purchase-frequency, seasonal product change* and *annual or periodic product change*) in their structural market share equation, but do not mention accounting for the main effects of these variables. Since there is no mention of these main effects variables, we do not include them in either the second-stage market share equation or in the first-stage equations; in the market share models where *pioneer* is assumed to be exogenous, we do include the *pioneer* interactions in the first stage. The other four structural equations include *pioneer* and *pioneer**20 years*, but explicitly exclude the other *pioneer* interactions. Therefore, we include these variables as exogenous predictors in creating instrumental variables for use in the *relative product quality, product-line breadth, price*, and *direct cost* equations. To assure ourselves that our results were not dependent on the treatment of these interaction variables, we re-estimated all of the equations in this chapter including the main effects of each interaction variable in both the first- and second-stage equations. The results were not qualitatively different from the results reported here, and are available from the authors on request. See Tables 9.10–9.18.

variables themselves.[14] Second, it illustrates the effects of their inclusion on the estimated effects of the right-hand-side endogenous variables, which no longer have the variation of these now-included instruments as an identifying influence. Third, it illustrates the effects of including the exogenous instruments on the previously included exogenous variables.

In the market share equation, there are dramatic results in each of these areas. Of the three endogenous predictors, two change sign and are statistically significant in each version: the *relative product-line breadth* and *relative price* variables now have negative signs, and are statistically significant, although the significance of the former is weak. Among the previously included exogenous variables, the results are considerably different as well. The main effect of the *pioneer* variable becomes quite large, positive, and statistically significant, whereas it was small and insignificant in the previous results. Likewise, the *relative advertising* variable becomes larger, and much more precisely estimated, when the "new" exogenous variables are added. In the interactions of the pioneer variable with other indicators, the variables *pioneer x 20 years*, *pioneer x low customer service*, and *pioneer x seasonal product change* are all now statistically significant, relative to our replication and relative to the original R-F results. Perhaps most importantly, these results taken at face value would indicate that the pioneering advantage is not permanent, given the estimated coefficient on the 20 years variable.

It is not correct, however, to take these results at face value, because of concerns over the endogeneity of the pioneering variable itself. Column 4 presents estimates of the model treating pioneering as endogenous, and using as identifying instruments only those variables that pass the overidentification test. The results here are also dramatic: the direct effect of the *pioneer* variable is no longer statistically significant. However, the interaction *pioneer x 20 years* is now positive and significant. Finally, the *pioneer x low customer service* interaction is no longer statistically significant when pioneering is treated as an endogenous variable.

[14] We refrain from ascribing a causal interpretation here, as it would detract from our main purpose, and also require a substantial additional econometric effort. Determining the status of these variables as causal is, of course, very important, and a potentially fruitful avenue for future research.

Table 9.4. *Market share equations: specification tests*

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	122.4	1.07	0.11
Degrees of freedom	7	2	1
Prob. $X>\chi^2$	.00	.59	.74
Tests for relevance of excluded variables			
Product quality			
F-statistic	28.00	20.27	22.29
Degrees of freedom	10, 3653	5, 3653	5, 3661
Prob. $X>F$	.00	.00	.00
Product-line breadth			
F-statistic	119.15	29.77	23.47
Degrees of freedom	10, 3653	5, 3653	5, 3661
Prob. $X>F$	.00	.00	.00
Relative price			
F-statistic	10.77	11.74	10.32
Degrees of freedom	10, 3653	5, 3653	5, 3661
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			23.70
Degrees of freedom			5, 3661
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	4.05		4.63
Degrees of freedom	8, 3652		8, 3647
Prob. $X>F$	.00		.00

Table 9.4 summarizes the specification tests that are the subject of this chapter, as applied to the market share equation. The first test in Table 9.4 presents the chi-square test statistics for the test of overidentifying restrictions. Clear rejection of the identifying restrictions in our replication of the original R-F model is indicated. Upon including those exogenous variables in the market share equation that have significant estimated coefficients in that equation, the value of the test statistic for overidentification falls to an easily acceptable level.

Table 9.5a. ***Product quality equations: coefficient estimates and*** t-***ratios***[1,2]

	R-F results (1)	*Replicate R-F (2)*	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Relative price	1 (1.87)	2.47 (7.95)	3.02 (5.17)	3.26 (7.40)
Relative direct costs	−2.59 (−3.12)	−2.61 (−10.04)	−4.54 (−10.46)	−4.62 (−14.4)
Pioneer	20.99 (3.61)	8.55 (3.88)	7.39 (2.52)	−5.56 (−0.92)
Pioneer*20 years	−10.78 (−1.92)	−5.70 (−2.68)	−5.50 (−2.04)	3.97 (1.86)
# competitors			2.61 (3.64)	2.39 (4.23)
Relative advertising & promotion/sales	0.55 (0.27)	−0.22 (−0.32)	−1.27 (−1.15)	−1.40 (−1.61)
Percentage new products	0.27 (2.72)	0.06 (1.57)	0.12 (2.11)	0.12 (2.72)
# immediate customers			−2.30 (−4.21)	−2.45 (−5.73)
Employee productivity			0.07 (2.35)	0.06 (2.75)
Low price			4.64 (2.19)	5.46 (3.17)
High purchase-frequency			10.14 (6.34)	9.62 (8.34)
Low customer service importance			−6.21 (−3.60)	−6.92 (−4.53)
Low purchase-frequency			10.55 (5.22)	9.88 (6.38)
Seasonal change			−7.56 (−2.30)	−7.00 (−3.01)
Annual/periodic change			3.55 (2.02)	3.87 (2.82)
Constant	171.7 (2.12)	30.04 (0.89)	175.02 (2.92)	163.56 (3.73)

Notes: [1] All standard errors corrected for heteroskedasticity.
[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.5b. ***Product quality equations: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	167.3	1.52	1.83
Degrees of freedom	14	5	4
Prob. $X>\chi^2$	.00	.91	.77
Tests for relevance of excluded variables			
Relative price			
F-statistic	7.28	6.82	7.61
Degrees of freedom	16, 3653	7, 3653	7, 3655
Prob. $X>F$	.00	.00	.00
Direct cost			
F-statistic	22.36	26.45	26.15
Degrees of freedom	16, 3653	7, 3653	7, 3655
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			22.85
Degrees of freedom			7, 3655
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	22.86		5.96
Degrees of freedom	2, 3665		2, 3657
Prob. $X>F$	.00		.00

The next three rows of tests in Table 9.4 summarize the specification tests for the identifying power of the excluded instruments. In the original R-F model (as replicated), the identifying instruments are highly significant predictors of all three endogenous right-hand-side variables: price, product quality, and product-line breadth. When the set of identifying instruments is restricted to those that are consistent with the test of overidentification, the values of the *F*-statistic fall.[15] However, the still-excluded variables retain a considerable amount of power for

[15] Note that the value of the *F*-statistic increases slightly in the reduced-form equation for price. While surprising at first glance, this result is not inconsistent with the algebraic formula for the *F*-statistic, as it adjusts the denominator by the degrees of freedom, which are lower for the restricted set of instruments.

Table 9.6a. *Product-line breadth equations: coefficient estimates and t-ratios*[1,2]

	R-F results (1)	*Replicate R-F (2)*	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Relative direct costs	−0.05 (−2.13)	−0.03 (−4.51)	−0.02 (−1.93)	−0.02 (−1.99)
Pioneer	0.62 (4.31)	0.25 (6.08)	0.27 (6.80)	−0.08 (−0.25)
Pioneer*20 years	−0.22 (−1.63)	−0.05 (−1.28)	−0.05 (−1.30)	0.20 (4.00)
Relative advertising & promotion/sales			0.02 (2.33)	0.03 (1.37)
Percentage new products	0 (−0.34)	0.00 (−0.49)	−0.00 (−1.01)	−0.00 (−0.45)
Relative customer type	0.29 (3.67)	0.24 (9.28)	0.26 (10.06)	0.25 (7.18)
Relative number of customers	0.25 (4.42)	0.30 (16.36)	0.28 (15.18)	0.28 (7.74)
Relative customer size	0.03 (0.44)	0.11 (5.43)	0.12 (6.16)	0.12 (5.66)
# immediate customers			0.02 (2.38)	0.02 (1.97)
Relative backward integration			0.04 (1.80)	0.04 (1.95)
Employee productivity			−0.00 (−2.29)	−0.00 (−1.76)
Percentage unionized			−0.00 (−2.04)	−0.00 (−0.53)
Low price			−0.16 (−4.58)	−0.13 (−2.27)
High purchase-frequency			0.07 (2.67)	0.05 (1.42)
Low customer service importance			−0.05 (−1.88)	−0.07 (−1.41)
Low purchase-frequency			0.04 (1.23)	0.03 (0.70)
Seasonal change			−0.16 (−3.55)	−0.17 (−3.69)
Constant	5.46 (2.28)	3.35 (5.23)	2.12 (2.31)	2.49 (2.34)

[1] All standard errors corrected for heteroskedasticity.

[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.6b. ***Product-line breadth equations: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	107.3	0.13	0.67
Degrees of freedom	13	3	2
Prob. $X>\chi^2$	.00	.99	.71
Tests for relevance of excluded variables			
Direct cost			
F-statistic	19.08	30.27	30.65
Degrees of freedom	14, 3653	4, 3653	4, 3655
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			5.75
Degrees of freedom			4, 3655
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	2.73		2.80
Degrees of freedom	2, 3664		2, 3665
Prob. $X>F$	.07		.06

purposes of identification, as indicated by their collective significance as predictors of each of the endogenous regressors. Thus, conditional on other specification issues, such as the endogeneity of other explanatory variables, and of the remaining excluded instruments, these results suggest that the effects of price, product quality, and product-line breadth in the market share equation reported in column 3 can be interpreted as structural effects.

The final results in Table 9.4 pertain to the question of whether the pioneering variables are also endogenous. Recall that, in previous research, the results of this test indicated that endogenous treatment of the entry order variables was warranted. However, given the results on the exclusion restrictions, it is necessary to revisit this test. As indicated in Table 9.4, evidence of endogeneity in the pioneering variables remains, despite the exclusion of the additional variables from the set of identifying instruments. Given that the remaining variables explain a significant amount of variation in the pioneering variable, i.e. given that there is still identifying power in the reduced form for pioneering,

Table 9.7a. ***Relative price equations: coefficient estimates and*** **t*-ratios***[1,2]

	R-F results (1)	*Replicate R-F (2)*	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Market share	0.08 (1.54)	0.08 (5.01)	0.05 (2.67)	0.04 (1.08)
Relative product quality	0.18 (2.81)	0.09 (4.6)	0.17 (5.47)	0.17 (4.19)
Relative direct costs	1.08 (3.77)	0.62 (7.75)	0.75 (6.95)	0.70 (5.17)
Pioneer	−4.4 (−1.69)	0.61 (0.97)	−0.54 (−0.77)	3.32 (1.30)
Pioneer*20 years	0.46 (0.23)	−1.03 (−1.77)	0.14 (0.22)	−3.00 (−4.05)
Relative advertising & promotion/sales	1.67 (2.89)	1.07 (7.51)	0.80 (4.89)	0.77 (2.88)
Percentage new products	−0.01 (−0.31)	0.03 (2.68)	0.01 (1.23)	0.01 (0.74)
# immediate customers	0.89 (2.06)	0.32 (2.47)	0.40 (2.78)	0.45 (2.83)
Plant & equipment newness			0.02 (1.38)	0.01 0.83)
Capacity utilization			−0.02 (−2.04)	−0.02 (−1.59)
High purchase-frequency			−1.98 (−4.76)	−1.69 (−3.69)
Low customer service importance			1.06 (3.16)	1.11 (2.44)
Low purchase-frequency			−1.03 (−2.31)	−0.75 (−1.56)
Annual/periodic change			−0.96 (−2.65)	−0.98 (−2.37)
Constant	−18.97 (62)	31.24 (3.72)	18.83 (1.63)	23.37 (1.64)

[1] All standard errors corrected for heteroskedasticity.
[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.7b. ***Relative price equations: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	65.5	6.93	5.81
Degrees of freedom	12	6	5
Prob. $X>\chi^2$	.00	.32	.33
Tests for relevance of excluded variables			
Market share			
F-statistic	179.03	275.02	291.20
Degrees of freedom	15, 3653	9, 3653	9, 3655
Prob. $X>F$	.00	.00	.00
Product quality			
F-statistic	22.60	25.18	27.34
Degrees of freedom	15, 3653	9, 3653	9, 3655
Prob. $X>F$	.00	.00	.00
Direct cost			
F-statistic	23.73	24.53	24.36
Degrees of freedom	15, 3653	9, 3653	9, 3655
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			24.41
Degrees of freedom			9, 3655
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	7.91		8.84
Degrees of freedom	2, 3663		2, 3657
Prob. $X>F$	.00		.00

our faith in this result is strengthened. On the other hand, given the large number of observations and the relative low, albeit "significant," result on the test statistic, the treatment of pioneering as exogenous, as in the original R-F formulation, is perhaps legitimate after all.

9.5 Conclusion

Our primary purpose in this chapter has been to highlight the relationships among three important specification tests, and to argue for their

Table 9.8a. *Direct cost equations: coefficient estimates and t-ratios*[1,2]

	R-F results (1)	Replicate R-F (2)	New vars.; PION exog. (3)	New vars.; PION endog. (4)
Market share	−0.08 (−3.43)	−0.11 (−8.8)	−0.12 (−6.71)	−0.13 (−6.59)
Relative product quality	−0.02 (−0.83)	0.03 (1.98)	0.02 (0.90)	0.01 (0.25)
Pioneer	2.22 (1.71)	0.99 (2.05)	0.96 (1.82)	6.16 (2.72)
Pioneer*20 years	−2.77 (−2.79)	−1.28 (−2.89)	−1.09 (−2.39)	−3.50 (−7.18)
Percentage new products			0.04 (4.60)	0.04 (3.56)
Relative customer type			−1.10 (−4.32)	−0.89 (−2.94)
Relative number of customers			0.72 (3.25)	0.59 (2.21)
Plant & equipment newness	−0.02 (−1.38)	−0.03 (−3.12)	−0.03 (−2.83)	−0.02 (−2.01)
Capacity utilization	−0.06 (−3.87)	−0.06 (−8.66)	−0.05 (−7.27)	−0.05 (−6.71)
Relative backward integration	−0.92 (−2.09)	−1.13 (−5.04)	−0.99 (−4.30)	−0.96 (−3.63)
Employee productivity	0.01 (0.94)	0.02 (4.24)	0.02 (3.36)	0.02 (2.42)
Percentage unionized	0.02 (2.14)	0.02 (4.67)	0.01 (3.71)	0.01 (1.09)
Low price			2.46 (6.85)	2.05 (4.48)
High purchase-frequency			0.45 (1.44)	0.95 (2.48)
Low customer service importance			−0.96 (−3.46)	−0.60 (−1.57)
Low purchase-frequency			1.74 (5.17)	2.24 (4.90)
Seasonal change			−2.04 (−4.36)	−2.34 (−4.53)
Constant	110.6 (59.11)	109.86 (97.93)	108.78 (85.33)	106.78 (64.43)

[1] All standard errors corrected for heteroskedasticity.

[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.8b. ***Direct cost equations: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	130.1	1.81	0.55
Degrees of freedom	11	3	2
Prob. $X>\chi^2$	.00	.61	.76
Tests for relevance of excluded variables			
Market share			
F-statistic	221.73	290.03	364.88
Degrees of freedom	13, 3653	5, 3653	4, 3655
Prob. $X>F$	.00	.00	.00
Product quality			
F-statistic	28.69	38.44	55.08
Degrees of freedom	13, 3653	5, 3653	4, 3655
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			22.78
Degrees of freedom			4, 3655
Prob. $X>F$			.00
Hausman tests for endogeneity of pioneering			
F-statistic	22.40		22.35
Degrees of freedom	2, 3662		2, 3653
Prob. $X>F$	.00		.00

de rigeur inclusion in the toolkit of empirical researchers in the marketing strategy area. It is difficult to argue otherwise. In the absence of the application of these tests, we have no way of knowing whether published results in the literature have any meaning in terms of their ability to advance our understanding of how various strategic choices operate. Likewise, we have no way of knowing whether these same results have any relevance for practice.

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Table 9.9a. ***First-stage estimates for market share equation: coefficient estimates and*** **t*-ratios***[1,2]

	Relative product quality	*Relative product-line breadth*	*Relative price*	*Pioneering*
# competitors	−1.52 (−3.39)	0.00 (0.19)	−0.34 (−2.16)	−0.03 (−4.02)
Relative advertising & promotion/sales	3.86 (9.83)	0.03 (3.25)	1.51 (10.99)	0.06 (9.61)
Relative customer size	4.62 (5.52)	0.12 (6.47)	0.62 (2.12)	0.01 (1.02)
Capacity utilization	0.13 (4.99)	0.00 (2.12)	−0.04 (−4.83)	0.00 (0.60)
Relative backward integration	4.21 (4.76)	0.07 (3.38)	−0.16 (−0.51)	0.01 (0.37)
Employee productivity	0.07 (4.15)	0.00 (−3.86)	0.03 (4.40)	0.00 (−0.47)
Relative number of customers	4.25 (5.36)	0.31 (17.09)	1.04 (3.73)	0.10 (7.66)
Percentage new products	0.12 (3.70)	0.00 (−2.24)	0.07 (5.80)	0.00 (0.60)
# immediate customers	−3.05 (−7.55)	0.01 (0.85)	−0.07 (−0.51)	0.02 (2.43)
Plant & equipment newness	0.22 (6.66)	0.00 (−0.03)	0.04 (3.09)	0.00 (−2.28)
Relative customer type	0.33 (0.32)	0.26 (10.60)	−1.13 (−3.06)	−0.05 (−2.98)
Percentage unionized	−0.03 (−1.96)	0.00 (−1.09)	0.00 (0.25)	0.00 (9.97)
Constant	−14.05 (−2.57)	0.33 (2.61)	99.40 (51.88)	0.15 (1.67)

[1] All standard errors corrected for heteroskedasticity.
[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.9b. ***First-stage estimates for other than market share equation: coefficient estimates and* t*-ratios*[1,2]**

	Market share	*Relative product quality*	*Relative product-line breadth*	*Relative price*	*Relative direct cost*	*Pioneering*
Low price	1.98	−4.01	−0.17	0.21	2.15	0.10
	(3.27)	(−3.01)	(−5.50)	(0.45)	(6.70)	(4.26)
High purchase-frequency	0.59	5.75	0.05	−0.58	0.48	−0.07
	(1.09)	(4.87)	(1.72)	(−1.40)	(1.68)	(−3.44)
Low customer service importance	0.05	−0.08	−0.06	0.71	−0.94	−0.11
	(0.09)	(−0.07)	(−2.35)	(1.75)	(−3.40)	(−5.81)
Low purchase-frequency	0.94	5.76	−0.01	1.08	1.71	−0.11
	(1.54)	(4.29)	(−0.34)	(2.27)	(5.28)	(−5.05)
Seasonal change	−4.25	−10.26	−0.12	−3.47	−1.76	0.08
	(−5.02)	(−5.51)	(−2.75)	(−5.29)	(−3.92)	(2.43)
Annual/periodic change	−1.58	−1.64	−0.01	−1.09	0.42	0.03
	(−2.99)	(−1.41)	(−0.29)	(−2.65)	(1.49)	(1.69)
# of competitors	−7.17	−1.92	−0.02	−0.22	0.81	−0.03
	(−33.88)	(−4.12)	(−1.85)	(−1.34)	(7.23)	(−3.37)
Relative advertising & promotion/sales	2.40	4.28	0.04	1.55	−0.15	0.06
	(13.42)	(10.89)	(4.00)	(11.20)	(−1.60)	(8.73)
Relative customer size	3.78	4.79	0.13	0.65	−0.39	0.02
	(9.97)	(5.75)	(6.82)	(2.23)	(−1.95)	(1.15)

Capacity utilization	0.00	0.12	0.00	−0.04	−0.05	0.00
	(−0.38)	(4.51)	(1.38)	(−4.30)	(−7.88)	(0.97)
Relative backward integration	2.61	4.21	0.06	−0.27	−1.19	0.01
	(6.49)	(4.77)	(3.14)	(−0.86)	(−5.58)	(0.39)
Employee productivity	0.02	0.08	0.00	0.03	0.01	0.00
	(2.78)	(4.46)	(−3.11)	(3.96)	(3.13)	(−1.57)
Relative number of customers	7.92	4.00	0.30	1.02	−0.20	0.10
	(22.04)	(5.07)	(16.55)	(3.68)	(−1.04)	(7.49)
Percentage new products	−0.03	0.14	0.00	0.07	0.05	0.00
	(−2.03)	(4.42)	(−2.01)	(6.42)	(5.90)	(0.22)
# of immediate customers	−0.64	−2.48	0.02	0.02	0.05	0.01
	(−3.43)	(−6.05)	(2.40)	(0.14)	(0.48)	(1.53)
Plant & equipment newness	0.01	0.23	0.00	0.04	−0.02	0.00
	(0.36)	(6.82)	(0.41)	(3.41)	(−2.74)	(−2.29)
Relative customer type	−0.23	0.78	0.27	−1.10	−1.07	−0.05
	(−0.48)	(0.74)	(11.22)	(−2.97)	(−4.21)	(−2.77)
Percentage unionized	0.02	−0.04	0.00	0.00	0.01	0.00
	(2.64)	(−2.45)	(−1.14)	(0.73)	(2.75)	(9.51)
Constant	3.90	−18.43	0.39	97.82	107.78	0.26
	(1.54)	(−3.32)	(3.04)	(49.90)	(80.55)	(2.74)

[1] All standard errors corrected for heteroskedasticity.
[2] All equations were estimated with year dummies to allow for time-specific effects.

Table 9.10. ***Product quality equations – main effects included: coefficient estimates and*** **t*-ratios***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Relative price	2.63 (8.33)	3.06 (5.28)	3.26 (6.41)
Relative direct costs	−2.48 (−9.28)	−4.57 (−10.10)	−4.64 (−14.41)
Pioneer	9.82 (4.35)	6.15 (2.14)	−13.04 (−1.24)
Pioneer*20 years	−8.57 (−3.38)	−3.23 (−1.03)	16.04 (2.15)
# competitors		2.63 (3.64)	2.41 (3.89)
Relative advertising & promotion/sales	−0.45 (−0.66)	−1.31 (−1.19)	−1.39 (−1.59)
Percentage new products	0.05 −1.33)	0.12 (2.06)	0.12 (2.63)
# immediate customers		−2.27 (−4.11)	−2.36 (−5.55)
Employee productivity		0.07 (2.29)	0.06 (2.55)
20 years	3.44 (1.90)	−2.28 (−0.91)	−7.27 (−1.72)
Low price		4.57 (2.15)	5.07 (2.71)
High purchase-frequency		10.46 (6.40)	10.22 (7.64)
Low customer service importance		−6.26 (−3.60)	−6.92 (−4.13)
Low purchase-frequency		10.62 (5.12)	9.80 (5.53)
Seasonal change		−7.22 (−2.26)	−6.98 (−2.81)
Annual/periodic change		3.54 (1.99)	3.84 (2.62)
Constant	0.58 (0.02)	175.68 (2.77)	168.46 (3.28)

Table 9.11. ***Product quality equations – main effects included: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	162.17	1.67	2.90
Degrees of freedom	14	5	4
Prob. $X>\chi^2$	.00	.89	.57
Tests for relevance of excluded variables			
Relative price			
F-statistic	7.02	6.84	7.62
Degrees of freedom	16, 3652	7, 3652	7, 3654
Prob. $X>F$	.00	.00	.00
Direct cost			
F-statistic	21.05	24.18	25.29
Degrees of freedom	16, 3652	7, 3652	7, 3654
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			13.79
Degrees of freedom			7, 3654
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	22.01		6.54
Degrees of freedom	2, 3664		2, 3655
Prob. $X>F$	.00		.00

Table 9.12. *Product-line breadth equations – main effects included: coefficient estimates and* t*-ratios*

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Relative direct costs	−0.02 (−4.15)	−0.02 (−1.85)	−0.02 (−1.61)
Pioneer	0.28 (6.41)	0.31 (6.89)	0.53 (1.54)
Pioneer*20 years	−0.12 (−35)	−0.12 (−2.33)	−0.48 (−2.85)
Relative advertising & promotion/sales		0.02 (2.32)	0.02 (1.37)
Percentage new products	−.00 (−0.50)	−.00 (−0.95)	0.00 (−0.96)
Relative customer type	0.24 (9.37)	0.26 (10.08)	0.26 (7.38)
Relative number of customers	0.30 (16.44)	0.27 (15.13)	0.28 (8.69)
Relative customer size	0.10 (5.32)	0.12 (6.01)	0.12 (5.94)
# immediate customers		0.02 (2.26)	0.02 (2.28)
Relative backward integration		0.04 (1.86)	0.05 (2.02)
Employee productivity		−0.00 (−2.15)	0.00 (−2.14)
Percentage unionized		−0.00 (−2.09)	0.00 (−0.98)
20 years	0.07 (2.08)	0.07 (1.85)	0.22 (1.77)
Low price		−0.15 (−4.54)	−0.14 (−2.14)
High purchase-frequency		0.06 (2.30)	0.06 (1.42)
Low customer service importance		−0.05 (−1.88)	−0.06 (−1.25)
Low purchase-frequency		0.04 (1.17)	0.04 (1.06)
Seasonal change		−0.15 (−3.50)	−0.15 (−3.39)
Constant	3.10 (4.81)	2.06 (2.20)	1.89 (1.82)

Table 9.13. ***Product-line breadth equations – main effects included: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	105.74	0.18	0.28
Degrees of freedom	13	3	2
Prob. $X>\chi^2$	.00	.98	.87
Tests for relevance of excluded variables			
Direct cost			
F-statistic	19.26	29.74	30.36
Degrees of freedom	14, 3652	4, 3652	4, 3654
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			5.72
Degrees of freedom			4, 3654
Prob. $X>F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	8.09		2.91
Degrees of freedom	2, 3663		2, 3653
Prob. $X>F$	.00		.05

Table 9.14. ***Relative price equations – main effects included: coefficient estimates and*** **t*-ratios***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Market share	0.08	0.05	0.06
	(4.96)	(2.66)	(1.34)
Relative product quality	0.10	0.17	0.16
	(4.82)	(5.57)	(3.51)
Relative direct costs	0.58	0.74	0.76
	(7.10)	(6.58)	(4.92)
Pioneer	−0.31	−1.06	−2.08
	(−0.47)	(−1.49)	(−0.45)
Pioneer*20 years	0.63	1.11	1.41
	(0.90)	(1.47)	(0.47)
Relative advertising & promotion/sales	1.05	0.79	0.86
	(7.42)	(4.88)	(2.83)
Percentage new products	0.03	0.01	0.02
	(2.61)	(1.17)	(0.93)
# immediate customers	0.34	0.41	0.39
	(2.68)	(2.89)	(2.38)
Plant & equipment newness		0.01	0.02
		(1.21)	(1.04)
Capacity utilization		−0.02	−0.02
		(−2.01)	(−1.34)
20 years	−1.69	−0.99	−0.80
	(−3.67)	(−1.91)	(−0.51)
High purchase-frequency		−1.86	−1.93
		(−4.30)	(−3.66)
Low customer service importance		1.04	0.96
		(3.09)	(2.07)
Low purchase-frequency		−0.97	−1.08
		(−2.16)	(−1.99)
Annual/periodic change		−0.98	−0.93
		(−2.72)	(−2.22)
Constant	36.40	20.62	18.29
	(4.24)	(1.71)	(1.13)

Table 9.15. ***Relative price equations – main effects included: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	59.69	7.06	5.97
Degrees of freedom	12	6	5
Prob. $X > \chi^2$	.00	.32	.31
Tests for relevance of excluded variables			
Market share			
F-statistic	177.20	272.88	290.30
Degrees of freedom	15, 3652	9, 3652	9, 3654
Prob. $X > F$	.00	.00	.00
Product quality			
F-statistic	22.08	24.78	27.36
Degrees of freedom	15, 3652	9, 3652	9, 3654
Prob. $X > F$	.00	.00	.00
Direct cost			
F-statistic	22.29	22.41	23.57
Degrees of freedom	15, 3652	9, 3652	9, 3654
Prob. $X > F$	.00	.00	.00
Pioneering			
F-statistic			18.82
Degrees of freedom			9, 3654
Prob. $X > F$			.00
Hausman tests for exogeneity of pioneering			
F-statistic	0.56		0.35
Degrees of freedom	2, 3662		2, 3656
Prob. $X > F$	.57		.70

Table 9.16. ***Direct cost equations – main effects included: coefficient estimates and* t*-ratios***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Market share	−0.11 (−8.57)	−0.12 (−6.78)	−0.13 (−6.36)
Relative product quality	0.04 (2.63)	0.02 (1.11)	0.01 (0.32)
Pioneer	−0.56 (−1.08)	−0.32 (−0.57)	2.55 (0.83)
Pioneer*20 years	1.38 (2.48)	1.27 (2.27)	1.28 (0.70)
Percentage new products		0.04 (4.27)	0.03 (3.34)
Relative customer type		−0.99 (−3.90)	−0.84 (−2.62)
Relative number of customers		0.79 (3.57)	0.67 (2.68)
Plant & equipment newness	−0.03 (−3.63)	−0.03 (−3.25)	−0.03 (−2.45)
Capacity utilization	−0.06 (−8.36)	−0.05 (−7.02)	−0.05 (−5.88)
Relative backward integration	−1.23 (−5.51)	−1.05 (−4.59)	−1.05 (−3.95)
Employee productivity	0.01 (3.52)	0.01 (2.85)	0.01 (2.39)
Percentage unionized	0.02 (5.18)	0.01 (4.01)	0.01 (1.65)
20 years	−2.63 (−8.01)	−2.43 (−7.42)	−3.35 (−3.09)
Low price		2.35 (6.60)	1.94 (3.76)
High purchase-frequency		0.71 (2.30)	1.09 (2.24)
Low customer service importance		−0.94 (−3.43)	−0.66 (−1.68)
Low purchase-frequency		1.75 (5.24)	2.10 (4.54)
Seasonal change		−1.99 (−4.30)	−2.27 (−4.67)
Constant	111.24 (98.68)	109.77 (86.08)	108.83 (69.24)

Table 9.17. ***Direct cost equations – main effects included: specification tests***

	Replicate R-F (2)	*New vars.; PION exog. (3)*	*New vars.; PION endog. (4)*
Tests of overidentifying restrictions			
Chi-square statistic	123.21	2.00	1.22
Degrees of freedom	11	3	2
Prob. $X>\chi^2$	.00	.57	.54
Tests for relevance of excluded variables			
Market share			
F-statistic	218.08	289.58	301.87
Degrees of freedom	13, 3652	5, 3652	5, 3654
Prob. $X>F$	.00	.00	.00
Product quality			
F-statistic	27.96	38.22	45.42
Degrees of freedom	13, 3652	5, 3652	5, 3654
Prob. $X>F$	.00	.00	.00
Pioneering			
F-statistic			16.00
Degrees of freedom			5, 3654
Prob. $X>F$			.00
Hausman tests for endogeneity of pioneering			
F-statistic	3.46		0.57
Degrees of freedom	2, 3661		2, 3653
Prob. $X>F$	.03		.56

Table 9.18. *First-stage equations – main effects models: coefficient estimates and* t*-ratios*

	Market share	*Product quality*	*Product-line breadth*	*Price*	*Direct cost*	*Pioneer*
20 years	2.15	1.24	0.13	−1.91	2.06	0.33
	(4.48)	(1.17)	(5.49)	(−5.12)	(−8.15)	(19.19)
Low price	2.09	−3.94	−0.16	0.11	2.04	0.11
	(3.46)	(−2.96)	(−5.3)	(0.23)	(6.41)	(5.29)
High purchase-frequency	0.34	5.61	0.03	−0.37	0.71	−0.11
	(0.63)	(4.72)	(1.16)	(−0.87)	(2.52)	(−5.55)
Low customer service importance	0.14	−0.03	−0.06	0.63	−1.02	−0.10
	(0.26)	(−0.02)	(−2.2)	(1.56)	(−3.74)	(−5.35)
Low purchase-frequency	1.01	5.80	−0.01	1.02	1.65	−0.10
	(1.65)	(4.31)	(−0.2)	(2.15)	(5.13)	(−4.83)
Seasonal product change	−4.44	−1037	0.13	3.31	1.58	0.05
	(−5.25)	(5.56)	(3.00)	(5.05)	(−3.55)	(1.6)
Annual/periodic product change	−1.59	−1.64	−0.01	−1.08	0.43	0.03
	(−3.02)	(−1.41)	(−0.3)	(−2.64)	(1.55)	(1.68)
# competitors	−7.21	−1.94	−0.02	−0.18	0.85	−0.03
	(−34.1)	(−4.17)	(−2.1)	(−1.12)	(7.63)	(−4.35)
Relative advertising & promotion/sales	2.35	4.25	0.03	1.60	−0.10	0.05
	(13.2)	(10.8)	(3.67)	(11.53)	(−1.11)	(7.97)

Percentage new products	−0.03	0.15	0.00	0.07	0.04	0.00
	(−1.68)	(4.5)	(−1.6)	(6.03)	(5.32)	(1.69)
Relative customer type	−0.27	0.76	0.27	−1.07	−1.03	−0.06
	(−0.57)	(0.72)	(11.2)	(−2.88)	(−4.09)	(−3.29)
Relative number of customers	7.79	3.93	0.29	1.14	−0.07	0.08
	(21.7)	(4.96)	(16.1)	(4.09)	(−0.39)	(6.29)
Relative customer size	3.66	4.72	0.12	0.76	−0.28	0.00
	(9.67)	(5.66)	(6.46)	(2.58)	(−1.4)	(−0.11)
# immediate customers	−0.73	−2.53	0.02	0.10	0.13	0.00
	(−3.89)	(−6.14)	(1.82)	(0.68)	(1.34)	(−0.42)
Plant & equipment newness	0.01	0.23	0.00	0.03	−0.03	0.00
	(0.8)	(6.9)	(0.95)	(2.9)	(−3.55)	(−0.5)
Capacity utilization	−0.01	0.12	0.00	−0.04	−0.04	0.00
	(−0.81)	(4.37)	(0.85)	(−3.8)	(−7.14)	(−0.82)
Relative backward integration	2.72	4.28	0.07	−0.37	−1.30	0.02
	(6.78)	(4.83)	(3.49)	(−1.18)	(−6.13)	(1.61)
Employee productivity	0.03	0.08	0.00	0.02	0.01	0.00
	(3.11)	(4.54)	(−2.7)	(3.58)	(2.55)	(−0.22)
Percentage unionized	0.01	−0.04	0.00	0.01	0.01	0.00
	(2.00)	(−2.59)	(−1.9)	(1.44)	(3.88)	(7.22)
Constant	3.61	−18.60	0.37	98.07	108.05	0.21
	(1.43)	(−3.35)	(2.91)	(50.19)	(81.44)	(2.39)

10 PIMS and the market share effect: biased evidence versus fuzzy evidence

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Simple econometric models often produce results that may be interpreted in different ways. In response to disagreements over how to interpret such models, researchers have begun to apply increasingly sophisticated econometric models and estimation techniques. However, it is not always clear that available data are appropriate for the task presented by the more sophisticated models. In this chapter we address such a problem.

10.1 The controversy

One of the key early findings from the PIMS database was the positive effect of market share on business profitability (Buzzell and Gale 1987; Buzzell, Gale, and Sultan 1975). The argument was that higher market share yielded advantages in efficiency and thus resulted in lower average cost. Based on the empirical evidence from PIMS and other studies, such as those with the Federal Trade Commission's Line of Business database (e.g. Ravenscraft 1983), Scherer *et al*. (1987) contended that the market share effect is "robust," and a number of analysts and consultants promoted the unbeatable logic of market share building strategies (e.g. Henderson 1979).

However, a number of researchers raised serious questions about the validity of the market share effect. Some pointed out that the observed regularity lacked a theoretical base (e.g. Rumelt and Wensley 1980). In fact, knowledge of such a strategic relationship would force all firms to compete more forcefully for market share, which would eliminate the returns implied by the relationship, unless "isolating mechanisms" existed that limited competition (Wensley 1982). Others argued that market share was a consequence of greater efficiency rather than its cause, which implied that the observed effect of market share on profitability was, at least to some degree, spurious (e.g. Jacobson 1988; Jacobson and Aaker 1985). Demsetz (1973) posited that superior performance was a combination of luck and excellent management quality. Superior managers can be expected to recognize attractive markets more readily and develop more attractive products and effective marketing efforts, which should lead both to higher market share and greater profits. The resource-based theory of the firm explicitly states that there can be no sustainable advantage unless firms have inimitable resources (e.g. Barney 1991; Wernerfelt 1984).

Failing to account for difficult-to-observe or unobserved factors, such as management quality or luck, would lead to the attribution of higher profitability to higher market share even without any link between the two. Subsequent research showed indeed that the apparent effect of market share on ROI goes away after controlling for various unobserved effects (e.g. Ailawadi, Farris, and Parry 1999; Boulding and Staelin 1993; Jacobson and Aaker 1985).[1] Ailawadi, Farris, and Parry (1999) analyze the accounting components of the share–profit correlation and argue that these patterns can provide indirect evidence of the identity of variables that cannot be directly observed. They conclude that reducing the costs of purchases is a key element of directly unobservable management skills or luck that link share and profitability, regardless of how the direction of causality is interpreted. Moreover, they find a highly significant market share effect on ROI of 0.537 (s.e. = 0.025) with PIMS data pooled across all industries when using OLS estimation. When using fixed-effects estimation to control for management quality and removing contemporaneous shocks such as luck, the estimated effect becomes insignificant and changes to −0.272 (s.e. = 0.553). The same pattern of results is reported for ROS: with OLS there is a significant market share effect of 0.230 (s.e. = 0.010), which becomes insignificant and changes to −0.238 (s.e. = 0.219) when controlling for various unobserved factors.[2]

[1] Boulding and Staelin (1995) advocate an estimation approach that is capable of controlling for the potentially biasing effect of the following three types of unobserved factor: (1) firm-specific factors that do not change over the time of analysis; (2) contemporaneous random shocks; and (3) dynamic factors whose influence dissipates over time.

[2] Random-effects estimation yields results that are very similar to the OLS results.

Today's beliefs about the market share effect are to a large extent based on empirical results such as these that support the argument that initial results were spurious rather than causal. While a market share effect may exist in some circumstances, for example in markets with large network externalities such as software or telecommunications equipment, it is not believed to exist for the "average" business.

The debate about the presence of unobserved factors and the estimation approach that is therefore required has largely focused on obtaining *unbiased* estimates, but has paid little attention to the potential costs of achieving this objective. In particular, the recommended statistical procedures often lead to large variances of the parameter estimates. Fixed-effects estimation removes *all* variance between business units and relies solely on the variance that remains within a business unit, i.e. the variance over time. In most cases, persisting differences *between* business units are much more extensive than changes over time *within* a particular business unit. This holds particularly true for strategic firm factors and the time horizon analyzed in most empirical studies (i.e. five to ten years). In the extreme case when the strategic factor of interest does not change over time, fixed-effects estimation cannot be applied at all. For the market share variable, the data transformation required by fixed-effects estimation removes over 97 percent of the variance in the market share variable, which leads to the sharp increase in standard error in the estimates such as those reported by Ailawadi, Farris, and Parry (1999).

On the other hand, using random-effects estimation, in addition to potentially yielding biased estimates, requires an estimation of the variance components. For a detailed discussion of fixed-effects and random-effects estimation, we refer the reader to Hsiao (1986).

In sum, we face this question: is it possible that the market share effect is insignificant not because it does not exist but because fixed-effects estimation cannot detect it with available data such as PIMS data? In other words, are we stuck with basing our beliefs about the market share effect on either a precise but biased estimate or an unbiased but imprecise estimate?

Unfortunately, PIMS data (and other available databases) cannot directly help with this conundrum. Adding unobserved factors is all but impossible and market share changes over time are what they are. Using instrumental variable (IV) estimation (Hausman and Taylor

1981) that controls for unobserved fixed factors and does not suffer from inefficiency when there is little within-variance has its own limitation. Finding appropriate instruments is difficult and using weak instruments, i.e. instruments that do not correlate well with the market share variable, can exacerbate the bias problem (Bound, Jaeger, and Baker 1995; Staiger and Stock 1997).

To circumvent these limitations and gain some insights about the trade-off between bias and efficiency, we use results from a large simulation that we developed to examine the relationship between various estimation approaches under different conditions (Christen and Gatignon 2003). Of particular interest is the comparison between random-effects estimation, which takes into account the specific error structure of panel data but assumes that error is uncorrelated to market share, and fixed-effects estimation, which removes any potential (time-fixed) correlation between error and market share. The difference between the random-effects and fixed-effects estimators disappears as the number of observations per business unit (within cross-section) approaches infinity. Taylor (1980) compares the performance of random-effects and fixed-effects estimation in small samples when the factors of interest are independent of unobserved factors and, thus, both approaches yield unbiased estimates. Even in this case, there is a trade-off between the two because *feasible* random-effects estimation requires estimates of the variances of the time-fixed and time-variant error components. He found that except for very small panel datasets – considerably smaller than the PIMS database – the random-effects estimator is preferred even when the variance components are unknown and must be estimated.

When the comparison includes a potentially biased (random-effects) estimator, the appropriate measure, from a decision-analytic point of view, is its mean square error (MSE), which is defined as the sum of the square of the bias and the variance of the estimate (Bass and Wittink 1975, 1978; Judge *et al.* 1985; Wallace 1972). This measure captures the trade-off between bias and inefficiency. Mundlak (1978) provides analytic results for this trade-off but assumes that the variance components needed for random-effects estimation are *known*. In practical applications, they need to be estimated. However, these estimates are also biased, which complicates the trade-off between random-effects and fixed-effects estimation and makes a mathematical analysis virtually impossible.

10.2 Some insights

Our MonteCarlo simulation yielded a database that allowed us to link factors that are observable and available to an analyst (i.e. the estimation results from different estimation approaches) with factors that we manipulated in the simulation but are usually unobserved or unobservable (i.e. the correlation between the error and an explanatory variable).

The model that we calibrated with simulated data (see Christen and Gatignon 2003) can be applied to the market share effect. The problem of choosing between a biased random-effects estimate and an inefficient fixed-effects estimate for the market share effect is difficult because market share for a given business unit varies very little over time. Depending on the business sector (consumer durables, consumer non-durables, capital goods, raw material, components, and supplies), the variance within a cross-section, W, varies between 2 and 9 percent of total variance. For these values, the gains of fixed-effects estimation in terms of mean squared error are not obvious (Christen and Gatignon 2003).

In order to focus on firm fixed effects, we control for other random factors that change over time. We first remove contemporaneous correlation by using lagged instruments. We also remove first-order serial correlation with the usual ρ-differencing method (see Erickson and Jacobson 1992). We then apply each of the methods that we compared analytically and through the simulation, i.e. OLS, fixed-effects estimator, and random-effects estimator. Table 10.1 shows the parameter estimates of the market share coefficients for each industry sector and when all the industries are combined. The sample sizes (combining cross-sections and time-series) and the values of W are shown for each sector. The chi-squared value corresponds to Hausman's specification test comparing the fixed-effects to the random-effects models (Hausman 1978). A lack of significance of the chi-squared value suggests that the random-effects model should be selected.

As observed in prior research, the estimation approach has a significant impact on the parameter estimates. For example, for the ROI model, there is only one significant coefficient (at $\alpha = 0.05$) among the fixed-effects estimates (for consumer non-durables) and only one insignificant among the random-effects estimates (for raw material). Although the coefficients tend to be more significant across

Table 10.1. *The effect of market share on different performance measures using PIMS data*

	All industries	*Consumer durables*	*Consumer non-durables*	*Capital goods*	*Raw material*	*Components*	*Supplies*
Sample size (N cross-sections × T time series)	3898	515	568	678	532	952	604
Within variance W	0.043	0.032	0.027	0.071	0.089	0.033	0.022
ROI							
Simple OLS model	0.41[a]	0.60[a]	0.65[a]	0.30[a]	0.05	0.41[a]	0.39[a]
	(0.026)	(0.072)	(0.065)	(0.062)	(0.078)	(0.052)	(0.064)
Fixed-effects model	0.09	0.02	0.98[a]	−0.29[c]	−0.25	0.33[c]	0.07
	(0.074)	(0.194)	(0.153)	(0.160)	(0.171)	(0.184)	(0.251)
Random-effects model	0.37[a]	0.72[a]	0.78[a]	0.38[a]	0.14[c]	0.51[a]	0.40[a]
	(0.035)	(0.089)	(0.083)	(0.065)	(0.088)	(0.066)	(0.083)
Spec. test (χ^2)	15.9*	16.4*	1.6	20.9*	7.3*	1.1	1.9
Estimated $\rho_{x\alpha}$	0.48	0.60	0.65	0.66	0.55	0.67	0.58
ROS							
Simple OLS model	0.17[a]	0.22[a]	0.19[a]	0.15[a]	0.12[a]	0.17[a]	0.20[a]
	(0.011)	(0.027)	(0.024)	(0.024)	(0.041)	(0.020)	(0.022)
Fixed-effects model	−0.04	−0.03	0.42[a]	−0.15[a]	−0.22[b]	0.13[c]	0.08
	(0.031)	(0.077)	(0.052)	(0.059)	(0.097)	(0.069)	(0.084)

(*cont.*)

Table 10.1. *(cont.)*

	All industries	*Consumer durables*	*Consumer non-durables*	*Capital goods*	*Raw material*	*Components*	*Supplies*
Random-effects model	0.16^{a}	0.23^{a}	0.25^{a}	0.19^{a}	0.15^{a}	0.20^{a}	0.25^{a}
	(0.014)	(0.033)	(0.032)	(0.027)	(0.046)	(0.025)	(0.034)
Spec. test (χ^2)	11.4*	13.7*	17.2*	42.7*	19.2*	1.4	5.1*
Estimated $\rho_{x\alpha}$	0.39	0.32	0.41	0.34	0.20	0.37	0.30
Net Income							
Simple OLS model	0.30^{a}	0.75^{a}	0.14	0.44^{a}	−0.56	0.43^{a}	0.45^{a}
	(0.059)	(0.139)	(0.133)	(0.062)	(0.354)	(0.085)	(0.063)
Fixed-effects model	−0.07	0.07	0.48^{a}	-0.26^{b}	−0.12	0.16	0.57^{a}
	(0.101)	(0.244)	(0.152)	(0.101)	(0.424)	(0.228)	(0.161)
Random-effects model	0.16^{b}	0.69^{a}	0.39^{a}	0.41^{a}	−0.12	0.60^{a}	0.58^{a}
	(0.076)	(0.148)	(0.136)	(0.066)	(0.346)	(0.106)	(0.099)
Spec. test (χ^2)	7.2*	10.2*	1.9	76.1*	0.0	14.1*	0.0
Estimated $\rho_{x\alpha}$	0.57	0.65	0.48	0.58	0.16	0.65	0.55

Notes: Standard errors are reported in parentheses.
[a] Significant at 0.01 level; [b] significant at 0.05 level; [c] significant at 0.1 level (based on two-tail *t*-tests).
* χ^2-test statistic for the Hausman specification test is significant at 0.05 level.

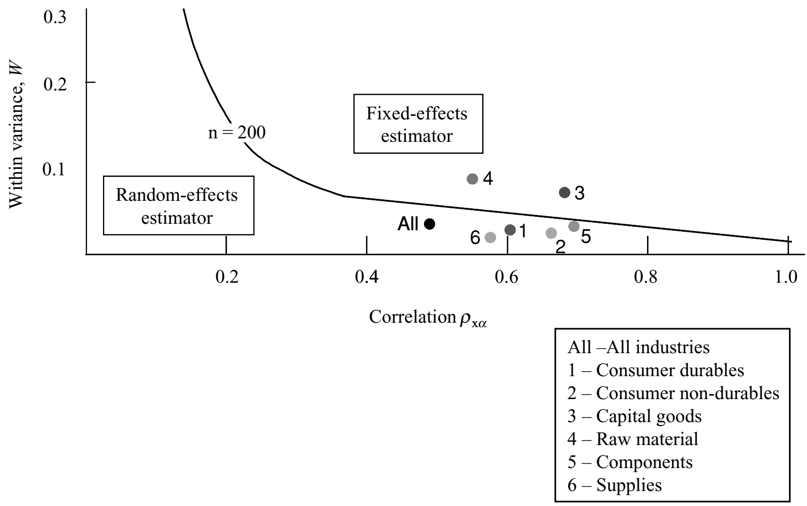

Figure 10.1. Estimator selection for market share effect on ROI with PIMS data for different industries.

estimation methods for the ROS model, similar results are obtained for the net income model (three significant coefficients for the fixed-effects model and one insignificant for the random-effects model). This clearly demonstrates that the lack of support for a market share effect can be due to the inefficiency of the estimation approach. Table 10.1 also shows that the specification test rejects the random-effects model in at least half of the six sectors, as well as in the pooled sample for the models with any one of the three dependent variables. However, the test ignores the efficiency issue to concentrate purely on the bias while using the inefficient estimator variances to perform the test.

Using the simulation results, we obtain an estimate of the correlation $\rho_{x\alpha}$ between the fixed error component and market share (see last rows for each section in Table 10.1). Given these values and the values of W, we now can identify which estimates are likely to have a lower mean square error. This trade-off for all the business sectors is shown in Figure 10.1 for the ROI model. Figure 10.1 also shows that, even for significant correlation coefficients above 0.4, the random-effects estimator is selected when the within-variance W is small, as in many cases where the strategic variable of interest varies little over time.

According to the suggested rules for estimator selection based on a mean squared error criterion, we would therefore recommend for

Table 10.2. ***Market share effects: summary of results***

Selection criterion	*Bias*			*MSE*					
Dependent variable	*ROI*	*ROS*	*Net income*	*ROI*		*ROS*		*Net income*	
	Fixed-effects estimates			*Estimator*	*Est.*	*Estimator*	*Est.*	*Estimator*	*Est.*
All industries	ns	ns	ns	RE*	0.37	RE*	0.16	RE*	0.16
Durables	ns	ns	ns	RE*	0.72	RE*	0.23	RE*	0.69
Non-durables	0.98	0.42	0.48	RE	0.78	RE*	0.25	RE	0.39
Capital goods	ns	−0.15	−0.26	FE*	ns	RE*	0.19	FE*	−0.26
Raw material	ns	−0.22	ns	FE*	ns	RE*	0.15	FE	ns
Components	0.33	0.13	ns	RE	0.51	RE	0.20	RE*	0.60
Supplies	ns	ns	0.57	RE	0.40	RE*	0.25	RE	0.58

Notes: ns not statistically significant.
* χ^2-test statistic for the Hausman specification test is significant at 0.05 level.

the ROI model and the NI model to use the fixed-effects model in two business sectors (raw material and capital goods, which have the highest values for *W*), and the random-effects model in the other sectors, including when the data are pooled. Table 10.2 summarizes these results. The random-effects model of ROS is selected for all business sectors. This table would allow us to conclude that, if the researcher considers only bias, the choice of the fixed-effects model leads to mostly insignificant effects. However, if one considers the trade-offs between bias and efficiency in estimation, which leads to the use of the fixed-effects estimator in some cases and the random-effects estimator in others, significant positive effects of market share on ROI are found in four out of the six business sectors, while they are insignificant in the other two. When the sectors are pooled, the evidence shows a significant positive effect. For the ROS model, consideration of the bias only leads us to conclude that market share has a positive effect in two sectors (non-durables and components), a negative effect in two other sectors (capital goods and raw material), and no effect in the last two (durables and supplies). Using our model selection procedure, we conclude with the inference of significant positive effects in all business sectors and in the aggregate. The results of the NI model parallel those of the ROS model, with positive significant effects of market share on net income in four sectors as well as in the aggregate model, one negative effect in capital goods, and an insignificant effect for raw materials.

10.3 Conclusion

While the evidence that this chapter presents is not strong enough to prove the existence of a market share effect "beyond reasonable doubt," it points to a significant weakness in the case against the existence of a market share effect. Even though they are biased, the random-effects estimates are likely to be closer to the true market share effect than the inefficient fixed-effects estimates.

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11 *PIMS in the new millennium: how PIMS might be different tomorrow*

PAUL W. FARRIS AND MICHAEL J. MOORE WITH KEITH ROBERTS

FROM one perspective, the objective of this chapter is to develop a researcher's "wish list" for an idealized dataset to address questions in marketing strategy and elsewhere. From another viewpoint, the topics in this chapter indicate how our field has shifted since the early seventies. In the process of studying "the profit impact of marketing strategy" we have learned that "profit" is not so easily defined and that "strategy" is a somewhat ambiguous term.

While the subject of this chapter is mainly what a revised and revived PIMS project might look like, we should note that PIMS Europe is alive and well. (See Box 11.1 for a brief update of the current PIMS management philosophy.) While PIMS Europe is also open to proposals from academics and others for joint research projects, the organization is clearly more consulting-oriented than either the original PIMS project or what we have in (wishful) mind.

Our final chapter is organized as follows. With the assumption that form and substance will follow function, we begin with a discussion of how the marketing mix has changed. Section 11.1 discusses changes in marketing programs, dimensions of marketing strategy, and the possibilities for defining marketing costs that would be encompassed by a present-day PIMS project. Collectively, these changes have substantially redefined the strategic marketing mix for many companies. Section 11.2 discusses new performance measures that may redefine or augment traditional measures of ROI and ROS, which occupied center stage for the original PIMS project. We then briefly indulge ourselves in a digression on the dangers of ill-defined research questions, sending us on collective fool's errands. Section 11.3 offers our assessment of what the New Economics of Industrial Organization might contribute to strategy research and how the concept of positive feedback and increasing returns, like an intellectual boomerang, keeps coming back

Box 11.1 Keith Roberts updates us on PIMS UK

What makes PIMS different?

PIMS gives participants a strategic edge. PIMS is a consulting firm born from a pioneer initiative in the analysis of competitive strategy. The results are now part of business culture: hundreds of strategy texts draw from the fundamental PIMS principles. The concepts and business measures we have developed, such as served market, relative market share, and customer value, and their proven links to a company's potential profitability, remain the cornerstone of business strategy. Our recommendations are based on hard evidence of what has worked for management teams facing the same challenges as your own business. We do not use simple-minded league tables – we research the drivers of performance and learn from "look-alike" situations. We take pains to measure each situation correctly. Our approach clearly quantifies how nonfinancial measures like customer value and market structure drive performance. Our unique objective analytical frameworks help our clients prioritize the evidence and achieve superior results.

Where does PIMS stand today?

Our three European offices, in London, Cologne, and Milan, employ more than seventy consultants. We work with over 30 percent of the top 100 European companies as well as US multinationals. The classic PIMS database is regularly updated and contains nearly 4,000 business units across the range of consumer and industrial products and services. In addition we have drill-down databases with over 1,000 observations on costs and processes in salesforce, finance, HR, IT, advertising, and promotion. These make a participant's balanced scorecard a calibrated management tool rather than a wish list. Finally, we have developed a number of tightly focused within-industry benchmarking circles where our expertise in "apples for apples" comparison, and reputation for data confidentiality, help participants learn and improve in a within-industry context.

PIMS and the academic community

For a business researcher, PIMS is a godsend: a broad validated dataset of empirical business experiences. Of course it is a self-selected set and is biased towards growing, successful companies, but even the best company has some "dogs" in its portfolio, so there are plenty of opportunities to contrast failure against success.

In the 1980s and 1990s we made the database widely available to researchers; this occasionally resulted in the PIMS name being associated with flawed research. Sometimes too the interest was more in having a dataset to field test a pet tool than in learning new truths about business success. We prefer now to work closely with a limited number of academic partners so that we can marry together the joint knowledge and experience to address suitably defined questions. Please contact PIMS London with a short description of your proposed topic and methodology.

no matter how many times we throw it away. The last section summarizes our hope that a new PIMS, based on some of these concepts, might emerge as an open project, perhaps like the Linux operating system, that could be shared among researchers, providing open access and full ability to replicate findings and models.

11.1 Marketing programs and marketing costs

The original PIMS project asked responding companies and business units to describe and evaluate several aspects of their marketing strategies. Respondents were also asked to evaluate their own business strategies versus those of competitors. In Chapter 1 we reviewed these variables, noting that they not only were relatively exhaustive compared to other existing databases but also broke new ground in developing questions such as relative quality, product-line breadth, and the percentage of new products. In this section we discuss a number of marketing programs that were not included in the original PIMS but would likely be required today. These are Customer Relationship Management (CRM), joint ventures, discount and revenue management strategies, salesforce and key account programs, and hybrid channel strategies and margins.

CRM can be interpreted to include a general class of marketing and management programs designed to personalize, customize, and improve the customer experience. *Budgets for crm* will undoubtedly be difficult to identify and separate from information technology expenditures. Funds employed to develop and maintain company websites are an example of cross-functional confusion of what might or might not be marketing. (It is not that such confusion is new, just that it has expanded far beyond the old Printers' Ink "black, white, and gray" list of what does not, does, and might possibly, belong in the advertising budget.) The supervision of these budgets is a shared activity and the metrics used to assess their productivity are evolving.

The rise of CRM has been accompanied by growth in loyalty and customer retention programs. Increasingly, marketers are interested in differentiating between the programs that are designed to acquire customers and those intended to retain them (Blattberg and Deighton 1996). Although there are few standards to guide data collection in this area, even simple questions asking managers to estimate how much of their marketing efforts are devoted to customer acquisition versus retention would be valuable.

Formal *loyalty programs* and *customer retention efforts* are a specific form of CRM effort that merits separate treatment and measures. Although these programs have existed for many years in earlier forms, the emphasis has increased over the past few years. American Airlines' program has been claimed to be one of the first, but it was quickly imitated by other airlines and it spread to other industries, grocery chains, hotels, car rental agencies, and more recently, "frequent gambler" programs for casinos.

Joint ventures and cooperative marketing efforts are important areas that were addressed in the original PIMS questionnaire, but the questions about shared marketing programs emphasized within-company, across-business-unit cooperation. In the last few years, such shared programs have grown to encompass a range of partnerships that are claimed to go beyond simple transactional relationships. Many are contractual in nature, and quite a few involve exchanging promotional cooperation for equity interest, warrants, or stock options. AOL, for example, negotiated with several partners for equity in exchange for prominent locations on key pages. How should the value (and option value) of these equity trades be reflected in marketing budgets for the company receiving the promotion or revenues for the firms trading eyeballs for equity?

Discounts and revenue recognition are not merely questions for financial accounting. They affect how marketers calculate and report prices, gross margins, growth rates, and marketing budgets. Discount on prices for customers and resellers are certainly nothing new. PIMS included a separate variable for promotions in the original questionnaire. However, the size and types of program used have continued to expand. As such, marketers would appreciate being able to separate promotional funds into finer classifications such as coupons, rebates, off-invoice, cooperative advertising allowances, bill-back display allowances, market development funds, slotting allowances, and payments for incremental volume sold such as "scan-downs."

Yield and revenue management programs are some of the terms associated with dynamic pricing capabilities that belong to the core skills needed to compete in many industries. A revived PIMS should classify and collect information on these important marketing activities.

Of course, the impact of the sophisticated discounting and pricing strategies is seen not only in the size of marketing budgets. Originally, many of these programs were accounted for in "dollar" terms as separate items in the marketing budgets. However, as the types of promotional discount have grown more varied and the amounts devoted to them have increased as a percentage of sales, the accounting treatment has undergone significant changes. In 2002, a new Financial Accounting Standards Board (FASB) ruling recommended that companies report sales after such discounts to avoid the confusion that can arise. Confusion is not limited to those reading the profit–loss statements, but also extends to those working with these discounts. Retailers have difficulty attributing all discounts to individual items, so costs and margins become problematic. Some have booked advance payments for promotional efforts as sales revenue, thus incurring the disapproval of the financial community.

Salesforce and key account management. The PIMS questionnaire included a separate item for salesforce budgets, distinct from media advertising, promotions, and other marketing. Collection of this item enabled researchers to estimate the ratio of salesforce expenses to advertising in Chapter 6 (approximately 3:1, salesforce: media advertising). Spending for salesforce efforts continues to outstrip all other marketing. Yet, the detail on these efforts is missing. For example, more detail on how companies combine salary, commissions, and quotas to motivate their salesforces would be of interest in understanding how marketers manage the largest marketing expenditure.

Channel strategies and margins. One of the most important aspects of marketing is management (influence) of the trade margins that are incurred through the supply chain/distribution channel. Vertical cooperation and competition in the supply chain is becoming more important as firms increasingly employ hybrid marketing channels to address their target markets. An understanding of the channel margins/costs that are incurred is needed to put pricing, profit margins, and other marketing spending into strategic context and to control for vertical differences.

11.2 Performance measures to augment traditional profit measures

Shareholder value added. The origin of the term "shareholder value" is not known to us, but it is often used as a synonym for higher stock prices. Part of the concern for shareholder value may be the fact that it is not uncommon for companies to appear, grow, and then disappear without *ever* making or reporting a profit. Still, some of these firms may be successes or failures from the point of view of their shareholders and investors. Strategies that focus on building a business that will be an attractive acquisition candidate for larger businesses are quite consistent with the rapid pace of technological change and an emphasis on strategic partnerships. The assets of these businesses may include technologies, patents, employees, systems, and strategic alliances. Therefore, we need metrics that will reflect the potential shareholder value without necessarily chasing the whims of the markets. Certainly stock price is one ingredient, but other performance metrics are desirable to augment traditional measures of profit and profitability.

Economic value added, or EVA, is a measure of profit that has received much attention in the past ten years. EVA is "calculated by reducing the full costs of capital from net operating profit after taxes. The full cost of capital captures the opportunity costs of equity and debt" (Taub 2003). The acronym EVA is a trademark of Stern-Stewart. It is also known by several other names, including "economic profit" and "residual income." Taub claims that EVA "became popular in the 1990s when companies used it to measure profitability not just at the corporate level, but also at the level of business units and individual projects."[1] We use the term "EVA" to refer to the concept also known

[1] *Market value added* (MVA) is often linked to EVA, although there is no definitional or computational link. MVA is the "difference between total market value (value of equity and debt) and invested capital contributed to the business. It is approximately the difference between "market" and "book" values (as opposed to dividing the former by the latter, which defines market/book ratio.) It is another measure of shareholder value.

as "residual income." It is a dollar (as opposed to percentage) measure of profit: operating profits less a dollar charge for capital employed. EVA can be either positive or negative. (Certain proprietary versions of EVA involve depreciating advertising, R&D, and other "soft" investments.)

One of the most controversial questions to emerge from the PIMS-based research is that of whether firms with high market shares are more profitable *because* of the high share. As the Wal-Mart data for the period 1982–1992 demonstrate (Figures 11.1 and 11.2), to focus on ROI, ROS, or ROA as a measure of profits risks ignoring one of the more important benefits of scale: growth and dollar value of profits. Shareholder value is inextricably linked not only to profitability *rates*, but also to absolute size and growth. When businesses have acceptable (above the cost of capital) returns, the benefit of share increases is greatest. In the case of Wal-Mart and many other high-growth companies, relying on traditional, ratio-based measures of profitability to separate winners from losers would risk using the wrong scorecard and undervalue the effect on share price of growth in sales.

Brand equity is a term that probably had not been coined and certainly was not in widespread use at the time PIMS was launched. While no single standard has emerged as the clear leader, Interbrand's valuations of brands relies on estimates of the portion of a firm's earning that are attributable to "brand equity." Other systems have been developed that focus less on establishing a dollar value of the brand and more on monitoring whether brand equity is increasing or decreasing as result of marketing strategy. Recently, Ailawadi, Lehmann, and Neslin (2003) have illustrated the use of a combination of price and volume premiums to estimate a "revenue premium" as compared to private labels and unbranded competitors. While clearly related to PIMS measures of relative price and relative share, "revenue premiums" are more concrete and less subject to wishful thinking and measurement error. Undoubtedly, some of these brand equity measures will be helpful in understanding how marketing strategies are performing. Softer intervening measures of brand equity, such as awareness, perceptions of differentiation, and other brand associations would also be welcome additions to "outcome" measures of brand equity such as revenue premiums.

Customer lifetime value. In the 1990s the concept of customer lifetime value (CLV) gained currency and popularity. CLV was typically defined as the discounted value of future cash flows from a customer "relationship." To calculate CLV requires estimating customer

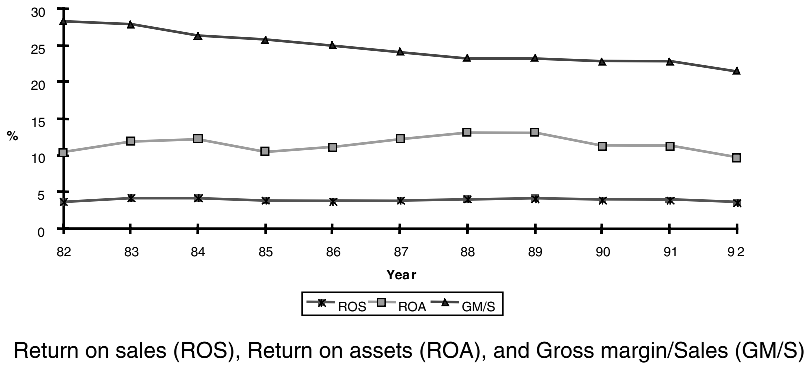

Figure 11.1. Traditional measures of Wal-Mart's profitability, 1982–1992 (*Source*: Adapted from Ailawadi, Borin, and Farris 1995).

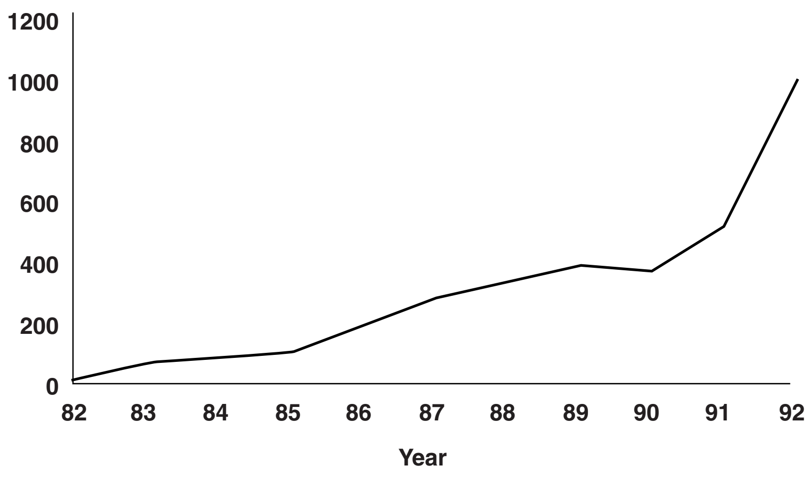

Figure 11.2. EVA for Wal-Mart, 1982–1992 (*Source*: Adapted from Ailawadi, Borin, and Farris 1995).

acquisition costs, retention spending, and customer retention rates, as well as expected revenues, margins, and a discount rate commensurate with the cost of capital and relevant risks (Berger and Nasr 1998; Dwyer 1989). CLV has been used to measure the return on marketing campaigns and has been especially useful for "subscription" services as well as those for which customer retention calculations are appropriate (e.g. telephone services, credit cards, and banking relationships). Many researchers believe that CLV "provides a useful metric for judging both firm actions and financial market valuations" (Gupta and Lehmann 2003). Others argued that the benefits of loyalty have been overestimated and the risks for long-term customer relationships, perhaps, underestimated. However, CLV has added insights into how companies organize and focus their marketing efforts. Customer-specific profit-and-loss statements are needed to monitor marketing performance.

Loyalty metrics include retention rates and the now widely used "share of requirements." Share of requirements is often used as part of an identity which breaks share down into three components:

$$\text{Share of Market} = \text{Share of Customers} * \text{Share of Requirements} * \text{Usage Index},$$

where Share of Customers = Number of customers divided by customers buying in the category or market; Share of Requirements = Average share of customers' purchases that are for the company or brand; and Usage Index is equal to the average purchases per brand customer divided by the average purchases per customer for all customers in the market. These new identities for market share may provide a richer description of what companies have achieved, adding insights into how and why marketing strategies do or do not work.

Customer satisfaction is now regularly monitored by a number of firms and consulting groups (Fornell *et al.* 1996). Our wish list would have to include this leading indicator of customer defections and loyalty.

11.3 Strategic questions, data, and methodologies: choosing horses for courses

Assuming that we are able to distinguish meaningful empirical questions from fool's errands[2] and focus our research attention on the

[2] Without some accepted standards and definitions, we believe that many of the marketing strategy questions that have been posed must be regarded as fundamentally impossible to answer. For example, consider the "true" effect of market share on profitability. Researchers continue to "control" for other influences with no accepted list of what constitutes conceptually valid intervening variables. Hence what is a "direct," and what an "indirect," effect is more a matter of taste than consensus.

former, the problem of matching questions and appropriate datasets will arise. There is still a strong need or at least a strong desire among academics to have access to a "single-source" database that will permit rigorous research into marketing strategy. This requires clear agreements not only on what constitutes strategy, but also on what makes a particular research effort "rigorous." An honest appraisal, or perhaps only a careful review, of differing standards across fields, should convince anyone that rigor is a fleeting concept as well. We will not attempt to offer our own epistemology here. But we will offer some thoughts about what constitutes rigorous strategy research and how these thoughts would guide the design of a next-generation PIMS database.

What is strategy? It is difficult to find a definition that does not get mired in classification schemes regarding levels or types of decisions, and semantic or artificial attempts to discriminate among "strategies," "policies," "tactics," and so forth. Economics probably comes closest to a methodological definition, i.e. by defining strategic choices as those choices whose results depend on the corresponding choice of another. This definition, if accepted, would require that the next PIMS allow us to (1) identify the various parties to a strategic interaction, and (2) to recognize, and control for, the fact that strategies are in fact endogenous. It would also steer attention away from the use of outcome measures, such as market share, as "causal" predictors of other outcomes, such as ROI.

Both of these criteria are consistent with what Bresnahan (1989) terms the New Economics of Industrial Organization, or NEIO. While no longer very new, the empirical revolution in industrial organization continues to the current day. It is in sharp contrast to much of the existing PIMS research, which is more firmly rooted in the structure–conduct–performance paradigm (SCP) most closely identified with Bain and his colleagues. According to Bresnahan, NEIO is distinguished from SCP in the following ways:[3]

1. Key economic magnitudes are inherently unobservable. While Bresnahan focuses on price–cost margins (especially marginal cost), the same could be said for "profitability," other dimensions of costs, and many more of the accounting-based measures that have been

[3] The following is an unashamed, almost literal summary of Bresnahan (1989).

the focus of much of the PIMS research. Rather, economic magnitudes, and the parameters of functions that describe them, are inferred indirectly in NEIO from observations of firm behavior, and the structure offered by the joint hypotheses of rationality and equilibrium.[4] One does not, for example, need to observe profits to estimate the parameters of a profit function!

2. Individual industries are felt to have important idiosyncrasies. In this regard, much of the PIMS research falls short of the mark. That which is essentially cross-sectional implicitly makes a large number of restrictive assumptions about the behavior of firms across industries in a given cross-section. That which attempts to exploit the longitudinal nature of PIMS and identify structural coefficients in the "within" dimension fails to articulate a clear model of deviations from long-run equilibrium that would help guide these interpretations.
3. Firm and industry conduct are viewed as unknown parameters to be estimated. As in (1) above, a key feature of the NEIO is the articulation of structural models that yield estimates of economic magnitudes that are either difficult or impossible to measure.

It is important to note that Bresnahan's comments are made in the context of the problem of measuring market power. Since much of what interests marketing strategy research goes beyond this important issue, it remains to be seen whether similar principles can guide research in marketing strategy. At the very least, the recognition that cross-sectional studies of dissimilar industries yield little useful understanding of structural parameters seems relevant. Relatedly, studying individual or closely related industries would be an important way of studying the problems of unobserved heterogeneity that plague much of the existing literature. And finally, the *ad hoc* nature of many of the models estimated in the marketing strategy literature makes true progress difficult.

As an adjunct to the relevant lessons from the NEIO, it is useful also to consider some of the lessons of microeconometrics. In particular, structural analyses are important. We cannot ignore elements of structure such as identities (Chapter 8), or fail to develop behavioral models of strategic choice variables that appear as "explanatory" variables in much of the published research. Neither can we ignore the

[4] See Becker (1993) for a general discussion.

distinction between the outcomes of such choices (e.g. market share) and the choices themselves, in attempting to understand the effects of strategic choices on performance. In a similar vein (Chapter 9), we cannot ignore the limitations of any non-experimentally generated dataset, and the batteries of tests available to determine how much we actually can say about a given set of results.

So, the question remains what a good single-source dataset would look like. It would have to be longitudinal and have a fairly long temporal dimension. It would have to allow some identification of industry or strategic group, so that similar companies could be included in the same study. It would require that we be able to link the sample observations with data from external sources, so that "natural experiments," such as regulatory changes, could be utilized to examine the effects of, for example, cost changes on the nature of competition, on profitability, and so forth. It would ideally allow vertical linkages of firms, and somehow allow links with data on end users. Finally, it would allow us to link the observations with external performance measures, such as stock price and patenting activity

11.4 Emerging methodological issues and opportunities

In approximately the time since PIMS was launched, economics and business strategy have cautiously begun to accept as legitimate some aspects of dynamic systems. By no means is the acceptance universal or enthusiastic, even if figures such as Kenneth Arrow have given their imprimatur. Network effects, positive feedback, increasing returns, multiple equilibria, path dependence, sensitivity to initial conditions, self-organization, and chaos theory are just some of the terms that are attributable to this field. The methodologies include numerical analysis and simulations as well as mathematical techniques.

With the inevitable risk of vastly oversimplifying, we will characterize most of this work as focusing on finding, explaining, and modeling "feedback" effects that enable systems to exhibit adaptive, evolutionary behavior. Winner-take-most outcomes are often assumed to result from positive feedback and increasing returns, but predicting the winners may be difficult or impossible, because of the complex, nonlinear nature of the systems and the feedback loops.

At the time of PIMS' founding, the literature on the importance of market share included its own notion of "positive feedback." The discussion of learning curves of that era posited that increases in sales volume would enable firms to lower production costs. Further the lower production cost would increase margins, enabling lower prices or greater investments in marketing. Either way, the positive feedback loop meant the rich (those with high shares) would get richer and the poor (low-share) businesses would eventually be forced to exit (Alberts 1989). The window of opportunity for making these commitments or decisions was not unlike the more recent views of how firms in the new technology sectors had to compete (Arthur 1994, 1996).

Even older than learning curves is the assumption of positive feedback in business systems that was built into the classic business game of Monopoly. Once a player accumulates a critical mass of property, the "network" is complete, and houses and hotels can be built. Each addition brings higher rents until the cash that each venture capitalist brought to game is stretched thin. Then, one or two unlucky rolls of the dice decide the winner (Farris and Pfeifer 2000).

The basic concept of positive feedback and increasing returns has a long history in economics (e.g. Alchian 1950; Forrester 1961). Although such feedback loops play havoc with many of our methodologies and are banished periodically from the mainstream literature, they keep coming back in new disguises. Slowly, the research questions and methodologies of complex systems will find ways to be integrated with other streams of empirical study of marketing strategy.

11.5 Summary

One view of the advancement of knowledge holds that scientific development is characterized by long periods of incrementalism, and occasional disruptions due to truly fundamental changes. PIMS was an ambitious attempt to provide an empirical basis for marketing strategy. We have reviewed its many accomplishments. For now, it appears that all of the advances that could have been made with PIMS have been made, and there is not much left in these data to advance our understanding of how markets and marketing work. Much of the old debate also seems misguided in retrospect: the worn-out battle of causal direction between market share and ROI, for example, centered on a flawed measure of performance (ROI), and a misplaced outcome measure (MS). As Christen and Gatignon show in Chapter 10, even if the topic debate were legitimate, the evidence was insufficient to reach a verdict.

On the other hand, the fact that the PIMS of yesterday has run its course suggests that a fundamental change in how research of this nature is conducted might be in order. Would a new PIMS dataset figure in some kind of transformational advance in research in this area? A few things would be necessary. First and foremost, standards of good social scientific research, such as replicability, would need to be met. This is meant to include not only clarity and transparency in presentation, so that one's method of analysis can be followed, but also open sharing of datasets and programs. Thus, a new PIMS dataset would need to be comparable to other available data, and it would need to be made available to all interested parties.

Second, emphasis should not be placed on marginal contributions to an existing body of knowledge. Consequently, a new PIMS dataset would have to look radically different from its predecessor. Third, the new dataset would have to recognize the changed nature of our economy, with its emphases on services, intellectual capital, standards, globalization, and dynamics. The nature of competition has changed in many respects, as has the nature of monopoly.

A new PIMS, we believe, should never have a monopoly on access to the data. Without "property rights," however, another motivation to collect and share data will have to be found. Because data have (or seem to have) a limited life unless they are maintained and refreshed, there is a parallel here to the "tragedy of the commons." The result is that many papers are published from "proprietary" data that are collected by authors from companies and managers that are not named in the research. On the other hand, Linux and many aspects of the Internet demonstrate the power of academic cooperation that springs from a genuine dedication to higher ideals of constructing a common means to an end.

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