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A probabilistic model for predicting management buyouts

Salamone, Diane Marsan, Ph.D.

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U·M·I
300 N. Zeeb Rd.
Ann Arbor, MI 48106

A PROBABILISTIC MODEL FOR PREDICTING MANAGEMENT BUYOUTS

Diane Marsan Salamone, B.S., M.B.A.

A Dissertation Presented to the Faculty of the Graduate
School of Saint Louis University in Partial
Fulfillment of the Requirements for the
Degree of Doctor of Philosophy

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COMMITTEE IN CHARGE OF CANDIDACY:

Associate Professor John N. Kissinger,
Chairperson and Advisor

Associate Professor Doyle W. Banks

Professor Ik-Whan Kwon

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Empirical studies indicate that large abnormal returns accrue to shareholders of a public firm in the period immediately preceding a formal announcement that the firm will go private. Investors might take advantage of these abnormal returns if they were able to identify management buyout candidates from publicly available information. The present study therefore attempts to develop a financial profile from publicly available information that can identify firms that will go private via a management buyout.

The study uses a sample of 112 management buyouts that occurred during 1979-1988 and a random sample of 112 firms that remained public as of 1988 to estimate a logit model. Specifically, the model establishes for each sample firm the probability the firm will go private via a management buyout. The variables included in the estimation procedure are as follows: cash flow volatility, fixed charge coverage, LBO-intensive industry indicator, ratio of capital expenditures to cash flow, ratio of research and development expenditures to cash flow, ratio of buyout value to market value, dividend payout ratio, and the squander index.

In order to depict accurately the model's performance in the population, the study tests the predictive ability of the model using a large group of firms that resemble the entire population of firms. This test results in the correct classification of 39% of the management buyout firms and 66% of the public firms. Because the number of management buyout firms in the test sample is extremely small, the overall classification accuracy of the estimated model also approximates 66%.

Under the proportional chance criterion, the expected probability of correct classifications over both groups is 98%. A comparison of the correct classification percentage expected by chance (98%) with the overall accuracy of the estimated model (66%) thus leads to a conclusion that the performance of the model is *less than* that expected on the basis of chance alone.

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CHAPTER I

INTRODUCTION

The management buyout of a publicly-traded corporation restructures ownership by replacing the entire public stock interest with private ownership by an incumbent management group. Because the available evidence suggests public stockholders experience significant wealth increases when associated with these transactions, a model that identifies firms that will go private via a management buyout should be useful to corporate managers and outside investors interested in sharing in the potential gains. Given the specific interests of these parties and others who may find a prediction model useful, the fundamental objective of the study is to develop a model that can reliably distinguish firms that will go private via a management buyout from firms that will remain public.

A few earlier studies attempted to identify the financial characteristics of public firms that convert to private status via a management buyout (Maupin, Bidwell and Ortegren 1984; Lawrence 1986; Maupin 1987). These studies typically used multiple discriminant analysis (MDA) to estimate a linear function of some financial performance measures for a sample of public firms and "ex-public" firms in an effort to classify firms as management buyout candidates. The results in terms of identifying management buyout candidates were mixed.

This study attempts to improve upon these earlier works in a number of different ways. First, the study provides a framework for the establishment of a hypothesis regarding the underlying rationale for the going-private transaction. Second, whereas earlier studies primarily used the financial performance measures of traditional financial statement analysis, this study relies, in large part, on the technical literature (i.e., investment banking industry publications) to identify a set of potentially relevant variables. This literature is important in that it examines the going-private decision from the perspective of practitioners--the investment banking firms that act as both advisors and participants in these transactions. In addition, because most of this literature is in the form of regularly published newsletters, the information contained therein is extremely current and topical. Third, the study uses management buyouts from the period 1979-1988 to develop the model, representing a later period than previous empirical studies employed. This could be a particularly important contribution because the characteristics of firms that go private via a management buyout have likely changed in the past decade with increased availability of leveraged buyout financing.

CHAPTER II

STATEMENT OF THE PROBLEM

The problem this study addresses is the lack of a reliable model to assess the likelihood of a management buyout of a publicly-held corporation. Prior to the mid-1970s, a management buyout prediction model would have warranted little attention by researchers because it was very uncommon to see a publicly-held corporation convert to private ownership. For example, during the period 1963-1972, *Moody's Industrial Manual* reports that only two firms reverted to the private domain. However, subsequent years (particularly those of the eighties) have seen a dramatic increase in the number of firms that have changed to private status.

To illustrate why this problem has become more important in recent years, the following reviews some published statistics. *Mergerstat Review* reports the completion of 369 going-private transactions during the period 1979-1987, with the total dollar value paid for these firms exceeding $91 billion. In each of the first three years of this period, these transactions numbered only in the teens. However, by 1985, "going-private" had become so popular the numbers were reaching well into the seventies on an annual basis.

These statistics also reveal that, in addition to steady increases in the number of transactions, the average size of a transaction has also increased over that same period. For example, the average purchase price paid in a going-private transaction in 1979 was \$39.8 million. In 1987 that figure rose to \$469.3 million. Further, if one considers the \$24.88 billion buyout of RJR Nabisco in 1988, it becomes clear that the size of these going-private transactions now knows no bounds.

Despite the growing popularity of management buyouts as a means of restructuring corporate ownership, there appears to have been only a few attempts to develop a model that can reliably predict management buyouts. However, there are a number of reasons for attempting to develop such a model. First, according to a study by DeAngelo, DeAngelo and Rice (1984, 388), pre-buyout stock price movements indicate that the market receives most of the signals regarding the probability of a buyout during a very short period around the announcement of a formal proposal to go private. In light of this evidence, it may be difficult for the market to predict future buyout candidates. However, if a statistical model could identify firms that will likely go private via a management buyout earlier than the stock market, then it may be possible to earn abnormal returns by using the prediction model.

Second, a management buyout prediction model may be useful to investors who choose to avoid investing in corporate bonds when there exists a risk that the issuing company may be the subject of an "event." In this case, an "event" refers to a leveraged acquisition of the company, a leveraged buyout, or a defensive recapitalization that reduces the company's debt rating below investment grade (J. P. Morgan Securities 1989, 1). The proposed management buyout of RJR Nabisco serves as a case in point. When the senior executives of RJR Nabisco proposed a leveraged buyout in 1988, the bondholders immediately lost a significant amount of the value of their investment--on outstanding debt of $5.4 billion, paper losses were approximately $800 million (Chew 1989, 72). These losses were due to speculation that the rating agencies would replace RJR's A/A1 rating with a sub-investment grade rating common to leveraged buyout debt (J. P. Morgan Securities 1989, 1). It is important to note, though, that the downgrading of RJR's debt due to the proposed leveraged buyout by management was not an isolated incident. Downgradings of this sort have actually become commonplace in recent years. For instance, from 1984 to 1988, there were 284 special-event downgrades affecting a total of 238 U. S. companies. These events caused a total of approximately $154 billion of outstanding U. S. and Euromarket debt to be downgraded over the same period (Moody's Investors Service 1989, 9).

In addition to being useful to investors in corporate bonds, a management buyout prediction model may be useful to corporate bond issuers in determining the value of event risk language incorporated as bond covenants. These covenants are designed to protect investors from a dramatic decline in the value of their bonds in the case of an event such as a leveraged buyout. For example, the most commonly used provision is a "poison put," which permits the holder of a debt instrument to redeem the debt at its par value if a designated "event" occurs and the market downgrades the debt (J. P. Morgan Securities 1989, 3).

In order to determine the value of including special covenants in bond indentures to protect investors from event risk, the issuing corporation must weigh the benefits of inclusion against the cost. The *benefits* of including event risk covenants are clear in most cases: issuers are able to issue debt at a lower all-in cost than otherwise would have been possible. Fortunately, it is a fairly simple task to quantify this benefit. While the all-in costs will differ for each issuer, there have been a sufficient number of issues done with and without event risk covenants to give a reasonable assessment of the additional yield required to sell bonds without these protective clauses (J. P. Morgan Securities 1989, 9). If the all-in cost of debt *without* event risk covenants is known, the benefit of including these covenants is thus equal to the present value of the additional yield required to borrow without such provisions over the life of the debt.

Unfortunately, it is not as simple for issuers to quantify the *costs* of including event risk covenants in their bond indentures. J. P. Morgan Securities (1989, 9) suggests one way to quantify the cost of such provisions is to estimate the probability of occurrence of a designated event during the life of the debt. The issuer would apportion this probability to each year over the life of the debt according to some rule, e.g., pro rata allocation. The *future* cost of the event risk covenant is then equal to the additional cost per annum of refinancing the debt weighted by each year's assigned probability of the designated event. The issuer would discount that result back to the present to determine the *present* cost of including the event risk covenant. By balancing the benefit of including such a provision against its cost, an issuer can determine whether the event risk covenant adds or subtracts value.

Third, although management has a fiduciary responsibility to public shareholders in a management buyout to negotiate a fair value for their shares, management as the purchaser of those shares has a countervailing incentive to minimize the price paid. A model that is able to identify potential buyout firms may, therefore, be useful to minority shareholders who want to avoid the risk of investing in firms that are likely buyout candidates that may later "freeze" them out at less favorable terms. In this same regard, the Securities and Exchange Commission may find a prediction model an important surveillance tool, the use of which may place them in a better position to protect these minority shareholders from managerial self-dealing in going-private transactions. In some respects, it would be similar to the "early warning systems" that bank regulatory agencies now use to detect problem banks (Lawrence 1986, 2).

Finally, FASB *Statement of Financial Accounting Concepts No. 2* suggests:

> Information can make a difference to decisions by improving decision makers' capacities to predict or by confirming or correcting their earlier expectations. . . . Disclosure requirements almost always have the dual purpose of helping to predict and confirming or correcting earlier predictions . . . (pars. 51-52).

The development of a model that is able to identify accurately the financial characteristics of firms with a high potential for going private may result in additional disclosure requirements. For example, if researchers determine that "cash flow volatility" has predictive value in achieving the specific objective of assessing the likelihood of a management buyout, the SEC may require public firms to disclose such information on a routine basis.[1]

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[1] Note that the FASB defines 'predictive value' as ". . . value as an *input* into a predictive process, not value directly as a prediction" (SFAC No. 2, para. 53).

CHAPTER III

REVIEW OF RELEVANT LITERATURE

Management Buyouts

General Background

Public companies have been selling off parts of their existing business to management since the early 1970s. Usually, these divestitures involved companies that were generating an inadequate return on investment or did not fit into the seller's long-term strategic plans. More recently, however, management buyouts have become an increasingly popular technique for taking a public corporation private amid a frenzied market for corporate control.

The management buyout (MBO) of a publicly-held corporation is feasible only if adequate resources are available to buy back the entire public stock interest. In certain management buyout transactions, incumbent managers have sufficient personal resources to purchase the public stock interest without the participation of nonmanagement equity partners and without significantly increasing the level of firm debt. In other cases, personal resources of the incumbent management group are limited, and managers must allow third-party equity investors to participate in the buyout. The financial community commonly refers to management buyouts with third-party equity investors as leveraged buyouts (LBOs) because of the significant increase in the level of company debt that accompanies these transactions. For example, DeAngelo and DeAngelo (1987, 39-40) report that firms proposing a leveraged buyout during the period 1973-1982 planned increases in the level of corporate borrowing up to an average 86% of total capitalization. In contrast, when these firms were publicly traded, the mean and median ratios of long-term debt to total assets were only 16.9% and 12.9%, respectively.

Obviously, third-party equity investors in these transactions provide a significant portion of the equity base needed to position the LBO firm to borrow large sums of cash. However, the term "equity investor" is somewhat a misnomer because frequently these outside investors also provide other forms of financing. For example, Diamond (1985, 82) suggests that venture capitalists will, on occasion, invest their equity dollars in common stock side by side with owner-managers. More often, though, these investors prefer to invest the majority of their equity dollars in securities that yield current income and have seniority to the securities issued to management. Under these arrangements, it is common for the venture capitalist to provide financing as an investment in yield-bearing subordinated notes or redeemable preferred stock. The venture investor's agreed-upon "equity play" is then represented by common stock purchased at the price per share management pays or by warrants or conversion rights to acquire common stock at that price.

LBO specialists (such as Kohlberg Kravis Roberts & Co. and Forstmann Little & Co.) frequently operate in a similar manner. For example, in 1984 Forstmann Little & Co., in conjunction with management, purchased Topps, the manufacturer of "Bazooka" bubble gum and baseball bubble gum picture cards. Forstmann Little provided $22 million of subordinated debt toward the purchase price of $98 million. In addition, Forstmann Little and its management partners contributed $9.9 million of common equity. In 1984, Forstmann Little also acquired Dr Pepper, the nation's fourth largest soft drink maker. The purchase price paid for Dr Pepper's stock was $521 million. Total acquisition financing, including the repayment of existing debt, was $647 million. Of this amount, Forstmann Little and its partners provided $120 million of subordinated debt and $30 million of equity (Little and Klinsky 1989, 72-74).

At the time management buyouts first became popular in the early 1970s, the participation of outside equity investors was certainly not the norm.

For example, of the eighteen management buyout proposals initiated during the period 1973-1977, only one-third were leveraged buyouts. However, LBOs constituted nearly 60% of management buyouts proposed during 1978-1982, and approximately 85% of the management buyouts proposed in 1982 alone (DeAngelo and DeAngelo 1987, 39).

Analysts attribute this greater incidence of leveraged buyout activity in recent years to a variety of economic factors. The most noteworthy of these factors has been the persistent inflation in the U. S. and other worldwide economies. Because experts believed inflation would continue throughout the 1980s, it was prudent (at least in this respect) for firms to engage in any form of leveraged transaction. Borrowers pay back existing debt with dollars that have less value, while the strength of their balance sheets increases with periodic reductions in principal. A complement to this analysis is also the fact that persistent rises in specific price level indices make the replacement value of leveraged assets greater each day. From the lender's perspective, this is particularly appealing because replacement values are usually well above depreciated costs. The undervaluation of assets thus lowers the risk to the lender that, in the event of an economic downturn, assets will fail to fully collateralize the value of the loan (Garguilo and Levine 1982, 15-16).

Another factor that has contributed to the proliferation of leveraged buyouts is the erosion of the U. S. productivity advantage over other advanced industrial nations. Prior to World War II, American output per worker was nearly twice as great as that of Germany and France and seven times larger than that of Japan. However, after the War, the American advantage dwindled, with U. S. productivity increasing only about one-fourth as fast as that of Germany and France and one-seventh as fast as that of Japan. A decline in the real return on capital also coincided with the deterioration of American's competitive advantage. From 1949 onward, real returns steadily declined from well over 20% to just above 5% in 1987 (Paulus and Waite 1989a, 2-4).

Experts primarily attribute the deterioration in the U. S. productivity advantage and the decline in American competitiveness to the slower accumulation of capital in the postwar years. Since 1950, for example, the real stock of physical capital in Japan, Germany, and France has grown at annual rates of 12%, 7%, and 5%, respectively. The U. S. annual growth rate of physical capital over that same period was only 3.6%. While the slow pace of capital formation since the end of World War II appears to be largely responsible for

America's competitive decline, Paulus and Waite (1989a, 4) suggest another factor may help to explain this deterioration--that is, the inefficient resource deployment of both physical and human capital. In a market economy, an inefficient deployment of capital can occur when resource decisions are made by managers who do not have meaningful equity stakes in the firm and who, therefore, do not necessarily attempt to maximize shareholder wealth. In some instances, the leveraged buyout can represent a solution to this problem. Leveraged buyouts change the incentives of managers (decision makers) by giving them meaningful equity stakes in the private firm. In turn, these managers make decisions on the basis of rate of return criteria and, hence, efficiency considerations.

There are naturally other factors that have contributed to the greater incidence of leveraged buyout activity in recent years. For instance, large amounts of cash have been available to finance these transactions, and investment banking firms have been very aggressive in seeking out these opportunities. The venture capital market has also exploded in anticipation of the opportunities to invest. The most subtle factor, though, that has stimulated activity in this market is a heightened awareness on the part of the investment community that leveraged buyouts are essentially the same as real estate transactions. In real property transactions, eighty to ninety percent mortgages are commonplace because lenders focus on cash flow and/or liquidation values. Leverage in the real estate world has never been considered a negative, but in the corporate world many frown upon its use. In recent years, however, lenders and investors have gradually come to the realization that leveraged acquisitions possess all of the qualities of real property acquisitions: low risk, high return, and enormous upside potential (Garguilo and Levine 1982, 16-17).

The Gains from Going Private

In the 1950s, the commercial and industrial scene saw the first wave of encouragement for corporations to become publicly held. Since then, several thousand corporations have done so expecting to achieve liquidity for their existing stockholders and internal and external growth stimulated by an active secondary public market for their shares (Maupin, Bidwell and Ortegren 1984, 435). However, despite these and other benefits of public ownership, an increasing number of public corporations are reconsidering their ownership status. Maupin (1987, 319) suggests this is due, in part, to a growing disenchantment in recent years with public ownership and an apparent widespread conviction that management buyouts represent a way for managers to make their own fortunes. Of course, for managers to profit from these transactions, the firm must also flourish. Accordingly, the remainder of this section discusses the potential benefits to the firm of a reversion to private status, as well as the added potential benefits of a debt-financed recapitalization (i.e., a leveraged buyout).

The firm that changes to private status potentially experiences real resource gains through reductions in registration, listing, and other stockholder servicing costs, and through the introduction of an ownership structure that links more closely managerial performance and reward. The savings in stockholder servicing costs alone can be sizable. For example, Schneider, Manko and Kant (1981, 5) suggest firms considering going public should expect recurring direct costs of public ownership in the range of $30,000 to $100,000 per year (not including management time). Borden (1974, 1007) estimates the annual direct costs of public ownership are $75,000 to $200,000 for an average public company of Amex size, and considerably more if special problems arise (again excluding management time and indirect costs such as additional audit fees). While it is relatively easy to estimate the savings in stockholder servicing costs, the magnitude of real resource gains from a more efficient (private) ownership structure is more difficult to determine. DeAngelo, DeAngelo and Rice (1984, 372) suggest the firm may realize such a benefit when management's increased equity ownership percentage reduces their incentive to shirk.[2]

Generally, the firm will also realize productive gains from an organizational structure change that links more closely managerial performance and reward (Easterbrook and Fischel 1982, 705). Because some profitable investment projects require a disproportionate amount of management effort, managers will undertake these projects only if they can capture a corresponding (disproportionate) share of the proceeds. Therefore, compensation arrangements that deviate from a strictly proportionate sharing of investment returns among all shareholders (public and management) can enhance productive efficiency by encouraging managers to forgo fewer profitable projects. Under public ownership, these management compensation schemes may appear "overly generous" and, thus, are subject to legal challenge by outside shareholders. Private ownership reduces this threat of litigation, making such arrangements more feasible.

[2] In a pure going-private transaction, management's equity ownership percentage necessarily increases because, by definition, management acquires a 100 percent equity interest in the private firm. Management's residual interest increases in a leveraged buyout as well through increased stock ownership and, indirectly, through employment contracts that tie managerial income more closely to firm profits.

In addition to the potential benefits from a reversion to private status indicated above, there are a number of reasons why a debt-financed recapitalization may further enhance the value of the firm. First, debt is a less expensive form of financing than equity because interest payments are tax-deductible while dividend payments are not. When the firm substitutes debt for equity, the overall amount of capital the business uses does not change, nor does the rate of return investors require to compensate them for assuming business risk. However, the explicit tax-deductible cash cost of debt at least partially replaces the implicit cost of equity. If done within prudent limits, this substitution of debt for equity increases a company's intrinsic market value because the debt shelters operating profits from being fully taxed (Stewart and Glassman 1988, 86).

Second, the presence of third-party equity participants in a leveraged buyout can also strengthen the link between managerial performance and reward.[3]

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[3] Consistent with DeAngelo and DeAngelo (1987), the study uses the term *leveraged buyout* to describe a management buyout with third-party equity investors. This term has gained wide acceptance among the investment community because, in these buyouts, managers and a group of third-party equity investors purchase all of the publicly-held common stock with funds obtained, to a large degree, by additional corporate borrowing. In other buyouts, incumbent managers have sufficient personal resources to purchase the entire public stock interest without having to solicit the participation of outside equity partners

Because these outside parties take a substantial equity position in the private firm, they have greater incentive to monitor managerial decisions (and distribute rewards appropriately) than a dispersed group of public shareholders. Further, the fact that certain investor groups specialize in these transactions suggests such third-party participants have a comparative advantage in monitoring the actions of management. Thus, a potential benefit from going private via a leveraged buyout is improved managerial performance resulting from the buyout specialist's superior ability and strong incentive to monitor the decisions of management (DeAngelo, DeAngelo and Rice 1984, 373).

Third, the aggressive use of debt in a leveraged buyout substantially reduces management's control over the deployment of cash flows. According to Jensen's (1986) "control hypothesis," when operating cash flows of a highly leveraged company become committed to making interest and principal payments, management faces no temptation to reinvest surplus cash at below the cost of capital or waste it on organizational inefficiencies. This reduces the agency costs of free

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and without materially increasing the level of corporate debt. In the present context, the study refers to these 'other' buyouts simply as *management buyouts*.

cash flow which means, all other things being equal, investors should see higher returns.[4]

The Lost Benefits of Public Ownership

While the proponents of leveraged buyouts are quick to point out the potential benefits from a reversion to private status, they are generally not as eager to discuss the potential drawbacks to this particular type of ownership structure. Because managers must weigh the potential benefits of going private against the benefits of public ownership that potentially will be lost, the primary limitations of a private ownership structure warrant discussion here.

First, one of the most serious limitations of private ownership is the firm is no longer able to access the public equity markets. Under private ownership, new investment will be limited by (1) the availability of senior debt financing, (2) the amount of funds the company is able to generate through operations, and (3) the current shareholders' ability and willingness to provide additional equity capital. Managers thus face the prospect that, with implied limits on new capital investment, the privately-owned firm may have to forgo otherwise profitable projects in

[4] For a more complete discussion of the role debt plays in motivating managers and their organizations to be efficient, see Michael C. Jensen, "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers," *American Economic Review*, May 1986, pp. 323-329.

order to keep the corporation closely-held (DeAngelo and DeAngelo 1987, 45).

Second, reduced marketability of the private company's common stock can also impose direct costs on managers by forcing them to hold personal portfolios that are poorly diversified or otherwise not well suited to their individual financial objectives. The costs of reduced marketability are relevant not only for incumbent managers, but also for those managers the firm expects to hire in periods after the buyout. To the extent these costs impair the firm's future ability to hire and retain qualified managers, they too should be a consideration in the decision to go private (DeAngelo and DeAngelo 1987, 45).

Third, the absence of a ready market for the private company's stock makes it difficult for shareholders to resolve disagreements over corporate policy issues. In a highly liquid equity market, investors who find the public company's risk profile or dividend policy suboptimal can sell their shares and find other investments more suited to their individual preferences. Under private ownership, however, investors cannot as readily sell their shares. Because, under this type of ownership structure, each shareholder wants corporate policy tailored to suit his or her own specific consumption preferences (e.g., for portfolio risk versus return, liquidity of investment, timing of cash distributions, etc.), costly disagreements can arise. To the extent that shareholders are unable to settle a policy dispute by selling their shares, the compatibility of prospective equity-holders' individual preferences can be an important consideration in the decision to take a company private. This is particularly true in the case of the leveraged buyout where, not only individual investor preferences will vary, but the investment horizons of outside equity holders and management are likely to differ as well. For instance, outside equity participants in a leveraged buyout typically expect to sell their interest in the private firm after five or ten years. While this horizon will usually suit the needs of managers near retirement age, it may not suit the needs of managers in the earlier stages of their careers (DeAngelo and DeAngelo 1987, 46).

The Division of Gains from Going Private

Although the existence of real resource gains from going private does not by itself imply that public stockholders benefit from these transactions, the available evidence suggests that public stockholders do share in these gains. Black and Grundfest (1988, 6) suggest that shareholder gains from takeovers (including leveraged buyouts) reflect the market's expectation that these transactions will increase the value to investors of the operations being sold. In large part, the gains reflect investors' expectations that the new owners will run the acquired businesses more efficiently. The *amount* of gains represents the market's best estimate of the present value of the future improvements in the acquired firm's financial performance.

DeAngelo, DeAngelo and Rice (1984) examined the average change in stockholder wealth (open-market share values) at the time of the initial public announcement of a going-private proposal for seventy-two firms that proposed going private during the period 1973-1980. They reported an average increase in stockholder wealth of 22.27% on the day of the announcement. When they measured average cumulative returns beginning forty trading days prior to the initial public announcement date, the average increase in stockholder wealth was 30.40%. In fifty-seven sample proposals involving strictly cash compensation, public stockholder gains were even more substantial. In relation to the market price that existed two months prior to the formal proposal, managers offered a 56.31% average premium. Bradley (1980) observed similar wealth effects in his examination of interfirm tender offers and concluded the price behavior in the period immediately preceding the announcement of an offer was attributable to the leakage of information about the offer itself. This leakage interpretation is also consistent with Keown and Pinkerton's (1981) study of merger announcements, which reported evidence of unusually large trading volume in target firms' shares in the three weeks prior to merger proposals.

Prediction Literature

In addition to a small body of literature that attempts to distinguish firms that go private from firms that remain public, there are two other bodies of work that are related and important to this study: bankruptcy prediction and acquisition target prediction. The study first examines research dealing with business failure prediction, because much of that earlier work formed the foundation for predicting acquisition targets. Next, the study reviews research involving takeover target prediction and, finally, research directly related to the problem of predicting management buyouts. Tables 11, 12, and 13 in the Appendix summarize the main characteristics of each of the studies surveyed.

Bankruptcy Prediction

Since the mid-1960s, researchers have made numerous attempts to develop models that accurately predict corporate failure using financial statement variables. Beaver (1966) was among the first to employ financial ratios in empirical analysis to predict the failure of business firms after the fact. His initial study examined individually the predictive ability of fourteen ratios selected on the basis of their popularity in the literature, performance in previous studies, and adherence to a "cash flow concept."

Beaver (1966, 80) suggested his introduction of a cash-flow model was *not* to have the model develop an optimal set of ratios, but rather to use the model as a vehicle for explaining the ratios being tested. He viewed the firm as a reservoir of liquid assets, supplied by inflows and drained by outflows. Accordingly, he used four basic propositions to draw a relationship between the liquid-asset-flow model and the ratios (Beaver 1966, 80):

[1] the larger the reservoir, the smaller the probability of failure,

[2] the larger the net liquid-asset flow from operations (i.e., cash flow), the smaller the probability of failure,

[3] the larger the amount of debt held, the greater the probability of failure, and

[4] the larger the expenditures for operations, the greater the probability of failure.

Using these propositions, Beaver formed predictions regarding the mean values of six financial ratios. The six ratios were cash flow to total debt, net income to total assets, total debt to total assets, working capital to total assets, current assets to current liabilities, and the no-credit interval.[5]

Beaver (1966, 85) found the ratio with the strongest ability to predict failure was cash flow to total debt. Using that ratio alone, he reported a classification accuracy rate of 90% in the first year prior to failure and rates that never fell below 76% in the two to five preceding years. Although the predictors in Beaver's study performed fairly well, Zavgren (1983, 10) suggested the main difficulty with his approach was classification could take place for only one ratio at a time. Thus, the potential existed for finding conflicting classifications of a given firm depending on the specific ratio employed. Because the financial status of a firm is actually multidimensional, and no single ratio can adequately capture those dimensions, several authors saw promise in a multiple discriminant analysis technique which would analyze the predictive ability of several financial ratios jointly and resolve this conflict (Zavgren 1983, 10).

Altman (1968) recognized that a univariate approach to ratio analysis for predicting bankruptcy would not give a comprehensive profile of a firm and

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[5] Beaver indicated the interval measure appeared in Sorter and Benston (1960, 633-640).

pioneered the use of linear multiple discriminant analysis for this particular problem. Discriminant analysis is a statistical technique for distinguishing among defined groups which, for the purpose of Altman's study, consisted of failing and nonfailing firms. This method characterizes an individual or a phenomenon by a vector of attributes which constitutes a multivariate density function. The discriminant function maps the multidimensional characteristics of the density function onto a one-dimensional measure by forming a linear combination of the attributes (variables) along a single axis (Zavgren 1983, 10).

Altman selected the twenty-two variables initially included in his study on the basis of their popularity in the literature and potential relevance to the study. He also included a few other ratios developed specifically for the study as part of the original variable set. To condense the variable set, Altman evaluated the statistical significance of various alternative discriminant functions, including the relative contributions of each independent variable. In addition, he assessed the intercorrelations between the relevant variables, observed the predictive accuracy of the various profiles, and applied author judgment. Ultimately, he selected for inclusion in his model the five variables that did the best overall job together in the prediction of corporate bankruptcy. A comparison with the results of Beaver's study indicated that Altman's "Z-Score" model outperformed Beaver's model in the first year prior to bankruptcy (95% versus 90% accuracy). However, the predictive accuracy of Altman's model fell off sharply (72%) in even the second year prior to bankruptcy, and continued to decline to a low of only 29% in the fourth preceding year.

Because Beaver's model was able to predict bankruptcy for as many as five years prior to failure, Deakin (1972) modified Altman's model in an attempt to improve upon the accuracy of earlier predictions. Deakin included in his model the fourteen ratios Beaver initially used and modified the sample selection procedure such that he selected nonfailed firms on a random basis. In Altman's (1968) study, the author used a nonrandom procedure to select an equal number of bankrupt and nonbankrupt firms. However, because the discriminant analysis technique employs an estimation procedure that assumes random sampling, Deakin (1972, 172) suggested more complex procedures than Altman used were needed to overcome the limitations of having a nonrandom selection. Specifically, when the research fails to employ procedures in model estimation that explicitly consider the unique nature of this sampling process, some characteristics may be overrepresented in the sample, and the resultant discriminant function may be sample specific (Zavgren 1983, 17).

In a later study, Deakin (1977, 73) further indicated the use of equal-sized samples of bankrupt and nonbankrupt firms distorts the actual prior probabilities of group membership. The earlier studies by Beaver (1966), Altman (1968) and others suffered from this bias.[6] Because these studies failed to consider the frequency of errors one would likely obtain in a real world use of the models, the stated error rates may not have reflected the extent of each type of error. The most serious effect would be the tendency to understate the misclassification of nonfailing firms into the failing category.

Rather than use a critical value for classifying each case, Deakin (1972) used a modification of discriminant analysis that assigns probabilities for membership to the respective classes. Although earlier studies used a critical value to classify firms into specified categories (see Altman 1968; Frishkoff 1970;

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[6] To illustrate the potential distortion in prior probabilities, consider the population of firms from which Beaver (1966) drew a sample of bankrupt and nonbankrupt firms. Beaver's sample included all public firms that failed during the period 1954-1964 plus nonfailed firms selected from a list of 12,000 firms (i.e., *12,000 Leading U. S. Corporations*). If one could assume the distribution of these 12,079 firms accurately represented the prior probabilities in the population, the prior probabilities during 1954-1964 would have been .654% (failed firms) and 99.346% (nonfailed firms).

Frank and Weygandt 1971), Deakin (1972, 174-175) suggested this approach fails to take into account the relative scores of each case. As Frank and Weygandt (1971, 123) showed, the greatest number of classification errors occurs when scores fall close to the critical value. Hence, Deakin's (1972) use of probabilities to classify firms into failed and nonfailed categories was an attempt to achieve more accurate classification results.

In order to assign a probability of group membership to each case, Deakin (1972, 175) used a multivariate extension of the univariate *Z* test:

$$d' \Sigma^{-1} d \sim \chi_p^2, \qquad [3.1]$$

where d' = the row vector of deviation scores,
d = the column vector of deviation scores,
Σ = the population variance-covariance matrix,
and
p = the degrees of freedom of the chi-square distribution and equals the number of elements in the deviation score vector.

Use of this technique relies on the additional assumption that the vectors of the scores follow a p-variate normal distribution, and the variance-covariance matrix of each subgroup matches the population variance-covariance matrix.

To explain this technique further, consider the case of two variables X_1 and X_2 and the bivariate normal density function (Tatsuoka 1971, 63):

$$\phi(X_1, X_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left[\frac{-1}{2(1-\rho^2)}\left\{\frac{(X_1-u_1)^2}{\sigma_1^2} + \frac{(X_2-u_2)^2}{\sigma_2^2} - 2\rho\frac{(X_1-u_1)(X_2-u_2)}{\sigma_1\sigma_2}\right\}\right], \qquad [3.2]$$

where u_1 and σ_i^2 are the mean and variance of X_i (i = 1, 2), and ρ is the correlation coefficient. Because matrix notation facilitates the generalization to p variables, Tatsuoka (1971, 66) rewrites the quantities in equation [3.2] using that special notation.

First, for a bivariate population, the variance-covariance matrix is as follows:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho\,\sigma_1\sigma_2 \\ \rho\sigma_2\sigma_1 & \sigma_2^2 \end{bmatrix}. \qquad [3.3]$$

The determinant of this matrix is

$$|\Sigma| = \sigma_1^2\sigma_2^2(1-\rho^2), \qquad [3.4]$$

and the inverse of Σ is

$$\Sigma^{-1} = 1/\sigma_1^2\sigma_2^2(1-\rho^2)\begin{bmatrix} \sigma_2^2 & -\rho\,\sigma_1\sigma_2 \\ -\rho\sigma_2\sigma_1 & \sigma_1^2 \end{bmatrix}$$

$$= 1/(1-\rho^2)\begin{bmatrix} 1/\sigma_1^2 & -\rho/\sigma_1\sigma_2 \\ -\rho/\sigma_2\sigma_1 & 1/\sigma_2^2 \end{bmatrix}. \qquad [3.5]$$

One can now readily see that the expression in the exponent of equation [3.2], aside from the factor -1/2, is equivalent to the quadratic form (Tatsuoka 1971, 66):

$$[X_1 - u_1,\ X_2 - u_2]\ \Sigma^{-1} \begin{bmatrix} X_1 - u_1 \\ X_2 - u_2 \end{bmatrix}. \qquad [3.6]$$

Letting χ^2 symbolize this expression and introducing

$$d' = [X_1 - u_1,\ X_2 - u_2], \qquad [3.7]$$

Tatsuoka (1971, 66) rewrites equation [3.6] as

$$\chi^2 = d'\Sigma^{-1}d. \qquad [3.8]$$

Since $\sigma_1\sigma_2\sqrt{1-\rho^2}$ is the square root of $|\Sigma|$, as seen from equation [3.4], one may write the constant factor $1/2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}$ of the expression for $\phi(X_1,X_2)$ as $(2\pi)^{-1}|\Sigma|^{-1/2}$ (Tatsuoka 1971, 66).

Therefore, one can write equation [3.2], the specification of the bivariate normal density function, as

$$\phi(X_1,X_2) = (2\pi)^{-1}|\Sigma|^{-1/2}\exp(-\chi^2/2), \qquad [3.9]$$

with Σ and χ^2 previously defined (Tatsuoka 1971, 66).

The extension to the *p*-variate case now becomes apparent. First, define the variance-covariance matrix:

$$\Sigma = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \cdots & \rho_{1p}\sigma_1\sigma_p \\ \rho_{21}\sigma_2\sigma_1 & \sigma_2^2 & \cdots & \rho_{2p}\sigma_2\sigma_p \\ \vdots & & \ddots & \vdots \\ \rho_{p1}\sigma_p\sigma_1 & \rho_{p2}\sigma_p\sigma_2 & \cdots & \sigma_p^2 \end{bmatrix} \qquad [3.10]$$

where σ_i^2 is the variance of X_i, and ρ_{ij} $(i \neq j)$ is the coefficient of correlation between X_i and X_j. Let

$$\chi^2 = d' \Sigma^{-1} d \qquad [3.11]$$

with

$$d' = [X_1 - u_1,\ X_2 - u_2,\ \ldots,\ X_p - u_p], \qquad [3.12]$$

then the p-variate normal density function is

$$\phi(X_1, X_2, \ldots, X_p) = K \exp(-\chi^2/2) \qquad [3.13]$$

where only the constant K remains to be determined (Tatsuoka 1971, 67).

A comparison with the univariate normal density function,

$$\phi(X) = \frac{1}{\sqrt{2\pi\sigma}} \exp[-(X - u)^2/2\sigma^2], \qquad [3.14]$$

in which the normalizing constant is

$$(2\pi)^{-1/2}(\sigma^2)^{-1/2} \qquad [3.15]$$

leads to the following inference: the power of 2π is -1/2 times the number of variables, while the power of $|\Sigma|$ (which reduces to σ^2 in the univariate case) is -1/2 regardless of the number of variables. Thus, for the p-variate case (Tatsuoka 1971, 67):

$$K = (2\pi)^{-p/2} |\Sigma|^{-1/2}. \qquad [3.16]$$

Finally, the complete equation for a p-variate normal density function is as follows (Tatsuoka 1971, 67):

$$\phi(X_1, X_2, \ldots, X_p) = (2\pi)^{-p/2} |\Sigma|^{-1/2} \exp(-\chi^2/2) \qquad [3.17]$$

with Σ and χ^2 previously defined in Eqs. [3.10] and [3.11] respectively. One denotes this distribution by the symbol $N(\mathbf{u},\Sigma)$, meaning a multivariate normal distribution with centroid $\mathbf{u} = [u_1, u_2, \ldots, u_p]'$ and dispersion matrix Σ. Note the close analogy between the *p*-variate normal density function (Eq. 3.17) for $N(\mathbf{u},\Sigma)$ and the familiar univariate normal density function (Eq. 3.14) for $N(u,\sigma^2)$. In particular, the expression

$$-\chi^2/2 = -(d'\,\Sigma^{-1}d)/2 \qquad [3.18]$$

that occurs in the exponent in Eq. [3.17] is a "natural" generalization of the expression

$$-(X-u)^2/2\sigma^2 = -[(X-u)(\sigma^2)^{-1}(X-u)]/2 \qquad [3.19]$$

that occurs in the univariate case (Tatsuoka 1971, 67-68).

Although various measures of *profile* (or *pattern*) *similarity* and of distance (that is, *dissimilarity*) have appeared in the literature (Mahalanobis 1936; Cattell 1949; Du Mas 1949), Tatsuoka (1971, 218) suggests that the selection of the χ^2 statistic as a measure of *dissimilarity* is a reasonable choice. Specifically, the larger the χ^2 value of an individual (or firm) with reference to a given group, the farther away is the point $[X_{1i}, X_{2i}, \ldots, X_{pi}]$ representing a set of scores from the *k*th population centroid $u'_k = [u_{1k}, u_{2k}, \ldots, u_{pk}]$. Otherwise stated, an individual (or firm) is more deviant from the "average member" of that group, the larger its χ^2 value. Conversely, an individual (or firm) with a small χ^2 value with reference to a group is "closer" to the average member of that group.

To summarize this simple classification scheme, the study refers to Tatsuoka (1971, 218) and what he calls the *minimum chi-square rule* :

> Compute the χ^2 value of the unclassified individual (firm) with respect to each of the K groups, and assign the individual (firm) to that group with respect to which the χ^2 value is the smallest.

Note that this rule has the property of minimizing the probability of misclassifications for K populations with multivariate normal distributions and equal variance-covariance matrices.

When Deakin validated his results against the sample used to derive the discriminant functions, this technique produced classification error rates that were significantly lower than either Beaver or Altman found (less than 5% in each of the first three years prior to failure). However, when he validated his results against a holdout sample of bankrupt and nonbankrupt firms, the error percentages deteriorated. Zavgren (1983, 19-20) suggested this may have been an indication of sample-specific results. Further, although Deakin's technique relied on the assumption that the variables are multivariate normal, he performed no test of multivariate normality. Deakin (1976) determined in a later study that financial ratios were nonnormal. Diamond (1976) conducted similar tests that indicated financial ratios were approximately normal only if outliers were rejected (Zavgren 1983, 20). Because univariate normality is a necessary but not sufficient condition for normality of the ratios' joint distribution, Zavgren (1983, 20) suggested adherence to the assumption of multivariate normality is doubtful in Deakin's case. She further indicated violation of this assumption could seriously affect the accuracy of prediction results. In addition to failing to test for multivariate normality, Deakin did not test for equality of the variance-covariance matrices. Eisenbeis (1977, 877) suggested relaxation of this assumption can affect the significance test for the difference between "in-group" means, as well as the appropriate form of classification rule (linear versus quadratic).

Diamond (1976) adopted a technique called *pattern-recognition* for identifying the significant characteristics of firms that are failing. Pattern recognition is a data reduction technique which reduces the variable set to the best differentiating dimensions. The procedure involved three stages: collection of data for use in identification, selection of the most important features, and classification. The data used for identification were financial ratios. The feature selection techniques used to optimize discrimination according to select criteria were (1) stepwise discriminant analysis, (2) principal components analysis, and (3) the optimal discriminant plane.

Stepwise discriminant analysis is a variant of discriminant analysis that includes variables on the basis of discriminating power. Specifically, the procedure tests whether the adding or deleting of variables alters the value of the Mahalanobis D^2, a measure of the distance between the groups. This technique is similar to stepwise regression analysis, except the latter procedure tests whether the adding or deleting of a variable alters the value of the multiple R^2. The R^2 measures the degree to which the regression equation fits the data (Afifi and Clark 1984, 136).

Principal components analysis is a variant of factor analysis that transforms a set of interrelated variables into new, uncorrelated variables called *principal components*. Because the variance of each principal component is a measure of the amount of information conveyed by that component, principal components appear in order of decreasing variance. Thus, the principal component that is most informative is the first, and the principal component that is least informative is the last (i.e., a variable with zero variance does not distinguish between members of the population) (Afifi and Clark 1984, 309-310).

The optimal discriminant plane technique is a transformation procedure that "projects the data onto a subspace in such a way that the difference between means is maximized relative to the sum of the projected within-class variability." The optimal discriminant plane technique differs from principal components analysis in that the former emphasizes classification (i.e., separation of the means) and the latter emphasizes data reduction (i.e., maximum variance). The optimal discriminant plane technique considers all variables, rather than a reduced set of variables, and transforms them to optimize a discriminating criterion.

Diamond also used three different classifiers with each of the feature selection techniques: a linear discriminant, a quadratic discriminant, and a Bayesian predictor classifier. The first two are distance classifiers, and the third one is a probability classifier. Discriminant classifiers use a linear function if the variance-covariance matrices are equal across all groups, and a quadratic function if they are dissimilar. The Bayesian classifier allows the use of sample parameters rather than population parameters.

Because principal components analysis resulted in poor classification accuracy, Diamond dropped this as a feature selection technique. Also, the linear classifier was statistically inappropriate because the variance-covariance matrices were unequal. In the first year prior to failure, both the stepwise and optimal discriminant plane techniques achieved overall classification accuracy of 90%. The Bayesian classifier appeared to identify failing firms more accurately. In the second and third years prior to failure, overall prediction ability was over 90% for both feature selection techniques. In this case, the optimal discriminant plane technique with either the quadratic or Bayesian classifier appeared to be the best predictor of bankruptcy.

An analysis of the results of Diamond's refinement of the multivariate approach to predicting bankruptcy indicates that adherence to the basic assumptions of statistical techniques and proper attention to the characteristics of the data can provide a more realistic model. Diamond further refined his approach by explicitly considering the costs of misclassification and the prior probabilities of group membership. However, such refinements in technique and meticulous adherence to statistical assumptions failed to produce a significant improvement over other studies in terms of predictive accuracy. It thus appears the benefits to further improvements in the discriminant analysis approach have neared their limit (Zavgren 1983, 23).

Later studies (Martin 1977; Ohlson 1980; Zavgren 1982) employed a probability model for estimating the likelihood of financial failure. This type of model estimates the probability of occurrence of a choice or outcome (financial failure, in this case), conditional on the attribute vector of the individual (firm) and the choice or outcome set that is available. The "logit" and "probit" models are two of the most commonly used nonlinear forms of the probability model. Their derivation stems from the linear probability model as detailed below.

Consider the regression model with $p - 1$ independent variables:

$$Y_i = \sum b_k X_{ik} + u_i, \qquad [3.20]$$

where Y is the dependent variable, p is the number of parameters, X_k for $k = 1, \ldots, p - 1$ are the exogenous or independent variables, u is the random error or disturbance term, b_k are unknown constants, and the subscript i denotes the ith observation from the sample of size N.[7] The model assumes that u_i is not

[7] For the sake of simplicity, the study uses abbreviated notation for the expression of the

correlated with any of the independent variables, X_k, and that it has a mean of zero. This implies that, given the X_i, the expected value of Y_i is:

$$E(Y_i | X_{i1}, \ldots, X_{ik}) = \sum b_k X_{ik}. \qquad [3.21]$$

The regression model places no restrictions on the values of the independent variables, except that they not be exact linear combinations of each other. The model does, however, assume that the dependent variable is continuous. In the case of a dichotomous dependent variable (i.e., Y_i can take on only two values), the violation of this assumption is so extreme, it warrants special attention.

Suppose Y_i equals either zero or one. The expected value of Y_i reduces to the probability that Y_i equals one [i.e., $P(Y_i = 1)$]:

$$E(Y_i) = \{[1 \cdot P(Y_i = 1)] + [0 \cdot P(Y_i = 0)]\} = P(Y_i = 1) \qquad [3.22]$$

The combination of equations [3.21] and [3.22] yield the following result:

$$E(Y_i) = P(Y_i = 1) = \sum b_k X_{ik}. \qquad [3.23]$$

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regression model. Using full notation, the study would express equation [3.20] as follows (Neter, Wasserman and Whitmore 1982, 514):

$$Y_i = b_0 + b_1 X_{i1} + b_2 X_{i2} + \ldots + b_{p-1} X_{i,p-1} + u_i,$$

or, alternatively,

$$Y_i = \sum_{k=0}^{p-1} b_k X_{ik} + u_i$$

where $X_{i0} \equiv 1$.

Therefore, the right-hand side of the regression equation must be interpretable as a probability, i.e., restricted to between zero and one. For this reason, the designation for a linear regression model with a dependent variable that is either zero or one is the *linear probability model* or LPM (Aldrich and Nelson 1984, 11-13).

For a variety of reasons, Aldrich and Nelson (1984, 30) suggest the assumption that a probability model is linear in the independent variables is unrealistic in most cases. Therefore, the obvious solution to this problem is to specify a nonlinear probability model in place of the linear probability model. The problem with the specification of the linear probability model is that the model uses $\sum b_k X_{ik}$ to approximate a probability number P_i [$P_i \equiv P(Y_i = 1)$], constrained to range from 0 to 1, while there are no such constraints on $\sum b_k X_{ik}$. One solution to this problem is to transform P_i to eliminate one or both constraints (i.e., the upper and lower bounds, one and zero, respectively). To eliminate the upper bound, $P_i = 1$, one turns to the ratio $P_i/(1 - P_i)$. This ratio must be positive because $0 < P_i < 1$, however, there is no upper bound. As P_i nears one, $P_i/(1 - P_i)$ approaches infinity. To eliminate the lower boundary, $P_i = 0$, one takes the natural logarithm, $\log [P_i/(1 - P_i)]$, the result of which can be any real number from negative to positive. One can now (arbitrarily) assume that the transformed dependent variable P_i is a linear function of X:

$$\log [P_i / (1 - P_i)] = \sum b_k X_{ik} = Z_i . \qquad [3.24]$$

For the sake of simplicity, the study uses Z_i to represent the summation $\sum b_k X_{ik}$.

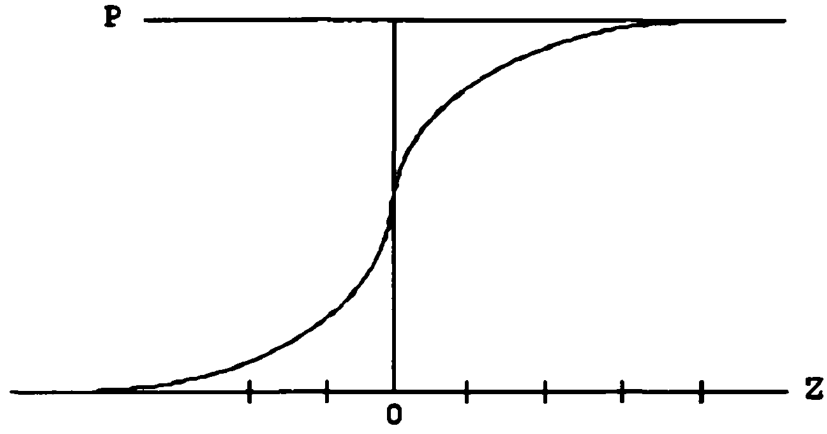
One can obtain an expression for P_i by using antilogarithms and algebraic manipulation. The base number of the natural logarithm is e, an irrational number, where $\log(e^x) = x$ and, thus, the antilog of x is e^x. The more common notation is "exp(·)" which means e raised to the power of the term inside the parentheses. The solution to equation [3.24] for P_i is:

$$P_i = \exp(Z_i) / (1 + \exp(Z_i)) = 1/(1 + \exp(-Z_i)). \qquad [3.25]$$

This *logistic function* is continuous and can only take on values ranging from 0 to 1. The function is near 0 when Z_i approaches negative infinity. It increases monotonically with Z_i, and reaches 1 as Z_i goes to positive infinity. As Figure 1 indicates, the logistic function is a smooth S-shaped curve that is symmetric about the point $Z_i = 0$ (Aldrich and Nelson 1984, 31-33).

A frequently used alternative to the "logit" model is the "probit" model. When one uses the *cumulative normal distribution* to constrain the predicted values, the probit model results:

Figure 1
The Logistic Function

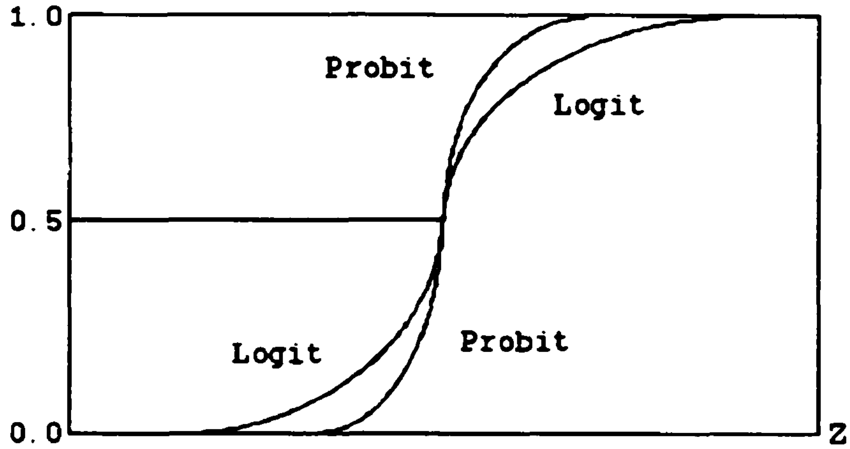


Source: Aldrich and Nelson (1984, 33)

$$P_i = F(Z) = \int_{-\infty}^{Z} \frac{1}{\sqrt{2\pi}} \exp(-u^2/2)\,du. \qquad [3.26]$$

A comparison of the logistic and cumulative normal functions appears in Figure 2. As the drawing indicates, the logistic and cumulative normal functions are very close in the midrange, but the logistic function has slightly heavier tails than the cumulative normal function. Kmenta (1986, 555) suggests this is of little concern except in cases where the data are heavily concentrated in the tails. Further, because the logistic function represents a close approximation to the cumulative normal function and is apparently easier to work with, most researchers prefer to use the

Figure 2
The Logistic and Cumulative Normal Functions



Source: Kmenta (1986, 555)

logistic function. In fact, the logit and probit models produce very similar results when the dependent variable is dichotomous. Only when the dependent variable is polytomous are there major differences between the two models (Kmenta 1986, 555).

Because one can use a probability model in place of a discriminant model, certain factors must exist that influence the researcher's preference for one model over another.[8] Zavgren (1983, 24-25) suggests the choice between a discriminant analysis model and probability model depends largely on the use for which one intends the results. For instance, discriminant

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[8] Note that one can use a discriminant model to classify subjects into one of *two or more* groups or populations. Generally, however, one is able to use a probability model when classifying subjects into one of *two groups only*.

analysis may be adequate when the decision under consideration requires only the dichotomous classification of failing versus nonfailing firms, even if violation of the statistical assumptions makes the evaluation of any result other than sample-specific prediction impossible. However, she further suggests, few decisions exist for which such a partitioning of the outcome space is adequate. For example, for the purchaser of bonds, the investor in capital stock, or the banker faced with making a commercial loan decision, an assessment of financial risk is generally more appropriate. Thus, if the probability of business failure is estimable, one is able to determine more readily the optimal investment strategy or appropriate risk premiums.

In addition to providing an estimate of the probability of an occurrence, logit analysis enables direct interpretation of the various explanatory variable coefficient estimates. MDA coefficients, on the other hand, are only unique up to a factor of proportionality, rendering interpretation of their relative importance difficult if not impossible. Therefore, when the purpose of the research is to isolate variables that are to be given further theoretical consideration within a specific decision context, the use of a probability model may be more desirable.

Ohlson's (1980) bankruptcy prediction study represents one of a limited number of studies that attempted to predict financial distress using a probability (logit) model. Ohlson selected nine variables for inclusion in his study on the basis of their frequent appearance in the literature (e.g., total liabilities divided by total assets, current assets divided by current liabilities, and net income divided by total assets). Using the nine variables, he estimated three models: the first to predict failure within one year prior to bankruptcy, the second to predict failure within two years prior to bankruptcy given that the firm did not fail in the first year, and the third to predict failure within one or two years prior to bankruptcy. Using an arbitrary cutoff probability of .50, Ohlson (1980, 120-121) reported classification accuracy rates of 96.1%, 95.6%, and 92.8% for models 1, 2, and 3, respectively.

Recognizing that the marginal (unconditional, prior) probability of bankruptcy was important in determining predictive accuracy, Ohlson also assessed classification accuracy using a cutoff probability that incorporated that information. The classification procedure he used assumed the effects of Type I and Type II errors are additive and that the best model minimizes the sum of errors. The cutoff probability that resulted from this procedure was .038. At that point, Ohlson (1980, 126) reported classification accuracy rates of 87.6% and 82.6% for the bankrupt and nonbankrupt firms, respectively, in the first year prior to failure. He did not perform this same analysis for the other two models.

Although generally Ohlson reported classification accuracy rates that were fairly high, a number of methodological problems may have biased the results. One problem is that he did not use a holdout sample to test the predictive accuracy of the model. As suggested earlier, when one uses the same set of data to estimate and validate the model, the potential exists for producing sample-specific results (Zavgren 1982, 19-20). Ohlson (1980, 125), however, indicated there were four reasons for not using a holdout sample in his study. First, it was not Ohlson's intention to find a "best" model or even a model that was "superior" to model 1. Second, the logit technique is not an econometric method designed to find an "optimal" frontier, trading off one type of error against another. This is in contrast to multiple discriminant models that satisfy optimality conditions under certain assumptions. Third, the sum of the percentage of errors appeared to be relatively robust across a wide range of cutoff points. Finally, Ohlson believed the relatively large sample size would reduce the bias stemming from the failure to use a holdout sample.

Another problem with Ohlson's (1980) study was the ad hoc specification of the model in the absence of a theory. This same problem was noted in all prior business failure studies. Also, it was likely the observed presence of a number of closely correlated variables biased the resulting function toward the sample from which it was developed, thus producing sample-specific results.

Acquisition Target Prediction

The bankruptcy prediction studies used techniques which were also applicable to the prediction of corporate takeovers. Simkowitz and Monroe (1971) were among the first to attempt to distinguish acquired firms from nonacquired firms on the basis of financial characteristics. They used a stepwise discriminant analysis procedure to classify firms into acquired/ nonacquired categories and determined that acquired firms were smaller in size, had lower price-earnings ratios and dividend payouts, and had low growth in equity. Simkowitz and Monroe (1971, 11-12) reported classification accuracy rates of 83% for targets and 72% for non-targets in the sample used to estimate the model. When they validated their results against a holdout sample, the model correctly classified 64% and 61% of the targets and non-targets, respectively. Although the classification accuracy rates were fairly high (at least in the former case), the presence in this study of closely correlated variables raised some doubt as to which financial characteristics were significant (Stevens 1973, 149). Also, as indicated earlier, highly correlated input data can bias the resultant discriminant function producing sample-specific results, which may account for the fact that classification accuracy rates were lower when they used a holdout sample.

In order to reduce the problem of multicollinearity in the Simkowitz and Monroe study, Stevens (1973) selected a different variable set and employed a factor analysis procedure. Factor analysis is a technique for examining the interrelationships among a set of variables. Its primary purpose is to reduce a large number of variables to a few interpretable constructs (factors) (Aaker 1971, 209). Due to the high level of multicollinearity, Stevens was able to reduce his original group of twenty ratios into only six factors. Once he determined these factors, he then entered the ratio with the highest factor loading from each dimension (factor) into a linear multiple discriminant model. When validated against the sample used to develop the model, the model's accuracy was approximately 70%. The accuracy was approximately 68% when Stevens validated the results against a holdout sample. Stevens performed a second type of validation to determine if the variables in the model and their coefficients remained stable over time. Again, he achieved a 70% accuracy rate for the two years subsequent to the year from which he developed the model, indicating support for the stability of the financial variables and the discriminant model over other time periods. While results of this study are encouraging, one should note that when Stevens substituted the ratios for the factors, he reintroduced some correlation among the variables (Stevens 1973, 154). This implied that the redundancy problem was still present and the resulting discriminant function retained the potential for being biased toward the sample from which it was developed.

Dietrich and Sorensen (1984) employed a logit technique for identifying merger targets that was similar in methodology to Ohlson's (1980) bankruptcy prediction study. Because the merger decision is similar to any other capital investment decision, they adopted a net-present-value approach for selecting the variables that measure the attractiveness of a given firm as a merger target. Specifically, they expected those factors that tended to increase the net present value of cash flows to increase the attractiveness of a particular merger candidate, while factors tending to increase the cash outflows associated with a merger would reduce its attractiveness. Given this framework, it was only those potential targets with large, positive net-present-values that were likely to dominate an acquiring firm's set of alternative investment opportunities.

While the target firm's operating data will reflect some of the factors that affect current and expected future cash flows, Dietrich and Sorensen (1984, 394) suggested many sources of future cash benefits or costs associated with a merger are not observable in financial data. For example, firm attributes that produce recognizably valuable or costly economies may exist only in conjunction with the characteristics of potential acquirers or may simply be the result of conditions in product and factor markets. The target firm's financial data may not reflect legal, information, and/or regulatory costs associated with identifying and realizing anticipated benefits from a merger. Also, there are other factors associated with a merger, such as management's willingness to resist a takeover, that are not subject to quantification. In their analysis, Dietrich and Sorensen assumed the unmeasurable factors that increase or detract from the attractiveness of a particular candidate are randomly distributed across all potential target firms. Their model thus postulated the firm's likelihood of becoming a merger target is a function of both observable characteristics and a random element resulting from characteristics that are not subject to measurement.

As discussed in the previous section, logit analysis allows one to estimate the probability of occurrence of a choice or outcome, dependent on the attributes of the individual and the choice or outcome set that is available. According to Dietrich and Sorensen (1984, 398), there are a number of reasons why logit analysis is particularly well suited to the prediction of acquisition targets. First, by evaluating the logit probability function for a firm using its measured attributes and comparing the outcome to similar calculations for other firms, one is able to rank these firms as to their relative probability of becoming a merger target. Second, the use of this method does not depend on the assumption that variables are multivariate normal which, in contrast, is a requirement when using multiple discriminant analysis. Third, logit analysis allows for a comparison of the relative importance of the explanatory variables in determining a given firm's likelihood of being a merger candidate.

The classification accuracy rates that Dietrich and Sorensen reported were quite high. When validated against the sample used to develop the model, the model correctly classified 62 of the 67 (93%) observations into the merged or nonmerged categories.[9] When validated against a holdout sample, the model correctly classified 5 of the 6 (93%) merged firms and 15 of the 16 (94%) nonmerged firms. While the results of this study and other prior studies suggested statistical models using public data can accurately predict acquisition targets, it appears the stock market is unable to predict acquisition targets with a high degree of accuracy as little as three months prior to the announcement of a takeover bid. Asquith's (1983) and Dodd and Ruback's (1977) examinations of the pre-takeover stock price movement of merger targets support such a theory.

Asquith (1983) investigated the stock market's response to a merger bid over several event time periods, including the period immediately preceding the announcement of a merger bid, and the day of the announcement of the merger bid. He examined average daily cumulative excess returns of target firms for the period $t = -480$ to $t = -20$ trading days before the press date. Asquith defined "press day" as the day the news of the merger bid first appeared in the *Wall Street Journal*. For the 211 firms for which the merger

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[9] Dietrich and Sorensen did not report separately classification accuracy rates for the merged and nonmerged categories. However, they did indicate there were 24 merged and 43 nonmerged firms in the sample used to estimate the model.

bid was successful, the target firm's residuals declined on average from -0.2% at t = -480 to -14.1% at t = -20. For the 91 firms for which the merger bid was unsuccessful, the target firm's residuals declined on average from -0.1% at t = -480 to -10.5% at t = -20. Average daily excess returns in the period t = -15 to t = -1 ranged from +0.1% to +3.5% for the target firms with successful bids. For the target firms with unsuccessful bids, the average daily excess returns ranged from -0.4% to +5.0%. The average daily excess returns on press day, t = 0, were +2.7% and +2.0% for the target firms with successful and unsuccessful bids, respectively. On day t = -1, the excess returns for these same target firms were +3.5% and +5.0%, respectively. Excess returns were actually larger for day t = -1 than for day t = 0 as a result of the data collection technique. Frequently, company officials announce a merger bid on day t = -1, but the announcement does not appear in the *Wall Street Journal* until day 0. If the announcement comes before the market closes, the market's response to the news actually pre-dates the press day. If the announcement comes after the market closes, the market responds on publication day. Thus, to measure the effect of the announcement, one must consider the two-day period: t = -1 and t = 0.

Although the average daily cumulative excess returns for all target firms steadily decreased during the period *t* = -480 to *t* = -20, the cumulative excess returns exhibited an increasing trend in the 20 days preceding the announcement of a merger bid. As one would expect, the largest average daily excess return occurred on the day of the announcement (*t* = -1 or *t* = 0, as the case may be). Asquith (1983, 64-65) suggested the abnormal performance in the 20 trading days prior to the formal announcement of a merger bid was attributable to the leakage of information about the merger bid itself. However, because the two-day press day excess returns dominated all other daily returns, Asquith concluded that most of the new information becomes available on these days.

An earlier study by Dodd and Ruback (1977) also examined the stock market's response to tender offers, both successful and unsuccessful. Rather than examining *daily* excess returns as Asquith (1983) did, they measured the stock market's response to the tender offer by using *monthly* excess return data. They also examined monthly excess returns over a longer period of time--the 60-month period prior to the month of the first public announcement of a tender offer (month 0). While the results of the two studies are not directly comparable, there are some similarities. Dodd and Ruback (1977, 351) determined that the stockholders of both successful and unsuccessful target firms earn large positive abnormal returns from tender offers, and most of these returns occur in the month of the offer. In their study, the cumulative average excess return in the month of the announcement was +20.89% and +18.96% for the successful and unsuccessful target firms, respectively. In comparison, Asquith (1983, 61) reported average daily cumulative excess returns for the period t = -15 to t = 0 of +12.6% and +11.8% for target firms with successful and unsuccessful bids, respectively. Average daily cumulative excess returns for the period t = +1 to t = +15 were +2.6% and -3.2% for these same respective firms.

In their review of this and other evidence on the market for corporate control, Jensen and Ruback (1983, 29) concluded it may be extremely difficult, if not impossible, for the market to predict future takeover targets. However, it would appear the models developed in earlier acquisition studies (e.g., Simkowitz and Monroe 1971; Stevens 1973; Dietrich and Sorensen 1984) are better able than the stock market to identify future takeover targets. Otherwise stated, if the claims of these studies are valid, investors may be able to earn abnormal returns by using the prediction models.

Palepu (1986) examined the methodologies employed in these earlier acquisition studies and concluded that methodological flaws may have biased the results, making the reported prediction accuracies unreliable. The three principal methodological flaws that Palepu addressed are: (1) the failure to adjust the estimators for the non-random nature of the sampling process, (2) the use of non-random equal-share samples in prediction tests, and (3) the arbitrary establishment of a cutoff probability. The following paragraphs explain further.

First, it is typical in the earlier acquisition prediction studies for the sample of firms to consist of an approximately equal number of targets and non-targets. This type of sample, referred to a state-based or choice-based sample, is not a pure random sample because, unlike in random sampling, a firm's probability of being selected into the sample is a function of its acquisition status, i.e., whether a firm is a target or not. Palepu (1986, 4), Zmijewski (1984, 65) and others suggest that unless the research employs estimators that have been appropriately modified, the use of choice-based samples in model estimation can lead to inconsistent and biased estimates of the model parameters and hence biased estimates of the acquisition probabilities. As the following paragraph illustrates, possible biases in the estimator of 30% or more can result.

Using simulation analysis, Coslett (1981) examined the magnitude of the bias in the estimator $\boldsymbol{\theta}$ for a choice-based sample estimated as a random sample. He examined the bias in $\boldsymbol{\theta}$ assuming different values of Q_i [Q_i = the proportion of the population choosing alternative i]. For each proportion Q_i [i.e., Q_i = .50, Q_i =.75, Q_i =.90, etc.], he also examined the bias in $\boldsymbol{\theta}$ assuming three different designs for relative subsample sizes: {1} a pseudo random sample in which the subsample sizes H_i were proportionate to the population shares [i.e., $H_i = Q_i$], {2} equal subsample sizes, [i.e., H_i = .50], and {3} subsample sizes chosen so as to minimize the asymptotic variance of $\boldsymbol{\theta}$, i.e., the optimal sample design. For example, assume the true value $\boldsymbol{\theta}^*$ = .348, Q_i = .75, and H_i = .50. If $\boldsymbol{\theta}$ = .368, the asymptotic bias is 5.75% [(.368 - .348)/ .348]. As Q_i increases, the asymptotic bias increases as well. If the true value $\boldsymbol{\theta}^*$ = 3.12, Q_i = .995, H_i = .50, and $\boldsymbol{\theta}$ = 4.14, then the asymptotic bias is 32.69% [(4.14 - 3.12)/3.12]. Given the latter assumptions, but H_i = .75, the asymptotic bias is 29.17% [(4.03 - 3.12)/3.12] for $\boldsymbol{\theta}$ = 4.03 (Coslett 1981, 95).

To illustrate the difference between a random sample and a choice-based sample, consider a population of N firms comprised of N_1 targets and N_2 non-targets. Assume the desired sample size is n. In the case of random sampling, researchers select n firms randomly from the entire population. Under a choice-based sampling procedure, however, researchers randomly draw n_1 firms from the target subpopulation and n_2 firms from the non-target subpopulation. Researchers typically set n_1 and n_2 at amounts that are approximately equal. The n_1 and n_2 total to n.[10]

Because the number of targets is very small compared to the number of non-targets in the entire population, Palepu (1986, 6) suggests there is valid

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[10] At this point, the distinction between a choice-based sample and a stratified sample is worthy of mention. In stratified sampling, researchers first classify the population into subsets on the basis of one or more *exogenous* variables. They then draw a random sample from each subgroup, but not necessarily at the same rates. For example, assume researchers are interested in studying the choice of transportation mode for travel between home and work. They may sample both city and suburban residents as to their choice of transportation, but they may sample suburban residents at a higher rate. According to Coslett (1981, 56), stratified sampling does *not* present a problem in obtaining consistent estimates of the model parameters.

In choice-based sampling, researchers base the classification of the population into subsets to be sampled on the choices or outcomes. For each alternative, researchers then draw a random sample of those individuals who chose that alternative. One can consider this an *endogenous* sampling process, as opposed to the exogenous stratification described above. For example, assume researchers are interested in determining the probability an individual uses the bus as his or her primary mode of transportation between home and work. They will sample individuals that use that mode of transportation, as well as individuals who use other modes of transportation (e.g., automobile, train, etc.). Unlike stratified sampling, choice-based sampling *does* pose a problem in obtaining consistent estimates of the parameters. However, Coslett (1981, 56) and others suggest that researchers can avoid this problem by modifying accordingly the estimation technique.

economic justification for preferring a choice-based sample over a random sample when estimating an acquisition prediction model. If researchers were to draw a random sample from such a population, the sample would likely consist of an overwhelming number of non-targets and very few targets. The 'information content' of such a sample for model estimation is obviously quite small and leads to relatively imprecise parameter estimates. A choice-based sample, on the other hand, enriches the sample informationally by making the sample proportion of targets and non-targets more evenly balanced.

Various studies address the potential gains in efficiency from using choice-based samples. For instance, Manski and Lerman (1977) and Manski and McFadden (1981) show that, in a population like the one described in the preceding paragraph, an appropriate choice-based sample provides more efficient parameter estimates compared to a random sample of the same size. Alternatively, for a given level of precision, a choice-based sample reduces the required sample size (Palepu 1986, 7). Coslett (1981, 103) further reports that the efficiency of a choice-based sample of equal proportions is usually close to the efficiency of the optimal sample design.

The second methodological flaw of the earlier acquisition studies that Palepu (1986) addresses is the use of non-random, equal-share samples in prediction tests. As the previous discussion shows, valid econometric justification exists for preferring a choice-based sample over a random sample in estimating the model parameters. However, there is no such justification for the practice in previous studies of employing choice-based samples in prediction tests.

In the acquisition prediction studies, researchers use a model to identify firms in the population as targets and non-targets. When judging the forecasting usefulness of these models, the statistic of interest is usually the expected error rates in the population. Because a choice-based sample is non-random by definition, the error rate inferences based on this type of sample are not directly generalizable to the population. Thus, the very unequal distribution of targets and non-targets in the population, which justifies the use of a choice-based sample when estimating model parameters, argues strongly against its use in prediction testing. Palepu (1986, 10) suggests that predicting acquisition targets is like "searching for a needle in a haystack" because only a small fraction of the firms are actually targets. He contends the use of a contrived sample with a large proportion of targets tends to obscure this difficulty.

If using a choice-based sample in prediction tests leads to error rate estimates that fail to reflect accurately the model's predictive ability in the population, the researcher must attempt to develop an alternate test sample. Because the actual use of a model involves the entire population of targets and non-targets, Palepu (1986, 11) suggests it is desirable to make the prediction test sample resemble that population as closely as possible. Once the researcher has estimated the model parameters, the cost to compute state probabilities for prediction tests is relatively low. Thus, it is reasonable to suggest that prediction tests employ a large sample, or even the entire population of firms, to avoid the potential bias referred to above.

The third methodological flaw Palepu (1986) addresses concerns the establishment of an arbitrary cutoff probability. Palepu (1986, 4) indicates that the earlier acquisition prediction studies employed an arbitrary cutoff probability in prediction tests, usually 50%, without specifying the decision context in which one is to use the model's predictions. When the research derives the cutoff within a specific decision context (e.g., the purpose of the estimated acquisition model is to provide predictions which become part of a stock market investment strategy), the observed prediction accuracies indicate the extent to which the model's predictions are useful in that context. Otherwise, the results of prediction tests are difficult to interpret (Palepu 1986, 12). Also, rather than using an arbitrary cutoff probability, one can readily determine an 'optimal' cutoff probability by specifying the decision context of interest, the prior state probabilities, and an appropriate payoff function. One need only then apply standard decision theory methodology to derive the optimal classification scheme (Palepu 1986, 12).

Palepu carried out a fresh empirical study after correcting the above methodological flaws. Further, he improved upon earlier studies in two additional ways. He employed an acquisition probability model developed from the economics of the acquisition process, and he derived his variables from a set of six hypotheses the academic and/or popular financial literature frequently suggests regarding the types of firms that are likely to become acquisition targets. When he tested the model on a group of 1117 firms, the model correctly classified 24 of the 30 (80%) actual targets; however, of the 1087 actual non-targets, the model correctly classified only 486 (45%). Palepu found the strategy of investing in the 625 firms the model identified as potential targets did not result in statistically significant excess returns. Therefore, it did not appear the ability of the model to predict acquisition targets was superior to that of the stock market. Also, because the results of this study showed that it is difficult to predict targets, Palepu (1986, 3) concluded it is likely that methodological flaws in the earlier studies resulted in overstatements in predictive accuracy.

Management Buyout Prediction

Maupin, Bidwell and Ortegren (1984) examined the financial characteristics of firms that went private via a management buyout during the period 1972-1983. In addition, they differentiated these characteristics from the characteristics of firms that remained publicly held during that same period. Their study employed a nonrandom, paired-sampling technique that included sixty-three public firms and sixty-three ex-public firms matched on the basis of similar industry and asset size. Maupin, Bidwell and Ortegren selected twenty-five variables for inclusion in the study on the basis of the relationship between the variables and the reasons managers of ex-public firms indicated for undertaking a management buyout. They ascertained the reasons for 'going private' via a telephone survey of financial officers of forty-three of the sixty-three ex-public firms sampled.

The study employed discriminant analysis to test the null hypothesis that the group means of the twenty-five financial and market ratios were equal for the public and ex-public groups. When validated against the sample used to develop the model, the model correctly classified 94% of the ex-public firms and 89% of the public firms in the first year prior to the management buyout. In the second year prior to the management buyout, classification accuracy rates were 86% and 89%, respectively.

In an attempt to identify a *subset* of variables that differentiated ex-public firms from public firms better than all other subsets, Maupin, Bidwell and Ortegren employed three different variable reduction procedures. First, they used a stepwise procedure based on the contribution of the individual ratios to the *F* statistic. This procedure indicated that a twelve-ratio subset was the smallest subset exceeding the chosen minimum significance level of 99%. Using the twelve-ratio subset determined to have the highest level of significance, they employed a complete set-up procedure in which they tested all possible subset models for classification accuracy. The subset model that produced the lowest total of misclassified firms (9% misclassified in the year prior to going private and 11% misclassified in the second year prior to going private) was the five-ratio model composed of concentration of ownership by management and directors, cash flow to net worth, cash flow to total assets, price to book value ratio, and dividend yield. Finally, they employed a factor analysis technique to derive reduced variable subsets with minimized correlation between variables. Because the factor analysis technique produced lower classification accuracy rates than the complete set-up procedure, Maupin, Bidwell and Ortegren omitted the classification results of these models.

Although the reported classification accuracy rates in this study were fairly high, there were limitations to the study which bring the results into question. First, the use of nonrandom samples in prediction tests greatly restricted the ability to generalize the study's results to the population of publicly-held firms (Maupin, Bidwell and Ortegren 1984, 442-443). As Palepu (1986, 4-11) suggested, a prediction test sample should resemble the population as closely as possible. Therefore, when testing prediction accuracy one should employ a large sample, or even the entire population of firms, to avoid a potential bias in the estimated error rates.

Second, while pairing firms on the basis of industry and asset size mitigated the disruptive effects of the industry and asset-size factors, it also virtually eliminated any predictive power these factors may have had. Otherwise stated, had Maupin, Bidwell and Ortegren incorporated industry and size effects into the multivariate analysis--e.g., size is easily quantifiable--the research findings would have provided insight into the potential predictive power of these factors.[11] In the case of a management (leveraged) buyout, there does appear to be a significant concentration of LBO activity in selected industries. For example, during the period 1978-1988, LBO activity was heavily concentrated in four industries: Stone, Clay and Glass; Apparel; Textiles; and Food (Waite and Fridson 1989, 9). Further, such a concentration is reasonable because one expects highly leveraged capital structures to appear in the industries most capable of handling the added risk (Waite and Fridson 1989, 10).

Although it is conceivable that the concentration of LBOs by industry represents chance factors, it is also quite possible that certain industries are by their nature more suited than others to this particular form of restructuring. In support of the latter contention that an industry's characteristics prior to

[11] Maupin, Bidwell and Ortegren's purpose in using a paired-sample design was to provide a control over factors that may have blurred the relationship between financial ratios and going-private. Beaver (1966), for instance, used a similar design when he examined the ability of financial ratios to predict financial failure. Consistent with the literature, Beaver (1966, 74) contended that the "differences" that exist among industries preclude a direct comparison of the ratios of firms from different industries. In other words, the same numerical value of a ratio (e.g., a current ratio of 2.0) implies a different probability of failure in different industries. Beaver (1966, 74-75) also suggested there are certain statistical reasons for believing that asset size alters the relationship between ratios and failure. For example, the larger of two firms may have a lower probability of failure, even if the ratios of the two firms are identical.

reorganization influence its propensity for LBOs, Waite and Fridson (1989) examined the credit characteristics of fifteen LBO-intensive industries over the period 1971 to 1985. They found that fourteen of fifteen industries were characterized by low cash flow volatility in both pre- and post-LBO periods. Thus, despite a change in balance sheets, low cash flow volatility continued to provide strong credit support in post-LBO periods. A majority of the LBO-intensive industries (eight of fifteen) also maintained high coverage of fixed charges prior to restructuring. Of course, fixed charge coverage will decline if a firm restructures via a leveraged buyout. However, high coverage of fixed charges in the pre-LBO period suggests the new debt lies on a comparatively solid base (Waite and Fridson 1989, 12-14).

Size also appears to be a determinant of whether a firm goes private via a management buyout. Although the median purchase price for a firm taken private has increased significantly over the years (from $7.9 million in 1979 to $123.3 million in 1987), in all but one year, the majority of these transactions had a singular value of under $100 million (*Mergerstat Review* 1987, 80). These facts thus indicate that firms that go private via a management buyout *tend* to be ones of smaller size.

Third, because Maupin, Bidwell and Ortegren used the same sample to derive and validate the discriminant function, the resulting proportions of correctly classified and misclassified firms underestimated the true probabilities of misclassification (Afifi and Clark 1984, 266). Ideally, one would derive the discriminant function from one sample and apply it to another sample to estimate the proportion misclassified. However, in this case, a relatively small sample of ex-public firms may have made such a procedure impractical.

Fourth, given the relatively small sample and the large number of variables used in the complete set-up procedure, it is likely that some combination would have predicted well merely as the result of chance. Also, the combination of a small sample with numerous variables tends to deflate F statistics which can lead to erroneous inferences.

Finally, Maupin, Bidwell and Ortegren (1984, 439) tested the null hypothesis that classification accuracy does not differ from the 50% accuracy expected from a random classification process. They rejected the null hypothesis at the 0.001 significance level for both years. In the absence of prior probabilities, the proportion of correct classifications expected by chance is equal to 100% divided by the number of groups, k. Thus, in Maupin, Bidwell and Ortegren's study, the percent of correct classifications expected by chance equalled 50%. However, the number of firms that have gone private via a management buyout is very small relative to the number of firms that have remained public. Therefore, in a case such as this, where the prior probabilities are so unequal, alternative models better express the proportion of correct classifications expected by chance. For example, the maximum chance criterion assigns observations to the group that has the largest prior probability (Pinches 1980, 443). In the case of management buyout prediction, this criterion would dictate that the researcher classify all sample firms as public firms. While clearly the researcher would misclassify the firms that had gone private, overall classification accuracy would still be very high due to the extreme dissimilarity of prior probabilities.

Lawrence (1986) examined the financial characteristics of public and ex-public firms using both a univariate and multivariate approach. In order to perform these analyses, he matched a group of fifty-six firms that went private during the period 1974-1981 with fifty-six firms that remained public during that same time period by industry and asset size. He selected sixteen independent variables for inclusion in the study on the basis of their performance in past financial studies, data availability, and traditional financial relationships one often uses in financial statement analysis. The study also included three additional variables that the academic and professional literature frequently suggests are major factors influencing the decision to go private.

The univariate analysis, which compared the aggregate data of public and ex-public firms, suggested that no real differences existed in the financial characteristics of these two groups. The sole exception related to the voting control of insiders and major stockholders. Specifically, insiders and major stockholders controlled approximately fifty-eight percent of the vote in private firms versus only thirty-nine percent in the public firms.

Lawrence also used a forward and backward stepwise procedure to determine a subset of variables that were jointly the best predictors of a going-private transaction. Using the Lachenbruch-Mickey holdout method, a four variable linear model achieved the highest accuracy by correctly classifying 80% of the ex-public firms and 57% of the public firms. With respect to contribution of the individual variables, voting control was always the first to enter or the last to leave the various models. Thus again, the ability to control dominated the other financial characteristics in terms of explanatory power. Except for an improved validation procedure, this study generally had the same limitations as the Maupin, Bidwell and Ortegren (1984) study.

Maupin (1987) also employed a stepwise procedure to identify the characteristics that differentiated fifty-four firms that had gone private during the period 1972-1981 from a matched sample of fifty-four firms that remained public during that same period. Similar to the practice in prior studies, this study matched firms according to industry and asset size. The study included variables selected on the basis of a survey of corporate managers of ninety-seven ex-public firms regarding the factors they believed were most important in the decision to revert to private status.

Maupin tested the predictive ability of the model by applying the discriminant function to a holdout sample of forty-three firms that went private during the period 1982-1984, as well as to a paired sample of forty-three firms that remained public during that same period. Her model correctly identified 85% of the firms that went private during the period 1972-1981 and 70% of the firms that remained public during that same period. For 1982-1984 grouped data, the classification accuracy rates were 86% and 77%, respectively. The discriminant function that produced the highest accuracy rates included seven variables: concentration of ownership and cash flow to total assets (both significant at the .05 level); cash flow to net worth, price to earnings, price to book value, book value of depreciable assets to original cost, and dividend yield (all significant at the .10 level).

The method of variable selection in this study and in the earlier study by Maupin, Bidwell and Ortegren (1984) appears to be superior to the method Lawrence (1986) employed. This may very well account for the improved classification accuracy rates of the two former studies. However, again with the exception of an improved validation procedure, Maupin's (1987) study generally had the same limitations as the Maupin, Bidwell and Ortegren (1984) study. To reiterate, the limitations of the latter study included the use of nonrandom samples in prediction tests, the pairing of firms on the basis of industry and asset size, and the use of a single sample to derive and validate the discriminant function.

CHAPTER IV

THEORY AND HYPOTHESES

Theoretical Framework

The practice in the earlier bankruptcy prediction studies has been to start with a large number of popular financial ratios and then let a stepwise procedure determine a subset of variables to be retained on the basis of their statistical significance (see Altman 1968; Deakin 1972; Diamond 1976). Simkowitz and Monroe (1971) used a similar technique to identify the variables that are the best predictors of acquisition targets, as did Lawrence (1986) in distinguishing between the financial characteristics of public and ex-public firms. Zavgren (1983, 28), however, suggested that variable selection in the absence of a theory tends to be problematic because it necessarily restricts the theoretical importance of the results. Palepu (1986, 16) further suggested this method of variable selection is arbitrary and results in statistical 'overfitting' of the model to the sample at hand, i.e., a given function derives its discriminatory power from the characteristics of a particular sample and not from any rationale regarding the actual importance of particular characteristics in general (Zavgren 1983, 17). In constructing his acquisition likelihood model, Palepu attempted to overcome this problem by selecting variables on the basis of a set of pre-established hypotheses. These hypotheses appear frequently in the academic and/or popular financial literature and suggest the types of firms that are likely to become acquisition targets.

The present study also intends to avoid the problems associated with the arbitrary selection of variables by establishing a logical framework for the predictor variables. Specifically, this framework or "theory" hypothesizes why management engages in a going-private transaction. Bhide (1989, 40) suggests that, for corporate acquisitions in general, it is difficult to observe directly the acquirer's underlying motives. To be sure, he suggests, acquirers often make public statements about the expected benefits for the firm and its public shareholders. However, frequently these statements are misleading and do not provide a reliable guide to the real motives. Thus, one must infer the expected benefits from a broader set of circumstantial evidence (Bhide 1989, 40).

Because the management buyout is a special type of corporate acquisition, the study uses the proposed management buyout of RJR Nabisco to illustrate these points. When the bidding war began for RJR Nabisco in late 1988, competing bidders (including management) insisted their primary concern was for the company's stockholders (Reibstein and Friday 1988, 42). Observers naturally questioned the real driving force behind the buyout, leveling severe criticism on all potential participants. Among the targets of criticism were the "dealmakers"--the investment banks and other advisers who were expected to earn nearly $1 billion in fees. In fact, some observers may have gone so far as to suggest it was these enormous advisory fees that truly "drove" this deal (Lyons 1989, 22). Probably, the most visible object of criticism, though, was F. Ross Johnson, former president and chief executive of RJR Nabisco, who spearheaded the attempt by management to take RJR private. His critics claimed he pursued a buyout strictly to satisfy his own personal greed--with a successful bid, Johnson potentially would earn $100 million over a seven-to-eight year period ("Ex-CEO Now Quiet Consultant" 1989, 8E). Understandably, Johnson denied the claim asserting that "making $100 million was not my motive by any stretch of the imagination" ("Ex-CEO Now Quiet Consultant" 1989, 8E). Observers also castigated Johnson for his initial low bid of $17 billion (the winning bid by Kohlberg Kravis Roberts & Co. was nearly $25 billion) and the built-in rewards for Johnson in the management offer ("Ex-CEO Now Quiet Consultant" 1989, 8E).

At the height of the bidding war for RJR Nabisco, suitor Kohlberg Kravis Roberts & Co. declared the fundamental business decision is "how to maximize values for the shareholders" (Reibstein and Friday 1988, 42). The managers of firms taken private via a management buyout have frequently made similar declarations. In fact, in a survey of financial officers of ex-public firms, a majority of managers contended that a primary reason for the management buyout was it represented the best way for shareholders to realize the maximum amount on their investment (Maupin, Bidwell and Ortegren 1984, 441-442). While research findings have established that public shareholders in a management buyout do receive significant premiums above the pre-offer open market stock price (DeAngelo, DeAngelo and Rice 1984, 388-389), a claim that going private is primarily for the benefit of the shareholders is dubious at best. Clearly, one need only assess the potential rewards for the management group to arrive at the logical premise that manager self-interest is at the heart of the going-private decision, not the maximization of shareholder wealth.

If, indeed, management's desires to further its own interests drives the going-private transaction, public censure and shareholder disapproval preclude management from making that fact widely known. As indicated earlier, an outside observer must therefore rely on the circumstances surrounding the buyout to support such a theory. These "circumstances" frequently include: (1) generous compensation packages for management, (2) a purchase price paid with borrowed monies, (3) disproportionate shares of equity ownership in relation to the capital contributed, (4) a bargain purchase price, and (5) transitory ownership by outside equity participants. In the section that follows, the study discusses these prevailing circumstances and the expected benefits for management that derive therefrom.

The Expected Benefits for Management from LBO Participation

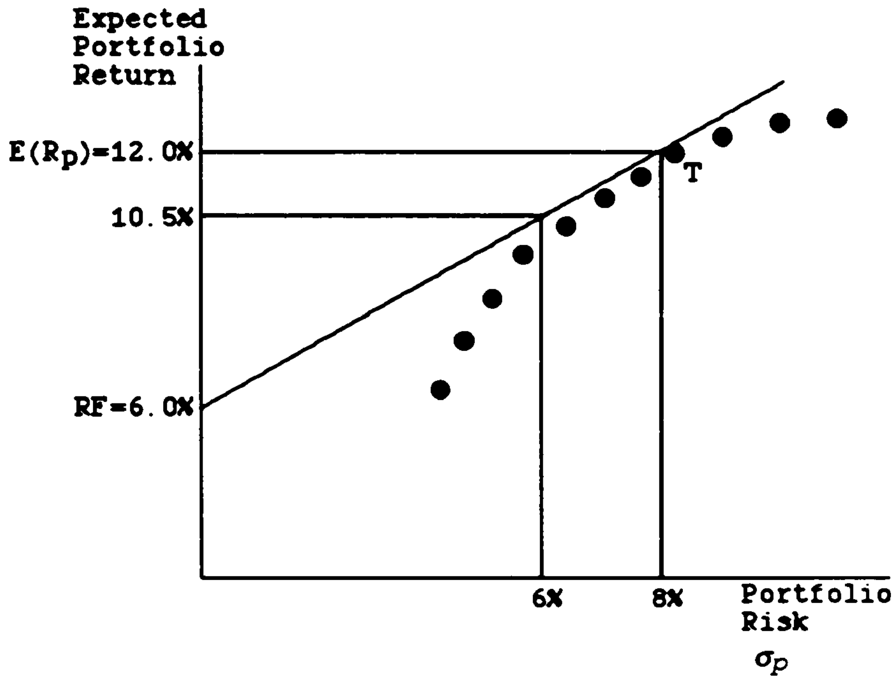
In a previous section, the study addresses the potential gains the *firm* may experience as the result of a reversion to private status (e.g., real resource gains through reductions in stockholder servicing costs and productive gains from an organizational change that creates a stronger link between managerial performance and reward). The study addresses in only an indirect manner the potential gains for the management group itself. For example, the study suggests compensation agreements that tie more closely managerial income and performance generally enhance the firm's productive efficiency. Because the focus of the statement is the improved efficiency of the *firm*, one might easily overlook managers' beneficial interest in these compensation arrangements. Clearly, management also stands to profit from going private because these employment contracts assure management receives an increased (disproportionate) share of all investment returns.

Of course, the strengthening of ties between managerial income and performance is but one potential benefit of going private for the management group. Other potential benefits include: above-average returns on equity investments stemming from the aggressive use of leverage; receipt of a disproportionate share of common equity in relation to capital contributed; the purchase of existing shareholder interest at a bargain price; and the potential for managers to become sole owners of the private firm. The following discussion explains each of these benefits, in turn.

Lyons (1989, 22) suggests the driving force behind many management buyouts comes from the management of the company itself. Not only does the management buyout free executives from the market's preoccupation with short-term profits, it gives managers the chance to realize "otherwise impossible wealth" (Lyons 1989, 22). Leverage obviously plays a key role in magnifying the returns to the investors (including members of management) in a leveraged buyout. The paragraphs below now illustrate exactly how leverage works to enhance the returns to the equity investors.

The essence of portfolio theory is that there exists a single efficient portfolio of risky securities that investors can combine with borrowing or lending at the risk-free rate to provide a level of risk and return that is optimal (Radcliffe 1982, 172). Assume that in Figure 3, investors have calculated the efficient frontier of risky portfolios (denoted by the dotted curve) and determined that various combinations of the risk-free security *RF* and risky security portfolio *T* would provide maximum expected returns per unit of risk. If investors are extremely risk-averse, they could invest the portfolio 100% in *RF* to provide a 6% return with no risk. If risky security portfolio *T* provides investors with an ideal mix of risk and expected returns, they will place 100% of the portfolio in *T*. If investors desire a risk level somewhere between *RF* and *T*, they can achieve this by placing a portion of the portfolio's funds in *T* and lending the remaining portion by acquiring risk-free securities, such as Treasury bills, commercial paper, or negotiable certificates of deposit. However, if portfolio *T* does not provide investors with as large an expected return as desired--perhaps they desire an expected return of 16%--they could attain this by borrowing funds at 6% and placing both the borrowings and their own equity in

Figure 3
Borrowing and Lending Portfolios



Source: Radcliffe (1982, 177)

portfolio *T*. In fact, if investors borrow \$.67 for each dollar of equity and invest both in *T*, the expected return is 16%. By investing \$1.67 in *T*, investors earn 12% on the dollar, or \$0.20. They pay 6% interest on the \$.67 loan for a total of \$0.04, which results in a net income after interest of \$0.16. This \$0.16 return on a \$1.00 equity is exactly equal to the desired return of 16%.

One can determine the precise mix of borrowing and equity which is necessary to achieve a desired level of expected return by employing the following two equations (Radcliffe 1982, 173-177):

$$\sigma_C = (1 - X)\sigma_P, \qquad [4.1]$$

where σ_C = the standard deviation on the combined portfolio of risky and risk-free securities,
σ_P = the standard deviation of the single, optimal portfolio of risky securities,
X = the percentage of resources placed in the riskless security,

and
$$E(R_C) = RF + \sigma_C \frac{E(R_P) - RF}{\sigma_P}, \qquad [4.2]$$

where $E(R_C)$ = the expected return on the combined portfolio,
RF = the risk-free rate of interest,
$E(R_P)$ = the expected return on the risky security portfolio.

The substitution of Equation 4.1 into Equation 4.2 produces the following result:

$$E(R_C) = RF + (1 - X)[E(R_P) - RF]. \qquad [4.3]$$

If investors know RF and $E(R_P)$, they can solve for the value of X expected to provide a particular return. When X (the fraction of funds held in the riskless security) is positive, that percentage is lent. When X is negative that fraction is borrowed. For example, using the data from the illustration above:

$$16\% = 6\% + (1 - X)(12\% - 6\%).$$

X must be -2/3 or -0.666. In other words, for each dollar of equity available, investors must borrow 67 cents and invest that sum in portfolio T.

Of course, the leveraged buyout carries the idea of "trading on the equity" to a logical extreme. The LBO specialist, venture capitalists, and others (including management) who provide the equity base necessary to obtain the required debt financing generally provide the highest-risk financing tier in a leveraged buyout. Because of the degree of financial risk these equity participants assume, their targeted compound annual rates of return are generally very high. For instance, Inselbag and Kaufold (1989, 94) suggest the LBO specialist requires minimum returns of between 30% and 40%. Diamond (1985, 76) indicates that venture investors expect compound annual rates of return that are rarely less than 35% and often exceed 50%. In the case of management, Kitching (1989, 75) suggests that the average manager expects a 90% internal rate of return on his or her LBO investment.

Using representative rates of return and borrowing rates, the following example illustrates the required relationship between borrowing and equity in the typical LBO. Assume there is a single security (call it "LBO Co.") in the portfolio of risky securities, and the expected return $E(R_p)$ on that portfolio is 18%. Also assume the average borrowing rate is 14%, and the targeted rate of return $E(R_c)$ on the combined portfolio of risky securities and funds borrowed is 45%. The substitution of this data into Equation 4.3 yields the precise mix of borrowing versus equity needed to achieve the desired return of 45%:

$$45\% = 14\% + (1 - X)(18\% - 14\%).$$

X must be -6.75. In other words, it takes \$6.75 of borrowed funds for every \$1.00 of equity to achieve the desired return of 45%. For the firm that goes private via a leveraged buyout, this represents a typical financial structure in the first year of the buyout, 87% debt and 13% equity. This structure is also consistent with the general parameter Diamond (1985, 87) sets forth for leveraged buyouts financed by responsible venture capital groups--the ratio of senior debt plus subordinated debt to equity should be less than seven to one.

While the ability of debt to magnify the returns to shareholders is paramount in the going-private decision, the extreme use of debt in a leveraged buyout can benefit the firm and equity investors in still other ways. As already discussed, there are tax benefits associated with the private firm's issuance of debt. Because interest payments are tax deductible, the debt shelters operating profits from being fully taxed. In turn, this increases a company's intrinsic market value (Stewart and Glassman 1988, 86). In addition, because the commitment to repay debt removes from management the temptation to invest surplus cash in substandard projects, the LBO firm should see the elimination of a discount for reinvestment risk placed on the value of the company.[12] The elimination of this discount means investors are more inclined to value future cash flows fully and, all else being equal, the market value of the stock should rise (Stewart and Glassman 1988, 91).

Thus far, the study has indicated two primary ways in which the management group potentially profits from the going-private transaction--employment contracts that closely link managerial performance and reward, and the aggressive use of debt that produces above-average returns on equity. A third way managers potentially profit from participation in a buyout is through receipt of a disproportionate share of common equity in relation to the capital they contribute. Diamond (1985, 78) suggests venture capitalists are uniform in their requirement that the active management of a business acquired in a leveraged buyout has an equity stake in the company. However, the venture capitalist is generally willing to accept less than its proportionate share of the common stock in exchange for its senior position and dividend income, *and* to provide

[12] *Reinvestment risk* is the risk the firm will invest cash flows in projects that yield below the cost of capital. One can liken it to *coupon reinvestment risk*, i.e., the risk of reinvesting bond coupon payments received at yields that differ from the yield that existed on the date of bond purchase (Van Horne 1978, 121).

added economic incentive to management. As the example below illustrates, the potential rewards can be very attractive for both the venture investor and managers.[13]

Assume the management of Company X reaches an agreement with the company's board of directors to purchase X for $20 million in cash. The purchase price represents a multiple of five times X's prior year's earnings (preinterest and pretax) of $4 million. A bank agrees to provide term loan financing of $16 million if the management of X can raise the remaining $4 million in equity. Management is willing to invest $500,000 in equity and approach a venture capitalist for the remaining $3.5 million of equity required. Upon reviewing X's businesses and management's projections, the venture capitalist concludes that even under a pessimistic interest rate and economic scenario:

[1] Company X's earnings before interest and taxes in the fifth year following the buyout should be at least $6 million,

[2] Company X should generate sufficient cash flow to repay $12 million of the $16 million acquisition debt by the end of the fifth year, and

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[13] The example that follows is from Diamond (1985, 77-78).

[3] the equity holders should be able to resell Company X after five years for $30 million, or five times its fifth-year pretax, preinterest income (the same multiple at which the company originally sold).

Accordingly, if after five years the equity holders sell the Company for $30 million, they would receive $26 million after the remaining $4 million of acquisition debt is repaid.

The venture capitalist is willing to provide the $3.5 million in equity in exchange for cumulative redeemable preferred stock with a 10% annual dividend rate, and for the right to convert $750,000 of the preferred stock into 60 percent of Company X's common stock. Management contributes $500,000 in equity in exchange for 40 percent of X's common stock. With this offer, the venture capitalist is attempting to achieve three investment goals: (1) invest in a position senior to that of management, (2) receive a preferential return in the form of current income, and (3) earn an overall compound annual rate of return that exceeds 40 percent.

Table 1 summarizes the comparative economic effects of this transaction on the venture capitalist and management. This analysis assumes the equity holders receive $26 million from the sale of the entire company to a third party after five years, and after

Table 1
The Financing Effects of Company X Buyout[a]
($ Thousands)

	Total equity dollars invested	*Percent of equity dollars invested*	*Percent of common received*	*Annual dividend*	*Dollar split of sale proceeds*	*Compound annual rate of return*[b] *(includes dividends)*
V.C.	$3,500	87.5%	60%	$350	$15,600	41%
Mgt.	500	12.5%	40%	—	10,400	83%
	$4,000	100.0%	100%	$350	$26,000	50%

V.C. = Venture Capitalist
Mgt. = Management

[a] Table is from Diamond (1985, 77-78).
[b] To determine the compound annual rate of return, take the *N* th root of the holding-period value-relative (V_n / V_o), and then subtract 1:

$$r_g = \sqrt[N]{V_n / V_o} - 1$$

where r_g = the equivalent return per period,
N = the number of periods in the holding period,
V_n = the value of the investment at the end of the *N* th period,
V_o = the value of the initial investment.

This analysis assumes the venture capitalist reinvests dividends received at the compound annual rate of return of 41%. Therefore, the value of the venture capitalist's investment at the end of the *N* th period (V_n) is $19,547,000. This is equal to the investor's 60% share of sale proceeds ($15,600,000), plus the value of the dividends at the end of the *N* th period ($3,947,000).

the $4 million remaining debt is repaid. Here management invests 12.5 percent of the equity dollars in exchange for a 40 percent share of the common stock.

The venture capitalist provides 87.5 percent of the equity dollars and receives a 60 percent share of the common stock. As indicated earlier, the venture capitalist is willing to accept less than its proportionate share of the common stock to provide added incentive to management to operate the business with a view toward maximizing return on investment. From the perspective of both the venture investor and management, these returns can be substantial (41% and 83%, respectively) and, to be certain, make the buyout attractive to both groups of equity participants.

Although the facts of the above example are purely hypothetical, they are an accurate representation of a real-world situation. For example, in 1971, Gibbons, Green & Rice arranged the buyout of Syracuse China Corporation, a restaurant chinaware manufacturer. The investor group, which purchased the firm for $7.7 million, included the Syracuse China management, led by Robert J. Theis, the firm of Gibbons, Green & Rice, and a group of institutional investors. Teachers Insurance and Annuity Association provided $5 million in long-term debt, while the $2.7 million in equity capital came from three primary sources: Allstate Insurance Company, the Henry L. Hillman family of Pittsburg, Pennsylvania, and Robert J. Theis. Theis contributed 8% ($216,000) of the equity capital in exchange for a

25% interest ($675,000) in the private firm (Garguilo and Levine 1982, 41-42).

The circumstances of the Syracuse China buyout are also consistent with Kitching's (1989, 74) recent analysis of management buyouts occurring since 1980 in the United States and Great Britain. The study determined that while, on average, managers contribute only 3% of the cost of the buyout, they control 30% of the ownership in the private firm. This suggests that, rather than supplying large sums of cash to facilitate the buyout, managers contribute a significant amount of "sweat equity."

A fourth way managers potentially profit from the going-private transaction is by purchasing the existing public shareholder interest at a bargain price. Although the evidence suggests public shareholders in a management buyout receive significant premiums above the pre-offer open market price (DeAngelo, DeAngelo and Rice 1984, 388-389), the non-arm's-length nature of the transaction almost always raises doubt as to the fairness of price. In a management buyout, managers face a potential conflict between their own interests and those of the public shareholders. In terms of their own interests, managers would prefer to acquire the publicly-held stock at the lowest possible price. At the same time, managers have a fiduciary responsibility to shareholders to negotiate fair compensation for their shares. This inherent conflict of interest generally makes shareholders suspicious that a management buyout proposal represents a self-interested attempt by management to acquire outsiders' shares at an unduly low price. Unfortunately, management's access to inside information about the firm's future profitability serves to reinforce that suspicion.

Because of the unusual nature of these transactions, management buyouts are under the close scrutiny of the SEC and subject to special disclosure requirements promulgated by that body. Rule 13e-3, adopted in 1979, requires managers to state whether they believe the proposed transaction is fair or unfair to outside shareholders and provide a list of factors upon which they base that judgement. Generally, in order to comply with that rule, the incumbent board of directors hires at least one--and sometimes two--investment banking firms to express independent opinions on the fairness of the proposed transaction. As the taking of such action would indicate, managers apparently go to great lengths to structure the buyout so as to mitigate conflicts of interest. However, despite management's efforts in this regard, managers frequently increase their initial offer to public shareholders. For example, of the 64 management buyouts proposed during the period 1973-1982, managers of 26 firms (40.6 percent) raised their initial bid; none lowered it (DeAngelo and DeAngelo 1987, 48). Of course, these statistics do not confirm that, on the basis of inside information, managers intended to construct an initial bid that was artificially low (i.e., managers may have increased their initial offer simply to counter a competing bid or to settle litigation brought by public shareholders). These statistics do, however, suggest that, at least in some cases, manager self-dealing was a possibility.

Finally, because outside equity participants are not permanent investors in a leveraged buyout, the potential exists for managers to become sole owners of the private firm. Given the firm's ability to operate successfully as a private concern, this would eventually mean managers need not share investment returns with outside parties. At any given time, the venture capitalist and/or LBO specialist hold equity stakes in a number of privately-held concerns. At some point, for a given buyout, management will have restructured operations to yield whatever increase in profitability is feasible. It is at this point that the venture investor/specialist has an incentive to sell its ownership interest in the private firm, and redeploy its efforts and equity capital in a new buyout where its incremental contribution to value will be greater. According to Diamond (1985, 80), venture capitalists generally invest with a view to liquidating their investment within a five-to-seven year time frame. DeAngelo and DeAngelo (1987, 43) suggest the specialists expect to sell their equity in a given firm within five to ten years after the buyout of public shareholders. In any event, one can view the firm's post-buyout equity ownership structure--like its immediate post-buyout debt level--as temporary or transitional.

DeAngelo and DeAngelo (1987, 43) indicate there are a number of ways in which outside equity participants in a leveraged buyout can dispose of their investments. For instance, they may dispose of their stock through a public offering, thereby effectively returning the corporation to public ownership, or they may simply sell their shares to another group of outside investors. Managers and third-party investors might also agree to merge the privately-held firm into another corporation, one that is either publicly traded or privately held. Alternatively, third-party investors may sell their shares to insiders--e.g., directly to management--or to the corporation or an employee stock ownership plan (ESOP), leaving the firm wholly owned by management (perhaps in partnership with employees). One cannot infer, though, sole ownership of the private firm is the end-goal for all managers. For example, as of the end of 1988, owners in over half of the management buyouts surveyed by Kitching (1989) had initiated some form of exit.[14] However, for those managers who wish to remain with the firm indefinitely, this may be an attractive alternative.

The Reasons for Going Private

The previous section discussed the potential rewards for the management group resulting from its participation in a management buyout. The study has yet to address the primary impetus that motivates management to consider changing a firm from public to private status. While various theories attempt to explain the rationale that underlies management's decision to take the firm private, it appears a common element in all of these theories is that management desires control to serve its own self-interests. Specifically, the literature suggests that management engages in a going-private transaction for primarily one of three reasons: (1) to defend against an existing or expected takeover threat, (2) to resolve a conflict between managers and shareholders regarding dividend policy, or (3) to improve the firm's productivity and profitability. The paragraphs that

[14] Kitching's (1989) survey of management buyouts consisted of both U. S. and British companies (roughly a 60-40 split). Of the 320 transactions covered, approximately one-fourth represented public firms going private; about three-fourths represented divisional spinoffs, corporate breakups, or private-to-private sales.

follow explain in greater detail these reasons for going private and address why management may be the ultimate beneficiary in the going-private transaction.

First, in certain cases, the leveraged buyout may represent a response to market pressures to change the corporate financial structure, while at the same time permitting incumbent management to remain in control (Kleiman 1988, 49). Sometimes management adopts the LBO as a "defensive" tactic when there exists a prior public indication of an outstanding or an expected takeover bid. Still other LBOs are "pre-emptive" in nature, i.e., there has been no prior public indication of a takeover threat, however, the LBO represents a measure to deter unwelcome suitors. In either case, the leveraging of the firm mimics the actions of corporate raiders who would otherwise borrow against the assets of the target firm to finance an acquisition. Jensen and Ruback's (1983, 42) view of the takeover market as an "arena in which alternative management teams compete for the rights to manage corporate resources" lends support to this theory of control. Bradley's (1980, 346) theory of interfirm tender offers also recognizes "the existence of rivalrous firms that compete for the right to control target resources."

Managers naturally have a number of legitimate concerns when there exists a real or perceived threat of an unwanted or "hostile" takeover. For example, management may worry that if the firm falls into unfriendly hands, it will be unable to fulfill its commitment to the corporation's employees. For the firm that is socially responsible, management may also feel concern for the community that houses the corporation. The most apparent concern of managers, though, is the impact of an unwanted takeover on the security of their own jobs. To probably no one's surprise, the reported statistics justify this concern. Bhide (1989) examined management changes in the nineteen successful hostile takeovers that occurred in 1985. He determined that in seventeen of these takeovers, acquirers made significant changes in key personnel. In as many as seven cases, the takeover appeared to have resulted in the elimination or drastic reduction of an entire corporate level of management.

The question of course then is: Did "good" managers lose their jobs, or did these managers "deserve" to go? Unfortunately, the evidence suggests that the performance of targets of hostile takeovers is mediocre at best when judged by both industry and market standards. Bhide (1989, 50) reported seventy percent of the (41) targets of hostile takeovers in 1985 and 1986 had lower average returns on equity than those of their industry. The average difference was -2.2%. Fifteen of the twenty targets of hostile takeovers in 1985 provided risk-adjusted total returns that were lower than the return shareholders would have earned had they invested in a diversified pool of equities. The average difference between target and market returns was -4.0%.

In spite of lackluster performance, managers still expend enormous amounts of corporate resources (including management time) to defend against a hostile takeover attempt or the explicit threat of one. Of course, one cannot say with certainty that management's primary motivation in these cases is a base instinct of self-preservation. Most likely, management considers the consequences of a takeover to all parties who have a stake in the corporation (e.g., employees, shareholders, the management group, and so forth). What one can say with certainty is that when faced with a takeover threat, managers prefer to acquire and restructure the target in an ostensibly friendly transaction rather than allow corporate raiders to perform that task for them. If, in the process, the management buyout places managers in the position to reap the largest rewards, hopefully other corporate stakeholders will benefit as well.

While avoiding sale of the firm to another company is a frequently cited reason for the management buyout, there are other reasons managers may want to buy their companies. For instance, managers may view the buyout as a means of resolving a conflict between managers and shareholders regarding the optimal dividend policy (Maupin, Bidwell and Ortegren 1984, 442). According to managers of ex-public firms surveyed, the public company is under pressure to report high profits and pay large dividends to outside shareholders. However, the higher tax-bracket management shareholders are more interested in long-term capital gains. Managers view the management buyout as a vehicle for resolving this goal conflict. Outside shareholders receive substantially above the current market price for their shares, while managers that remain with the company as private investors are able to manage the company in their own best interests (Maupin, Bidwell and Ortegren 1984, 442).

The literature refers to the investor's preference for high-yield versus low-yield stocks as the "clientele effect," and suggests different securities have somewhat different clienteles. Specifically, because taxpayers with different marginal tax rates have differing attitudes toward dividends vis-à-vis capital gains, high-bracket taxpayers have a preference for low-yield stocks, while low-bracket and tax-exempt investors have a preference for high-yield stocks (Sharpe 1981, 219). Ex-dividend price behavior reflects this preference as well. Elton and Guber (1970) examined the average one-day price fall relative to the dividend involved for each of ten groups of stocks based on dividend yield. In the five highest-yield groupings, the average ratio of price change to dividend ranged from approximately .87 to 1.18. This indicated that, on average, a $1.00 per share dividend was accompanied by a decline in price as low as $.87 per share, or as high as $1.18 per share. This also suggested that investors in these high-yield groups were generally unwilling to give up a dollar of dividends unless they received at least a dollar in expected capital gain. In the lowest-yield groupings, the range for the average ratio of price change to dividend was significantly below that of the high-yield groups--.49 to .80. This suggested that investors in the low-yield groups did appear willing to forego a dollar of dividends in exchange for considerably less than a dollar in capital gain.

When Maupin, Bidwell and Ortegren (1984) surveyed managers of ex-public firms, many of the managers cited the clientele effect argument as a reason for the management buyout. In a follow-up survey in the year after the management buyout, financial reports did indeed reveal dramatic decreases in cash dividends, and in many cases, the complete elimination of cash dividends. Of course, managers may have reduced or eliminated cash dividends because of the firm's requirements for debt service. However, lacking full knowledge of the reasons for the dividend reductions, these facts lend credence to managers' assertions that the clientele effect argument motivated the going-private transaction (Maupin, Bidwell and Ortegren 1984, 442).

While empirical evidence tends to support the clientele hypothesis, in the past, some have questioned the existence of the phenomenon and/or the interpretation of its causation. Those who questioned the interpretation used the argument that clever tax planning may make it possible for investors to turn dividends into capital gains (Sharpe 1981, 220). However, if the taxation interpretation is indeed valid, recent tax law changes may have implications for this study. Prior to 1987, the Internal Revenue Code allowed individuals who sold a capital asset at a gain a capital gain deduction equal to 60% of any net capital gain for the taxable year. The Code defines "net capital gain" as the excess of net long-term capital gains over net short-term capital losses. However, the Tax Reform Act of 1986 repealed the capital gain deduction for individuals, thus taxing long-term capital gains at the same rates as ordinary income. Of course, the study suggests that some managers undertake the going-private transaction in order to resolve a conflict surrounding the firm's dividend policy. At the center of the controversy is a managerial preference for long-term capital gains versus a shareholder preference for current dividend income. If, by eliminating preferential tax treatment for capital gain property, the Tax Reform Act of 1986 negates the clientele effect, then the study cannot use the clientele argument as justification for going-private transactions in at least three years--1987 (the year the Tax Reform Act became effective), 1988 and 1989. As a later section addresses, the study uses management buyouts from 1987 and 1988, along with buyouts from prior years, to develop a management buyout prediction model; the study uses management buyouts from 1989 to test that model.

Whether or not investors are now indifferent to capital gains vis-à-vis dividends is, of course, an empirical question. Sharpe (1981, 220) suggests, though, that the clientele effect phenomenon may be due, at least in part, to other factors that tend to go with dividend yield. For example, investors may be motivated to invest in low-yield securities because they prefer to postpone the recognition of income to some time later in the future. This is consistent with the premise that a primary concept underlying all tax strategies is the investor does not pay taxes on capital gains until the gain is *realized* (Radcliffe 1982, 575). Investors may also seek capital gains as an offset to capital losses previously incurred.

Although individuals can use ordinary income to offset capital losses in excess of capital gains, there is a $3,000 limit to this offset in a given taxable year. Because there is no such limit to the offset of capital losses against capital gains, the individual investor may still find capital gains attractive. Also, investors may anticipate another change in the law which would reinstate preferential tax treatment for capital gain property. This expectation is reasonable because, at the date of this writing, Congress is debating a provision in its proposed 1990 budget bill that would exclude 30% of income from capital gains on the sale of assets between September 14, 1989 and December 31, 1991 (*Journal of Accountancy* 1989, 118-120).[15]

In conclusion, although the recent elimination of preferential tax treatment for capital gain property may have reduced the impact of the clientele effect, this study ascribes to a theory that factors other than preferential tax rates can influence the investor's choice between capital gains and ordinary income. As such, the study considers the clientele effect a legitimate reason for the management buyout, even in

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[15] The Revenue Reconciliation Act of 1990 which became effective January 1, 1991 did *not* include a provision excluding a percentage of income from the sale of capital assets. However, the Act did limit the top statutory rate on net capital gain to 28%.

years affected by the Tax Reform Act of 1986 (i.e., 1987, 1988 and 1989, for the purpose of this study).

To this point, the study has discussed two primary reasons why managers undertake a going-private transaction--to defend against a takeover threat, or to resolve a dividend policy dispute. A third and final reason for the management buyout is the buyout may represent a strategy that enables managers to improve the firm's productivity and profitability. Because these transactions increase the equity stakes of managers and thus change their incentives, the firm moves from a position of passive ownership to active ownership of assets. Passive ownership occurs when resource allocation decisions are made by managers who do not have meaningful equity stakes in the firm and who, therefore, do not necessarily make such decisions based on maximization of return criteria (Paulus and Waite 1989a, 1). Prior to the buyout, managerial compensation packages based on the size of the enterprise (e.g., total assets, sales revenue, etc.) encourage decisions to expand operations, sometimes in marginally profitable lines. After the buyout, because of the shift from passive to active ownership, managers make decisions based on return on capital and, hence, efficiency considerations (Paulus and Waite 1989a, 1).[16]

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[16] One should not assume that the basis for all managerial compensation packages is the size of the

In addition to avoiding the costs associated with managers' emphasis on increasing the size of the firm, proponents of LBOs believe there are other reasons a management buyout can improve the company's efficiency and/or profitability. For instance, Kohlberg Kravis Roberts & Co. (1989, 68) suggests that after a management buyout, managers tend to run the company with an eye toward long-run profitability, and not quarter-to-quarter earnings. This de-emphasis on short-term profitability stems from the increased equity stakes of managers that serve as motivation for maximizing the value of the firm over the long-term. Further, because the common equity of the LBO company is generally no longer publicly traded, managers need

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firm. For instance, Fox (1980) reports that in 1980 ninety percent of the one thousand largest U.S. manufacturing corporations used a bonus plan based on accounting earnings to compensate managers (Healy 1985, 85). These earnings-based bonus schemes usually relate managerial compensation to earnings per share, return on total assets, or return on equity (Healy 1985, 85).

Under public ownership, though, managers must divide the residual profits of managerial decisions with a dispersed group of public stockholders. Consequently, managers have incentives to run the enterprise in a manner that generates perquisites or otherwise directs resources to themselves at the cost of a reduction in overall corporate profitability (DeAngelo and DeAngelo 1987, 44). The larger the managers' share of the firm's common stock--or, more precisely, their share of residual profits--the smaller is their incentive to sacrifice profitability in order to advance some narrow self-interest. As DeAngelo and DeAngelo (1987, 44) suggest, a buyout that enables managers to increase their equity stake strengthens the managers' incentives to operate the company efficiently.

not concern themselves with short-term movements in stock price, including movements which may be the result of quarterly performance.

Another way the leveraged buyout promotes overall efficiency is through the sale of non-productive assets and operations to other owners. Although Kohlberg Kravis Roberts & Co. (1989, 69) suggests asset sales or disposals are not necessary as a general matter in a leveraged buyout, in some cases, the firm will sell unprofitable businesses or other businesses or assets to help repay debt incurred in the buyout. A third way the leveraged buyout can cause a more efficient allocation of a company's resources is through the LBO firm's assumption of sizable amounts of debt. The study has already discussed how the "discipline of debt" prevents managers from wasting free cash flow. Finally, the leveraged buyout brings to the company the oversight of sophisticated investors (i.e., the LBO specialists) who are experienced in identifying and achieving operating efficiencies and in developing overall financing and investment strategies.

While LBO proponents are quick to defend their position that leveraged buyouts improve the operating efficiencies of the firm, only a limited number of studies have attempted to examine empirically the post-buyout performance of LBO firms (Kohlberg Kravis Roberts & Co. 1989; Kaplan 1988b; Bull 1988; Muscarella and Vetsuypens 1989; National Science Foundation 1989). For the most part, these studies examined the impact of the leveraged buyout on employment, research and development, and capital expenditures. A few of these studies, though, examined the purported positive impact of LBOs on efficiency. Long and Ravenscraft (1989, 4), who reviewed and compared the finding of these studies, suggested such efficiency improvements should show up as increases in operating income/sales, and, perhaps, sales. Using sales as a performance measure, Kaplan (1988b), Bull (1988), and Muscarella and Vetsuypens (1987) each reported significant positive percentage changes in the pre- and post-LBO sales figures of sample firms (17.4%, 20.2%, and 9.4%, respectively). Both Kaplan and Muscarella and Vetsuypens also reported increases in operating income/sales (2.6% and 26.2%, respectively); only Bull indicated there was no significant change in the pre- and post-LBO operating income/sales figures. When adjusted for industry trends, the findings changed somewhat. Both Kaplan and Bull found that the LBOs' sales were not growing as fast as their industries' sales. In Bull's sample, industry profits were on the decline, so the LBO firms looked good by comparison. In Kaplan's study, the results were the same as reported above, i.e., industry profits improved, but by a lesser amount than the LBO firms'. Muscarella and

Vetsuypens did not compare their results with industry trends.[17]

In addition to the obvious impact on the firm, these efficiency considerations have implications for the management group as well. Maupin, Bidwell and Ortegren (1984, 441) reported that, in the majority of cases, the shares of firms that went private via a management buyout were selling below book value prior to the buyout. These relatively low stock market prices, which managers and stockholders felt did not reflect the significantly higher 'real' value of the company, meant stock options and stock incentive programs were of less value to key management personnel. According to Maupin's (1987) survey of managers of ex-public firms, this indicated management was not sharing in the profitability of the firm to the extent expected. The lower the stock price relative to

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[17] Given the different methodologies of the various studies, their results are not strictly comparable. For example, each study used a different set of sample firms (many of which were divisional spinoffs). Each employed different dates for measuring pre- and post-LBO performance (e.g., Kaplan compared performance one year prior to the buyout to performance two years after; Bull compared performance two years before and two years after the buyout). Also, because none of these studies identified the source of the profit gains, one cannot be certain that the gains were due to real efficiencies, i.e., the gains may have been the result of cutbacks that will eventually hurt long-run profitability. Therefore, the study's intent in presenting these results is not to provide unqualified support, but rather limited support for proponents' claims that the LBO firm experiences improved operating efficiencies after the buyout.

the potential return from a successful management buyout, the more attractive the buyout became to managers who believed a change in ownership status would allow them to run the company more efficiently and in accordance with their own best interests. The basic proposition managers advanced for this belief was that concentrated, private ownership by the incumbent management group (i.e., control) constituted a valuable asset that held the potential for revitalizing management efficiency and company profitability (Maupin 1987, 323-326).[18]

In conclusion, while there are a number of potential beneficiaries in the going-private transaction other than members of management (e.g., shareholders, employees, and the community), the evidence suggests the management group may stand to gain the most from a successful buyout. For instance, when managers use the buyout as a defense against an

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[18] The reader should not infer from the above discussion that the purported benefits of a management buyout are always sufficient to induce managers to participate in a buyout. For instance, differing personal preferences for risk versus return of prospective equity holders can make managers reluctant to undertake a buyout if they forecast extensive disagreements over the private company's optimal set of risky projects. Another potential conflict arises when each stockholder wants corporate policy tailored to his or her specific consumption preferences. For example, managers who are especially averse to risk may want to operate the private company with lower leverage and, thus, may be willing to sacrifice potential profits in the process (DeAngelo and DeAngelo 1987, 46).

impending threat of takeover, the buyout protects the security of the managers' own jobs. When managers use the buyout to settle a dividend policy dispute, the buyout secures for managers the right to choose how their investment income will be taxed. Probably most important, though, is the fact that managers' participation in a buyout enables managers to share to a greater extent in the firm's profitability. Given the success of the firm as a private concern, this could eventually mean substantial monetary reward for the management group.

Kitching (1989, 75) suggests the monetary rewards are well deserved because managers assume huge financial risks to participate in the buyout. He indicates, on average, managers invest greater than 25% of their personal net worth in the buyout firm. In addition to managers' personal wealth being at risk, there are other drawbacks to these transactions. For instance, Lyons (1989, 23) suggests debt can sometimes do more harm than good. The rigidity of fixed interest payments dramatically increases the financial risk of the firm, which means management cannot afford to adopt any ill-conceived actions. Further, even if the performance of the LBO firm is outstanding, an economic downturn can potentially destroy the business (Lyons 1989, 23).

In spite of these drawbacks, the potential rewards for the management group, in combination with other factors, argue strongly for the study's conclusion that manager self-interest underlies the going-private decision. To be exact, the study assumes managers undertake a going-private transaction in order to acquire or maintain control over corporate resources so the firm can better serve the interests of the management group. The study uses this logical premise as the basis for selecting variables for the management buyout prediction model. The next section discusses the variable selection process and the specific variables the model employs.

Variable Selection

The previous section discusses three principal reasons managers undertake a going-private transaction: (1) to defend against a real or perceived threat of takeover, (2) to resolve a controversy surrounding the firm's dividend policy, and (3) to improve the firm's productivity and profitability. In each case, the study establishes that, by adopting this particular course of action, managers are then able to serve their own best interests. Using this framework as the basis for selecting variables, the study next identifies certain ratios or measures that the literature suggests are important in the going-private decision. In determining the appropriate set of ratios and measures, the study relies on three different bodies of literature--the academic, professional, and technical literature.

The first reason the study suggests managers undertake a going-private transaction is to defend against a takeover threat. While, in certain cases, managers have the personal resources necessary to effect a buyout, in other cases, managers' personal resources are simply not adequate to buy back the entire public shareholder interest. In the latter case, managers (in conjunction with third-party investors) purchase all of the publicly-held common stock with funds obtained, to a large degree, by additional corporate borrowing.

While limited personal resources of managers may dictate the use of borrowed funds in a buyout, the infusion of debt into the capital structure potentially serves another purpose. The leveraging of the firm discourages corporate raiders because they can no longer borrow against the assets of the target firm to finance an acquisition (Kleiman 1988, 47). Generally, managers prefer to acquire and restructure the target in a friendly transaction rather than allow corporate raiders to perform that task for them.

When management buyouts first became popular in the early 1970s, the majority of these transactions were not leveraged deals. However, *Mergerstat Review* (1986, 85) suggests "most, if not all, of the [recent] going-private transactions are also leveraged buyouts." In part, experts attribute the greater incidence of leveraged buyout financing in recent years to a heightened awareness among the investment community regarding the benefits of leverage. However, as indicated above, limited managerial wealth may also be an important determinant of whether managers effect a buyout using borrowed funds. DeAngelo and DeAngelo (1987, 40) report that company size and managerial stock ownership statistics suggest managers undertake an LBO (versus an MBO) when managers' personal resources are especially small relative to the size (value) of the public shareholder interest.[19] In these

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[19] In this particular context, the study uses the term *leveraged buyout* [LBO] to describe a management buyout that includes the participation of third-party equity investors and significant increases in the level of corporate borrowing. It uses the term *management buyout* [MBO] to describe a buyout that does *not* include third-party investors and corresponding increases in the level of corporate debt. Further,the study recognizes the possibility that a company may effect a buyout by significantly increasing the level of corporate borrowing, but without involving third-party equity investors. However, as explained below, it appears this type of situation is not the norm.

DeAngelo and DeAngelo (1987, 39-40) reviewed *pro forma* financial statements included in proxy disclosures for companies that proposed going-private during the period 1973-82. Although companies that went private without third-party equity investors rarely included *pro forma* statements, an analysis of a limited sample of such disclosures indicated that managers of these firms generally planned only small increases in the level of corporate debt. In contrast, cases, managers by themselves are unable or unwilling to buy the outstanding public shares. Consequently, the only way managers can attain a closely-held equity ownership structure is to take on outside equity partners and materially lever the firm. The increase over time in the average size of going-private transactions also lends support to this theory. In 1979, the average purchase price paid in a going-private transaction was $39.8 million; by 1987 that figure had increased nearly twelve times over (*Mergerstat Review* 1987, 80).

In the typical going-private transaction, investors obtain the majority of the stock purchase price through debt financing. The study indicated earlier, for example, that firms proposing an LBO during the period 1973-1982 planned significant increases in the level of borrowing up to an average 86% of total capitalization. Because the firm must use internal cash flows to service the debt, borrowers and lenders necessarily concern themselves with the leveraged company's ability to cover these costs. A key measure of the firm's ability to service the debt

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pro forma financial statements of firms that went private with third-party equity participants revealed significant planned increases in corporate borrowing (to an average of 86% of total capitalization). DeAngelo and DeAngelo (1987, 40) suggest this empirical regularity explains why the investing public assigns the LBO label to the latter type of buyout (i.e., buyouts *with* third-party equity participants).

is stable cash flow (Waite and Fridson 1989, 13). Stability of cash flow is important because it indicates the firm has an invariable and predictable ability to service fixed interest costs. This study includes cash flow volatility as a variable and measures it by the standard deviation of a firm's annual cash flows over a given time period relative to a similar measure of cash flow volatility for a broad market segment (e.g., the S&P 400 Industrials). Low cash flow volatility relative to the cash flow volatility of the S&P 400 Industrials (i.e., relative cash flow volatility less than 1.0) increases the likelihood that the firm will be a suitable candidate for a leveraged buyout.

The study has established here and in an earlier section that infusing large amounts of debt into the capital structure may be the only way managers can keep the firm out of the hands of corporate raiders. In addition to the obvious importance of a steady cash flow to service the debt, there is another reason stability of cash flow is consistent with the study's posited theory of managerial control. Frequently, it is the steady stream of cash that flows into the prospective LBO firm that places managers in the position of having to adopt measures to secure control.

When an organization runs out of natural growth opportunities as its industry matures, it no longer needs large sums of cash to finance fledgling projects. The firm may well have already served the purpose for which it was conceived. Nonetheless, managers feel strong emotional and political pressures to extend the firm's existence. As a result, managers may redirect the firm's resources (i.e., cash flows) into some new set of activities, even though these activities may not be the most highly-valued use for those resources. Whereas at one time investors were content to let corporate managers decide the direction of the firm's resources, investors are now demanding a return of control to their own hands. In fact, Kensinger and Martin (1988, 17) suggest that the broader spectrum of opportunities now available to investors (e.g., venture capital funds, initial public offerings, etc.) has played a major role in stimulating takeovers in the 1980s.

While stability of cash flow of the prospective LBO firm is desirable from the perspective of lenders and managers alike, the strength (size) of the cash flow is equally important. One way lenders assess the strength of the prospective LBO firm's cash flow is though examination of fixed charge coverage ratios in the pre-LBO period (Waite and Fridson 1989, 12-13). Although the company's coverage of interest expense and rentals will obviously decline if it restructures via a leveraged buyout, its ability to achieve high relative coverage in the pre-LBO period suggests that the new debt lies on a comparatively solid base. The study includes fixed charge coverage as a variable and measures it by the firm's mean fixed charge coverage in the pre-LBO period, relative to the mean coverage for the S&P 400 Industrials over the same period. A value greater than 1.0 indicates that the firm's fixed charge coverage ratio is higher than the S&P 400 Industrials, which suggests the firm has above-average credit quality, all other things being equal (Waite and Fridson 1989, 12). Above-average credit quality increases a firm's likelihood of becoming a suitable candidate for an LBO, and consistent with the prior discussion regarding the role leverage plays in value creation, fits well within the established framework (i.e., managers seek control to serve their own best interests).

Waite and Fridson (1989, 13) suggest the above two measures of credit quality (i.e., relative cash flow volatility and relative fixed charge coverage) provide the basis for placing industries into one of four categories. The best candidates for LBOs are in Category IV, representing industries with both low relative cash flow volatility and high relative fixed charge coverage. Industries in Categories III and I are the next most desirable because they rate better-than-average with regard to one of the two credit quality measures (i.e., low relative cash flow volatility coupled with low relative fixed charge coverage *or* high relative cash flow volatility combined with high relative fixed charge coverage). By this analysis, the least desirable LBOs are in Category II, which includes industries that have both high relative cash flow volatility and low relative fixed charge coverage (Waite and Fridson 1989, 12-13).

Waite and Fridson (1989, 10) hypothesize that a concentration of LBO activity in certain industries suggests the debt burden created by LBOs is generally placed on industries most capable of handling the added risk. In order to provide support for their hypothesis, Waite and Fridson place industries they identified as LBO-intensive into one of the above four categories. The resulting classifications clearly point to a concentration of leveraged buyout activity in the industries that are best equipped to support them. Fourteen of the fifteen LBO-intensive industries possess low relative cash flow volatility (Categories III and IV). A majority (eight of the fifteen) of the LBO-intensive industries are in Category IV, representing the "best of all worlds" from a credit standpoint (i.e., low relative cash flow volatility and high relative fixed charge coverage) (Waite and Fridson 1989, 14).[20]

Because there appears to be a significant concentration of LBO activity in certain industries, the study includes a dummy variable indicating the individual firm's membership (or lack of membership) in an industry that is LBO-intensive. The study justifies the variable's inclusion on the premise that if one randomly chooses a firm from an industry that is LBO-intensive, it is more likely that firm is an LBO rather than a non-LBO. Otherwise stated, membership in an industry that is LBO-intensive contributes to the likelihood the firm will be a management buyout candidate.

The requirements for capital investment, research and development are also related to the firm's ability to make fixed interest payments. Kleiman (1988, 49), Doyle and Ammidon (1988, 6) and others suggest that a firm will be a more suitable candidate for a leveraged buyout if the requirements for both classes of expenditure are relatively low. Because the LBO firm has strict limitations on additional borrowings, and its cash flow from operations is dedicated primarily to making interest and principal payments, the candidate's

[20] For the purpose of this exercise, Waite and Fridson (1989) classify industries as LBO-intensive on the basis of a narrowly defined four-digit SIC code.

asset base must be capable of supporting near-term growth with relatively minimal capital investment. Further, with the firm's operating cash flows committed to debt service, the candidate's product lines must not require significant technological innovation or research and development expenditures. Because relatively lower requirements for capital investment, research and development increase the firm's likelihood of going private via a leveraged buyout, the study includes as separate variables the ratio of average capital expenditures to average cash flow and the ratio of average research and development expense to average cash flow. Although these classes of expenditure are not direct measures of the firm's ability to service the debt, they are peripherally related to the feasibility of a leveraged transaction and, as such, are consistent with the study's established framework.

Finally, while fixed charge coverage in the pre-LBO period gives an indication of the firm's capacity to take on added debt burden, this measure fails to consider the amount of borrowed monies needed to buy back all of the outstanding shares. For example, a firm can have relatively high coverage of fixed charges in the pre-LBO period, yet due to limited cash flow and high interest rates, not be able to borrow enough to effect the purchase of its shares. 'Buyout value' represents the maximum price a firm could pay for all of its outstanding shares. This study determines buyout value by dividing available cash flow by an interest rate that reflects the inherent risk to investors, and then dividing that result by the total number of shares outstanding. Lenders compare the buyout value to the most recent stock price to determine the feasibility of the going-private transaction.

An example serves to illustrate the concept of buyout value. First, assume the firm has available cash flow of $100 million, and that it would be able to effect the purchase of its 40 million outstanding shares by borrowing the required cash at an interest rate of 14%.[21] Also assume the most recent stock price is $25 per share. Given these assumptions:

[1] Divide available cash flow (in millions of dollars) at the assumed rate of interest to determine the maximum amount the firm could borrow to effect the purchase of its outstanding shares:

$100 /.14 = $714.3 Maximum Borrowing.

In other words, if the firm borrows $714.3 million at an interest rate of 14%, the annual interest payments

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21 The study selects 14% as a representative borrowing rate for transactions of this kind. Kidder Peabody (1989, 9) uses similar high-yield interest rates (12%, 13%, and 14%) in an analysis of estimated buyout values in the beverage industry.

would be exactly equal to the cash flow available on an annual basis [$714.3 x .14 = $100.0].

[2] Divide the maximum borrowing by the total number of shares outstanding (in millions) to determine the maximum borrowing (buyout price) per share:

$714.3 /40 = $17.86 Maximum Buyout Price Per Share.

[3] Compare the maximum buyout price to the most recent stock price to determine the premium (discount) of maximum buyout price relative to the recent stock price:

$17.86 - $25.00 = ($7.14) ⇒ ($7.14)/$25.00 = 28.6% Discount.

Firms with a substantial discount of buyout price relative to stock price will not likely be suitable candidates for a leveraged buyout because, under most circumstances, the firm will be unable to borrow the total cash needed to repurchase its shares.[22]

The second reason the study suggests managers undertake a going-private transaction is to resolve a controversy surrounding the firm's dividend policy. Under public ownership, managers feel compelled to report high profits and pay large dividends to outside shareholders. Conversely, higher tax-bracket

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[22] For further discussion of 'buyout value,' see Roy D. Burry, Kidder Peabody Equity Research, Beverage Industry Report, January 24, 1989, pp. 8-9. The report suggests that maximum buyout value may be somewhat understated due to (1) borrowings at lower rates, (2) reduced capital expenditures, and (3) sales of operations. However, generally the author believes the understatement is minor.

management shareholders are more interested in long-term capital gains. Therefore, a high dividend payout ratio should contribute to the likelihood that a firm will be a management buyout candidate.

Both Maupin, Bidwell and Ortegren (1984, 442) and Maupin (1987, 326) reported that the pre-buyout dividend yields of ex-public firms were significantly higher than the dividend yields of firms that remained public. This fact lends support to the frequent allegations that the more likely candidates for management buyouts are mature, slow-growth companies with a relatively high, stable cash flow (Maupin, Bidwell and Ortegren 1984, 442). In other words, a firm in a slow-growth industry (e.g., cigarette manufacturing and textiles) would tend to have more cash than good investment opportunities. Thus, one expects these firms to pay out a relatively high percentage of their earnings in dividends (Weston and Brigham 1981, 686).

While a high "dividend yield" may be an indication of the firm's propensity to pay out its earnings in the form of a dividend (rather than reinvest them in the business), companies do not establish a dividend policy on the basis of dividend yield. On the contrary, most corporations establish dividend policy on the basis of a targeted dividend per share and targeted payout ratio (Weston and Brigham 1981, 679). Therefore, it would seem "dividend payout" is a more accurate representation of a high dividend- versus low dividend-paying firm.

For instance, assume Firm A maintains a stable dividend of $1.50 per share each year. At the end of Year 1, the market price per share is $25.00, resulting in a dividend yield of 6.0%. If the market price drops to $15.00 per share by the end of Year 2, the dividend yield increases to 10.0%. On the basis of dividend yield alone, one might erroneously assume that Firm A is paying out more of its earnings in the form of a dividend in Year 2. In fact, the dollar amount of dividend is exactly the same in both years.

Although firms will allow the dividend payout ratio to fluctuate in an attempt to maintain a targeted dividend per share, Weston and Brigham (1981, 679) suggest firms will eventually adjust the dividend in order to re-establish the targeted payout ratio. Because firms that pay out a high percentage of their earnings in dividends appear to be the more likely candidates for a management buyout, the study includes dividend payout as a predictor variable. The study measures dividend payout as the annual dividend per common share divided by annual earnings per share.

The third and final reason the study suggests managers undertake a going-private transaction is to improve the firm's productivity and profitability.

This is consistent with Maupin's (1987, 323) survey of managers of ex-public firms in which managers indicated a primary reason for going private was the current stock price did not represent the 'true' value of the company. Paulus and Waite (1989b, 5) suggest that the misuse of free cash flow leads to the undervaluation of corporate assets. They also propose a measure that is able to quantify the extent of the misuse of free cash flow in the U.S. economy. Their so-called "squander index" combines (adds) an index of free cash flow with a measure of investment spending in the macroeconomy. The paragraphs that follow fully detail the development of the squander index and provide examples where appropriate.

Paulus and Waite (1989b, 5) define "free cash flow" as cash flow that the firm cannot profitably invest internally. For example, assume a company has cash flow from operations of $1 million and a cost of capital of 10%. Also assume the firm can profitably invest in the business only $600,000 of this $1 million. A profitable investment, in this case, would be one that yields more than the 10% cost of capital. The remaining $400,000 is free cash flow because the firm is unable to invest this sum in projects that earn greater than the required return of 10%.[23]

[23] Paulus and Waite (1989) use the term 'free cash flow' in a manner that is somewhat inconsistent with

Of course, not all firms have positive free cash flow. Typically, those that do *not* are firms in growth industries. These firms are likely to have internal investment opportunities that greatly exceed their cash flow. They should therefore place all of their cash flow in these internal projects and, in addition, borrow from the market to invest further. On the other hand, companies with positive free cash flow should pay out such funds to shareholders, who can then invest their monies outside the firm at a higher rate than that offered by internal projects. Paulus and Waite (1989b, 5) suggest that, if these firms do invest free cash flow internally, the unprofitable projects will

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usage in the finance literature. Per Copeland and Weston (1983, 386) free cash flow (*FCF*) is equal to:

$$(R-VC-FCC-\text{dep})(1-\pi_C)+\text{dep}-I,$$

where R = revenues
VC = variable costs of operation
FCC = fixed cash costs
dep = noncash charges
π_C = corporate income tax rate
I = replacement investment.

To reconcile the difference in usage, let the term $[(R-VC-FCC-\text{dep})(1-\pi_C)+\text{dep}]$ equal cash flow from operations expressed on an after-tax basis. If replacement investment yields more than the cost of capital, the two definitions of free cash flow are the same (e.g., cash from from operations of $1 million less $600,000 investment equals free cash flow of $400,000). If, on the other hand, the $600,000 investment yields less than the cost of capital, Paulus and Waite's definition of free cash flow implies that *FCF* is $1 million. The Copeland and Weston definition of free cash flow would still imply *FCF* equals $400,000.

Despite this inconsistency, the study continues to use the term 'free cash flow,' but cautions the reader to apply that term only within the context that Paulus and Waite intended.

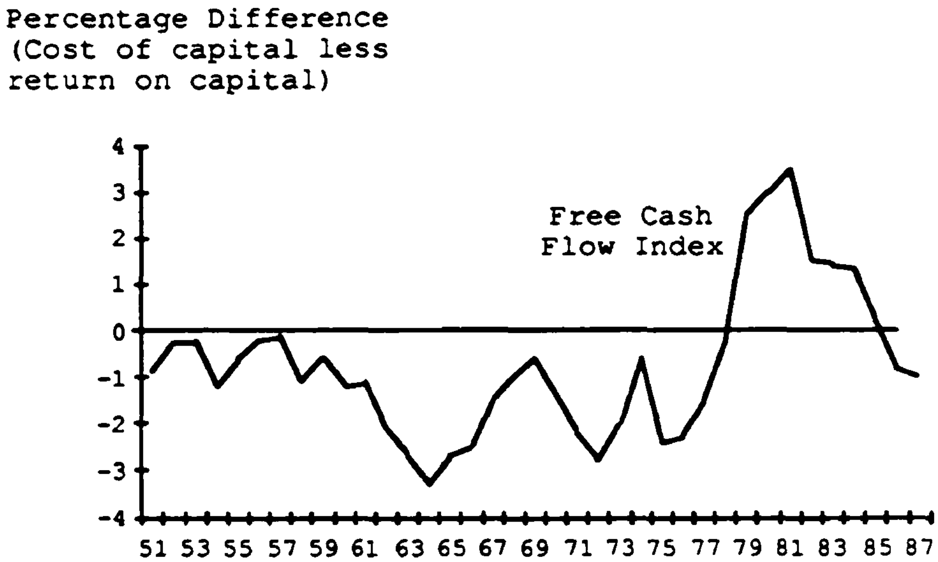
depress the average rate of return on company assets as well as the net return. This, they indicate, leads to an undervaluation of corporate assets and renders the company a takeover target.

From a macro-economic perspective, when the cost of capital becomes high relative to the return on capital, free cash flow should also be high. This is because there would be fewer investments available yielding returns above the cost of capital. Conversely, when returns are very high and the cost of capital is low, free cash flow in the economy would likely be low. Thus, by calculating the difference between the overall rate of return on capital and its cost, one can derive an index of free cash flow for the economy (Paulus and Waite 1989b, 7).[24] As Figure 4 suggests, from around 1980 to 1986, there appears to have been an inordinate amount of free cash flow in the U. S. economy. Paulus and Waite (1989b, 7) suggest this was due to relatively low rates of return on capital and a rapid escalation in the cost of corporate financing.

As suggested above, the existence of free cash flow does not necessarily lead to an undervaluation of assets and, therefore, to takeover or restructuring

[24] Note that the overall rate of return on capital includes (is reduced by) actual investments in suboptimal projects. Thus, the "index" is probably biased toward understatement (i.e., conservative).

Figure 4
Free Cash Flow



Note: Free cash flow represents the area above the 0 line where the cost of capital exceeds the return to capital.

Source: Paulus and Waite (1989b, 7)

activity. It is the *misuse* of free cash flow--that is, investing internally in projects that yield less than the cost of capital--that results in such undervaluation and the need to restructure.

Paulus and Waite (1989b, 7-8) suggest one way to capture the "squandering" of free cash flow in the economy is to add the free cash flow index and the measure of investment spending. If high levels of investment spending accompany increased amounts of free cash flow, it is likely that firms on an economy-wide basis are misusing a significant volume of free cash flow.

Paulus and Waite measure the misuse ("squandering") of free cash flow as follows:

$$\text{Squander Index} = \text{Free cash flow index} + \begin{array}{c}\text{Ratio of investment}\\ \text{spending to cash flow}\end{array}$$

In order to make the scales of the two addends comparable, Paulus and Waite first multiply the ratio of investment spending to cash flow by .20. They then combine a rescaled measure of the ratio of investment spending to cash flow with the free cash flow index, to arrive at a measure for the misuse of free cash flow (i.e., the squander index).[25]

An example serves to illustrate the squander index. Assume the free cash flow index is 4 percent and the ratio of investment spending to cash flow is 60 percent. Using a rescaled measure for "investment

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[25] Steven Waite justified the rescaling of the "ratio of investment spending to cash flow" via a telephone conversation on April 2, 1990. Waite suggested the authors' concern was not with the actual level of investment expenditures, but rather with relative changes in the level. In other words, they were interested in determining how increased or decreased levels of capital expenditures would affect the squander index. Waite suggested an "eyeball" approach proved twenty percent to be an appropriate scalar for this purpose. By the same token, the authors' intent in developing the "squander index" was not to determine the actual level of squandering, but rather to determine how changes (increases or decreases) in the squander index would affect the probability of a takeover.

spending to cash flow" (i.e., 60 percent x .20 = 12 percent), a relatively high squander index results:

4 + 12 = 16 Squander Index.

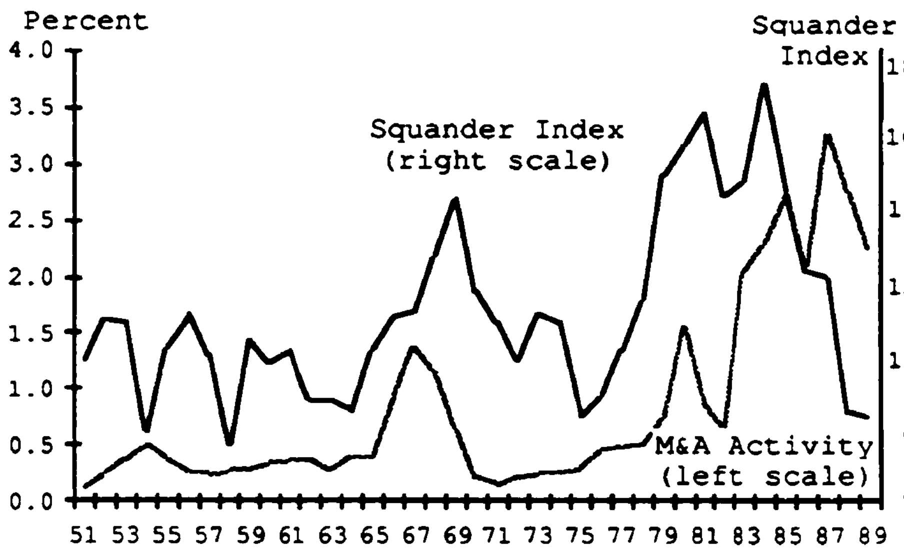
On the other hand, if the free cash flow index is 4 percent, but the ratio of investment spending to cash flow is only 20%, the squander is relatively low:

4 + 4 = 8 Squander Index.

Paulus and Waite (1989b, 9) tracked the squander index against the actual level of mergers and acquisitions activity in the manufacturing and mining sectors over the past four decades. As Figure 5 suggests, the squander index tracked the level of M & A activity reasonably well throughout the years. In fact, the index served as a "lead indicator" of such activity in the late 1970s and the first half of the 1980s. Interestingly, the index hit its highest level in thirty years in the early 1980s, immediately before the onset of a wave of M & A activity in the latter half of that decade. Further, the high level of squandering in the early 1980s was the result of a combination of two factors: large amounts of free cash flow in the U.S. economy in the early eighties (see Figure 4) and high levels of investment spending (between 60% and 80% of cash flow) during that same period (Paulus and Waite 1989b, 8).

Although Paulus and Waite (1989b) apply the concept of a squander index to the economy as a

Figure 5
The Squander Index and
Mergers and Acquisitions Activity



Note: M&A transactions data is for the manufacturing and mining sectors only, expressed in constant 1982 dollars as a percent of real GNP. Also, 1988 and 1989 data represent Morgan Stanley projections.

Source: Paulus and Waite (1989b, 9)

whole, it would seem one could similarly apply this concept at the individual firm level. However, a closer examination of the development of the index reveals the index may produce certain anomalies when applied on a micro-economic basis. The paragraphs that follow now describe the potential problems that may arise.

As explained earlier, the squander index is equal to the difference between the cost of capital and the actual return on capital (i.e., the "free cash flow index") plus a rescaled measure of capital expenditures as a percentage of cash flow. Because the ratio of investment spending to cash flow within the macro-economy always falls within a fairly narrow range (between 50% and 80%), the squander index generally lies somewhere between 6 and 18. However, when the study applies this same measure on an individual firm basis, the broad range of the ratio of investment to cash flow (0% to greater than 100%) can produce results whose interpretation is questionable.

For instance, assume Firm A has a positive free cash flow index of 4 (e.g., cost of capital equals 14% versus an actual return on capital of only 10%). The presence of positive free cash flow suggests the firm should *not* be making capital investments. Assume, however, that the firm makes capital expenditures such that the ratio of capital investment to cash flow is 40%. The rescaling of this measure by .20 and combination of that result with the free cash flow index produces a squander index of 12.

Now assume Firm B has free cash flow of negative 4 (e.g., cost of capital equals 12% versus an actual return on capital of 16%). The presence of negative free cash flow indicates the firm *should be* investing in capital projects. Assume the firm invests 100% of its cash flow in capital projects. The rescaled measure, when combined with the free cash flow index, produces a squander index of 16. This scenario would suggest that Firm B is squandering its resources to a greater extent than Firm A. Of course, Firm B is not squandering its resources at all. In fact, the firm is doing precisely what it should be doing--spending all of its cash flow on capital investments.

Because of the potential anomalies in the squander index of the individual firms in the estimation sample, the study revises the squander index in an attempt to achieve results that would be consistent on a firm-by-firm basis. First, the study reverses the sign of the free cash flow index (i.e., actual return on capital minus cost of capital equals a revised index of free cash flow). The study then *multiplies* the revised free cash flow index by a rescaled measure of the ratio of capital investment to cash flow. The following paragraphs illustrate with an example.

Assume for Firm A that the difference between the actual return on capital and cost of capital is -4 (i.e., -.04 x 100). When the study multiplies -4 by the rescaled measure of capital expenditures to cash flow equal to 8 (i.e., .20 x .40 x 100), the revised squander index is -32. This negative result implies that the firm is squandering its resources. It also implies that the greater the ratio of capital investment to cash flow, the greater is the squandering (i.e., the more negative the revised squander index becomes).

In contrast, assume for Firm B that the difference between the actual return on capital and cost of capital is +4 (i.e., .04 x 100). The study multiplies this difference by a rescaled measure of capital expenditures to cash flow of 20 (i.e., .20 x 1.0 x 100) to produce a revised squander index of +80. This positive result implies that the firm is *not* squandering its resources and also implies that the greater the level of capital investment to cash flow, the more efficient is the firm's use of its resources.

As indicated earlier, when firms misuse their free cash flow, this leads to an undervaluation of assets and the need to restructure. Because it is likely that firms that go private via a leveraged buyout fall into this category, the study includes a measure of the firm's misuse of free cash flow. The study employs the revised squander index specified above and provides further explanation regarding the development of this measure in the following paragraphs.

The previous discussion suggests a measure that captures the misuse of free cash flow is the squander index, i.e., the product of the free cash flow index (cost of capital less return on capital) and the ratio of investment spending to cash flow, where the former is multiplied by -1 and the latter is scaled by a factor of .20. While the amount of investment spending and cash flow are easily accessible from the Compustat file, measures for return on capital and cost of capital are not as easy to obtain. Paulus and Waite (1989b, 6) measure return on capital as the sum of after-tax profits and net interest payments divided by the replacement value of the business capital stock (i.e., property, plant and equipment) plus inventories. Because replacement value information is available for only a limited number of years during the period under study, use of this particular measure is not possible. Further, the lack of readily available information precludes development of a measure of the weighted average cost of debt and equity capital. Therefore, in order to measure the firm's misuse of free cash flow, the study must employ a surrogate for the free cash flow index.

Seitz (1990, 435-437) shows that when one discounts cash flows at the cost of equity capital, the resulting net present value is the same as when one discounts cash flows at the weighted average cost of capital.[26] Therefore, a logical alternative to the weighted average cost of debt and equity capital is the cost of equity capital. The formulation for the

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[26] This conclusion is the embodiment of the "separation" principle that states the selection of capital investments is independent of the selection of financing methods.

standard *net present value method* using a weighted average cost of capital to discount future cash flows is as follows:

$$\text{NPV(WACC)} = \left[\sum_{t=1}^{n} \frac{EBIT_t\ (1-T_c)\ +\ Dep_t}{(1+k_o)^t} \right] - I_o \qquad [4.4]$$

where $EBIT_t$ is earnings before interest and tax in period t, T_c is the corporate tax rate, Dep_t is depreciation in period t, and I_o is the initial investment. The factor, k_o, is the weighted average cost of capital. The numerator includes depreciation as an addition in arriving at cash flow because depreciation served as a deduction in arriving at $EBIT_t$, and depreciation is not a cash expense. Also, because the standard net present value method focuses on the cash flows to both the equity holders and debt holders, the formulation for net cash flow [$EBIT_t$ (1-T_c) + Dep_t] *excludes* payments made to debt holders (i.e., interest).

An alternative to the standard net present value method, the *equity residual method* focuses entirely on the cash flows to the equity holders:

$$\text{NPV(ER)} = -(I_o - B_o) + \sum_{t=1}^{n} \frac{(EBIT_t - Int_t)(1-T_c) + Dep_t + (B_t - B_{t-1})}{(1+k_e)^t} \qquad [4.5]$$

where B_t is the amount of debt the investment supports at time t, B_0 is the initial amount of debt used to finance the investment, and k_e is the marginal cost of equity capital. Because this method focuses solely on the cash flows to the equity holders, the formulation for net cash flow $[(EBIT_t - Int_t)(1-T_C) + Dep_t + (B_t - B_{t-1})]$ *includes* both interest and principal payments made to debt holders. Further, as long as debt remains a constant proportion of the present value of future cash flows from the project (based on the standard net present value formulation), the equity residual method and the standard net present value method are the same (Seitz 1990, 437).[27]

The following example from Seitz (1990, 434-437) illustrates these concepts. Fullerton Corporation is considering buying a new machine that has a cost of $1 million. For the sake of simplicity, assume the machine has a useful life of two years and will have no

[27] Seitz (1990, 437) stresses the importance of the specific assumptions that underlie capital budgeting techniques. For instance, the basis for justification of the standard net present value method is the assumption that the investment under consideration does *not* affect risk and optimal capital structure of the firm. A further assumption is that debt remains a constant percentage of the remaining value of cash flows throughout the life of the asset.

As stated above, if these assumptions hold, the standard net present equals the equity residual net present value. However, when the assumptions needed to justify the net present value method are not met, one must consider the interactions between the investment and financing decisions of the firm in capital budgeting (Seitz 1990, 437).

salvage value. Depreciation per year is $500,000. The machine will generate earnings before interest and tax of $150,000 a year. Fullerton maintains debt equal to 75 percent of value, where the present value of future cash flows represents *value.* The company is able to borrow at 12 percent and the required return on equity is 15 percent. Given a tax rate of 34 percent, the weighted average cost of capital is 9.69 percent [i.e., .75(.12)(1 -.34) + .25(.15)].

Using the formulation for NPV(WACC), the standard net present value is (in thousands of dollars):

$$\text{NPV(WACC)} = \frac{\$150(1-.34)+\$500}{1.0969} + \frac{\$150(1-.34)+\$500}{(1.0969)^2} - \$1,000$$

$$= \underline{\underline{\$43.93}}$$

[See Table 2 for a schedule of debt repayment.] Using the formulation for NPV(ER), the equity residual net present value is (in thousands of dollars):

$$\text{NPV(ER)} = -(\$1,000.00 - \$782.95)$$

$$+ \frac{(\$150.00 - \$93.95)(1 -.34) + \$500 + (\$409.56 - \$782.95)}{1.15}$$

$$+ \frac{(\$150.00 - \$49.15)(1 -.34) + \$500 - (\$0 - \$409.56)}{(1.15)^2}$$

$$= \underline{\underline{\$43.93}}$$

Given the equality of the formulations for NPV(WACC) and NPV(ER), the study uses the cost of equity capital in developing the index of free cash

Table 2 (In thousands of dollars)
Debt Schedule

	Year 0	Year 1	Year 2
Cash flow (before deduction of interest and principal)	-$1,000.00	$599.00[a]	$599.00[a]
Present value of remaining cash flow (k_o =9.69%)	1,043.00[b]	546.08[c]	0
Debt at end of period	782.95[d]	409.56[e]	0
Interest (12% of debt at end of previous period)		93.95[f]	49.15[g]

[a] 150(1 -.34) + 500
[b] $599/1.0969 + 599/(1.0969)^2$
[c] 599/1.0969
[d] 1043.93 x .75
[e] 546.08 x .75
[f] 782.95 x .12
[g] 409.56 x .12

flow. To determine whether the firm is investing at rates *below* the cost of equity, it is necessary to compare the cost of equity to some measure of actual return. Because the "return on assets" (net income/assets) measures the return to all of the providers of funds, use of such a measure would be inappropriate in this case. It would seem a more appropriate measure is the actual return to the equity providers (i.e., net income/equity). The study therefore uses the following measure to estimate the misuse of free cash flow at the individual firm level:

$$\text{Squander Index} = -1\left(\text{Free cash flow index}\right) \times \text{Ratio of investment spending to cash flow}$$

where the "free cash flow index" is equal to the difference between the required return on equity (i.e., the cost of equity capital) and the actual return on equity (i.e., net income/equity), and the "ratio of investment spending to cash flow" is scaled by a factor of .20.

The study suggested earlier it is likely that firms are misusing cash when the required return on capital exceeds the actual return return on capital, *and* the firm continues to invest in capital projects. Because the misuse of free cash flow (as measured by the squander index) is an indication that the firm is undervalued and needs to restructure, the study concludes that a "low" squander index (i.e., a negative result) at the individual firm level increases the likelihood the firm will go private via a leveraged buyout.

Table 3 summarizes the variables the management buyout prediction model employs (including operational definitions) and the formal hypotheses the study will test.

Table 3
Summary of Variables,
Operational Definitions, and Hypotheses

<u>Cash flow volatility</u> » Standard deviation of cash flows for firm *i* ÷ Standard deviation of cash flows for S&P 400 Industrials

H_{01}: The cash flow volatility of the LBO firm is greater than or equal to the cash flow volatility of the public firm.
H_{A1}: The cash flow volatility of the LBO firm is less than the cash flow volatility of the public firm.

<u>Fixed charge coverage</u> » Mean fixed charge coverage for firm *i* ÷ Mean fixed charge coverage for S&P 400 Industrials

H_{02}: The fixed charge coverage of the LBO firm is less than or equal to the fixed charge coverage of the public firm.
H_{A2}: The fixed charge coverage of the LBO firm is greater than the fixed charge coverage of the public firm.

<u>LBO-intensive industry dummy</u> » Membership in LBO-intensive industry equals 1; non-membership equals 0

H_{03}: The likelihood an LBO firm belongs to an LBO-intensive industry is less than or equal to the likelihood a public firm belongs to an LBO-intensive industry.
H_{A3}: The likelihood an LBO firm belongs to an LBO-intensive industry is greater than the likelihood a public firm belongs to an LBO-intensive industry.

<u>Capital expenditures to cash flow</u> » Average capital expenditures ÷ Average cash flow

H_{04}: The level of capital expenditures of the LBO firm is greater than or equal to the level of capital expenditures of the public firm.
H_{A4}: The level of capital expenditures of the LBO firm is less than the level of capital expenditures of the public firm.

Table 3 (continued)
Summary of Variables,
Operational Definitions, and Hypotheses

Research and development expense to cash flow	» Average research and development expense ÷ Average cash flow

H_{05}: The level of research and development expense of the LBO firm is greater than or equal to the level of research and development expense of the public firm.

H_{A5}: The level of research and development expense of the LBO firm is less than the level of research and development expense of the public firm.

Buyout value to market value	» Discounted annual cash flow ÷ Year-end market value

H_{06}: The ratio of buyout value to market value of the LBO firm is less than or equal to the ratio of buyout value to market value of the public firm.

H_{A6}: The ratio of buyout value to market value of the LBO firm is greater than the ratio of buyout value to market value of the public firm.

Dividend payout	» Annual dividend per common share ÷ Earnings per share

H_{07}: The dividend payout of the LBO firm is less than or equal to the dividend payout of the public firm.

H_{A7}: The dividend payout of the LBO firm is greater than the dividend payout of the public firm.

Squander index	» (-1)(Cost of equity capital less return on equity capital) x (.20)(Capital expenditures to cash flow)

H_{08}: The squander index of the LBO firm is greater than or equal to the squander index of the public firm.

H_{A8}: The squander index of the LBO firm is less than the squander index of the public firm.

Management Buyout Prediction Versus Takeover Target Prediction

In prior sections, the study provides rationale for each of the variables included in the management buyout prediction model. Because the study bases inclusion of a number of these variables on a premise that the firm goes private to avoid a threat of takeover, one naturally questions the ability of the model to distinguish between LBO candidates and takeover targets that are not LBO candidates. In the present study, the majority of the variables focus on the firm's ability to service LBO debt. As a previous section shows, leverage plays a key role in magnifying the returns to equity investors in a leveraged buyout. However, restructuring profit (e.g., increasing leverage) is not the primary motivation in all hostile takeovers. Thus, in cases where acquirers do not intend to alter materially the financial structure of the target firm, the target firm's ability to service acquisition debt is not a key consideration.

Bhide (1989) examined the benefits sought by acquirers in hostile acquisitions attempted in 1985 and 1986. Based on his examination, he classified the most likely motives for these acquisitions into the following six categories:

[1] Create operating synergies.
[2] Build or redeploy corporate portfolio.
[3] Acquire undervalued asset.

[4] Improve efficiency by restructuring.
[5] Maintain independence.
[6] Tax motives.

Bhide's definition of *operating synergies*, the first category, included only those benefits expected from combining or coordinating non-financial functions such as production or marketing. He intentionally excluded from this category cases where acquirers expected to create value by coordinating only the financial or resource allocation functions of the target with their existing businesses. He included in the second category, building or redeploying the *corporate portfolio*, all cases in which the primary expected benefit of the acquirer was furtherance of the acquirer's diversification strategy. Bhide placed acquirers in the third category, acquiring an *undervalued asset*, when he could determine that the acquirer believed the target was worth more than the purchase price. He indicated this undervaluation may have been due to a stock market undervaluation or to some anticipated change in demand, price, or costs affecting the firm's value.

The fourth category, *restructuring*, included all cases where the acquirer expected to profit from changing the target's strategy, e.g., by increasing leverage, divesting certain business units, implementing cost reductions, or discontinuing unprofitable reinvestment. The fifth category, maintaining *independence*, included cases where acquirers themselves were under an imminent threat of takeover. In these cases, acquirers sought an acquisition to neutralize the threat. Finally, Bhide assumed *tax* considerations were the primary motivation for an acquisition when the acquirer sought to take advantage of existing tax credits or tax loss carryforwards. Bhide ignored "general" tax considerations as a primary motivation in these acquisitions because it was difficult to determine how important these tax benefits were in the decision to proceed with a takeover.

In order to classify acquirers into one of these six categories, Bhide devised reasonable rules of inference based on available information. He devised these rules, rather than rely on public statements about the acquirers' motives, because he believed these statements would not provide a reliable guide to the *real* motives. Bhide asked four questions of each acquisition attempted:

• *What was the acquirer's form?* For instance, if the acquirer was an ongoing operating company, Bhide assumed synergistic benefits, especially when the company operated in a single industry. He ruled out synergistic or portfolio benefits if the acquirer was a private partnership organized for the transaction or a private investment shell.

- *What was the acquirer's diversification strategy and track record in previous takeovers?* For instance, Bhide assumed synergistic benefits if the acquirer exhibited a pattern of making acquisitions in the same or related industry and integrating the acquired businesses into existing operations. He assumed portfolio benefits if the acquirer exhibited a pattern of making opportunistic acquisitions in a variety of businesses and industries, treating these companies on a stand-alone basis and making little effort to coordinate non-financial functions across businesses. Also, rarely would the acquirer divest these acquisitions unless they perceived them as failures. If, on the other hand, acquirers sold these stand-alone businesses at a profit, Bhide assumed investment benefits (i.e., acquiring an undervalued asset) were the acquirer's motive.

- *Was the acquirer under attack before it initiated the takeover?* Bhide assumed defensive benefits (i.e., maintaining independence) if a raider had accumulated a substantial and unwelcome stake in the acquirer or had actually made an overture.

- *Did the acquirer need to utilize substantial tax credits or tax loss carryforwards?* If so, Bhide assumed tax considerations motivated the acquirer.

Based on these rules of inference, Bhide classified the 47 hostile takeovers attempted in 1985 and 1986 according to their primary motivation(s):[28]

Synergy (13)	28%
Portfolio (8)	17%
Investment (2)	4%
Restructuring (32)	68%
Tax (2)	4%

While it is evident that "restructuring" profits appeared to be the primary motive in over two-thirds of the hostile takeover attempts, increasing leverage was just one of the ways the acquirers hoped to generate such profits. Bhide (1989, 43) indicated that in 27 of the 32 attempts involving a restructuring motive, hostile acquirers intended to sell subsidiaries. He expected a change in financial structure in approximately 15 of the 32 attempts, while cutting costs appeared to have been a major factor in only six cases.

As the above paragraph indicates, restructuring profits from changing the target's financial structure (i.e., increasing leverage) appeared to have been a primary factor in less than one-third (15 out of 47) of the hostile takeovers attempted. Further, if one

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[28] The percentages total greater than 100% because, in 4 of the 47 cases, Bhide inferred portfolio plus synergistic benefits as the primary motivation for the takeover attempt. In 6 other cases, he inferred restructuring plus synergistic benefits as the acquirer's primary motive.

considers the actual role leverage plays in these transactions, a still different picture emerges. Bhide (1989, 46) suggests that most hostile acquirers did not intend to use junk bond financing as a permanent method of financing, but rather only as a stop-gap measure. For takeovers that were successful, asset sales, stock issues or innovative financing arrangements quickly raised substantial funds for acquirers and put them on more solid financial footing. In fact, in 9 of the 12 cases where acquirers used junk bond financing, there were immediate and major reductions in leverage. Thus, Bhide (1989, 46) concluded that acquirers did not use leverage as an end in itself, but rather as a means for gaining control of the target firm.

Bhide (1989, 43) also examined the distribution of expected benefits in friendly takeovers (i.e., acquisitions where the target firm did not contest the tender offer). He found the distribution of expected benefits in friendly takeovers was markedly different from the distribution of expected benefits in hostile acquisitions. Whereas restructuring profits were the primary motivation of the majority of acquirers in hostile attempts, restructuring profits were the expectation of only 5 of the 30 (17%) acquirers in friendly transactions. In fact, Bhide (1989, 50) reports that 64% of the friendly takeovers resulted in the addition of little to no financial risk. Rather than using high-risk debt (as was done in the majority of hostile takeovers), acquirers in these transactions typically made payment to target shareholders with the acquirer's own stock or excess cash.

In conclusion, the primary emphasis of the management buyout prediction model developed in this study is the firm's ability to borrow and repay on a scheduled basis the monies needed to effect the purchase of its shares. In contrast, it would appear the primary emphasis of a model predicting acquisition targets is *not* the target firm's ability to borrow the purchase price and service fixed interest costs. This is particularly so given the fact that most hostile acquirers immediately pay down acquisition debt after a takeover. Of course, in some acquisitions, the unused debt capacity of the target firm is an important consideration. However, the findings of Bhide's (1989) research indicate that restructuring profits via increasing leverage are *not* the primary emphasis in the majority of takeovers (both friendly and unfriendly).

General Hypotheses

The general hypothesis of the study is that firms that go private via a management buyout possess different attributes from other public firms as much as one year prior to the change to private status. Also a part of the study's general hypothesis is that these attributes are readily determinable using publicly available financial and/or market data.

The null hypothesis and the alternative hypothesis are as follows:

H_0: Differentiation between public firms and firms that go private via a management buyout is not possible through analysis of the selected ratios and measures developed from financial and/or market data.

H_A: Differentiation between public firms and firms that go private via a management buyout is possible through analysis of the selected ratios and measures developed from financial and/or market data.

The study tests the null hypothesis for the first-year-prior to going private via a management buyout. The study defines the "first-year-prior to going private" as that year included in the most recent financial statements prior to the year the firm achieved private status via a management buyout.

CHAPTER V

SAMPLE SELECTION AND ANALYSIS OF DATA

Sample Selection

The fundamental objective of the present study is to develop a model that can reliably distinguish firms that will go private via a management buyout from firms that will remain public. The model estimation procedure uses the financial characteristics of firms that have gone private via a management buyout during the period 1979-1988, along with the financial characteristics of firms that remained public as of 1988. The year 1979 appears to be a reasonable starting point for data collection for the three reasons that follow.

First, although public companies have engaged in going-private transactions since the early 1970s, the literature suggests that 1979 was the year in which leveraged buyouts "officially became of age" (Garguilo and Levine 1982, 15). Second, *Mergerstat Review* began tracking going-private transactions in 1979, signalling the importance of the leveraged buyout in the market for corporate control. Third, it was also in that year that the first highly visible, large leveraged buyout took place. While there had long been a universe of closely-held firms involving principals seeking to sell their companies in order to liquify their holdings, these tended to be companies of smaller size. When Kohlberg, Kravitz, and Roberts (KKR) orchestrated the buyout of the Houdaille Machinery Company in 1979, it was in fact a landmark acquisition. Not only did it establish a leadership role for KKR in structuring unsecured leveraged buyouts, but it extended the application of leveraged buyouts to a size of transaction that had never before been contemplated (Diamond 1985, 6).

While the estimation sample includes management buyouts from the period 1979-1988, it does *not* generally include firms that remained publicly-held during that same period. Rather, the estimation sample includes firms that remained public as of a given date (i.e., 1988). Although the ideal situation may be to include data points for the public firms from each of the years under study (1979-1988), the cost to compute the various data points would be prohibitive in terms of researcher time.

For instance, the study employs the capital asset pricing model to determine the cost of equity capital, a necessary component of the squander index.[29] While

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[29] The capital asset pricing model allows one to determine the cost of equity capital as follows (Weston and Brigham 1981, 600):

risk-free rates and market returns are readily available, no single source contains beta values for each firm in the estimation sample. This circumstance makes it necessary to compute a beta value for each of these firms in order to maintain consistency. Further, if the estimation procedure uses data points for public firms from each year under study, the researcher would have to make repeated beta calculations because beta values are not stationary over time (Francis 1980, 367-369).

Others have faced similar problems related to size of the estimation sample. For instance, Palepu (1986) suggested computer memory constraints may have been a problem in his attempt to estimate an acquisition target prediction model. In his case, the estimation sample included acquired firms from the period 1971-1979. However, rather than include data points for non-acquired firms for the entire period of study (1971-1979), he included data points as of a single period, 1979. Ohlson (1980) used a somewhat different

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$$k_i = R_f + (R_m - R_f)\beta_i,$$

where: k_i = the required rate of return on the common equity of firm i

R_f = the risk-free rate of return

R_m = the expected rate of return on the market portfolio

β_i = $\mathrm{Cov}(R_i, R_m)/\sigma^2_m$.

$\mathrm{Cov}(R_i, R_m)$ = the covariance between the returns on security i and the returns on the market

σ^2_m = the variance of the market returns.

procedure in developing a model to predict bankruptcy. In his study, he selected failed firms from the period 1970-1976 and nonfailed firms from various years. Ideally, Ohlson (1980, 117) suggested that the control sample would have included financial reports for each nonfailed firm during the period 1970-1976. However, due to cost and size constraints, Ohlson deemed this impractical. Instead, he concluded that each nonfailed firm should contribute with only one vector of data points. He selected that year for each nonfailed firm using a random procedure.

In order to prepare a list of firms that have *gone private via a management buyout* during the period 1979-1988, the study uses the following sources: (1) IDD Information Services, Inc., a private information tracking service, whose data base includes leveraged buyouts that have occurred since 1984, (2) *Mergerstat Review* which publishes annually a list of the twenty largest going-private transactions that have occurred during the period 1979-present, and (3) *Mergers and Acquisitions* which publishes a quarterly roster of the top 25 transactions by dollar volume, including leveraged buyouts. *Mergers and Acquisitions* also publishes on a quarterly basis a description of each merger and acquisition completed. An examination of these descriptions is necessary in order to determine the identity of LBO firms and MBO firms whose acquisitions do not appear among the largest 25 transactions. Also, because *Mergers and Acquisitions* provides details on approximately two to three thousand transactions each year, the study limits its examination of this source to the years prior to 1984.

Each of these sources has various limitations for the purpose of this study which necessitates some modification in the search procedure employed. The paragraphs that follow discuss these particular limitations and the study's resolution of the problems they present.

IDD Information Services, Inc. The IDD data base maintains descriptions of transactions that the financial press commonly refers to as leveraged buyouts. As such, certain transactions included in the data base fall outside the scope of this study's definition of an LBO. In addition to the buyout of a public firm by an acquisition group that includes members of management (this study's definition of an LBO), the IDD data base includes under the heading "leveraged buyouts" the following types of transactions: the buyout of a public firm by an operating concern or an acquisition group that does not include members of management; the buyout of a private firm by an operating concern or an acquisition group that may or may not include members of management; and the buyout of an operating division by an operating concern or an acquisition group that may or may not include members of management. In each case, the acquiring group obtains the necessary funds to effect the purchase by borrowing heavily against the assets of the acquired firm (division). Because the descriptions that IDD Information Services, Inc. provides generally do not indicate the participation of a management group, one must consult other sources (e.g., *Mergers and Acquisitions*, *Wall Street Journal Index* or *Wall Street Journal*) to verify management's involvement. One must also verify the status of the acquired firm (public or private) and, in certain instances, determine whether the buyout is actually a corporate divestiture.

The IDD listing also imposes other restrictions on the search process which requires the use of alternative sources when compiling the list of MBO firms. First, the IDD listing of leveraged buyouts includes only those transactions greater than $25 million in value (purchase price paid). Second, the listing excludes transactions that did not involve the use of debt (e.g., equity-financed buyouts of public firms by a management group). Third, IDD Information Services, Inc. did not begin tracking these transactions until 1984 which potentially leaves the study with a void for the period 1979-1983.

Mergerstat Review. This information base is useful in corroborating details of transactions obtained from other sources, and also in providing the names of additional firms that have gone private prior to 1984. However, *Mergerstat Review* makes no indication of management's participation in the buyout and thus, in order to satisfy the purpose of the study, one must verify that fact by consulting other sources (e.g., *Mergers and Acquisitions*, *Wall Street Journal Index* or *Wall Street Journal*).

Mergers and Acquisitions. While *Mergers and Acquisitions* generally identifies members of the acquiring group, in a limited number of cases, it does not indicate the participation of management. In these cases, one must consult other sources to verify management's involvement (e.g., *Wall Street Journal Index* or *Wall Street Journal*).

Analysis of Data

Operational Definitions

A previous section (Chapter IV, 113-144) discussed the variable selection process and, in general terms, described the variables the study employs. This section gives greater empirical meaning to these terms and specifically details the measurement process.

Cash flow volatility. Because, in the typical management buyout, investors borrow heavily against the assets of the acquired firm, an important consideration in these transactions is the acquired firm's ability to service fixed interest costs. As indicated earlier, a key measure of the firm's ability to cover these costs is stable cash flow. This study defines "cash flow" as earnings before the deduction of taxes, interest, and noncash charges such as depreciation.[30] For firms that have been taken private, the study measures cash flow volatility over the ten-year period preceding the year in which the management buyout occurred. For firms that are still publicly held, the study measures cash flow volatility over the period 1978-1987 (i.e., the ten-year period preceding 1988). When Waite and Fridson (1989) examined the credit characteristics of LBO-intensive industries, they computed cash flow volatility over a fifteen-year period. Because Gibson (1989, 245) suggests a five-year period should be adequate to give insight into the stability of a given ratio, the study selects an intermediate period of ten years.

Depending on the year in which the firm goes private, there may be little overlap in the measurement

[30] The study excludes interest when determining cash flow because the intent here is to determine the degree of operating risk for the firm. Per Waite and Fridson (1989, 13), stable cash flow implies low operating risk, and vice-versa. Obviously, the inclusion of interest in the determination of cash flow would imply consideration of, not only the operating risk, but also financial risk of the firm.

periods of the public and private firms. Consider, for example, a firm that goes private in 1982. The study measures cash flow volatility of the private firm over the period 1972-1981. For publicly-held firms, the study measures cash flow volatility over the period 1978-1987. Because the sample observations come from essentially different time periods, there may be concern that population characteristics have shifted over time, decreasing the homogeneity among the observations. Further, macro-economic conditions, such as recession, war, and changes in economic policy, may be possible confounding events. However, in the case of cash flow volatility, the study measures volatility of the firm relative to the volatility of an entire population of firms (i.e., the S&P 400 Industrials). Therefore, possible changes in population characteristics over time or confounding events should not present a major problem in this case.

In order to calculate cash flow volatility, one must first make an assumption about the trend of annual cash flow. If annual cash flow increases or decreases by a constant *amount* each year, the trend in cash flow follows a straight line (i.e., the trend is linear). However, if annual cash flow increases (decreases) by a constant *rate* each year, the long-term pattern bends upwards (downwards), indicating the series follows an exponential trend (Neter, Wasserman and Whitmore 1982, 639). Weston and Brigham (1981, 120) suggest that the stream of future net cash inflows of the firm follows one of three major patterns: {1} *no growth* over an infinite time period, {2} *constant* or *"normal" growth* over an infinite time period (i.e., cash flows increase by a constant rate each year), and {3} *temporary supernormal growth* over a finite time period followed by an infinite period of normal growth (e.g., cash flows grow at a 20 percent annual rate for ten years, then the growth rate falls to 4 percent annually, the norm for the economy). While a few firms may fall into the first category of zero growth (some may even experience negative growth), most firms fall into the middle category where growth is expected to continue indefinitely at about the same rate as the Gross National Product (Weston and Brigham 1981, 689). Therefore, without inflation, the cash flows of an average or "normal" company would grow at a constant rate of approximately three to five percent per year.

Firms typically go through life cycles during part of which their growth exceeds that of the economy as a whole. Auto manufacturers in the 1920s and computer and office equipment manufacturers in the 1960s serve as good examples. In these cases, for instance, the firm may grow at a twenty percent rate for ten years, then have its growth rate fall to four percent, the norm for the economy. Because the cash flows of the typical LBO candidate stem from activities that have matured, cash flows in the period immediately preceding the management buyout are likely to have followed a "normal" growth pattern. Therefore, the assumption that the cash flows of the LBO firm follow an exponential trend (i.e., cash flows increase by a constant rate each year) is appropriate here. This approach is also consistent with the methodology Waite and Fridson (1989) employ to calculate cash flow volatility of LBO-intensive industries during the period 1971-1985.

Before examining the approach for estimating an exponential trend function, first consider the function for a series that displays a linear trend:

$$E\{Y_t\} = T_t = b_0 + b_1 X_t, \qquad [5.1]$$

where T_t = the trend value for period t (t = 1, 2, . . . n)
X_t = a numerical code denoting period t (e.g., $X_1 = 1$, $X_2 = 2$, . . . $X_t = t$, . . . , $X_n = n$)
n = the number of t periods in the time series (e.g., for annual data from 1978 to 1987, n = 10)
b_0 = the intercept of the trend line
b_1 = the slope of the trend line.

In other words, when the independent variable has the value X_t, the expected value of Y_t is $E\{Y_t\} = b_0 + b_1 X_t$, where Y_t represents the individual observations. In order to determine b_1 and b_0, one uses the method of least squares:

$$b_1 = \frac{\sum x_t Y_t - \frac{(\sum x_t)(\sum Y_t)}{n}}{\sum x_t{}^2 - \frac{(\sum x_t)^2}{n}} \qquad [5.2]$$

$$b_0 = (1/n)(\sum Y_t - b_1 \sum x_t). \qquad [5.3]$$

Now consider the case in which the long-term sweep of a series displays an exponential trend. In this circumstance, the *logarithms* of the series will display a linear trend. Hence, in order to obtain an exponential trend, one must first take the logarithms of the individual observations Y_t and then fit a linear trend to the logarithms of Y_t. In general notation, the exponential trend function, when fitted to the logarithms of the observations, is:

$$T'_t = b_0 + b_1 X_t \qquad [5.4]$$

where: T'_t = log T_t.

One can determine b_1 and b_0 using the method of least squares indicated above. However, one should replace Y_t in the least squares formulas for b_1 and b_0 with Y'_t, the logarithms of the individual observations. To obtain the trend value T_t for the original series, one simply takes the antilog of T'_t. Thus, fitting an exponential trend is the same as fitting a linear trend, once one has taken the logarithms of Y_t (Neter, Wasserman and Whitmore 1982, 640).

Using specific notation, the study calculates cash flow volatility by estimating the following exponential trend function for each sample firm:

$$\log(CF_{it}) = a + bX_t + e_t, \qquad [5.5]$$

where: $\log(CF_{it})$ = log of firm i's cash flow at time t
X_t = year coded in one-year units (i.e., 1978 = 1, 1980 = 2, . . ., 1987 = 10)
e_t = error at time t

a, b : unknown parameters (b is the trend growth of cash flow).

For the sake of illustration, assume that annual cash flows (CF) for firm i are $45 million in 1978, $49 million in 1979, . . . and $89 million in 1987. To obtain the exponential trend of annual cash flows, fit a linear trend to the logarithms of the individual observations, CF_{it}. The resulting fitted trend equation is:

$$\log(CF_{it}) = 1.64085 + .0182844X_t,$$

and the logarithmic trend value for 1978 ($X_1 = 1$) is:

$$\log(CF_{i1}) = 1.64085 + .0182844(1) = 1.65913.$$

To obtain the trend value in original units (millions of dollars), take the antilog of that value:

$$CF_{i1} = \text{antilog } 1.65913 = \$45.6 \text{ million}.$$

Denote the residual for firm i in each of the respective years by e_{it} and define it as:

$$e_{it} = CF'_{it} - CF_{it}, \qquad [5.6]$$

where: CF'_{it} = the observed value of CF for firm i in year t
CF_{it} = the trend (fitted) value of CF for firm i in year t.

To continue the illustration from above, calculate the residual for firm i in 1978:

$$e_{i1} = \$45 - \$45.6 = -\$.6 \text{ million.}$$

To obtain a measure of the variance of the error terms for firm i, sum the squared residuals, e, for firm i across all years and divide that sum by t - 2:

$$\sum e_{it}^2/(t - 2). \qquad [5.7]$$

The standard deviation of the error terms (cash flow volatility for firm i) is:

$$\sqrt{\sum e_{it}^2/(t - 2)}. \qquad [5.8]$$

In the same manner, estimate an exponential trend function for the S&P 400 Industrials. Then express cash flow volatility for firm i as a relative measure, i.e., cash flow volatility of firm i /cash flow volatility of the S&P 400 Industrials.[31,32]

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[31] Information regarding the development of an exponential trend function is per John Neter, William Wasserman, and G. A. Whitmore, *Applied Statistics*, 1982, pp. 467-472 and 639-641.

[32] The study could more simply determine cash flow volatility of the firm (and the S&P 400) by computing the deviation of cash flow about the mean (i.e., the variance or standard deviation). However, this method of determining volatility would be appropriate *only if* cash flows remained relatively stable over time. Given the assumption that cash flows of the normal firm increase at a constant rate each year, the study more aptly measures cash flow volatility as the deviation from the estimated trend line.

Fixed charge coverage. In addition to stability of cash flow, lenders are concerned with the strength (size) of the prospective LBO firm's cash flow. One way lenders assess the strength of the firm's cash flow is through examination of fixed charge coverage ratios in the pre-LBO period. While coverage of fixed charges will necessarily decline once the buyout becomes effective, high relative coverage in the pre-LBO period gives lenders an indication of the firm's ability to assume additional debt.

Although earnings coverage ratios can properly include various types of fixed charges, Bernstein (1978, 522) indicates the most widely used measures of 'fixed charges' are interest expense and the interest portion of rentals. There are those who suggest that principal repayment obligations are as onerous as obligations to pay interest and, as such, should be given recognition in earnings-ratio calculations. However, opponents to this line of thinking have advanced at least two different reasons for not doing so.

First, because principal repayments do not presumably have the same degree of urgency as interest payments, they should be excluded from coverage ratios. Of course, this assumes that creditors would be willing to agree to a temporary suspension of such payments (Bernstein 1978, 523). The second and more serious problem with including principal repayments among fixed charges is the fact that not all debt agreements provide for repayment of principal in the early years of the life of the debt obligation (Bernstein 1978, 523-524). This would seem a most appropriate argument in the case of high-yield bonds, where even interest payments need not create an immediate drain on the cash resources of the enterprise.[33]

The only fixed charge Compustat includes in its earnings-coverage ratio is interest expense. Using this definition of fixed charges, the study measures fixed charge coverage for the LBO firm over the ten-year period preceding the year in which the leveraged buyout occurred, relative to the mean coverage of the S&P 400 Industrials over that same period. For firms that are still publicly held, the study measures fixed charge coverage by the mean fixed charge coverage over the period 1978-1987, relative to the mean coverage of the S&P 400 Industrials over the same period. As with cash flow volatility, the measurement periods of the public and private firms can be quite different in certain instances. However, the expression of fixed charge coverage of the firm relative to the fixed

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[33] Payment-in-kind debt instruments (commonly referred to as "PIK Debentures" or "parent bonds") provide the issuer with the option over part or all of the life of the instrument to make interest payments in either cash or additional debt instruments ("baby bonds") (Barnes 1989, 11).

charge coverage of the S&P 400 Industrials substantially reduces the problem resulting from changing population characteristics over time.

LBO-intensive industry dummy. Waite and Fridson (1989, 14) contend there is a significant concentration of leveraged buyout activity in certain industries. Because membership in an LBO-intensive industry appears to contribute to the likelihood a firm will be a management buyout candidate, the study includes a dummy variable indicating the firm's membership (or lack of membership) in an industry that is LBO-intensive.

On the basis of a two-digit SIC code, the study assigns a value of 1 to firms that belong to one of twelve industries that Morgan Stanley identifies as LBO-intensive.[34] The study assigns a value of 0 to all other firms indicating they are not a part of an industry that is LBO-intensive.

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[34] Morgan Stanley identifies the following twelve industries as LBO-intensive:

SIC Code	Industry Name
2000	Food & Kindred Products
2200	Textile Mill Products
2300	Apparel & Other Finished Products
2600	Paper & Allied Products
2700	Printing, Publishing & Allied Products
3200	Stone, Clay, Glass & Concrete Products
3400	Fabricated Metals
3500	Industrial & Commercial Machinery
3600	Electrical Equipment
5300	General Merchandise Stores
5400	Food Stores
5600	Apparel & Accessory Stores

<u>Capital expenditures to cash flow; research and development expense to cash flow</u>. Because a higher proportion of cash flow of the LBO firm must be free to service the debt, the firm should have relatively lower requirements for capital investment and research and development. Therefore, the study includes as separate variables the ratio of average capital expenditures to average cash flow and the ratio of average research and development expense to average cash flow. The study determines these averages for the LBO firms and non-LBO firms over the same respective time periods as indicated for cash flow volatility and fixed charge coverage.

Because the study measures capital expenditures and research and development expense relative only to the cash flow of the individual firm (not to a population average), it may be necessary to rescale the independent variables to increase the homogeneity among observations from different time periods. Palepu (1986, 21) employed such a procedure to deal with a similar problem when estimating an acquisition target prediction model. In his case, he estimated two versions of the logit model. In one version, he used the raw values of the independent variables. In a second version, he scaled each of the individual variables of an observation in a given year by the population average in that year. In doing so, he intended to eliminate the mean shift in the population characteristics that may have occurred from year to year during the period under study, thereby making the observations more comparable.

The two versions of Palepu's model produced similar results, which may indicate a rescaling of the independent variables was unnecessary. This is an especially important result given that, in certain instances, the disparity between measurement periods was as great as eight years. For example, he measured the "net book assets" of firms acquired in 1971 (the earliest year of the study) as of 1970, and the "net book assets" of non-acquired firms as of 1978.

The measurement periods in the present study can also be different. For instance, if a management buyout occurred in 1979 (the earliest year in the study), the study would measure "capital expenditures to cash flow" of the MBO firm over the period 1969-1978. For public firms, the measurement period would be 1978-1987. However, because such a divergence occurs in only a limited number of instances, the study concludes that a rescaling of the independent variables is unnecessary in this case. Further, the results of Palepu's (1986) study described above provide added support for this conclusion.

Buyout value to market value. Buyout value represents the maximum price a firm could pay for all of its outstanding shares. To determine buyout value, one capitalizes available cash flow at an assumed rate of interest, then divides that result by the total number of shares outstanding. If the buyout value is significantly lower than the most recent stock price, the firm will probably not be able to accumulate the cash required to effect the purchase of its shares.

In order to estimate the maximum amount the sample LBO firms can borrow, the study capitalizes cash flow in the year preceding the buyout using an interest rate that reflects the inherent risk of the investment at that time.[35] Although the ratings for speculative grade debt range from 'BB' to 'C,' historical rates are available only for debt rated 'AAA' to 'BBB.' Because the yield spread changes over time, approximating a 'BB' or lower grade rate does not appear feasible. Thus, the study uses the average 'BBB' rate in the last month of the fiscal year preceding the buyout for each sample LBO firm.[36]

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[35] The study measures the financial characteristics of the sample LBO firms as of the end of the fiscal year prior to the year of going-private. As such, the study uses *actual* cash flow in the year preceding the buyout to determine buyout value, rather than *estimated* trend cash flow in the year of buyout. Similarly, for the non-LBOs, the study uses actual cash flow in 1987 versus estimated trend cash flow in 1988.

[36] Use of a 'BB' or lower grade rate is consistent with Kidder Peabody's (1989,9) analysis of estimated buyout values in the beverage industry. Specifically, the analysis uses alternative high-yield borrowing rates of 12%, 13%, and 14%.

The study compares the maximum buyout value (i.e., capitalized cash flow) to the market value of the entity at the end of the fiscal year preceding the buyout. For firms that go private via a leveraged buyout, one expects the ratio of buyout value to market value to be relatively large. In a similar manner, for the non-LBO firms, the study calculates the ratio of buyout value to market value in the year 1987.

Dividend payout. Managers frequently claim that a primary reason for the going-private transaction is to settle a policy dispute regarding dividends. It would appear the higher-tax-bracket management shareholders prefer long-term capital appreciation, whereas outside shareholders generally prefer high dividend income. Because the empirical evidence suggests that the shares of stock in most ex-public firms had been selling in the market as 'yield' stocks (Maupin 1987, 326), the study includes a measure of the firm's tendency to pay out its earnings in the form of a dividend.[37]

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37 Ray (1986, 37) suggests firms that pay substantial dividends are natural LBO candidates because these firms may divert cash flow from dividends to help pay interest and principal after a buyout. One might argue, though, that if a firm has sufficient cash to pay dividends, it also has sufficient cash to support capital expenditures, research and development.

Because of the potential drain on cash, Gaffin (1986, 16) suggests that a capital intensive business (i.e., one that must continually buy new equipment or plants) is a poor candidate for an LBO. High technology companies, in particular, do not make good candidates for an LBO because they must frequently change their equipment to keep up with technology.

Generally, companies establish dividend policy on the basis of a targeted dividend payout, hence, the study includes dividend payout as the appropriate predictor variable. The study measures dividend payout as the annual dividend per common share divided by the annual earnings per share. The time periods over which the study measures this ratio are the same as indicated for "buyout value to market value."

Squander index. When the prospective LBO firm is publicly held, managers and stockholders often claim that the current stock price does not accurately reflect the true value of the company (Maupin 1987, 323). Paulus and Waite (1989b, 5) suggest such an undervaluation is due to the firm's misuse of its free cash flow. Therefore, the study includes a measure of the firm's misuse of cash as indicated below:

$$\begin{matrix}\text{Squander}\\ \text{Index}\end{matrix} = -1\begin{pmatrix}\text{Free cash}\\ \text{flow index}\end{pmatrix} \times \begin{matrix}\text{Ratio of investment}\\ \text{spending to cash flow}\end{matrix}$$

where the "free cash flow index" equals the difference between the cost of equity capital and the return on equity capital. The study uses annual capital expenditures and annual cash flow to derive the "ratio of investment spending to cash flow." Similar to Paulus and Waite (1989), the study rescales this ratio

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Further, these companies must constantly spend vast amounts of money in research to stay abreast of the 'state of the art' and ahead of their competitors.

by multiplying by a factor of .20. The study defines annual cash flow as earnings before the deduction of taxes, interest and noncash charges such as depreciation.

The study determines the cost of equity capital using computed beta (β) values in conjunction with theory set forth by the capital asset pricing model (Weston and Brigham 1981, 600):

$$k_i = R_f + p \quad [5.9]$$

where: k_i = the required rate of return on the common equity of firm i

R_f = the risk-free rate of return

p = the risk premium.

The risk premium, p, is equal to:

$$(R_m - R_f)\beta_i, \quad [5.10]$$

where: R_m = the expected rate of return on the market portfolio

β_i = $\mathrm{Cov}(R_i, R_m)/\sigma^2_m$.

$\mathrm{Cov}(R_i, R_m)$ = the covariance between the returns on security i and the returns on the market

σ^2_m = the variance of the market returns

In general terms, *beta* is a measure of the volatility of the individual security returns in relation to the market returns. Although the *Value Line Investment Survey* and other sources regularly publish beta values for publicly-traded firms, none of these sources contain beta values for 100% of firms in the estimation sample. Given that each of these sources computes beta in a different manner, it does not appear reasonable to use beta values from varied sources. Thus, in order to be consistent, the study computes a beta for each of the sample LBO and public firms.

The study computes beta using monthly return data from the three years prior to the year of going private for the sample LBOs. For the non-LBOs, the study uses monthly return data from 1985-1987. Similar to the Standard and Poor's procedure for computing beta, the study regresses returns for the individual security i against returns for the S&P 500. Returns on the S&P 500 serve as a proxy for the market portfolio's returns (R_m).

To compute the risk premium p for the individual firm, the study uses the computed beta (β_i) along with the expected excess rate of return on the market portfolio ($R_m - R_f$). Consistent with Radcliffe (1982, 306), the study uses an historical market risk premium of 5.15% for ($R_m - R_f$). This 5.15% rate represents the average annual risk premium on the S&P 500 over the period 1977-1988. Finally, similar to Weston and Brigham (1981, 654), the study determines the risk-free rate of return by reference to the average six-month treasury bill rate.

A previous section referred to a component of the "squander index" as the "free cash flow index." In order to derive this index of free cash flow, the study compares the *cost* of equity capital (k_i) as determined above with the *return* on equity capital. The study measures "return on equity" as net income of the firm divided by total common equity. Then, the product of the free cash flow index (with the sign reversed) and the ratio of investment spending to cash flow (scaled by a factor of .20) yields a measure of the misuse or squandering of cash, i.e., the squander index. The time periods over which the study measures this index are the same as indicatea for "buyout value to market value."

Table 4 summarizes the variables the study includes and their operational definition:

Table 4
Summary of Variables and Operational Definitions

Variable	Operational Definition
[1] Cash flow variability	Standard deviation of residuals for firm *i* ÷ Standard deviation of residuals for S&P 400 Industrials (see note)
[2] Fixed charge coverage	Mean fixed charge coverage for firm *i* ÷ Mean fixed charge coverage for S&P 400 Industrials
[3] LBO-intensive industry dummy	Membership in LBO-intensive industry equals 1; non-membership equals 0
[4] Capital expenditures to cash flow	Average capital expenditures ÷ Average cash flow
[5] Research and development expense to cash flow	Average research and development expense ÷ Average cash flow
[6] Buyout value to market value	Discounted annual cash flow ÷ Year-end market value
[7] Dividend payout	Annual dividend per common share ÷ Earnings per share
[8] Squander index	(-1)(Cost of equity capital less return on equity capital) x (.20)(Capital expenditures to cash flow)

Note: The residuals for firm *i* in period *t* equal the observed value of annual cash flow for firm *i* less the fitted trend value of cash flow for firm *i*. Similarly, the residuals for the S&P 400 Industrials in period *t* equal the observed value of annual cash flow for the S&P 400 less the fitted trend value of annual cash for the the S&P 400.

The Logit Model

This study employs a probability technique (logit analysis) to estimate a management buyout prediction model. Probability models use the coefficients of the independent variables to estimate the probability of occurrence of a dichotomous (or polytomous) dependent variable. Use of these models requires a cumulative probability distribution assumption in order to constrain the predicted values to comply with the acceptable (0,1) limiting values of the probability distribution. Logit analysis, in particular, employs a logistic cumulative probability curve, which is almost identical to a normal curve, except that it is fatter at the tails of the distribution (i.e., it approaches 0 and 1 more slowly) (Aldrich and Nelson 1984, 34). One can interpret the coefficient of each variable as the effect of a unit change in an independent variable on the probability of the dichotomous (or polytomous) dependent variable.

One can use logit analysis as an alternative to multiple discriminant analysis. However, the present study chooses logit analysis to develop the management buyout prediction model for the three reasons that follow. First, logit analysis imposes less restrictive assumptions on the statistical properties of the data. For example, logit analysis does not require that the distribution of the independent variables be multivariate normal. Second, a logit model allows one to determine the relative importance of the independent variables. In discriminant analysis, the coefficients of the independent variables are not unique--only their ratios are. Third, logit analysis allows one to rank firms according to their relative probability of becoming a buyout candidate. Although one can use discriminant analysis to estimate probabilities, the empirical evidence suggests that probability estimates from the logit model are more accurate than probability estimates from the discriminant model. [Refer to the next section--"Logit Analysis Versus MDA"--for a more thorough discussion of the study's selection of a logit model versus a discriminant model.]

Previous studies have used probability models to predict business failure (see Ohlson 1980; Zavgren 1982) and corporate takeovers (see Dietrich and Sorensen 1984; Palepu 1986). In this study, the model postulates that the probability a firm will go private via a management buyout is a function of measurable firm characteristics (e.g., stable cash flows and high relative coverage of fixed charges) and a random element resulting from characteristics not subject to quantification (e.g., the risk preferences of managers and their willingness to remain with the firm). Specifically, the model takes the form:

$$p(i,t) = 1/[1 + e^{-Bx(i,t)}] \qquad [5.11]$$

where $p(i,t)$ is the probability that firm i will go private via a management buyout in period t; $x(i,t)$ is a vector of measured attributes of the firm; and B is a vector of unknown parameters to be estimated. In other words, $p(i,t)$ is a logit probability function of the firm's measured attributes. While the measurable firm characteristics $x(i,t)$ enter the model explicitly, the nonmeasurable characteristics of the firm that may influence its attractiveness as a potential buyout candidate, enter the model as stochastic random variables (i.e., the disturbance term u_i). It is the probability distributions of these random variables, which are endogenous to the buyout process, that determine the specific functional form of $p(i,t)$ (Palepu 1986, 15).[38]

By the nature of the problem, one never knows the specific form of the probability distributions of these random variables. Thus, one generally assumes some particular specification (e.g., logistic, normal, etc.). Because the choice of a nonlinear curve specification depends strictly upon the distribution of

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[38] One should note that elements other than the nonmeasurable characteristics of the firm enter the model through the disturbance term u_i. For instance, specification errors, such as omission of a relevant explanatory variable and inclusion of an irrelevant explanatory variable (Kmenta 1986, 442), affect u_i. Also, unobservable variables, such as those whose values are contaminated by errors of measurement (Kmenta 1986, 579), enter the model through this term.

the disturbance term u_i, to choose a particular nonlinear model (e.g., logit, probit, etc.) is to choose implicitly a distribution of u_i. Although a number of other distributions exist, researchers most frequently use the logistic and normal curve specifications as alternatives to the linear specification of the probability model. Aldrich and Nelson (1984, 34) suggest there is little to guide the choice between the two, and in practice, the logistic and normal curves are so similar as to yield essentially identical results.

Logit Analysis versus MDA

Earlier discussions have indicated a number of reasons why a probability technique may be more suitable in certain business research applications than multiple discriminant analysis. One of the primary reasons is that probability models impose less restrictive assumptions on the statistical properties of the data. For example, MDA assumes that the variables one uses for classification have a multivariate normal distribution. However, Eisenbeis (1977, 875) suggests that, at least in economics and finance, deviations from the normality assumption appear more likely to be the rule rather than the exception. He stresses the importance of determining whether this assumption holds, because violations of the normality assumption may bias the tests of significance and estimated error rates.

In discriminant analysis, the purpose of significance tests is to determine whether the populations are truly unique. Generally, such a test involves testing for the difference of the means of the two groups. The test statistic researchers commonly employ to derive the *F*-statistic is Hotelling's T^2. Given that the maximum likelihood estimator and its test statistic are based on the assumption of normality, their use in the case of nonnormality is not appropriate. The extent to which a violation of this assumption affects the results, depends upon the degree of violation. If the violation of the normality assumption is significant, the research should employ a data transformation technique or a quadratic classification rule (Zavgren 1983, 14).

In addition to the assumption of normality, classical linear discriminant analysis also assumes that the group dispersion (variance-covariance) matrices are equal across all groups. Eisenbeis (1977, 877) suggests relaxation of this assumption can affect not only the significance test for the difference in group means, but also the appropriate form of the classification rules (linear vs. quadratic). The basis for each of the variance-covariance matrices is a multivariate data matrix, with *n* rows for the individual observations and *m* columns for the variables. Because the focus of multivariate analysis is the group dispersion matrices (i.e., not variable means), one generally transforms these original data matrices into matrices where columns have *zero means*, and where numbers in the columns represent *deviations from the mean.* The variance-covariance matrix of each subgroup has *m* rows and *m* columns, where numbers on the diagonal represent the variance of the variables. For variable *i*, for example, the variance is $\sum x_i{}^2/n$. All other numbers in the variance-covariance matrices represent the covariance of pairs of variables. For two variables *i* and *j*, the covariance is $\sum x_i x_j/n$, where x_i and x_j represent deviations from the mean (Van de Geer 1971, 4).

Holloway and Dunn (1967) investigated the robustness of Hotelling's T^2 for the two-group case with unequal dispersions. They concluded that the robustness of the test depends upon both the number of variables and relative sample sizes in the groups. For the univariate case, T^2 becomes the square of a Student *t* variate, and the problem of unequal covariance matrices reduces to that of unequal variances. In general, if the two samples are of equal size, the distribution of *t* remains virtually unchanged by inequality of population variances, especially for large sample sizes. If the sample sizes are widely disparate, the actual significance level is greater than the hypothesized level. This implies frequent rejection of the null hypothesis when, in fact, the means are equal. When the number of variables increases, the significance level also increases, as does the sensitivity to unequal sample sizes. According to Holloway and Dunn (1967, 125), equal sample sizes are helpful in keeping the level of significance close to the hypothesized level, but they do not help in maintaining the power of the test.

In terms of the effects of unequal dispersions on the classification procedures and results, unequal dispersions require the use of a quadratic versus linear classification rule. Gilbert (1969) investigated and compared the effects of using a linear rule (assuming equal dispersions) when, in fact, the dispersions were unequal. For the two-group case with known parameters, the results indicated that significant differences can occur which are directly related to the differences in the dispersions, the number of variables, and the separation between the groups. As the differences between the dispersions and the number of variables increases, the extent of agreement between the two classification procedures lessens. Also, as the separation between the groups for given dispersions becomes more pronounced, the differences between the linear and quadratic results become less important (Gilbert 1969, 512-514).

A second reason for preferring a probability (logit) model over a multiple discriminant model is that use of a logit model allows one to determine the relative importance of the individual variables. Eisenbeis (1977, 882-883) suggests this particular aspect of discriminant analysis is one that business researchers often misunderstand. He points out that, unlike the coefficients in the standard linear regression model, the discriminant function coefficients are not unique, rather only their ratios are.[39] Therefore, it is not possible, nor would it be logical, to test whether specific discriminant function coefficients are significantly different from a particular value.

To deal with this problem, researchers have proposed a number of alternative methods to ascertain the importance of individual variables in discriminant analysis. Some of these methods are (1) individual

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[39] Fisher's linear discriminant function is a combination of *m* variables:

$$y = X'B = b_1x_1 + b_2x_2 + \ldots + b_mx_m,$$

where X' is an mx1 variable vector ($X' = x_1, x_2, \ldots, x_m$) and B is an mx1 coefficient vector ($B = b_1, b_2, \ldots, b_m$). The choice of a vector B maximizes the *ratio* of the between-groups variance of y to the pooled within-groups variance of y (Eisenbeis and Avery 1972, 4).

variable F-statistics, (2) scaled standardized discriminant coefficients, (3) stepwise inclusion based on the F-statistic, (4) stepwise exclusion based on the F-statistic, and (5) stepwise exclusion based on discriminatory power (Zavgren 1983, 14). According to Eisenbeis (1977, 883), the first two techniques are undesirable because they treat the variables independently. Cochran (1964, 182), for instance, has shown that however seemingly insignificant or unimportant variables may be in terms of individual discriminatory power, they may contribute significantly to the joint discriminatory power of the variables. Methods (3) through (5) consider the intercorrelations among the variables and are thus more desirable in this respect.

The stepwise forward and backward methods (3) and (4) measure the contribution of a given variable against an increasing (decreasing) number of variables. For example, in the stepwise forward method, the second variable to enter is the second most important variable, given that the first variable has already been included. Eisenbeis (1977, 884-885) suggests the conditional deletion method (5) probably has the greatest intuitive appeal because it assesses the importance of each variable based on the inclusion of all other variables. He cautions, though, that while the fifth method may be superior to all others, each of these methods relies on the assumption of equal group dispersions. Therefore, rejection of this assumption implies these methods are subject to the same limitations as the tests for significance of the difference in group means.

A third and final reason for preferring a probability technique is that use of such a technique allows one to rank firms as to their relative probability of becoming a buyout candidate. Although one can use discriminant analysis to generate probabilities[40], the procedures business researchers most often employ involve subjective assessment of the probability associated with a particular discriminant score (Zavgren 1983, 24). Subjective assessment, in this case, refers to the researcher's failure to incorporate prior probabilities into the choice of a cutoff point. The *a priori* or prior probabilities refer to the probability of an observation actually arising from each of the specified groups in a given

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[40] To compute the probability of belonging to Population I under Fisher's (1936) linear discriminant function, one uses the following formula:

$$\text{probability of belonging to Population I} = \frac{1}{1 + e^{(-Z + C)}}$$

where Z is the discriminant score for each individual from each population, and C is the dividing point between Population I and Population II that minimizes the total probability of misclassification. The probability of belonging to Population II is 1 minus the probability of belonging to Population II (Afifi and Clark 1984, 262).

population. Typically, researchers select as a dividing point the point that produces an equal percentage of errors of both types (i.e., the probability of classifying an individual from Population I into Population II is the same as the probability of classifying an individual from Population II into Population I). However, if the objective of discriminant analysis and classification is to minimize the probability of incorrect classification over all groups, then the research must employ *known or estimable* population prior probabilities in the classification procedure (Pinches 1980, 443).

While the use of prior probabilities is important in establishing accurate probabilities of occurrence, there are other more basic reasons one should incorporate prior probabilities into the choice of a cutoff point. Pinches (1980, 443), for instance, suggests the use of prior probabilities has two direct consequences for discriminant analysis. The first such consequence is prior probabilities help to establish the appropriate classification percentage expected by chance. In turn, this influences the null hypothesis (relative to the classification results).

In order to determine total classification accuracy, one sums the number of correct classifications over all *k* groups, and divides that sum by the total number of observations N. To assess the significance of this result, it is important to compare total classification accuracy with the proper proportion of correct classifications expected by chance. In the absence of prior probabilities, one would expect the percentage of correct classifications by chance to equal 100% divided by the number of groups k. This establishes the chance results of a classification model whose predictive ability is no greater than that expected by chance. However, in the case of unequal prior probabilities, alternative models better express the percent of correct classifications expected by chance. The proportional chance criterion is one such model that is appropriate in this case. Under this criterion, the expected probability of correct classifications over all groups k equals $(\pi_1)^2 + (\pi_2)^2 + \ldots + (\pi_k)^2$, where π_1 equals the prior probability in the population of an observation arising from the first group, π_2 equals the prior probability for the second group, and so forth. By establishing under this criterion the percentage of correct classifications expected by chance, one is then able to accept or reject accordingly the null hypothesis (i.e., the ability of the model to discriminate between groups is no greater than that of a chance model).

The second consequence of using prior probabilities is that prior probabilities directly influence the classification accuracy of the discriminant model. Eisenbeis (1977, 889) shows that unless the groups are equally likely, the estimated error rates assuming equal *priors* might bear little relationship to what one might expect in the population. Consider the example from Eisenbeis (1977, 889-890) of an actual business loan study that reports six group quadratic classification results assuming equal *a priori* probabilities, and also assuming unequal estimated population *a priori* probabilities. The overall expected probability of misclassification was 51.1 percent for the equal *a priori* probability case versus 45.5 percent for the unequal *a priori* probability case. More important, though, than the overall improvement in classification accuracy using unequal *priors* was the fact that some of the individual group error rates shifted dramatically. For example, classification accuracy for one of the groups was 88% assuming equal *priors*, whereas the reported accuracy rate for this group in the unequal *priors* case was 0%. This example thus serves to illustrate how the erroneous assumption of equal *priors* can produce grossly inaccurate classification results.

Although somewhat paradoxical, there is evidence that suggests the probability estimates obtained from the discriminant function may be inaccurate even though classification accuracy may be high. Martin (1977) employed a variant of discriminant analysis that uses the maximum likelihood estimation procedure to assess the probability of bank failure. He tested the results of this estimation and an estimation on the same data using a logit model against the null hypothesis that the probability of failure is equal to the prior probability in the population. The estimation procedure consisted of finding a set of coefficients that maximize the likelihood function $L(Y,B)$. Given the vector $Y = Y_1, \ldots, Y_N$ of actual outcomes, and a vector of coefficients $B = b_0, b_1, \ldots, b_m$, the likelihood function of the sample of N observations appears as follows:

$$L(Y,B) = \prod_{i=1}^{N} P_i^{Y_i} (1 - P_i)^{1-Y_i}, \qquad [5.12]$$

where m equals the number of explanatory variables; the dependent variable Y takes on only one of two values ($Y_i = 1$ for failed banks and $Y_i = 0$ for non-failures); and P_i represents the estimated probability of bank failure. $L(Y,B)$ is a function of the coefficients B as well as the actual outcomes because the coefficients B determine the probabilities P_i.

For computational purposes, and for convenience in applying the tests of significance to the results, one generally restates the problem as the equivalent one of minimizing -2 log likelihood:

$$-2 \ln L(Y,B) = -2 \sum_{i=1}^{N} Y_i \ln P_i + (1-Y_i) \ln(1-P_i). \quad [5.13]$$

As $-2 \ln L(Y,B)$ approaches zero, the probability estimates approach prediction with certainty, the ideal situation where $P_i = Y_i$ for all observations. The other extreme is $-2 \ln L_0$, which is -2 log likelihood evaluated at the null hypothesis that $P_i = N_1/N$ for all observations and the explanatory variables have no influence. In this case, N_1 equals the number of actual bank failures among the entire population of member banks (Federal Reserve System) at a given date, i.e., N_1 equals the number of observations with $Y_i = 1$. One would reject a coefficient vector B resulting in probability estimates with $-2 \ln L(Y,B) > -2 \ln L_0$ as producing less accurate probability estimates than the null hypothesis. In Martin's (1977, 265) study, he determined that both linear and quadratic discriminant functions had $-2 \ln L(Y,B)$ significantly higher than the null hypothesis, indicating the null hypothesis provided a better probability estimate than either discriminant function. Conversely, the logit model had $-2 \ln L(Y,B)$ significantly lower than the null hypothesis, which suggested the logit model provided significantly better probability estimates. Interestingly enough, when Martin compared the different models in terms of classification rather than probability estimation, he found the classification accuracy of the logit and discriminant models was very high and virtually the same (Martin 1977, 266).[41]

Use of a State-based Sample to Estimate Model Parameters

In order to estimate the model parameters, this study uses all firms included on the listing of firms that have changed to private status via an MBO along with a random sample of approximately the same number of firms that remained public as of 1988. This type of sample is not a pure random sample because the probability of including the firm in the sample is a function of the firm's ownership status, i.e., private via an MBO versus public. However, valid economic justification exists for preferring a state-based sample over a random sample for this particular application. Because the number of firms that have gone private is very small compared to the number of firms that have remained public, a random sample drawn from such a population would likely consist of an overwhelming number of public firms and very few private firms. Palepu (1986, 6) contends that because such a sample has little information content for model estimation, its use can lead to relatively imprecise

[41] For a more thorough discussion of the problems associated with the use of MDA, see Eisenbeis (1977) and Pinches (1980).

parameter estimates. He suggests the researcher can enrich the sample informationally by making the sample proportions more evenly balanced, and a state-based sample accomplishes this.

Studies have shown that, in a population such as the one described above, an appropriate state-based sample provides more efficient estimates compared to a random sample of the same size. Equivalently, for a given level of precision, use of a state-based sample can often reduce the size (and cost) of the sample (Coslett 1981, 52-53). Based on the results of an extensive simulation analysis, Coslett (1981, 103) reports that the efficiency of a state-based sample of equal proportions is usually close to the efficiency of the optimal sample design (i.e., a design for which the choice of sample proportions minimizes the asymptotic variance of the estimator). This condition seems to exist because efficiency is not very sensitive to sample design if the sample proportions are reasonably close to their optimal value (Coslett 1981, 103).[42]

It has been common practice in the prediction literature to use state-based samples in conjunction with inference procedures that assume random sampling. However, Palepu (1986, 7) suggests that in order to

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[42] For further discussion of sample design and estimation from state-based samples, see Manski and McFadden (1981) and Lerman and Manski (1978).

realize the efficiency gains from using a state-based sample, the research must employ an estimation procedure that recognizes the nature of the state-based sampling process. Manski and Lerman (1977) show that failure to use an appropriate estimator leads to inconsistent and biased estimates of the model parameters and state probabilities. This, in turn, overstates the model's ability to provide accurate predictions.

In order to examine the nature of this bias, consider a firm *i in the population* with a probability p of being a management buyout firm.[43] Let p^* be the probability that the firm *i in the sample* is a management buyout firm. Using Bayes' formula for conditional probability,

$$p^* = p(i \text{ is MBO} \mid i \text{ is sampled})$$

$$= \frac{p(i \text{ is MBO}) \times p(i \text{ is sampled} \mid i \text{ is MBO})}{[p(i \text{ is MBO}) \times p(i \text{ is sampled} \mid i \text{ is MBO}) + p(i \text{ is non-MBO}) \times p(i \text{ is sampled} \mid i \text{ is non-MBO})]} \quad [5.14]$$

In the case of random sampling, the probability of firm i being sampled is the same whether it is an MBO or not. Hence, the above expression simplifies to p. If N_1 and N_2 are the number of MBO firms and non-MBO firms in the population and n_1 and n_2 are the corresponding numbers in the sample, then

43 The study bases the following discussion on Palepu (1986, 6-10).

$$p^* = \frac{p(n_1/N_1)}{p(n_1/N_1) + (1 - p)(n_2/N_2)} \neq p. \qquad [5.15]$$

The magnitude of the bias $(p^* - p)$ varies across samples and is directly proportional to the differences in the sampling ratios of the MBO and non-MBO firms, n_1/N_1 and n_2/N_2, respectively. For a given sample design, the bias varies across firms as a function of the true buyout probability. One can calculate the bias as follows:

$$p^* - p = \frac{(n_1/N_1 - n_2/N_2)p(1 - p)}{(n_1/N_1)p + (n_1/N_2)(1 - p)}. \qquad [5.16]$$

Because in a state-based sample N_1 is usually much smaller than N_2, and n_1 is equal to n_2,

$$(p^* - p) > 0,$$

except for the uninteresting cases of p equal to 0 or 1. In other words, the estimated acquisition probability always overstates the true value.

To illustrate the seriousness of the bias, consider the estimation sample Stevens (1973) uses which consists of 40 acquisition targets and 40 non-targets. Also assume, for the purpose of illustration, that the total population consists of 1000 firms. Because Stevens samples all of the targets, the sampling ratio for the targets is 40/40; for the non-targets the sampling ratio is 40/960. Now consider a firm whose true acquisition probability is .10. Given the above sampling scheme, the model estimates for that firm an acquisition probability p^* of approximately .73, resulting in a bias ($p^* - p$) of .63.[44]

Palepu (1986, 8-9) further shows that when the research employs biased estimates of the acquisition probabilities to predict acquisition targets and non-targets, the observed prediction accuracies do not reflect the true predictive ability of the model. Specifically, the observed error rates understate the model's true error rate in predicting targets and overstate the true error rate in predicting non-targets. Zmijewski (1984, 72-73) examines this same issue empirically and reports results consistent with the conclusions of Palepu's analysis.

One can avoid the biases that result from the use of state-based samples in model estimation by modifying the simple maximum likelihood estimators. Zmijewski (1984, 65) identifies three techniques that are appropriate for estimating models using state-based samples: conditional maximum likelihood estimator (CML), weighted exogenous sample maximum likelihood (WESML), and full information concentrated maximum likelihood (FICML). He also indicates each of the three estimation procedures provides asymptotically

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[44] Substitution of values in the formulas for p^* and ($p^* - p$), respectively, confirms these results:

$$\frac{.1(40/40)}{.1(40/40)+.9(40/960)} = .73; \quad \frac{(40/40 - 40/960).1(.9)}{(40/40).1+(40/960)(.9)} = .63$$

consistent normal parameter estimates; however, only FICML's estimates are asymptotically efficient.[45]

Prediction Tests

Predictions in a holdout sample. The previous section discusses the economic justification for employing state-based samples in model estimation. However, as also indicated, using state-based samples in prediction tests can result in a potentially serious bias in the expected prediction error rates in the population (Palepu 1986, 10). In order to understand the nature of this bias, consider a population of N_1 MBO firms and N_2 non-MBO firms.[46] If one uses a management buyout prediction model to classify a sample of n firms consisting of n_1 MBO firms and n_2 non-MBO firms, and if m_1 and m_2 are the number of misclassified MBO firms and non-MBO firms, respectively, the sample forecast error rate is:

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[45] The *asymptotic* property of the estimator refers to the distribution of the estimator when the sample size is large and approaches infinity. An estimator is asymptotically *consistent* if, as the sample size approaches infinity, the distribution of the estimator collapses on one point --hopefully that representing the true value of the population parameter. A consistent estimator is also asymptotically *efficient* if its distribution has a finite mean and finite variance, and if no other consistent estimator has a smaller asymptotic variance (Kmenta 1986, 163-168).

[46] The study bases the following discussion on Palepu (1986, 10-11).

$$e^* = \frac{m_1 + m_2}{n_1 + n_2} + \frac{m_1 + m_2}{n} \qquad [5.17]$$

The expected prediction error rate in the population, which generally does not equal e^*, is:

$$e = \frac{N_1(m_1/n_1) + N_2(m_2/n_2)}{N_1 + N_2}$$

$$= \frac{m_1(N_1/n_1) + m_2(N_2/n_2)}{n} \times \frac{n}{N_1 + N_2}. \qquad [5.18]$$

Palepu (1986, 11) suggests that, despite their potentially large difference, it is customary in the acquisition prediction literature for researchers to use e^* as an estimate of e. The size of the bias resulting from the use of e^* instead of e is proportional to the difference in the two types of sample error rates, as well as the difference in the ratios of population and sample shares of targets and non-targets. One calculates this bias as follows:

$$e^* - e = \frac{(n_1 N_2 - n_2 N_1)}{n_1(N_1 + N_2)} \times (m_1/n_1 - m_2/n_2). \qquad [5.19]$$

To illustrate the potential seriousness of the bias, again consider Stevens' (1973) study that reports a prediction error rate of 15% for targets, 45% for non-targets, and an overall prediction error rate of 30%. The expected population error rate, e, based on the reported sample error rates is 44%, resulting in a bias (e^* - e) of 14%.[47] Hence, the expected prediction

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[47] To confirm these results:

accuracy in the population is 56%, and not 70%, as Stevens reports.

In order to avoid this bias, one should make the prediction test sample resemble the population as closely as possible (Palepu 1986, 11). This means employing a large sample or even the entire population of firms at a given time. In this study, the prediction test sample includes firms that changed to private status via a management buyout during 1989 and firms that remained public during that same year. These firms represent all those listed on Compustat in 1989 that meet the criteria for inclusion in the study and have the required data. The study does not use any of these firms in estimating the model parameters.

Estimation of cutoff probability. The prediction tests involve classifying a group of firms into 'buyout' candidates and 'non-buyout' candidates based on their estimated buyout probability p. To classify a firm, one compares the estimated buyout probability with a predefined cutoff probability. If the estimated probability is greater than the cutoff probability, one classifies the firm as a buyout candidate.

$$e = \frac{40(.15)+960(.45)}{1000} = .438 \text{ or } 44\%;$$

$$e^{*} - e = \frac{40(960)-40(40)}{80(1000)} \times (.15 - .45) = .138 \text{ or } 14\%.$$

While many of the earlier prediction studies use arbitrary cutoff probabilities in prediction tests, usually 50%, one can derive an 'optimal cutoff probability' by specifying the decision context of interest, an appropriate payoff function, and the prior state probabilities (Palepu 1986, 12). As indicated earlier, it is important to derive the cutoff within a well-defined decision context because the observed prediction accuracies indicate the extent to which the model's predictions are useful in that context. Otherwise, it is unclear what the observed prediction accuracies indicate. In addition, Eisenbeis (1977, 889), Pinches (1980, 443-444) and others suggest that failing to incorporate prior probabilities into the choice of a cutoff point may significantly influence the classification accuracy rates.

The discussion that follows describes the process for determining an optimal classification scheme.[48] First, define the decision context in which one intends to use the model's predictions. This specific analysis assumes the purpose of the model is to provide predictions that will become part of a stock market investment strategy. Next, consider a firm *i* from the test sample in order to determine the classification scheme that maximizes expected payoff. Let

[48] The study bases this discussion on Palepu (1986, 12-14).

q = the market's assessment of the probability that firm i goes private via an MBO
S_1 = the stock price if the firm goes private via an MBO
S_2 = the stock price if the firm remains public.

Assume the variables q, S_1 and S_2 are common knowledge and that the market is efficient with respect to this information. Thus, the current stock price S would be such that

$$S = qS_1 + (1 - q)S_2. \qquad [5.20]$$

Denoting $C_1 = (S_1 - S)$ as the payoff if the firm goes private via an MBO and $C_2 = (S_2 - S)$ as the payoff if the firm remains public, the price S in eq. [5.20] ensures that the expected payoff, based on a market probability q, is zero. That is,

$$E(C) = qC_1 + (1 - q)C_2 = 0.^{49} \qquad [5.21]$$

Now, suppose one develops a statistical model that predicts a probability of going private p for firm i. Assuming the model's prediction is new information unavailable to the market, one seeks to exploit this private information to earn abnormal returns. The expected payoff from investing in firm i now changes (at least for that individual) in light of this new information, p.

[49] For the sake of illustration, let $q = .20$, $S_1 = \$50$, and $S_2 = \$40$. The current stock price S equals \$42 [.20(\$50) + .80(\$40)]. If C_1 and C_2 equal \$8 and -\$2, respectively, then the expected payoff if the firm goes private via an MBO is \$0 [.20(\$8) + .80(-\$2)].

Given the market prior q and the model prediction p, determine the posterior probability q' using Bayes' formula:

$$q' = \frac{q\, f_1(p|i = \text{MBO})}{q\, f_1(p|i = \text{MBO}) + (1 - q) f_2(p|i = \text{non-MBO})}, \quad [5.22]$$

where $f_1(p|i = \text{MBO})$ is the conditional probability density of observing p if i is an MBO, and $f_2(p|i = \text{non-MBO})$ is the conditional probability density of observing p if i is not an MBO. One obtains empirical approximations of $f_1(\bullet)$ and $f_2(\bullet)$ by plotting the distributions of the estimated probabilities for the MBOs and non-MBOs in the sample the study uses to estimate the model.

Given the posterior probability q' and the state payoffs C_1 and C_2, the expected payoff from investing in firm i is $[q'C_1 + (1 - q')C_2]$. Thus, one expects firm i to have a positive payoff if

$$q'C_1 + (1 - q')C_2 \geq 0. \quad [5.23]$$

Using eq. [5.22], one can rewrite eq. [5.23] as

$$\frac{f_1(p|i = \text{MBO})}{f_2(p|i = \text{non-MBO})} \geq \frac{-(1 - q)C_2}{q\, C_1} \quad [5.24]$$

Therefore, any firm with a predicted buyout probability p that satisfies condition [5.24] has an expected positive payoff. In order to maximize the expected payoff, one should classify all firms that satisfy condition [5.24] as potential buyout candidates and invest in them.[50]

The relation between q, C_1 and C_2 that eq. [5.21] implies allows one to rewrite condition [5.24] as

$$\frac{f_1(p \mid i = \text{MBO})}{f_2(p \mid i = \text{non-MBO})} \geq 1. \qquad [5.25]$$

This condition implies that one classifies a firm as a buyout candidate if the predicted buyout probability is such that the marginal probability of observing p *if* the firm actually goes private via an MBO is greater than the corresponding marginal probability *if* the firm remains public. The optimal cutoff probability is the value where the two conditional probability densities are equal.

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[50] To continue the previous illustration, assume the model predicts a probability of going private p for firm i of .80. Also assume the marginal probability of observing p = .80. for firm i is .60 if firm i is an MBO and only .10 if firm i is not an MBO. The posterior probability q' equals .60:

$$\frac{.20(.60)}{.20(.60) + .80(.10)} = .60,$$

and the expected payoff of investing in firm i is \$4:

$$.60(\$8) + .40(-\$2) = \$4.$$

In other words, because the marginal probability of observing p = .80 is greater if firm i is an MBO rather than a non-MBO, investors can expect a positive payoff if they invest in firm i. Per condition [5.24]:

$$\frac{.60}{.10} > \frac{-(.80)(-\$2)}{(.20)(\$8)},$$

or rewritten, 6 > 1.

CHAPTER VI

RESULTS

Estimation Sample

The procedure to estimate the model parameters uses a sample of 112 management buyouts that occurred during the period 1979-1988 and a random sample of 112 firms that remained public as of 1988. In total, there are 142 firms that went private via a management buyout during 1979-1988, that are also listed on Compustat and meet the data requirements [see Table 5] for inclusion in the sample. Therefore, the 112 management buyouts included in the estimation sample represent approximately 79% of the management buyouts that occurred during 1979-1988. The 30 remaining management buyout firms (approximately 21% of the total number of MBOs) represent a holdout sample used to test the classification accuracy of the model during 1979-1988. A random number generator facilitated the selection of the holdout sample of 30 management buyouts.

The 112 public firms included in the estimation sample are among the population of Compustat firms that satisfied the data requirements for inclusion in the sample. The total number of firms that satisfied

Table 5
Data Requirements for MBO Firms in Estimation Sample

Variable	Requirements
Cash flow volatility	Cash flow in 10 years preceding buyout
Fixed charge coverage	Fixed charge coverage in 10 years preceding buyout
Capital expenditures to cash flow	Capital expenditures in 10 years preceding buyout (if applicable)
Research and development expense to cash flow	Research and development expense in 10 years preceding buyout (if applicable)
Buyout value to market value	Cash flow and market value in year preceding buyout
Dividend payout	Dividend payout in year preceding buyout
Squander index	Capital expenditures, cash flow, and return on equity in year preceding buyout; monthly returns for 3 years prior to buyout

Note: In certain cases, required information for management buyout firms may not have been available for the stipulated time period. For instance, cash flow information may have been available for only eight years preceding the buyout because the MBO firm was public for that sole period. In an effort to maintain an adequate sample of MBOs, the screening process resulted in the elimination of firms lacking required data only if the firm was unable to meet reasonable alternative requirements (e.g., cash flow for a minimum of five years preceding the buyout).

Also Note: Except for the measurement period, data requirements for non-MBOs included in the estimation sample are the same as those for MBOs. As suggested above, measurement of the independent variables is as of the end of the year *prior to the year of buyout* for MBOs. In the case of non-MBOs, the measurement period is as of the end of the year *prior to 1988*. Thus, for example, the data requirement for cash flow volatility is cash flow in the ten years preceding 1988.

Table 6
Composition of Estimation Sample

Management Buyouts	
Fiscal Year of MBO	No. of Firms
1979	3
1980	1
1981	6
1982	11
1983	13
1984	16
1985	15
1986	16
1987	11
1988	15
1989[a]	5
Total MBOs	112
Firms that remained public as of 1988	112
Total sample	224

[a]Compustat classifies the firm whose fiscal year ends in the first five months of the calendar year (January through May) as having a fiscal year-end as of the *preceding* year. It classifies the firm with a fiscal year ending June through December as having a fiscal year-end as of the *current* year. To illustrate how this affects the classification of the sample MBOs, consider the firm with a fiscal year ending May 1989 that goes private November 1988. According to the Compustat convention, this firm would have gone private in fiscal year 1988. On the other hand, a firm that goes private November 1988, but has a fiscal year ending June 1989, would have gone private in fiscal year 1989. Thus, although the estimation sample includes firms that went private in calendar year 1988, several firms actually went private within fiscal year 1989.

these requirements was 2089. Table 6 summarizes the composition of the estimation sample.

Univariate Test of Difference in Group Means

A multivariate analysis allows one to consider variables simultaneously and the possible interactions between variables. Further, this type of approach is necessary in order to assess the ability of the researcher to develop a model that can accurately discriminate between public and ex-public firms.

A univariate approach, while not as powerful, can provide some interesting and useful insights into the financial characteristics of management buyout firms. Therefore, the study first examines on a univariate basis the difference between groups means of the proposed variable set for the 112 MBOs and 112 non-MBOs included in the estimation sample.

As Table 7 suggests, for four of the eight variables proposed in Chapter IV, the difference between group means is statistically significant at conventional levels of significance (.01 and .05). Specifically, the difference between between group means for Variable 05 (research and development as a percent of cash flow) is statistically significant at the .01 level. The differences between group means for Variables 04, 06, and 07 (capital expenditures as a percent of cash flow, buyout value to market value, and dividend payout, respectively) are statistically significant at the .05 level. For Variables 01, 02, 03, and 08 (cash flow volatility, fixed charge coverage, LBO-intensive industry dummy, and the squander index, respectively), the differences between

Table 7
Means and Standard Deviations of Independent Variables

Var.	Private Firms Mean	Private Firms Std. Dev.	Public Firms Mean	Public Firms Std. Dev.	t Value	Sign. Level
01	1.72	2.39	1.82	1.77	-.36	.3590
02	10.63	72.38	1.98	4.54	1.26	.1045
03	.52	.50	.43	.50	1.34	.0910
04	.52**	.34	.69**	.75	-2.19	.0150
05	.03*	.07	.12*	.24	-3.67	.0000
06	2.94**	2.55	2.30**	2.05	2.07	.0195
07	.27**	.27	.19**	.30	1.92	.0285
08	-49.89	269.43	-86.30	281.28	.99	.1620

Key:
Var 01 = Cash flow volatility
Var 02 = Fixed charge coverage
Var 03 = LBO-intensive industry dummy
Var 04 = Capital expenditures as % of cash flow
Var 05 = Research and development as % of cash flow
Var 06 = Buyout value to market value
Var 07 = Dividend payout
Var 08 = Squander index

Note: * Indicates difference in means is significant at the .01 level
** Indicates difference in means is significant at the .05 level

group means are not significant at either the .01 or .05 levels of significance.

Model Estimation

The statistical package used to estimate the model parameters is SPSS. As discussed earlier (Chapter V, 194-199), the estimation procedure should *not* use the population buyout probability $p(i,t)$ to compute the sample likelihood function. Rather, the procedure should employ the conditional probability that a firm is a management buyout given its inclusion in the sample. One can compute this probability $p^*(i,t)$ as the paragraph below describes.

The estimation sample includes 112 (or 78.87%) of the management buyouts that occurred during the period 1979-1988. Of the 2089 public firms that meet the data requirements, 112 (or 5.36%) are in the sample. Hence, the probability that firm in the population is in the sample is .7887 if it is a management buyout and .0536 if it remains a public firm. Under this sampling scheme and suppressing the arguments for i and t for convenience,

$$p^* = \frac{(.7887)(p)}{(.7887)(p)+(.0536)(1-p)} . \qquad [6.1]$$

Since

$$p = 1/(1+e^{-Bx}), \qquad [6.2]$$

then

$$p^* = .7887/(.7887+.0536e^{-Bx}) . \qquad [6.3]$$

Note that a convenient feature of the logistic probability model is that the functional form of p^* is also logistic. Therefore, the likelihood function that the estimation procedure must maximize uses the above expression for p^*. Also, subsequent to the estimation one can easily recover the parameters that determine the population probability *p*. This is because all parameters except the constant term remain unaffected, and the constant terms in the two models differ by a known value, ln(.0536/.7887) or -2.69. For example, in the present study, the constant term in the model that uses *p* to estimate the sample likelihood function is -.4578. The constant term in the model that uses $p*$ is 2.2311. The difference between -.4578 and 2.2311 is -2.6889 or ln(.0536/.7887).

Logit Model Estimates

The estimated model includes eight independent variables in addition to a constant term. Table 8 presents the parameter estimates of the logit model, associated Wald statistics, and significance levels.[51] Of the eight independent variables, only two have coefficients that are statistically significant: "research and development expense as a percent of cash flow" and "buyout value to market value" (significance levels of .01 and .05, respectively). In the case of R&D, a higher percentage of research and development expense in relation to cash flow *decreases* the

[51] SPSS bases it test that a coefficient is equal to zero on the Wald statistic which has a chi-square distribution. When a variable has a single degree of freedom, the Wald statistic is simply the square of the ratio of the coefficient to its standard error (SPSS Advanced Statistics Student Guide 1990, 122).

Table 8
Estimates of Logit Management Buyout Likelihood Model

Variables[a]	Expected Sign	Estimates[b]	Sign. Level
Cash flow volatility	-	.0689 (.8454)	.1789
Fixed charge coverage	+	.0433 (2.6047)	.0533
LBO-intensive industry dummy	+	.3010 (1.0791)	.1495
Capital expenditures as % of cash flow	-	-.4435 (1.6344)	.1006
Research & development as % of cash flow	-	-4.2653[c] (8.4722)	.0018
Buyout value to market value	+	.1441[d] (3.4589)	.0315
Dividend payout	+	.8726 (2.2381)	.0673
Squander index	-	-.0002 (.1638)	.3429
Constant		2.2311[e] (.9668)	

[a] The study measures the independent variables as of the end of the fiscal year prior to the year of going-private for MBOs and as of the end of the fiscal year prior to 1988 for non-MBOs.

[b] The figure that appears in parentheses below each parameter estimate is the Wald statistic.

[c] Significant at the .01 level, one-tailed test.

[d] Significant at the .05 level, one-tailed test.

[e] The constant term in the model that uses p to estimate the sample likelihood function is -.4578. The difference between -.4578 and 2.2311 (the constant term when using p^*) is -2.6889, or ln(.0536/.7887).

likelihood of a management buyout. Conversely, buyout value to market value has a positive sign, i.e., a higher value for this variable *increases* the likelihood of a management buyout. With respect to the other six variables included in the model, the results of the logit estimation indicate the coefficients of these variables are statistically insignificant, suggesting these variables do little to distinguish between MBOs and non-MBOs.

One way to assess the performance of the logistic model is to determine how well the model classifies the observed data. [Note that the study defers discussion of the classification accuracy of the model to a later section]. There are, however, various other statistics that one can employ to test the goodness of fit of the model. The *likelihood* is the probability of obtaining the observed sample results given the parameter estimates. Because the likelihood is a small number less than 1, SPSS suggests it is customary to use -2 times the log of the likelihood (-2LL) as a measure of how well the estimated model fits the data. One would consider the model a good one if it results in a high likelihood of the observed results. This means a small value for -2LL. Otherwise stated, if the model is a perfect fit, the likelihood is 1, and -2 times the log likelihood is 0 (SPSS Advanced Statistics Student Guide 1990, 126).

Table 9
Test Statistics

Statistic	Chi-Square[a]
-2LL	278.226 (.0024)
Goodness-of-Fit	216.810 (.4526)
Likelihood Ratio Statistic	32.304 (.0001)
Likelihood Ratio Index	.1040

[a] Parenthetical figure represents the significance level of the test statistic.

Under the null hypothesis that the model fits perfectly (i.e., the observed likelihood does not differ from 1), -2LL has a chi-square distribution with $N - p$ degrees of freedom, where N is the number of observations and p is the number of parameters estimated. For the present model, this translates to 215 degrees of freedom (224 cases less 9 parameters estimated). As Table 9 indicates, the observed significance level (.0024) is small. Thus, on the basis of this statistic, the study rejects the null hypothesis that the model fits well.

In addition to -2LL, Table 9 includes the *goodness-of-fit statistic*. Per Neter, Wasserman, and Whitmore (1982, 410), goodness-of-fit tests involve the question of whether or not a particular probability distribution is a good model for the population sampled. This determination is made on the basis of whether or not the specified probability distribution is a good fit for the sample data. The goodness-of-fit statistic (Z^2) that SPSS provides compares the observed probabilities to the model predictions as described below:

$$Z^2 = \sum \frac{Residual_i^{\,2}}{P_i\ (1 - P_i)}\ , \qquad [6.4]$$

where the residual is the difference between the observed value, Y_i, and the predicted value, P_i. If the model fit is the correct one, this statistic also has a chi-square distribution with $N - p$ degrees of freedom (SPSS Advanced Statistics Student Guide 1990, 126). In this case, the large observed significance level (.4526) indicates that the specified model (i.e., probability distribution) does *not* differ significantly from the "perfect" model.

The *likelihood ratio statistic* (SPSS refers to this statistic as the "Model Chi-Square") tests the hypothesis that all parameter estimates in the model, except the constant, are simultaneously equal to zero. The likelihood ratio statistic is equal to the difference between -2LL for the model with only a constant and -2LL for the full model. The degrees of freedom for this statistic are the difference between the degrees of freedom for the two models subject to comparison (SPSS Advanced Statistics Student Guide 1990, 127). A low significance level (.0001 per Table 9) for the likelihood ratio statistic implies rejection of the null hypothesis that all coefficients are simultaneously equal to zero in the estimated model.

Finally, the *log likelihood ratio index* is similar to the R^2 statistic employed in multiple regression analysis and provides an indication of the logit model's explanatory power. One computes this index as (1 - log likelihood at convergence/log likelihood at zero) (Palepu 1986, 23). The likelihood ratio index for the model is .1040 (see Table 9). This suggests that, although the model provides a statistically reliable explanation of a firm's management buyout probability [refer to the likelihood ratio statistic], the magnitude of this explanation is quite small. In other words, the model explains a maximum of only 10.40% of the variation in a firm's management buyout probability.

Prediction Tests

Estimation of Cutoff Probability

In order to test the predictive usefulness of the estimated model [refer to Table 8], it is necessary to estimate the optimal cutoff probability. One determines this probability by reference to the distribution of management buyout probabilities for the

MBOs and non-MBOs. Specifically, the study uses the computed estimated management buyout probabilities for the 112 MBOs and 112 non-MBOs in the estimation sample to obtain an empirical approximation of these distributions.

The estimated probabilities in the estimation sample range from 0 to 1. However, the majority of probabilities fall within the range .90 to 1.00. As Table 10 suggests, at probabilities below .90, the non-MBOs clearly dominate. Thus, the optimal cutoff probability must lie somewhere between .90 and 1.00.

To obtain the sample distributions of the buyout probabilities, the study divides the range .90 to 1.00 into ten equal intervals. Table 10 shows the number (and the percentage of the total) of MBOs that fall within each of these intervals. To obtain a discrete approximation of the distribution of the buyout probabilities for MBOs, the study plots the percentage of MBOs in each probability interval against the mid-value of that interval. Similarly, the study plots the percentage of non-MBOs in each probability interval against the mid-value of that interval to get a discrete approximation of the density function for the buyout probabilities of non-MBOs. See Figure 6 for a plot of these graphs.

The graphs show that, while the two probability distributions intersect at three different values

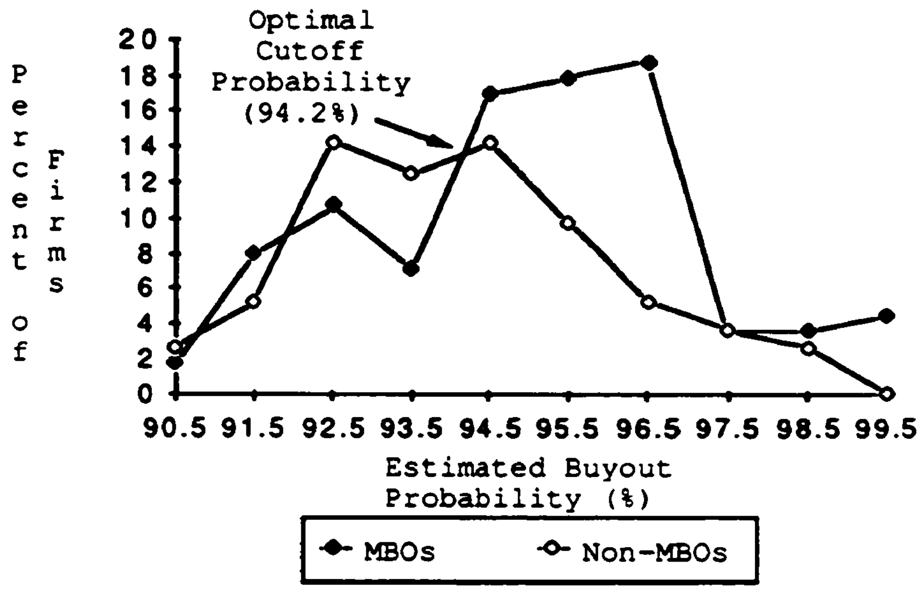
Table 10
Distribution of Estimated Buyout Probability
for MBOs and Non-MBOs in Estimation Sample[a]

Estimated Buyout Probability		MBOs		Non-MBOs	
Range	Mid-value (p^*)	Number	Percent $f_1(p^*)$	Number	Percent $f_2(p^*)$
<.90	-	8	7.1%	33	29.5%
.900-.909	.905	2	1.7	3	2.7
.910-.919	.915	9	8.0	6	5.3
.920-.929	.925	12	10.7	16	14.3
.930-.939	.935	8	7.1	14	12.5
.940-.949	.945	19	17.0	16	14.3
.950-.959	.955	20	17.9	11	9.8
.960-.969	.965	21	18.8	6	5.3
.970-.979	.975	4	3.6	4	3.6
.980-.989	.985	4	3.6	3	2.7
.990-1.00	.995	5	4.5	0	0.0
Total		112	100.0	112	100.0

[a] The study computes the buyout probabilities for the 112 MBOs and 112 non-MBOs using the coefficient estimates of the model presented in Table 8. The figures in the column labeled $f_1(p^*)$ are equal to the number of MBO firms that fall within each of the specified intervals divided by the total number of MBOs included in the estimation sample. Similarly, the figures under $f_2(p^*)$ are equal to the number of non-MBOs in each interval divided by the total number of non-MBOs in the sample. Figure 6 plots $f_1(p^*)$ and $f_2(p^*)$ against p^*.

(.908, .919, and .942), the MBOs clearly dominate at only one point *and beyond,* .94167 (.942 rounded). In other words, the number of MBOs with an estimated buyout probability greater than .94167 exceeds (or at least equals) at all points the number of non-MBOs with an estimated buyout probability greater than .94167. The next section therefore uses .94167 as the optimal

Figure 6
Empirical Probability Density Function of Buyout Probability



cutoff probability in tests to determine the ability of the model to predict MBOs in advance.[52]

Predictions in a Holdout Sample

One can use the optimal cutoff probability estimated in the preceding section to examine the ability of the model to predict MBOs in advance. Because the estimation sample provides the basis for obtaining the model parameters and cutoff probability,

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[52] Although the majority of firms in the estimation sample appear to have a high probability of buyout (p^*), the *population* buyout probability (p) for each of these firms is significantly lower. For instance, when p^* equals .94167, p equals .52317, a more reasonable percentage.

any test based on this sample will likely be biased. Hence, the tests described below use a separate set of firms.

In order to asses the classification accuracy of the model over the period 1979-1988 (the time period over which MBOs included in the estimation sample actually went private), the test procedure uses 30 MBOs from that period. As suggested earlier, these 30 firms represent a random selection of firms from the entire population of MBOs that occurred during 1979-1988. The test sample also includes 30 non-MBOs randomly selected from the population of Compustat firms that remained public as of 1988. In each case (MBO and non-MBO), the firms necessarily met the criteria for inclusion in the study and had the required data. The logit procedure does not use any of these 60 firms in estimating the model parameters.

One uses the estimated parameters of the logit model to compute for each firm the probability the firm will be a management buyout in the year following the year of measurement of the independent variables. These probabilities (in conjunction with the optimal cutoff probability) then form the basis for the following classification rule:

> Classify firms with an estimated buyout probability greater than or equal to the optimal cutoff probability .94167 as MBOs; classify firms with an estimated buyout probability less than .94167 as non-MBOs.

This exercise results in the correct classification of 16 out of the 30 (53.3%) MBOs. In the case of the non-MBOs, classifications are correct for 25 out of the 30 (83.3%) public firms. This implies an overall accuracy rate of 68.3% (41 correct classifications out of 60 total firms).

In order to test the predictive ability of the model over a time period other than 1979-1988, the study uses a different set of firms. Specifically, the study employs all management buyouts that took place during 1989, that were listed on Compustat and met the data requirements. Thirteen firms met these criteria. In addition, the test sample includes 1,567 firms that remained public as of 1989. Likewise, these 1,567 firms met the criteria for inclusion in the study and had the required data.

Using a cutoff probability of .94167, the model correctly classifies 5 out of the 13 (38.5%) MBOs that occurred in 1989. Of the 1,567 non-MBOs, the model correctly classifies 1,040 (66.4%) firms. Stated differently, the model incorrectly identifies 527 public firms as management buyouts in 1989. Thus, while the model achieves a fairly high degree of accuracy in predicting non-MBOs (approximately 66%), these results suggest the model has little ability to predict MBOs (the primary purpose of the study). Assuming for a moment that the two types of classification errors are additive, the overall accuracy rate of the model is 1,045/1,580 or 66.1%. This rate is just slightly lower than the accuracy rate for non-MBO prediction because the number of MBOs the model attempts to identify is very small (only 13 firms).

CHAPTER VII

SUMMARY AND CONCLUSIONS, LIMITATIONS, AND SUGGESTIONS FOR FUTURE RESEARCH

Summary and Conclusions

Empirical studies indicate the presence of large abnormal returns accruing to shareholders of ex-public firms in the period immediately preceding the formal announcement of a proposal to go private. For example, by measuring cumulative returns twelve months prior to the first going-private proposal, Maupin (1987) determined that stockholders of 97 firms that went private during the period 1972-1984 earned significant abnormal returns during this twelve-month period. In a similar analysis, DeAngelo, DeAngelo and Rice (1984) measured cumulative returns beginning two months prior to the first going-private proposal. Their analysis revealed an average increase in stockholder wealth of 30.40 percent by the proposal date.

In order to take advantage of these abnormal returns, investors would have had to purchase the stocks of the ex-public firms prior to the first public announcement of a going-private proposal. However, because investors are generally unaware of forthcoming buyouts, they could not expect to participate in the gains unless they were able to identify management buyout candidates from publicly available information. Accordingly, the present study uses a financial profile developed from publicly available information to identify firms that will go private via a management buyout.

The results of the prediction tests reported in the preceding section were generally disappointing. Specifically, in a holdout sample of 30 MBOs that occurred 1979-1988 and 30 firms that remained public as of 1988, the model correctly classified only 16 out of 30 (53%) MBOs. With respect to the 30 public firms, there was a marked improvement in classification accuracy--the model correctly identified 25 out of 30 (83%) of these firms. In a separate test using a different set of firms, the model correctly identified 5 out of 13 (38%) MBOs that occurred in 1989 and 1,040 out of 1,567 (66%) firms that remained public as of that same date.

As these results suggest, the model's ability to predict MBOs is less than precise. A comparison with the correct classification percentage expected by chance provides added confirmation of the model's failure to predict accurately MBOs. Under the proportional chance criterion, the expected probability of correct classifications over all groups is equal to $(\pi_1)^2 + (\pi_2)^2 + \ldots + (\pi_k)^2$, where π_1 equals the prior probability of an observation belonging to the first group, π_2 is the prior probability for the second group, and so forth (Pinches 1980, 443-444). If one uses the distribution of firms in the 1989 test sample to obtain empirical approximations of the prior probabilities in the population, MBOs and non-MBOs represent approximately .8% (13/1,580) and 99.2% (1,567/1,580), respectively, of the total number of firms. Then, the expected probability of correct classifications over both groups under this criterion is 98.4% (i.e., $(.008)^2 + (.992)^2$).

As inferred from above, the overall classification accuracy of the model using the 1989 test sample is 66.1% (1,045 correct classifications out of 1,580 total firms). The overall accuracy of the model using the holdout sample of 30 MBOs and 30 non-MBOs is only slightly higher--68.3% (41 correct classifications out of 60 total firms). In either case, a comparison of the expected probability of correct classifications (98.4%) with the overall accuracy of the estimated model (66.1% and 68.3% for the respective test samples) leads to a conclusion that the performance of the model is *less than* that expected on the basis of chance alone. Further, because the study selects variables for inclusion in the model on the basis of a posited theory (i.e., managers engage in going-private transactions to further their own self-interests), one must conclude that the reported results *cannot* confirm the theory.

Similar to the present study, a few earlier studies developed statistical models that attempt to distinguish firms that go private via a management buyout from firms that remain public. The financial characteristics of the public and ex-public firms formed the basis for each of these models. Although Lawrence's (1986) univariate analysis of the financial characteristics of public and ex-public firms generally revealed no significant differences in the financial characteristics of these two groups, a multivariate analysis achieved a relatively high degree of classification accuracy (80% and 57% of ex-public and public firms, respectively, correctly classified).

Maupin, Bidwell and Ortegren (1984) and Maupin (1987) also reported classification accuracy rates for ex-public and public firms that were fairly high. In the former study, the estimated model correctly classified 94% and 89% of the ex-public and public firms, respectively. The latter study reported classification accuracy rates of 86% and 77% for the same respective groups. However, each of these studies had limitations that may have resulted in overstatements in predictive accuracy. These limitations may partially account for the differences in accuracy rates reported in this and other similar studies.

First, it appears each of these other studies used a nonrandom sample in model estimation without appropriately modifying the estimators. Because failure to modify the estimators for the non-random nature of the sampling procedure can lead to biased estimates of the buyout probabilities (Palepu 1986, 4), the present study employed the conditional maximum likelihood estimator that Palepu (1986) used in order to obtain unbiased and consistent estimates from a choice-based sample.

Second, these earlier studies used equal-share samples in prediction tests which can lead to error rate estimates that fail to represent the model's predictive ability in the population (Palepu 1986, 4). In order to depict accurately the model's performance in the population, the present study tested the predictive ability of the model using a large group of firms that resemble the population in a realistic use of the model.

Third, it appears the earlier studies used arbitrary cutoff probabilities in prediction tests which make the computed error rates difficult to interpret (Palepu 1986, 4). In order to avoid this problem, the present study derived an optimal cutoff probability within a well-defined decision context. Specifically, the study assumed that the purpose of the estimated management buyout model is to provide predictions that will become part of a stock market investment strategy.

While the results of the earlier studies suggest one can use publicly available information to develop a model that reliably predicts MBOs, the present study can make no such claim. In fact, the results of this study are consistent with the results of the DeAngelo, DeAngelo and Rice (1984) study reported below that indicate the stock market has little ability to predict going-private transactions in advance.

Beginning forty trading days prior to the initial public announcement date, DeAngelo, DeAngelo and Rice (1984, 388) measured average cumulative returns for seventy-two firms that proposed going private during 1973-1980. While the average increase in stockholder wealth during this period was 30.40 percent, stockholders experienced most of this increase (22.27 percent) at the announcement of the going-private proposal. Because abnormal price behavior in the forty-day period preceding the announcement is generally attributable to the leakage of information regarding the proposal itself (DeAngelo, DeAngelo and Rice 1984, 389), it appears the stock market does not predict management buyouts with a high degree of accuracy even two months prior to a going-private proposal.

Limitations

The first limitation of the study is the fact that the set of independent variables included in the model is not an exhaustive set of all possible variables. The assumption of little or no residual effect of other potentially significant variables may provide a partial explanation of the model's poor performance in predicting MBOs. For instance, the literature suggests many managers undertake a buyout of their firms to defend against an existing or expected takeover threat (Kleiman 1988, 49). Inclusion of a variable indicating whether or not the firm has been the target of a possible takeover may add significantly to the predictive power of the model.

A second limitation is that all firms within the study appear on Standard & Poor's Compustat and necessarily satisfy certain data requirements (e.g., availability of ten years of historical financial statement data and three years of monthly market returns). Consequently, firms which would otherwise qualify for inclusion in the study may be excluded.

Finally, the study examines the financial characteristics of management buyout firms in relation to the actual date of going private, and not the point in time when management first decided to make the change to private status. As such, inferences concerning cause and effect relationships are more restricted than might otherwise be the case.

Suggestions for Future Research

The present study uses publicly available information to distinguish firms that go private via a management buyout from firms that remain public. In order to estimate model parameters, the study includes firms that achieved private status during the period 1979 to 1988. Since 1979, the number of going-private transactions has increased dramatically. Given the heavy debt loads and marginal nature of some of these transactions, it is no surprise that the number of subsequent business failures (e.g., Revco Drug Stores and Southland Corporation) has also been on the rise. One possible extension of the present study is therefore an examination of the characteristics of two separate groups of MBO firms--those that retain their private ownership status for a specified period of time and those that subsequently fail. An examination of the characteristics of these two separate groups prior to the buyout may provide insight into why certain business failures occur.

Next, while the model developed in the present study does not perform well in terms of classification accuracy, other similar studies (Maupin, Bidwell and Ortegren 1984; Lawrence 1986; Maupin 1987) report highly accurate results. Given the claims by experts that the restructuring boom of the 1980s is over, the motivation and environment for these transactions may have now changed. Because a model that performed well during the 1980s may be inappropriate for use in the 1990s, a revision of these earlier models may be warranted at some future point.

Finally, the present study measures the financial characteristics of MBO firms as of the end of the fiscal year prior to the year of going private. In an effort to increase the likelihood that investors capture any abnormal returns associated with these transactions, an investigation of the financial characteristics of MBO firms in the second-year-prior to going private may prove valuable.

Table 11

Main Features of Representative Bankruptcy Prediction Models

		Beaver	Altman	Deakin	Diamond	Ohlson
FEATURES	Ratios included	Cash flow/ total debt Net income/ total assets Total debt/ total assets Working capital/ total assets Current ratios No credit interval	Working capital/ total assets Retained earnings/ total assets EBIT/total assets Market value of equity/book value of total debt Sales/total assets	Cash flow/total debt Net income/ total assets Total debt/ total assets Current assets/ total assets Quick assets/ total assets Working capital/ total assets Current assets/ current liabilities Quick assets/ current liabilities Cash/current liabilities Current assets/ sales Quick assets/ sales Working capital/ sales Cash/sales	Profitability (4 ratios) Activity (turnover-- 5 ratios) Liquidity (5 ratios) Leverage (5 ratios) Cash flow (4 ratios)	Log (total assets/GNP price level index) Total liabilities/ total assets Working capital/ total assets Current liabilities/ current assets Dummy variable for total assets > total liabilities Net income/ total assets Funds from operations/ total liabilities

Table 11 (continued)

Main Features of Representative Bankruptcy Prediction Models

		Beaver	Altman	Deakin	Diamond	Ohlson
	Type and number of firms	79 Industrials	33 Manufacturers	32 Industrials	75 failed manufacturing; 75 matching	105 industrials
	Time period	1954-1964	1946-1965	1964-1970	1970-1975	1970-1976
FEATURES	Controls:					
	--Matching	Industry, asset size	Year, industry, asset size	No--nonfailed firms selected randomly	4 digit SIC code, asset size	No
	--Holdout Sample	No	Only first year	Yes	n-1 holdout *Ex post* prediction	No
	Refers to an underlying theory?	"Cash flow concept"	No	No	No	No
	Multivariate approach?	No	Yes--discriminant analysis	Yes--discriminant analysis	Yes--pattern recognition	Yes--logit analysis

Table 12

Main Features of Representative Acquisiton Target Prediction Models

		Simkowitz and Monroe	Stevens	Dietrich and Sorensen	Palepu
FEATURES	Ratios included	Market turnover of equity shares Price-earnings ratio Sales Dividend payout (2 measures) Growth in common equity Dummy variable for negative earnings	Profitability (7 ratios) Liquidity (2 ratios) Activity (3 ratios) Leverage (5 ratios) Other (3 ratios)	Price/earnings EBIT/sales Long-term debt/ total assets EBIT/interest payments Dividends/ earnings Capital expenditures/ total assets Sales/total assets Current assets/ current liabilities Market value of equity Trading volume in year of acquisition	Average excess return on stock Accounting ROE Growth resource dummy (to indicate growth-resource mismatch) Industry dummy (to indicate history of acquisitions in a specific industry) Size (as measured by net book assets) Market value of common equity-to-book value of common equity

Table 12 (continued)

Main Features of Representative Acquisition Target Prediction Models

FEATURES	Simkowitz and Monroe	Stevens	Dietrich and Sorensen	Palepu
Type and number of firms	23 merged industrials; 25 nonmerged industrials randomly selected	40 merged industrials; 40 matching	24 merged firms from: Food and beverage (SIC 20), Chemicals (SIC 28), Electronics (SIC 26), Transportation (SIC 37); 43 nonmerged firms from same industries	163 targets in manufacturing and mining; 256 nontargetrs randomly selected from same industries
Time period	1968	1966	1969-1973	1971-1979
Controls: --Matching --Holdout Sample	 No Yes	 Asset size Yes	 Industry Yes	 No Yes
Refers to an underlying theory?	No	No	Net present value framework	Hypotheses suggested by the literature
Multivariate approach?	Yes--discriminant analysis	Yes--discriminant analysis	Yes--logit analysis	Yes--logit analysis

Table 13

Main Features of Representative Management Buyout Prediction Models

		Maupin, Bidwell and Ortegren	Lawrence	Maupin
FEATURES	Ratios included	Concentration of ownership Cash flow to net worth Cash flow to total assets Price/book value ratio Dividend yield	Liquidity (2 ratios) Activity (2 ratios) Leverage (3 ratios) Profitability (4 ratios) Other (8 ratios)	Concentration of ownership Cash flow to net income Cash flow to total assets Price/earnings ratio Price/book value ratio Book value of depreciable assets/original cost Dividend yield
	Type and number of firms	63 ex-public firms; 63 matched public firms	56 ex-public firms; 56 matched public firms	54 ex-public firms; 54 matched public firms
	Time period	1972-1983	1974-1981	1972-1981
	Controls: --Matching --Holdout Sample	 Industry, asset size No	 Industry, asset size Lachenbruch and Mickey holdout method	 Industry, asset size Yes
	Refers to an underlying theory?	Survey of managers of ex-public firms	No	Survey of managers of ex-public firms
	Multivariate approach?	Yes--discriminant analysis	Yes--discriminant analysis (Univariate approach also adopted)	Yes--discriminant analysis

BIBLIOGRAPHY

Aaker, David A. *Multivariate Analysis in Marketing: Theory & Application*. Belmont, California: Wadsworth Publishing Company, Inc., 1971.

Afifi, A. A., and Virginia Clark. *Computer-Aided Multivariate Analysis*. Belmont, California: Lifetime Learning Publications, 1984.

Aldrich, John H., and Forrest D. Nelson. *Linear Probability, Logit, and Probit Models*. Beverly Hills: Sage Publications, 1984.

Altman, Edward I. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance* 23, no. 4 (September 1968): 589-609.

Asquith, Paul. "Merger Bids, Uncertainty, and Stockholder Returns." *Journal of Financial Economics* 11 (April 1983): 51-83.

Barnes, Michael J. "Federal Income Tax Treatment of PIK Preferreds and PIK Debentures." Morgan Stanley *High Performance*, May 1989.

Beaver, William H. "Financial Ratios as Predictors of Failure." *Empirical Research in Accounting: Selected Studies, 1966*, supplement to Vol. 5, *Journal of Accounting Research*, 71-111.

Bernstein, Leopold A. *Financial Statement Analysis: Theory, Application, and Interpretation*. Homewood, Illinois: Richard D. Irwin, Inc., 1978.

Bhide, Amar. "The Causes and Consequences of Hostile Takeovers." *Journal of Applied Corporate Finance* (Summer 1989): 36-59.

Black, Bernard S., and Joseph A. Grundfest. "Shareholder Gains From Takeovers and Restructurings Between 1981 and 1986: $162 Billion is a Lot of Money." *Journal of Applied Corporate Finance* (Spring 1988): 5-15.

Borden, Arthur M. "Going-Private--Old Tort, New Tort or No Tort?" *New York University Law Review* 49 (December 1974): 987-1042.

Bradley, Michael. "Interfirm Tender Offers and the Market for Corporate Control." *Journal of Business* 53, no. 4 (1980): 346-376.

Burry, Roy D. *Beverage Industry Report*, Kidder, Peabody Equity Research, January 24, 1989.

Chew, Lillian. "Overtaken by Events." *Risk* (November 1989): 72-77.

Cochran, William G. "On the Performance of the Linear Discriminant Function." *Technometrics* 6, no. 2 (May 1964): 204-205.

Copeland, Thomas E., and J. Fred Weston. *Financial Theory and Corporate Policy.* Reading, Massachusetts: Addison-Wesley Publishing Company, 1983.

Coslett, Steven R. "Efficient Estimation of Discrete-Choice Models." In *Structural Analysis of Discrete Data with Econometric Applications*, eds. C. F. Manski and D. McFadden, 51-111. Cambridge: MIT Press, 1981.

Deakin, Edward B. "A Discriminant Analysis of Predictors of Business Failure." *Journal of Accounting Research* 10, no. 1 (Spring 1972): 167-179.

________. "Distributions of Financial Ratios: Some Empirical Evidence." *The Accounting Review* (January 1976): 90-96.

________. "Business Failure Prediction: An Empirical Analysis." In *Financial Crises: Institutions and Markets in a Fragile Environment*, eds. E. Altman and A. Sametz, 72-88. New York: John Wiley and Sons, 1977.

DeAngelo, Harry, and Linda DeAngelo. "Management Buyouts of Publicly Traded Corporations." *Financial Analysts Journal* (May-June 1987): 38-49.

DeAngelo, Harry, Linda DeAngelo, and Edward M. Rice. "Going Private: Minority Freezeouts and Stockholder Wealth." *Journal of Law and Economics* 27 (October 1984): 367-401.

Diamond, Steven C., ed. *Leveraged Buyouts*. Homewood, Illinois: Dow Jones-Irwin, 1985.

Dietrich, J. Kimball, and E. Sorensen. "An Application of Logit Analysis to Prediction of Merger Targets." *Journal of Business Research* 12 (1984): 393-402.

Dodd, Peter, and Richard Ruback. "Tender Offers and Stockholder Returns: An Empirical Analysis." *Journal of Financial Economics* 5, no. 3 (December 1977): 351-373.

Doyle, Brian M., and Hoyt Ammidon III. "The Anatomy of a Leveraged Buyout: Profile, Process, Capitalizations, and Implications." Salomon Brothers Corporate Bond Research/High-Yield Research, January 1988.

Easterbrook, Frank H., and Daniel R. Fischel. "Corporate Control Transactions." *The Yale Law Journal* 91, no. 4 (March 1982): 698-737.

Eisenbeis, Robert A. "Pitfalls in the Application of Discriminant Analysis in Business, Finance, and Economics." *The Journal of Finance* 32, no. 3 (June 1977): 875-900.

Eisenbeis, Robert A., and Robert B. Avery. *Discriminant Analysis and Classification Procedures: Theory and Applications*. Lexington, Massachusetts: D. C. Heath and Company, 1972.

Elton, Edwin J., and Martin J. Gruber. "Marginal Stockholder Tax Rates and the Clientele Effect." *Review of Economics and Statistics* 52, no. 1 (February 1970): 68-74.

"Ex-CEO Now Quiet Consultant." *St. Louis Post-Dispatch*, 29 October 1989, 1(E) and 8(E).

Francis, Jack C. *Investments: Analysis and Management*. 3rd ed. New York: McGraw-Hill, Inc., 1980.

Frank, Werner G., and Jerry J. Weygandt. "A Prediction Model for Convertible Debentures." *Journal of Accounting Research* 9, no. 1 (September 1971): 116-126.

Gargiulo, Albert F., and Steven J. Levine. *The Leveraged Buyout*. New York: AMA Membership Publications Division, 1982.

Gibson, Charles H. *Financial Statement Analysis.* 4th ed. Boston: PWS-Kent Publishing Company, 1989.

Gilbert, Ethel S. "The Effect of Unequal Variance-Covariance Matrices on Fischer's Linear Discriminant Function." *Biometrics* 25, no. 3 (September 1969): 505-515.

Healy, Paul M. "The Effect of Bonus Schemes on Accounting Decisions." *Journal of Accounting and Economics* 7 (1985): 85-107.

Holloway, Lois Nelson, and Olive Jean Dunn. "The Robustness of Hotelling's T^2." *Journal of the American Statistical Association* 62 (March 1967): 124-136.

Inselbag, Isik, and Howard Kaufold. "How to Value Recapitalizations and Leveraged Buyouts." *Journal of Applied Corporate Finance* (Summer 1989): 87-95.

Jensen, Michael C. "Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers." *American Economic Review* 76, no. 2 (May 1986): 323-329.

Jensen, Michael C., and Richard S. Ruback. "The Market for Corporate Control: The Scientific Evidence." *Journal of Financial Economics* 11 (April 1983): 5-50.

Journal of Accountancy, Washington Update, November 1989, 118 and 120.

Kensinger, John W., and John D. Martin. "The Quiet Restructuring." *Journal of Applied Corporate Finance* (Spring 1988): 16-25.

Keown, Arthur. J., and John M. Pinkerton. "Merger Announcements and Insider Trading Activity: An Empirical Investigation." *The Journal of Finance* 36, no. 4 (September 1981): 855-869.

Kitching, John. "Early Return on LBOs." *Harvard Business Review* (November-December 1989): 74-81.

Kleiman, Robert T. "The Shareholder Gains from Leveraged Cash-Outs: Some Preliminary Evidence." *Journal of Applied Corporate Finance* (Spring 1988): 46-53.

Kmenta, Jan. *Elements of Econometrics.* 2d ed. New York: Macmillan Publishing Company, 1986.

Kohlberg Kravis Roberts & Co. (with Deloitte Haskins & Sells). "Leveraged Buyouts." *Journal of Applied Corporate Finance* (Spring 1989): 64-70.

Lawrence, Edward C. "A Comparative Analysis of Public Firms Going Private." *Review of Business and Economic Research* 21, no. 2 (Spring 1986): 1-17.

Little, Wm. Brian, and Steven B. Klinsky. "How Leveraged Buyouts Can Really Work: A Look at Three Cases." *Journal of Applied Corporate Finance* (Spring 1989): 71-75.

Long, William F., and David J. Ravenscraft. "The Record of LBO Performance." A report prepared for the Conference on Corporate Governance, Restructuring, and the Market for Corporate Control, Salomon Brothers Center for the Study of Financial Institutions, May 17, 1989.

Lyons, Timothy G. "What's the Deal?" *Business Today* 26, no. 2 (Spring 1989): 21-27.

Manski, Charles F., and Steven R. Lerman. "The Estimation of Choice Probabilities from Choice Based Samples." *Econometrica* 45, no. 8 (November 1977): 1977-1988.

Martin, Daniel. "Early Warning of Bank Failure." *Journal of Banking and Finance* (1977): 249-276.

Maupin, Rebekah J. "Financial and Stock Market Variables as Predictors of Management Buyouts." *Strategic Management Journal* 8 (1987): 319-327.

Maupin, Rebekah J., Clinton M. Bidwell, and Alan K. Ortegren. "An Empirical Investigation of the Characteristics of Publicly-Quoted Corporations which Change to Closely-Held Ownership through Management Buyouts." *Journal of Business Finance and Accounting* 11, no. 4 (Winter 1984): 435-450.

Mergerstat Review. Schaumburg, Illinois: W. T. Grimm & Co., 1986 and 1987.

Moody's Investor Service. "Special Event Risk in the U.S. and Eurobond Markets: 1984-1988." Moody's Special Report, May 1989.

J. P. Morgan Securities. "'Event Risk' and Domestic Securities." A report prepared for Anheuser-Busch Companies, Inc., November 17, 1989.

Murphy, Kevin J. "Corporate Performance and Managerial Remuneration: An Empirical Analysis." *Journal of Accounting and Economics* 7 (1985): 11-42.

Neter, John, William Wasserman, and G. A. Whitmore. *Applied Statistics*. 2d ed. Boston: Allyn and Bacon, Inc., 1982.

Ohlson, James A. "Financial Ratios and the Probabilistic Prediction of Bankruptcy." *Journal of Accounting Research* 18, no. 1 (Spring 1980): 109-131.

Palepu, Krishna G. "Predicting Takeover Targets: A Methodological and Empirical Analysis." *Journal of Accounting and Economics* 8 (1986): 3-35.

Paulus, John D., and Steven R. Waite. "LBOs and the American Competitive Challenge." Morgan Stanley *High Performance*, July 28, 1989.

________, and Steven R. Waite. "Mergers and Acquisitions Activity in the 1990s." Morgan Stanley Special Economic Study, November 17, 1989.

Pinches, George E. "Factors Influencing Classification Results from Multiple Discriminant Analysis." *Journal of Business Research* 8 (1980): 429-456.

Radcliffe, Robert C. *Investment Concepts, Analysis, and Strategy*. Glenview, Illinois: Scott, Foresman and Company, 1982.

Reibstein, Larry, and Carolyn Friday. "The Biggest Winners in the LBO Game." *Newsweek*, 5 December 1988, 42.

Schneider, Carl W., Joseph M. Manko, and Robert S. Kant. "Going Public: Practice, Procedure, and Consequences." *Villanova Law Review* 27, no. 1 (November 1981): 1-51.

Seitz, Neil E. *Capital Budgeting and Long-Term Financing Decisions*. Hinsdale, Illinois: The Dryden Press, 1990.

Sharpe, William F. *Investments*. 2d ed. Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1981.

Simkowitz, Michael and Robert J. Monroe. "A Discriminant Analysis Function for Conglomerate Targets." *Southern Journal of Business* (November 1971): 1-16.

SPSS, Inc., and Marija J. Norusis. *SPSS Advanced Statistics Student Guide*. SPSS, Inc., 1990.

Statement of Financial Accounting Concepts No.2. "Qualitative Characteristics of Accounting Information." Financial Accounting Standards Board, May 1980.

Stevens, Donald. L. "Financial Characteristics of Merged Firms: A Multivariate Analysis." *Journal of Financial and Quantitative Analysis* (March 1973): 149-158.

Stewart, G. Bennett III, and David M. Glassman. "The Motives and Methods of Corporate Restructuring." *Journal of Applied Corporate Finance* (Spring 1988): 85-99.

Tatsuoka, Maurice M. *Multivariate Analysis: Techniques for Educational and Psychological Research.* New York: John Wiley, 1971.

Van de Geer, John P. *Introduction to Multivariate Analysis for the Social Sciences*. San Francisco: W. H. Freeman and Company, 1971.

Van Horne, James C. *Financial Market Rates and Flows.* Englewood Cliffs, New Jersey: Prentice-Hall, Inc., 1978.

Waite, Steven R., and Martin S. Fridson. "The Credit Quality of Leveraged Buyouts." Morgan Stanley *High Performance*, January 1989, 9-15.

Weston, J. Fred, and Eugene F. Brigham. *Managerial Finance*. 7th ed. Hinsdale, Illinois: The Dryden Press, 1981.

Zavgren, Christine V. "The Prediction of Corporate Failure: The State of the Art." *Journal of Accounting Literature* 2 (1983): 1-35.

Zmijewski, Mark E. "Methodological Issues Related to the Estimation of Financial Distress Prediction Models." *Journal of Accounting Research 22,* Supplement 1984, 59-82.

BIOGRAPHY OF THE AUTHOR

Diane Marsan Salamone was born March 9, 1953 in Chicago, Illinois. She attended Southern Illinois University at Carbondale from 1970 to 1974, receiving a Bachelor of Science degree in Accounting in 1974.

From 1981 to 1983, the author attended Saint Louis University, receiving a Master of Business Administration with a concentration in Finance in 1983. She entered the Ph.D. program at Saint Louis University in 1984 and served as an instructor in the Department of Accounting at the University from 1984 to 1990. She is also a Certified Public Accountant.