Analyzing an Acquisition Model

and

Optimizing Stock Abnormal Return

Using Simulation Techniques

by

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Author's Declaration for Electronic Submission of a Thesis

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Ying Liu

Abstract

The relative economic efficiency of acquisitions as a means of restructuring financially distressed firms is investigated. Yearly accounting and daily stock price data are extracted for the period between 1979 and 1998 on firms entering financial distress The behaviour and performance of these firms were traced for a five year period following their entry into distress or until their shares were no longer trading. These collected data forms the basis for analyzing the returns acquired from investing in potential takeover targets.

Survival analysis is used to analyze the hazard rate for both the acquisition and bankruptcy of distressed firms. The results of the analysis indicate that the ZSCORE, a predictor of the probability of failure, and SPCSRM, the rating by Standard and Poor's, can be used as financial indicators in the screening mechanisms for financially distressed firms.

A multinomial-logit acquisition model is used to predict three outcomes of financially distressed firms: survival, acquisition and failure. This model is tested using two methods by simulating the probability of acquisition. The first uses to compare the predicted versus the actual corporate events to maximize the predicted acquisition event. The second uses to compute abnormal return to maximize portfolio return over a given time period, continual on the ZSCORE, probability of acquisition, and the length of holding period. The predictive model of the acquisition probability is applied as a stock entry rule in a buy-sell system. The success of the model will serve two purposes. One is to predict the economic value of acquisition. The other is to provide successful strategies for investing in stocks.

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Abbreviations and Symbols

BEGDT	The first day that a stock enters any stock market
CUSIP	A nine-digit code and unique identifier for each company on COMPUSTAT®
DCLRDT	Distribution declaration date, the date on which the board of directors declared a distribution
DLDTE	The effective date (month and year) of the acquisition, merger, liquidation, or other reason for deletion
DLRET	Delisting return, the return of a security after it has delisted from the New York, American, or Nasdaq stock exchange
DLRSN	A two-digit code representing the reason a company has been moved from the active file to the research file
DLSTCD	A three-digit delisting code, see appendix A
F(A)	Percentage of acquisitions
F(B)	Percentage of bankruptcies
GVKEY	A unique, six-digit number used by Research Insight to identify the company
DitressYears	Number of years that a financially distressed firm is being tracked after the onset of distress
OLS	ordinary least square
P(A)	Probability of acquisitions
P(B)	Probability of bankruptcies
PERMNO	CRSP permanent number
RET	Holding period total return, the change in the total value of an investment in the security over some period of time per dollar of initial investment
SPCSRM	S&P common stock ranking of Standard and Poor's and Moody's
ZSCORE	A measure of bankruptcy

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Chapter 1

Introduction

1.1 Background

Over the last one hundred or more years, there were four major takeover waves sweeping into the world economic market. The characteristics of these takeovers are defined chronologically as follows: monopoly in the 1890s, oligopoly in the 1920s, conglomerate in the 1960s and hostile bust-up takeovers in the 1980s. Jensen (1993) states that the takeovers and restructuring of the 1980s are linked to widespread technological, regulatory and economic change.

There are extensive empirical studies of takeovers in the literature. Powell (1997) summarizes three views of takeovers. Firstly, the takeover mechanism exists to discipline management teams who engage in inefficient behaviour. Jensen (1986) and Grossman and Hart (1980) find that shareholders gain benefits if an inefficient management team is replaced by a more efficient team when a takeover occurs. Secondly, takeovers exist to exploit synergy between firms. Bradley, Desai and Kim (1983) observe that shareholders will benefit if a takeover is undertaken to exploit synergy. Lastly, the firm managers pursue their own self-interest in looking for takeover opportunities. They sacrifice the benefits of shareholders. Since there exist conflicting views about the desirability of takeovers, it often requires government regulations to increase or decrease the degree of takeovers. As a consequence, takeovers become a concern for public policy.

Another important aspect of takeovers that sparks broad public interest is the value of acquisitions. The share price of firms subject to a takeover bid tends to increase between the time a bid is announced and the date at which a takeover is completed. Andrade, Mitchell and Stafford (2001). show that stock returns over the period just prior to the announcement to the completion of the takeover increase 24% for targets. Therefore, modelling the probability of a firm's takeover may have significant economic value. Successfully picking takeover targets in advance of the announcement of a takeover bid could become a profitable investment strategy in the stock market.

1.2 Research Goals

My research is focused on investigating financially distressed firms. The economic value of acquisitions as a means of restructuring financially distressed firms provides the motivation for building a buy-sell simulation system. Survival analysis is used to determine the screening mechanisms for extracting financially distressed firms. Twenty years of accounting data from COMPUSTAT files and market data from the Centre for Research in Security Prices (referred to as "CRSP" files) were merged into an Oracle database. These large data samples form the basis for analyzing the returns achieved from investing in potential takeover targets. A stock's abnormal return is optimized using the ordinary least square (abbreviated as "OLS") estimation model. This optimization model is coded in the Java programming language. A multinomial-logit model, describing the probability of acquisition, failure, and survival developed by Åstebro and Winter (2000) is examined in terms of its accuracy of acquisition prediction. Finally, business rules are set up to determine stock entry and exit rules for corporate events such as acquisition, failure and survival in a buy-sell system.

1.3 Outline of the Study

Chapter 2: focuses on investment analysis. There are two topics discussed in this chapter. The first topic is about takeovers. The research gives an overview of takeovers by describing the concept of takeovers, motives for takeovers, classifications of takeovers and takeover characteristics. The second topic moves to financially distressed firms. Those firms are extensively examined in the two areas: 1) causes of financial distress, 2) behaviour and characteristics of financially distressed firms.

Chapter 3: discusses three analytical models: 1) the capital asset pricing model, 2) the 3-factor model of Fama and French and 3) the OLS estimation model. This chapter provides the description, the structure, and the advantages and disadvantages of each model applied in risk investment.

Chapter 4: describes the multinomial-logit model as applied in the prediction of acquisition model that Åstebro and Winter developed (2001). Each variable in the model is declared and specifies a firm's characteristics. A data trimming method for each variable is described at 95 and 99 confidence levels.

Chapter 5: defines the objective function to compute the abnormal return, the rules of data extraction, and the screening mechanisms for financially distressed firms.

Chapter 6: renders three results achieved from the simulation results analysis: a validation of the acquisition model, the impact of ZSCORE on portfolio return, and a null hypothesis testing for excess return.

Chapter 7: gives the overall picture of a buy–sell trading system. The creation of use cases and processing models is described. The fundamental analysis and technical analysis join together in providing trade entry and exit rules. Detailed design functions are defined for the system implementation.

Chapter 8: summarizes the contributions of the thesis and provides some suggestions for the future research.

Chapter 2

Investment Analysis

2.1 Introduction

This chapter covers the topics on takeovers and financial distress.

In the late 1990s, the scale and pace of takeover activity increased. For example, Bell Atlantic acquired NYNEX for the sum of 21.0 billion $US. Travelers Group Inc acquired Citicorp for a much higher amount of reaching 83.0 billion $US. What makes two firms worth more together than apart? “Motives for takeovers” will address this question in detail. How are the takeovers achieved? The section on “Takeovers” describes the classification of takeovers and explains factors deterring takeovers. The purpose of this section is to discuss how to define the characteristics of an acquisition candidate. Thus the choosing firms with particular characteristics will be employed in modeling takeover likelihood.

The “Financial distress” section discusses what happens when a firm experiences financial distress. Clark and Ofek (1994) find that financially distressed targets are more likely to be successfully restructured than targets that are only operationally distressed. Furthermore, I will discuss how the takeover of distressed firms requires higher purchasing premiums than the takeover of non-distressed firms. This section also illustrates the characteristics of the financially distressed firms.

2.2 Takeovers

2.2.1 Definition of Takeovers

Takeover is a general and imprecise term referring to the transfer of control of a firm from one group of shareholders to another (Ross, Westerfield and Jaffe 1993). Takeovers are driven in part by industry shocks. Industry shocks as factors that alter industry structure are a source of takeover activity. Empirical studies find that for high-takeover industries, the industry shocks include deregulation, input price volatility, energy dependence, foreign competition, and financing innovations (Mitchell and Mulherin 1996).

- Deregulation

Deregulation is positively related to takeover and restructuring activity. The act of deregulation removes artificial constraints on the size of existing firms and attracts new entrants into the market. The adaptation to these changes in industry organization could be facilitated by takeovers. The empirical evidence for the acquisition activity caused by deregulation can be found as follows: in the 1980s, deregulation induced significant merger activity in industries such as air transport, natural gas and trucking. In the 1990s, deregulation was directed toward other sectors including banking, electric utilities, and telecommunications. The deregulation was widely spread over many types of industries (Mitchell and Mulherin 1996).

- Energy dependence

Jensen (1993) states that one shock driving takeover activity during the 1980s was oil price volatility. He suggests that this shock not only directly affected the oil industry itself, but also was an important factor in the structure of industries in which energy was a major input. The regression test (Mitchell and Mulherin 1996) shows that the volatility of oil prices positively affected takeover activity.

- Foreign competition

During the 1980s, import penetration increased in many industries. Prior research documents that the changes in foreign competition influence price-cost margins and other measures of industry efficiency. Mitchell and Mulherin (1996) in their regression analysis shows that foreign competition does not have a significant effect on takeover and restructuring activity. However, they found that foreign competition heightens the takeover and restructuring activities in high-tech industries, such as computer data processing and electronics that are expanding at a fast pace in the world market.

- Financing innovations

Another shock during the 1980s was the significant increase in high-yield debt financing. Empirical research records that the enhanced ability to use leveraged financing removed obstacles to takeovers, especially for larger firms (Kaplan 1989). The result was that the number of takeover targets was relatively large in the 1980s merger wave. Several empirical papers document that the fraction of debt in capital structure is inversely related to R&D/sales at the industry level (Long and Malitz 1985). The above regression analysis tested the assumption that industry R&D/Sales is negatively and significantly related to takeover and restructuring activity. It concludes that innovations in financing techniques are very important for the takeover and restructuring activity.

It is a well known fact that shareholders of target companies definitely gain from mergers and tender offers(Franks and Harris 1989). However, critics argue as to what is the source of takeover gains. They support redistributive theories that claim shareholder gains are offset by economic losses to others. Some reviews of the most important redistributive theories are listed as follows:

1) Tax motives have long been suspected as an important cause of merger and acquisition activity. Acquiring a firm's tax losses and credits, and the option to step-up the basis of the target's assets without paying corporate level capital gains, are two tax benefits that appear to have had some impact on merger activity (Jarrell, Brickley and Netter 1988). However, most recent studies assign tax benefits a minor role in explaining merger and takeover activity. Much of the takeover activity in the last twenty years was not tax motivated.

2) Bondholders' losses from takeovers is strongly supported by the redistributive theories. Nevertheless, in recent empirical research, Denis and McConnell (1986) indicate that "on average holders … in the acquired firm gain from a merger. Those … in the acquiring firm neither gain nor lose in a merger." They also find some evidence that the acquiring firms' common shareholders do not lose and may even gain from mergers, especially in the days immediately following the announcement. This evidence provides no support for the view that the supposed gains from acquisitions are actually transfers from the holders of senior securities to the holders of common stock; the source of takeover gains seems to be a result of wealth enhancing changes.

3) The theory that losses of the labour force financial takeovers has not been tested widely. The statistical results based on Michigan's employment and wages survey reveals that wages and employment rise on average for firms that are involved in acquisitions (Brown and Medoff 1987). This evidence is

contradictive to the redistributive theory that claims a shift of wealth from labour to shareholders.

To summarize, the above evidence points to that the premiums in takeovers maybe represent real wealth gains and are not simply wealth redistributions.

2.2.2 Motives for Takeovers

Significant stock price increases occur prior to formal announcements of takeovers. The evidence for this is provided by Andrade, Mitchell and Stafford (2001). They show that stock returns over the period from just prior to the announcement up until the completion of the takeover increase 24% for targets. This study shows that the shareholders of target companies clearly benefit from takeovers.

From the literature review, there are three common motives for takeovers that are widely accepted. First is the managerial discipline motive (Grossman and Hart 1980). Second is complementary resources motive. The last is the free-cash-flow motive.

The central finance theory states that takeovers are a mechanism by which managers of a firm who fail to maximize the firm's market value are replaced by more efficient managers (Asquith 1983). Takeovers act as a means of restructuring financially distressed firms. Managerial discipline acquisitions have been suggested as an important mechanism to induce the efficient redeployment of assets of a bankrupt firm (Jensen 1991). The result of these types of takeovers will be an improvement in the operating performance on average.

Complementary resources are another motive for takeovers. In this case, acquirers and targets have complementary resources. This means that each has what the other needs. For example, a small firm may have a unique product but lack the engineering and sales organization required to produce and market it on a large scale. Instead of spending large resources and time in developing engineering and sales forces on their own, the board managers of the target firm may seek to undergo an acquisition process in order to obtain these resources. It is a quicker and cheaper way for the target to obtain these missing resources. On the other hand, the acquirer also benefits from the acquisition process. The unique products and intelligent human resources from the target firm will add impetus to the acquirer's existing production line and bring profit in any expanding market. In short, the acquisition initiated by the complementary resources motive makes the two firms function better than they would as separate entities. Each firm acquires something it does not have and gets it cheaper than it would by acting on its own.

Generally speaking, a firm with surplus funds is in a mature industry. The firm has a large amount of free cash flow, but it has few profitable investment opportunities. Some of these firms are often reluctant to pay out dividends to stockholders. They seek to be acquired so they can have the opportunity to redeploy their capital. The acquirers, on the other hand, want to capture this firm's cash flow in order to invest in new productive projects. Therefore, this free-cash-flow motivates both parties to become involved in the acquisition process.

To summarize, the managerial discipline motive, the complementary resources motive and the cash-free-cash-flow motive allow a takeover to add value to both firms. These takeovers eliminate inefficient management, make better use of existing resources, add revenues and create growth opportunities.

Different types of takeovers generate different kinds of value to both firms. What are the varieties of takeovers? The next topic will explain the classification of takeovers in depth.

2.2.3 Classification of Takeovers

The classification of takeovers includes tender offers, mergers, and leveraged buyouts. Tender offers are classified as friendly or hostile. One common distinction between friendly and hostile offers is based upon whether or not the initial offer is rejected. Friendly tender offer refers to offers that are supported by target management. Hostile tender offers are those that are opposed by the target management.

Nuttall (1999) in his paper of estimating takeover likelihood models finds that friendly and hostile takeover likelihood have statistically distinct determinants. The firm's age, size, leverage and even takeover rumours are individually significantly different across the takeover types at the 6% level. He reported the following findings:

- Being relatively young on the stock market has a much stronger positive effect on the likelihood of a firm becoming a friendly target rather than a hostile target.
- A firm's size has a strong negative effect on the probability of being friendly acquired, but an insignificant effect for being hostile-acquired. This supports the view that larger firms are better able to defend themselves against hostile takeovers. Small firms with

financial constraints have an incentive to merge with larger companies without financial constraints.

- A firm's leverage has a strong positive effect on the probability of being friendly acquired, but not on the probability of being hostile-acquired. This is consistent with the view that the financially distressed companies are more likely to accept rescue offers.
- Lastly, takeover rumours equally positively affect both the likelihood of being friendly acquired and being hostile-acquired.

Although both friendly and hostile targets have poor pre-bid performance, the stock returns for firms subject to hostile takeovers normally average about 14% more than for those firms subject to friendly takeovers (Franks and Harris 1989). Shareholders of target companies therefore clearly benefit from takeovers.

A "takeover" can also be induced from within the firm, as became apparent in the 1980's. Defensive asset restructuring includes any major asset restructuring or recapitalization induced by implicit takeover pressure, such as a large block purchase by a corporate raider or the growing occurrence of takeover activity in the firm's industry. Jarrell, Brickley and Netter.(1988) define leveraged buyouts as: "Leveraged buyouts are buyouts of shareholder's equity, heavily financed with debt by a group that frequently includes incumbent management." In terms of profit from defensive asset restructuring, Lehn and Poulsen (1987) find premiums of 21 percent to shareholders in 93 leveraged buyouts taking place from 1980 to 1984.

2.2.4 Characteristics of Takeover Targets

There is a couple of potentially interesting areas of study on the differential characteristics of takeover targets. One is from the academic perspective. Research on takeover targets' characteristics can lead to constructing a likelihood model of acquisitions. Second, from an industry perspective, studying the underlying differential characteristics of target firms will shed light on their restructuring. An empirical analysis assesses differences in the financial characteristics of takeover targets and non-takeover targets. The results indicate that the unique characteristics of takeover targets, relative to nontargets are: small firm size, young age when the firm enters the stock market, rumour sensitivity which implies having a high takeover speculation, low profitability, low Tobin's Q and low leverage (Hasbrouck 1985).

Tobin's Q is a measure of the ratio of the market value of financial claims on the firm to the current replacement cost of the firm's assets. It is considered to be an important variable in investigating takeover activities. Firms displaying Q's greater than unity are judged as using scarce resources effectively, and those with Q's less than unity are seen as using resources poorly (Wilbur G. Lewellen and Badrinath 1997). Tobin's Q is indicative of managerial performance. A firm with a low Q value relative to other firms is assumed to seek acquisitions to acquire valuable resources.

Low leverage is viewed as a signal of managerial incompetence. Studies show that takeover targets will have lower pre-existing levels of debt. The relationship is likely to be firm-specific rather than industry-specific between this variable and takeover likelihood (Hasbrouck 1985).

Financial liquidity calculated as the combination of current financial assets and liabilities is also an indicator of takeover behaviour. Petruzzi (1983) found, “The tax consequences of distributing cash to the shareholders may be unfavourable, and acquisition may be a vehicle for reallocating these funds in a fashion that minimizes taxes. The takeover targets that have excess liquidated assets may lead to either firm- or industry-specific relationship to takeover likelihood.”

Firm size is a firm-specific control variable. The likelihood of takeovers decreases with the size of the firm. Firstly, it is for financial synergy reasons, as outlined above in motives for takeovers. Secondly, there are transaction costs of takeovers related to size. Several studies illustrate that it is a costly process and a prolonged battle to absorb the target into the acquirer’s organizational framework. Size is a significant factor in determining the probability of acquisitions (Palepu, 1986).

The age of the firm also plays an important role in the takeover activities. The likelihood of a takeover increases when the age of the target is quite young. Two reasons are found from the empirical studies in explaining this point. One reason is financial synergy. When the target is quite young, it usually strongly performs well. From the aforementioned, acquirers being cash-rich and targets being small or strongly performing are more likely to have synergy acquisitions. The integration between two firms makes both function better than they perform separately. Financial synergy increases productivity (Nuttall 1999). The other reason is more uncertainty about a market entrant. Since there is a very high turnover amongst entrants, young firms are more likely to go bankrupt, or at least experience financial distress, than older firms. Consequently, younger firms may be more apt to eagerly look for rescue bidders.

Having a high takeover speculation implies that a firm is expected more likely to be acquired in the public press. It is another positive characteristic of takeover targets. Investors overweight their prior beliefs about the stock's value and the stock price over-reacts. It results in huge profit making for takeover shareholders on the day that the acquisition announcement is made (Nuttall 1999).

In short, investigating the financial characteristics of takeover targets will yield insight into the economic forces underlying takeover activities (Hasbrouck 1985). This will be fundamental in analysing the virtue of takeover targets.

2.2.5 Factors Deterring Acquisition

There are a couple of major factors deterring the process of acquisition.

One is that firms with more complex debt structures encounter more difficulty in achieving the completion of acquisition. An acquisition is a substitute for reorganization and requires creditor approval. Therefore, for firms with more complex debt structures, gaining creditor approval for an acquisition is likely to be more difficulty because of possible disagreements among creditor groups over the distribution of the proceeds from the sale. Takeover activity will more likely happen in the firms whose management has already been replaced and for firms with less complex debt structures.

The other factor deterring acquisition is industry conditions. Generally speaking, potential bidders as acquiring firms in the same industry are also likely to be financially distressed and thus be constrained in their ability to raise funds to acquire the more poorly performing firm (Shleifer and Vishny 1992). The financially distressed firms with better future prospects (good firms) are likely to choose to reorganize as independent companies rather than attempt a sale in a market where both good firms, and firms with poor prospects (bad firms), sell at a low price. This adverse selection process leads to, on average, a lower quality pool of potential acquisitions.

2.3 Financial Distress

2.3.1 Definition of Financial Distress

John (1993) in the article of Managing Financial Distress states, “a firm is in financial distress at a given point in time when the liquid assets of the firm are not sufficient to meet the current requirements of its hard contracts”. He categorizes the financing contracts of a firm into hard and soft contracts. Hard contracts can be either a coupon debt contract which specifies periodic payments by the firm to the bondholders, or contracts with suppliers and employees. Common stock and preferred stock fall into a category of soft contracts.

Clark and Ofek (1994) define financial distress as violation of debt covenants, inability to service debt, default on debt, or needing cash for operations, or having filed for Chapter 11 protection.

There are thus varying definitions of financial distress. Some are quite specific while others include a host of financial difficulties.

2.3.2 Causes of Financial Distress

In general, financial economists find it difficult to tell whether a firm’s poor performance is driven by financial distress or not. Altman (2000) finds large indirect costs of financial distress, but does not distinguish them from negative operating shocks. Recent studies find that many firms are not only financially distressed, but also economically distressed (Clark and Ofek 1994). It increases the difficulty to identify whether the costs of distressed firms are trigged by financial distress, economic distress, or by an interaction of both. My literature review finds that high leverage is one of the primary causes of distress, but it is difficult to conclude from this evidence whether it is economic or financial distress causing high leverage.

In this study, I am not interested in trying to explain the underlying factors of distress. Rather, I use measurable firm and industry characteristics that apparently predict financial distress and take them as given.

2.3.3 Behaviour of Financially Distressed Firms

Poor stock performance could be the first indication that a firm is in financial trouble. However poor performance does not lead to financial distress without high leverage. The organizational change is unlikely to occur in an all-equity firm. Financial distress is often accompanied by comprehensive organizational changes in management, governance, and structure. A firm under financial distress seeks revitalisation. Financial distress often frees resources to move to higher-valued uses by forcing managers and directors to reduce capacity and to rethink operating policies and strategic decisions. Financial distress leads to negotiation with a firm's creditors. The creditors have a legal right to demand restructuring because their benefits are breached when the firm is under financial distress. To summarize, financial distress is resolved in an environment of imperfect information and conflicts of interest. The specific behaviours in response to financial distress are described as follows:

- Restructuring management and governance

Poor management decision-making and weak governance can cause financial distress. Incumbent management teams and director boards can also deter the pace of technological changes. In order to increase the efficiency of management, shareholders strongly demand changing the top management structure. Changes in top management and boards of directors become a means of the firm restructuring to deal with their financial crisis. Gilson (1989) observed that distressed firms experience a 52% annual turnover of top management. This observation further supports the fact that financial distress provides a mechanism to initiate top-management changes. He also finds that turnover among directors is high following distress, and the size of the director board shrinks following distress as well.

- Reforming organizational strategy and structure

Empirical papers document that some firms in financial distress undergo dramatic organizational changes as part of their recovery, refocusing their strategy and undertaking restructurings (Hotchkiss and Mooradian 1998). To protect their interests, major shareholders attend board meetings, intervene in the company's strategy making and monitor its restructuring process. Financial distress can force managers to undertake value-increasing organization changes, such as selling, reorganizing or restaffing part of its assets. This restructuring creates value for the firm's claimholders. It also illustrates how the financial structure interacts with investment decisions: financial distress forces a change in the firm's economic activities and the way these activities are organized (Wruck 1990).

2.3.4 Characteristics of Financial Distress Firms

The violation of a debt covenant gives a warning that distress is imminent. A firm in financial distress is insolvent. The present value of the firm's cash flows is less that its total obligations.

As financial distress affects a firm's ability to conduct business as usual, the distressed firm exhibits the following three common characteristics:

1) Decreasing power on decision making

As claimholders intervene in the daily operation of a distressed firm, managers lose the right to make certain decisions without legal approval. In contrast to the pre-distress situation, the firm cannot spend money or sell assets without agreement from their claimholders.

2) Decreasing market demand

To some extent, the value of products and services that a firm provides to customers is highly related to the firm's performance. This is consistent with the view that customers like purchasing goods with a famous brand name. Therefore, a financial distress situation may ruin the company's image. This can result in a decrease in demand for the firm's products and services, which threatens the firm's ability to survive.

3) Decreasing power in price negotiation

Financial distress affects a firm's ability to negotiate favourable input prices or credit terms. Since the distressed firm doesn't have sufficient cash to pay its debts, suppliers often charge a risk premium through increasing prices, tightened credit terms. Some suppliers even redefine their relationship with the firm as a short-term one (Wruck 1990). All of those negative effects resulting from the financial distress decrease the firm's bargaining power in negotiations on input material prices and other services.

4) Increasing time in resolving financial distress

When a firm faces financial distress, the managers of the firm are eager to engage in restructuring management and governance, and changing organizational strategy and structure. All these activities require that management spend considerable time resolving financial distress. The increased time spent by the managers in productive restructuring will hopefully lead to increasing the value of the firm.

2.3.5 Takeover of Financially Distressed Firms

The takeover of distressed firms requires higher purchasing premiums than the takeover of non-distressed firms because the market adds a risk discount to a distressed firm(Åstebro and Winter 2000).

The takeovers of distressed firms are more likely to involve firms in the same industry and are less likely to be hostile takeovers. Clark and Ofek (1994) discover this characteristic by examining thirty-eight takeovers of distressed firms. In their test, they also find that financially distressed targets are more likely to be successfully restructured than targets that are only operationally distressed. Buyers of distressed firms seldom gain concessions, but concessions do increase the probability of successfully restructuring targets. Furthermore, the smaller the target is relative to the buyer, the higher is the likelihood of a successful takeover.

When a firm experiences financial difficulties, they look at the following courses of action to survive. The first remedy is to voluntarily restructure its operations. The second alternative is to restructure its operations and financial claims under the protection of the bankruptcy court. Another effective means of restructuring for distressed firms is a merger of their operations with those of an acquirer. The following discussion will focus on the characteristics of both takeover targets and acquiring firms.

- Bidder performance

Distressed targets perform very poorly; however, the bidders' performance is not significantly different from other firms in their industry or risk class. Bidders are less leveraged than targets. The bidder's average ratio of debt to assets is 28.8 percent, compared to 39.2 percent for targets, and the difference between these ratios is significant at the 10-percent level (Clark and Ofek 1994).

- Concessions

An acquiring firm may need to reduce the level of fixed claims on a target to be able to revive a distressed firm. Concessions reduce the stringency of financial contracts by reducing interest rates, delaying repayment, or temporarily lifting other debt covenants. This cost savings allows the acquiring firm more flexibility in using its available cash flow. Receiving concessions is important for a distressed firm to successfully complete its takeover restructuring.

- Industry similarity

An acquiring firm that is in the same industry as their takeover target may be better able to restructure the distressed firm. Industry-specific management expertise, synergies, and market power are three possible reasons for industry-related bidders to be more capable of saving a failing firm. Clark and Ofek (1994) find that twenty-one out of thirty-eight firms match the four-digit SIC of the takeover targets in their sample acquisitions.

- Abnormal returns

Tobin's Q is an important determinant of the size of abnormal returns available around the time of the takeover announcement (Servaes 1991). High Q firms are considered to have more intangible assets, such as management expertise, than are low Q firms. Clark and Ofek (1994) find that bidder and target cumulative abnormal returns (CARs) are larger when the bidder is a high Q firm and the target is a low Q firm, and CARs are smaller when the situation is reversed. The implication of this result is consistent with the market expectation that more return will be forthcoming to shareholders when a firm with good management takes over a firm with poor management.

2.4 Summary

There are three conclusions that can be derived from the investment analysis. First, the characteristics of the takeover targets differ from nontargets in that the firms are small in size and young in age, have a high takeover speculation and possess low profitability, low Tobin's Q and low leverage (Hasbrouck 1985). These unique characteristics except having a high takeover speculation and low Tobin's Q, are included as input variables in the acquisition model discussed in chapter 4. However, having a high takeover speculation and low Tobin's Q should not be ignored. A high takeover speculation triggers investors to overweigh their prior beliefs about the stock's value and the stock price subsequently over-reacts. It has been shown that Tobin's Q as an indicator of managerial performance has an effect on the acquired firm's behaviour.

Second, the characteristics of firms taken over via a friendly bid differ from the characteristics of firms taken over via a hostile bid (Morck, Shleifer and Vishny, 1988).

Lastly, a takeover generates an economic gain if the two firms are worth more together than as separate entities. Gains from takeovers may reflect improved efficiency of management, the combination of complementary resources, or redeployment of free cash flow. Gains bring profit to shareholders. How do we measure the stock return resulting from investing in firms' that are being acquired? The next chapter will provide several different analytical methods used to answer this question.

Chapter 3

Analytical Methods

3.1 Introduction

The stock market is risky because there is a wide spread of possible outcomes. When the stock market goes up, an investor has the potential of high returns. When the stock market goes down, an investor faces the risk of losing money. For example, the stocks of Nortel Networks Corporation soared to more than $120 per share in 2000, but fell to less than $1 per share in 2002. Most investors lost money from investing in Nortel stocks. How is risk defined? What are the links between risk and return? Are there any analytical methods to measure the risk?

This chapter will define risk and return. The capital-asset pricing model (CAPM), the 3-factor model and the ordinary least square (OLS) estimation model will be presented as different methods for calculating return. At the end of the chapter, the decision is made to choose one of the above models to use in my research for computing the excess return.

3.2 Risk

The definition of risk varies based upon each individual investor. The *American Heritage Dictionary* defines risk as the possibility of suffering harm or loss. Malkiel (1996) defines risk as the chance that expected security returns will not materialize and, in particular, that the securities a person holds will fall in price. It is a fact that risk is the probable variability or dispersion of future returns. So financial risk is defined as the variance or standard deviation of returns in general. The higher the standard deviation is, the greater is the risk. It is a well known fact that higher returns have been associated with higher risks.

Risk includes unsystematic risk and systematic risk. Unsystematic risk stems from the fact that many of the perils that surround an individual company are peculiar to that company and perhaps its immediate competitors. Systematic risk stems from the fact that there are other economy wide perils which threaten all businesses (Ross, Westerfield and Jaffe 1993).

The unsystematic risk can be eliminated by diversification. Because prices of different stocks do not move exactly together, diversification can provide a substantial reduction in variability. Systematic risk measures the degree of sensitivity that a security has as it moves in the stock market. It cannot be eliminated by diversification. However, an investor can select a diverse portfolio to reduce the systematic risk by selecting stock that have negatively correlated returns (Malkiel, 1996).

There are several methodologies to model and measure risk such as the CAPM, the 3–factor model and the OLS estimation model. All of these show an investor how to minimize risk by combining stocks in their portfolios to maximize the return they seek while minimizing risk.

3.3 The Capital-Asset Pricing Model (CAPM)

Principles of CAPM:

The general formula for CAPM is:

$$R_{it} = R_{ft} + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it} \qquad (1)$$

where:

R_{it} : is rate of return.

R_{ft} : : is risk free Rate.

R_{mt} : : is return from market.

β_i : is the standard risk measure for individual securities and describes the covariance between the particular stock and the market.

ε_{it} : The unexplained component of R_{it} represented by the disturbance term epsilon.

The above formula implies that the risk premium[1] an investor received on any stock or portfolio increases directly with the beta β_i value. The return on a stock or a portfolio is over and above the risk free rate of interest.

The efficiency of the market portfolio has two implications: one is that the expected return has a positive relationship with market betas. The other is that market betas are sufficient to describe the cross-section of expected returns.

Flaws of CAPM:

Malkiel (1996) summarizes the major flaws of the CAPM as follows:

1) Beta is a fickle short term performer and sometimes fails to work over long periods of time.

   Black, Michael and Sholes (1972) found an anomaly for the period from April 1957 through December 1965 in terms of the relationship between beta and returns. Not only does the zero-beta exceed the riskless rate during this period, but securities with higher risk also produced lower returns than

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[1] Risk premium is defined as the difference between risky returns and risk-free returns. Risk-free return is the return invested in Treasury bills with a 90-day maturity.

less-risky (lower beta) securities. This finding is in contradiction with the prediction of the CAPM. Malkiel (1996) also found that mutual fund returns bore no relationship to their beta measures of risk for the entire decade of the 1980s. Therefore, investors who use the CAPM may risk being penalized for some periods of time.

2) Estimated betas are unstable

Criticism of the asset-pricing model is prompted by the size effect (Banz 1981). Banz finds that average returns on small stocks are too high given their beta estimates, and average returns on large stocks are too low. The research further shows that the prediction of beta that is only based on past experience is very inaccurate. In an uncertain market environment, the economical change, industry shocks, changes of company structure, business strategy, or competitors status will impact the sensitivity of the company's stock to market fluctuations. Betas of individual stocks should vary over time. It is concluded that historical betas may be quite imperfect indicators of future betas. Investors who overly trust betas as a useful predictor of the behaviour of individual stocks may suffer great loss.

3) Beta is easily rolled over

Roll (1984), a financial theorist says that it is impossible to estimate the market's return. In principle, the market includes all stocks, a variety of other financial instruments, and even non-marketable assets such as an individual's investments in education. The S&P index (or any other index used to represent the market) is therefore a very imperfect market proxy. Thus I may obtain a quite imperfect estimate of market sensitivity. Roll stated, “When the change of the market index against betas is measured, one could obtain quite different measures of the risk levels of individual stocks or portfolios. As a consequence, one would make very different predictions about the expected returns from the stocks or portfolios.”

Malkiel (1996) sums up the evidence for the CAPM:

> “Beta, the risk measure from the capital-asset pricing model, looks nice on the surface. It is a simple, easy-to-understand measure of market sensitivity. Unfortunately, beta also has its warts. The actual relationship between beta and rate of return does not correspond to the relationship predicted in theory. Moreover…Betas are not stable from period to period, and they are sensitive to the particular market proxy against which they are measured.”

3.4 The 3-Factor Model of Fama and French

Variables Analysis:

Banz (1981) documents a strong negative relationship between average return and firm size. Bhandari (1988) finds that average return is positively related to leverage, and Basu (1983) finds a positive relationship between average return and earnings-price ratio (E/P). Stattman (1980) and Rosenberg Reid and Lanstein (1985) document a positive relationship between average return and book-to-market equity for U. S. stocks. These interesting findings indicate that the simple relationship between beta and average return disappeared during the recent 1963-1990 period. Fama and French (‘FF” is used as following) (1992) demonstrate that for the 1963-1990 period, firm size and book-to-market equity capture the cross-sectional variation in average stock returns associated with size, E/P, book-to-market equity, and leverage. Their results conflict with the asset-pricing model. It is well known that variables like size, E/P, leverage, and book-to-market equity are important factors. They are all scaled versions of a firm's stock price, and may somehow overlap in explaining average return. These factors and their relationship with stock returns will be analyzed in detail as follows:

Size

Portfolios are formed on size because size produces a wide spread of average returns and beta (Chan and Chen 1988). Size and beta are highly correlated. FF, using the two-pass sort on size and beta, say that variation in beta that is tied to size is positively related to average returns, but variation in beta unrelated to size is not compensated for the average returns of 1963-1990. FF concludes that there is a negative relationship between size and average return, but when firm size is controlled for, there is no reliable relationship between beta and average return.

Book-to-market equity

FF shows that there is a strong positive relationship between average return and book value of assets to market equity. This relationship is unlikely to be a beta effect. The average returns for both negative book value firms and high book value of assets to market equity firms are high. FF documents that the results of negative book value form persistently negative earnings and high book value of assets to market equity. This means that stock prices have fallen. Both negative book value and high book value of assets to market equity are both signals of poor earnings prospects. It is also noticed that book value of assets-to-market equity captures cross-sectional variation in average returns that are related to relative distress.

Earnings-price ratio (E/P)

Ball (1978) points out that earnings–price ratio is a catch-all for omitted risk factors in expected returns. Earnings-price ratio is a proxy for expected returns when earnings are positive, but it is not when earnings are negative.

FF find that the relationship between earnings–price ratio and average returns seems to be absorbed by the combination of firm size and book value of assets-to-market equity in their experiments. The conclusion they make is that size and book value of assets–to-market equity provide a simple and powerful characterization of the cross-sectional average stock return.

Formula of the 3-Factor Model:

The three-factor model is applied by regressing the pre-event monthly excess returns for a firm based on a market factor, a size factor, and a book-to-market factor:

$$R_{it} - R_{ft} = \partial_i + \beta_i (R_{mt} - R_{ft}) + s_i SMB_i + h_i HML_t + \varepsilon_{it} \qquad (2)$$

Data description in the 3-factor model:

R_{it} : the simple return on the common stock of firms i.

R_{ft} : the return on three-month treasury bills.

R_{mt} : the return on a value-weighted market index.

SMB_t : the return on a value-weighted portfolio of small stocks less the return on a value-weighted portfolio of big stocks.

HML_t : the return on a value-weighted portfolio of high book-to-market stocks less the return on a value-weighted portfolio of low book-to-market stocks.

∂_i: the intercept, representing the value that $R_{i,t}$ is expected to occur when the explanatory variables are zero. It is zero for all assets.

β_i : the covariance between the particular stock and the market.

$\varepsilon_{i,t}$: the unexplained component of $R_{i,t}$ represented by the disturbance term epsilon.

Advantages:

The three–factor model offers the advantage that it does not require size or book-to-market data for sample firms, and explains the value premium better than the CAPM. It implies:

- Firms without available data on market value of equity or book-to-market ratios can be included in the analysis.
- Some large firms or firms with low book-to-market ratios may in fact have common stock returns that more closely mimic those of small firms with high book-to-market ratios.
- The model largely captures the average returns on U.S. portfolios formed on size, book-to-market ratio and other variables known to cause problems for the CAPM such as earnings/price, cash flow/price, past sales growth, and long-term past return (Fama and French (1992).

Disadvantages:

- Given four parameters in the regression, it requires at least five observations of pre-event monthly returns. This creates a survivor bias among remaining sample firms.
- When long-horizon returns are considered, the regression estimates are assumed stable over the estimation period.

3.5 Abnormal Return – the OLS Estimation Model

Properties of Daily Stock Return and Excess Return:

Empirical studies show that daily stock data has significant differences from monthly stock data. It brings the following properties of daily excess return: the first is a non-normality property. Fama (1976) found evidence that the distributions of daily returns are fat-tailed relative to a normal distribution. It illustrates the fact that the daily stock return departs significantly from normality which is not the case with monthly data. The second is the non-synchronous trading issue. When using the ordinary least square (OLS) estimation model to calculate the excess return, the return on a security and the return on the market index are measured differently in terms of the trading time interval. This difference is the cause of bias and inconsistency in the estimates of the OLS model parameters. With the daily data, the bias becomes "especially severe" (Scholes and Williams 1977). The third is that serial dependence exists in daily excess returns (Ruback 1982). The fourth is cross-sectional dependence in excess returns. Beaver (1968) found benefits to incorporating cross-sectional dependence into the variance estimation. The last property is stationarity of daily variance. It is a well known fact that the share price of firms increases greatly during the time when a takeover bid is announced. Therefore, the variance of stock returns increases as well around the time of announcements, implying non-stationality of daily variance when focussing on takeovers.

Excess Return Methodology:

The OLS estimation model is based on the Scholes–Williams procedure and assigns a dummy variable to measure the excess return during a holding period. Since this research is interested in the acquisition event, the excess return is assumed generated from this abnormal event of a takeover announcement. The excess return is also called abnormal return. It is defined as the difference between risky returns and risk-free returns. The formula uses a multiple regression model similar to the CAPM, but is expanded to measure the abnormal return specifically related to the takeover event.

$$R_{i,t} = \partial_i + \beta_i * R_{m,t} + g_i * D_{i,t} + \varepsilon_{i,t} \qquad (3)$$

Data description in abnormal return formula:

1) $R_{i,t}$: the return on stock i on day t.
2) $R_{m,t}$: the return on the CRSP value weighted market index on day t.
3) $D_{i,t}$: a dummy variable that takes the value of 1 when the stock is held; otherwise, it takes the value of 0.
4) $\varepsilon_{i,t}$: the unexplained component of $R_{i,t}$ represented by the disturbance term epsilon.
5) g_i : abnormal return for stock i. The abnormal return is generated when a stock is held in a portfolio.

6) ∂_i : the intercept, representing the value that $R_{i,t}$ is expected to occur when the explanatory variables $R_{m,t}$ and $D_{i,t}$ are zero. Compared to the CAPM, this intercept represents R_{ft} .

7) β_i : the slope regression coefficients, representing the marginal effect of the explanatory variables $R_{m,t}$ and $D_{i,t}$ respectively. Since on average it is a short stock holding period, it is assumed that β_i, which is the correlation between $R_{i,t}$ and R_{ft}, is equal to 0.

3.6 Summary

From the above description of the three models, it is found that the actual relationship between beta and rate of return does not correspond to the relationship predicted in the CAPM model. Moreover, betas are not stable from period to period. Using the 3-factor model creates a survivor bias.

In my research, the OLS estimation model chosen as the one to use to compute the excess return for a stock. Since this research is interested in investing in the financially distressed firms with a high probability of acquisition, the stock holding period is assumed to be relatively short, up to a maximum of four years, with a mean of one to three years (see tables 7 and 8). Thus the new listing bias and skewness bias[2] are small. Furthermore, in the abnormal return calculation (equation 3 on page 33), $R_{m,t}$ uses the CRSP value weighted market index instead of the equally weighted market index. Thus, the

[2] New listing bias, which arises because in event studies of long-run abnormal returns, sampled firms generally have a long post-event history of returns, while firms that constitute the index (or a reference portfolio) typically include new firms that begin trading subsequent to the event month. Skewness bias, which arises because long-run abnormal returns are positively skewed.

returns calculated from the OLS model will diminish the rebalancing bias[3].

[3] Rebalancing bias, which arises because the compound returns of a reference portfolio, such as an equally weighted market index, are typically calculated assuming periodic (generally monthly) rebalancing, while the returns of sample firms are compounded without rebalancing.

Chapter 4

Acquisition Model

4.1 Introduction

It is well known that the popularity of the model for predicting the likelihood of acquisition is due to the huge profit potential. The target shareholders in a friendly takeover are paid a premium (price above current stock price) between 20% and 40%, while the target shareholders in a hostile takeover are paid a premium of as much as 70%. Under such circumstances, the ability to pick takeover targets successfully could provide the basis for an investment strategy whereby firms with high estimated probabilities of takeover are invested in prior to the takeover announcement.

Based on the above, modelling takeover likelihood can focus on the characteristics of firms since the characteristics of target firms are the driving forces behind the takeover. Thus a knowledge of these characteristics can be used to cast some light upon the motives underlying takeover activity (Powell 1997). In my research, I use the multinomial-logit model that Åstebro and Winter (2000) developed to forecast the probability of financially troubled firms being acquired, going bankrupt or surviving. This chapter will discuss in detail the reasons for using this model. It also explains the variables used in composing this model and the data trimming method.

4.2 A Multinomial-Logit Model

The multinomial-logit model predicts three possible outcomes of financial distress: survival, acquisition and failure. This model specifies the probability of each outcome as a function of some vectors of measured characteristics for a distressed firm. The most important reason for distinguishing between different outcomes of financial distress is, for banking practices, recovery rates might differ substantially between firms that are actually liquidated and firms that are acquired by other firms (Hotchkiss and Mooradian 1998).

The prediction model developed is based on data for firms assumed to be in financial distress, as given by a ZSCORE <= 0.5. It specifies the functional relationship between a firm's characteristics and its takeover likelihood for a given time period of distress. The multinomial logit model specifies the probability p_{ij} that firm i will belong to outcome j (e.g., failure if j = 0, survival if j = 1 or acquisition if j = 2) as a function of some vectors of measured characteristics x_i for firm i. The model is represented as follows:

$$P_{ij} = \frac{e^{x_i \beta_j}}{\sum_{j=0}^{2} e^{x_i \beta_j}} \tag{4}$$

β_j is a vector of parameters. There are two vectors of regressors, one vector for each outcome j = 1, j=2. The third outcome of the other two can be computed from using the vectors of the two outcomes j = 1 and j = 2 since $\sum_j P_{ij} = 1$. Thus, the normalization $\beta_0 = 0$ is imposed. Therefore, the probability of acquisition is interpreted as follows:

$$P_{i1} = \frac{e^{X_1\beta_1}}{1 + e^{X_1\beta_1} + e^{X_2\beta_2}} \quad (5)$$

The parameters of the model are provided from the paper "The Probability of Failure, Survival and Acquisition of Firms in Financial Distress" (Åstebro and Winter 2000). The characteristics of firm i that are chosen to feature in this prediction model of acquisition are indicated as x_i . The x_i input variables for this model are explained in the next topic on "input variables".

4.3 Input Variables

The input variables in the prediction model are accounting variables. They consist of (1) cash position, (2) leverage, (3) liquidity (4) profitability, (5) the value of a firm's intangible assets, (6) the value of a firm's R&D expenses, (7) estimated firm age and its square, and (8) firm size measured by total sales. The data description can be seen in table 1.

Variables	Descriptions
Age	time period from the entry year when a stock enters the stock market to the year when a firm enters financial distress as defined by a zscore <= 0.5
Size	total sales
Cash position	cash/total assets
Leverage	total debt/total assets
Liquidity	current assets/current liabilities
Profitability	net income/total assets
R&D	R&D expenses/total sales
Intangible assets	intangible assets/sales

Table 1: Data description in acquisition model

When calculating age, the entry year is derived from a field called the beginning date, which is denoted by "begdt", from the CRSP daily stock file. Except for this data item, all other data are taken from the COMPUSTAT files.

4.4 Data Trimming

The influence of outliers can be severe in regression analysis particularly for ratios of two potentially miss-measured quantities. In Åstebro and Winter's sample, the value of the above accounting variables are trimmed at the 99th percentile in the sample period from 1980 to 1989. In this research, these values are updated at the 99th and 95th confidence levels for the expanded sample period from 1979 to 1998 to avoid influence of outlier data. Table 2 lists the trimming procedure[4]:

Trim all non-null financial variables							
				95% confidence		**99% confidence**	
				t(1-a/2; v) =t(0.975;v) = 1.960		t(1-a/2; v) = t(0.995;v) =2.576	
				Low boundary	High boundary	Low boundary	High boundary
Variables	N	Mean	Standard deviation (stddev)	Mean - stddev * t(0.975; v)	Mean + stddev* t(0.975; v)	Mean - stddev * t(0.995; v)	Mean + stddev* t(0.995; v)
firmsize	12502	81.4996	165.2986	-242.4856	405.4849	-344.3095	507.3088
cashposition	12563	4.7747	28.6759	-51.4301	60.9795	-69.0945	78.6439
leverage	12309	19.0085	94.6405	-166.4868	204.5039	-224.7854	262.8024
liquidity	12968	3.2612	36.7518	-68.7724	75.2949	-91.4116	97.9340
profitability	12926	2.6484	24.6261	-45.6188	50.9157	-60.7885	66.0854
rdexpenses	1406	4.2312	12.9907	-21.2307	29.6931	-29.2330	37.6954
intangible	5088	10.0595	58.4064	-104.4170	124.5361	-140.3953	160.5144

Table 2: Accounting data trimmed at 99th and 95th confidences

[4] v = n-1 > 120 where n is number of records for the variable in the database.

The research also considers the case where missing values occur in the above accounting variables. The rules to deal with missing values are summarized as below:

- INTANGIBLE: when missing, the data item is assumed to be zero.
- RDEXPENSES: when missing, the data item is assumed to be zero.
- AGE: Age cannot be null, otherwise, this record is invalid.
- FIRMSIZE, LIQUIDITY, CASHPOSITION, LEVERAGE,

PROFITABILITY: when missing, the industry mean values are used instead. Industry mean values are computed across all firms in the corresponding 3-digit industry code.

In order to control measurement and functional form problems, Åstebro and Winter's used dummy variables which are therefore implemented here as well. There are three dummy variables used in the referenced paper. One, called the cash-dummy, takes the value of 1 when a negative value of the cash-position variable is observed. Another is called profitability-dummy and is assigned to a value of 1 when profitability is negative. The last dummy variable, called the age-dummy, was used to indicate when age was estimated. This is no longer used since the real age of a firm can be calculated using the method that was defined in the above data description.

4.5 Summary

Literature studies show that the use of a binomial specification to model takeover likelihood is likely to be incorrect and conclusions based on such a model are likely to be misleading and result in incorrect inferences regarding the characteristics of firms subject to takeover (Powell 1997). The multinomial framework in which the outcomes of financial distress are classified into survival, acquisition and failure is shown to be a better specification than the binomial specification (Åstebro and Winter 2000). Applying the multinomial-logit model serves two purposes in my research.

First, it can examine how the characteristics of firms that are taken over differ from those of firms going bankrupt and surviving. Second, since the model is based solely on the characteristics of firms, the optimal cut-off probability of acquisition is used as a fundamental stock entry rule in order to select firms that exhibit high estimated probabilities of takeover.

Chapter 5

Objective Function, Data and Analysis Design

5.1 Introduction

In order to examine the acquisition model described in the previous chapter, I want to use a robust data sample which includes all potential firms that have a high probability of being acquired. Since the acquisition model is a function of the characteristics of a firm, yearly accounting data is used to compute the probability of acquisition. The daily market data is used to compute the stock abnormal return. These two data sets will be integrated to create the expanded data source. What are the data extraction rules that can be developed to maximize the inclusion of all financially distressed firms? This question will be addressed here.

This chapter also discusses two financial distress indicators: the ZSCORE, a measure of bankruptcy, and SPCSRM, the rating by Standard and Poor's. Survival analysis is used to examine these financial distress indicators as screening mechanisms for financially distressed firms.

The objective function uses the OLS estimation model to compute the excess return g_i for each stock. This chapter examines the decision rules that are set up to determine the values for all variables such as the occurrence of the missing values and the occurrence of coded description instead of actual values for $R_{i,t}$ and $R_{m,t}$ in the function.

5.2 Definitions of Financial Distress Indicators

The ZSCORE, defined as a measure of bankruptcy by Altman (1968), is a weighted sum of five financial ratios: (1) working capital over total assets, (2) retained earnings over total assets, (3) earnings before interest and taxes over total assets, (4) market value of equity over book value of total liabilities, and (5) sales over total assets. Altman (2000) suggests that the ZSCORE model is an accurate forecaster of failure for up to two years prior to distress. If a value less than 1.81 is returned, there is a high probability of bankruptcy. If a value greater than 3.0 is returned, there is a low probability of bankruptcy (COMPUSTAT files). In my research, the ZSCORE was examined as a financial indicator for predicting financially distressed firms.

SPCSRM stands for S&P common stock ranking of Standard and Poor's and Moody's. In the COMPUSTAT files, SPCSRM is explained as an appraisal of past performance of a stock's earnings and dividends and the stock's relative standing at the end of company's current fiscal year. Growth and stability of earnings and dividends are key elements in establishing Standard & Poor's earnings and dividends rankings for common stocks. This rating assesses the likelihood of timely payment of debt having an original maturity of no more than 365 days. A rating of "A" means that capacity for timely payment is strong. A rating of "B" implies that capacity for timely payment is adequate. A rating of "C" indicates that capacity for timely payment of short-term obligations is doubtful, and a rating of "D" shows that the issue is in default or is expected to be in default upon maturity. A financial journal reports that fifty-six out of ninety-one firms that went bankrupt in the US and Canada in the first half of 2001 had a bad credit rating between CCC and CC. Therefore, SPCSRM is selected to be examined as an alternative screening mechanism in this thesis as well.

Standard & Poor's Compustat codes, description of rankings, and the S&P ranking are presented below.

SPC Code	S&P Description	Ranking
7	Highest	A+
8	High	A
9	Above Average	A-
16	Average	B+
17	Below Average	B
18	Lower	B-
21	Lowest	C
22	In Reorganization	D
99	Liquidation	LIQ

Table 3: S&P rating codes and descriptions

5.3 Data Extraction

This research examines firms undergoing financial distress. The ZSCORE as a measure of financial distress is used as a criterion to extract financially distressed firms. Yearly financial data on firms entering financial distress are extracted from the COMPUSTAT files for the period between 1979 and 1998. Daily market data for these financially distressed firms are extracted from the CRSP files. These two data sets are merged with the linking file that maps CRSP PERMNO to COMPUSTAT GVKEY and CUSIP. All the data are loaded into an Oracle database. The behaviour and performance of these extracted firms were traced for a certain number of years following their entry into distress or until their shares were no longer trading. The collected data sample includes all potential firms that have a high probability of being acquired.

5.3.1 Sampling

There are two criteria for data extraction. One is the cut-off ZSCORE value whereby a firm is indicated as being at the onset of financial distress. The other is the cut-off extracting years that a financially distressed firm is tracked following the onset of financial distress. In order to determine these two cut-off values, I extracted all data containing the ZSCORE, the deletion reason (abbreviated as "DLRSN") and deletion date (abbreviated as "DLDTE") from the COMPUSTAT files. DLRSN is a two-digit code representing the reason a company has been moved from the active file to the research file. The codes and their meanings are as follows:

Code	Reason for Deletion
1	Acquisition or merger
2	Bankruptcy
3	Liquidation
4	Reverse acquisition (1983 forward)
5	No longer fits original format (1978 forward)
6	Leveraged buyout (1982 forward)
9	Now a private company
10	Other (no longer files with SEC among other possible reasons)

Table 4: DLRSN codes and descriptions

DLDTE represents the effective date (month and year) of the acquisition, merger, liquidation, or other reason for deletion. Based on this large set of data, I analysed the percentage of acquisitions and the percentage of bankruptcies when the value of the ZSCORE and the number of extracting years are changed.

Notation declaration:

- DistressYears: is the number of years that a financially distressed firm is being tracked after the onset of distress.

- Percentage of acquisitions (abbreviated as "F(A)"): is defined as the number of firms that are acquired within the time period of the distressYears over the total number of extracted firms.
- Percentage of bankruptcies (abbreviated as "F(B)"): is defined as the number of firms that go bankrupt within the time period of the distressYears over the total number of extracted firms.

5.3.2 Observations

When the distressYears is controlled at 3, 4, or 5 years, F(A) and F(B) are computed by simulating the ZSCORE from 0 to 12 in steps of 0.1. The following observations are found:

1) The curve of F(A) vs. ZSCORE is an up trend curve for the distressYears of 3, 4, or 5. In other words, when the ZSCORE increases, F(A) increases for all the different distressYears. (See figure 1)

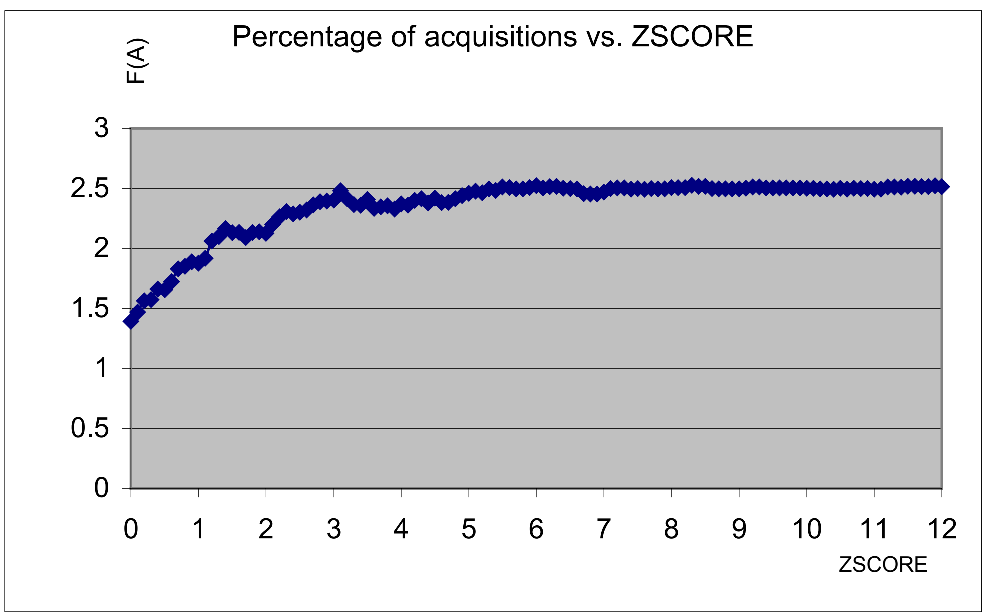

Figure 1: F(A) vs. ZSCORE when the distressYears = 4

2) F(A) reaches its maximum value of 2.9 when distressYears is 3, but this maximum value changes to 2.5 and 2.4 when the distressYears value increases to 4 and 5 respectively. The details are listed in table 5. The table shows that when the distressYears value increases, the number of firms being acquired decreases, implying that a financially distressed firm has a high probability of being acquired in the 3rd or 4th year after the onset of distress, and has less probability of undergoing acquisition when the number of distress years is longer.

Maximum F(A)	**ZSCORE**	**#DistressYears**
2.9	6.1	3
2.5	8.3	4
2.4	7.1	5

Table 5: Maximum F(A) for the different distressYears

3) The curve of F(B) vs. ZSCORE is a down trend curve when the value of distressYears is 3, 4, or 5. In other words, when the ZSCORE increases, F(B) decreases for all the different distressYears. (see figure 2)

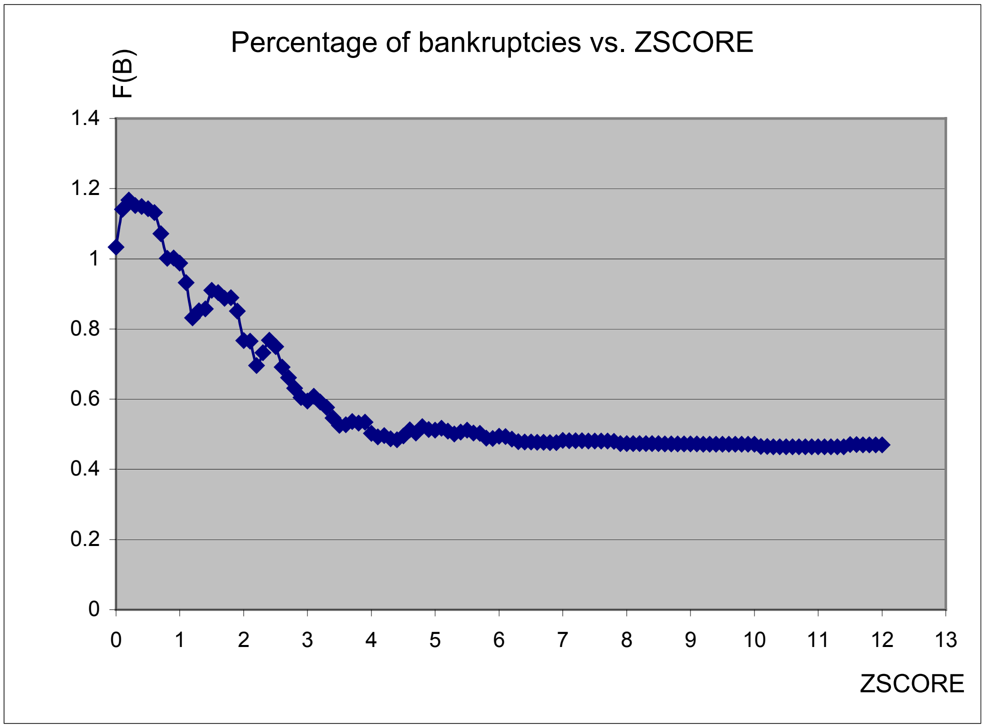

Figure 2: F(B) vs. ZSCORE when the distressYears = 4

4) F(B) reaches its maximum value of 1.6 when distressYears is 3, but this maximum value of F(B) decreases to 1.2 and 0.7 when the value of distressYears increases to 4 and 5 respectively. The details can be seen in table 6. This illustrates that when the value of distressYears increases, the number of firms going bankrupt decreases as well. It implies that the longer a firm can tolerate distress the less likely that the firm will go bankrupt.

Maximum F(B)	ZSCORE	DistressYears
1.6	0.0	3
1.2	0.2	4
0.7	0.8	5

Table 6: Maximum F(B) for the different distressYears

From the above observations, It can be seen that when the ZSCORE increases, F(A) also increases, but the F(B) decreases. It can also be seen that when the number of the distress years is longer, the total number of firms being acquired or going bankrupt decreases. It implies that the financially distressed firms have a high probability of undergoing acquisition or bankruptcy in the early stages after the onset of financially distress. On the other hand, when a firm endures through a longer number of distress years, the firm may be successful in internally restructuring itself. The result is the number of firms undergoing acquisition or bankruptcy goes down if they experience a longer period of financial distress.

5.3.3 Cut-off Values for the ZSCORE and Extracting Years

There are two reasons to determine an appropriate ZSCORE cut-off value: 1) having as large a proportion of acquisitions as possible, while 2) allowing for a reasonable predictive accuracy of financial distress because the ZSCORE does not predict bankruptcy events when the value of the ZSCORE > 6, and nor does it predict acquisition events when the value of the ZSCORE is beyond 5.

In order to derive these values, I intended to use the mapping theory to maximize both the percentage of acquisitions and the percentage of bankruptcies. The mathematical procedure is as follows:

Objective:

Maximize (F (A) + F (B))

Subject to:

ZSCORE

distressYears (t)

The optimal solution for (F(A) + F(B)) with the ZSCORE variable and the distressYears variable is listed in table 7:

DistressYears (t)	3	4	5
Max (F(A) + F(B))	3.38	3.09	2.78
ZSCORE	2.1	3.1	7.1

Table 7: Maximum (F(A) + F(B)) vs. ZSCORE for the different distressYears

In this research, I also applied the mapping theory to examine a ZSCORE of less than 0.5 as a financial indicator to extract the financially distressed firms because a ZSCORE of less than 0.5 is a score low enough to guarantee virtually no false positives (Altman, Haldeman and Narayanan 1977), (Altman 1984). The result is that the sum of F(A) and F(B) decreases when the value of distressYears increases, which is similar to the result obtained by simulating the value of the ZSCORE (See table 8).

DistressYears(t)	3	4	5
F(A) + F(B)	3.02	2.80	1.76

Table 8: Sum of F(A) and F(B) vs. distressYears when ZSCORE = 0.5

From tables 7 and 8, it can be seen that the optimal solution is constrained by the distressYears variable. The rules used for data collection attempted to include as many potential financially distressed firms as possible. So it is necessary to get a large data sample. Increasing the value of ZSCORE can produce a large sample. For example, when the value of distressYears is 4, the percentage of acquisitions and bankruptcies increases from 2.8 to 3.09 as the value of ZSCORE increases from 0.5 to 3.1. However, increasing the sample beyond ZSCORE > 6 is useless as the ZSCORE does not discriminate failures. Based on the requirements of the data sample, the final solutions for the cut-off values for ZSCORE and number of extracting years are:

1) Number of extracting years = 4
2) Cut-off value of the ZSCORE = 3.1

Although the optimal solution for the number of extracting years is 3 and the cut-off value of the ZSCORE is 2.12, the final solutions for the number of extracting years expands to 4 years and the cut-off value of ZSCORE takes 3.1. The major reason to use 4 years for the number of extracting years is that I want to be sure to move beyond the values that generate maximum sampling efficiency and can then in the analysis reduce sample size to that which is optimal as judged by this analysis to check for robustness of this sampling choice.

In short, the rules of data extraction from the COMPUSTAT files is summarized as follows:

- Extract all firms with ZSCORE <= 3.1 amongst all industries between 1979 and 1998.
- If a firm has multiple years with ZSCORE <= 3.1, extract the financial data for the firm for the first year when ZSCORE <= 3.1 is observed, and track the behaviour and performance of the firm for another continuous four years after the year of distress onset or until the firm's shares were no longer trading. The decision to track a firm for another 4 years following their entry into distress is

consistent with a previous empirical study where Åstebro and Winter (2000) document, "Approximately 32 percent of firms likely to be distressed are acquired or merged with another company within five years of the onset of distress."

This collected data form the basis for analyzing abnormal returns based on investing in potential takeover targets.

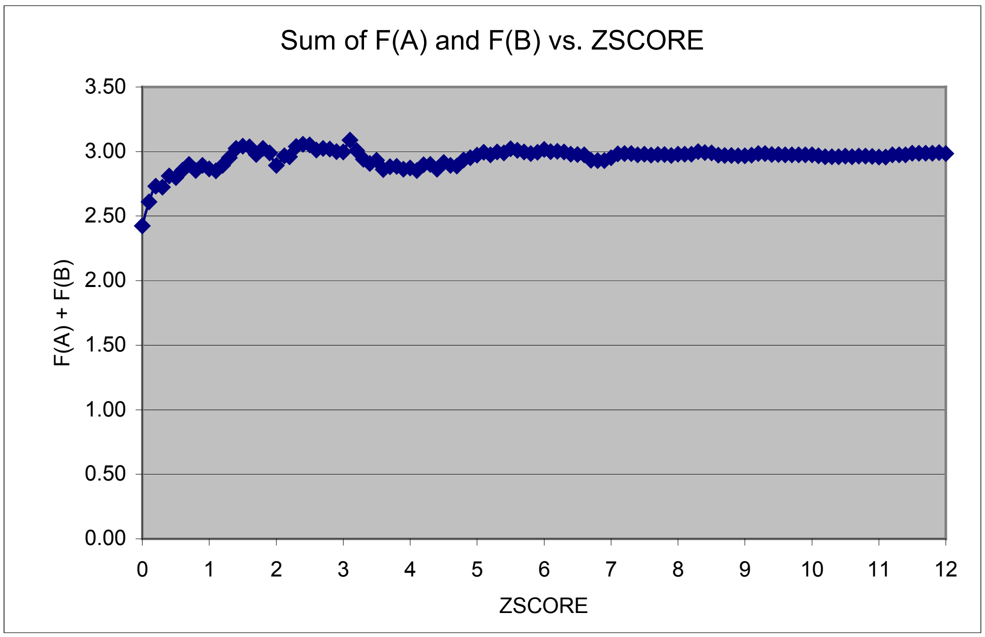

Figure 3: Sum of F(A) and F(B) vs. ZSCORE when the distressYears = 4

5.4 Survival Analysis

5.4.1 Survival Time

Definition of survival time:

Survival is defined as the time starting from the beginning of financial distress until one of several possible events happens. These possible events are defined as acquisition, bankruptcy, liquidation and other deleting reasons that cause the firm to be deleted from the active stock market. The other deleting reasons are described by the DLRSN code in the COMPUSTAT files.

Formula of Functions of Survival Time:

The distribution of survival time is usually described or characterized by three functions: (1) the survivorship function, (2) the probability density function, and (3) the hazard function. The functions for the survival time for stock firms are as follows:

Survivorship function:

S(t) = (number of firms surviving longer than year t) /

(total # of distressed firms in the observed year)

where:

number of firms surviving longer than year t

= number of distressed firms in the observed year

- number of firms deleted before year t

The purpose of s(t) is to obtain the median value of the survival function.

Probability density function (also called unconditional failure rate):

f(t)=(number of firms acquired in the interval beginning at time t) /

(total number of distressed firms in the observed year)*(interval width)

The purpose of f(t) is to show which time period has a high frequency of acquisition.

Hazard function (called conditional failure rate):

h(t) = (number of firms acquired per year in the interval) /denominator

denominator = (number of firms surviving at t) – (0.5 * number of firms acquired in the interval)

The purpose of h(t) is to obtain the maximum value for the probability of acquisition.

The survival analysis is used to compute the survival function, probability density function and hazard rate for different deleting events.

5.4.2 Results of Survival Analysis

There are two financial indicators, ZSCORE and SPCSRM, which are used as control variables in analyzing financially distressed firms. The use of these two financial indicators results in fairly different data sample sizes because the number of firms extracted with a non-null SPCSRM is much lower than the number of firms extracted with a non-null ZSCORE (see table 11).

Results of survival analysis using the ZSCORE:

Table 9 gives the summarized information for the survival analysis using two different values of ZSCORE as extraction criteria. The first criterion is to assign ZSCORE a cut-off value of 3.1. The other criterion is that ZSCORE takes the value of 0.5 as the probability of the default as a measure of distress because a ZSCORE of less than 0.5 is a score low enough to guarantee virtually no false positives (Altman, Haldeman and Narayanan 1977, Altman 1984).

The results achieved from using the two different values of ZSCORE are as follows: it takes 20 years to reach the median of the survivorship function for acquisition, bankruptcy, and other deleting reasons. The probability density function reaches its maximum in 3 years after the onset of distress for the acquisition event. See figure 4. The hazard rate reaches its peak value at 3 or 4 years for the acquisition event. See figure 5. Another observation is that for the acquisition event, the maximum values of the probability density function are quite low, around 2 to 3 percent. This implies that in 3 or 4 years after the onset of financial distress, there are 2 or 3 out of 100 financially distressed firms that are actually being acquired. The hazard rate data shows that in year 3 with the extraction criterion of ZSCORE = 3.1, the probability of acquisition in that year is 0.029. Thus it is concluded that the ratio of acquired firms is fairly low.

Deleting reason	ZSCORE	Median of s(t) (year)	Max of f(t)		Max of h(t)	
			Year	Value	Year	Value
Acquisition	0.5	> 20 years	2,3	0.018	4	0.02
	3.1	> 20	3	0.027	3	0.029
Bankruptcy	0.5	>20	3	0.012	4	0.014
	3.1	>20	4	0.006	4, 5	0007
Others	0.5	>20	3	0.047	4	0.056
	3.1	>20	4	0.029	4	0.033

Table 9: Survival analysis using ZSCORE

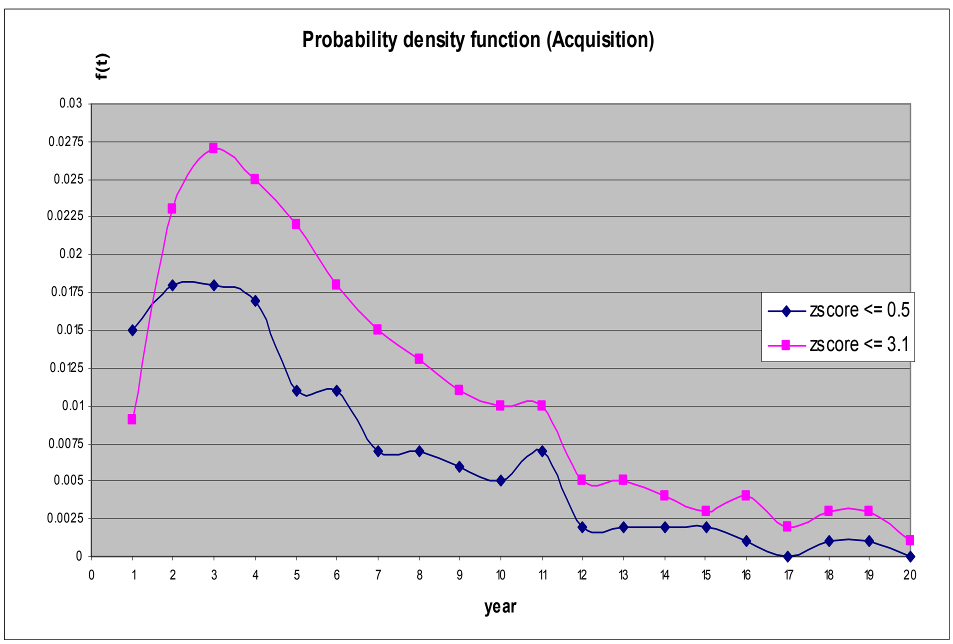

Figure 4: Probability density function of acquisitions using ZSCORE

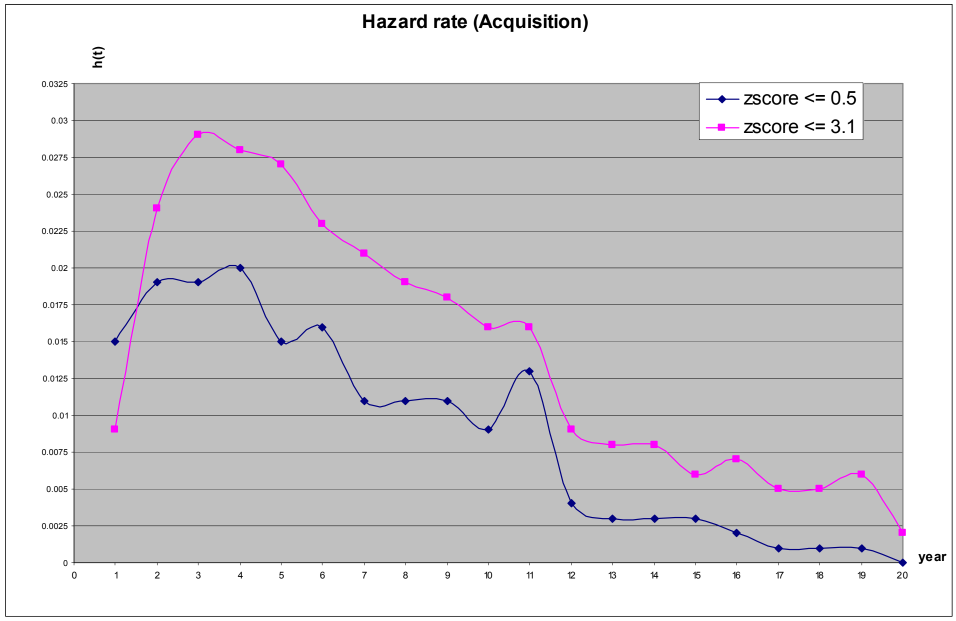

Figure 5:Hazard rate of acquisitions using ZSCORE

Results of survival analysis using SPCSRM:

Table 10 summarizes the results of the survival analysis using SPCSRM as an extraction criterion. I decided to extract data using the cut-off ratings: B, B-, and C where those rated C and below have the lowest corporate ratings. The detailed description of SPCSRM can be seen in table 3. The median of survivorship function takes 20 years for all deleting reasons which is the same as the result of survivorship function using ZSCORE. The probability of density function reaches its maximum in 1 year after the onset of distress for the acquisition event (see figure 6), in 2 years for the bankruptcy event, and in 5 years for the other deleting reasons. The hazard rate takes the same number of years as the probability density function in reaching its peak value for different deleting reasons. Figure 7 displays the hazard rate of acquisition using SPCSRM. For the acquisition event, the maximum values for probability density function and the hazard rate are higher than those using the ZSCORE, around 4 to 4.5 percent. It means that using SPCSRM, the acquisition event will be reached early, and the probability of acquisition is higher as well.

Deleting reason	SPCSRM	Median of s(t) (year)	Max of f(t)		Max of h(t)	
			Year	Value	Year	Value
Acquisition	B (>= 17)	> 20 years	1	0.042	1	0.043
	B- (>= 18)	> 20	1	0.044	1	0.045
	C (>=21)	>20	1	0.042	1	0.043
Bankruptcy	B (>= 17)	>20	2	0.006	2	0.006
	B- (>= 18)	>20	2	0.008	2	0.009
	C (>=21)	>20	2	0.012	2	0.013
Others	B (>= 17)	>20	5	0.005	5	0.007
	B- (>= 18)	>20	5	0.006	5	0.007
	C (>=21)	>20	5	0.007	5	0.009

Table 10: Survival analysis using SPCSRM

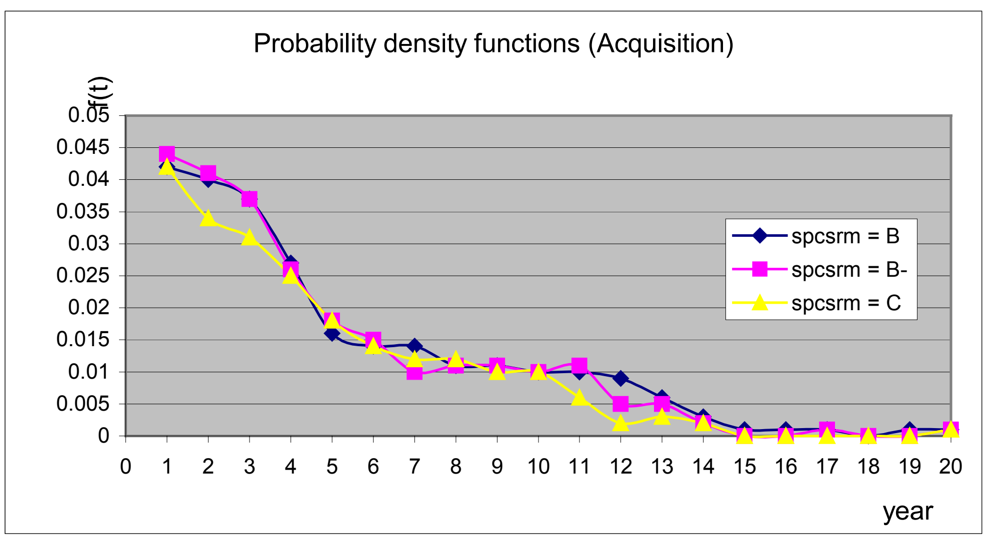

Figure 6: Probability density function of acquisitions using SPCSRM

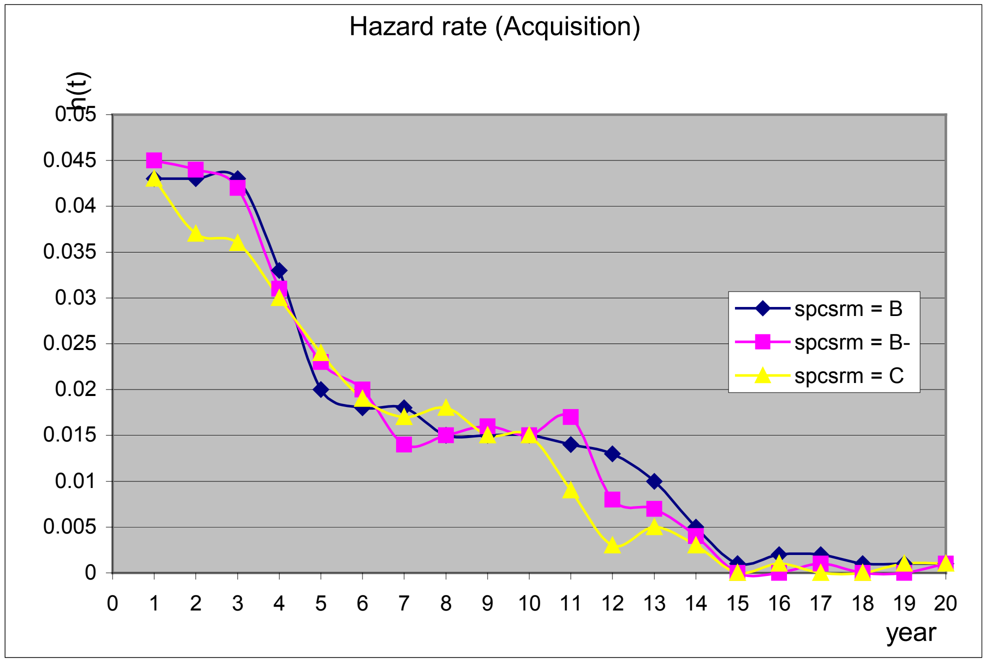

Figure 7: Hazard rate of acquisitions using SPCSRM

5.4.3 Conclusions

Three results are obtained from the survival analysis by using these two different financial indicators.

1) The average probability of acquisition using SPCSRM is twice as high as when ZSCORE is used as a selection criterion.
2) Using SPCSRM as an indicator of financial distress, the hazard rate reaches its maximum in a shorter number of years than when using ZSCORE.
3) As discussed above, the sample size is conditioned heavily on which indicator was chosen to be used to extract data for the financially distressed firms. There are 20047 firms extracted from the COMPUSTAT files. Among these firms, there are 15885 firms

with non-null values of ZSCORE, which comprises 79 percent of the total number of firms. However, there are 5766 firms with non-null values of SPCSRM extracted from the COMPUSTAT files. This proportion is only around 30 percent of the total number of firms. The details can be seen in tables 11 and 12. Thus, in the survival analysis, the number of firms extracted with a non-null SPCSRM is much lower than the number of firms extracted with a non-null ZSCORE. Therefore, I can conclude that this is possibly one major reason for the resulting higher hazard rate using SPCSRM although there is no clear reason for why there would be proportionally more acquisitions using the SPCSRM criterion.

Extraction Conditions	All firms from the COMPUSTAT files	All firms with non-null ZSCORE	All firms with non-null SPCSRM
Number of Firms	20047	15885	5766

Table 11: Number of firms extracted from the COMPUSTAT files

Financial indicators	ZSCORE		SPCSRM		
	<= 0.5	<= 3.1	Lower than B	Lower than B-	Lower than C
Number of extracted distress firms	5862	12987	4605	3602	2325

Table 12: Number of the distressed firms extracted using financial indicators

Based on the above analysis, it is concluded that because of the larger sample it provides due to less missing data, the ZSCORE should be used as the first screening mechanism in extracting financial distressed firms, and SPCSRM can be considered as an alternative screening mechanism.

5.5 Daily Excess Return

In the financial literature, the linear predictability and nonlinearity predictability of stock excess returns are heavily investigated. Qi (1999) examines the relationship between the excess returns and the predicting variables using a nonlinear neural-network model. The linear regression model is the most popular model found in studies of stock return prediction, and therefore applied in the excess returns estimation measure. The OLS estimation model, which is studied in chapter 3, is examined for the excess return prediction. The decision rules in the excess return calculation and excess return optimization are discussed in very detail as follows:

5.5.1 Decision Rules Used in the Excess Return Calculation

The firms in financial distress are selected without replacement from the population of all firms, which have their daily stock returns $R_{i,t}$ available on the CRSP files. A value weighted stock index return $R_{m,t}$ is obtainable from the CRSP files. The following decision rules are used when computing the daily excess return g_i for stock i using equation 3 on page 33:

1. Determine the event observation time period

Data from the CRSP files is split into two parts: testing data and validating data. The testing data covers the ten year period from the beginning of trading in 1980 to the end of trading in1989. The validating data covers the eight year period from 1990 to 1998.

Therefore, the event observation time period for testing of the acquisition model is initialized as:

- event observation beginning date denoted by eventBegDt : 1/Jan/1980
- event observation ending date denoted by eventEndDt : 31/Dec/1989

The event observation time period for validation of the acquisition model is initialized as:

- event observation beginning date denoted by eventBegDt : 1/Jan/1990
- event observation ending date denoted by eventEndDt: 31/Dec/1998

2. Determine a stock's beginning trading date (denoted by Begdt)

   Begdt is the first day that a stock enters any stock market. The value of Begdt is derived from the CRSP daily file.

3. Determine the date to start tracking a stock

   This date is called the tracking beginning date (denoted by track_begdt). All stocks trading between eventbegDt and eventEndDt are targets of interest to be investigated. The beginning of tracking date uses the later time of the event observation beginning date and a stock's beginning trading date. The formula to calculate track_begdt is:

$$track\_begdt = \max(begDt, eventBegDt)$$

4. Determine the date when a stock starts to become financially distressed (denoted by distressBegDt)

When a firm meets the criterion of being below a given value of the ZSCORE, the last day of the current fiscal year (@DAY(DATEYR)) from the COMPUSTAT files is assigned to the distressBegDt.

5. Determine the date when a stock is acquired (denoted by acquistionDt)

When a firm meets the cut-off probability of acquisition model (equation 5 on page 37), the date computed using the function @DAY(DATEYR) is assigned to acquistionDt.

6. Determine the announcement date (denoted by announceDt)

This date is required if and only if a firm is undergoing acquisition. In the testing period, the state of a firm is determined either by the data item called "research company reason for deletion" (abbreviated as "DLRSN") from the COMPUSTAT files, or by the data item called "delisting code" (abbreviated as "DLSTCD") from the CRSP delisting events file. When DLRSN takes a value of 1, or DLSTCD is assigned a code between 200 and 390 (code description can be seen in appendix 1), a firm is declared to be acquired. The announcement date then takes the value of the distribution declaration date (abbreviated as "DCLRDT") from the CRSP distribution events file.

The investment analysis reveals that the share price goes up dramatically during the days surrounding the acquisition announcement, thus showing that the acquisition event is associated with its announcement in the media. However, in the cross-sectional data analysis, there are some observations which are not consistent with such announcement effects. The details are listed as below:

1) Not all acquisitions have their announcement dates recorded in the CRSP distribution event files. Around 36% of acquisition firms have announcement dates recorded. See table 13.

Data sources for acquired firms	COMPUSTAT		CRSP files	
Condition for an acquisition	DLRSN = 1		DLSTCD = 200 to 390	
With announcement date	Yes	No	Yes	No
Number of acquisition firms	1417	2513	2045	3488
Percentage of firms with announcement days	36.1	63.9	37.0	63.0

Table 13: Acquisition firms with announcement date

Based on these data, the decision rules to deal with in this case are defined as follows:

- Use DLSTCD from the CRSP files as a control variable rather than DLRSN to indicate the acquisition event. There are two reasons for making this rule. The first is that the number of acquisitions found with announcement dates by using DLSTCD from the CRSP files is almost double the number of acquisition firms found by using DLRSN from the COMPUSTAT files. The second reason is that firms recorded in the COMPUSTAT files may not have their market data information in the CRSP files; however, firms residing in the CRSP files have their corresponding accounting data information in the COMPUSTAT files. The latter condition is due to the fact that the linking file does not have a match between all COMPUSTAT identification numbers and the CRSP identification numbers.

- Treat a firm with a null announcement date as a survival. From the above table 13, there are 3488 acquisition firms indicated by DLSTCD with null announcement dates from the CRSP files. Among these firms, there are 961 of them which are found in the survival category in the COMPUSTAT files due to a null value found in their DLRSN code. Furthermore, there are only 18 firms that went bankrupt as indicated by their DLRSN value of 2. Therefore, it is reasonable to assume that the firms without announcement dates can be treated as survival firms.

2) An acquisition may have one or more announcement dates. Since the prediction model is used to predict the likelihood of takeovers, the first announcement date after the onset of financial distress is more meaningful for this research, and is used from here on.

7. Determine the distressYears

This research is interested in tracking firms over a short time period, for example for three or four years after financial distress occurs. This short time period is denoted by the variable watchYear in the Java program. Thus the distress end date will be the distress beginning date (distressBegDt) plus watchYear.

8. Determine the end date when a stock is sold (denoted by EndDt)

It is established that a firm's delisting date is extracted from the CRSP delisting events file due to the inaccuracy of DLRSN from the COMPUSTAT files. Therefore, the end date used is the earliest of the following three dates: event observation ending date, distress observation date, and delisting date. The formula for calculating EndDt is:

EndDt = Min (eventEnddt, distress observation date, dlstdt)

9. Determine the value of a dummy variable D_t in the OLS estimation model

This dummy variable reflects an investment strategy. If it takes a value of 1, it implies that an investor holds a stock; however, if it takes a value of 0, a stock is not in the investor's portfolio. There are three scenarios that should be taken into consideration.

I. Scenario 1 is associated with acquisition events. There are two cases. One case is when stocks being acquired with announcement dates, D_t is declared as follows:

D_t = 0 between track_begdt and distressbegdt (excluding the day of distress onset)

D_t = 1 between distressbegdt and announceDt

D_t = 0 between announceDt (not including announcement day) and EndDt

The other case is when stocks being acquired without announcement dates. The excess returns for these stocks are computed using the same method in scenario 3.

II. Scenario 2 is associated with failure events. DLSTCD from the crsp delisting event file is selected as the control variable to indicate the failure events. In this research, the values of the delisting code between 400 and 591 (code description can be seen in appendix 1) classify events into the liquidation and dropped categories. If a stock is delisted on day t and the firm goes bankrupt, liquidated or for other reasons is worthless, then sell the stock on delisting day (day t). The following business rules are used to calculate a firm's stock return on the delisting day:

1) Since the delisting return (denoted by "DLRET") deals with the bankruptcy and liquidation events or for other reasons are declared worthless in the CRSP delisting event file, the value of DLRET already indicates a 100% loss as per descriptions quoted from the CRSP delisting event file:

   - "If there is evidence that no distribution will ever be paid to shareholders, then the stock is considered worthless. The delisting return is set to –1 (i.e. a 100% loss).
   - If there is evidence that the stock has been declared worthless, then the delisting return is set to –1 (i.e. a 100% loss)."

   Therefore, a firm's stock return on the delisting day uses the formula:

   daily stock return ("RET") + delisting return ("DLRET")

2) From the data retrieved from the CRSP delisting event file, it is observed that there are 84 firms with a null delisting return when the delisting code falls in either of the liquidation or dropped categories. Because there are no distributions paid to shareholders, those stocks are treated as worthless. The delisting return is subjectively assigned to a value of –1 (i.e. a 100% loss.)

3) In the data analysis, there are a large number of negative values appearing in the results. These numbers are not delisting returns, but are actual codes used to describe the reason for the missing delisting returns. The descriptions of the missing delisting return codes are shown in table 14.

Code	Reason For Missing Return
-55	CRSP has no sources to establish a value after delisting or is unable to assign a value to one or more known distributions after delisting
-66	more than 10 trading periods between a security's last price and its first available price on a new exchange.
-88	security is still active.
-99	security trades on a new exchange after delisting, but CRSP currently has no sources to gather price information.

Table 14: Missing delisting return codes

When a stock with a missing delisting return code is found, the following rules are used for the delisting return:

- delisting return = -1 when missing code is –55.
- delisting return = 0 when missing code is –66, -88 or -99.

4) D_t takes a value of 0 from a stock's tracking day to the trading day previous to the date of distress onset, and takes a value of 1 from the onset of distress day untill the delisting day. It is displayed as:

   D_t = 0 between track_begdt and distressbegdt (excluding the day of distress onset)

   D_t = 1 between distressbegdt and EndDt

III. Scenario 3 is associated with survival events. D_t takes a value of 0 from a stock's tracking day to the trading day previous to the day of the distress onset, and takes a value of 1 from the onset of distress years until the end of tracking year. The formula for the dummy variable is the same as described in item 4) of case 2 above – failure events.

10. Determine the value of a stock daily stock return (denoted by "RET")

When a large negative value occurs, RET is defined as the holding period total return in the CRSP daily file. RET is "the return for a sale on the given day. It is based on a purchase on the most recent time previous to this day when the security had a valid price. Usually, this time is the previous calendar period". A series of special return codes that specify the reason a return is missing is shown in table 15.

Code	Reason For Missing Return
-66	valid current price but no valid previous price. Either first price, unknown exchange between current and previous price, or more than 10 periods between time *t* and the time of the preceding price *t*.
-77	not trading on the current exchange at time *t*
-88	outside the range of the security's price range
-99	missing return due to missing price at time *t*; usually due to suspension in trading or trading on unknown exchange

Table 15: Missing return codes

When the trading day has the security's daily return indicated by one of the reason codes in table 15, or null, then that particular trading day will not be counted in the trading period. The trading time period will thus be compressed by excluding the days when RET is actually a reason code or null.

11. Determine the stock holding days (denoted by holdingDays)

Holding days are calculated as the number of days a stock is held in the portfolio. In other words, holding days is the number of days when the dummy variable takes a value of 1.

5.5.2 Daily Excess Return Optimization

The daily excess return calculation for stock i applies an OLS estimation model to control risk and maximize the return on investment. The formula of the objective function to compute excess return for stock i is equation 3 on page 33.

In this OLS model, the purpose is to minimize error and optimize a stock's excess return. There are two scenarios to be considered. The first scenario is based on a dummy variable $D_{i,t}$ having the mixed values of 0 and 1. In the second scenario, the dummy variable $D_{i,t}$ only takes a value of 1 from the beginning of tracking date to the selling date.

Scenario 1: multi-regression model

$$R_{i,t} = \partial_i + \beta_i * R_{m,t} + g_i * D_{i,t} + \varepsilon_{i,t} \qquad (3)$$

The above formula for each stock can be written in matrix form as:

$$y_i = X_i B + \varepsilon_i$$

where:

$$y_i = \begin{bmatrix} R_{i,1} \\ R_{i,2} \\ \vdots \\ R_{i,t} \end{bmatrix} \quad X_i = \begin{bmatrix} 1 & R_{m1} & D_{i,1} \\ 1 & R_{m2} & D_{i,2} \\ \vdots & \vdots & \vdots \\ 1 & R_{mt} & D_{i,t} \end{bmatrix} \quad B = \begin{bmatrix} \partial_i \\ \beta_i \\ g_i \end{bmatrix} \quad \varepsilon_i = \begin{bmatrix} \varepsilon_{i,1,} \\ \varepsilon_{i,2} \\ \vdots \\ \varepsilon_{i,3} \end{bmatrix}$$

The least square estimator b for the coefficients in *B* satisfies the following:

$$\tfrac{\partial}{\partial b}\left[(y - Xb)'(y - Xb)\right] = 0$$

As a result:

$$b = (X'X)^{-1} X' \text{ y}$$

Therefore, the excess return g_i for the stock i is the third value in the matrix $b_{3,1}$

Scenario2: Simple linear regression model

When $D_{i,t}$ = 1 for all values of t, abnormal return formula is written:

$$R_{i,t} = g_i + \beta_i * R_{m,t} + \varepsilon_{i,t} \tag{6}$$

It is simplified using matrix function as:

$$y_i = X_i B + \varepsilon_i$$

so:

$$y_i = \begin{bmatrix} R_{i,1} \\ R_{i,2} \\ \vdots \\ R_{i,t} \end{bmatrix} \quad X_i = \begin{bmatrix} 1 & R_{m,11} \\ 1 & R_{m,2} \\ \vdots & \vdots \\ 1 & R_{m,3} \end{bmatrix} \quad B = \begin{bmatrix} g_i \\ \beta_i \end{bmatrix} \quad \varepsilon_i = \begin{bmatrix} \varepsilon_{i,1,} \\ \varepsilon_{i,2} \\ \vdots \\ \varepsilon_{i,3} \end{bmatrix}$$

The least square estimates $\hat{g}_i, \hat{\beta}_i$ are:

$$\begin{bmatrix} g_i \\ \beta_i \end{bmatrix} = \begin{bmatrix} n & \sum x_{i,t} \\ \sum x_{i,t} & \sum x^2{}_{i,t} \end{bmatrix}^{-1} \begin{bmatrix} \sum y_{i,t} \\ \sum x_{i,t} y_{i,t} \end{bmatrix}$$

where n is the number of trading days for stock i and g_i is the excess return.

5.6 Conclusions

Given the above decision rules used in the excess return calculation, it can be seen that there are two criteria for selecting stocks into a portfolio. The ZSCORE as a measure of bankruptcy is used as the first criterion to choose the financially distressed firms. When the ZSCORE for a stock is lower than 0.5, the stock starts being tracked as a financially troubled firm. The dummy variable $D_{i,t}$ is assigned a value of 0. When the second criterion for the cut-off probability is met, the stock is brought into the portfolio. The dummy variable $D_{i,t}$ then takes a value of 1.

In my research, I track stocks for 3 years after their onset of financial distress. This implies that if there is no delisting date occurring within 3 years, the stocks are all sold at the end of the distress years.

The stock holding period is computed as the time from when the stock is bought until the stock is sold. The length of the holding period is shorter than the distress years because it starts being recorded when the probability of acquisition meets the cut-off value and is also compressed by excluding the days when a stock's daily return is actually a reason code or null.

Chapter 6

Simulation Results

6.1 Introduction

Simulation analysis is a powerful problem-solving technique. Hoover and Perry (1989) define simulation as follows:

> "The process of designing a mathematical or logical model of a real system and then conducting computer-based experiments with the model to describe, explain, and predict the behaviour of the real system."

Simulation models can describe very complex systems. They can be used to predict systems which are not yet in existence or experiment with existing systems without actually altering the system. However, simulation models have their deficiencies. There are no closed form solutions to simulation models; each change of input variables requires a separate solution or set of runs. Therefore, complex simulation models are costly and time consuming to build and run.

Generally speaking, simulation can be applied when either of the following conditions is met. The first is when the assumptions required for the analytical model are not sufficiently well satisfied by the real system. The other is when there is great difficulty in forming the mathematical formula for the analytical model. Simulation models, to some degree, reflect the appropriate amount of realism and accuracy in the system description and provide the optimum solutions.

In simulation models, the relationships among the elements of the system are expressed using an algorithm encoded in a computer program. Unlike analytical models, simulation models do not provide direct answers but reveal the system's properties as the computer executes the algorithm. The simulation results must be analyzed before conclusions can be made about the system's properties.

6.2 Purposes of Simulation

In the stock market, investment choices are made in an attempt to balance risk and return. The main challenge for investors is to determine the best portfolio on a given investment horizon, which may be short, medium, or long term. This horizon is based on quantifiable expectations of risk and returns.

The portfolio used in my research attempts to 1) select as many acquired financially distressed firms as possible in a given trading period, while 2) avoiding choosing firms which have a high probability of bankruptcy. The reasoning is that acquisitions can bring huge profits to an investor, but bankruptcies can make investors incur great losses.

To maximize the value of the portfolio, three parameters are simulated: the length of a stock's holding days, the ZSCORE and the probability of acquisition (abbreviated as "P(A)"). The length of a stocks holding days is simulated from 1 year to 3 years by incrementing in steps of 1. The ZSCORE ranges between 0.5[5] to 3.1 (cut-off ZSCORE value), and the probability of acquisition varies from 0.5 to 1. Both the ZSCORE and the probability of

[5] a ZSCORE of less than 0.5 is a score low enough to guarantee virtually no false positives (Altman, Haldeman and Narayanan 1977, Altman 1984).

acquisition are simulated by incrementing in steps of 0.1. The simulation results will address the following questions:

1) Can the acquisition model predict takeover's behaviour?

2) Can a particular choice of the ZSCORE increase the return for investors?

3) Is the null hypothesis for daily excess return = 0 accepted or rejected?

6.3 Estimation of cut-off probability of acquisition

To test the predictive ability of the acquisition model the optimal cut-off probability of acquisition has to be estimated. Two methods are applied in simulating the probability of acquisition to derive the cut-off probability of acquisition. The first is to compare the predicted versus the actual corporate event. The other method is to compute abnormal return g_i for each stock and to compute average daily return across all stocks. Results derived from these two methods will be used to estimate the cut-off probability and validate the accuracy of the acquisition model.

6.3.1 Comparing the Predicted versus the Actual Corporate Events

The purpose of this section is to derive a cut-off probability of acquisition by examining the relationship between predicted and actual corporate events for various cut-off values of the probability of acquisition. I want to find a cut-off probability of acquisition having the most firms, which are predicted to be acquired, being actually acquired within the given trading time, and at the same time, having the fewest firms, which are predicted to be acquired, actually go bankrupt or still survive.

A ZSCORE of less than 0.5 is chosen as the default probability of distress for selecting the financially distressed firms in an estimation sample since a ZSCORE of less than 0.5 is a score low enough to guarantee virtually no false positives (Altman, Haldeman and Narayanan 1977, Altman 1984).

For all financially distressed firms I vary the estimated cut-off probability from 0.5 to 1.0 by incrementing it in steps of 0.1. When the probability of acquisition for a stock meets or exceeds the value of the estimated cut-off probability, the stock is selected into the portfolio.

The value of DLSTCD which describes delisting reason is used from the CRSP delisting event file to indicate if the predicted targets are actually targets. When DLSTCD takes a value between 200 and 390 (code descriptions can be seen in appendix A, a firm is considered to be in either the acquisition or merge category. When DLSTCD has a value from 400 to 591 a firm is categorized as a failure. When DLSTCD has a value which is not in the above two categories a firm is put into the survival category.

The distribution of estimated acquisition probability for targets and non-targets in the estimation sample is described in figure 8.

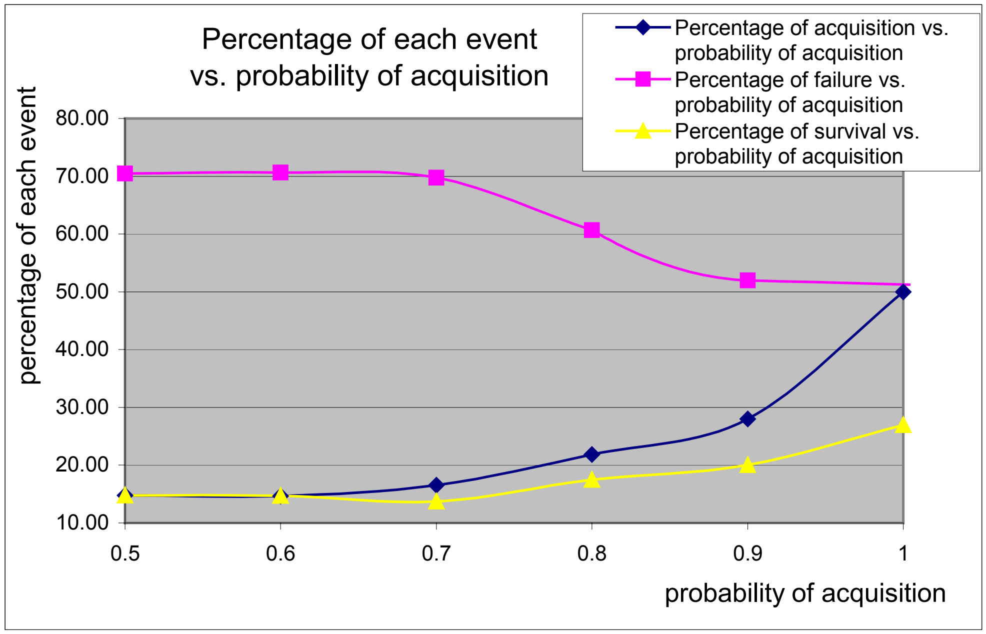

Figure 8: Distribution of estimated P(A) for targets and non-targets

There are three conclusions that can be derived from the above analysis:

1) The acquisition model lacks accuracy in predicting actual takeovers.

From the above curve it is observed that when the estimated cut-off probability increases the percentage of actual acquired targets does not increase very much. Furthermore, when the cut-off probability takes the maximum value of 1.0 the percentage of actual acquisition reaches only 50%. It is concluded that the acquisition model lacks accuracy.

2) There is a positive relationship between the model's prediction and outcomes for higher predicted values.

Although, the accuracy of acquisition prediction is not high, the acquisition model does forecast the trend that the percentage of actual acquired targets increases when the probability of acquisition increases, and also the trend that the percentage of failure decreases when the probability of acquisition increases. Therefore, to some degree, this model has a certain amount of applicability in predicting different event categories.

3) The best cut-off probability of acquisition may be a value of 0.9.

Although the curve of survival is very flat, the other two curves of acquisition and failure events reveal some things. One interesting outcome is that when the estimated cut-off probability takes a value of 0.8, the acquisition event starts increasing and the failure event begins to decrease. The second important finding is that when the probability of acquisition takes a value of 0.9 or above these two curves have very steep slopes, indicating that the value of 0.9 may be chosen as the cut-off probability of acquisition if necessary.

6.3.2 Computing Abnormal Returns

Two types of portfolio returns that are computed:

- Average daily portfolio return[6] is defined as the sum of individual stock daily excess return g_i' which is the abnormal returns g_i divided by stock i's holding days, averaged over the total number of stocks held in a portfolio.
- Average holding-period portfolio return is defined as the sum of individual stock's abnormal returns g_i divided by the total number of stocks held in a portfolio.

Using this method I intend to find an optimal cut-off probability where both types of portfolio return get maximized. The two parameters are simulated when the length of the stock holding period is set to 3 years. The ZSCORE and

[6]A stock daily return doesn't exclude the case when the stock's holding day is 0.

P(A) are simulated from 0.5 to 1.0 by incrementing in steps of 0.1. The data from the simulation results is shown to be quite accurate. Data validation and methods limitation can be see in appendix D.

The following observations are found from the simulation results:

1) Table 16 describes the relationship between the daily portfolio return, the ZSCORE and P(A). The weighted average return is calculated as each cell value of return times its number of observations and divided by the total number of observations. For each value of the ZSCORE, the weighted average daily return receives a negative value or is close to zero. Moreover, the values of weighted average daily return are very similar for the different values of the ZSCORE. It means that there is little impact of the ZSCORE on daily return. On the other hand, for each value of P(A), when the estimated probability is above 0.9 the weighted average return starts increasing. For example, when the estimated probability varies between 0.9 and 1.0, the weighted average daily return increases from 0.107% to 0.589%.

ZSCORE <= / Daily return / P(A) >=	0.5	0.6	0.7	0.8	0.9	1.0	weighted average daily return
0.5	-0.068%	-0.037%	-0.048%	-0.072%	-0.046%	-0.033%	-0.050%
0.6	0.012%	0.042%	0.024%	-0.008%	0.011%	0.021%	0.017%
0.7	-0.224%	-0.043%	-0.062%	-0.056%	-0.063%	-0.035%	-0.077%
0.8	-0.001%	0.024%	0.041%	-0.008%	0.001%	-0.249%	-0.044%
0.9	0.294%	0.283%	0.249%	0.155%	0.151%	-0.261%	0.107%
1	0.741%	0.832%	0.661%	0.576%	0.497%	0.465%	0.589%

weighted average daily return	-0.054%	0.004%	-0.010%	-0.033%	-0.017%	-0.022%

Table 16: The relationship between daily return, ZSCORE and P(A)

2) The relationship between the holding-period portfolio return and the estimated cut-off probability for each ZSCORE is listed in table 17. The portfolio has a positive holding period return. When P(A) is 0.8 the portfolio receives the minimum value (0.081%) of weighted average holding period return, but when P(A) = 1.0 the portfolio reaches its maximum value (0.501%) of weighted average holding-period return. For the different values of the ZSCORE, the weighted average holding period return is very close to 0.4%. It implies that the ZSCORE doesn't have a significant impact on the weighted average holding period return.

ZSCORE <= holding period return / P(A) >=	0.5	0.6	0.7	0.8	0.9	1.0	weighted average holding-period return
0.5	0.431%	0.451%	0.417%	0.361%	0.391%	0.386%	0.404%
0.6	0.502%	0.517%	0.477%	0.429%	0.450%	0.438%	0.467%
0.7	0.222%	0.421%	0.372%	0.333%	0.348%	0.358%	0.344%
0.8	0.186%	0.208%	0.199%	0.093%	0.094%	-0.178%	0.081%
0.9	0.378%	0.354%	0.306%	0.192%	0.178%	-0.259%	0.147%
1	0.815%	0.693%	0.542%	0.452%	0.406%	0.396%	0.501%

weighted average holding-period return	0.391%	0.462%	0.422%	0.369%	0.390%	0.364%

Table 17: The relationship between holding-period return, ZSCORE and P(A)

To summarize, there are three conclusions that can be derived from the analysis of the above observations.

First, there seems to be no cut-off probability of acquisition which can be derived using this method because weighted average return varies when P(A) increases. The optimal cut-off probability is used to maximize both daily portfolio return and holding-period portfolio return. In the above tables 16 and 17, before P(A) reaches its maximum value of 1.0 the weighted average daily return receives its maximum value when P(A) = 0.9, but the weighted average holding-period return achieves its maximum value when P(A) = 0.6. Both types of return reach their maximum value at different cut-off values for the probability of acquisition. Therefore, it is concluded that there is no optimal cut-off probability found by examining the abnormal return method.

Second, it is observed that both the weighted average daily return and weighted average holding-period return start increasing when P(A) has a value greater than 0.8, This may imply that investing in distressed stocks may be profitable irrespective of the value of P(A).

Lastly, when the ZSCORE varies, there is little change in both the weighted average daily return and the weighted average holding-period return. It is concluded that the choice of ZSCORE does not have a significant influence on portfolio return.

6.4 Null Hypothesis Testing for Mean of Daily Abnormal Return

From the regression analysis I want to examine the null hypothesis that the mean of daily abnormal return variable $g_i' = 0$. A t-test is used to analyze whether the null hypothesis is accepted or rejected. I choose a confidence level of 99%. The estimation sample is extracted by using ZSCORE <= 0.5 and having P(A) >= the estimated probability which varies between 0.5 and 1.0 The following formulas are used in the analysis.

- The sample mean is $\overline{g} = \frac{\sum_{i=1}^{n} \mu(\widehat{g}')_i}{n}$ where there are n stocks held in a sample.
- The sample deviation is $s_{sample} = \frac{\sum_{i=1}^{n} (\widehat{g}_i' - \overline{g})^2}{n-1}$.
- The Null hypothesis for the mean of daily excess return is H_0: $\overline{g} = 0$.

  If $\left| \frac{\overline{g}}{S_{sample}/\sqrt{n}} \right| \geq t_{(n-1,\frac{\partial}{2})}$, then the null hypothesis is rejected, so the value of $\overline{g}$ is significantly different from zero.

The daily abnormal return g_i' for each stock is the holding period abnormal return g_i divided by the holding days for stock i. Table 18 lists the results of t-tests [7].

[7] Negative t-values are displayed in table 18 to illustrate when $\overline{g}$ <0.

Estimation probability of acquisition (P(A))	Number of stocks held (n)	Sample mean ($\bar{g}$)	Sample standard deviation (S_{sample})	t-value
0.5	1573	-0.068%	0.006	4.323
0.6	1527	0.012%	0.008	0.618
0.7	786	-0.224%	0.004	17.404
0.8	116	-0.001%	0.002	0.079
0.9	60	0.294%	0.002	10.163
1.0	19	0.741%	0.005	6.104

Table 18: t-statistics using the OLS estimation model

From the above analysis, I conclude that whether $\bar{g}$ = 0 is rejected or accepted depends on P(A). When P(A) takes values of 0.5, 0.7 , 0.9 and 1.0, the null hypothesis for $\bar{g}$ is rejected. The value of $\bar{g}$ is then significantly different from zero. However, when P(A) takes values of 0.6 and 0.8, the null hypothesis is accepted. The value of $\bar{g}$ is close to zero. Furthermore, when significant, $\bar{g}$ is negative in two instances and positive in the other two instances. These tests show that the acquisition model lacks accuracy in predicting abnormal returns.

6.5 Benchmark results on abnormal return

Although the acquisition model lacks forecasting accuracy, it may be worth investing in distressed firms irrespective of the probability of acquisition. When the ZSCORE is less than 0.5, the average daily return for all firms is 0.126% and the average holding period return for all firms is 0.422% with the average holding days being 273. See table 19. Since 273 days is greater than the 250 trading days in one year, the annual return for all firms can be assumed to be around 0.4%. In this sample, the average daily return for acquired firms is 0.371%. The annual return for acquired firms can also be assumed to be around

0.5% since the average holding period return is 0.599% with the holding period being 300 days. See table 20.

Probability of acquisition P(A)	Number of stocks held	Average daily portfolio return	Average holding-period portfolio return	Average holding period (days)
0.5	1573	-0.068%	0.431%	257
0.6	1527	0.012%	0.502%	257
0.7	786	-0.224%	0.222%	252
0.8	116	-0.001%	0.186%	285
0.9	60	0.294%	0.378%	296
1.0	19	0.741%	0.815%	289
Mean of return		0.126%	0.422%	273

Table 19: Statistics on total number of stocks held in a portfolio

I also empirically studied the performance of other approaches for developing a return benchmark. Palepu, in his acquisition prediction test, reports the average daily cumulative excess return for the 625 predicted targets over the 250 days is –1.62%. The average cumulative return for the predicted targets is small and hovers around zero throughout the holding period. In contrast, the average cumulative excess return for the subgroup of 24 predicted targets which actually became targets during the holding period is large. The 250-day cumulative excess return for the group actually being acquired is 20.98%.

Compared to the Palepu's prediction result, the annual excess return computed using the abnormal return method is positive and higher than the annual return derived from Palepu's test. However, annual excess return for the acquired firms which I computed is only 0.5%, much lower than the annual return of 20.98% computed from Palepu's test. The results from these two different tests are very impressive and show that the annual excess return for all firms derived by the abnormal return method is in acceptable range.

6.6 Statistics on Abnormal Return for the Corporate Events

Since average excess return $\overline{g}_i$ is averaged over three different corporate events: acquisition, failure and survival, it is interesting to examine the number of stocks going into each corporate event in the portfolio, and the mean of their daily portfolio return for each event.

The data sample is obtained using the distributions of acquisition probability and the ZSCORE less than 0.5. The statistic results are listed in table 20, 21 and 22.

From the results, I find that when P(A) increases the size of the sample decreases and the number of stocks in each corporate event decreases as well. When P(A) >= 0.5, the number of stocks actually being acquired is 245 out of 1573 (15.58%) distressed firms are acquired. The number of failed stocks makes up a large proportion of the predicted sample. There are 1010 out of 1573 (64%) going bankrupt or being liquidated or deleted for other delisting reasons. There are 318 out of 1573 (20.22%) firms being survived. These results show that a large number of distressed firms failed and the number of distressed firms actually acquired are close to the number of firms surviving.

The tables below also show the daily portfolio return for each corporate event. The average daily portfolio return for failed stocks is the lowest of all three groups around 0.019%. The average daily portfolio return for survival stocks is the highest of all three groups for the value of 0.484%. I also find that the average daily portfolio return for acquired firms is much higher than the average daily portfolio return for failed firms. This is consistent with the view that investing in stocks being acquired gain more profit than investing in stocks going bankrupt or liquidated.

From the average holding period, a stock that goes bankrupt or liquidated has the shortest holding days (214). A stock being acquired has the longer holding days (300) than a failed stock. A stock that survives has the longest trading holding days (321). The results show that the holding period is shorter for acquisitions and failure is obvious since these events must occur within the 3-year limit. Apparently bankruptcies and other failures occur earlier after the onset of distress than acquisition. This is consistent with the Åstebro and Winter's finding.

Probability of acquisition P(A)	Number of stocks being acquired	Average daily portfolio return	Average holding-period portfolio return	Average holding period (days)
0.5	245	0.179%	0.478%	308
0.6	234	0.101%	0.409%	313
0.7	144	0.120%	0.507%	305
0.8	28	0.344%	0.528%	307
0.9	17	0.566%	0.713%	306
1.0	10	0.914%	0.956%	260
Mean of return		0.371%	0.599%	300

Table 20: Statistics on number of stocks being acquired

Probability of acquisition P(A)	Number of failed stocks	Average daily portfolio return	Average holding-period portfolio return	Average holding period (days)
0.5	1010	-0.349%	0.258%	222
0.6	984	-0.222%	0.365%	221
0.7	499	-0.571%	-0.031%	214
0.8	59	-0.400%	-0.152%	248
0.9	27	-0.050%	0.020%	254
1.0	3	1.707%	1.825%	125
Mean of return		0.019%	0.381%	214

Table 21: Statistics on number of failed stocks

Probability of acquisition P(A)	Number of stocks being survived	Average daily portfolio return	Average holding-period portfolio return	Average holding period (days)
0.5	318	0.634%	0.947%	331
0.6	309	0.689%	1.006%	328
0.7	143	0.640%	0.817%	327
0.8	29	0.476%	0.544%	338
0.9	16	0.586%	0.627%	357
1.0	6	-0.031%	0.077%	418
Mean of return		0.499%	0.670%	350

Table 22: Statistics on number of stocks that being survived

In tables 21 and 22, it is observed that when P(A) = 0.8, 0.9 or 1.0, the average daily portfolio return is very close to the average holding-period portfolio return. This is due to the fact that the stock daily return is a function of the stock holding days. In this case, there are more stocks having large returns over their short holding periods, while stocks with long holding periods have smaller returns. The return for those stocks having long holding periods does not have a significant effect on the average portfolio return. Thus, the result is that the average daily portfolio return is very close to the average holding period portfolio return. Table 23 illustrates the distribution of both average daily return and average holding period return for the surviving firms extracted when P(A) >=0.7 and ZSCORE <= 0.5 in the different ranges of holding days

Range (holding days)	Count	Average daily return	Average holding period return
0–9	34	2.685%	2.685%
10-49	3	0.034%	1.013%
50-249	25	0.005%	0.561%
250-490	28	0.000%	0.145%
500-750	53	0.000%	0.084%

Table 23: The distribution of return when P(A) = 0.7 and ZSCORE <= 0.5

6.7 Conclusions

From the above analysis, I can answer the questions which are posed at the beginning of the chapter. First, the acquisition model lacks accuracy in predicting actual acquisitions. There is no optimal cut-off probability of acquisition derived from either comparing the predicted versus the actual corporate events or by computing abnormal return. Second, a particular choice of the ZSCORE between 0.5 and 1.0 has no impact on both types of portfolio return: daily portfolio return and holding-period portfolio return. Lastly, since excess returns are a random function of the cut-off probability the hypothesis that the average daily excess return $\overline{g}$ = 0 is randomly rejected or accepted.

The simulation results also show that the average daily return $\overline{g}$ across all values of P(A) is positive and the implied annual return is around 0.4% since the average holding period return is 0.422% for 273 days greater than 250 trading days in one year. It implies that it is worthwhile to invest in financially distressed firms irrespective of the probability of acquisition. If the acquisition model gets updated, the accuracy of likelihood of acquisition may be improved. The more accurate the acquisition model is, the more profits it may bring to an investor. Based on these two motives I am going to design the prototype of a buy-sell trading system. The detailed system design is described in chapter 7.

Chapter 7

A Buy-Sell Trading System

7.1 Introduction

The ability to pick takeover targets successfully in advance of the announcement of a bid could form the basis for a successful investment strategy. This is the one incentive to develop a buy-sell trading system. The model that Åstebro and Winter (2000) developed using a multivariate methodology will be used as a fundamental stock entry rule in the buy-sell system. There are two motives for developing this system. First, although the acquisition model was shown to be approximately unrelated to excess return, there might be other stock entry rules that show greater promise in the future. Second, this system can easily test the selected stock trading rules in order to optimize the investor's portfolio return.

This chapter discusses how use cases, data flow diagrams (DFDs) and trading rules can be used to develop a prototype for a buy-sell system.

7.2 Creating Use Cases

There are many ways to develop DFDs. Dennis and Wixom (2000) strongly recommend that use cases can be used as the first step in creating DFDs. A use case is a set of activities that the system performs to produce some results. Each use case describes how the system reacts to an event that occurs to trigger the system. There are five use cases that describe the whole system. They are: screen stocks, buy stocks, sell stocks, update stock portfolio and compute stock portfolio return.

For each use case, its trigger and the major inputs and outputs are identified. The first use case: screen stocks, is triggered by the event of an investor wanting to invest in stocks. The major inputs are a firm's accounting data from COMPUSTAT files. The major outputs are the cut-off probability of acquisition and the size of the stock portfolio. The matched firms are stored in a stock portfolio file.

The second use case: buy stocks, is triggered when the matched stocks are selected. The major inputs are market data from the CRSP files. The buying constraints are the limitation of the purchasing volume and a buying signal based on moving averages. The major outputs are the volume of each stock and the purchasing date. These outputs are stored in the stock portfolio file.

The third use case: sell stocks, is triggered by any exit signal from the selected trading exit strategies. The major inputs are trading exit strategies such as financial trade stops, time stop, probability of bankruptcy, moving average and parabolic rules. The major outputs are the excess return of each stock sold and the selling date. These outputs are stored in the stock portfolio file.

The fourth use case: compute portfolio return, is triggered when the trading period is over. The major inputs are the return on each existing stock, and the trading holding days of each stock in the portfolio. The major outputs are the average daily portfolio return and the average holding-period portfolio return. The details of these use cases can be viewed in appendix B.

7.3 Processing Models

A process model is a formal way of representing how a business system operates. It illustrates the processes or activities that are performed and how data moves between them. A process model can be used to document this proposed system. There are many different process-modeling techniques in use today (Dennis and Wixom, 2000). A data flow diagram is a technique that diagrams the business processes and the data that passes amongst them. The set of DFDs simply integrates the individual use case reports. The first DFD provides a summary of the overall system, with additional DFDs providing increasingly more detail about each part of the overall business process. The main result of using DFDs is the decomposition of the business process into a series of DFDs.

The context diagram has two external entities which are the investors and the stock market. The buy-sell trading system is the internal entity. Investors provide investment information such as buy and sell decisions to this trading system. The buy-sell system selects the stocks from the stock market if the buy signal occurs, and sells the stocks if the sell signal occurs. The sold stocks return to the stock market, and the excess stock return generated from this trading system is returned to investors.

The level 0 diagram integrates the DFD fragments. Each use case is transferred into one process. The level 0 diagram illustrates the overall picture of the processes and their inter relationship very intuitively. Besides the context diagram and the level 0 diagrams, the level 1 diagrams specify each process in further detail. The processing models can be viewed in appendix C.

7.4 Stock Entry and Exit Rules

Since the aforementioned model of probability of acquisition predicts the ability to pick stocks with some accuracy, it can be used as an investment strategy. In the buy-sell system, the probability of acquisition is used as the stock entry rule for the fundamental analysis[8]. A moving average indicator is used as a stock entry rule for the technical analysis. The moving average indicator is a lagging indicator, meaning that it identifies a trend or trend reversal after it has begun. It works equally well in trending or non-trending markets.

The decision rule for stock entry is to select the stocks that meet the cut-off probability of acquisition and the buy signal from the moving average indicator.

The decision rule for stock exit can apply the following trade exit rules: financial trade stops, time stop exit rule, probability of the bankruptcy indicator and parabolic indicator.

1) Financial Trade Stops

Financial stops are based on monetary (profit/loss) criteria. An average directional index is used as a measure of the trend of a stock. When the price of the security has a down trend, a maximum loss stop is applied. When the price of the security has an up trend, a profit trailing stop is used instead. These two types of stops are implemented as follows:

- A maximum loss stop: is trigged when a trade is losing more money than a specified amount. The stop loss price is displayed in the buy-sell system for each trade. The trade is exited at the close price

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[8] This rule may be changed or dropped in the future, other rules may be added.

when the stop loss price is less than the high price and the close price.

- A profit trailing stop: is initially set according to information based on the close price on that day. Trailing stops can be moved up for long trades or down for short trades. The profit trailing stop price is evaluated using the following formula:

proftTrailingStop = closePrice – maxProfitPcnt * (closePrice – entryPrice)

where:

entryPrice: the price when a new trade is entered.

maxProfitPcnt: a percentage of the maximum profit level. For example, 10% of the maximum profit.

There are two cases that should be considered:

Case 1: if the close price is lower than the profit trailing stop price, the stop executes at the close price or the open price of the next day.

Case 2: if the close price is higher than the profit trailing stop price, the stop is not hit. Instead, the new profit trailing stop price is adjusted using the new close price according to the above formula.

2**) Time stop trading rule**

There are two reasons for using a time stop trading rule. First, the aim of an investment is to earn money within a given period of time if nothing happens the stock should be sold. Generally speaking, an active investor would set time limits on purchasing stock. Second, the number of the distress years after the onset of financial distress is limited. The maximum hazard of acquisition for the financially distressed firms is reached around 3 or 4 years after entering distress. Thus at the end of the financial distress years, the distressed firms have either survived, gone bankrupt or have been acquired. In this trading system, when the time stop is reached, all securities held in the stock portfolio should be sold. Their excess returns are calculated using the OLS estimation model.

3) Probability of bankruptcy indicator

If the updated probability of bankruptcy indicator is greater than the tolerance value ϕ, the trade is exited. The stock return is calculated at the price when the stock is sold. The probability of bankruptcy can be computed from Åstebro and Winter's multi-nomial logit model.

4) Moving average indicator

This is a lagging indicator, meaning that it identifies a trend or trend reversal after it begins. It works equally well in trending or non-trending markets. The trade is exited when the 5 day moving average is below the 10 day moving average.

5) Parabolic indicator

This indicator is designed for use in trending markets. Once a trend has begun, the system allows for moderate anti-trend movements, but as the trend matures, the system's protective trailing stop (referred to as "stop-and-reverse (SAR)" follows the price movements at a progressively closer rate. Once the SAR is reached, an equal and opposite position is taken in the market.

Formula:

SARbuy = SAR-1 + AF(Low – SAR-1)

SARsell = SAR-1 + AF(High – SAR-1)[9]

7.5 Design Specifics

In this buy-sell trading system, the user-defined trading strategies are set and simulation are run on historical data. The aims of a buy-sell trading system are:

- Though repeated trading methods, an investor can find out the best trading strategy for making maximum profit.
- Individual investors can set up their own customized trading rules by modifying the formula of the existing trading rules to achieve the best return.
- Individuals also can learn about the decision making process and the risks associated with trading.

There are five functional aspects of the design that should be taken into consideration: simulation, time track, announcements, report, and optimization. The simulation, announcement, reports and optimization are accessed by tabs

[9] SAR-1: stop-and-reverse value from the previous price.

SARbuy: stop-and-reverse price on the buy side.

SARsell: stop-and-reverse price on the sell side.

High: the highest price since the initial position has been taken.

Low: the lowest price since the initial position has been taken.

AF: an acceleration factor.

placed on the top of web pages. The tabs are actually links to other pages to allow for easy intuitive navigation. See a screen shot as below:

The detailed implementation is as follows:

Time Track:

The trading beginning date and ending date are placed on the upper left and right side of each page. The two dates are implemented using input boxes so that a user can select their own trading time period. The default trading dates are given.

Simulation:

There is a “Simulation” icon on the top of each web page. There are three processes available in the simulation system namely “screen stocks”, “buy stocks”, and “sell stocks”. These three processes are implemented using text links.

Process 1: Screen stocks - determine which stocks to buy

a) Select the cut-off probability of acquisition.

This can be implemented using an input box, but defaults to the value of cut-off probability of acquisition.

b) Construct a trade table with the potential securities.

The table includes information about ZSCORE, reporting date, and the probability of acquisition for each security. This can be implemented using a "Trade Table" button. When a user clicks on "Trade Table" button, a trade table window is displayed, which provides a list of potential selected securities information.

Process 2: Buy stocks – triggered by the buy signal.

a) Search for a buy signal using a moving average for all chosen stocks.

In the "trade table" window, there is a "buy signal" button. When a user clicks on the "buy signal" button, It will display the date on which stocks are bought.

b) Enter the trading conditions.

The following conditions can be implemented using input boxes.

- Limited percentage of the traded shares purchased (initial percentage is 20%).
- Maximum volume of any stock (initial volume is 1000).
- Limited percentage of stock weight in the budget.
- Budget constraint.

a) Process an order.

By clicking on the "submit order" button, a user commits to a buy process.

b) Display current position.

Clicking on the "current position" button displays an investor's account activity which represents what they have in their portfolio as well as any recent trades.

Process 3: Sell stocks – is triggered when exit signals appear.

Clicking on the "sell stock signal" button will bring up a window with a list of trading exit rules. Select any trading exit rule, then click on the "test" button. If it displays the sell signal, then clicking on the "sell stock" button to complete selling stock process.

Announcements:

"Announcements" is an icon placed on the top of each web page. When a user clicks it, a window displays all the stocks in the user's stock portfolio file. Clicking any stock will display the stock's delisting information and distribution information. Announcements affect an investor's buy and sell decisions.

Reports:

"Reports" is an icon placed on the top of each web page. To review a list of all past executed trades, click on this button. In this report, an abnormal return is computed for each security during the trading period. The time of stock entry and exit is listed in the report as well. The total portfolio return is displayed at the bottom of the report.

Optimization:

"Optimization" is an icon placed on the top of each web page. A user can edit the formula for any exiting technical trading rules. When a user clicks "Optimization", trading system templates will be displayed in a dropdown list. The user can select any trading exit rule, then click on a "formula" button to edit, save or use the default trade exit rule.

Chapter 8

Conclusions and Future Work

8.1 Conclusions

Takeovers as a means of restructuring financially distressed firms have significant effects in the industry. There are three motivations for takeovers summarized as follows: the managerial discipline motive, the complementary resources motive and the cash-free-cash-flow motive. These takeovers eliminate inefficient management, make better use of existing resources, add revenues and create growth opportunities. A notable influence of acquisitions on the share prices of targets is that share price increases significantly during the time when the acquisition announcement is publicized.

The acquisition prediction model developed by Åstebro and Winter (2000) was tested for its ability to predict actual acquisition during the period from 1979 to 1998 and across all industries. There was a trend of acquisition events rising as the value of the probability of acquisition increases. However, the model wasn't that successful in predicting outcomes. One reason is that the use of data sample is extended both in time and across industries. The acquisition model was based on eight years of financial data from 1980 to 1989 from 16 randomly selected three-digit industries, with a total of 3013 firms covered by COMPUSTAT. In the process of validating model, twenty years of data, from 1979 to 1998, was applied. Therefore, the limited size of the original data sample used in creating the acquisition model may be a reason for the lack in accuracy of the acquisition prediction for the twenty year data sample. The second reason is that the COMPUSTAT financial data may not be very timely and in general are not very predictive (Chava and Jarrow 2000).The third reason is that the age dummy variable is no longer used in calculating the probability of acquisition because the actual stock entry year is found in the CRSP daily stock files.[10]

This research applies several statistical methodologies in the analysis. These methodologies form the basis to substantiate the result of the analysis.

I examined the hazard rate of acquisition and bankruptcy for financially distressed firms. The results of the analysis indicate that ZSCORE and SPCSRM can be used as financial distress indicators in the screening mechanisms. I also analysed the cut-off values for ZSCORE and extracting years. There two cut-off values forms the rules for data extraction An abnormal return estimation model is used to maximize a stock's excess return over a given period of time for a given ZSCORE, probability of acquisition and the length of holding period.

A simulation technique is applied to derive the best cut-off probability of acquisition and construct the hypothesis test. There are three results from the simulation analysis: 1) Null hypothesis for the mean of daily excess return $\overline{g}$ is randomly rejected, which implies $\overline{g}$ may be significantly or insignificantly different from 0. 2) The prediction model of acquisition lacks accuracy. There seems to be no clear relationship between excess portfolio return and the

[10] Input variables used in creating the acquisition model only comes from the COMPUSTAT files, where the earliest year of available information is 1979. Thus for any stock entering the market before 1979, the entry year must be set to 1979. This inaccuracy of recording the stock entry year is mathematically complemented by the variable "age dummy" in the creation of the model.

probability of acquisition. 3) Increasing ZSCORE has little impact on the portfolio return.

Another contribution of this research is the development of a sophisticated computer systems used for data extraction, analysis and modelling. The Perl programming language is used across multiple computer platforms for data collection. For example, accounting data is retrieved from the COMPUSTAT files in the Windows platform, and market data is extracted from the CRSP files in the UNIX environment. These two sources of data are integrated through a linking file which is provided by Dr.Norli from the Rotman School of Management. An Oracle database is created to install the accounting data and market data. An Entity Relationship Diagram (abbreviated as "ERD") is set up, representing the relationship of the tables. The Java programming language is used to compute Matrix functions, which derives the value of the excess return. These accomplishments allow abnormal return model to be put to practical use for computing returns using stock price data. The simulation model is coded in the Java programming language as well, which means the cut-off probability can be calculated and updated very easily.

8.2 Future Work

Although there have been some interesting and potentially useful results obtained from the research done here, there are many aspects to be considered in terms of developing an actual buy-sell system:

1) The decision rules used to define the corporate events are based on the CRSP delisting files instead of the deletion reason code from the COMUPSTAT files. Research finds that the distribution code in the CRSP distribution files has detailed information for the announcement on each

distribution declaration date. In future development, it is recommended that the distribution code should be combined with the delisting code to clearly identify three financial outcomes: acquisition, failure and survival.

2) In the above conclusions, it is pointed out that the expanded data sample and updated age dummy variable may be the reasons for the decrease in the degree of accuracy of the acquisition prediction model. If the model of acquisition is recalculated based on a larger data sample, the coefficients of all variables in the model can be updated to improve the efficiency of the model. This modified acquisition model may be able to provide a more accurate prediction of acquisition events in the buy-sell system.

3) From statistics on abnormal return for corporate events, the average holding period return computed using the OLS estimation model is a function of the length of holding period. A stock with the short holding period has the large value of holding period return. I would suggest investigating the function relationship between the excess return and the holding period in the future work.

4) In the buy-sell system, the stock entry rules apply the fundamental analysis using ZSCORE and cut-off probability. In the real trading system, technical analysis is also very important in determining the stock entry rules. Tobin's Q as a measure of managerial performance can be considered as one of the stock entry rules.

5) What is the cost of the financial distress? It is suggested here that an econometric model be built to estimate this cost. Qualitative as well as quantitative measures of the costs of financial distress could be researched in future development. If it is determined that financial distress is too costly,

then another valuable research topic would be to investigate the value of successfully internally restructuring distressed firms.

Appendix A

Delisting Code (DLSTCD) Descriptions

Mergers

200 Issue acquired in merger, payment details unknown.
201 Merged into or in order to form an issue trading on NYSE.
202 Merged into or in order to form an issue trading on AMEX.
203 Merged into or in order to form an issue trading on Nasdaq.
205 When merged, shareholders primarily receive shares of mutual funds.
231 When merged, shareholders primarily receive common stock or ADRs. Replaces codes 201, 202 and 203. Codes 201-203 are no longer assigned.
232 When merged, shareholders primarily receive common stock or ADRs. (Merged stock is not maintained on the CRSP file.) Replaces codes 210-220. Codes 210-220 are no longer assigned.
233 When merged, shareholders primarily receive common stock. Merged stock is not mailtained on the CRSP file.
234 When merged, shareholders primarily receive preferred stock or warrants or rights or debentures or notes.
235 When merged, shareholders primarily receive other property.
240* Flags merger with missing final distribution information.
241 When merged, shareholders primarily receive common stock and cash, issue on CRSP file.
242 When merged, shareholders primarily receive common stock and preferred stock or warrants or rights or debentures or notes, issue on CRSP file.
243 When merged, shareholders primarily receive common stock, issue on CRSP file and other property, issue on CRSP file.
244 When merged, shareholders primarily receive common stock or ADR, and cash and preferred stock or warrants or rights or debentures or notes. Issue on CRSP file.
251 When merged, shareholders primarily receive common stock or ADRs and cash. (Merged stock is not maintained on the CRSP file.)
252 When merged, shareholders primarily receive common stock or ADRs and preferred stock, or warrants, or rights, or debentures, or notes.
253 When merged, shareholders primarily receive common stock or ADRs and other property.
261 When merged, shareholders primarily receive cash and preferred stock, or warrants, or rights, or debentures, or notes.
262 When merged, shareholders primarily receive cash and other property.
271 When merged, shareholders primarily receive preferred stock or warrants, or rights, or debentures, or notes and other property.
280 Issue delisted due to merger attempt, but merger attempt failed.
290 Flags a merger with missing final distribution information. Replaces code 240. Code 240 is no longer assigned.

Exchanges

300 Issue acquired by exchange of stock, details unknown.
301 Issue exchanged for issue trading on NYSE.
302 Issue exchanged for issue trading on AMEX.
303 Issue exchanged for issue trading on Nasdaq.
320 Issue exchanged for stock trading Over-the-Counter.
331 Issue exchanged, primarily for another class of common stock. Replaces codes 301, 302, and
303. Codes 301-303 are no longer assigned.
332 Issue exchanged, primarily for another class of common stock. (Other stock is not maintained on the CRSP file.)
333 Issue exchanged, primarily for cash.
334 Issue exchanged, primarily for preferred stock, or rights, or warrants, or debentures, or notes.
335 Issue exchanged, primarily for other property.
340* Flags an exchange with missing final distribution information.
341 Flags an exchange, shareholders receive common stock and cash. Issue on CRSP file.
342 Flags an exchange, shareholders receive common stock and preferred stock or warrants or rights or debentures or notes. Issue on CRSP file.
343 Flags an exchange, shareholders receive common stock and other property. Issue on CRSP file.
350* Flags an exchange attempt that was not sufficient to "kill" issue.
351 Flags an exchange, shareholders receive common stock and cash. Issue not on CRSP file.
352 Flags an exchange, shareholders receive common stock and preferred stock, or warrants, or rights, or debentures, or notes. Issue not on CRSP file.
353 Flags an exchange, shareholders receive common stock and other property. Issue not on CRSP file.
390* Flags an unsuccessful exchange attempt with missing distribution information.

Liquidations

400 Issue stopped trading as result of company liquidation.
401 Issue liquidated, for issue trading on NYSE.
403 Issue liquidated for issue trading on Nasdaq.
450 Issue liquidated, final distribution verified, issue closed to further research.
460 Issue liquidated, no final distribution is verified, issue closed to further research.
470 Issue liquidated, no final distribution is verified, issue pending further research.
480 Issue liquidated, no distribution information is available, issue is pending further research.
490 Issue liquidated, no distributions are to be paid, issue closed to further research.

Dropped

500 Issue stopped trading on exchange - reason unavailable.
501 Issue stopped trading current exchange - to NYSE.
502 Issue stopped trading current exchange - to AMEX.
503 Issue stopped trading current exchange - to Nasdaq.
505 Issue stopped trading current exchange - to Mutual Funds.
510 Issue stopped trading current exchange - to Boston Exchange.
513 Issue stopped trading current exchange - to Midwest Exchange.
514 Issue stopped trading current exchange - to Montreal Exchange.
516 Issue stopped trading current exchange - to Pacific Stock Exchange.
517 Issue stopped trading current exchange - to Philadelphia Stock Exchange.
519 Issue stopped trading current exchange - to Toronto Stock Exchange.
520 Issue stopped trading current exchange - trading Over-the-Counter.
535 Delisted by current exchange - unlisted trading privileges.
550 Delisted by current exchange - insufficient number of market makers.
551 Delisted by current exchange - insufficient number of shareholders.
552 Delisted by current exchange - price fell below acceptable level.
560 Delisted by current exchange - insufficient capital, surplus, and/or equity.
561 Delisted by current exchange - insufficient (or non-compliance with rules of) float or assets.
570 Delisted by current exchange - company request (no reason given).
572 Delisted by current exchange - company request, liquidation.
573 Delisted by current exchange - company request, deregistration (gone private).
574 Delisted by current exchange - bankruptcy, declared insolvent.
575 Delisted by current exchange - company request, offer rescinded, issue withdrawn by underwriter.
580 Delisted by current exchange - delinquent in filing, non-payment of fees.
581 Delisted by current exchange - failure to register under 12G of Securities Exchange Act.
582 Delisted by current exchange - failure to meet exception or equity requirements.
583 Delisted by current exchange - denied temporary exception requirement.
584 Delisted by current exchange - does not meet exchange's financial guidelines for continued listing.
585 Delisted by current exchange - protection of investors and the public interest.
586 Delisted by current exchange - composition of unit is not acceptable.
587 Delisted by current exchange - corporate governance violation.
588 Conversion of a closed-end investment company to an open-end investment company.
589 Delisted by current exchange - unlisted trading privileges
590 Delisted by current exchange - underlying assets have merged with another company
591 Delisted by current exchange - delist required by Securities Exchange Commission (SEC)

Appendix B

Creating Use Cases

<table>
<tr><td colspan="3">Use case name: Screen stocks</td><td>ID number: <u>1</u></td></tr>
<tr><td colspan="4">Short description: This describes how to select stocks to compose the portfolio.</td></tr>
<tr><td colspan="4">Trigger: Investors want to invest stocks.

Type: <u>External</u> Temporal</td></tr>
<tr><td colspan="2">Major Inputs:</td><td colspan="2">Major Outputs:</td></tr>
<tr><td>Description</td><td>Source</td><td>Description</td><td>Destination</td></tr>
<tr><td>firms' accounting data from COMUPSTAT files</td><td>Table: tb_cplus</td><td>size</td><td>Stock portfolio file</td></tr>
<tr><td>firms'ZSCORE (initially set to 0.5, then incremented)</td><td>Table: tb_prob_value</td><td>ZSCORE cutoffs</td><td>Stock portfolio file</td></tr>
<tr><td>size of the portfolio (constraints for the number of stocks in a stock portfolio)</td><td>investor</td><td>probability of acquisition γ cut-offs</td><td>Stock portfolio file</td></tr>
<tr><td colspan="4">Major Steps Performed

1. Use ZSCORE as a first screening mechanism to select the financially distressed firms.
2. Compute the probability of acquisition for each selected firm.
3. Add up the total number of firms for each γ.
4. Simulate γ to get the lowest value of γ so that the number of matched firms (n) is less than or equal to the required size of the portfolio (N); or alternative is: fixed γ, top 40 stocks are selected.</td></tr>
</table>

Use case name: Buy stocks		ID number:2	
Short description: This describes the volume of each matched stock an investor can buy to compose their stock portfolio.			
Trigger: The matched stocks are selected. Type: External Temporal			
Major Inputs:		Major Outputs:	
Description	Source	Description	Destination
Select starting trading date	investor		
Trading volume V_{itc} for each security i on day t	Table: tb_stockDailyPrice		
Marketing data (such as bid price b_{itc}, ask Price p_{itc})	Table: tb_stockDailyPrice		
Investor's budget (B) (Constraints of buying ability for an investor)	investor		
Read limited percentage of total trading volume for each purchased security (10% is initially set)	investor		
Read maximum volume of stocks purchased (1,000 is initially set)	investor	Budget	Stock portfolio file
Read the limited weight of each purchased security in its budget (10% is initially set)	investor	Purchasing volume V_{it} for each matched security i	Stock portfolio file

Major Steps Performed

1. Select starting trading date.
2. Use a firm's permno to get trading volume, ask price and bid price of each matched stock from table tb_stockDailyPrice.
3. Calculate the volume of each stock purchased in the portfolio, so that V_{it} satisfies the following equations:

V_{it} <= Limited Percentage (10%) * V_{itc}

V_{it} <= Maximum volume for any security (1,000)

p_{it} * V_{it} = limitedWeight (10%) * B

$$\sum_{i=1}^{N} p_{it} * V_{it} <= B$$

Use case name: Sell stocks ID number: 3

Short description: This applies trade exit rules to decide whether to sell stocks or stay in stock market on day t.

Trigger: when any one of the applied trading exit rules is met, sell the stoc stock.

Type: External

Major Inputs: Description	Source	Major Outputs: Description	Destination
Financial trade stops. Apply either profit trailing stop or maximum loss stop	ADX indicator	Stock return and its selling date	Stock portfolio file
Time stop	Target date or announcement date is met		
Probability of bankruptcy indicator on day t	Table: tb_cplus		
Moving average indicator	Stock prices from table: tb_stockDailyPrice		
Parabolic indicator	Stop-and-reverse prices and acceleration factor		

Major Steps Performed

1. A trader selects any combination of trade exit rules.
2. Compute the formula for the selected trade exit rules.
3. Make a decision whether to stay or exit the stock market according to each different trade rule.
4. If stock i exits the market, compute the return for this stock using OLS estimation model.
5. Repeat steps from 1 to 4 for each security in the stock portfolio file.

<table>
<tr><td colspan="4">Use case name: Compute portfolio return ID number: <u>4</u></td></tr>
<tr><td colspan="4">Short description: calculate the return for each existing stock, then compute the portfolio return.</td></tr>
<tr><td colspan="4">Trigger: Trading ending date is met
Type: <u>External</u> Temporal</td></tr>
<tr><td colspan="2">Major Inputs:

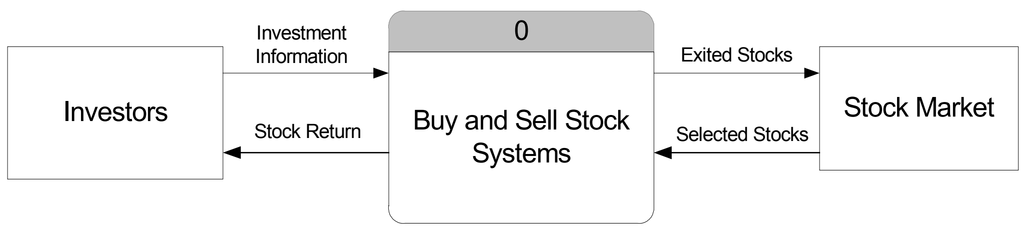
Description Source</td><td colspan="2">Major Outputs:

Description Destination</td></tr>
<tr><td>Return of each security</td><td>Stock portfolio file</td><td>Portfolio return</td><td>Stock portfolio file</td></tr>
<tr><td>Total trading days for each security</td><td>Stock portfolio file</td><td></td><td></td></tr>
<tr><td colspan="4">Major Steps Performed
1. Compute abnormal return for all existing stocks using OLS estimation model.
2. Calculate two types of the portfolio return: average daily portfolio return and average holding-period portfolio return.</td></tr>
</table>

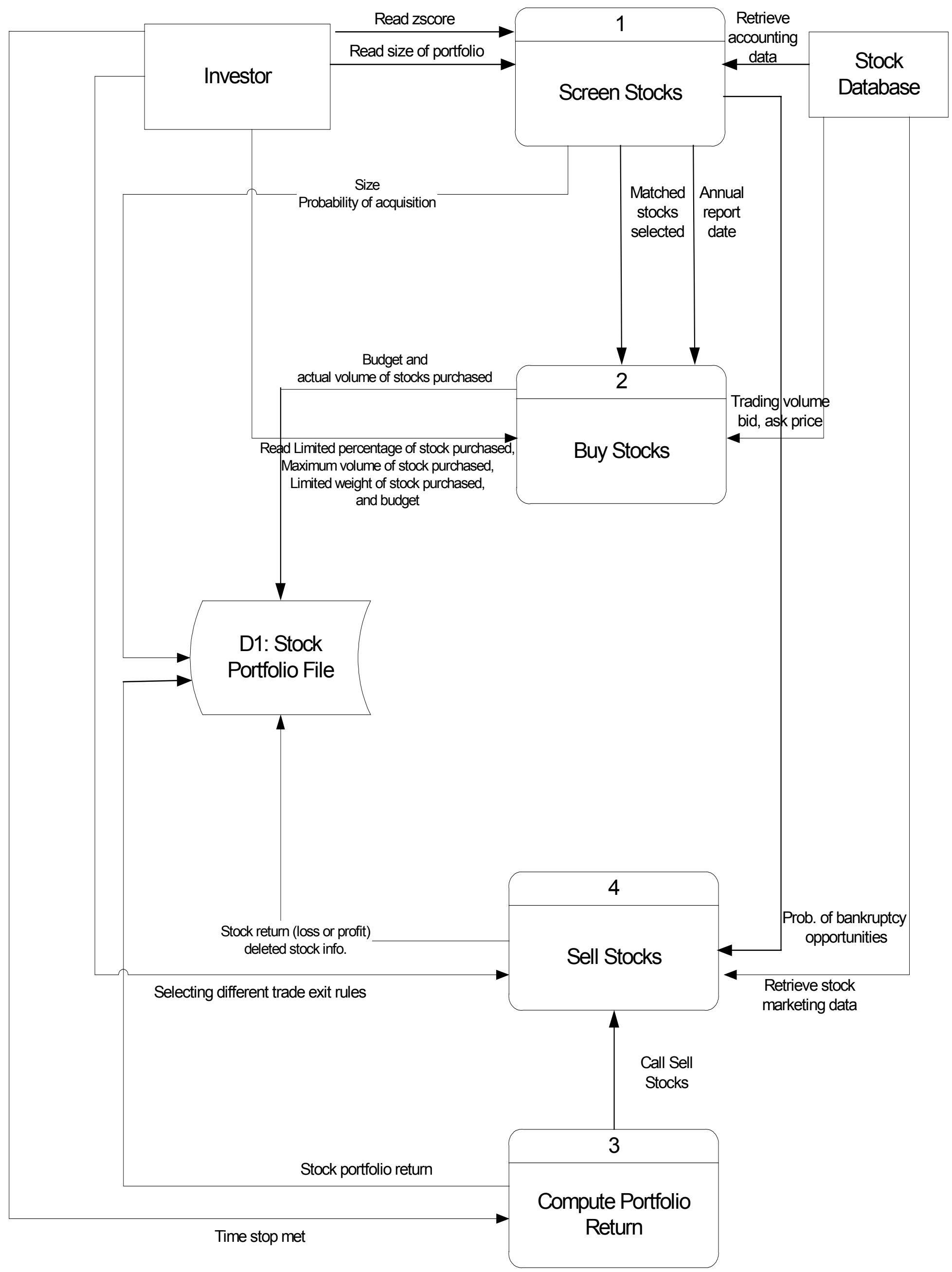
Appendix C

Data Flow Diagrams (DFDs)

Context Diagram



Level 0 Diagram



Appendix D

Data Validation and Methods Limitation

1. Observations

In the collected data, there are four significant observations:

Observation 1: the percentage of the firms with excess stock returns that range between –0.4 and 0.4 (abbreviated as "valid firms") reaches 99% of the total number of screened firms.

Observation 2: when both probability of acquisition and ZSCORE are simulated from 0.5 to 1.0, the valid firms with excess stock returns reach the maximum of 100% when the value of probability of acquisition is greater than or equal to 0.8 for any simulating ZSCORE value except when ZSCORE is equal to 1.

Observation 3: all firms with excess returns outside the range of -0.4 to 0.4 have the stock holding days equal to or less than 10 days. In other words, when a stock is held longer than 10 days, the excess return is observed in the valid range between –0.4 and 0.4.

Observation 4: in the output analysis, the maximum excess return is 1.05614513, and the minimum excess return is -0.86666668. The firms corresponding to the above extremes of excess returns have the stock held for only one day.

2. Data Validation Analysis

When a stock price jumps up or down by 40% on the next day, it is considered as the extreme event case. It implies that a firm either goes into bankruptcy or is being acquired soon. The investor decision for this event is to sell the stock. In the output analysis, it is observed that if a stock is held for only one day, the excess return is comparably higher; however, if the time that the stock stays in a portfolio becomes longer, its excess return gets flat and smaller. This observation is consistent with the mathematical fact that when a value is averaged by a large number, its quotient gets smaller. Therefore, the 1% of the so-called extreme number of excess returns in the output data sample can be explained by the above buying decision business rule.

3. Data Measurement Error Analysis

When the probability of acquisition takes a value of 0.5 and the ZSCORE takes a value of 0.5, the following relatively large values of excess returns are observed as listed in table 24:

Permno	track_begdt	enddt	distressbegdt	excess_return	holding_days	dlstcd
11562	7/31/1987	12/31/1989	12/29/1989	-0.76162174	1	561
45082	4/16/1984	7/2/1985	2/28/1985	-0.65438008	1	550
50630	1/1/1980	12/31/1984	12/31/1981	0.48512334	3	580
51335	8/9/1983	12/31/1989	12/29/1989	-0.46617167	1	574
56980	1/1/1980	9/24/1980	4/30/1980	-0.86666668	1	500
63264	8/15/1980	10/12/1988	9/30/1988	0.66643798	1	550
73921	7/15/1983	12/31/1989	12/29/1989	0.91008658	1	450
78036	4/25/1983	12/31/1989	12/29/1989	-0.4782581	1	550
81454	8/4/1981	12/31/1989	12/29/1989	1.05614513	1	550
91062	10/8/1984	10/23/1985	3/29/1985	-0.57251078	0	560
92161	11/5/1984	6/30/1989	6/30/1986	0.60113149	7	233

Table 24: Extreme values of stock excess returns

The output analysis concluded that the records derived with an excess return greater than 0.4 and less than -0.4 are due to measurement error. The first measurement error is that the observation event period is subjectively defined as the constant in this simulation experiment. The value of the event period arbitrarily chooses 10 years which starts from Jan 1, 1980 and ends on Dec 31, 1989. In the above table, there are five out of eleven firms whose stock selling dates are on Dec. 31, 1989. Their bias excess returns are associated with the error that relates to the event ending date. The firms that are found to be related to another error constrained to the beginning of the event period Jan 1, 1980 are firms with permno 50630 and 56980. For those two firms, the research finds that in the CRSP stock daily price file, the firm with permno 50630 first enters the stock market on May 26, 1970, and the firm with permno 56980 starts on Dec 14, 1972. However, these two firms are tracked starting on Jan 1, 1980 instead of their real first trading date.

The other measurement error is related to the value of the distress years selected. In this simulation, the number of distress years that a firm is allowed to survive is chosen as three years. In the above table, there are two firms with permno 50630 and 92161 that are forced to exit the market 3 years after the onset of financial distress. However, the firm with permno 50630 exits the stock market 7 years after the onset of financial distress, and the firm with permno 92161 exits the stock market 13 years after the onset of financial distress.

Combining these two measurement errors, there are eight out of eleven firms which have bias values. The measurement error is calculated to be around 73% for the number of firms with invalid excess returns. As a comparison, these bias firms with accurate beginning and ending trading dates are listed in table 25.

PERMNO	BEGDT	ENDDT
11562	7/31/1987	6/25/1998
50630	5/26/1970	5/26/1988
51335	8/9/1983	6/26/1990
56980	12/14/1972	9/24/1980
73921	7/15/1983	2/14/1992
78036	4/25/1983	11/13/1990
81454	8/4/1981	10/16/1990
92161	11/5/1984	8/3/1999

Table 25: Bias firms with accurate beginning and ending trading dates

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