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An Investment Strategy for Prediction of Takeover Targets using High Frequency Data

Bruno Dore Rodrigues

A thesis submitted in partial fulfilment of
the requirements for the degree of
Doctor of Philosophy

Discipline of Finance
Business School

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Bruno Dore Rodrigues

Dedication

To my beloved parents, and

To my precious wife.

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Abstract

The ability to identify likely takeover targets at an early stage should provide an investor with valuable information to profit from investing in potential target firms. Based on the hypothesis that agents with asymmetric information operate in the securities market, the objective of this study is to develop an investment strategy able to achieve high portfolio returns and reduce risks by investing in takeover targets. The analysis is conducted on tick-by-tick data from shares traded on the Australian Securities Exchange (ASX) using a range of models from the logistic, neural network, forecast combination, Autoregressive Conditional Duration (ACD), along with associated market timing rules.

The first part of this thesis makes a contribution to the takeover prediction literature by showing that the combination of probability forecasts as an alternative approach improves forecast accuracy in takeover prediction with improved economic return from portfolios made up of predicted targets. The second part investigates the joint impact of market microstructure variables on return volatility in the months prior to the public release of the takeover announcement. The last part introduces an innovative market timing approach to capture information from the intraday trading and to guide portfolio investments. The information content of each trade is analysed in the search for trading behaviour consistent with the use of privileged information before the takeover announcement.

Three general conclusions come from the results. First, an investment in a portfolio comprising predicted targets is capable of achieving significant abnormal returns. Second, the intraday trading behaviour in takeover targets is affected by traders who may hold private information before the event. Finally, the proposed Forecast Range Strategy is shown to be successful in predicting market trends and providing an alternative method for reducing risk without sacrificing return.

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Preface

Some of the work presented in this thesis has been published in referenced journals.

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CHAPTER 1

Introduction

This thesis focuses on the development of an investment strategy to predict market events and to manage the portfolio of potential targets for maximum economic gain. It concentrates on the efficient use of publicly available information to forecast future events and to use trading data to identify the timing of an event. In particular, the methodology is customised to achieve a more accurate prediction of a takeover announcement and to manage efficiently the timing of the investments in those companies based on intraday market information. Despite the specific focus on takeovers, the models and techniques can be adapted to other applications.

The research presented in the thesis is organized in an orderly manner for the development of an efficient investment strategy. Each section is designed to have an independent structure and creates new knowledge in a specific field. Each chapter interacts with the others to clearly present the construction of the investment strategy based on the prediction of takeover announcements. It starts with the takeover prediction, is followed by the analysis of the intraday market behaviour, and concludes with the introduction of a new market-timing strategy. In the following these topics will be discussed.

1.1 Takeover Prediction

In the past few years a surge in takeover activity has emerged both globally and in Australia. The Australian market is the second biggest mergers and acquisitions activity in the Asia-Pacific area after Japan. A takeover is by definition the purchase of one company (the target) by another (the bidder, or acquirer). The term refers to the acquisition of a public company whose shares are listed on the stock exchange. As defined in Dunlop (1997), the takeover mechanism can be seen as a natural market correction which allows shareholders, who don't have effective control over the management of their company, to confer control to someone who is prepared to pay them a premium over the current market price for their shares. Takeovers represent a dynamic part of the corporate finance field and play an important role in the reallocation of resources in the economy.

Mergers and acquisitions have long been a major research area in finance. Several studies have demonstrated that the target's share price increases substantially during the period before the bid announcement. It has also been observed that most gains from takeover deals accrue to the shareholders of the target firm. Consequently, the ability to identify likely takeover targets at an early stage could provide an investor with valuable information to profit from investing in potential target firms. Assuming that abnormal returns can be achieved by trading in advance of acquisitions, the development of takeover prediction models based on publicly available information are important tools to guide investment strategies in this area.

Even after considering the methodological improvements from several studies in takeover prediction, the answer to the question of whether takeover targets can be predicted remains unclear. There is a number of criticism concerning takeover prediction models. Problems related to the profitability of the predictions and the efficiency of the forecast methodologies in alternative markets are common. In fact, the conclusions from most studies are based on one single forecast, with little information available on the robustness of these predictions. From an investment perspective, it is crucial to be aware of the risk and accuracy of a model on different economic environments. It hardly seems optimal for an investor to invest capital in a portfolio of potential target companies unless the selection process is based on other than robustly evaluated predictions. This is especially the case where the return of a portfolio of potential targets is directly related its forecast accuracy, since the correctly predicted targets are the stocks bringing abnormal returns to the portfolio.

The use of a forecast combination model provides an alternative method to address the literature shortfalls by improving the robustness of the model's predictions and its forecast accuracy. It has the advantage of grouping in one model the best of different methodologies and, therefore, has a higher potential to achieve more accurate and stable results. It has been tested with success in many other areas, such as predicting bond rating, and presents itself as a strong candidate to improve on the current takeover prediction methodologies.

1.2 Intraday Market Analysis

Due to the widespread automatization of financial markets and increased developments in computer power, a large number of exchanges have started to record every single market update and make it available to researchers and investors. This new dataset moves away from the traditional discrete sampling of data over calendar time (based on a reduced information set) to a very active and information intensive mass of data. It includes not only all trades and associated characteristics, such as time, volume and traders, but also all changes in the order book and quote updates. A new area of financial research, known as high-frequency financial analysis, has emerged from the availability of these large intraday data sets. In the last ten years it has rapidly grown as a burgeoning research area with contributions from finance, econometrics and time series analysis, leading to a deeper understanding of market activity. More recently, the analysis of High Frequency Data (HFD) has moved from the academic domain to the trading environment, influencing important strategies in many companies of the financial sector, such as hedge funds.

High-frequency financial data have been used to study several market microstructure related issues. This includes price discovery, competition among related markets, strategic behaviour of market participants, and modelling of market dynamics. In the past, liquidity analysis has been achieved using multiple and disassociated variables, such as daily traded volumes or average bid-ask spreads rather than a single metric of liquidity. However, the recent availability of high frequency transaction data from financial markets has guided the development of econometric techniques that have greater capacity for extraction of information than pre-existing technologies. It has led to the introduction of a very important variable related to information and liquidity, that is duration. In the context of market microstructure analysis, duration is by definition the time elapsed between two subsequent events.

Research in market microstructure has advanced several hypotheses and conclusions concerning information flows in traded markets. For example, the periods of time in which no trades occur are considered by Diamond and Verrechia (1987) as periods where the information revealed to the market is not of the type that has encouraged trading. On the other hand, Easley and O'Hara (1992) developed a plausible theory which proposed that a lack of trades meant 'no' news in the market. Another hypothesis discussed in the study of Grammig and Maurer (2000) is that the duration between events shows significant serial correlation due to clustering of news. While microstructure models generally assume informational asymmetries among investors, a takeover announcement reveals information unknown to most market participants. The arrival of this information generally has a positive effect on the price of the target firm. It gives informed investors with privileged information a strong incentive to trade on their knowledge prior to the takeover announcement. In the case of a takeover announcement, it includes companies involved in negotiations, or third parties that have specific knowledge of the planned offer.

Time plays an essential role on the market microstructure literature and, in particular, on the analysis of volatility. The HFD are characterized by transactions in which events are recorded as they arrive, resulting in observations that are irregularly time-spaced. This distinctive feature of the data does not allow it to be analysed with the standard time series techniques. Accordingly, Engle and Russel (1998) developed the Autoregressive Conditional Duration (ACD) model, which models the time between transactions. The ACD model has become a leading tool in modelling the behaviour of irregularly time-spaced financial data. As a consequence, it has opened an extensive area for both theoretical and empirical developments on the information content hidden on high frequency trading.

Understanding volatility is very important for identifying informed investors' activity in the market. The contribution made by individual microstructure variables to volatility might create information patterns that are consistent across a large number of companies. This unusual market behaviour is expected to happen especially within the trading environment of actual takeover targets prior to the event announcement, and are associated with the well–documented price effect of takeovers on target firms. Consequently, it is assumed that the arrival and dissemination of information through the trading can be observed on the analysis of the intraday data. To this context, the ACD-GARCH of Engel (2000) becomes a strong tool to analyse volatility in high frequency data and detect abnormal intraday market behaviour before information events, such as takeover announcements.

1.3 Market-timing Strategy

The "Buy-and-Hold" approach is a well-known strategy among investors in stock markets. Essentially, if a company looks promising the investor buys and keeps its assets over a relatively long period. An alternative approach, known as market-timing, is more dynamic and focuses on short-term fluctuations in stock prices. The hypothesis behind the market-timing strategy is straightforward. An investor remains long in the stock when expected returns are high, but temporarily exits the market by switching to cash investments when the stock is expected to underperform. The timing of the switch is indicated by signals based on investment timing rules that are built on indicators assumed to predict future stock returns. It implies that stock returns are correlated with indicator levels and investors should, therefore, switch from the stock to cash (and vice-versa) when an indicator crosses certain thresholds. The method involves detecting weak stock market movements in time to close positions with minimal losses, while remaining invested during active periods. However, this is a difficult task given it is unclear what are the indicators to look for in the trading environment.

In general, market participants are reluctant to react to price changes because of the uncertainty concerning the efficient price value. Thus, there is variation in the stock price only if investors are truly convinced that the efficient price is sufficiently far from the last traded price. If a transaction leads to a price change, then new information has arrived that convinces traders to move the efficient price. Market microstructure theory basically hypothesizes the information dissemination by two types of agents in the market. The first kind is the uninformed traders who are simply trading to adjust their portfolio. Their transactions are often assumed to be random since they have no superior information about the stock than what is publicly available. The second type is the informed trader who possesses privileged information that can influence future efficient prices. It is reasonable to assume that privately informed agents would use their knowledge to submit large volumes of market orders that guarantees quick execution of their transaction. This action clearly minimizes the risk of the market learning of the private information from trading in the stock before they can benefit from it. Accordingly, it is assumed that their behaviour is reflected in the trading environment. For example, if a large price variation is observed in a very short period of time, it could indicate that informed traders are trading on privileged information.

The intuition underlying this trading strategy is as follows. Suppose there is a fall in the stock price of a particular company. This could be related to public information that has resulted in investors reducing their valuation of the stock, or it could be caused by the selling pressure of informed traders. In the former case, there is no reason why the expected return on the stock should change instantaneously. The new information takes time to be processed by all agents. This will be reflected in a more or less gradual negative trend in prices over a period and associated with numerous trades. In the latter case, the sellers opt for selling their position quickly and will even accept a negative return in the process. The resultant unexpected high volume tends to consume the order book and a sharp price decrease can be expected on the same trade, or on subsequent near trades. This buying or selling pressure from informed traders should reveal itself in sudden unusual returns and volumes over short periods of time. It follows that informed trading behaviour should be detectable using data from publicly available trading variables. Once detected, this informed trading information can be used to support investment decisions by uninformed traders.

In summary, uninformed traders can use trading characteristics to understand informed traders' actions and, as a consequence, create value by closing the gap before the information becomes publicly available, or an information event happens. An appropriate environment in which to verify the reliability of any market-timing strategy is the period surrounding an information event such as a takeover announcement. The development of a strategy that can actually capture information changes in the intraday market and relate it to information events has a great potential to be used to manage portfolios of stocks. The Forecast Range Strategy (FRS) proposed in this thesis fits into this category. It monitors the intraday trading of several potential takeover targets and aims to use information from this action to time investments based on the presence of informed trading.

1.4 Objective

The objective underlying the takeover prediction in the first stage of the thesis is to explore the possible economic gains accruing to a portfolio of predicted target companies. The forecasts are estimated from a combination of probability forecasts generated by established takeover prediction models. It is anticipated that by combining forecasts from individual models, a portfolio of targets will be created that achieves abnormal returns and lower misclassification rates.

Under the assumption that agents with asymmetric information are operating in the market, the second part of this study aims to describe how the intraday market is affected by the release of private information before a takeover event. This analysis incorporates the use of the ACD-GARCH model to search for intraday trading variables and patterns that reveals information prior to an announcement being made public. More specifically, the trading behaviour of targets and bidders is studied to determine how economic and market microstructure variables are affected by the event.

The last stage of the thesis endeavours to create a new and efficient approach to market-timing in high frequency trading. The investment strategy sets sights on capturing informed transactions from the intraday trading to derive trade recommendations to buy or sell stocks. The method focus on incorporating the high frequency trading dynamics into the strategy by addressing the transactions as a sequence of arrival times with associated information. The so called Forecast Range Strategy (FRS) takes into consideration the multivariate filtration of arrival times through the ACD-GARCH model in order to assign a range of future values for the next trade. This market-timing strategy attempts to take a simple form in order to predict the market behaviour so that the recommendations are easily interpreted and the returns evaluated.

1.5 Contribution

The takeover prediction research contributes to the literature by exploring the gains that can be achieved by predicting potential targets using forecast combinations from a number of panel data logistic regression models and neural network models. This methodology significantly reduces misclassification errors and forms an optimized portfolio of companies with high likelihoods of becoming a takeover targets. The first part of the investment strategy introduces the forecast combination methodology to the prediction of takeover announcements and extends previous research by observing model consistency over time, analysing a wider range of companies over a decade, and considering firms of different sizes from a variety of industries. In addition, new explanatory variables are recommended on top of those already discussed in the literature.

The analysis of market behaviour before a takeover announcement developed in the second part of the strategy is one of relatively few studies to directly analyse the high-frequency trading environment before an information event and, in doing so, to use the ACD model to answer a finance-related question concerning the mergers and acquisitions market. This is the first work to compare the results from the basic ACD-GARCH model by observing the evolution of parameters over time and among groups of target, bidders and non-targets. The analysis of the microstructure model on a large group of companies in an order driven market and the introduction of new variables is also innovative. In order to achieve generalized results, this study extends previous research by investigating a wide range of companies that comprise firms of varying sizes, levels of liquidity and industries.

The union of the information from a model of high frequency data to the empirical application of an innovative market-timing methodology is an original and the main contribution of the thesis. The intraday market-timing strategy, named Forecast Range Strategy (FRS), outlines a new approach by using the volatility forecasts from a model based on durations, together with trading rules, to capture information from the intraday trading on which to base a related portfolio investment strategy. The approach proposes the use of a variation of the ACD-GARCH model of Engle (2000) to model the volatility of the stock and to forecast a probable range of future values. For the first time it formalizes the association of the forecast of the intraday return and its prediction interval with timing rules for investing in stocks. The method is flexible enough to capture the information content from individual trades and the complex temporal dependence typically displayed by high frequency transactions data.

1.6 Structure and Content of the Thesis

The thesis is organized in six chapters with its methodology and results structured in three independent but subsequent parts. The review of the literature that supports the discussions and methodologies on the thesis is presented in three subsections in Chapter 2 and appearing in the same order that the research was introduced here in Chapter 1. The consecutive three chapters present the three stages of the thesis, with each containing separate subsections for the methodology, the data, the model estimations and the results. Chapter 3 evaluates takeover prediction using forecast combinations. Chapter 4 expands on the analysis of the intraday market behaviour before takeover announcements. Chapter 5 brings to a close the methodological part of the thesis with the development and assessment of the Forecast Range Strategy in order to time investments on the Australian stock market. Concluding remarks on the methodologies and results presented throughout the thesis are discussed in Chapter 6.

CHAPTER 2

Literature Review

This chapter reviews the important empirical and theoretical literature concerning market microstructure and prediction models and their relation with previous mergers and acquisitions studies. As the results from the replication of these models will be incorporated into a proposed market-timing strategy in subsequent chapters, existing market-timing studies will also be reviewed.

2.1 Takeover Prediction Review

From a theoretical perspective, knowing the motivation behind a takeover bid should prove useful and provide a key to understanding merger and acquisition dynamics and motivations. On the other hand, the economic benefit derived from the management of a portfolio of forecasted targets depends not only on the drivers of the deal but critically on the accuracy of the predictions from the forecasting model utilized. Barnes (2000) explains that, although there may have many reasons for takeovers, targets are not selected arbitrarily. Instead they arise from a desire by a bidding company to gather benefits from an acquisition.

Proposed and evidenced theories explaining the grounds behind takeovers include profitability (Hogarty, 1970), economies of scale

(Silberson, 1972), market power (Sullivan, 1977; Thomadakis, 1976), information signaling [Bradley *et al.* (1983)], and management efficiency (Jensen and Ruback, 1983). In particular, researchers have found that financial synergy is a strong motive for mergers (Gahlon and Stover, 1979). However, each individual takeover has a specific rationale and, due to its complexity, the finance literature has been unable to determine a definite list of hypothesis and variables that are able to anticipate these events.

An important challenge for the researcher who attempts to forecast takeover targets is also the issue of identifying the most appropriate model or models. An assortment of models has been applied in an attempt to define common characteristics of takeover targets. Stevens (1973) defends the use of multiple discriminant analysis as a model that is well suited to many financial problems where the dependent variable is dichotomous. However, most of the studies conducted in the 1980's and 1990's switched to logistic regression models. Dietrich and Sorensen (1984) was one of the first researches to apply logistic regression to forecast binary variables, in the field of bankruptcy prediction, following the article by Ohlson (1980). Logistic models were later established in the takeover prediction literature with Meador *et al.* (1996). The application of more computationally intensive models such as these from the neural network class came later with Cheh *et al.* (1999) and was followed by Dencic-Mihajlov and Radovic (2006). However, Powell (2004) advises that modelling takeovers exclusively using a binomial framework may be misleading since takeovers may occur for many reasons not presented in the selected hypotheses and consequently in the corresponding predictor variables.

The study of Palepu (1986) was the first to formally improve the validity and the consistency of the prediction procedure by analysing the influence of a cut-off probability on the predicted output.

Subsequently, the direction taken in this very specific field concentrated on the development of alternative methods to determine the optimal cut-off probability in order to reduce misclassification error. The end of the 1990s saw the emergence of additional methodological improvements such as the profit maximization criterion proposed by Barnes (1999).

The classification accuracy reported in the literature has demonstrated varying degrees of success with predictive accuracy of up to 90% better-than-chance in-sample, while out-of-sample ranging from below 50% to around 120% better-than-chance. For example, the best results in Powell (1995) are achieved by the use of multinomial models that reported an overall classification accuracy of 4.76%. The methodology from Stevenson and Peat (2009) used a combined logistic model to achieve results up to 118% better-than-chance. However, the ability to generate abnormal returns has been questioned by many authors who could not replicate the results of previous studies when applying the same methodologies in different markets, or periods. In many cases the out-of-sample classification ability in empirical applications has generally failed to live up to the predictive expectations formed from the in-sample results.

In contrast, forecast combination has long been viewed as a simple and effective way to improve the robustness of forecasting performance over that offered by forecasts from just one model. The perception that model instability is an important determinant of forecasting performance and a potential reason for combining forecasts from different models started with Bates and Granger (1969). It was further supported by Diebold and Pauly (1987), as well as Pesaran and Timmermann (2007). Nonetheless, the combination of probability forecasts of a binary variable defined in the [0, 1] interval appeared later when Kamstra and Kennedy (1998) introduced a method to combine log-odds ratios using logit regressions. Further development was carried out in this area with Riedel and Grabys (2004) by generating multilevel forecasts, and later with Clements and Harvey (2007) comparing several methods for combining probability forecasts. However, the combination of forecasts is an alternative forecasting approach not found in the takeover prediction literature. The first stage of the thesis, in Chapter 3, replicates the best takeover prediction models found in the literature and combines their predictions to improve model accuracy and stability. The methodology addresses important criticisms surrounding the takeover prediction literature, including the testing of the models in different economic environments.

2.2 Intraday Market Review

As active mergers and acquisitions markets expand, new opportunities appear for the profitable use of information through trading in anticipation of bids. The use of microstructure techniques to decompose the impact of microstructure variables' on trading characteristics has allowed more precise perceptions regarding asymmetric dissemination of information over time. In previous studies strong evidence of this impact on various corporate events has been gathered from high-frequency data analysis. Easley and O'Hara (1987) developed an alternative explanation for the price-quantity relationship by showing that traded volume is important due to its correlation with the private information related to the security's true value. In particular, they suggested that adverse selection problems arise due to the preference of informed traders to trade larger amounts at any given price. Further, Foster and Viswanathan (1990) found that bid-ask spreads are elevated as many as seven days before the date of a corporate announcement. In contrast, Jennings (1994) supported the view that there is little evidence related to spread increases before announcements. He did, however, support the idea that there is some anticipated intraday trading activity before takeover announcements. It was hypothesized that the thesis is that the contribution made by microstructure variables to volatility within the trading environments prior to an announcement creates information patterns that are consistent across a large number of targets. This view has support in the work of Frino and Wearing (2005) also which found that intraday patterns are relevant for identifying when profitable trading opportunities are likely to appear.

Several studies analyse stock-price activity preceding takeover bids made in the sixties and seventies, with many of them reporting that stock prices begin to move upwards in anticipation of takeover announcement as early as two weeks before formal announcement. Although most researchers do not attribute these price rises to widespread illegal activity, others consider this to be direct evidence of insider trading studies. The research of Asquith *et al.* (1983) have discovered abnormal returns before acquisition announcements and conclude that they are caused by insider trading. In contrast, Sanders and Zdanowicz (1992) do not find enough proof of pre–announcement insider trading when analysing the target company's abnormal return and trading activity. Jarrel and Poulsen (1989) find that stock prices and trading volumes of target companies increase dramatically during the weeks immediately preceding public takeover bids. In addition, Haw *et al.* (1990) have discovered the occurrence of substantial market activity prior to disclosure of acquisition information.

Mergers and acquisitions are events with high information content and the impact on the trading environment have been the focus of numerous studies in the past years. With the development of the microstructure theory, a number of researchers have approached the firm acquisition and agent behaviour around an event using variables such as spread, market depth, return volatility and traded volume [for example, see Conrad and Niden (1992), Foster and Viswanathan (1995), Smith *et al.* (1997), Jabbour *et al.* (2000), Farinós *et al.* (2002) and Marshal (2006)]. The works of Easley and O'Hara (1987) and Admati and Pfleiderer (1988) are based on the expectation that changes in trading activity will depend on liquidity. Easley and O'Hara (1992) suggest that order size and volume traded contain a direct signal for the market concerning informed trading with measures in these variables resulting in an increase in the bid-ask spread. In contrast, Admati and Pfleiderer (1988) assume a negative relation between spread and trading activity. The work of McInish and Wood (1992) is based on the assumption of a negative relation between trading activity and transaction costs, with the greater trading activity can lead to lower spread due to economies of scale in trading cost. On the other hand, Harris and Raviv (1993) claim that higher trading volumes reflect a lack of agreement among market participants. They assume that high volume periods mean limit order arrivals at both sides of the spread and the rise in volume is associated with increases in liquidity without the need for inside information to be traded in the market. As suggested in Farinos *et al.* (2002), increases in adverse selection cost are expected before the event–day (announcement) which would lead, ceteris paribus, to increases in bid–ask spread.

For a long time the variable 'time' was considered as exogenous, with the implication that time between market events contains only information regarded as noise. In a broad range of empirical microstructure studies, for example Kyle (1985), Glosten and Milgrom (1985), Glosten and Harris (1988) and Hasbrouck (1991), the time between market events is not even considered in the analysis. Nevertheless, in recent market microstructure literature, the time variable was found to be of particular importance in order to model the behaviour of market agents. In Easley and O'Hara's (1992), time has a deep impact on the way market makers update their quotes. Further, Giot (1999) proposes that a market featuring short periods between trades (an active market) is usually associated with possible informed trading and leads to an increase in the quoted spread. In fact, the time between events, such as trades, quote updates, price changes, and order arrivals, has proved to be important in understanding the processing of public and private information in financial markets [see Easley *et al.* (1996), Diamond and Verrecchia (1987), Glosten and Milgron (1985), Hasbrouck (1991) and O'Hara (1995)].

The models of Diamond and Verrechia (1987) and Easley and O'Hara (1992) were among the first to recognize that traders are likely to learn from the timing of their trades. The presence of either informed traders, or uninformed traders, in the market is signalled by the incidence of short or long duration clustering. Diamond and Verrechia (1987) argues that long duration clustering is associated with "bad" news. Their explanation relied on the assumption that no short-selling is permitted in the market. When "bad" news hits the market, informed traders are unable to take advantage of it by short-selling and do not trade. Whilst, Easley and O'Hara (1992) suggest that the sequence of trades implies information flows relating to agents and systematic market news. Their theory assumes that informed traders would only trade when new information enters the market, while uninformed traders are assumed to trade with constant intensity. Information events (either good or bad news) are assumed to be associated with short duration clustering through the increased activity of informed traders. In general, takeover announcements are interesting events in a study of stock market trading activity related to durations, market microstructure variables, and the spread of market information.

With the advances in data collection and computational sources in recent years, more empirical research has been conducted in the market microstructure area. As a result, new models and structures have been developed. One such group of microstructure models that has become popular are the information-based models. These models are supported by asymmetric-information and adverse selection theory which takes into consideration the different degrees of information existent in the market. The interface of microstructure with other areas of finance is a growing subject.

Considering its importance to markets, liquidity has always attracted further investigation. Madhavan (2000) argues that a more complete understanding of the time-varying nature of liquidity, and its relation to expected returns, appears warranted given the growing evidence that liquidity is related to information. Consequently, changes in liquidity over time may explain variation in the risk premium and hence influence stock price returns. The use of economic (or transaction) time, as measured by duration, has formed the basis for several studies that analyse liquidity and equity volatility of traded stocks. In the context of the model developed in this study, the time elapsed between trades (duration) is considered a measure of liquidity. By incorporating several trading characteristics, a link is provided between volatility analysis and other market-microstructure variables. From the idea that duration between trades is a proxy for liquidity arose the use of Autoregressive Conditional Duration (ACD) model as a means to measure it. Since its introduction in Engle and Russell (1998), the ACD model has become the basic modelling tool for intraday data associated with duration. Their work has developed a great interest in the implication of price and trade durations in finance research.

Following the Engle and Russell (1998) seminal contribution, many modifications to the basic ACD model have been proposed. Ghysels and Jasiak (1998a) and Ghysels *et al*. (2004) developed the stochastic volatility duration models to identify higher order dynamics in the duration process. Bauwens and Giot (1998) proposed extensions to deal with competing risks, whilst Engle and Lunde (1998) use bivariate models to model trade and quote processes. The studies of Engle (2000) and Ghysels and Jasiak (1998b) are important in the measurement process. They combine the conditional duration models with the GARCH model advanced by Bollerslev (1986). A more recent study by Bauwens (2006) statistically analyses the trade durations. He found that the usual stylized facts (intra-daily seasonality clustering and excess dispersion) found in Japanese data are similar to those found in data from the New York Stock Exchange.

Although empirical applications using the ACD model have been well covered in many studies and books [see Pacurar (2006), Bauwens and Giot (2000), Engle and Russell (1998), Tsay (2002), and Hautsch (2002)], none of these studies is related to either work reporting mergers and acquisitions results, or use large groups of companies. Most of the papers in the ACD literature have characteristics in common, such as the use of highly liquid stocks. Usually, the results are from stocks traded on the New York Stock Exchange that is characterized by the presence of a market maker and an order book. However, their findings may differ for either (or both) a pure order-driven market and less frequently traded stocks. Indeed, more markets and stocks need to be researched to gain a better understanding of how the information flows in different trading environments.

While the above studies provide important insights, they do not offer a complete understanding of the scope of this thesis. The methodology developed in Chapter 4 focuses on the application of the ACD-GARCH model of Engle (2000) for the very specific purpose of detecting abnormal trading information before takeover announcements. The results from the ACD-GARCH modelling, along with those from the takeover prediction models are incorporated into a market-timing rule for portfolio creation and management in a later chapter. A review of the existing market-timing rules is in the following section.

2.3 Market-timing Strategy Review

It is possible to distinguish two clear assumptions in the investment literature. First, investors will hold a security if its expected return at the market price provides an adequate trade-off with the risk exposure the security brings. Second, if capital markets are efficient, market-timing rules should not be able to achieve higher returns than a buy-and-hold strategy. In other words, as mentioned in Neuhierl and Schlusche (2011), publicly available information should not be useful for predicting future stock market movements. Despite that opinion, market-timing rules have frequently appeared in the literature in the past 50 years. It started in the early 60's with filter rules used by Alexander (1961) to assess the efficiency of stock price movements. The work of Fama and Blume (1966) explains the standard filter which constitutes the basis of most work after that. It relates a threshold percentage change in the closing prices of a security to long and short trade recommendations. Small percentage variations in either direction are ignored. Following studies have identified many useful indicators associated with future stock performance besides daily stock prices. Such indicators include the earnings-to-price and dividend-to-price ratios in Campbell and Shiller (1988), the dividend yield in Shiller (1984) and in Fama and French (1988), as well as the dividend payout ratio in Lamont (1998), among others.

Given the persistent use of market-timing rules over time, Technical Analysis (TA) is common-place among market practitioners. Research has been conducted on the effectiveness of TA by Goodhart and Curcio (1992). They tested the usefulness of support and resistance levels published by Reuters. Brock *et al.* (1992) tested two of the simplest and most popular trading rules; the moving average and trading range break. The performance of a wide range of filter rules is also examined in Curcio *et al*. (1997) and Sullivan *et al*. (1999). More recently, Copeland and Copeland (1999) analyses the performance of market-timing rules based on index volatility changes, while the profitability of market-timing based on financial ratios was thoroughly explored in Fisher and Statman (2006). However, most studies on market-timing performance are based on technical trading analysis with their efficiency questioned over time.

Neely and Weller (2003) found no evidence of excess returns to the trading rules derived from genetic programming when realistic transaction costs and trading hours are taken into account. In Neuhierl and Schlusche (2011), even though individual market-timing rules significantly outperform a buy-and-hold strategy at both daily and monthly frequencies they find that their advantage does not remain significant after correcting for data snooping. In fact, Shen (2003) proposed that few investment strategies have a worse reputation than market-timing. He mentioned that investors are constantly told that the best strategy is a simple buy-and-hold strategy. However, despite the practical importance of trading rules and the vast literature on market-timing, there has been little study of high-frequency trading rules.

The intention behind the various market-timing strategies is to automatically capture information about what is happening in the market so it can be used to support investment decisions. In this context, by giving indications to buy or sell stocks, the trading activity plays an important role related to information content in the trading. There are two main theoretical studies that provide explanation for the nature of dependence between transactions and information. They are the previously discussed studies of Diamond and Verrecchia (1987) and Easley and O’Hara (1992). Both studies declare that price adjustments made by investors are sensitive to order flow and will result in increasing volatility. Consequently, trades occurring continuously have very different information content than trades largely spaced in time, thus disclosing the discrepancies between clock time and trade time.

Despite all advances in market security, it is still very difficult, if not impossible, to clearly distinguish informed from uninformed traders directly. Instead, the existence of private information must be inferred from transactions and general market characteristics. Basically there are two widely recognized motives for trading: information and liquidity. Informed traders trade on the basis of private information. Uninformed or liquidity traders, on the other hand, trade for reasons that are not directly related to the future payoffs. The premise by Easley and O'Hara (1991) advocates that informed traders will transact only when they possess private information. In a rational expectations setting, this suggests that both the demand for liquidity and the supply of liquidity should be affected by informed traders. Consequently, it will affect the returns, volumes, spreads, and transaction rates. Admati and Pfleiderer (1988) explain that informed traders tend to trade when the market is "thick" and, consequently, the volume of trades will reflect the increased level of informed traders. They concluded that informed traders trade more actively in periods of high liquidity to take advantage of their information and reduce the chance of being detected through their number of trades or large volume. These hypotheses have strong support in the literature, with studies such as Russell (1999). He explains that if both uninformed and informed traders are strategic, then the patterns of transaction and limit order submission should give an indication that informed traders are present in the market. Earlier studies also focused on the reaction of specific variables in the presence of informed traders. For example, Copeland and Galai

(1983) suggest that spreads should widen, while Hasbrouck (1988) observes a greater price impact for larger volume transactions than for smaller ones.

Research on the effects of trading and information flows on stock price volatility has developed into an important topic in finance. The research of French and Roll (1986) and Foster and Viswanathan (1993) compare the behaviour of volatility during exchange opening hours versus closing hours. Admati and Pfleiderer (1988) developed a theoretical model explaining the high volatilities during exchange trading periods. Complementing these studies, Robert and Rosenbaum (2011) presented a model which users the assumption of a continuous efficient price as an inherent property of ultra-high-frequency transaction data. Articles interested in the relationship between volatility and the time dependence on the arrival of information utilise models, such as the ACD, to explain how such dependence occurs and how it affects the price process. The work carried out by Engle (2000) suggested the combination of the ACD point process with a GARCH model of prices in order to create ultra-high-frequency measures of volatility.

The structure of the ACD-GARCH model of Engle (2000) provides the framework used in this thesis to forecast the intensity of the price change before takeover announcements, conditional on the information content of exogenous variables and the duration between trades. In Chapter 5 the ACD-GARCH model is used in a trading strategy to guide investments on predicted takeover targets. This innovative approach is a practical use of microstructure models in the formulation of a market-timing investment strategy which aim is to achieve consistent abnormal returns and reduce the investor’s exposure to risk.

CHAPTER 3

Takeover Prediction Using Forecast Combination

3.1 Introduction

Even after considering the methodological improvements from several recent studies in the takeover prediction area, the answer to the question of whether takeover targets can be predicted remains unclear. From an investment perspective, it is crucial to be aware of the risk and the stability of a takeover model. Forecast combination has long been viewed as a simple and effective way to improve the robustness of forecasting performance over that offered by forecasts from just one model.

Literature on the Market for Corporate Control presumes that takeover targets can be forecasted using publicly available data. The crucial question raised however is whether future economic events, including takeovers, can be predicted without the market presence of inside information. Barnes (1998) expressed the view that, while these events cannot be normally predicted, some of them may at least be anticipated. This chapter tests the hypothesis of whether takeover announcements can be predicted with reasonable accuracy using public available information from annual financial reports and additional market data. It attempts to confirm the premise that abnormal returns can be achieved by investing for one year in a portfolio of predicted targets. This part of the thesis replicates the main methodologies involved in the prediction of takeover announcements, and proposes the use of an alternative method to improve not only the forecast accuracy but also to achieve abnormal returns under changing economic conditions in the Australian market.

It has not yet been demonstrated in the literature that such a complex problem as takeover prediction can be solved efficiently using only one forecasting model. It requires a more robust approach. The discrete choice modelling framework proposed in this chapter is divided into three segments. Firstly, a logistic regression and two other specifications of panel data logistic models are estimated, each assuming a different time relationship between the variables. Secondly, three architectures of feed-forward neural networks are trained to forecast takeover likelihood using the same database as the logistic models. Last of all, a forecast combination method (KK Combination) is used to combine the forecasts from the previous models.

In theory the Neural Network models should be more efficient in generating predictions given their associated high complexity and computational intensity. However, the transparency of the logistic models in relation to variable selection and time structure adds flexibility for the researcher to adapt the model. The takeover literature provides compelling arguments and results in favour of both types of models, but two points are still untested. They are the use of forecast combinations to improve prediction accuracy of takeover announcements, along with how each model behaves over different time periods. It is anticipated that by combining forecasts from individual models, a portfolio of targets can be created that constantly achieves abnormal returns and lower misclassification rates. This research contributes by way of showing that good and consistent forecast accuracy can be achieved when predicting potential takeover targets using forecast combinations from both a number of panel data logistic regression models and neural network models.

3.2 Takeover Prediction Models

3.2.1 Logistic Models

M1 - Logistic regression

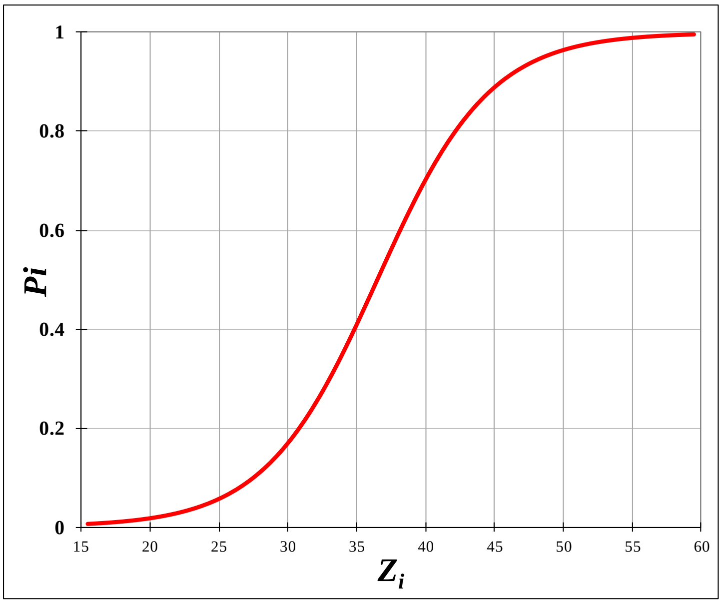
The first modelling procedure used is the logistic regression, commonly utilised for dichotomous state variable problems. Despite having a simple structure, it achieves good results in various applications. The model is specified in equations (3.2.1) and (3.2.2) below:

$$\mathrm{P_i} = \mathrm{E}(\mathrm{Y} = 1|\mathrm{X_i}) = \frac{1}{1+e^{-Z_i}} \tag{3.2.1}$$

$$\mathrm{L_i} = \ln\left(\frac{\mathrm{P_i}}{1-\mathrm{P_i}}\right) = \mathrm{Z_i} = \beta_0 + \beta_1 \mathrm{X_{1i}} + \cdots + \beta_k \mathrm{X_{ki}} \tag{3.2.2}$$

Where *Pi* is the probability of company *i* being taken over, $ß_0$ is the intercept, and each $ß_k$ (k = 1, …, N) is the coefficient corresponding to the vector of financial variables X_k. The logistic regression model was developed to overcome the rigidities of the linear probability model in the presence of a binary dependent variable. Equations (3.2.1) and (3.2.2) show the existence of a linear relationship between the log-odds ratio and the explanatory variables. However, the relationship between the probability of the event and acquisition likelihood is non-linear. This non-linear relationship has a major advantage in that it measures the change in the probability of the event as a result of a small increment in the explanatory variables. However, the incremental impact of a change in an explanatory variable on the likelihood of the event is compressed, requiring a large change in the explanatory variables to change the classification of the observation. Figure 3.2.1 has a representation of the logistic function, where P_i refers to the probability attributed to the vector of values, Z_i.

Figure 3.2.1 Example of Logistic Function



M2 - Panel data logistic regression with mixed effects

Panel data models make the most of the data on hand with the ability to analyse the relationship between variables simultaneously within a time dependent structure. Although these models share similar structure to the logistic regression model, the panel structure allows the historical records for each variable to be considered in the estimation procedure. The mixed-effects logistic regression adds other components to the panel structure by estimating both fixed effects and random effects. The presence of fixed effects captures the effect of all the unobserved time-invariant factors that influence the dependent variable. For this reason it is referred to as unobserved heterogeneity, or company effect, and represents all factors affecting the takeover announcements that do not change over time. In contrast, the random effects capture the intra-panel correlation. That is, observations in the same panel (year) are correlated because they share common panel-level random effects. The fixed effects are estimated directly as an additional regressor and the random effects take the form of either random intercepts or random coefficients.

An important characteristic of such models is the grouping structure of the data. It consists of multiple levels of nested groups that allow for one or more levels. In this study, a two-level model assumes that industries are the first level and companies the second level. Therefore, companies are nested within industries and random effects are unique to companies within an industry. Assuming that company effects are nested within industries is natural given that companies are generally unique to industries. Equation (3.2.3) reveals the model structure.

$$L_{ij} = \ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = Z_i = \beta_0 + \beta_1 X_{ijk} + Z_{ijk}u_i + \varepsilon_{ij} \qquad (3.2.3)$$

In the above model i=1...M represents panels (years), with each panel i consisting of j=1,..., N observations. In a two-level panel, k=1,...,L corresponds to the industry sectors, while the X_{ijk} are the covariates for the fixed effects that quantify a general mean process for the company j from industry k in panel i. The covariates corresponding to the random effects are given by Z_{ikj} and can be used to represent random intercepts and random coefficients, respectively (see Rabe-Hesketh *et al.*, 2005 for further explanation). The random effects, u_i, are not directly estimated as model parameters but are instead summarized according to the unique elements of the covariance matrix. The errors ε_{ij} are distributed as logistic with mean zero and variance $\pi^{2/3}$ and are independent of the u_i.

M3 - Panel data logistic regression with crossed effects

This model inherits the same structure from the previous panel data model, but with a different approach to the random structure. While it is safe to assume that all mixed-effects models contain nested random effects, in this analysis it makes sense to test the assumption that the random effects are not nested, but instead crossed. This means that the random effects are the same regardless of the industries, making it a simpler model with one less random covariate. The panel data crossed effects logistic model with the j^{th} company within the i^{th} panel in the k^{th} industry is given by equation (3.2.4) below.

$$L_{ij} = \ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = Z_i = \beta_0 + \beta_1 X_{ijk} + Z_{ij}u_i + \varepsilon_{ij} \qquad (3.2.4)$$

where X_{ijk} are the covariates for the fixed effects, similar to the previous model, and Z_{ij} are the random effects covariates for company j in panel i.

3.2.2 Neural Network Models

Logistic regression is the most commonly used technique in the takeover prediction literature. However, such parametric models require a pre-specified functional relationship between the dependent and independent variables. This is difficult to validate in many empirical studies due to the complexity of the problem and the relationship between variables. The advantages of neural networks over conventional methods of analysis dwell in their ability to analyse complex patterns quickly, with a high degree of accuracy and with no assumptions about the nature of the underlying distribution of the data. As explained in Dencic-Mihajlov and Radović (2006), the limitations of this model lie in its inability to explain the relative importance of the inputs separately, as well as the requirement to have a sufficiently large dataset to train, validate and generalize the network.

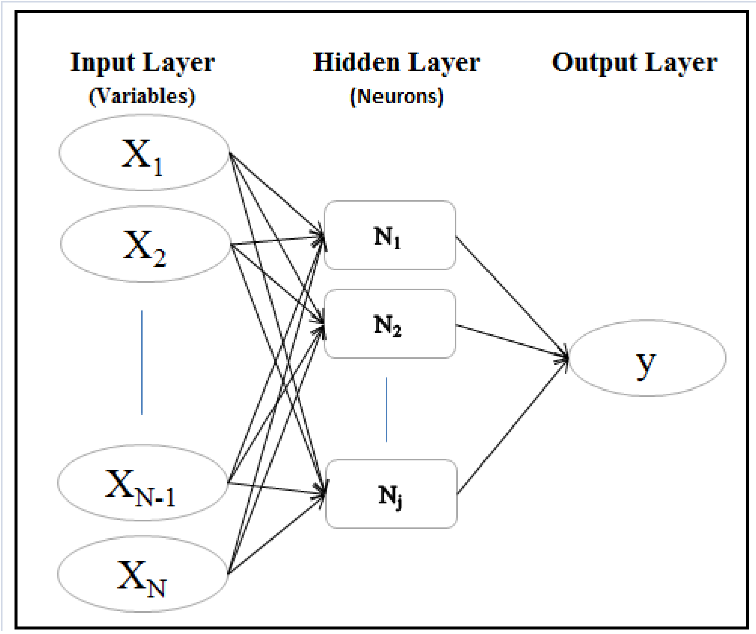
Neural networks consist of a large number of processing elements, known as neurons. At the input level they are represented by a weighted sum that is squashed by a non-linear function. The squashing function maps a set of input-output values by finding the best possible approximation to the function. This approximation is coded in the neurons of the network using weights that are associated with each neuron. The weights are calculated using a training procedure during which examples of input-output associations are successively exposed to the network. After each interaction, the weights are updated so that the network starts to mimic the desirable input-output behaviour. Due to its structure, the feed-forward neural network uses parallel processing to capture complicated non-linear relationships between the dependent and independent variables. The neural network is specified in equation (3.2.5) below:

$$y = v_0 + \sum_{j=1}^{NH} v_j \, g\,(w_j^T X) \qquad (3.2.5)$$

where X represents the inputs (explanatory variables), w_j is the weight vector for j^{th} hidden node, while $v_0, v_1, \ldots, v_{NH}$ are the weights for the output node and y is the output (dependent variable). The function g represents the hidden node output and, in this study, it is given in terms of the logistic and tangent sigmoid squashing functions.

Specifying the architecture of the net determines the network complexity and is a critical task in the process of fitting a neural network. If the network size is not adequately controlled, the network can easily overfit the data in-sample resulting in poor out-of-sample forecasts. Unfortunately, no clear rule has yet been developed for determining the optimal number of hidden nodes. Usually, the number of nodes is determined empirically through trial-and-error by selecting the number that produces the best in-sample result. In theory, a single hidden layer feed-forward neural network can approximate any nonlinear function to an arbitrary degree of accuracy with a suitable number of hidden neurons (White, 1992). Figure 3.2.2 illustrates the basic architecture of a single layer feed-forward neural network.

Figure 3.2.2 Neural network representation



A Feed-Forward Backpropagation Neural Network was selected for this study with one hidden layer and the choice of logistic-sigmoid and tangent-sigmoid activation functions. The models were trained using from one to a maximum number of thirty five neurons in the hidden layer. The following architectures achieved the best results in-sample and, therefore, were selected as the models.

M4 - 1 hidden layer, 10 neurons, logistic-sigmoid squashing (activation) function

M5 - 1 hidden layer, 3 neurons, tangent-sigmoid squashing function

M6 - 1 hidden layer, 4 neurons, tangent-sigmoid squashing function

In general, the models with the higher number of neurons resulted in over-specification in-sample and lower ability to forecast out-of-sample. Additionally, the tangent-sigmoid function performed slightly better and is represented in two of the three models. The scoring rule used to assert the best model between 70 combinations of activation functions and number of neurons in the hidden layer is the in-sample fit. All model architectures are trained in the first sub-sample of ten years of data. The above three models were used to forecast the takeover targets[*].

3.2.3 Forecast Combination

High levels of misclassification are of great concern when using probabilistic predictive models for takeover predictions. This is especially the case when costly Type II errors occur, that is, when non-targets are predicted to be targets. Practical experience has shown that the best model in-sample might not be the more accurate when forecasting future values. This gives rise to a main objective of this study which is to improve accuracy of the prediction of takeover announcements by introducing the methodology of probability forecast combinations. Although forecast combination has been proven to be an effective methodology in many other forecast applications, to our knowledge it has not been used to date in the takeover prediction literature.

The methodology consists of combining the predictions obtained from different forecasting models using an aggregation function. The forecast combination methodology accounts for the diversity of the underlying forecasting models, instead of being focused on the narrow specification from one model. Timmermann (2006) documented that

[*] More details about variables, scoring rule and samples are discussed later in section 3.3.

forecast combinations are often superior to their constituent forecasts. In our study, the combined forecast is the output of a function that gathers the results from a number of takeover prediction models using neural network and logistic modelling approaches as inputs. The utilization of the unique non-linear relationships between takeover targets and explanatory variables captured by each single output and used as inputs in the construction of a forecast combination represents the key difference of this methodology from that of a single model forecast.

The forecast combination method of choice for this study is the established KK Combination, given its flexibility to deal with logistic functions in its structure. It basically uses the output from single models as input into a combination function. The output of this model is a vector of combined forecasts. The method attributes weights (coefficients) to each of the inputs and, as pointed out in Kamstra, Kennedy and Suan (2001), the weights show the contribution of each corresponding forecast input to the final forecast. The key point in the determination of the weights is the choice of the combination function. In this study a logistic regression is used to determine the optimal weights to combine each forecast and, based on the model estimations, predict takeover targets one year ahead. This methodology was first presented in Kamstra and Kennedy (1998), and is known as KK Combination in the forecast combination literature. This is a simple methodology for combining forecasts in order to lessen bias. The main advantage of the methodology is that it confines the resulting forecasts to the unit interval while permitting unrestricted coefficient and intercept values. The KK methodology is specified in equation (3.2.6) below. It advocates the use of log-odds ratios as input to a logistic regression.

$$\mathrm{C_i} = \frac{\exp[\mathrm{cons} + \mathrm{W_1}\ln\left(\frac{\mathrm{M1_i}}{1-\mathrm{M1_i}}\right) + \mathrm{W_2}\ln\left(\frac{\mathrm{M2_i}}{1-\mathrm{M2_i}}\right) + \ldots + \mathrm{W_6}\ln\left(\frac{\mathrm{M6_i}}{1-\mathrm{M6_i}}\right)}{1-\exp[\mathrm{cons} + \mathrm{W_1}\ln\left(\frac{\mathrm{M1_i}}{1-\mathrm{M1_i}}\right) + \mathrm{W_2}\ln\left(\frac{\mathrm{M2_i}}{1-\mathrm{M2_i}}\right) + \ldots + \mathrm{W_6}\ln\left(\frac{\mathrm{M6_i}}{1-\mathrm{M6_i}}\right)} \qquad (3.2.6)$$

C_i is the probability of company i being taken over, cons is the intercept, while W1 to W6 are the weights for each input which are estimated by maximum likelihood from the logistic regression. The vectors M1 to M6 contain the probability forecasts from each specific model. M1, M2 and M3 represent vector of predicted probability forecasts from the logistic models, while M4, M5 and M6 refer to the probability forecasts from the neural network models, respectively. The result for all companies is found in the vector of combined forecasts, *C*. Overall, the aim behind the use of such a variety of models is to capture different non-linear relationships among the variables in order to improve the robustness of the forecast. The forecast combination literature typically assesses the out-of-sample accuracy of combinations whose weights have been determined in-sample. Maintaining that consistency, the logistic model is estimated by maximum likelihood and a hold-out period of one year is used to generate predictions out-of-sample.

3.2.4 Forecast Benchmark

As means of comparison, two benchmark methodologies are estimated. The first is commonly referred as Linear Combination. This form of regression is estimated by applying OLS to equation (3.2.7) below:

$$\mathrm{LC_i} = \mathrm{cons} + \beta_1 \mathrm{M1_i} + \beta_2 \mathrm{M2_i} + \ \ldots\ + \beta_6 \mathrm{M6_i} \qquad (3.2.7)$$

LCi represents the probability of company i being taken over, cons is the intercept, β1 to β6 are the coefficients for each input and, as before, the vectors M1 to M6 are the probability forecasts from each single model. It is suggested as a general form for a combination of point forecasts in Clements and Harvey (2011). However, this method does not ensure that the predicted output from the model lies in the unit interval.

The second methodology for comparison is the Chance Criterion. It basically calculates the probability of picking a takeover target by blindly selecting a stock listed on the ASX without any prior information about the company. Under this method all traded stocks are classified as targets and, consequently, all companies that were a takeover target on the period are considered correctly predicted targets. This is a very naive method that is used as bottom line for model useability in many takeover prediction studies, such as in Barnes(1999) and in Stevenson and Peat (2009). If a model is unable to outperform the Chance Criterion, the investor has a higher probability of selecting takeover targets by randomly picking stocks to include in the portfolio.

3.2.5 Cut-off probability

Typically, binary models generate a probability as output. This, in turn, requires the specification of a threshold probability (cut-off) to assess the classification accuracy of the models. This refers to the predicted probability of an acquisition offer being made for a specific firm within the prediction period. The specification of an optimal threshold probability (cut-off) allows the assessment of the classification accuracy for the model.

Before the discussion about the optimal cut-off probability it is important to define Type I and Type II errors in this context. The Type I error occurs when a firm is predicted to not become a takeover target when it does, while a Type II error occurs when a firm is predicted to become a target but does not become a target. The costs involved with both error types created some controversy in the literature, with Palepu (1986) assuming that the cost of these two types of errors are identical and Barnes (1999) suggesting that they should be weighted differently. Barnes (1999) proposes the minimisation of the Type I error in order to maximise returns from an investment in predicted targets. He considers that the cost of investing in the company which did not become a takeover target (Type I error) is greater than the cost of not investing in the company that became a takeover target (Type II error). Accordingly, the minimisation of Type I error is equivalent to the minimisation of the number of incorrectly predicted targets. It follows that, the optimal cut-off probability under the Barnes conjecture is to maximise the proportion of correctly predicted targets in a portfolio, or model accuracy.

Our choice was to classify the prediction from each model based on a cut-off probability that provides the highest proportion of correctly predicted targets in the estimation sample. This method in known as the Maximum Chance Criterion (MCC) and was first used by Barnes (1999). As Barnes explains, minimizing the total error probabilities in takeover predictions is not the same as minimizing the total error costs. This is because the loss functions of Type I and Type II errors are not symmetrical. He proposes that the appropriate cut-off point for the identification of takeover targets is the probability cut-off that maximises returns. This is determined by maximizing the estimated returns obtained from investing in takeover targets compared to investing in non-targets. The MCC recognizes that the penalty of misclassifying a target firm as a non-target (Type I error) is significantly larger than misclassifying a non-target as a target (Type II error).

The cut-off probability refers to the probability, ρ, that maximizes the ratio presented in equation (3.2.8) below. The maximization of this function, which measures the accuracy rate, is based on the assumption that the proportion of correctly predicted targets is directly related to the returns of the portfolio.

$$\text{Cut} - \text{off}(\rho) = \text{Max}\left\{\frac{\text{Correctly Predicted Targets}}{\text{Predicted Targets}}\right\} \qquad (3.2.8)$$

Any company with an assigned probability equal to or higher than the cut-off probability is classified as a takeover target. Deriving the cut-off probability using the Maximum Chance Criterion sets the threshold within the decision context of selecting a parsimonious number of predicted targets in the portfolio[†].

This research uses the best cut-off probability estimated in-sample to classify the out-of-sample forecast. The calculation of the optimal cut-off under the MCC methodology uses the ratio of the number of correctly predicted targets by predicted targets. A simple grid search from 0 to 1 in increments of 0.001 is used. The optimal cut-off probability is assessed by selecting the highest classification accuracy from the in-sample model fit. Firms with predicted probabilities of acquisition above the optimal cut-off are classified as potential targets and those with probabilities below the cut-off classified as non-targets. As the purpose of this study is to replicate the problem faced by a practitioner, unawareness of the actual outcomes of the prediction process is assumed by forecasting out-of-sample. As the forecast horizon is moved forward in time, the model generates new out-of-sample forecasts by updating the model parameter estimates in-sample.

[†] Other common score methods were tested in this research, such as the Brier score and the Logarithm Probability score. Although they generated similar accuracy results for the same set of probabilities, the number of predicted targets was considerably larger causing increased costs in managing a portfolio of stocks.

3.3 Data

3.3.1 Hypothesis and Variables

Earlier studies in the field centred on motivations for corporate mergers and acquisitions. As a consequence, the use of operational and financial characteristics of target firms, along with accounting and market data, has become common place in recent studies. Literature on the Market for Corporate Control presumes that targets can be forecasted using mainly publicly available data. Barnes (1998) expressed the view that, while these events cannot normally be predicted, some of them may at least be anticipated. Earlier studies centred on motivations for corporate mergers and acquisitions and used operational and financial characteristics of target firms, along with accounting and market data to identify and predict takeover events. From the several theories purported to explain firm acquisition, eight main hypotheses have been formulated. The variables explained below and used in takeover target prediction models point to these motivations.

The resultant number of variables is thirty five and the full list of hypotheses with their respective proxy variables are described below.

H1: Inefficient Management

This hypothesis is based on the Market for Corporate Control theory that states that inefficiently managed firms will be acquired by more efficient firms to increase capital gains. Therefore, companies managed inefficiently are more susceptible to poor performance and acquisition. Accordingly, the explanatory variables suggested as proxies for this hypothesis include:

V1 – ROA: Return on Assets (EBIT / Total Assets - Outside Equity Interests);

V2 – ROE: Return on Equity (Net Profit After Tax / Shareholders Equity - Outside Equity Interests);
V3 – EBIT (Earnings Before Interest and Taxes) / Operating Revenue;
V4 – Dividend/Shareholders Equity;
V5 – Asset Turnover (Net Sales/Total Assets);
V6 – Growth in EBIT over past year;
V7 – Growth in EBIT over past three years;
V8 – Growth of 1 year Total Assets;
V9 – Growth of 3 year Total Assets;
V10 – Inventory / Working Capital;
V11 – Inventory / Total Assets;
V12 – Net profit / Market Value.

H2: Undervaluation

There is consistent agreement across most studies that the greater the level of undervaluation, the greater the likelihood a firm will be acquired. Undervalued stocks are seen as a bargain in the market, especially from overvalued entities. The explanatory variables suggested by this hypothesis are:

V13 – Market to Book ratio (Market Value of Securities / Net Assets);
V14 – Market Capitalisation / Total Assets.

H3: Price to Earnings Ratio

The price-to-earnings (P/E) ratio is closely linked to the undervaluation and inefficient management of a company. The earnings of a firm with low P/E ratio will be valued at the multiple of the acquirer, allowing an immediate gain to be realised. Consequently, a high P/E ratio will decrease the likelihood of acquisition. Thus, the P/E ratio is a likely candidate for inclusion in models.

V15 – Price/Earnings Ratio.

H4: Growth Resource Mismatch

Acquisition will create opportunities for a better allocation of the target firm resources to generate profitable investments. Firms which possess low growth / high resource combinations or, alternatively, high growth / low resource combinations will have an increased likelihood of acquisition. However, the explanatory variables used to examine this hypothesis capture growth and resource availability separately. The following explanatory variables suggested by this hypothesis are:

V16 – Growth in Sales (Operating Revenue) over the past year;
V17 – Growth in Total Sales over 3 years;
V18 – Capital Expenditure / Operating Revenue;
V19 – Quick Assets (Current Assets – Inventory) / Current Liabilities;
V20 – Invested Capital Turnover;
V21 – Long Term Asset Turnover;
V22 – Working Capital Turnover.

H5: Dividend Payout

The behaviour of some firms to pay out less of their earnings in order to maintain enough financial slack (retained earnings) leads to higher growth potential and, consequently, market value. It is assumed that low payout ratios will lead to an increased likelihood of acquisition. The explanatory variables suggested by this hypothesis are:

V23 – Dividend Payout Ratio;
V24 – Dividend Yield;
V25 – Dividend per share / Earnings per share.

H6: Inefficient Financial Structure

Rectification of capital structure problems is a motivation for takeovers given that increases in debt demands more return on equity. High leverage will lead to increased likelihood of acquisition. The explanatory variables for this hypothesis are:

V26 – Net Interest Cover (EBIT / Interest Expense);
V27 – Net Debt/Cash Flow;
V28 – Growth in Net Debt over past 1 year;
V29 – Growth in Net Debt over past 3 years;
V30 – Current Assets/Current Liabilities.

H7: Merger and Acquisition Activity

This hypothesis is proposed in this thesis given the strong bias of the trading on large companies and most investments concentrated on the highly traded companies in the Australian market. The more important industry sectors in the economy and the most traded companies will attract more investments and, as a result, create more opportunities for mergers and acquisitions. The use of a dummy variable for the mining industry was a natural choice given its significant representation in the sample of takeover announcements. The explanatory variables for this hypothesis are:

V31 – Industry Dummy variable for companies from the mining industry;
V32 – Dummy variable indicating company listing on the ASX300 in that year. The ASX300 is and index that incorporates the top 300 listed on the ASX.

H8: Size

There are two rationales underlying this hypothesis. The first states that smaller firms will have a greater likelihood of acquisition because larger firms are generally exposed to fewer bidding companies with sufficient resources to acquire them. In that case it follows that there is a negative effect of size on the probability of acquisition. The second proposes a positive relationship between size and takeover likelihood. It is based on the assumption that managers would prefer larger, rather than smaller, acquisitions to increase the size of the company. Both lines of argument are tested using the variables below. The second rationale prevails in the model estimations with the variables' coefficients assuming positive coefficients in all samples.

V33 – Log (Total Assets);
V34 – Market Capitalisation;
V35 – Sales and Revenues.

The descriptive statistics from the 35 variables used to estimate the models are reported in Appendix A.1.

3.3.2 Sample

The complex relationships between all variables listed in each of the hypotheses is assumed to provide the ability to discriminate between takeover target and non-target firms, and to predict future outcomes. These variables were collected at the firm level, as well as from within industry and market categories. The correlation matrix and the variance inflation factor (VIF) analysis are reported in Appendix A.1

The main sources used to collect the financial and corporate information are the AspectHuntley and Connect4 databases. The first database contains published available financial information from all listed companies in Australia, including industry classification and a complete list of financial variables and ratios. Connect4 complements the data set with historical records of takeover bids, including their respective dates and details of transactions.

The collected sample includes financial data from all listed companies on the Australian Stock Exchange (ASX) for 13 years, spanning the financial years from 1999 to 2011. It includes their respective accounting, market and historical takeover data. The dataset is divided into 12 panels, each corresponding to one financial year. The Financial Year (FY) in Australia extends from the first of July of the previous year until the 30th of June of the year under consideration. For example, the FY09 refers to the period from 01/07/2008 to 30/06/2009. A few companies have the financial year-end on different dates. On these specific cases the last available data was used for the Financial Year, but the forecast period is the same for all companies. One of the main objectives of this research is the determination of a methodology that is efficient for more than one period. Therefore, the dataset is divided into three sub-samples to allow for the verification of model stability in distinct economic environments.

The first sample forecasts takeover targets during the financial year 2009 using an in-sample panel from FY99 to FY08. This out-of-sample period happens to coincide with the market depreciation related to the Global Financial Crisis (GFC). The second sample has the financial years from 1999 until 2009 used as estimation period and the FY10 as the forecasting period. The out-of-sample period is considered a period of recovery from the GFC. The last sample uses twelve years to estimate the model, from FY99 to FY10, and forecast takeovers during FY11, a regular year for the Australian market. The out-of-sample data was used to evaluate takeover forecast accuracy based on the estimation and cut-off probabilities from their respective in-sample periods. Figure 3.3.1 diagrammatically depicts the sample division and in Table 3.3.1 reports the number of observations in each sample.

Figure 3.3.1 The three sub-samples

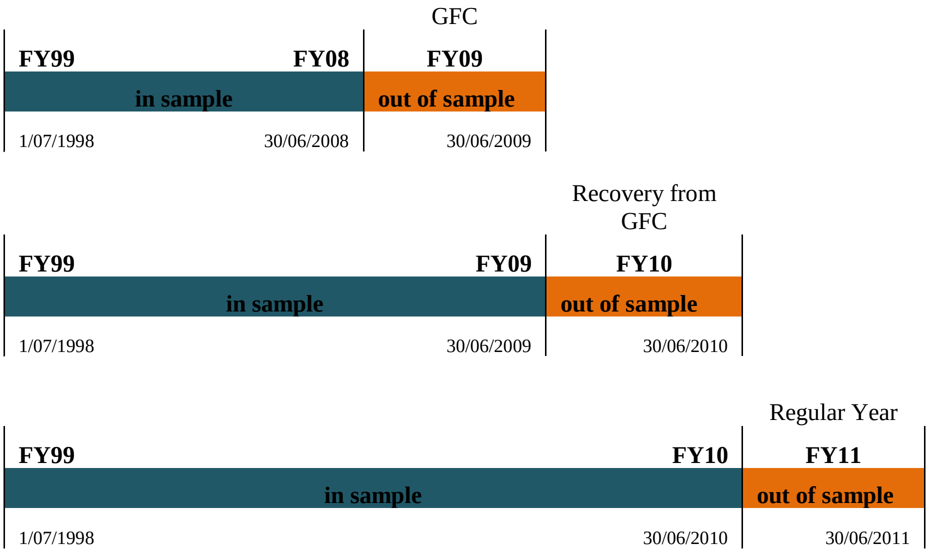


Table 3.3.1 Sample size in each sub-sample

Out-of-sample	**FY09**	**FY10**	**FY11**
Takeover Targets	57	75	94
Observations	1948	1924	1949
In-sample	**FY99 - FY08**	**FY99 - FY09**	**FY99 - FY10**
Takeover Targets	566	623	698
Observations	14132	16080	18004

Over the three subsequent out-of-sample periods the biggest change is noted in the number of takeover targets, while the numbers of observations remain reasonably the same. As expected, the in-sample number of observations used to estimate the model increases from 14132 in the first estimation period to 18004 in the last.

3.4 Results

The results from this study are reported in two interrelated sections. The first section analyses the performance of the individual and combined forecasts at predicting takeover announcements. The second section is concerned with assessing the economic usefulness of portfolios made up of predicted targets from the single models and combined forecasts. While the analysis of the final models is of theoretical interest, the primary aim of this chapter is to evaluate their classification accuracy and its economic usefulness. For that reason this chapter concentrates on the outcomes from the research while the estimation analysis and the outputs from all models are available in Appendix A.2.

All three logistic models in this subsection (M1, M2, and M3) are estimated by maximum likelihood. The selected logit models are the result of elaborate model search/specification procedures. In each case the best variables from the list of 35 candidates were selected. Although all the proposed variables are tested, not all variables were used in the final specification of each model. The selection of variables was done following a backward stepwise procedure during model estimation in-sample. This involves starting with all candidate variables and testing the deletion of each variable based on its significance level in the model. Only variables with a p-value lower than 0.2 stayed in the model and were used to generate the predictions out-of-sample. Consequently, each model specification, and year, will be based on a different set of variables.

Even though a neural network can yield a set of coefficients, it cannot provide logical descriptions, or cause-effect relationships. As a consequence all variables suggested in the hypotheses H1 to H8 are used to train the neural networks and generate the predictions one year ahead. The use of neural network models requires the division of the sample of companies into three parts: a training set, a validation set, and a prediction set. These sub-samples are selected by grouping a large part of the sample in the training set, validating the model during one year, and predicting takeover targets one year ahead (out-of-sample). This experimental design intends to facilitate a comparison of the results with the logistic models, which also have a one year forecast horizon, by allowing for the production of forecast combinations of all models at a later stage.

Therefore, all models are estimated over the entire sample, with the last year used as a hold-out period to create the forecast out-of-sample. For example, the last sample uses data from financial years 1999 to 2010 to estimate the model parameters and forecasted takeover targets for 2011(out-of-sample).

3.4.1 Performance Analysis

The accuracy rate is the only score rule used to measure the performance of the individual classification models and the forecast combination method. It is calculated by taking the ratio of the number of correct predictions to the number of predicted takeover targets in each sample. The better the predictive power of a model, the higher is the ratio. In fact it estimates the percentage of observations that a model predicts correctly.

Since the interest is in forecasting, the out-of-sample results will drive the conclusions. The results of both in-sample and out-of-sample forecasts are available in the next tables. All seven models were estimated over the three time periods to verify the model's stability over the years. The optimal in-sample cut-off probability was used to derive the out-of-sample forecasts. Tables 3.4.1, 3.4.2 and 3.4.3 present the accuracy rate in-sample and out-of-sample for the logistic models (M1 to M3) and the neural network models (M4 to M6). The lines indicating Classified Targets contain the number of predicted target companies from each model for both in-sample and out-of-sample periods. Similarly, The Correctly Classified lines refers to the number of successfully predicted takeover offers, while the Incorrectly Classified lines contains the number of misclassified companies for each model. Table 3.4.1 contains the single model results for the period between FY99 and FY09.

Table 3.4.1 Model Accuracy: FY99 - FY09

Sample 1999-2009	*Logistic Models*			*Neural Network Models*		
	M1	**M2**	**M3**	**M4**	**M5**	**M6**
Out-of-sample: 2009						
Classified Targets	23	14	25	26	27	15
Correctly Classified	3	2	3	2	2	2
Incorrectly Classified	20	12	22	24	25	13
Accuracy Out-of-sample	**13.04%**	**14.29%**	**12.00%**	**7.69%**	**7.41%**	**13.33%**
In-sample: 1999-2008						
Classified Targets	190	286	653	138	147	51
Correctly Classified	78	98	220	26	32	16
Incorrectly Classified	112	188	433	112	115	35
Accuracy In-sample	41.05%	34.27%	33.69%	18.84%	21.77%	31.37%

Table 3.4.2 contains the single model results for the period between FY99 and FY10.

Table 3.4.2 Model Accuracy: FY99 - FY10

Sample 1999-2010	*Logistic Models*			*Neural Network Models*		
	M1	**M2**	**M3**	**M4**	**M5**	**M6**
Out-of-sample: 2010						
Classified Targets	42	47	40	30	40	36
Correctly Classified	5	3	3	3	5	4
Incorrectly Classified	37	44	37	27	35	32
Accuracy Out-of-sample	**11.90%**	**6.38%**	**7.50%**	**10.00%**	**12.50%**	**11.11%**
In-sample: 1999-2009						
Classified Targets	315	840	1177	192	378	290
Correctly Classified	117	230	342	20	51	21
Incorrectly Classified	198	610	835	172	327	269
Accuracy In-sample	37.14%	27.38%	29.06%	10.42%	13.49%	7.24%

Table 3.4.3 contains the single model results for the period between FY99 and FY11.

Table 3.4.3 Model Accuracy: FY99 - FY11

Sample 1999-2011	*Logistic Models*			*Neural Network Models*		
	M1	**M2**	**M3**	**M4**	**M5**	**M6**
Out-of-sample: 2011						
Classified Targets	34	87	166	42	33	40
Correctly Classified	4	7	12	7	6	5
Incorrectly Classified	30	80	154	35	27	35
Accuracy Out-of-sample	**11.76%**	**8.05%**	**7.23%**	**16.67%**	**18.18%**	**12.50%**
In-sample: 1999-2010						
Classified Targets	253	1411	2587	411	211	327
Correctly Classified	53	321	559	34	62	37
Incorrectly Classified	200	1090	2028	377	149	290
Accuracy In-sample	20.95%	22.75%	21.61%	8.27%	29.38%	11.31%

From the group of logistic models (M1 to M3), it is noted that an increase in model complexity does not necessarily result in better forecasts. From Tables 3.4.1 and 3.4.2, the standard logistic specification (M1) has a greater level of accuracy than the more complex mixed and crossed effects models (M2 and M3, respectively) in the first two in-sample estimation periods. However, this characteristic is reversed somewhat in the third in-sample estimation period (see Table 3.4.3). The simplest model of all, the logistic regression (M1), was the more consistent out-of-sample and has the more accurate forecast for the financial years 2010 and 2011 among the panel data models. For 2009, however, the mixed model, M2, with an accuracy rate of 14.29% is preferred. As expected, the accuracy levels are reduced markedly for the logistic models in the out-of-sample periods.

In the neural network cases (M4 to M6), the three specifications that produced the best results in-sample were selected to predict one year ahead. When comparing the models M4 to M6, in the first period, FY09, the M6 model (one hidden layer and four neurons) performed best both in-sample and out-of-sample, with a accuracy rate of 31.37% and 13.33% respectively (see Table 3.4.1). The M5 model outperforms the other two neural network models in FY10 and FY11 with the highest level of accuracy of all single models for both periods (see Tables 3.4.2 and 3.4.3) with rates of 12.50% (FY10) and 18.18% (FY11) out-of-sample.

Overall, all models produced good forecasts, with the neural network models outperforming the logistic models out-of-sample in most cases, especially following the financial crises that hit during the financial year 2009. As expected, the levels of in-sample accuracy are reduced markedly for the out-of-sample periods. The highest level of accuracy out-of-sample is achieved by the panel data logistic with mixed effects (M2) in FY09 (14.29%) and the neural network with three neurons and tangential-activation function (M5) in FY10 (12.5%) and FY11 (18.18%). The in-sample results are slightly different with the basic logistic model (M1) doing better than the others in the first two samples (41.05% and 37.14% respectively), and M5 exceeding all models in Table 3.4.3 (29.38%). In line with the empirical literature, the results confirm that the neural network models appear to have an advantage over the logistic models, but at the cost of more complexity.

The model performance is extremely dependent on the market condition for each specific year. The market dynamics are visibly affected by periods of crises, such as the GFC in FY09, and affect the non-linear interaction between the variables. The changes in market dynamics from year to year provide a reasonable explanation to why the literature has been unable to find the best model to forecast takeover targets up to this point. Consequently, the replication of the same methodology in other periods and markets may not produce as good results consistently. In fact, the result of this study suggests there is no single model that can adapt to such strong changes in the economy and continue to generate as stable and accurate forecasts.

While theory offers assistance in the choice of explanatory variables, no single forecasting method consistently dominates the takeover prediction literature. Given the same data set, each model has different underlying assumptions and, therefore, assigns different probability estimates to each company. What is further investigated in this study is whether combining these different predictions can result in better forecasts than those offered by the individual models. The KK Combination method takes into consideration the vector of predicted probabilities from each single model to estimate the combined forecast C1. Again, the best in-sample cut-off probability was used to derive the best out-of-sample forecast. The results from the KK Combination model are reported in Tables 3.4.4, 3.4.5 and

3.4.6. The tables also contain the benchmark methods, Linear Combination and Chance Criterion. The lines indicating Classified Targets contain the number of predicted target companies from each model for both in-sample and out-of-sample periods. Similarly, The Correctly Classified lines refers to the number of successfully predicted takeover offers, while the Incorrectly Classified lines contain the number of misclassified companies for each method.

The Table 3.4.4 contains the forecast combination results for the period between FY99 and FY09.

Table 3.4.4 KK Combination Accuracy: FY99 – FY09

Sample 1999-2009	***KK Combination***	*Benchmark*	
		Linear Combination	Chance Criterion
Out-of-sample: 2009			
Classified Targets	19	87	1948
Correctly Classified	3	3	57
Incorrectly Classified	16	84	1891
Accuracy Out-of-sample	**15.79%**	**3.45%**	**2.93%**
In-sample: 1999-2008			
Classified Targets	457	238	14132
Correctly Classified	174	12	566
Incorrectly Classified	283	226	13566
Accuracy In-sample	38.07%	5.04%	4.01%

Table 3.4.5 contains the forecast combination results for the period between FY99 and FY10.

Table 3.4.5 KK Combination Accuracy: FY99 – FY10

Sample 1999-2010	***KK Combination***	*Benchmark*	
		Linear Combination	Chance Criterion
Out-of-sample: 2010			
Classified Targets	40	137	1924
Correctly Classified	9	11	75
Incorrectly Classified	31	126	57
Accuracy Out-of-sample	**22.5%**	**8.03%**	**3.90%**
In-sample: 1999-2009			
Classified Targets	374	448	16080
Correctly Classified	146	18	623
Incorrectly Classified	228	430	57
Accuracy In-sample	39.04%	4.02%	3.87%

Table 3.4.6 contains the forecast combination results for the period between FY99 and FY11.

Table 3.4.6 KK Combination Accuracy: FY99 – FY11

Sample 1999-2011	***KK Combination***	*Benchmark*	
		Linear Combination	Chance Criterion
Out-of-sample: 2011			
Classified Targets	18	168	1949
Correctly Classified	6	6	94
Incorrectly Classified	12	162	57
Accuracy Out-of-sample	**33.33%**	**3.57%**	**4.82%**
In-sample: 1999-2010			
Classified Targets	110	563	18004
Correctly Classified	42	30	698
Incorrectly Classified	68	533	57
Accuracy In-sample	38.18%	5.33%	3.88%

Except for the logistic model M1 in the first estimation period, the in-sample estimation of C1 was more accurate than the other logistic and the neural network models. It was also more stable over the years, with an accuracy rate of around 38% for the three in-sample periods. However, it was in the out-of-sample forecasts that the KK Combination model particularly distinguished itself from the single models. Its forecast accuracy was constantly higher than any other model in the three periods, achieving accuracy of 15.79% (2009), 22.50% (2010) and 33.33% (2011) and beating the best single model in each sample.

The KK method resulted in better predictive accuracy out-of-sample than the single models in the first forecast period (2009) when the financial crisis had taken hold of stock markets world-wide. The forecast accuracy in FY10 is 22.5%, 10% higher than the best single model, whilst the forecast combination predicted 6 takeover targets correctly out of 18 in FY11, an accuracy rate of 33.33%. These high rates are accompanied by reasonably small predicted portfolios compared to other studies. The only exception is FY10 where the predicted sample is more than double the size of the previous period FY09 in Table 3.4.4. It only reflects the uncertainty incorporated in the in-sample period when the period of the crisis is reflected in the model estimation. The crisis does not have the same impact in FY11 because the in-sample period comprises FY10, diluting its effect. The forecast accuracy from the KK Combination was also considerably higher than the benchmark methods, including the Linear Combination of forecasts. Appendix A.3 contains the statistical test for equality of proportions among the accuracy rates presented in Table 1. It confirms that the accuracy rates achieved out-of-sample by the KK Combination model are statistically significant.

Consistent with the literature, the forecast combination is more accurate than the single models both in-sample and out-of-sample across the different estimation periods. It is important to note that the forecast from the KK Combination model is still vulnerable to market changes, as observed by the increase in the out-of-sample accuracy and the larger number of predicted targets in FY10. Nevertheless, the aggregation of the forecasts using an underlying function provides stability in the estimations by auto-weighting the more stable and accurate models to take part in the combined forecast. The combination method also produced a parsimonious portfolio selection, which is important to minimize Type I error and keep transaction costs to a minimum. Due to the effect of transaction costs on returns, practitioners would be likely to limit themselves to smaller portfolios.

Overall, these results indicate high model classification ability. This is expected given that all regressors in the KK Combination estimation have reasonable prediction accuracy. Further, all models classified targets significantly better than chance on an individual basis. These results suggest that the use of forecast combination is appropriate for the prediction of takeover targets in the Australian context. The KK Combination model significantly outperformed the other models for predictive purposes, as well as being parsimonious with the number of predicted targets. The use of this methodology reduced the misclassification error and the level of forecast accuracy from the combined model in FY10 and FY11 and is higher than any similar published study in the area of takeover prediction. More importantly, the model is robust enough to achieve good results under diverse economic environments using the full population of listed companies each year.

These results contest the claims of Barnes (1999) and Palepu (1986) that models cannot be implemented that achieve predictive accuracies greater than chance. On the other hand, it is consistent with the forecast literature showing that the forecast combination using the KK Combination method is generally more accurate than the single models and the Linear Combination. The results from the KK Combination approach are stable across the different estimation periods both in-sample and out-of-sample. It further confirms the results of studies such as Kamstra and Kenedy (1998) and Kamstra, Kennedy and Suan (2001), that propose forecast combination using weights to enhance the performance of single models.

3.4.2 Economic Analysis

Although the above methodology provides us with a statistical assessment of model performance, it has nothing to say about the economic usefulness of the model. To make an assessment of the financial gains from our modelling approach, the predicted targets from the combined prediction models was used to create an equally weighted portfolio. Using this approach it is possible to measure whether the KK Combination model for predicting takeover targets was able to earn abnormal returns. The investment strategy consists of adopting a one year buy-and-hold approach for the portfolio made up of the out-of-sample predictions from the KK Combination model. The methodology consists of simulating buying the stock on the first day of the financial year and selling it on the last day. But there are cases where companies in the predicted portfolios are delisted from ASX before the year ends because they became a takeover target and the takeover is successful. In these cases it was assumed that the investor will take its position in cash and will reinvest the capital at the risk free rate until the end of the financial year. The risk free rate used is the Australian 10 year Treasury bond yield.

The returns from the portfolio of predicted takeover targets are calculated for the three out-of-sample periods, financial years 2009, 2010 and 2011, by simulating a buy-and-hold strategy. It is assumed that an investment is made on each company from the predicted portfolio in equal capital proportions for a period of one year. In addition, the returns for the predicted target companies have been adjusted by dividends and capitalization changes. Although I recognise that the use of a portfolio optimization method can improve the investment results, the use of such techniques would deviate from the main objective of the thesis. Palepu (1986) and Walter (1994) also implemented an equally weighted portfolio technique to assess whether their predictions of takeover targets were able to earn abnormal returns.

The results are presented in Tables 3.4.7, 3.4.8 and 3.4.9. The numbers of companies in the portfolios are the same as previously for the logistic and neural network cases namely 19 for 2009, 40 for 2010, and 18 for 2011. The returns from the portfolio are calculated for the three out-of-sample years since the first day of the financial year based on a buy-and-hold strategy. It provides the returns for each month. The first column shows the returns for the portfolio of predicted targets using the KK Combination model. The results in the second column represent the Cumulative Abnormal Return (CAR) of the portfolio since the first day of each financial year at monthly intervals relative to the market benchmark index All Ordinaries. The numbers in the third and forth columns represent the returns on two market benchmark indexes returns for the same period[‡].

During the financial year 2009, Table 3.4.7 reveals that the returns of the predicted portfolio was similar to what the market experienced. At the end of the year there was virtually no abnormal return when compared to the All Ordinaries (All Ords) index, with a

[‡] The All Ordinaries (All Ords) is an accumulation index that contains over 300 highly capitalized ordinary shares listed on the Australian Securities Exchange. In addition, the ASX 300 index is an accumulation market-capitalization weighted and float-adjusted stock market index of the top 300 Australian stocks listed on the ASX from Standard & Poors.

CAR of 0.74%. In fact, during three months the portfolio of predicted targets is performing worse than both indexes.

Table 3.4.7 Out-of-sample returns for the portfolios of predicted targets using the KK Combination model, FY09

FY09	*KK combination*		*Market Benchmark*	
	C1	**CAR**	**ALL ORDS**	**ASX300**
Portfolio	**19 Companies**			
31-Jul-08	-2.50%	2.75%	-5.26%	-4.70%
31-Aug-08	-7.27%	-5.07%	-2.20%	-1.70%
30-Sep-08	-16.85%	-3.69%	-13.16%	-12.04%
31-Oct-08	-22.00%	3.32%	-25.32%	-23.42%
30-Nov-08	-29.46%	1.68%	-31.13%	-28.73%
31-Dec-08	-33.19%	-1.81%	-31.38%	-29.03%
31-Jan-09	-29.74%	5.04%	-34.78%	-32.46%
28-Feb-09	-32.52%	5.65%	-38.18%	-36.19%
31-Mar-09	-30.18%	3.59%	-33.76%	-31.60%
30-Apr-09	-29.75%	0.03%	-29.78%	-27.72%
31-May-09	-25.88%	2.62%	-28.49%	-26.93%
30-Jun-09	**-25.23%**	**0.74%**	**-25.97%**	**-24.34%**

Despite the higher predictive accuracy of the KK Combination model, losses in downturn periods are not necessarily reduced when compared to the benchmark indexes. Nonetheless, the results for the financial years 2010 and 2011, as depicted in Tables 3.4.8 and 3.4.9, indicate that combining the predictions by KK Combination, not only improves the forecast accuracy but almost doubles the average market return. The final portfolio returns for the financial years 2010 and 2011 are 15% and 14.53%, respectively. It represents an abnormal return of 5.45% for FY10 and 6.78% for FY11 when compared to the All Ords index. It achieved even better results when compared to the ASX300 index.

Table 3.4.8 Out-of-sample returns for the portfolios of predicted targets using the KK Combination model, FY10

FY10	*KK combination*		*Market Benchmark*	
	C1	**CAR**	**ALL ORDS**	**ASX300**
Portfolio	**40 Companies**			
31-Jul-09	7.61%	-0.03%	7.64%	7.33%
31-Aug-09	18.06%	4.47%	13.58%	13.37%
30-Sep-09	25.97%	5.92%	20.05%	20.09%
30-Oct-09	31.92%	14.22%	17.71%	17.56%
30-Nov-09	27.66%	8.22%	19.45%	19.07%
31-Dec-09	29.20%	5.51%	23.68%	23.29%
29-Jan-10	28.72%	12.28%	16.44%	15.68%
26-Feb-10	24.11%	6.30%	17.82%	17.28%
31-Mar-10	32.52%	8.57%	23.94%	23.29%
30-Apr-10	36.12%	13.68%	22.44%	21.61%
31-May-10	20.01%	7.20%	12.81%	12.02%
30-Jun-10	**15.00%**	**5.45%**	**9.55%**	**8.72%**

Table 3.4.9 Out-of-sample returns for the portfolios of predicted targets using the KK Combination model, FY11

FY11	*KK combination*		*Market Benchmark*	
	C1	**CAR**	**ALL ORDS**	**ASX300**
Portfolio	**18 Companies**			
31-Jul-10	3.99%	-0.24%	4.22%	4.47%
31-Aug-10	4.72%	2.08%	2.64%	2.48%
30-Sep-10	9.25%	2.03%	7.22%	6.81%
30-Oct-10	17.31%	7.86%	9.45%	8.70%
30-Nov-10	17.64%	9.51%	8.13%	7.03%
31-Dec-10	18.18%	6.10%	12.07%	10.90%
29-Jan-11	15.25%	3.10%	12.14%	11.01%
26-Feb-11	23.83%	10.01%	13.82%	12.80%
31-Mar-11	19.90%	5.94%	13.96%	12.97%
30-Apr-11	16.60%	2.09%	14.51%	13.77%
31-May-11	14.94%	4.20%	10.73%	9.87%
30-Jun-11	**14.53%**	**6.79%**	**7.75%**	**7.34%**

In fact, the returns of the KK Combination method are significantly higher than the market performance over the last two out-of-sample periods, and also on a month-by-month basis. Importantly, this positive economic result is achieved through the combination method resulting in reasonably sized portfolios. This has the added advantage of reducing the risk of investing in incorrectly predicted targets. Interesting facts are the jumps in CAR on a monthly basis on the three out-of-sample periods. Not accidentally, these increases happen in the months where takeover offers were announced on companies from the portfolio. The numbers can easily be matched to the announcement dates shown on the next three tables.

While impressive in themselves, it should be recognised that these results could have been potentially driven by actual non-target firms within the portfolio of predicted targets. This would suggest that the abnormal returns in FY10 and FY11 were partly the result of the selection of over-performing non-target firms, rather than an accurate selection of target firms. The answer to this particular issue is in Tables 3.4.10, 3.4.11 and 3.4.12. Each table contains the average returns split by the sub-groups of correctly predicted targets and misclassified targets (non-targets) for each out-of-sample period. In spite of this, it is should be remembered that the portfolios have been formed using models that are designed to predict companies with a minimal misclassification rate.

From Table 3.4.10 it can be seen that the portfolio for the first prediction period contains 19 predicted target firms of which 3 actually became targets. While this is a good result per se, it is necessary to quantify the economic benefit from improving the model accuracy. The average losses for the non-target companies over FY09 were greater than the return of the actual targets, -25.82 against -22.08 respectively. The actual targets performed slightly better than the majority of the stocks and pushed the average result up.

Table 3.4.10 Returns by company, FY09

FY09				
Predicted Targets 19 Companies		**Buy and Hold Return**	**AVERAGE RETURN**	Announcement
Target	**LST**	**-27.32%**	**-22.08%**	24/06/2009
	QGC	**7.08%**		28/10/2008
	TPX	**-46.00%**		10/10/2008
non-target	**BEN**	**-36.41%**	**-25.82%**	
	CBH	**-42.11%**		
	CHQ	**-44.79%**		
	CIF	**-45.45%**		
	CNP	**-62.04%**		
	FLT	**-48.11%**		
	GPT	**-21.17%**		
	IPN	**1.92%**		
	MMX	**-43.05%**		
	NXS	**-33.23%**		
	QAN	**-33.88%**		
	REA	**35.84%**		
	SBM	**-36.99%**		
	SGB	**2.18%**		
	SST	**27.12%**		
	VBA	**-32.98%**		
Portfolio			**-25.23%**	

In contrast with the previous year, the financial year 2010 is characterised by a period of recovery from the global financial crisis, as shown in Table 3.4.11. Although the predicted sample is double the size of the previous period that reflects the uncertainty when the GFC's year is incorporated in the in-sample period, the high predictive accuracy certainly contributes to the high portfolio return. The 9 actual targets show an average return of 61.56%, what is considerably higher than the 1.48% return achieved by the 31 non-targets.

Table 3.4.11 Returns by company, FY10

FY10				
Predicted Targets 40 Companies		Buy and Hold Return	AVERAGE RETURN	Announcement
Target	AOE	36.62%	61.56%	22/03/2010
	CKT	154.88%		9/12/2009
	ERC	-52.40%		14/09/2009
	FLX	19.08%		14/08/2009
	LGL	46.10%		29/03/2010
	LLP	231.52%		28/09/2009
	PLI	75.00%		3/09/2009
	SSI	-58.04%		1/09/2009
	TKA	101.28%		8/02/2010
non-target	AAY	-61.54%	1.48%	
	AEM	0.00%		
	ANZ	31.05%		
	AQF	21.60%		
	AZO	-4.24%		
	CBZ	-26.39%		
	CDU	82.17%		
	CFE	1.56%		
	CSL	1.34%		
	CWK	51.06%		
	CXC	18.26%		
	EQX	-22.22%		
	HDI	0.00%		
	KMD	-1.76%		
	MDL	51.61%		
	MOO	-8.33%		
	MQA	3.26%		
	PTN	-48.24%		
	RMR	40.00%		
	ROB	-46.15%		
	RUL	-23.08%		
	RVE	127.27%		
	SHU	-10.00%		
	SNE	-20.00%		
	SOI	-44.44%		
	TBI	-32.69%		
	VGM	-25.00%		
	VIP	0.00%		
	WBC	4.84%		
	WCR	-21.95%		
	WIG	8.02%		
Portfolio			15.00%	

Table 3.4.12 Returns by company, FY11

		FY11		
Predicted Targets 18 Companies		Buy and Hold Return	AVERAGE RETURN	Announcement
Target	AKR	-6.33%	43.05%	22/11/2010
	ASX	4.42%		25/10/2010
	CRG	28.94%		15/12/2010
	DKN	41.07%		27/06/2011
	IIF	42.67%		23/12/2010
	JML	147.54%		9/02/2011
non-target	API	-28.21%	0.27%	
	CER	109.38%		
	CNP	-72.59%		
	DUE	5.26%		
	DXS	14.29%		
	EXT	19.08%		
	MDL	-39.57%		
	OMH	-37.20%		
	RIO	24.50%		
	SPN	23.53%		
	TAP	-2.92%		
	TPM	-12.24%		
Portfolio			14.53%	

The FY11 results in Table 3.4.12 only confirms that the high average returns is directly related to model accuracy. From the portfolio of 18 predicted target companies, the 6 actual targets achieved 43.05% return while the other two third of the sample had an average of only 0.27% of return. Once more the actual targets contributed significantly to the high portfolio returns.

Overall, the combination of forecasts appears to be an efficient technique to both improve the accuracy of takeover prediction and to achieve abnormal returns. The KK Combination method appears to be very stable across years and parsimonious for portfolio selection. The mixture of panel data logistic and neural network models has proved to be a good choice to capture and combine information from a range of different models in order to achieve abnormal returns.

3.5 Conclusion

Forecasts of events based on economic and financial variables that take the form of probabilities are becoming increasingly common. There is an extensive literature suggesting that forecast combination approach can improve on the individual forecasts. This chapter evaluates whether combining probability forecast methods for the prediction of takeover targets forms a consensus forecast that improves prediction accuracy and generates abnormal returns from the portfolios comprised of the predicted companies. The combination method used provides evidence in favour of good and consistent forecast accuracy. This is achieved when predicting potential takeover targets using forecast combinations from a number of panel data logistic and neural network models. Furthermore, the combination model results are consistent over time, confirming the robustness of such methodology to reduced misclassification error, an important consideration in takeover prediction.

Overall, all models produced forecasts considerably better than chance, with the KK Combination method outperforming the neural network and the logistic models out-of-sample in all cases, especially following the financial crisis that hit the economy during the financial year 2009. The results from this part of the thesis provide evidence in favour of the proposition that abnormal returns can effectively be made from an investment in predicted takeover targets from logistic and neural network models, and that these results can be significantly improved by using a combination of forecasts to achieve better returns and with lower misclassification risk.

Additionally, two general conclusions are drawn from the results. Firstly, the KK Combination method outperforms the single models and should be used to improve the prediction of takeover targets. In particular, the combination approach is both a stable and efficient method for combining probability forecasts in order to improve model accuracy and to achieve abnormal returns. Secondly, it has been demonstrated that an investment in the combined predicted targets in a regular year resulted in significant abnormal returns being made by an investor, in the order of up to two times the market benchmark return within a portfolio of manageable size. In fact, the use of models designed to predict companies with a minimal misclassification rate had a significant economical impact on the portfolio returns.

An issue that should be addressed on the technical implementation of this methodology is the time of availability of the information. The methodology I used by grouping the data by the end of the financial year and feeding it straight into the models is standard in forecasting studies and adopted in many papers that address takeover predictions and forecast combinations, such as Barnes (1998), Barnes (1999), Barnes (2000), Denčić-Mihajlov and Radović (2006), Kamstra et al (2001), Ohlson, J. 1980, Palepu (1986), Peat and Stevenson (2008), Powell (1995), Powell (2004) and Timmermann (2006). The use of the selected time frame allows comparisons of the results with other renowned papers in the literature.

CHAPTER 4

Analysis of Intraday Market Behaviour

4.1 Introduction

In Chapter 3 the economic usefulness of takeover prediction using a combination of predictions from logistic and neural network models is verified with abnormal returns in all simulations. However it does not guarantee a positive return. Despite the several methodological advances in takeover prediction, the practical use of takeover prediction models is questionable. The employment of advanced techniques to improve predictive accuracy, such as forecast combinations, certainly help to some extent but does not fully solve the misclassification problem.

The investor is still largely vulnerable to shocks in the economy that may lead to the depreciation of all companies in the portfolio with no time to react. Not only is the predictive accuracy of the model damaged during uncertain economic periods, but also the returns from the companies at the centre of the announcement are affected. For example, during the critical period related of the GFC just one of the three correctly predicted targets achieved a positive return.

The monitoring of the portfolio returns of the predicted targets over the one year investment horizon leads to questioning how better would be the profitability of the portfolio if it was possible to narrow the investment decision to periods when there are indications that a takeover is about to happen. The ideal strategy would reduce the misclassification error and skip all periods of negative returns in the target companies. In practice, the assumption is that timing of the investment in each company will further reduce the misclassification errors, potentially select the best periods to be invested in the stocks, and increase portfolio returns.

The implementation of such market-timing strategy raises two questions: where and how is it possible to find information related to a takeover announcement in the market? First, it requires moving from an annual frequency of the data to a much finer process, such as the intraday trading. The use of monthly or daily data groups together a substantial amount of information, making it too superficial to generate an informed trade timing strategy. Intraday data, however, takes each trade and market movement into consideration. That makes it the most appropriate data set to capture information from the market. Second, the chosen methodology needs to model market volatility and to be adaptable to the unique data characteristics. Consequently, the Autoregressive Conditional Duration model is chosen to try to capture information from the market.

Most financial market studies in the past have relied upon the collection of data at discrete and equally spaced points in time. The use of data that is discretized according to calendar time may not be synchronous with events or information flows and, therefore, may lead to the erroneous measurement of variables such as volatility. De Luca and Gallo (2004) suggest that the adoption of a fixed sampling frequency (e.g. hourly or daily) involves loss of information in the characterization of the underlying data process since the events between two consecutive data points are not considered. In fact, the market is so dynamic that a daily or even an hourly database may miscomprehend the market signs by joining several events together.

Moreover, observations may not match trades causing misleading information relationships among variables.

Data in calendar time formed the basis for the majority of previous market-microstructure research. This is partly due to the limited availability of high-frequency data in the past, along with the prevailing view that information shocks to a market are unlikely, or indeed improbable, over extremely short time frames. Rather than relying on discretely sampled data, or the aggregation of data at fixed intervals, this section of the thesis incorporates each transaction for the period into the analysis. This includes consideration of all the trades, as well as variables associated with those trades that conformed to the theoretical underpinnings of the market-microstructure literature. The use of high-frequency data allows the analysis of the statistical nature of information in real time, along with the addition of important explanatory variables for the information process such as the duration between trades.

An important assumption of the whole takeover prediction strategy is that publicly available data contains information related to a takeover announcement, and that includes the intraday trading data. Several studies report excessive returns in the period leading up to the announcement day, which might not be revealed in a lower frequency of the data. The information related to a future takeover announcement will at some point hit the market, presumably by an informed trader, affecting the intraday volatility. Therefore, the focus of this chapter is the analysis of the intraday trading using the ACD model to capture changes in information before the takeover announcement, and the selection of the microstructure variables that better explain volatility. The next subchapter has a description of the data process and the model used to detect the information changes in the intraday trading. Section 4.3 comprehends the sample selection and the description of the data set. The estimation and modelling results are in section 4.4, followed by the conclusions in section 4.5.

4.2 Model

4.2.1 A Financial Point Process

High frequency data is by definition irregularly spaced in time and is known statistically as a point process. It follows a stochastic process that generates a random accumulation of points along the time axis. In financial markets, a marked point process refers to the time of a trade and its corresponding characteristics, known as marks. These marks include microstructure variables, such as transaction volumes, bid-ask spreads, and other established market covariates. The duration process has attracted more attention in finance since Engle (2000) used it for the analysis of market behaviour. As defined in Florens *et al.* (2007), the trajectories of the duration process have at least one transition from state E_0 (no trade) to state E_1 (trade) at time T.

Microstructure research using tick-by-tick data calls for an alternative approach to time series analysis, given the uneven spaced observations in time. In this study the length of time between consecutive observations, or durations, is used to examine the information process. Let $\{t_0, t_1, \ldots, t_n, \ldots\}$ be the times of the sequence of trades of an asset traded on a financial market where $0 = t_0 \leq t_1 \leq \ldots \leq t_n \leq \ldots \leq t_{N(T)} = T$, and let $\{z_0, z_1, \ldots, z_n, \ldots, z_{N(T)}\}$ be the sequence of marks corresponding to the arrival times of trades. Duration is defined as $x_i = t_i - t_{i-1}$, where x_i is the i^{th} duration between trades that occur at consecutive times t_i and t_{i-1}. If $\boldsymbol{I}_{i-1}$ is the information set available at time t_{i-1}, then included in this set are past durations of financial trades and pre-determined marks.

When modelling durations, the first choice to ask is whether to model trade durations or a thicker process. A thicker process has less observations and higher duration values for the same data, for example in the case of price or volume durations. Price duration is the time interval between trades that cross a broader cumulative price threshold, that is the time needed to witness a given cumulative price change in the asset. Volume duration consists of the time difference needed to observe a certain cumulative volume traded of at least a predetermined number, or value, of shares.

Bauwens (2006) argued that for large samples the efficiency loss of using a thicker process is not likely to be a big concern, since both trade and price durations achieve very similar results. Price durations simplify the numerical aspect of estimation without sacrificing consistency of the estimator, at the cost of some loss of efficiency. However, for small samples the efficiency in the estimation is an important issue that specifically affects the selected group of companies in this study. The low liquidity level of many companies in ASX is linked to short number of observations. Hence the choice to work with the thinner trade durations process to estimate the ACD models in this thesis.

4.2.2 The Autoregressive Conditional Duration (ACD) Model

The time of trades is an important variable in understanding information flows. This subsection concentrates on the application of the Autoregressive Conditional Duration (ACD) methodology to capture the dynamics of the data. The structure of the basic ACD model gives a useful framework for jointly modelling durations and market characteristics. The ACD model is first presented in Engle and Russell (1998) as a model to analyse microstructure data that are recorded with irregular time spaces between observations. The model's architecture shares many features with the Generalized Autoregressive Conditional Heteroskedasticity models (GARCH) introduced in Bollerslev (1986). The first paper to suggest a joint model of durations and prices is Engle (2000), where it introduces the ACD-GARCH model. In that specification, the durations between transactions are fitted by an ACD model, while price changes are modelled by a GARCH model adapted to irregularly time-spaced data (conditional on contemporaneous and past durations).

The use of irregularly spaced data questions the use of standard time series models and calls for an ACD-type model. Engle and Russell (1998) introduce a marginal duration model called the Autoregressive Conditional Duration (ACD) model. They define the conditional expected duration, ψ_i , as:

$$\psi_i = E(x_i | I_{i-1}) = \psi_i(\tilde{x}_{i-1}, \tilde{z}_{i-1}; \theta) \tag{4.2.1}$$

where x_i is the duration, I_{i-1} represents the past duration set, Z_i are the marks and θ's are parameters.

A multiplicative error structure is assumed with $x_i = \psi_i \varepsilon_i$ and the standardized durations, ε_i , are assumed to be independent and identically distributed (i.i.d.). Then:

$$E(x_i) = E(\psi_i \varepsilon_i) = \psi_i E(\varepsilon_i) = \psi_i \text{, given } E(\varepsilon_i) = 1 \tag{4.2.2}$$

The standard ACD model of Engle and Russell (1998) relies on a linear parameterisation of equation (4.2.1), with expected duration expressed as an autoregressive equation of previous and expected durations, and specified below in equation (4.2.3).

$$\psi_i = \omega + \alpha x_{i-1} + \beta \psi_{i-1} \tag{4.2.3}$$

The restrictions $\alpha > 0$, $\beta > 0$ and $\alpha + \beta < 1$ ensure the existence of an unconditional expected duration and that durations are stationary and positive.

Return volatility is usually measured over fixed equally spaced time intervals. However, the volatility of asset prices over short between-trade intervals is likely to be different from volatility over a longer duration. To account for differences in asset price volatility corresponding to different duration between trades, and how these differences are affected by influential covariates, Engle (2000) introduced the ACD-GARCH model. It is based on an ACD model of the type defined in equations (4.2.1) to (4.2.3) and used to describe duration conditioned on the past information set. Engle (2000) argues that a volatility model in tick time is based on the decomposition of the density function of the sequence of durations and market characteristics (called marks). Accordingly, he provides a suitable framework for the joint modelling of durations between events of interest, x_i, and the marks, z_i.

The variance of returns is modelled by a GARCH model adapted for irregularly time-spaced data and, as a result, volatility is measured per unit of time conditional on contemporary and past durations. Engle (2000) uses the property that durations can be considered as weakly exogenous with respect to marks [Engle *et al.* (1983)] to simplify the estimation process. This property allows the two parts of the likelihood function to be maximised separately. The ACD model is estimated first, and the return volatility is then modelled from a GARCH model using expected and contemporaneous duration estimates from the first stage, along with selected covariates, or marks.[1]

As in Engle (2000), the return per unit of time, $\frac{r_i}{\sqrt{x_i}}$, is modelled as an ARMA(1, 1) process that is conditioned on duration. It follows that:

$$\frac{r_i}{\sqrt{x_i}} = \rho \frac{r_{i-1}}{\sqrt{x_{i-1}}} + e_i + \phi e_{i-1} \tag{4.2.4}$$

where, r_i is the return, and the innovation term is given by e_i .

The variance of returns is conditioned on contemporaneous duration and returns, per unit of time, in order to adapt for irregularly time-spaced data. Accordingly, the variance per unit of time, σ_i^2, becomes:

$$\sigma_i^2 = V_i \left(\frac{r_i}{\sqrt{x_i}} \middle| x_i \right) \tag{4.2.5}$$

Following this transformation, the ACD-GARCH (1, 1) model is used to model return volatility as a variable dependent upon both economic time and activity. The variance equation for the process is given by:

$$\sigma_i^2 = \gamma_1 + \gamma_2 {e_{i-1}}^2 + \gamma_3 \sigma_{i-1}^2 \tag{4.2.6}$$

where $\gamma_1 > 0, \gamma_2 \geq 0, \gamma_3 \geq 0, \gamma_2 + \gamma_3 < 1$.

The basic model given by equation (4.2.6) is extended to offer extra explanatory power and provide a better understanding of how individual variables affect volatility. Additional duration and market

[1] It is possible that the reverse situation holds where volatility has an impact on duration and ignoring this impact fails to recognise part of the complex relationship that exists between volatility and duration. However this hypothesis is assumed to be very weak in the data set analysed in the next subsection.

microstructure variables are appended to the model with the intention of jointly evaluating their impact. This approach has been successfully used in many previous studies [see Engle (2000), Bauwens and Giot (2000) and Wong *et al.* (2009)]. By including these new variables into the ACD-GARCH framework, the conditional return variance is given by:

$$\sigma_i^2 = \gamma_1 + \gamma_2 e_{i-1}^2 + \gamma_3 \sigma_{i-1}^2 + \gamma_4 x_i^{-1} + \gamma_5 \frac{x_i}{\psi_i} + \gamma_6 \varsigma_{i-1} + \gamma_7 \upsilon_i + \gamma_8 \partial_i + \gamma_9 \xi_i + \gamma_{10} \ell_i \qquad (4.2.7)$$

Assuming that durations and volatility can be driven by the same news events, the coefficient γ_4 in equation (4.2.7) provides some indication of the effects that duration have on the current period's volatility. If the theory of Easley and O'Hara (1992) is empirically verifiable, then short durations that follow an information event would increase volatility and γ_4 should be positive and significant. Therefore, a long duration between trades mean that no new information has been released to the market and, as a consequence, it is expected to have a correspondingly low level of trading and volatility. As duration is entered as a reciprocal, then a longer duration indicates no news, have shorter reciprocal values, and a reduced impact on volatility. Considering that informed trading activity is disclosed by the trading process, the volatility caused by informed trading might be related to more trades in potential target companies, what consequently reduces the time between trades. It can also be driven by bidders or informed speculation in anticipation of an announcement bid being made.

By looking at the reciprocal of duration in isolation, there may be an underestimation of the impact that duration has on volatility. Therefore, the use of another duration-related variable might offer a more precise specification. A measure of the surprise in durations, $\frac{x_i}{\psi_i}$, adopted from Engle (2000), is tested in the model. A positive surprise is where the actual duration is greater than the expected duration and, therefore, $\frac{x_i}{\psi_i}$ is greater than unity. When $\frac{x_i}{\psi_i}$ is less than unity, then the surprise is negative. The degree to which this ratio is greater than, equal to, or less than one captures the extent that the surprise related to new information indicates a reduction in volatility. A surprise could mean that either new information has been released, or that the actions of traders are of some interest, as long as the coefficient is negative. If the duration between the latest trade and the expected is different, this is seen as a reflection of the short-run impact of durations.

Some market-microstructure variables are introduced to analyse their relation to volatility, and to gain further explanatory power in the model. This approach is successfully used in many studies but with different variables [see Engle and Russell (1998) and Bauwens and Giot (2000)]. The market microstructure variables included as covariates in equation (4.2.7) are the lagged bid-ask spread (ς_{i-1}), contemporaneous volume-of-trade (υ_i), bid price (∂_i), and number of buyers (ℓ_i).

In much of the earlier literature, the spread is the focus of attention and takes the role of the dependent variable. However, in this thesis the lagged bid-ask spread, ς_{i-1}, plays a secondary role to the return process, acting as an indicator of information. In the presence of informed trading the spread is anticipated to narrow. A negative spread coefficient for a target company is implied as a result of a market information release and a corresponding increased level of informed trading. For the model estimation, the spread is lagged, and de-seasonalised in the same way as the duration variable. The use of the last period spread is based on the assumption that the investor is aware of the last period spread information to make the decision to trade. This is a different assumption related to spread from the original Engle (2000) study that used the lagged spread relating to market makers and their impacts upon the market quality. As opposed to the New York Stock Exchange, where the market-maker setting is in operation, the ASX is an electronic order-limit market. This means that the spread is a function of the orders placed with full transparency of the market to all investors. Therefore, the past spread may actually have an effect on current volatility but for different reasons.

The second microstructure variable added to the model is the contemporaneous volume-of-trades, υ_i . The relation between this variable and volatility has been often studied in the literature with a positive relation, as a result a positive sign is expected for γ_7 . Bauwens and Giot (2000) suggest that it is the unexpected flows in volume rather than the expected volume that are most pertinent to the price formation process. The volume in excess of normal liquidity is deemed to cause volatility due to traders taking advantage of their information to trade more actively.

The third and fourth additions are the bid price and the number of buyers, namely ∂_i and ℓ_i , respectively. The reasoning behind the inclusion of these variables is to capture some influence from the buyer side of the market as part of the explanation of volatility. Both these variables are expected to have positive coefficients. New information is expected to cause demand pressure, translated into higher bid price, or observed by a larger number of traders at the best bid price. Once information concerning the bidder's intention is absorbed by the market, greater trading volume, volatility, shorter durations and narrower spreads are expected.

Also incorporated into the specification above is a variable measuring short-run volatility, ξ_i . This parameter directly identifies the degree of persistence in the model. Assuming that volatility is not a process with long memory, the measure of short-run volatility is computed by exponentially smoothing the series, $\frac{r_i^2}{x_i}$, with a smoothing parameter equal to 0.5. This results in the exponential smoothing equation: $\xi_i = 0.5(r_{i-1}^2 / x_{i-1}) + 0.5\xi_{i-1}$. The parameter is intentionally set to 0.5 to test for the short-run volatility effects.

The afore mentioned variables are estimated together to capture the effects that changes in the level of information have on volatility. The decision to include the variables duration, duration surprise and the lagged bid-ask spread is based on the importance of these variables to relate information with trading activity. The variable short-run volatility is an extension of the variable used in previous studies to capture the persistence of changes in the variance. To our knowledge, the variables bid price, volume of the trade, and number of buyers at the best bid price presented in this work are used for the first time as explanatory variables in the variance equation.

4.2.3 The Error Distribution and the Hazard Function

In survival analysis the hazard function, $\lambda(t)$, is defined as the failure rate per unit of time, or the number of failures divided by the number of individuals at risk at that unit of time. This concept can be applied with success to duration analysis when considering the hazard as a function of the baseline hazard function, $\lambda_0(t)$, that measures the instantaneous rate of arrival of the next trade based on the history of durations and the magnitude of the expected duration, ψ_i. The hazard is derived by multiplying the baseline hazard function by the reciprocal of the expected duration, $\frac{1}{\psi_i}$. By incorporating the counting process, *N(t)*, that refers to the number of trades (event arrivals) that have occurred at, or prior to time t, the derived hazard rate function can be expressed as:

$$\lambda(t, \widetilde{x}_{i-1}, \widetilde{z}_{i-1}; \pi_x) = \frac{1}{\psi_{N(t)}} \lambda_0 (t, \frac{x_{N(t)}}{\psi_{N(t)}}; \pi_\varepsilon) \qquad (4.2.8)$$

Because ψ_i enters the hazard function as its reciprocal, and with duration measured in economic time, the hazard will be accelerated by a factor that depends on the magnitude of the expected duration. The smaller the expected duration, the faster is the acceleration of economic time relative to calendar time. As a consequence, equation (4.2.8) has been described as an accelerated failure time model in Engle (2000). Once the baseline hazard function is estimated non-parametrically using a Kaplan-Meier estimator, then equation (4.2.9) is used to estimate the hazard for a particular arrival. That is:

$$\hat{\lambda}_i(t) = \frac{1}{\hat{\psi}_i} \hat{\lambda}_0 (\frac{t - t_{i-1}}{\hat{\psi}_i}) \quad , \quad \text{for} \quad t_{i-1} \le t < t_i \qquad (4.2.9)$$

The distribution of the error term becomes important when the expected durations are incorporated into the ACD models. Some studies use more general distributions for the error term, however, because efficient maximum likelihood estimates are preferred, more careful consideration to specify an appropriate distribution is required. An inappropriate choice will have a negative impact on the conditional intensity and hazard function.

Although the exponential distribution provides consistent estimators, its specification generates a flat conditional hazard function which is regarded as restrictive by some authors [see Dufour and Engle (2000b); Feng *et al.* (2004); Lin and Tamvakis (2004)], and is rejected in most empirical financial applications. Additionally, a constant hazard function would imply that durations are random events. Engel and Russell (1998) suggested the use of the standardized Weibull distribution to overcome the problem of stiffness on the hazard function. The Weibull distribution is often used in the field of survival analysis due to its flexibility. It can simulate the behaviour of other statistical distributions such as the Normal [2] and the Exponential[3]. Also, under the Weibull distribution the hazard function is increasing for $\gamma > 1$, and decreasing for $\gamma < 1$. The use of the Weibull distribution proved a good choice for all applications of the ACD model in this thesis. The understanding of the hazard function may provide insights into what causes the duration behaviour. An increasing hazard function would suggest short durations early in the process and longer durations when the hazard function increases further over time. Further details related to the Weibull distribution are available in Appendix B.1.

4.3 Data

4.3.1 Sample of Companies

A selected sample of stocks that represents the broader Australian economy is used to describe the generalized trading behaviour prior to takeover announcement on the Australian equity market. The sample includes takeover target companies between 2004 and 2008 in the takeover target group. Related bidding companies are also included in the sample, separately in the bidder group. Additionally, a non-target

[2] When $\gamma = 3.4$, the Weibull distribution is similar to the Normal distribution.

[3] When $\gamma = 1$, the Weibull distribution reduces to the Exponential distribution.

(control) company, that did not experience an acquisition offer, is aligned with each target to form the control group. The data is obtained from the Securities Research Centre of Australia (SIRCA) and consists of six months of intra-day financial data for each selected ASX listed company.

The steps to define an appropriate sample of companies are as follows. First is the definition of the period. The years from 2004 to 2008 inclusive were chosen because it is a period that captures market behaviour of the business cycle. It comprises the period leading up to the peak, as well as reflecting the market adjustments made as the economy moved towards the bottom of the cycle. Not surprisingly, after reaching the highest number of announcements for a year in 2006, the annual records fell towards 2008 with the onset of the Global Financial Crisis. Differently from the other two chapters, this part of the research uses calendar year instead of financial year. The analysis of the intraday market behaviour was the first part of the thesis to be developed in 2009. During the research design process the intention was to gather the maximum amount of recent information, made the use of calendar years the best choice at the time. Nevertheless, the results should not be heavily affected by the choice of selected period in this chapter.

The second step is the sample definition. All companies that experienced a takeover announcement in the Australian market, along with their bidders, are considered for inclusion in the sample. However, several conditions are imposed that determined the membership of the target company in the final sample. They are:

(i) The target companies selected must have been the target of a takeover announcement at any point in time between 01/01/2004 and 31/12/2008.

(ii) The target firms needs stock market data available in the period that comprised 180 days before the event (announcement) day in order to allow for comparisons between time periods.

(iii) No other contaminating events exists in the five trading days prior to the announcement day that could have affected the target firm price, such as dividend payments, equity issues or stock splits.

(iv) No other takeover announcement has taken place on a target firm, either as a bidder or as a target in the 180 days before the event–day.

(v) The target company is required to have had enough trades in the period to allow for a consistent and efficient estimation of the model's parameters.

Most of the companies excluded from the sample are taken out under condition (v). The low liquidity of many target companies in the months before the announcement are usually related to the small size of the companies. The final number of takeover target companies included in the sample is two hundred and twenty eight (228). The target companies are the focus of this study because they represent the companies that received the acquisition offer independent of whether it is successful or not, and whether it is treated as friendly or hostile. As an ex-ante analysis, these outcomes will not affect the information leading to the announcement.

One hundred and thirty five (135) bidder companies related to the targets were included with the purpose of extending the analysis and offering a more complete study of market behaviour. Their trading behaviour leading up to the announcement of their bids is also of interest. Unfortunately, not all bidders were listed on the ASX at the time of the takeover announcement, forcing many of them to be excluded from the analysis.

A control group of two hundred and seven (207) companies was also added to the sample to ensure that the changes in the target's behaviour have no relation with its industry or the market as a whole. The control sample is formed by selecting companies from the same industry, and with approximately the same market value as companies in the target group. The selected control is the company with the smallest absolute difference in market value (positive or negative) to the target's value from its industry. This ensures that the observed changes in the trading behaviour of the target are not simply the result of a systematic shock. This increases the total number of companies analysed to 570. Table 4.3.1 presents the breakdown of the totals for each year among the targets, bidders and controls.

Table 4.3.1 Sample numbers for the targets, bidders and controls per year

		TARGETS (Announcements)	**BIDDERS**	**CONTROLS**	**Total Sample**
Year	2004	43	23	42	108
	2005	32	17	28	77
	2006	59	41	55	155
	2007	55	30	50	135
	2008	39	24	32	95
	Total	228	135	207	570

It is possible to observe from the table above an increase in the number of targets until 2006, and a subsequent decrease on the onset of the global financial crisis. Additional analysis comparing the selected sample with the population of target companies, and the sample break-down by industry is available in Appendix B.2.

4.3.2 Microstructure Data

The statistical and econometric modelling of high-frequency financial data exhibit challenges related to the unique features that are present in data sets at lower frequencies. First, the number of observations in high-frequency data sets can be overwhelming. Second, tick-by-tick data on trades and quotes are, by nature, irregularly spaced time series with random daily numbers of observations. Third, high-frequency data typically display periodic intra-day patterns reflecting market activity that are dependent on the characteristics of the exchange and the behaviour of market participants. And fourth, data are often recorded with errors and need to be cleaned prior to analysis.

The data set collected for each company consists of all trades and quotes during a period of six months, as well as corresponding microstructure variables that included: time, price, bid price, ask price, volume, and number of traders. For each stock at each trading day, the raw data comes as depicted in Table 4.3.2. Each line records new information as it arrives in the system, while the columns correspond to the variables that specify the trade or quote characteristics.

Table 4.3.2 Raw data

R	ASX CODE	Date	Time*	Type	Price	Volume	Bid Price	Ask Price
1	GAS.AX	20-Mar-06	245.64	Trade	2.54	1930		
2	GAS.AX	20-Mar-06	1201.88	Quote			2.54	
3	GAS.AX	20-Mar-06	1620.66	Quote				2.55
4	GAS.AX	20-Mar-06	1692.27	Trade	2.54	1434		
5	GAS.AX	20-Mar-06	1984.92	Quote			2.51	
6	GAS.AX	20-Mar-06	3029.45	Quote				2.54
7	GAS.AX	20-Mar-06	3029.45	Quote				2.53
8	GAS.AX	20-Mar-06	3979.20	Quote			2.52	
9	GAS.AX	20-Mar-06	3979.22	Trade	2.52	4000		
10	GAS.AX	20-Mar-06	4268.38	Trade	2.51	3952		

R	ASX CODE	Date	Time*	Type	Price	Volume	Bid Price	Ask Price
11	GAS.AX	20-Mar-06	4575.05	Trade	2.51	1600		
12	GAS.AX	20-Mar-06	4575.17	Quote			2.5	
13	GAS.AX	20-Mar-06	5613.16	Quote				2.51
14	GAS.AX	20-Mar-06	5613.16	Trade	2.51	3912		
15	GAS.AX	20-Mar-06	5613.16	Quote			2.51	
16	GAS.AX	20-Mar-06	6292.35	Quote				2.53
17	GAS.AX	20-Mar-06	6559.61	Quote			2.52	
18	GAS.AX	20-Mar-06	6975.03	Trade	2.52	2500		
19	GAS.AX	20-Mar-06	7410.87	Quote			2.51	
20	GAS.AX	20-Mar-06	7869.51	Quote				2.52
21	GAS.AX	20-Mar-06	10477.66	Trade	2.52	4675		
22	GAS.AX	20-Mar-06	10521.64	Trade	2.52	325		
23	GAS.AX	20-Mar-06	11303.87	Quote			2.52	
24	GAS.AX	20-Mar-06	11929.94	Quote				2.53
25	GAS.AX	20-Mar-06	12460.30	Trade	2.53	5000		
26	GAS.AX	20-Mar-06	12544.80	Quote			2.51	
27	GAS.AX	20-Mar-06	12582.14	Quote				
28	GAS.AX	20-Mar-06	12584.62	Quote			2.52	
29	GAS.AX	20-Mar-06	14328.69	Quote				2.54
30	GAS.AX	20-Mar-06	14364.03	Quote			2.53	

* Time in seconds from midnight

The table illustrates how the order book is presented, with limit sell orders, buy orders, trades and their characteristics. The time variable corresponds to the specific instant time of the trade or quote arrival in the system with the precision of 10^{-5} of a second. The price variable represents the price at which the trade is settled. On the sixth column of Table 4.3.2, a record with the label 'Trade' corresponds to a transaction when a trader crossed the spread between the bid and ask price. On the eighth and ninth columns, a record corresponding to the label 'Bid Price' ('Ask Price') represents the best bid (ask) price in the order book at the time that it changed. The variable volume represents the number of shares involved in each trade. The variables Price and Volume are related to trades and the variable Time displays the second that the trade or quote arrived in the system (resetting at the beginning of the trading hours of each day). As an example, the trade reported in record 9 happened at the price available at time 3979.22 seconds, and resulted from the execution of a market order of 4000 units of shares. Each trade is time stamped in seconds from midnight, with the trading hours being subsequently comprised of $t \in [36000, 56700]$ seconds (10 a.m. to 4 p.m.). A more detailed explanation of the ASX's trading hours is available on Appendix B.3.

High frequency data generally has a few special characteristics that need to be addressed before estimating models. To ensure accurate modelling, the data is filtered to remove unnecessary and erroneous observations such as opening and overnight trades. Any trade with a negative duration is discarded. Negative duration is an anomaly in the data as it would imply that the data is out of order, and is generally restricted to overnight trades. Trades at the same time (with identical time stamp) are aggregated into one observation. The trade volumes are summed and the volume weighted average price is adopted.

From an empirical point of view, it is advisable to remove the intraday seasonal component before analysing the stochastic properties of the duration process. Following both Engle and Russell (1998) and Engle (2000), the data is diurnally adjusted to remove any intraday seasonality that is likely to distort the estimation results. An assumption underlying the adjustment process made by Engle and Russell (1998) is that the intraday durations, x_i , can be multiplicatively decomposed into a deterministic time-of-day (seasonal) component at time t_i , $\phi(t_{i-1})$, and a stochastic counterpart $\tilde{x}_i$ that captured the dynamics of the durations such that $x_i = \tilde{x}_i \phi(t_{i-1})$. A piecewise-linear spline regression is fitted to the trades of the stock during trading hours with 12 knots, each representing half hour of trading (from 10 a.m. to 4 p.m.). Effectively, the durations are regressed on the time-of-day, with the diurnally adjusted durations obtained by taking ratios of the durations to their fitted values.[4] Following the adjustment process, the autocorrelation in the data is substantially reduced. While the seasonal adjustment process does not affect the main properties of durations, some authors have noted the need for further investigation to better understand its impact [see Meitz and Teräsvirta (2006)]. However, this process is mandated as can be observed through the analysis of the trading patterns in the next sections which exhibit strong intra-daily seasonality with higher trading activity at the beginning and the end of the trading day (shorter durations), and longer durations corresponding to slower activity outside these periods.

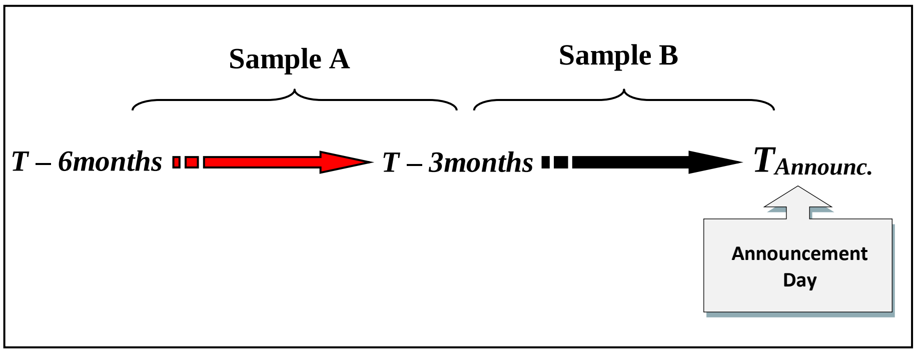
4.3.3 Sample Division

The sampling period comprises the six months prior to the takeover announcement made on the target company. This is later divided into two sub-samples of three months for a more detailed analysis. This three months window is arbitrarily set based on findings in the literature that reports changes in the market for up to 90 days before the official bid. The Sample A period comprises the period from six to four months before the takeover announcement and the Sample B period contains the data for the three months before the event announcement. It is assumed that Sample A shows ordinary trading behaviour for each company, while Sample B reflects the information-related changes in the intraday trading activity related to

[4] Alternative procedures have been applied by others in the literature. They include the use of cubic splines by Engle and Russell (1998) and Bauwens and Giot (2000), quadratic functions and indicator variables by Tsay (2002) and Drost and Werker (2004), while Dufour and Engle (2000a) include diurnal dummy variables in a vector autoregressive system.

the announcement. Figure 4.3.1 depicts the division in samples. The complete list with all selected target companies, its respective bidder and control pairs, and the sample dates division is on Appendix B.4.

Figure 4.3.1 Sample division



A set of typical companies (target, bidder and control) is chosen to demonstrate the changes in the intraday trading behaviour among the three groups of companies. These typical companies come from the utilities industry and are represented by the target company Alinta (ALN), the bidding company Australian Gas Light (AGL) and the control company Planet Gas (PGS). The sampling period for the typical companies spans from 11/09/2005 to 13/03/2006. The sample is divided in two three months sub-samples: Sample A from 6 to 4 months before the announcement; and Sample B from 3 months before the announcement to the takeover announcement day. The samples and dates for each typical company displayed in Table 4.3.2.

Table 4.3.3 Sample dates for the typical companies

Company (ASX code)		Sample			
		A		B	
		From	**to**	**From**	**to (Announcement Day)**
Target	**ALN**	11-Sep	12-Dec	13-Dec	13-Mar
Bidder	**AGL**				
Control	**PGS**				

Data for each of these companies includes all trades and quotes for both sample periods, with the summary statistics reported in Tables 4.3.4, 4.3.5 and 4.3.6. The duration between trades, the returns and the spread are listed in columns one to three, while volume of trades, the price, the bid and ask prices and the number of bidders (buyers) make up the remainder of the table. In the tables, duration corresponds to the specific time difference between trades with precision of 10^{-5} of a second. The price variable refers to the volume weighted average price of the trade. The bid price consists of the best buy offer on the market at the time of the trade and the ask price represents the best sell offer in the system at the time of the trade. The spread variable is computed by subtracting the bid from the ask quotes. The volume variable is the count of the number of shares involved in each trade. The last variable is the number of bidders in the market with the best bid price.

Looking carefully at the following tables, it is possible to observe negative spreads on the data. The negative spreads often happen at the opening of the market when not all overnight orders have been executed, as well as when the market is very liquid. These negative values are common only when the stock passes through a period of high liquidity. It does not have real economic meaning, but also there is no reason to justify the exclusion of this kind of observation from the sample. In addition to the summary statistics, Tables 4.3.4, 4.3.5

and 4.3.6 contain two-sample t-test results for the mean comparison between the Samples A and B periods for each of the variables in the set of typical companies.

Table 4.3.4 Typical Target summary statistics

TARGET Sample A								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N^0Buyers**
Mean	71.35	0.00	0.0013	1413	10.97	10.96	10.98	2.67
Median	26.17	0.00	0.0009	631	10.93	10.92	10.94	2.00
Maximum	1734.40	0.04	0.02	2000000	12.34	12.34	12.35	20.00
Minimum	0.00	-0.03	-0.35	1	10.02	10.01	7.87	1.00
Std. Dev.	114.95	0.00	0.0040	15537	0.37	0.37	0.37	1.93
Variance	13213.93	0.00	0.00002	2413993	0.14	0.14	0.14	3.71
Skewness	3.50	3.00	-70.56	113	0.78	0.77	0.72	1.88
Kurtosis	22.64	144.13	6026.14	14284	4.55	4.55	5.00	8.47

TARGET Sample B								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N^0Buyers**
Mean	54.00	0.00	0.0007	1575	10.83	10.83	10.84	2.17
Median	19.00	0.00	0.0009	645	10.84	10.84	10.85	2.00
Maximum	2339.00	0.04	0.01	255990	11.40	11.67	11.33	25.00
Minimum	0.00	-0.04	-0.35	1	10.26	2.75	2.76	1.00
Std. Dev.	91.30	0.00	0.0092	5169	0.21	0.23	0.23	1.59
Variance	8335.06	0.00	0.00009	2671962	0.05	0.05	0.06	2.52
Skewness	4.89	-2.60	-32.28	21	-0.19	-3.99	-4.64	2.96
Kurtosis	61.50	247.87	1189.39	736	3.03	140.73	135.24	21.96

Mean comparison between samples A and B (Two sample t-test) - H0 : Mean A = Mean B								
P-value (alpha 0.05)	0.000	0.930	0.000	0.050	0.000	0.000	0.000	0.000

From Table 4.3.4 for the target company (ALN) it is possible to observe differences between the two sample periods. In the Sample B period there are smaller averages for duration, spread and number of buyers, as well as a higher average volume traded. These results do not reject the assumption that there is more activity in the Sample B period. It is possibly induced by new information associated with a smaller average number of buyers who originated more trades with higher volume. In fact, a reduction in the average spread from Sample A to Sample B for the target company confirms the assumption of Admati and Pfleiderer (1988), among others, who postulated a negative relation between spread and trading activity.

Although the changes in the statistics for the bidder company (AGL) in Table 4.3.5, are not as marked as those of the target company, it is noticed an upward change in the average volume traded and the price variables, as well as a decrease in duration and spreads from the Sample A to the Sample B period. This result is in some way expected as the bidder company is not traditionally the focus of the takeover negotiations. Still the bidders are usually companies in solid financial situation and some rise in price is expected independently of the announcement.

Table 4.3.5 Typical Bidder summary statistics

BIDDER Sample A								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N⁰Buyers**
Mean	53.57	0.00	0.0009	1946	15.33	15.32	15.34	2.38
Median	21.05	0.00	0.0007	706	15.05	15.04	15.06	2.00
Maximum	1276.60	0.05	0.02	814660	17.20	17.19	17.20	25.00
Minimum	0.00	-0.02	-0.06	1	14.03	14.02	14.00	1.00
Std. Dev.	84.79	0.00	0.0009	9587	0.79	0.79	0.79	1.61
Variance	7188.97	0.00	0.00000	9191554	0.63	0.63	0.63	2.59
Skewness	3.62	7.23	-13.70	42	0.54	0.54	0.54	2.05
Kurtosis	24.70	411.50	1009.02	2664	1.90	1.90	1.90	13.54

BIDDER Sample B								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N⁰Buyers**
Mean	41.52	0.00	0.0005	2511	18.18	18.18	18.18	2.40
Median	13.08	0.00	0.0006	644	18.01	18.01	18.03	2.00
Maximum	1926.90	0.14	0.01	3000000	19.70	20.05	19.75	16.00
Minimum	0.00	-0.14	-0.19	1	16.77	16.77	16.00	0.00
Std. Dev.	74.11	0.00	0.0059	27250	0.79	0.79	0.79	1.85

Variance	5492.95	0.00	0.00003	7425895	0.63	0.63	0.63	3.44
Skewness	4.55	3.14	-26.52	71	0.01	0.03	0.00	1.77
Kurtosis	43.80	6620.07	788.31	6404	1.70	1.72	1.73	7.29

Mean comparison between samples A and B (Two sample t-test) - H0 : Mean A = Mean B								
P-value (alpha 0.05)	0.000	0.812	0.000	0.002	0.000	0.000	0.000	0.205

Table 4.3.6 shows the statistics for the typical control company (PGS). It presents changes in most averages, but in a different direction as hypothesised and not to the same degree compared to the target and bidder companies. For example, a longer duration is observed along with a reduction in the volume per trade. These movements are assumed to be not related to the takeover event. Instead, it may represent a company, industry or market movement.

Table 4.3.6 Typical Control summary statistics

CONTROL Sample A								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N^{0}Buyers**
Mean	798.65	0.00	0.0152	26723	0.30	0.31	0.31	2.03
Median	174.87	0.00	0.0174	17000	0.30	0.29	0.30	2.00
Maximum	16046.00	0.12	0.06	270000	0.42	2.53	2.55	8.00
Minimum	0.01	-0.12	-2.73	1	0.17	0.16	0.17	1.00
Std. Dev.	1672.12	0.01	0.0809	30888	0.07	0.13	0.11	1.18
Variance	2795982.63	0.00	0.00655	954046	0.00	0.02	0.01	1.39
Skewness	4.24	0.58	-33.42	3	-0.08	12.36	12.63	1.48
Kurtosis	25.67	25.69	1133.82	18	1.69	209.84	247.46	5.91

CONTROL Sample B								
	Duration	**Return**	**Spread**	**Volume**	**Price**	**Bid**	**Ask**	**N^{0}Buyers**
Mean	1319.32	0.00	0.0178	21948	0.37	0.37	0.38	1.59
Median	1319.32	0.00	0.0178	21948	0.37	0.37	0.38	1.59
Maximum	469.35	0.00	0.01	13800	0.38	0.37	0.38	1.00
Minimum	19408.00	0.10	0.14	350000	0.44	0.45	0.44	9.00

Std. Dev.	0.01	-0.06	-0.0788	1	0.30	0.26	0.30	1.00
Variance	2212.37	0.01	0.01272	28916	0.02	0.02	0.02	0.92
Skewness	4894562.93	0.00	0.00	8361356	0.00	0.00	0.00	0.85
Kurtosis	3.53	0.81	0.62	5	-0.26	-0.29	-0.25	2.11

Mean comparison between samples A and B (Two sample t-test) - H0 : Mean A = Mean B

P-value (alpha 0.05)	0.000	0.425	0.355	0.001	0.000	0.000	0.000	0.000

The average price is one of the variables that distinguish the target and bidder companies from the control. The target and the bidder reveal significant increases in the average price, bid price and ask price. Indeed, the effect that takeover announcements have on the prices of target firms is a strong motive for trading with privileged information. In accordance with these results is Jarrel and Poulsen (1989) which found dramatic increases in stock prices and trading volumes of target companies during the weeks preceding public takeover bids.

The changes in average volume are statistically significant for all companies. However, only the target exhibits an increase in the average volume traded, which is consistent with the hypothesis of higher level of information before the announcement. Easley and O'Hara (1992) also suggest that order size and volume traded contained a direct signal for the market concerning informed trading. The rise in the average number of buyers and sellers are variables that also differentiated the target behaviour. The increased average volume, in addition to the increase in the average number of buyers and sellers per trade in the target company, suggested a more active market with information flows specifically located in the target's trading environment. This result supported the assumption that informed traders are acting in the market to take advantage of the unreleased information.

While recognizing that what constituted the statistics in the previous tables are the results for a typical set of companies, it is interesting to note that from the Sample A period to the Sample B period the mean duration per trade shows a statistically significant decrease for the target and the bidder, while it increases for the control company. Positive changes in the volume of trades are only significant for the target and bidder companies. Furthermore, there is a statistically significant reduction in the average spread for the target company as a result of the lower bid and ask prices. This result is consistent with the assumption of Admati and Pfleiderer (1988), among others, who postulate a negative relation between spread and trading activity.

4.4 Results

4.4.1 Typical Company Hazard Rates

The hazard rate defines the instantaneous rate of change of the next trade at time *t*, conditional upon no trade until time *t*, and is often viewed as the "instantaneous probability" of leaving the current state. The hazard functions for the three typical companies are estimated from the filtered trades summarized in the previous section. In order to analyse the impact of information release on trading activity, the estimated hazard functions for the typical target, bidder and control companies across both samples are diagrammatically represented in Figures 4.4.1, 4.4.2 and 4.4.3 next.

What can be observed in Figure 4.4.1 is the rise in the level of the hazard function from the Sample A to the Sample B period for the target company, ALN. The higher hazard rate in Sample B and the rapid enlargement of the gap between the two samples' hazards is further confirmation of increased trading activity in the Sample B period. In contrast, the hazard function for the bidder company in Figure 4.4.2 shows little difference in trading intensity from the Sample A to the Sample B periods, as does its non-event related industry pair (control) in Figure 4.4.3.

Figure 4.4.1 Typical Target hazard function

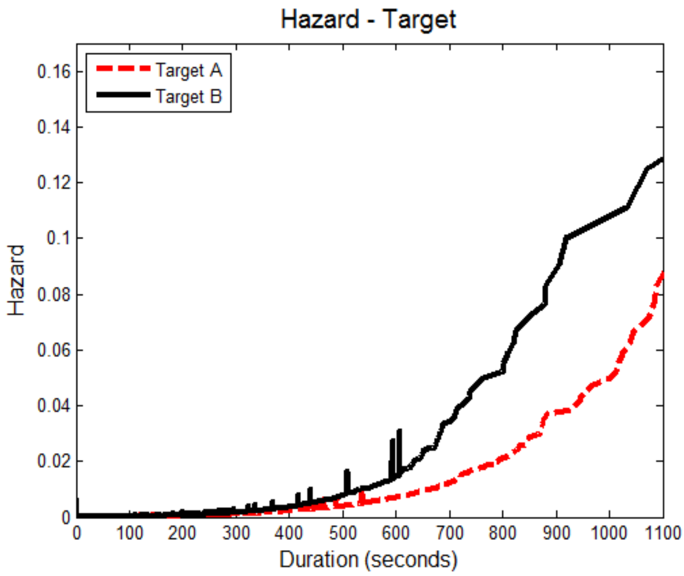


Figure 4.4.2 Typical Bidder hazard function

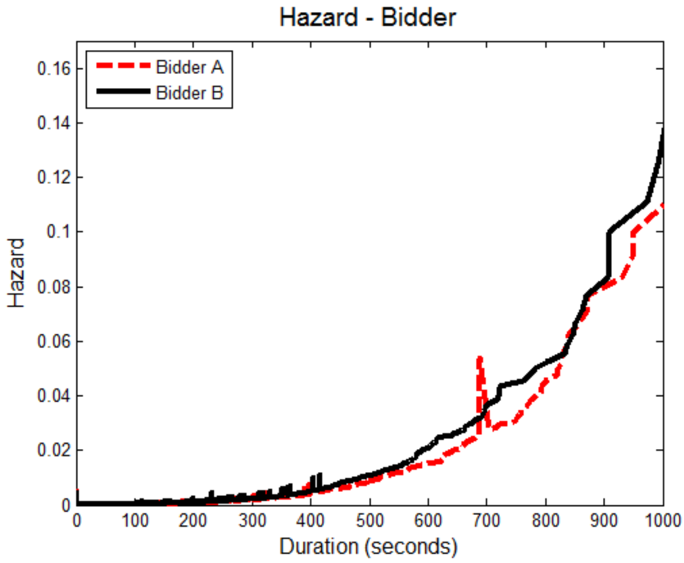
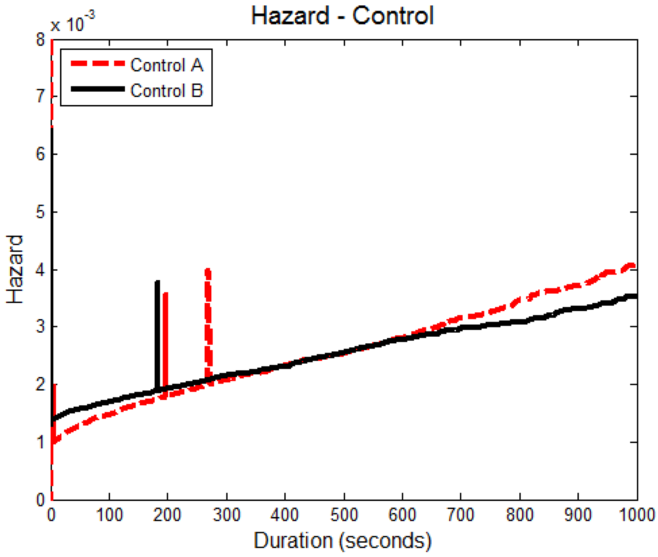


Figure 4.4.3 Typical Control hazard function



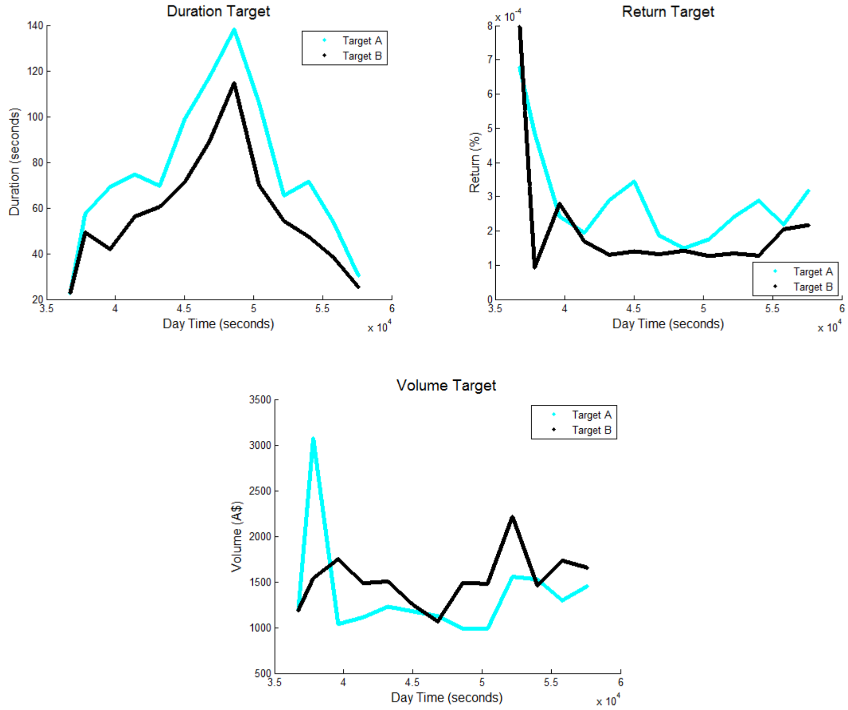
For the target company, ALN, the target hazard rate for both sample periods is the trade characteristic most affected by the upcoming takeover announcement date. By comparing all three hazard rates in the figures, it can be seen that the changes experienced by the target company have little relation to market or industry related movements as indicated when comparing to the control company (PGS). This result is supportive of the findings of Lunde (1999), Bauwens and Veredas (1999) and Grammig and Maurer (2000), who also find positive correlation between hazard rates and duration.

4.4.2 Intraday Trade Characteristics

The intraday patterns come from the mean average value of economic and microstructure variables at each point in time across the daily trading period. The averages in time are calculated through a piecewise- linear splice with 30 minutes interval. The graphs of the intraday duration, returns and volume variables for the typical companies are displayed in Figures 4.4.4, 4.4.5 and 4.4.6. The horizontal axis represents the time in seconds from midnight, where 36000 seconds represents 10 a.m. and 57600 seconds is 4 p.m.

The more pronounced intraday characteristic is the inverse V-shape from the duration graphs for the typical target and bidder companies, Figures 4.4.4 and 4.4.5 respectively. Both graphs contain periods of more trading activity at the beginning and at the end of the session, and longer durations in the middle of the day. This inverse V-shaped pattern is less pronounced for the typical control company, Figure 4.4.6. Of note is the higher volatility during the first hours of trading in the return graphs for the three companies. An important characteristic is the smaller volume traded in the target company in the middle of the day, as observed in Figure 4.4.4.

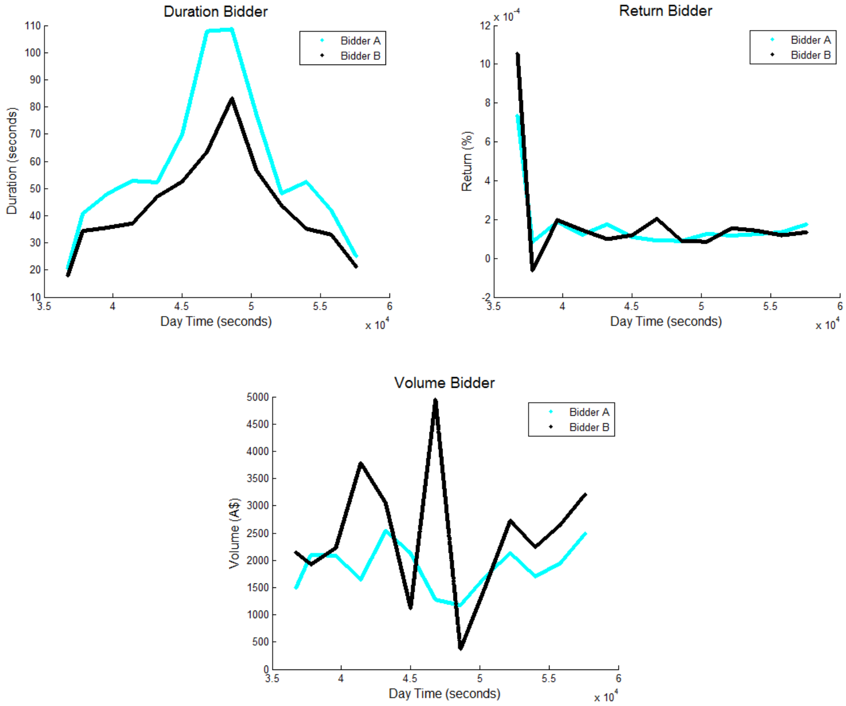
Figure 4.4.4 Graphs of intraday adjusted duration, returns and volume-of-trades for the typical Target company



In Figure 4.4.4, the higher level of trading activity in the typical takeover target in the later period is indicated by higher volume traded and the lower duration between trades throughout the day. This suggests that more information related to the takeover announcement was present in the market during the Sample B period.

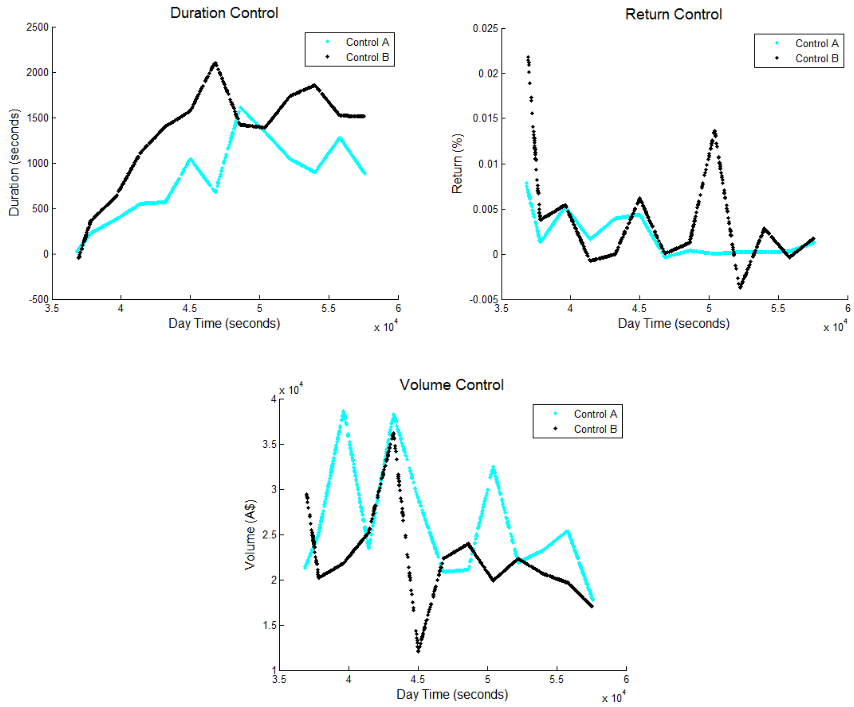
The bidder's graphs in Figure 4.4.5 exhibits a similar pattern to those of the target company for duration and return, with lower duration for Sample B period and high return volatility for both sample periods at the beginning of the day.

Figure 4.4.5 Graphs of intraday adjusted duration, returns and volume-of-trades for the typical Bidder company



The graphs of the intraday duration, returns and volume variables for the typical control company are characterized in the Figure 4.4.6. The control company, which has no relation to takeover involvement, does not exhibit similar patterns to the target and bidder companies. As expected, it does not show many pronounced changes in its trading characteristics from Sample A to Sample B. The durations and the spread are higher in Sample A, and the volume clearly lower in Sample B. This gives the impression that changes in trading activity in the target have virtually no relation to the general market or industry trading environment.

Figure 4.4.6 Graphs of intraday adjusted duration, returns and volume-of-trades for the typical Control company



Overall, interesting patterns are observed. They present higher volatility at the beginning of the day for most samples. Many studies confirm this behaviour reporting elevated price volatility and marginally wider spread at the open and close of trading session for several stocks, tightening gradually throughout the trading day. These results are supported by Admati and Pfleiderer (1988) that observed heavy trading at the beginning and at the end of the trading day. This clearly shows the influence of over-night information on the trade behaviour, distinctively strong in the Australian market due to its time zone. Studies such as French and Roll (1986) which examines the variance of daily returns on week-day exchange holidays proposed two important hypotheses for the high return volatility. First, public information may arrive more frequently during business hours. And second, private information may be brought to the market through the trading of informed agents, and this creates volatility.

The more pronounced intraday characteristic is the inverse V-shape from the duration graphs for the typical target and bidder companies, with periods of more active trading at the beginning and at the end of the session, and longer durations in the middle of the day. Of note is the higher volatility during the first hours of trading for the return graphs for the three companies. The more variability at the beginning of the trading session is attributed in many studies to the effects from the arrival of overnight information. Surprisingly, for both companies involved in the takeover, the volume graphs did not show the characteristic U shape pattern reported in the literature, with lower volumes traded in the middle of the day. This can be an evidence of information keeping the volume's volatility higher at least six months before the event. These patterns are typical during the trading day and have been attributed in many studies to effects that vary from the lunch-time break to more variability at the beginning of the trading session caused by the arrival of overnight information.

The graphs in this section showed indicative information related to changes in the trading behaviour for the target and the bidder companies, while the control company, that has no relation with takeover negotiations, is not affected by the announcement. The higher level of trading activity in the typical target in the later period is indicated by the lower duration between trades, the lower spread, and the higher volume traded throughout the trading period. This suggests that more information related to the takeover announcement is present in the market in the three months before the announcement. Not only did this confirm the hypothesis of higher diffusion of private information in the months just prior to the announcement, at least in the cases of these typical companies, it also showed that this diffusion can be captured by analysing the changes in intraday trading behaviour. This gives the impression that changes in trading activity in the target have virtually no relation to the general market or industry trading environment. These results are consistent with the assumption of the leakage of private information before takeover announcements being revealed through trading activity. Additionally, it is noted that the Australian market shares similar intraday trading patterns and characteristics with other markets [see Bauwens and Veredas (1999) and Grammig and Maurer (2000)].

4.4.3 ACD Model Results - Typical Companies

The information-based model given by equation 4.2.7 is estimated using the method of maximum likelihood. The choice of the method of maximum likelihood is based on its versatility to deal with different models and types of data, and also due to its robustness to estimate consistent and efficient estimators. The model endeavours to explain the complex relationship existing between information and observable economic and microstructure variables. The estimation of the volatility model built in transaction time (equation 4.2.7) for each of the typical companies is presented in Tables 4.4.1, 4.4.2 and 4.4.3.

Changes in the significance of the coefficients for the three typical companies demonstrated the impact on the trading across the two sample periods. An increase in the number of significant coefficients from Sample A to Sample B periods for the typical target company is observed in Table 4.4.1. This is not a feature detected for the bidder and control companies.

Table 4.4.1 Typical Target ACD estimation (eq. 4.2.7)

TARGET A				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	0.010	0.001	73.157	0
MA(1)	0.010	0.000	453.100	0
Variance Equation				
C	23.451	2.228	10.527	0
RESID(-1)^2	0.120	0.016	7.322	0
GARCH(-1)	0.592	0.029	20.412	0
1/DUR	0.688	0.079	8.695	0
DUR/EDUR	-0.008	1.585	-0.005	0.996
SPREADS(-1)	-0.002	0.044	-0.038	0.97
VOL	0.000	0.000	85.442	0
BIDS	0.000	0.000	0.772	0.4402
SHORTVOL	0.001	0.006	0.109	0.9133
NBUY	0.018	0.257	0.070	0.9445
TARGET B				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	-0.215	0.056	-3.875	0.0001
MA(1)	-0.201	0.050	-4.044	0.0001
Variance Equation				
C	84.656	10.250	8.259	0
RESID(-1)^2	0.125	0.009	14.134	0
GARCH(-1)	0.523	0.029	18.056	0
1/DUR	0.688	0.079	8.695	0
DUR/EDUR	-0.154	6.715	-1.331	0.0915
SPREADS(-1)	-0.175	0.003	-57.929	0
VOL	0.000	0.000	121.407	0
BIDS	0.000	0.000	6.357	0
SHORTVOL	0.041	0.003	4.728	0
NBUY	0.315	0.009	189.240	0

In Tables 4.4.1 and 4.4.2, it is observed that the trading intensity (measured by the reciprocal of duration) significantly increases in both samples for the target and the bidder company. While this implies that news events impact positively the volatility, this result supported the proposition that shorter (longer) durations would indicate news (no news) and result in a greater (lesser) impact on volatility. The Table 4.4.2 contains the estimation output for the typical bidder company. The coefficients for the duration surprise are not significant in both bidder samples, in Sample A of the target company, and in both control companies' samples.

Table 4.4.2 Typical Bidder ACD estimation (eq. 4.2.7)

BIDDER A				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	0.368	0.182	2.027	0.0427
MA(1)	-0.528	0.153	-3.455	0.0006
Variance Equation				
C	13.498	1.106	12.205	0
RESID(-1)^2	0.071	0.003	20.639	0
GARCH(-1)	0.669	0.007	98.914	0
1/DUR	0.001	0.003	43.732	0
DUR/EDUR	-0.001	0.000	-61.825	0
SPREADS(-1)	-0.011	0.002	-4.577	0
VOL	0.000	0.000	439.987	0
BIDS	0.000	0.000	0.052	0.9582
SHORTVOL	0.000	0.000	0.700	0.4838
NBUY	1.701	0.009	39.545	0

BIDDER B				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	0.910	0.053	17.311	0
MA(1)	-0.962	0.032	-30.286	0
Variance Equation				
C	35.636	0.300	118.960	0
RESID(-1)^2	0.186	0.001	276.326	0
GARCH(-1)	0.862	0.000	2019.881	0
1/DUR	0.041	0.000	95.734	0
DUR/EDUR	-35.940	0.300	-119.754	0
SPREADS(-1)	-0.011	0.003	1.191	0.2335
VOL	0.000	0.000	30.568	0
BIDS	0.000	0.000	27.598	0
SHORTVOL	-0.115	0.001	-136.329	0
NBUY	0.994	0.000	0.836	0.7984

When analysing the short-run volatility in the tables, it is perceived that in Sample B the target shows results in accordance with the assumption that the higher the volatility memory (and information retained) the higher the actual volatility, with the short-run volatility positively affecting volatility (SHORTVOL in the table). The exception are the bidder and the control companies with significant coefficient in Sample A and B but with negative coefficients, as presented in the control's estimation output in Table 4.4.3.

Table 4.4.3 Typical Control ACD estimation (eq. 4.2.7)

CONTROL A				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	0.876	0.018	34.457	0
MA(1)	0.876	0.007	28.379	0
Variance Equation				
C	30.985	10.170	3.047	0.0023
RESID(-1)^2	-0.003	0.001	4.305	0
GARCH(-1)	0.590	0.075	7.888	0
1/DUR	0.000	0.153	0.000	0.9996
DUR/EDUR	-0.001	10.217	3.719	0.9999
SPREADS(-1)	-0.001	0.214	-0.004	0.9971
VOL	0.000	0.000	-3.258	0.0011
BIDS	-0.001	0.000	-8.943	0
SHORTVOL	0.017	0.089	0.187	0.852
NBUY	-0.001	0.994	-0.001	0.9991
CONTROL B				
	Coefficient	*Std. Error*	*z-Statistic*	*Prob.*
AR(1)	-0.263	0.105	-2.498	0.0125
MA(1)	-0.638	0.048	-13.385	0
Variance Equation				
C	313.840	127.092	2.811	0.0049
RESID(-1)^2	0.123	0.057	2.165	0.0304
GARCH(-1)	0.594	0.050	11.799	0
1/DUR	-0.519	0.470	-0.191	0.8486
DUR/EDUR	-0.090	0.189	0.000	0.9997
SPREADS(-1)	-0.093	0.200	-0.153	0.8781
VOL	0.000	0.000	-1.447	0.1479
BIDS	0.000	0.000	0.057	0.9548
SHORTVOL	-0.096	0.026	-3.665	0.0002
NBUY	-0.209	0.631	-0.057	0.9542

A narrower (wider) spread means an increase (reduction) in information and impact on volatility. This suggests a negative coefficient for the spread variable when used in the expected conditional duration model. It is confirmed by the volatility model's results. Even though all coefficients are negative for all samples, only in the more information-influenced target's Sample B and the bidder Sample A they are significant. The volume in excess of normal liquidity is deemed to be the unexpected volume. This suggests a positive and significant coefficient, as noticed for both target and bidder samples, and at the control's Sample B. This type of volume has been suggested to be driven by informed traders and good news about the company in the market.

The variables bid price and number of buyers, BIDS and NBUY respectively, aim to add some influence from the buyer side of the market to the explanation of volatility. Its coefficients are expected to appear both with a positive sign, given the supposed relation between information and the rise in price and number of traders. These two variables have quite different behaviour when tested in the model. While the bid price is significant only for the target and bidder companies in Sample B, the number of buyers is insignificant for most of the samples, except for target Sample B and bidder Sample A. This result confirms what is observed previously from the descriptive statistics of these variables.

The persistence of volatility depends on the GARCH parameters as well as the durations and microstructure variables in the model. All GARCH coefficients for each of the typical companies and across both sample periods [that is, coefficients RESID(-1)^2 and GARCH(-1)] are statistically significant. This confirmed the suitability of the basic ACD-GARCH model as an appropriate specification for modelling of this kind of data. From the previous tables is noticed that the variables included in the model present changes depending on the sample analysed, especially for the target company. An increase in the number of significant coefficients from the Sample A to Sample B periods is observed and indicates information related changes in the market. This is not a feature detected so strongly for the bidder, while the control company exhibits a few changes but in the opposite direction. These results demonstrate that the microstructure variables added in the model can help to explain the market intraday volatility, especially when there is new information in the market that affects liquidity, such as takeover announcements.

4.4.4 ACD Model Results - Total Sample

In order to characterise a broad spectrum of the impact from the information related to the duration and microstructure variables, the ACD-GARCH model from equation (4.2.7) was estimated for all 570 companies. The Tables 4.4.4, 4.4.5 and 4.4.6 contain the percentage of companies where the variables' coefficients are significant and with the expected sign. The observation of the evolution from each variable in time is performed through a test of the equality of proportions. A significant and positive percentage change in the proportion of significant coefficients across the periods is assumed to indicate the dissemination of information related to a potential takeover before its announcement.

Several changes in the proportions of significant coefficients for the duration variables [1/DUR and DUR/EDUR], the spread [SPREAD(-1)], and the volume [VOL] variables are clearly observed in Table 4.4.4, 4.4.5 and 4.4.6. The conclusions drawn from these patterns are that the trading on the target companies is reflecting higher information content in the period before the announcement. It indicates that the informed trading in the targets started at least three months prior to the announcement. This illustrates how volatility and the higher trading intensity in the target companies is revealed to the market by informed trading activity. It indicates that the monitoring of the change in the covariates for a potential target contain information concerning a forthcoming takeover announcement. The Table 4.4.4

presents the proportions of significant coefficients for the group of target companies.

Table 4.4.4 Target Group proportion of significant coefficients from ACD estimation (eq. 4.2.7) with level of significance = 5%

	Target		
	228 Companies		P-Value (Test for equality of proportions)*
Percentage of companies with significant coeficients	**SAMPLE A**	**SAMPLE B**	
AR(1)	74.56%	79.39%	0.22
MA(1)	69.30%	63.60%	0.20
Variance Equation			
C	90.79%	86.84%	0.18
RESID(-1)^2	85.09%	90.79%	0.06
GARCH(-1)	87.28%	85.96%	0.68
1/DUR	50.44%	68.42%	0.00
DUR/EDUR	21.05%	32.02%	0.01
SPREADS(-1)	20.61%	38.60%	0.00
VOL	35.53%	51.75%	0.00
BIDS	11.84%	12.28%	0.89
SHORTVOL	26.75%	32.46%	0.18
NBUY	17.54%	13.60%	0.25

* H0: Proportion Sample A = Proportion Sample B

As is the case for the typical company's results, most GARCH coefficients are significant, irrespective of which sample period is considered. The target group of companies in Table 4.4.4 exhibit significant changes in the percentages from the Sample A to the Sample B periods in the variables the reciprocal of duration and the expected duration. Of the remaining market microstructure variables, the spread and the volume show significant differences across target and bidder companies and sample periods. A consistent pattern emerged from the trading in the target companies that suggests that the duration variables, along with the two market microstructure variables, revealed information about an impending takeover offer.

While the trading activity in the group of bidder companies in Table 4.4.5 suggests that there are significant changes in the percentages of significant coefficients across the samples for the same two microstructure variables as for the targets' group, changes in the percentages of the corresponding duration variables are not significant.

Table 4.4.5 Bidder Group proportion of significant coefficients from ACD estimation (eq. 4.2.7) with level of significance = 5%

	Bidder		
	135 Companies		P-Value (Test for equality of proportions)*
Percentage of companies with significant coeficients	**SAMPLE A**	**SAMPLE B**	
AR(1)	81.48%	77.78%	0.45
MA(1)	71.11%	74.07%	0.59
Variance Equation			
C	88.89%	82.96%	0.16
RESID(-1)^2	86.67%	84.44%	0.60
GARCH(-1)	79.26%	82.96%	0.44
1/DUR	37.78%	48.89%	0.07
DUR/EDUR	17.78%	23.70%	0.23
SPREADS(-1)	31.85%	43.70%	0.04
VOL	44.44%	56.30%	0.05
BIDS	14.07%	13.33%	0.86
SHORTVOL	33.33%	29.63%	0.51
NBUY	27.41%	23.70%	0.49

* H0: Proportion Sample A = Proportion Sample B

For the control companies, in Table 4.4.6, the only covariate where a significant change is found in the percentages of significant model coefficients from one sample period to the next is the duration surprise. However, that change is in the opposite direction to that of the target and bidder groups.

Table 4.4.6 Control Group proportion of significant coefficients from ACD estimation (eq. 4.2.7) with level of significance = 5%

	Control		
	207 Companies		P-Value (Test for equality of proportions)*
Percentage of companies with significant coeficients	**SAMPLE A**	**SAMPLE B**	
AR(1)	85.02%	90.82%	0.07
MA(1)	77.29%	82.61%	0.18
Variance Equation			
C	77.29%	84.54%	0.06
RESID(-1)^2	83.57%	84.06%	0.89
GARCH(-1)	90.34%	87.92%	0.43
1/DUR	29.47%	27.54%	0.66
DUR/EDUR	21.26%	10.63%	0.00
SPREADS(-1)	26.57%	25.60%	0.82
VOL	47.34%	41.06%	0.20
BIDS	9.18%	9.66%	0.87
SHORTVOL	10.63%	11.11%	0.87
NBUY	19.32%	22.22%	0.47

* H0: Proportion Sample A = Proportion Sample B

After analysing the model results for the three groups, comprising 570 companies, it is perceived that the target companies demonstrates more differences from Sample A to Sample B than the other groups. As expected, the bidder group presents fewer changes than the target group, and the control group of companies is not affected. The results for the three groups of companies show that the microstructure variables more affected by changes in information levels are the variables duration, duration surprise, spread and volume.

The use of the model for a large number of companies and the comparison of their evolution in time adds robustness to the results.

The application of the ACD model for such a diverse sample demonstrates the consistency of the model for different markets outside the United States. This is particularly important given that the trading in the ASX is not under the influence of market makers. The model also proved to be adequate for companies with lower levels of liquidity, a constant issue in the Australian market.

4.5 Conclusion

Mergers and acquisitions is an area with high information asymmetry and, consequently, abnormal profit opportunities for investors. Without doubt, the effect that takeover announcements have on the prices of target firms is a strong motive for trading with privileged information. As a consequence, movements in trading activity before a takeover announcement are expected and indicate the possible presence of informed trading and information leakage. This research has empirically justified the use of intraday trading to capture information associated with takeover announcements, with the ACD-GARCH model adapted for this purpose.

The market behaviour of a group of companies on the Australian Stock Exchange that are subjected to a takeover offer between 2004 and 2008 is observed in order to examine how intraday activity in these companies reacted to new information. It is established that changes in market behaviour are reflected in market observable features, such as liquidity, volatility of returns and other measures of trading activity. The empirical results are, in general, consistent with those suggested by market microstructure theories related to the presence of informed traders before information events. Modelling transaction time enabled the determination of the intraday effects of high frequency trades on the conditional volatility of the returns. This is made possible by the use of the ACD model to jointly estimate duration with other market-microstructure variables. The model allows for the identification and quantification of the impact that some trading variables have on return volatility, and how privileged information impacts it before the event of a takeover announcement.

Through the analysis of the intraday trades of a large sample of stocks, evidence was found in favour that the intraday trading behaviour of the takeover target companies was affected by brokers trading on private information. More intense trading activity in the targets is reflected in return volatility at least three months before the official announcement of the takeover offer. By observation of the bidders over the same period, it is concluded that the buyer side of the market is in some way affected, but to a much lesser degree. A control group of companies is also included in the analysis and the results rejected the hypothesis that the more intense trading behaviour associated with the target in the three months before the announcement is caused by publicly available industry or market related news.

Duration variables, along with spread and volume microstructure variables, are found to be important for explaining return volatility in target companies. It is also possible to observe a clear relation between trading intensity and information dissemination. The analysis supported the assumption that the intensified trading activity in the target companies closer to the event announcement is a consequence of traders who held private information. Using the approach adopted in this thesis, a consistent covariate pattern for targets is established over an extensive range of companies. As a consequence, the profitable introduction of potential targets into a portfolio may be timed and the portfolio rebalanced according to information suggested by changes in company intraday trading patterns. Importantly, the modelling approach outlined in this study suggests a means by which the timing of the inclusion of potential targets in a portfolio can be determined. This would require the creation of a trading rule, a task addressed in the next chapter of this thesis.

CHAPTER 5

Investment Timing in High Frequency Trading

5.1 Introduction

Takeover announcements reveal information unknown to most market participants. These events create incentives for traders who possess privileged information to negotiate large volumes quickly before the news reaches the market and the opportunity for profitable trading ceases. Evidence of the nature of corporate events can be gathered from high-frequency data analysis, as pointed in Chapter 4. Under the hypothesis of asymmetric information around a market event, changes in volatility are expected before takeover announcements. The analysis in the previous chapter showed that this pattern is believed to be reflected in the trading environment with higher returns, shortening of spreads, large volumes traded, and all this in a short period of time.

The proposed market-timing strategy is build on the knowledge generated in the previous two chapters. It refines the takeover prediction process by providing a flexible new method to manage takeover prediction risks. Moving from low-frequency annual data to high-frequency tick-by-tick data creates a vast range of information by jointly contemplating macro and micro information about a company. The use of these two levels of data in the methodology brings together information from a company's recent past, with up-to-date market's perception about what is happening in the market within a precision of seconds. This chapter brings together the takeover prediction strategy outlined in Chapter 3 with the high frequency market behaviour knowledge generated in Chapter 4. In doing so, the analysis of the increased available information has the effect of reducing risk and increase returns.

5.2 Forecast Model

The role of the model underlying the proposed market-timing strategy is to reflect market behaviour in its forecast. It jointly accommodates the empirical irregularities of high frequency data and durations in order to achieve a representative forecast of a true range where the market price can fluctuate. In particular, it models regular market behaviour and captures noise assumed to be dependent on uninformed volatility.

The use of microstructure techniques to decompose variable impact allows more precise perceptions regarding asymmetric spread of information over time. The duration, defined as the random time interval between two subsequent trades, is an important variable related to information arrival that is neglected by the market-timing literature. It is an indicator of the level of trading activity in the stock and is sensitive to private information. In fact, the use of duration jointly with other variables can produce powerful measures of liquidity. For example, a return of ten basis points in a trade with one minute duration has a different impact on the market than would the same return with just one second from the last trade.

The measurement of the volatility of asset prices over short intervals between trades is likely to be different from volatility over a longer duration. As mentioned in Chapter 4, the resultant irregularly spaced data questions the use of standard time series models and calls for an ACD-type model. Engle (2000) argues that a volatility model in transaction time is based on the decomposition of the density function of the sequence of durations and trade characteristics. Accordingly, that study provides a suitable framework for the joint modelling of durations between trades and microstructure variables. The direct approach to modelling the volatility through the ACD-GARCH model in Engle (2000) was selected because of its flexibility to work with unequally spaced observations while allowing for the input of independent variables. Overlooking the instantaneous causality effect of other variables, such as time between trades, volume and spread, leads to a significant bias in the estimation. A decisive point in favour of adopting this model is its capability of generating strong dependence spanning many transactions, given that high-frequency returns tend to exhibit strong and often complex temporal dependence. In contrast to the previous chapter, the ACD-GARCH model is now used for predictive purposes.

An ACD-GARCH(1,1) model detailed previously in Chapter 4 is used to model the return volatility as a variable dependent upon both economic time and trading activity. As a result, additional duration and market microstructure variables are appended to the model to jointly consider their impact. It offers support for the published theories regarding how informed trading can be disclosed by the trading process, as well as offering extra explanatory power to the forecast. This approach has been successfully used in many previous studies [see Engle (2000), Bauwens and Giot (2000) and Wong *et al.* (2009)]. Rodrigues *et al.* (2012) reports that those economic and microstructure variables indicating a significant change in the return volatility in a takeover target before the announcement.

The variance of the returns per unit of time is conditioned on contemporaneous durations and returns in order to adapt for irregularly time-spaced data. Recall from Chapter 4 the variance per unit of time from the ACD-GARCH framework, σ_i^2 , given by equation (5.2.1):

$$\sigma_i^2 = \gamma_1 + \gamma_2 e_{i-1}^2 + \gamma_3 \sigma_{i-1}^2 + \gamma_4 x_i^{-1} + \gamma_5 \frac{x_i}{\psi_i} + \gamma_6 \varsigma_i + \gamma_7 \upsilon_i \tag{5.2.1}$$

where ψ_i is the expected duration, ς_i is the spread, υ_i is the volume of the trade, and $\gamma_1 > 0, \gamma_2 \geq 0, \gamma_3 \geq 0, \gamma_2 + \gamma_3 < 1$.

Four explanatory variables are used to explain and forecast the volatility in the model. These variables are the same found to be significant in capturing the changes in information before a takeover announcement in Chapter 4. The first variable is the inverse of duration. Assuming that the theory of Easley and O'Hara (1992) is empirically verifiable, short durations that follow an information event would increase volatility. As duration is entered as a reciprocal, then a longer duration indicates no news, has shorter reciprocal values and a reduced impact on volatility. The second variable is the duration divided by the expected duration, where the expected duration is constructed using an autoregressive model. For example, a value greater than one occurs when the actual duration is greater than that expected and indicates a reduced impact on volatility, as long as the corresponding coefficient is negative.

The third variable is the bid-ask spread that is often associated with liquidity. Liquidity is characterized by the ability to trade large volumes of stock at a certain price. The larger the difference in the bid and ask prices, the further the transaction price will likely be from the efficient price. Typically low values of the spread indicate less uncertainty in the market. The fourth variable is the volume of trade, which contains information related to shifts in demand. For a trader wishing to transact a large volume, the price may be quite different than prices obtained for small quantities. Large sell volumes demand a lower price, while large buy volumes demand a higher price. Changes in demand that occur slowly through time are harder to detect using volume data alone because there are trends in volume associated with the whole market. However, an unusually large traded volume is likely to affect the price-volume relationship, especially in a short time interval. Since volume is inversely related to duration, the intensity with which the price changes will depend upon whether the volume is high or low.

5.3 Market-timing Strategy

5.3.1 Trading Rules

It is reasonable to assume that an investor can choose to wait for a trade that contains information before rebalancing the portfolio, albeit, that stock prices can only change a finite number of times over a given period. The proposed market-timing strategy presented in this thesis analyses the information content of each trade before the portfolio is rebalanced. It assumes that there will be a change in price only if buyers and sellers are truly convinced that the efficient price is different from the last traded price. The question that needs to be answered is then, how sufficiently far from the lasted traded price does this new price need to be in order to contain new information?

The suggested method to address this question is, in the absence of new information, to build a prediction interval. It needs to contain an estimate of the range in which future observations will fall with a given amount of confidence, and conditional on what has already been observed in the trading environment. The proposed timing strategy is, consistent with the belief that, on average, stock prices generally reflect market information. However, there are rare times when they reflect privileged information. The strategy used here has some points in common with the trading range break strategy reported in Sullivan *et al.* (1999) and similarities with standard filters used for outlier detection.

A prediction interval is created to identify observations which, according to past data, do not correspond to future probable market activity. Any trade in the region outside the prediction limits is regarded to have information content related to future market movements. The prediction limits are based on an alternative definition of locally defined minimum and maximum probable values, determined over a pre-specified history of trades. This probable range of values is based on a given level of confidence around the forecast of the mean and considering its standard errors as calculated from the ACD-GARCH model. Therefore, the model was built on the basis of the last traded price, the uncertainty about the next efficient price, and the reluctance of market participants to act on price changes.

The upper and lower prediction limits are used as the thresholds for the next trade. In practice, the strategy uses a default 5% level of significance for the prediction interval, along with a time delay filter that requires the buy or sell signal to remain valid until the next trade before any action is taken. These components of what is coined the Forecast Range Strategy (FRS) can be adjusted depending on stock characteristics and investor risk preferences.

The prediction interval generated from the ACD-GARCH model is coupled with standard trading rules from the market-timing literature. These rules that are based on the series of return per unit of time, which is an indicator believed to be related to information about future stock market returns. The set of rules is composed of the classical if–then–else relational Boolean operators: “and”, >, and <. Raw trading rules can be greatly simplified by Boolean expressions which, in this case, define three outcomes: Buy, Hold, or Sell the stock. The following timing rules are applied to the arrival of the actual return per unit of time which is then compared to either the upper, or the lower, or both prediction intervals from the latest model estimation. The rules are specified in the Table 5.3.1 next:

Table 5.3.1 Trade Timing Rules

For investors OUT-of-market:

Condition	Recommendation
If $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ > Upper Prediction Limit	**BUY**
If Lower Prediction Limit < $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ < Upper Prediction Limit	**HOLD**
If $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ < Lower Prediction Limit	**HOLD**

For investors IN-the-market:

Condition	Recommendation
If $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ > Upper Prediction Limit	**HOLD**
If Lower Prediction Limit < $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ < Upper Prediction Limit	**HOLD**
If $\frac{r_{t+1}}{\sqrt{x_{t+1}}}$ < Lower Prediction Limit	**SELL**

A trading signal is triggered by an unusually large movement in stock prices in a short period of time, generating either loss or profit. The timing strategy employed in this study differs for the investor that is either in-the-market, or out-of-the market at the time of arrival of the new trade. It consists of recommendations for buying, selling or staying out of the market, depending on whether the value of the return per unit of time breaches the prediction limits or not. No short-sales are allowed under this strategy.

In practice, the investor starts by holding a cash position. If the return per unit of time from the next trade arrives with a value above the upper threshold, the money is invested in the stock. The current position is maintained until the value crosses the prediction limit from the opposite direction. The entire portfolio is then liquidated by switching from stock to cash. If a sell signal is indicated when the investor holds cash, then the investor stays out of the market. At the end of the forecast horizon the investor sells his/her position (if any) and finishes holding cash. The range between the upper and lower prediction limits enables the filtering of false trading signals occurring in periods of regular trading volatility characteristic of no information. It avoids taking decisions based on noise by treating an output value close to the predicted value as a "hold position" signal independent of whether any money is invested or not. The portfolio is rebalanced based on two assumptions. Firstly, unusual values of the return series reflect new information in the market, while secondly, the autocorrelation bias in the time series trend will continue in the same direction.

Clearly, market-timing techniques cover a broad category of subjective trading rules and the proposed Forecast Range Strategy (FRS) is no different. The focus of the strategy applied in this chapter is to monitor the intraday volatility shocks in returns, along with other economic and market microstructure information related to the time of the trade. The reasoning supporting this method is that a high return over a short period of time indicates the presence of informed investors in the market buying large quantities of stock, often at any given price. A movement in the opposite direction, such as a large negative return in a short period of time, is also regarded to have information content. This inverse situation points to informed investors with "bad news” quickly abandoning their position in a stock. As a consequence, the trading recommendations from the FRS indicate the virtually instantaneous presence of new information in the market, which is not publicly available. These sudden changes in patterns can be used to guide the investment decisions of uninformed traders and reduce reaction time to a minimum. In addition, the strategy tends to minimize costs of trading in the presence of informed traders by using the same information to act quickly and profit on the stock, or portfolios of stocks. The approach outlined in this chapter tends to produce higher returns in periods of higher volatility. This happens because the investment is timed to avoid being invested in non-informational periods or in periods of heavy losses. The risk is consequently reduced by keeping the investment out-of-market for most of the time and in-the-market only based on new information. It gives freedom to invest the "stand-by" capital in other opportunities without being vulnerable to market risk when the market contains no new information on the stock.

5.3.2 Estimation Window

The estimation of the ACD-GARCH model and the prediction one trade ahead is based on a rolling window of observations. The rolling nature of the window is designed to capture information over a meaningful length of time, to mitigate the problem of non-stationary, to have a constant estimation sample, and to avoid zero variances produced by sequences of equal prices. After the analysis of the information from each trade, the first observation of the window is discarded and the most recent observation included in the sample. The model is then re-estimated over the new sample to produce the forecast for the next trade. Thus, the prediction always takes into account the most recent data. This approach assesses the validity of the forecast on the basis of its relative distance from the closest valid observations.

The shorter the length of the window of observations, the more sensitive is the decision rule and the greater the number of buy and sell signals. On the other hand, a longer window length implies a closer fit to the data, a smaller number of trade recommendations and a greater tolerance for random movement without triggering a change in the portfolio. The number of trades in the window is chosen on the basis of the level of trade intensity. The more active the stock, the larger the number of trades required within the window. If the stock is not traded very often, then the number of trades in the window should be long enough not to contain too distant prices.

The choice of window size in this empirical application of the Forecast Range Strategy is set to be the number of trades during the month before the timing strategy is initiated. This procedure is inevitably heuristic, but it has the virtue of simplicity. Preliminary experiments were performed with one month of data to determine the best estimation sample for the model in all selected potential takeover targets. Tests of goodness of fit and model stability were performed with estimation window sizes from 15 days to 90 days. In most cases the best results were achieved within a 30 day rolling window, with no significant improvement observed beyond that point. However, the greater is this parameter value beyond 30 days, the longer the computational times for estimation and forecasting, along with the likelihood of biases created by stale prices. To ensure that the market-timing strategy under scrutiny is in “real-time”, two important requirements have to be met. The strategy should be based on publicly available trading information and the forecasts generated out-of-sample.

5.4 Data

The portfolio of stocks selected for the empirical application of trade timing from the Forecast Range Strategy (FRS) comes from the analysis in Chapter 3. It is the output of the out-of-sample prediction generated from the use of a combination of logistic and neural network models reported in that chapter and also in Rodrigues and Stevenson (2012).

The data set consists of 77 stocks, predicted as takeover targets one year ahead and spread over three financial years; 2009, 2010, and 2011 (FY09, FY10 and FY11 respectively). The Australian financial year starts on July 1 of the previous calendar year until the following June 30 date. For example, the financial year 2009 (FY09) starts on 01/07/2008 and ends on 30/06/2009. The reasoning behind the selection of three consecutive periods is to verify the actual profitability of the proposed strategy under different economic conditions. FY09 was a year heavily affected by the Global Financial Crisis and was not a good year for investing in equity portfolios. The FY10 and FY11 were better years that reflected a gradual recovery of the world economy. The sample is inevitably biased towards the use of companies that were expected to have some kind of informed trading activity in relation to an acquisition. However, it does not mean that all companies became a target during those years, or that all targets had informed traders transacting and taking positions in it.

For each of the three out-of-sample financial years, the sample includes 13 months of intraday data for each company, the trade and quote data was collected from the SIRCA database. Every company analysed had an initial hold-out period of 30 days put aside to estimate the model's parameters and produce the initial forecast for the financial year. This period refers to the last month of the previous financial year. It follows that June is the month selected to determine the size of the rolling window of observations, since the financial year starts on first of July. The number of trades during the period is used as the size of the estimation window. A graphical example of the implementation of the market-timing strategy using the moving window is in Appendix C.1, and the window size for each company is reported in Appendix C.2.

An important feature of transaction data is the irregularly spaced observations, with random times separating two subsequent trades. Consequently, there are cases where more than one transaction is recorded at the same time, but at different prices. As high-frequency models usually require a unique price observation per time stamp, some form of aggregation had to be performed. Taking the volume weighted average price was regarded as a reasonable solution given the discrete nature of the transaction data. For transaction volumes, the usual way to aggregate observations is to substitute the individual trades with the sum of the simultaneous volumes.

A common market characteristic which can often be observed in intraday transaction price series is the bid–ask bounce. Roll (1984) explains that in the absence of any significant event, market orders will tend to be executed at the current bid and ask prices, displaying a "bouncing" pattern. In fact, bid–ask bounce and regular market volatility can show price movements where none has occurred in practice and are not considered to contain useful information. The method chosen to reduce the impact of the bid–ask bounce was the use of the mid-quote price to compute the returns. It is defined as the geometric average of the best bid and ask quotes at the time of the trade.

Another well-documented fact in high frequency data is the seasonality in the intraday process. Contrary to many empirical market microstructure studies, the seasonality adjustment was not performed in all companies in this chapter. Seasonal factors were tested and appeared not significant in some stocks, especially because of the low frequency of observations in several trading days. The low and unstructured trading levels prevent the detection of consistent intraday patterns, turning the intraday deseasonalization redundant in these cases. This fact contrasts some results presented in Chapter 4 which reported clear intraday patterns in Australian companies. A possible explanation for this change in behaviour from the period before 2009 to now is the impact that the Global Financial Crisis had in the trading, and more specifically in companies with medium to low liquidity such as the ones predicted as targets by the model.

Finally, in order to adequately capture the last trade of the day, the convention that the trading day hours span between 10:12am and 4:00 pm was adopted. This prevents the ASX opening and closing trading algorithms from creating false information patterns.

5.5 Results

The results from this chapter are reported in two interrelated parts. The first part presents the analysis of the market-timing strategy in detail for a typical stock, while the second part is concerned with assessing the economic usefulness of the method in a portfolio context. During the presentation of results the comparison between the proposed Forecast Range Strategy (FRS) and the benchmark Buy-and-

Hold (B&H) strategy permits inferences about how the information contained in intraday returns and durations are economically important to the management of a portfolio.

The buy-and-hold strategy consists of entering the market for a stock on the first day of the financial year and remaining fully invested in that stock for one year. In the case of the market-timing method, investments are determined according to recommendations from the Forecast Range Strategy (FRS), with gains or losses summed on a trade-by-trade basis over the financial year. The model's forecast, working jointly with the timing rules (from section 5.3), generate buy, hold, and sell signals that guide the investments under the FRS. However, in this specific empirical application an extra rule was added, namely, sell three days after the takeover announcement day. This allows for any post-announcement drift in stock prices and recognises that there are low incentives to take further risk in remaining invested in stocks after an announcement has occurred.

5.5.1 Typical Company Results

A typical predicted takeover target was selected to monitor the information flow over one year. The empirical application of the FRS on the stock with the ASX identifier CKT (Challenger Kenedix Japan Trust, from the Real Estate industry) demonstrates how the market-timing strategy performs. This company is analysed during the FY10 when it had a takeover offer announced on 09/12/2009, and was subsequently delisted from the ASX on 09/02/2010 after a successful bid. The data contains information from periods when there are run-ups in prices before the takeover announcements, as well as when the stock price is quite volatile at the beginning of the financial year. Worth noting is that what is observed for this stock may be different to what would be observed for a stock where a takeover bad was not forthcoming.

The Figure 5.5.1 below demonstrates the trade timing recommendations for the stock based on the predicted and actual return series per unit of time. The triangles facing upwards indicate buy recommendations while the ones facing downwards indicate selling actions. The plus markers represent the actual return series values. The full and dashed lines represent the predictions and the confidence intervals, respectively.

The FRS detected many occasions when there were signs of informed activity in the trading. Based on that information, it accurately indicated to stay invested in the stock for more than one month before the company received the takeover offer. Importantly, informed trading activity was suggested early in the financial year. This behaviour is not unusual since negotiations for an acquisition starts months before the public announcement. In its raw form, the market-timing strategy contained 13 trade recommendations distributed over the year, which resulted in 6 trades. As observed in the period around November of 2009, the model automatically widens the prediction range (or interval) in periods of high volatility to avoid false recommendations. Additionally, it seems to recognize risky periods by indicating the selling of the stock after unusually low returns.

Figure 5.5.2 displays the percentage stock returns since day one of the financial year and the returns from the FRS. Critically, the shaded area highlights the periods when the FRS is invested in the stock, the full line represents the FRS return, and the dashed line the stock return.

Figure 5.5.1 Trade recommendations produced by the forecast range strategy (CKT)

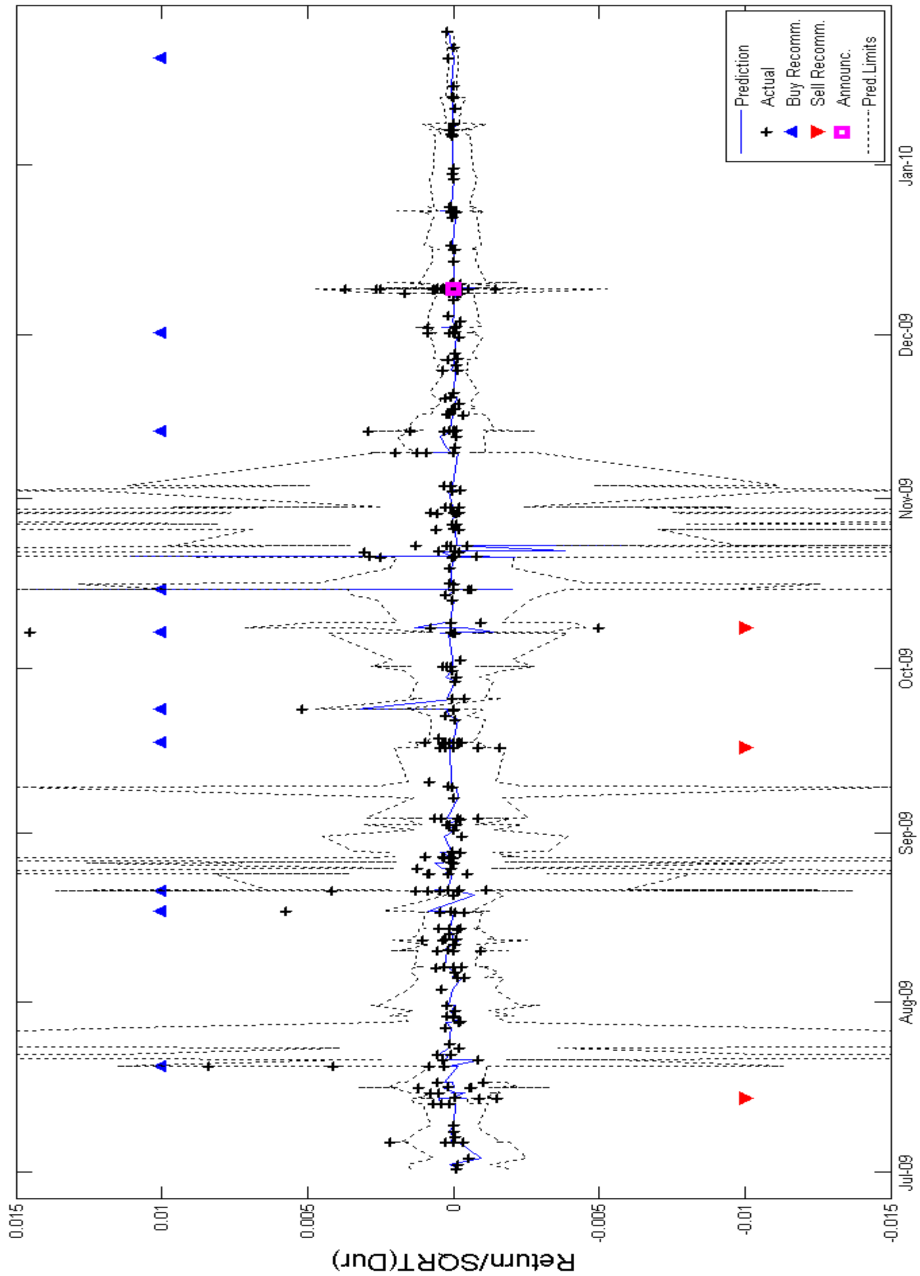


Figure 5.5.2 FRS and stock returns since the first day of FY10, and period invested (CKT)

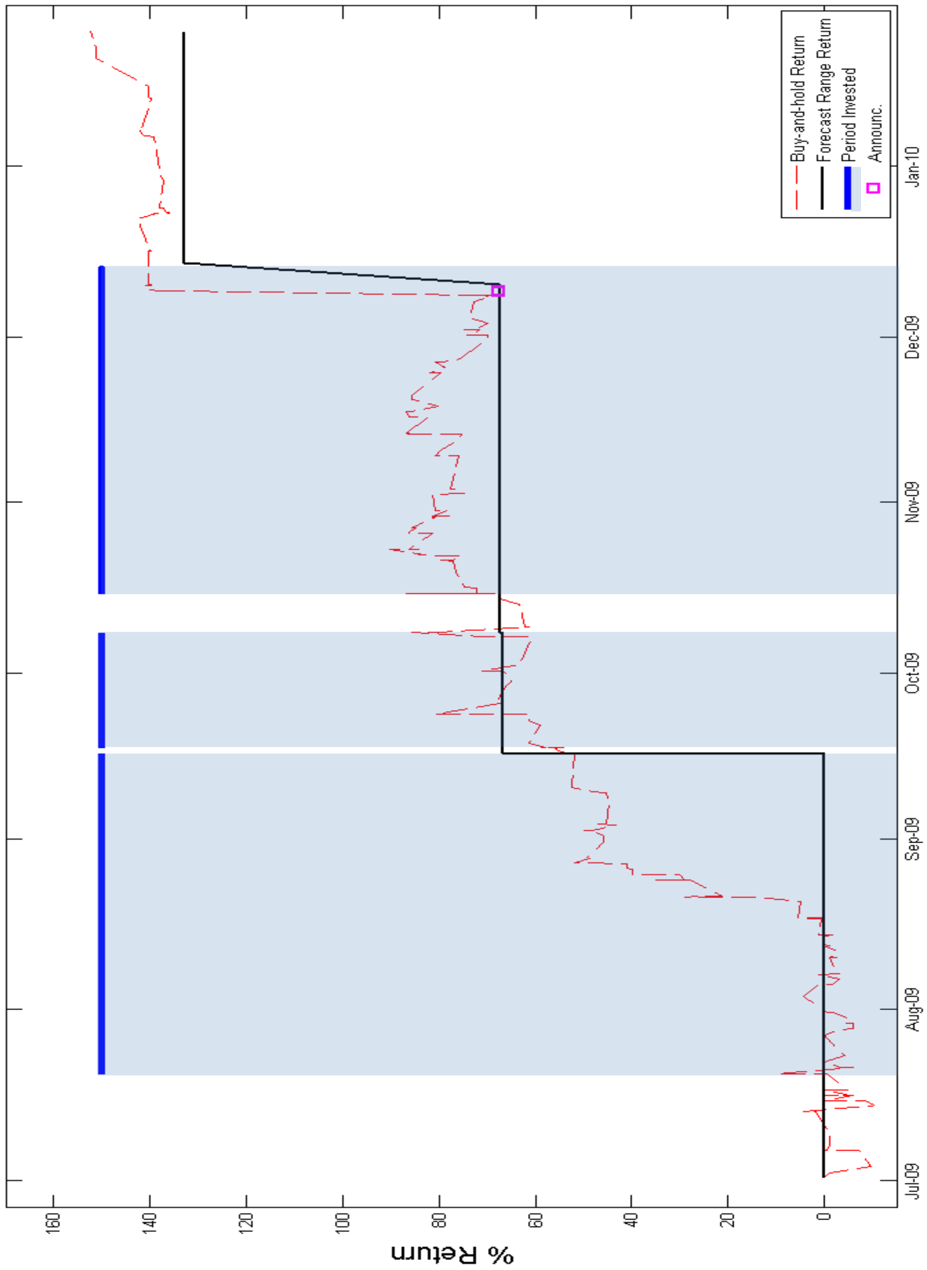


Figure 5.5.2 provides additional evidence that the strategy is actually capturing information about future movements in the stock price from intraday trading activity. In particular, it suggests the possibility of having informed traders active in the market before the event. Under the assumption of zero transaction costs, the timing strategy on CKT achieves an annualized return of 132.8%, against a 154.88% stock return. Although it did not outperform the benchmark for this typical company, the strategy executed a very rational approach by indicating to invest only after detecting favourable information. Under the FRS an investor is not in-the-market during the whole period, but invested only after some indication of new information related to a possible price run-up prior to the information event.

For this typical target, the FRS signalled to be invested before the strongest price jumps and months before the takeover announcement. The strategy indicated to be invested during 66.95% of the time, that is, 103.1 days of the 154 trading days that the stock was on the market during the financial year 2010. For the rest of the 51 days the investor had the option to invest in the risk-free rate, or allocate the resource to another investment. If transaction costs and reinvestment at the risk free rate are considered, the return from buying and holding the share until the last day is 143.20%, while the FRS return is 116.81%[*].

[*] The costs per trade are assumed to be half the average spread plus a fixed brokerage fee of 0.1%. The risk-free rate used for the reinvestment of the capital, when it is not being used by the FRS, is the average of the Bank Bill Reference Rate (BBSW) for the financial year. The details related to the transaction costs and the reinvestments of the stand-by capital for all companies are available in Appendix C.2.

5.5.2 Portfolio Results

The stock market has many drivers in its complex structure that are aggravated by the exclusive attributes of each stock. It is practically infeasible to conceive a trading strategy that works perfectly for every stock in all situations. Nevertheless, the analysis of the market-timing using the Forecast Range Strategy (FRS) on a portfolio of companies provides a more genuine measure of its performance. Different to other studies in the literature, this research applies an out-of-sample analysis of a significant number of stocks in order to validate the stability and robustness of the FRS approach. The sample contains companies for which a takeover announcement was predicted in Chapter 3.

The simulated returns conditional on buy, hold, or sell signals from the FRS timing strategy are compared to the benchmark B&H strategy in Tables 5.5.1, 5.5.2, and 5.5.3. In each table, the FRS and the B&H returns, including trading costs and reinvestment at the risk-free rate, are presented for each company whether it resulted in being an actual target or not. An interesting feature observed in the next three tables is the performance of the FRS in situations where the Buy-and-hold method generates negative returns. In those cases, the excess returns generated by FRS are generally positive. Unlike other market-timing rules in the literature, the FRS is extremely efficient in protecting the investor from periods of negative returns. This is particularly noticeable in the cases where the market-timing strategy suggested not trading in several stocks during the year.

Table 5.5.1 presents a comparison of the returns from the FRS and the B&H strategy for the FY09. In the first column are the returns for the FRS, while next to it are the FRS' results including trading costs and reinvestment of the non-invested capital in the risk free rate. The third column of the table reports the number of trades under the

FRS and the last column contains the average returns from the B&H including trading costs. The last line of each column has the return averages for the whole portfolio and the returns split by actual targets and non-targets.

Table 5.5.1 Buy-and-Hold and FRS returns: FY09

FY09						
Predicted Targets 19 Companies		FRS			B&H Return Inc. Trading Costs
		FRS Return	FRS Return Inc. Trading Costs + Reinv. RF rate	FRS Number of Trades	
TARGET	LST	56.32%	50.77%	8	-28.01%
	QGC	4.34%	-0.54%	10	5.38%
	TPX	0.00%	4.71%	0	-46.83%
NON-TARGET	BEN	-19.44%	-24.52%	18	-37.43%
	CBH	17.91%	10.31%	8	-41.98%
	CHQ	0.00%	4.71%	0	-20.29%
	CIF	0.00%	4.71%	0	-44.86%
	CNP	-28.24%	-31.72%	6	-64.01%
	FLT	3.86%	4.53%	4	-47.99%
	GPT	0.00%	4.71%	0	-78.64%
	IPN	0.00%	4.71%	0	-5.60%
	MMX	61.34%	64.46%	2	-45.97%
	NXS	0.00%	4.71%	0	-78.61%
	QAN	0.00%	4.71%	0	-36.18%
	REA	22.96%	14.45%	10	37.95%
	SBM	-21.22%	-29.52%	16	-40.93%
	SGB	-16.08%	-24.03%	24	-15.80%
	SST	0.00%	4.71%	0	5.38%
	VBA	40.76%	43.19%	2	-34.51%
PORTFOLIO AVERAGE		**6.45%**	**6.05%**	**5.68**	**-32.57%**
Avg. Targets		20.22%	18.31%	6.00	-23.15%
Avg. Non-Targets		3.87%	3.76%	5.63	-34.34%

From the 19 stocks in Table 5.5.1 the FRS recommended not to trade in 8 of them. Even when transaction costs and reinvestment of the capital at the risk-free rate are considered, the FRS portfolio average return is superior to the B&H return by a large margin, 6.05% against -32.57%, respectively. The low number of average trades during FY10 (5.68 trades) contributed to the small difference between the FRS return with and without trading costs, just 0.4%.

When the model detected sudden atypical negative returns, it automatically perceived activity by traders possibly in possession of unfavourable information about the company. This observation is important as it indicates an appropriate context, or "timing", for triggering the option of not investing in the presence of "bad news". Hence, by timing the investment using the FRS approach an investor would be unlikely to buy the stock in periods where negative information is observed through the trading process. Consistent with the results in Chapter 3, the actual targets had returns considerably higher than the non-targets, 18.31% against 3.76% on average. This further suggests that the FRS is making efficient use from event related information in the trading.

Table 5.5.2 presents the returns for the FY10, a year characterized by a slow recovery from the global financial crisis.

Table 5.5.2 Buy-and-Hold and FRS returns: FY10

<table>
<tr><th colspan="7">FY10</th></tr>
<tr><th colspan="2" rowspan="2">Predicted Targets
40 Companies</th><th colspan="3">FRS</th><th rowspan="2">B&H Return Inc. Trading Costs</th></tr>
<tr><th>FRS Return</th><th>FRS Return Inc. Trading Costs + Reinv. RF rate</th><th>FRS Number of Trades</th></tr>
<tr><td rowspan="9">TARGET</td><td>AOE</td><td>-6.78%</td><td>-15.20%</td><td>22</td><td>35.72%</td></tr>
<tr><td>CKT</td><td>132.80%</td><td>116.81%</td><td>6</td><td>143.20%</td></tr>
<tr><td>ERC</td><td>-6.59%</td><td>-8.89%</td><td>6</td><td>-52.23%</td></tr>
<tr><td>FLX</td><td>27.01%</td><td>27.15%</td><td>2</td><td>23.09%</td></tr>
<tr><td>LGL</td><td>-8.87%</td><td>-10.12%</td><td>8</td><td>48.24%</td></tr>
<tr><td>LLP</td><td>182.13%</td><td>171.13%</td><td>4</td><td>263.38%</td></tr>
<tr><td>PLI</td><td>63.88%</td><td>59.46%</td><td>4</td><td>74.56%</td></tr>
<tr><td>SSI</td><td>55.05%</td><td>50.77%</td><td>2</td><td>-60.59%</td></tr>
<tr><td>TKA</td><td>82.94%</td><td>79.85%</td><td>2</td><td>103.54%</td></tr>
<tr><td rowspan="10">NON-TARGET</td><td>AAY</td><td>0.00%</td><td>3.93%</td><td>0</td><td>-61.19%</td></tr>
<tr><td>AEM</td><td>58.62%</td><td>42.24%</td><td>4</td><td>-22.81%</td></tr>
<tr><td>ANZ</td><td>31.37%</td><td>31.94%</td><td>4</td><td>31.51%</td></tr>
<tr><td>AQF</td><td>0.00%</td><td>3.93%</td><td>0</td><td>20.15%</td></tr>
<tr><td>AZO</td><td>18.75%</td><td>17.10%</td><td>2</td><td>-11.61%</td></tr>
<tr><td>CBZ</td><td>0.00%</td><td>3.93%</td><td>0</td><td>-17.02%</td></tr>
<tr><td>CDU</td><td>76.03%</td><td>64.42%</td><td>14</td><td>84.72%</td></tr>
<tr><td>CFE</td><td>-8.13%</td><td>-16.35%</td><td>14</td><td>0.75%</td></tr>
<tr><td>CSL</td><td>-1.72%</td><td>-2.53%</td><td>4</td><td>1.84%</td></tr>
<tr><td>CWK</td><td>17.78%</td><td>8.60%</td><td>10</td><td>37.24%</td></tr>
</table>

FY10				
Predicted Targets 40 Companies	FRS			B&H Return Inc. Trading Costs
	FRS Return	FRS Return Inc. Trading Costs + Reinv. RF rate	FRS Number of Trades	
CXC	54.98%	48.61%	8	23.55%
EQX	0.00%	3.93%	0	22.19%
HDI	0.00%	3.93%	0	-7.92%
KMD	10.99%	8.58%	6	-1.75%
MDL	18.67%	8.30%	16	49.21%
MOO	11.34%	-9.66%	6	-31.42%
MQA	3.41%	2.62%	2	19.80%
PTN	50.98%	50.36%	2	-53.08%
RMR	17.36%	-6.52%	8	7.42%
ROB	0.00%	3.93%	0	-62.98%
RUL	23.21%	15.62%	8	-32.14%
RVE	-21.38%	-32.16%	6	43.09%
SHU	0.00%	3.93%	0	-8.50%
SNE	0.00%	3.93%	0	-21.33%
SOI	0.00%	3.93%	0	-21.46%
TBI	0.00%	3.93%	0	-34.45%
VGM	-31.94%	-37.75%	4	-38.17%
VIP	0.00%	3.93%	0	-7.96%
WBC	27.50%	20.84%	14	6.41%
WCR	0.00%	3.93%	0	-25.37%
WIG	3.98%	-2.07%	4	5.12%
PORTFOLIO AVERAGE	**22.08%**	**18.26%**	**4.80**	**11.82%**
Avg. Targets	57.95%	52.33%	6.22	64.32%
Avg. Non-Targets	11.67%	8.37%	4.39	-3.42%

The FRS still outperforms the B&H strategy during FY10, but with a lower advantage than the previous year. Again, the FRS indicated not to invest in many stocks for the whole period and achieved an average return of 18.26%, that is 6.44% higher than the buy-and-hold return (11.82%) for the same period. The FRS did not recommend a large number of trades. It performed on an average of 4.8 trades per stock during FY10. For most companies the FRS only indicated up to 4 “round-trip” trades (or 8 actual trades) for the entire period. This is a parsimonious number of trades when compared to other trading strategies in the literature. Notably, the portfolio return for the FRS and the B&H methods were penalised by the high trading costs that were high on that particular period. The average trading costs in FY10 was 2.73% per trade on the portfolio, against 1.38% in FY09 and 0.91% in FY11. The FRS return dropped from 22.08% to 18.26% when trading costs were included (see Appendix C2 for more information on trading costs). As was the case for FY09, the actual targets had a considerably higher return than the non-targets, 52.33% compared to 8.37%. This is evidence of the resourceful use of information by the FRS in order to profit.

Table 5.5..3 contains the results from FY11, which is considered a period with no strong influence of major economic events.

Table 5.5.3 Buy-and-Hold and FRS returns: FY11

FY11					
Predicted Targets 18 Companies		FRS			B&H Return Inc. Trading Costs
		FRS Return	FRS Return Inc. Trading Costs + Reinv. RF rate	FRS Number of Trades	
TARGET	AKR	17.60%	-0.25%	4	-20.51%
	ASX	27.22%	23.74%	12	5.62%
	CRG	15.91%	15.27%	4	30.97%
	DKN	40.40%	23.07%	8	20.15%
	IIF	17.28%	15.93%	4	40.45%
	JML	114.25%	91.02%	20	146.48%
NON-TARGET	API	3.88%	1.66%	6	-29.05%
	CER	80.84%	42.22%	24	116.41%
	CNP	-17.69%	-21.54%	8	-73.73%
	DUE	19.70%	5.26%	28	5.51%
	DXS	16.08%	7.38%	18	11.87%
	EXT	27.23%	16.90%	24	24.13%
	MDL	15.53%	16.91%	4	-39.19%
	OMH	6.56%	3.72%	10	-37.67%
	RIO	24.77%	23.70%	12	26.60%
	SPN	15.32%	12.32%	6	21.49%
	TAP	26.05%	19.32%	10	-5.25%
	TPM	5.60%	-8.08%	38	-11.66%
PORTFOLIO AVERAGE		**25.36%**	**16.03%**	**13.33**	**12.92%**
Avg. Targets		38.78%	28.13%	8.67	37.19%
Avg. Non-Targets		18.66%	9.98%	15.67	0.79%

The FRS portfolio return was significantly affected by the higher trading activity. The number of trades more than doubled relative to previous periods, achieving an average of 13.33 trades per stock.

Consequently the FRS portfolio return dropped from 25.36% to 16.03% when considering trading costs. Despite this reduction it still 3.11% higher than buying and holding the portfolio, 16.03% compared to 12.92%. For the first time the FRS average trades on targets (8.67) was lower than on the non-targets (15.67). In contrast to the previous years, there is not one stock in Table 5.6.3 where the FRS indicated not to invest for part of the whole period. As was previously the case for FY09 and FY10, the group of actual targets achieved higher returns (28.13%) than the non-targets (9.98%) under FRS recommendations. Once more, the proposed market-timing strategy protected investors from underperforming non-target stocks and signalled to invest before all six takeover announcements. In general, FY11 was more active and less volatile than the previous two years and this contributed to lower average trading costs and a higher number of trades. Inherent to the model is the construction of prediction intervals which are heavily influenced by the level of market volatility. In less volatile periods the forecast range becomes narrower and consequently more sensitive to the arrival of new information, even if it is not as strong as the information related to an announcement.

Overall, the FRS consistently outperformed the benchmark Buy-and-hold investment and, more importantly, indicated to trade in all actual takeover targets. It demonstrated to be very efficient in detecting information since it indicated to be invested in advance of every single takeover announcement. An investor who follows the FRS timing approach holds the securities for a considerably shorter period during the investment horizon than is the case for the B&H strategy. Further, they enter the market only when there is some indication of informed trading activity. Therefore, it should deliver lower risks than being exposed to the market volatility for the whole year. The comparisons between the time invested on both the FRS and the benchmark strategies given in Tables 5.5.4, 5.5.5 and 5.5.6. It is important to remember that an investment according to the FRS begins out-of-the-market and an action is only taken based on a significant sign of information. Consequently, the FRS will spend less time invested in each stock than is the case for the benchmark B&H strategy.

Table 5.5.4 contains the period invested in each stock during the FY09.

Table 5.5.4 Days invested in FRS and B&H: FY09

FY09				
Predicted Targets 19 Companies		Days Trading: Buy & Hold	FRS	
			Days Invested	Time Invested
TARGET	LST	252	88.52	35.13%
	QGC	193	72.65	37.64%
	TPX	252	0.00	0.00%
NON-TARGET	BEN	252	86.71	34.41%
	CBH	252	44.05	17.48%
	CHQ	252	0.00	0.00%
	CIF	252	0.00	0.00%
	CNP	252	220.69	87.57%
	FLT	252	65.94	26.17%
	GPT	252	0.00	0.00%
	IPN	252	0.00	0.00%
	MMX	252	34.30	13.61%
	NXS	252	0.00	0.00%
	QAN	252	0.00	0.00%
	REA	252	224.33	89.02%
	SBM	252	51.01	20.24%
	SGB	252	22.61	8.97%
	SST	252	0.00	0.00%
	VBA	252	23.98	9.52%
PORTFOLIO AVERAGE		**248.89**	**49.20**	**19.77%**
Avg. Targets		232.33	53.73	24.26%
Avg. Non-Targets		252.00	48.35	19.19%

The results in Table 5.5.4 show that the FRS portfolio stayed invested only 19.77% of the time available to trade. It represents an average of 49.2 days invested in each company during the one year investment horizon. Therefore, the capital was free to be used for other investments in more than 80% of the time. In fact, the FRS was very efficient in holding back trades from the stock market during the peak of the global financial crisis. As a result, an investment in the FRS tends to face less market risk and achieve higher returns than holding the stock for one year. Despite the large difference in returns, there was a small difference in the number of days invested in targets and non-targets under the FRS.

The FRS behaved differently during FY10 from FY09, as shown in Table 5.5.5.

Table 5.5.5 Days invested in FRS and B&H: FY10

FY10				
Predicted Targets 40 Companies		Days Trading: Buy & Hold	FRS	
			Days Invested	Time Invested
TARGET	AOE	252	127.48	50.59%
	CKT	154	103.11	66.95%
	ERC	130	2.93	2.26%
	FLX	127	24.67	19.42%
	LGL	252	24.16	9.59%
	LLP	125	37.48	29.98%
	PLI	107	43.01	40.20%
	SSI	252	16.47	6.54%
	TKA	252	14.12	5.60%
NON-TARGET	AAY	252	0.00	0.00%
	AEM	252	0.69	0.28%
	ANZ	252	68.52	27.19%
	AQF	252	0.00	0.00%
	AZO	252	70.54	27.99%
	CBZ	252	0.00	0.00%
	CDU	252	237.89	94.40%
	CFE	252	164.45	65.26%
	CSL	252	189.21	75.08%
	CWK	252	14.68	5.83%
	CXC	252	213.86	84.87%
	EQX	252	0.00	0.00%
	HDI	252	0.00	0.00%
	KMD	252	55.52	22.03%
	MDL	252	171.60	68.09%
	MOO	252	88.57	35.15%
	MQA	252	56.05	22.24%
	PTN	252	19.85	7.88%
	RMR	252	174.92	69.41%

FY10			
Predicted Targets 40 Companies	**Days Trading: Buy & Hold**	**FRS**	
		Days Invested	**Time Invested**
ROB	252	0.00	0.00%
RUL	252	115.35	45.77%
RVE	252	163.35	64.82%
SHU	252	0.00	0.00%
SNE	252	0.00	0.00%
SOI	252	0.00	0.00%
TBI	252	0.00	0.00%
VGM	252	79.64	31.60%
VIP	252	0.00	0.00%
WBC	252	201.24	79.86%
WCR	252	0.00	0.00%
WIG	252	200.00	79.37%
PORTFOLIO AVERAGE	**236.58**	**66.98**	**28.31%**
Avg. Targets	183.44	43.71	25.68%
Avg. Non-Targets	252.00	73.74	29.26%

The FRS recommended being on-the-market during 28.31% of the trading time in FY10. This represents an average of 66.98 days invested in each stock of the portfolio during the period, with the highest time ratio of 94.40% for the stock CDU. In contrast with the previous year, the strategy recommended to stay less time invested in the actual targets than the non-targets.

As expected, the economic conditions during FY11 have affected the way the FRS triggered its recommendation to buy and sell stocks. From Table 5.5.6 we observe that the average time on-the-market is considerably higher than the previous two years, on average 116.98 days invested during the year. This represents 48.90% of the time invested, a number that is higher for non-targets (52.06%) and considerably lower for the targets group (41.07%).

Table 5.5.6 Days invested in FRS and B&H: FY11

FY11				
Predicted Targets 18 Companies		**Days Trading: Buy & Hold**	**FRS**	
			Days Invested	**Time Invested**
TARGET	AKR	142	47.88	33.72%
	ASX	251	76.06	30.30%
	CRG	213	74.39	34.93%
	DKN	251	180.86	72.05%
	IIF	191	94.69	49.58%
	JML	245	63.27	25.82%
NON-TARGET	API	251	46.60	18.56%
	CER	251	231.25	92.13%
	CNP	251	13.50	5.38%
	DUE	251	99.54	39.66%
	DXS	251	201.44	80.25%
	EXT	251	64.08	25.53%
	MDL	251	12.16	4.84%
	OMH	251	58.27	23.21%
	RIO	251	153.19	61.03%
	SPN	251	226.53	90.25%
	TAP	251	225.63	89.89%
	TPM	251	235.95	94.00%
PORTFOLIO AVERAGE		**239.17**	**116.96**	**48.90%**
Avg. Targets		215.50	89.53	41.07%
Avg. Non-Targets		251.00	130.68	52.06%

As can be observed from Table 5.5.6, the FRS recommended trade in all stocks of the portfolio. It resulted in the smallest time invested in MDL (4.84%) and the greatest time in TPM (94%) during that year. Overall, the less volatile period changed the sensitivity of the FRS to the arrival of new information. This reduced volatility resulted in more trades during FY11 than in other years. Further analyses considering the time invested and dates are given in Appendix C.3.

In general the Forecast Range Strategy managed to keep investment away in period of losses, while suggested investment before the run-up in prices. This is reflected in the proportionally low time on-the-market and the high profits across the three separate years. It reacts appropriately by indicating more trades in volatile periods when new information and informed trading are more common, while suggesting spending less time invested in periods with bad information. Table 5.5.7 presents the total returns and trading costs for the FRS, the benchmark B&H, and the ASX index All Ordinaries (All Ords) over the three periods.

Table 5.5.7 Total returns

Portfolio	FY09 19 Companies	FY10 40 Companies	FY11 18 Companies
All Ords	-25.97%	9.55%	7.75%
Buy-and-Hold (B&H)	-32.57%	11.82%	12.92%
Forecast Range Strategy (FRS)	6.05%	18.26%	16.03%

The Forecast Range Strategy is stable across the different economic environments in FY09, FY10 and FY11. The timing strategy generates positive portfolio returns and outperforms the benchmark strategy in the three out-of-sample periods. The successful results from using FRS confirm the propositions of many authors concerning the economic value of market-timing strategies when managing an investment portfolio. Additionally, this empirical application of market-timing relies on the modelling of volatility and duration in high frequency data in order to time the investment. As such, it provides evidence to support the arguments of Easley and O'Hara (1992) and Rodrigues *et al.* (2012), among others, which discuss the trading of privileged information around events and how the presence of such information is likely to be found in the intraday trading.

5.6 Conclusions

The results from this chapter provide evidence in favour of three propositions. First, the intraday trading reveals information related to traders acting on privileged information in anticipation of market events, such as a takeover announcement. Second, a portfolio can achieve abnormal returns using investments based on a market-timing strategy. Third, timing the trade based on information from intraday trading improves the portfolio returns and reduces risk by avoiding being invested during periods of losses, and by correctly signalling to be invested in takeover targets before the announcement.

The innovative approach of using the ACD-GARCH model jointly with market-timing rules to capture information from high frequency data to generate trading recommendations revealed an area of research that can give origin to profitable methodologies for portfolio management in the Australian market. The FRS buy-and-sell signals consistently generated higher returns than the B&H strategy. The Forecast Range Strategy was successful in predicting market trends and provided a method for reducing risk without sacrificing return. As observed, the time invested on the stock was significantly lower than the buy-and-hold strategy. This allows for the investment of capital in other opportunities.

Overall, the results presented in this chapter provide evidence of the dissemination of private information in intraday trading, as well as being consistent with studies reporting that market-timing rules can achieve abnormal returns using publicly available information. The modelling approach recognises patterns in high frequency data in order to identify trading activity associated with informed trading and new information. The timing recommendations are observed to be generally beneficial in downturn periods, providing abnormal returns in those situations. The FRS market-timing method was stable over the years and led to a high average portfolio return under different economic conditions.

Although these findings provide investors with important asset allocation information in periods of uncertainty, four issues should be noted at the time of the application of the method: share dilutions, dividends, liquidity and short sales constrains. All of them may affect the results.

CHAPTER 6

Conclusion

Mergers and acquisitions is an area with high information asymmetry and, consequently, abnormal profit opportunities for investors. As observed in the thesis, the effect that takeover announcements have on the prices of target firms proved to be a strong motive for trading with privileged information, confirming the results from previous studies. As a consequence, movements in trading activity before a takeover announcement can be used to detect the presence of informed trading and information leakage as a result of that trading. This thesis develops an investment strategy to predict market events and to manage the portfolio of potential targets for maximum economic gain. It concentrates on the efficient use of publicly available information to forecast future events and adapt the trading according to market behaviour. The modelling approaches outlined in this study provide a means by which the timing of the inclusion of potential targets in a portfolio is determined.

The thesis explores the possible economic gains accruing to a portfolio of predicted target companies. By combining forecasts from individual models, a portfolio of targets is created that achieves abnormal returns and lower misclassification rates. The combination of probability forecasts from a diverse range of models is an effective method to improve forecast accuracy and gain consistency on predictions. The combination of panel data logistic regressions and neural network models used to predict takeover targets forms a consensus forecast that improves prediction accuracy and generates abnormal returns from the portfolios of predicted targets. The methodology significantly reduces misclassification errors and selects an optimized group of companies with high likelihood of becoming a takeover target.

The results from the takeover prediction method are in line with many studies suggesting that forecast combination can improve on the best individual forecast. Two general conclusions are drawn from these results. Firstly, the combination methods outperform the single models and should be used to improve the prediction of takeover targets. In particular, the Weights Combination approach is a stable and efficient method for combining takeover target predictions in order to improve model accuracy and to achieve abnormal returns. Secondly, it has been demonstrated that an investment in the combined predicted targets in a regular year resulted in significant abnormal returns being made by an investor, in the order of up to two times the market benchmark return within a portfolio of manageable size.

The modelling of transaction time enabled the determination of the effects of high frequency information on the conditional volatility of the returns. The market behaviour of a large sample of companies on the Australian Securities Exchange allowed the conclusion that the time between trades, microstructure variables and the intraday patterns are in fact affected by new information arriving in the market. It was observed that the information related changes in market behaviour are reflected in market observable variables and in features, such as liquidity, volatility of returns, and other measures of trading activity.

This analysis is made possible by using the ACD model along with the conventional GARCH model adapted for economic time. The estimated models allowed the identification and quantification of the impact that trading variables have on volatility, and how privileged information impacts it before the event of a takeover announcement. The analysis supports the assumption that the intensified trading activity in the target companies closer to the event announcement is a consequence of traders who held private information. Not only does the estimation of the models confirm the hypothesis of higher diffusion of private information in the months just prior to the announcement, but the intraday trading characteristics show that this diffusion can be captured by observing the changes in the intraday trading. In general, it is possible to observe a clear relation between trading intensity and information dissemination.

Using the approach adopted in this study, a consistent covariate pattern for targets is established over an extensive range of companies. The empirical application of the methodology shows that the intraday trading behaviour of the takeover target companies can be affected by brokers trading on private information. Through the observation of the bidder companies over the same period, it is concluded that the buyer side of the market is also affected, but to a much lesser degree. To confirm that these results are not contaminated by industry or market related news, a control group of companies was included in the analysis. The results in this study are, in general, consistent with those suggested by market microstructure theories related to the actions and presence of informed traders.

The last stage of the thesis proposes a market-timing strategy to indicate the best time for the introduction of potential targets into a portfolio. The portfolio is subsequently rebalanced according to information suggested by changes in company intraday trading behaviour. A new and efficient approach to market-timing in high frequency trading, namely the Forecast Range Strategy (FRS), demonstrates how to capture the information content from individual trades, along with the complex temporal dependence typically displayed by high frequency transactions data. The FRS investment strategy identifies possible inside information from the intraday trading which is being used to derive trade recommendations to buy and sell stocks. The FRS takes into consideration the multivariate filtration of arrival times through the ACD-GARCH model to assign a range of probable future values. As a result, the timing strategy measures the aversion to price changes of uninformed market participants by an allocated probability. The union of the information from the high frequency model with the empirical application of a market-timing methodology is a cornerstone of this thesis. The approach of using the ACD-GARCH model and trading rules to jointly capture information from high frequency data indicates a profitable area of research for takeover portfolio management in the Australian market.

Further, the FRS is shown to be successful in predicting market trends and provides a method for reducing risk without sacrificing return. The results of this study provide evidence in favour that a portfolio can achieve abnormal returns using an investment strategy based on public available data, and that timing the trade based on information from the intraday trading improves the portfolio returns. Timing recommendations are observed to be generally beneficial in downturn periods, or when the market is stable. In these situations the FRS buy-and-sell signals consistently generate returns that are higher than the buy-and-hold returns.

Overall, the results in this thesis provide evidence in favour of the hypothesis that an investment strategy can achieve abnormal returns using publicly available information. These findings provide investors with important asset allocation information especially in periods of uncertainty. In particular, the assembly of the three methodologies together achieves the main objectives of forecasting market events more precisely, obtaining information from the intraday trading, and developing a profitable market-timing strategy on high-frequency trading.

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Appendix A

A.1 Multicolinearity Analysis and Descriptive Statistics of Variables used in Chapter 3

The Variance Inflation Factor (VIF) is used to quantify the multicolinearity in an regression analysis. It basically provides an index to measures how much the variance of an estimated regression coefficient is increased because of collinearity between the independent variables. A common rule of thumb is that if VIF is greater than 5, then multicollinearity is high. The study originally started with 55 variables, but after the analysis of the VIF the number was reduced to 35 variables. The 20 excluded variables presented VIF coefficients bigger than 5 and are considered highly correlated with the other variables in this study. The remaining variables do not present a VIF coefficient higher than 2.7. The variance inflation factor for each variable in the sample listed in Chapter 3 is reported in Table A.1.1 below.

Table A.1.1 Variance inflation factor

Variable	VIF	1/VIF
v1	1.05	0.949
v2	1.00	1.000
v3	2.10	0.476
v4	1.18	0.845

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Variable	VIF	1/VIF
v5	1.03	0.969
v6	1.00	1.000
v7	1.04	0.965
v8	1.01	0.987
v9	1.25	0.800
v10	1.88	0.532
v11	1.06	0.948
v12	1.00	0.999
v13	2.52	0.396
v14	2.62	0.382
v15	1.00	0.997
v16	1.00	0.998
v17	1.04	0.961
v18	2.10	0.476
v19	1.00	0.998
v20	1.01	0.989
v21	1.00	0.999
v22	1.88	0.532
v23	1.11	0.904
v24	1.35	0.739
v25	1.08	0.924
v26	1.15	0.871
v27	1.00	1.000
v28	1.00	1.000
v29	1.15	0.867
v30	1.00	1.000
v31	1.06	0.941
v32	1.36	0.736
v33	1.56	0.640
v34	1.48	0.677
v35	1.28	0.781
Mean VIF	**1.300**	

In addition to the previous multicolinearity analysis, Table A.1.2 displays the correlation matrix for the variables used to estimate the model. The variables present very low correlation in this study. There are just a few cases where the correlation coefficient is above 0.5.

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Table A.1.2 Correlation matrix

	year	tkvr	V1	V2	V3	V4	V5	V6	V7	V8
Year	1.000									
Tkvr	0.014	1.000								
V1	-0.007	0.001	1.000							
V2	0.012	0.001	0.000	1.000						
V3	-0.019	0.003	0.000	0.000	1.000					
V4	0.005	-0.001	-0.003	-0.001	-0.009	1.000				
V5	-0.015	-0.001	-0.020	0.001	0.003	-0.009	1.000			
V6	-0.009	-0.002	0.000	0.000	0.000	0.003	-0.001	1.000		
V7	-0.002	-0.001	-0.003	0.007	-0.013	0.007	-0.001	0.000	1.000	
V8	-0.002	-0.005	0.001	0.000	0.000	0.004	-0.003	0.004	0.000	1.000
V9	0.059	0.000	0.018	0.002	-0.012	0.020	-0.033	0.003	0.171	0.032
V10	0.011	-0.001	0.000	0.000	0.001	-0.001	0.001	0.000	0.007	-0.001
V11	-0.084	0.015	0.005	0.004	0.019	-0.057	0.032	-0.004	-0.020	-0.014
V12	-0.006	-0.001	0.000	0.000	0.000	0.001	0.003	0.000	0.001	-0.001
V13	0.000	0.000	0.012	0.000	-0.001	-0.003	0.099	0.000	0.000	0.000
V14	-0.001	-0.002	-0.135	0.000	0.000	0.002	0.159	0.000	-0.002	-0.001
V15	0.011	0.001	0.000	0.000	0.002	-0.007	0.002	-0.002	-0.032	-0.003
V16	-0.001	0.001	0.000	0.000	0.001	0.003	0.000	0.000	-0.001	0.017
V17	0.008	-0.002	0.005	0.001	0.012	0.009	0.019	-0.002	0.071	-0.006
V18	0.004	0.001	0.000	0.000	-0.724	0.005	-0.002	0.000	0.010	0.000
V19	0.006	-0.002	0.000	0.000	-0.001	0.002	-0.001	0.000	0.033	0.000
V20	0.005	-0.001	0.000	0.000	0.001	-0.002	0.004	0.000	-0.003	0.099
V21	-0.001	-0.002	-0.001	0.000	0.001	0.002	0.009	0.000	-0.003	-0.001
V22	0.006	-0.001	0.000	0.000	0.000	0.003	-0.016	0.000	0.009	0.000
V23	-0.014	0.002	0.002	0.001	0.010	-0.052	0.001	-0.002	-0.012	-0.004
V24	0.008	0.004	0.004	0.002	0.015	-0.372	0.003	-0.003	-0.008	-0.010
V25	-0.004	-0.001	0.000	0.000	0.001	-0.008	0.000	0.000	-0.001	0.001
V26	0.037	-0.002	0.000	0.000	0.001	-0.008	0.000	0.000	-0.003	-0.001
V27	-0.011	-0.001	0.000	0.000	0.000	0.002	-0.001	0.000	-0.002	0.000
V28	-0.005	-0.002	0.000	0.000	0.001	0.002	-0.001	0.000	-0.001	0.010
V29	0.001	-0.001	0.005	0.000	-0.006	0.004	-0.010	-0.002	0.079	0.032
V30	0.008	-0.002	0.000	0.000	0.000	0.003	-0.001	0.000	-0.003	-0.001
V31	0.069	0.007	-0.012	0.005	-0.032	0.094	-0.026	0.001	0.026	-0.005
V32	-0.012	0.042	0.005	0.003	0.003	-0.115	-0.001	-0.005	0.029	-0.013
V33	0.056	0.051	0.029	-0.005	0.019	-0.112	-0.030	-0.005	0.036	0.006
V34	0.021	0.006	0.002	0.001	0.005	-0.043	-0.002	-0.002	-0.004	-0.004
V35	-0.004	0.011	0.001	0.001	0.005	-0.041	0.006	-0.002	-0.006	-0.004
	V9	**V10**	**V11**	**V12**	**V13**	**V14**	**V15**	**V16**	**V17**	**V18**

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	year	tkvr	V1	V2	V3	V4	V5	V6	V7	V8
V9	1.000									
V10	0.000	1.000								
V11	-0.032	0.027	1.000							
V12	-0.009	-0.001	0.020	1.000						
V13	-0.006	0.000	-0.003	0.000	1.000					
V14	-0.028	0.000	-0.009	0.000	0.768	1.000				
V15	-0.002	0.000	0.006	0.000	0.003	0.002	1.000			
V16	0.019	0.000	0.003	0.000	0.000	0.000	0.001	1.000		
V17	0.175	0.000	0.041	-0.001	0.000	-0.004	-0.006	0.038	1.000	
V18	0.010	0.000	-0.011	0.000	0.001	0.000	0.002	0.000	-0.007	1.000
V19	0.011	0.000	-0.007	0.000	0.000	0.000	0.000	0.000	0.019	0.001
V20	-0.004	-0.008	0.015	0.000	0.000	-0.001	0.001	0.000	0.002	-0.001
V21	-0.019	0.000	-0.006	0.000	-0.001	0.001	0.000	0.000	-0.006	0.000
V22	0.009	0.683	0.022	-0.001	0.000	-0.001	0.001	0.000	0.002	0.000
V23	0.001	0.000	0.037	-0.001	-0.001	-0.004	0.032	-0.002	-0.007	-0.005
V24	-0.004	0.000	0.073	-0.002	-0.002	-0.006	0.008	-0.003	-0.004	-0.006
V25	0.014	0.000	0.006	0.000	0.000	0.000	0.002	0.000	0.000	-0.001
V26	-0.004	0.003	0.003	0.000	0.000	0.000	0.001	0.000	-0.002	-0.001
V27	-0.002	0.000	-0.004	0.000	0.000	0.000	0.000	0.000	-0.001	0.000
V28	0.001	0.000	-0.004	0.000	0.000	0.000	0.000	0.000	-0.002	0.000
V29	0.362	0.002	-0.009	-0.007	-0.006	-0.015	0.001	-0.001	0.065	0.003
V30	-0.004	0.000	-0.009	0.000	0.000	0.000	0.000	0.000	-0.003	0.000
V31	0.031	-0.002	-0.143	-0.005	-0.009	0.003	-0.004	-0.004	-0.012	0.017
V32	0.090	0.005	0.057	-0.003	-0.001	-0.007	-0.013	-0.005	0.046	0.009
V33	0.178	0.005	0.152	-0.005	-0.019	-0.052	0.010	0.002	0.063	-0.003
V34	0.005	0.000	-0.004	-0.001	0.000	-0.002	0.005	-0.002	-0.003	-0.002
V35	-0.004	-0.013	0.062	-0.001	-0.001	-0.002	0.003	-0.001	-0.003	-0.003

	V19	V20	V21	V22	V23	V24	V25	V26	V27	V28
V19	1.000									
V20	0.000	1.000								
V21	0.000	0.000	1.000							
V22	0.000	0.008	-0.001	1.000						
V23	0.000	-0.001	-0.002	0.000	1.000					
V24	-0.003	-0.001	-0.002	-0.006	0.265	1.000				
V25	0.000	0.000	0.000	0.000	0.153	0.240	1.000			
V26	0.000	0.000	0.000	0.004	0.006	0.007	0.000	1.000		
V27	0.000	0.000	0.000	0.000	-0.002	-0.002	0.000	0.000	1.000	
V28	0.000	0.001	0.000	0.000	-0.001	-0.003	0.000	0.000	0.000	1.000
V29	-0.004	0.004	-0.008	0.008	0.003	0.007	-0.002	-0.009	-0.002	0.001
V30	0.000	-0.001	0.000	0.000	-0.003	-0.005	0.000	-0.001	0.002	0.000

	year	tkvr	V1	V2	V3	V4	V5	V6	V7	V8
V31	-0.008	-0.016	-0.008	0.005	-0.093	-0.130	-0.005	0.008	-0.002	-0.007
V32	-0.002	-0.003	-0.005	0.007	0.110	0.132	0.000	0.057	-0.003	-0.002
V33	0.002	0.003	-0.021	0.009	0.144	0.196	0.009	0.059	-0.004	-0.006
V34	-0.002	-0.002	-0.002	0.000	0.034	0.033	0.000	0.352	-0.001	-0.002
V35	-0.002	0.000	-0.001	-0.016	0.025	0.019	0.000	0.197	-0.001	-0.001
	V29	**V30**	**V31**	**V32**	**V33**	**V34**	**V35**			
V29	1.000									
V30	-0.003	1.000								
V31	0.014	0.012	1.000							
V32	0.050	-0.007	-0.091	1.000						
V33	0.086	-0.008	-0.151	0.499	1.000					
V34	-0.006	-0.002	0.001	0.227	0.297	1.000				
V35	-0.003	-0.002	-0.007	0.136	0.231	0.450	1.000			

Table A.1.3 contains the descriptive statistics from the variables used on the estimation and prediction of takeover announcements in Chapter 3. The respective definitions of the codes V1 to V35 are given following the hypotheses they represent in section 3.3.1 of Chapter 3.

Table A.1.3 Descriptive statistics from the variables for takeover prediction

Variable	Obs	Mean	Std. Dev.	Min	Max
year	19951	2004.93	3.45	1999.00	2010.00
tkvr	19951	0.04	0.19	0.00	1.00
V1	19951	-0.31	24.75	-54.00	242.41
V2	19951	0.50	4.15	-40.76	221.09
V3	19951	0.08	175.02	-93.87	358.41
V4	19951	0.12	0.17	0.00	4.96
V5	19951	1.44	5.82	0.00	67.13
V6	19951	3.38	73.84	-1.00	728.77
V7	19951	0.18	0.85	-1.00	70.85
V8	19951	1.25	13.92	-1.00	794.93
V9	19951	0.67	0.45	-1.00	11.11
V10	19951	1.34	9.97	0.00	98.31
V11	19951	0.17	0.09	0.00	0.91

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Variable	Obs	Mean	Std. Dev.	Min	Max
V12	19951	3.55	230.02	-21.41	317.01
V13	19951	5.44	136.12	0.00	231.33
V14	19951	4.99	143.80	0.00	269.66
V15	19951	1.19	39.50	0.00	331.41
V16	19951	8.81	44.23	-1.00	434.22
V17	19951	0.20	1.58	-1.00	52.62
V18	19951	176.76	899.81	0.00	1159.15
V19	19951	448.17	340.53	0.00	211.98
V20	19951	31.45	24.61	0.00	335.65
V21	19951	69.71	79.95	0.00	497.77
V22	19951	2.80	99.19	0.00	343.18
V23	19951	0.25	1.31	0.00	145.00
V24	19951	0.02	0.07	0.00	5.27
V25	19951	3.70	17.57	0.00	54.86
V26	19951	2034.09	32800	-98.9	131000
V27	19951	172.74	992.14	0.00	6610.00
V28	19951	9.45	13.71	-1.00	79.33
V29	19951	0.16	0.79	-1.00	34.12
V30	19951	42.96	112.79	0.00	808.45
V31	19951	0.30	0.46	0.00	1.00
V32	19951	0.15	0.35	0.00	1.00
V33	19951	17.28	2.81	0.00	27.25
V34	19951	76700000	573000000	0.00	24400000000
V35	19951	22200000	71000000	0	17600000000

A.2 Estimation Results from Chapter 3

The following tables portray the estimation results from the logistic models estimated in Chapter 3. They include the Logistic, panel data Logistic with Mixed Effects, panel data Logistc with Crossed effects, and the Weights Combination models. The Tables depict the outputs from the statistical package STATA 11 used for data analysis.

A backward stepwise procedure is performed for each logistic model specification using the selected variables after controlling for multicollinearity. The results are estimated using a common set of variables for each year. The significance level for retention of variables in the analysis is set at 0.2, with few exceptions in case the exclusion of the variable extremely deteriorates model statistics.

The first results presented in Tables A.2.1, A.2.2 and A.2.3 refer to the estimation of the logistic models for the three subsamples. It is possible to note that most hypotheses are represented in the model. In fact, six of the eight hypotheses have significant variables represented in the output of the three tables. The only two hypotheses that do not have significant variables in the estimation are Price/Earnings Ratio and Inefficient Financial Structure.

Table A.2.1 Logistic regression estimation output, FY99-FY08

M1 - LOGISTIC: FY99-FY08			
Logistic regression Number of obs = 14132			
LR chi2(13) = 233.92			
Prob > chi2 = 0.0000			
Log likelihood = -2258.7165 Pseudo R2 = 0.0492			
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.127	0.098	0.193
Market Capitalisation/ Total Assets	-0.055	0.027	0.042
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.009	0.006	0.104
Mining Industry Dummy	0.119	0.101	0.240
ASX300 Dummy	0.549	0.117	0.000
Log (Total Assets)	0.204	0.026	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.850	0.465	0.000

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Table A.2.2 Logistic regression estimation output, FY99-FY09

M1 - LOGISTIC: FY99-FY09			
Logistic regression Number of obs = 16080			
LR chi2(13) = 229.42			
Prob > chi2 = 0.0000			
Log likelihood = -2521.3028 Pseudo R2 = 0.0435			
tkvr	Coef.	Std. Err.	P>|z|
ROA	0.029	0.020	0.139
Growth of 3 year Total Assets	-0.143	0.092	0.118
Market Capitalisation/ Total Assets	-0.038	0.023	0.098
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.010	0.006	0.091
Mining Industry Dummy	0.126	0.095	0.186
ASX300 Dummy	0.520	0.113	0.000
Log (Total Assets)	0.196	0.025	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.738	0.449	0.000

Table A.2.3 Logistic regression estimation output, FY99-FY10

M1 - LOGISTIC: F FY99-FY10			
Logistic regression Number of obs = 18004			
LR chi2(13) = 236.25			
Prob > chi2 = 0.0000			
Log likelihood = -2834.7587 Pseudo R2 = 0.04			
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.135	0.085	0.113
Inventory/Working Capital	0.001	0.001	0.077
Market Capitalisation/ Total Assets	-0.032	0.021	0.129
Quick Assets	0.000	0.000	0.012
Dividend per share / Earnings per share	-0.010	0.006	0.082
Mining Industry Dummy	0.144	0.089	0.108
ASX300 Dummy	0.445	0.109	0.000
Log (Total Assets)	0.197	0.023	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-6.754	0.419	0.000

For the basic logistic estimation, most significant variables in the models are the same for the three periods, with exception of the addition of ROA in the sample comprising the period FY99 to FY09 and Inventory/Working Capital in Table A.2.3.

On the other hand, for the more complex panel data logistic regression with mixed effects it is possible to observe fewer hypotheses represented in the variables. The hypothesis embodied in Tables A.2.4, A.2.5 and A.2.6 is Inefficient Management, Dividend Payout, Merger and Acquisition Activity, and Size.

Table A.2.4 Panel data logistic regression with mixed effects estimation output, FY09

M2 - LOG. MIXED EFFECTS: FY99-FY08			
Mixed-effects logistic regression	Number of obs = 14132		
Group variable: id	Number of groups = 2516		
Obs per group: min = 1 avg = 5.6 max = 9			
Integration points = 7	Wald chi2(9) = .		
Log likelihood = -2255.4214	Prob > chi2 = .		
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.155	0.104	0.134
Quick Assets	0.000	0.000	0.017
Dividend per share / Earnings per share	-0.010	0.006	0.101
ASX300 Dummy	0.566	0.128	0.000
Log (Total Assets)	0.252	0.028	0.000
Market Capitalisation	0.000	0.000	0.001
_cons	-7.984	0.529	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.678	0.215	
LR test vs. logistic regression: chibar2(01) = 13.63 Prob>=chibar2 = 0.00			

Table A.2.5 Panel data logistic regression with mixed effects estimation output, FY10

M2 - LOG. MIXED EFFECTS: FY10

Mixed-effects logistic regression Number of obs = 16080
Group variable: id Number of groups = 2612
Obs per group: min = 1 avg = 6.2 max = 10
Integration points = 7 Wald chi2(9) = .
Log likelihood = -2512.2731 Prob > chi2 = .

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.170	0.098	0.083
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.011	0.007	0.088
ASX300 Dummy	0.560	0.126	0.000
Log (Total Assets)	0.248	0.028	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-7.983	0.516	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.853	0.213	

LR test vs. logistic regression: chibar2(01) = 24.25 Prob>=chibar2 = 0.00

Table A.2.6 Panel data logistic regression with mixed effects estimation output, FY11

M2 - LOG. MIXED EFFECTS: FY11

Mixed-effects logistic regression Number of obs = 18004
Group variable: id Number of groups = 2674
Obs per group: min = 1 avg = 6.7 max = 11
Integration points = 7 Wald chi2(9) =
.
Log likelihood = -2824.5732 Prob > chi2 = .

tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.165	0.091	0.071
Inventory/Working Capital	0.001	0.001	0.066
Quick Assets	0.000	0.000	0.017
ASX300 Dummy	0.496	0.121	0.000
Log (Total Assets)	0.243	0.026	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-7.891	0.486	0.000
Random-effects Parameters	Estimate	Std. Err.	
id: Identity var(_cons)	0.881	0.200	

LR test vs. logistic regression: chibar2(01) = 30.34 Prob>=chibar2 = 0.00

It seems that a considerable amount of the volatility, and consequently explanation, can be captured by the fixed effect and random effects models from the previous three tables. As a result fewer variables are significant in the estimation. Again, most variables are the same for the three samples, with exception of the addition of Inventory/Working Capital in Table A.2.6.

Although similar to the previous model, the panel data logistic regression with crossed effect relaxes one very important hypothesis. It allows the random effects to be crossed, and not nested. This means that the random effects are the same regardless of the industries. For that reason the results are expected to be different, and Tables A.2.7, A.2.8 and A.2.9 show that. Compared to the previous model, there is the additional appearance of the Growth Resource Mismatch hypothesis represented in the significant variables from the model. This suggests that growth should be measured relative to an industry benchmark when attempting to discriminate between target and non-target firms. It completes the list of hypotheses which include Inefficient Management, Dividend Payout, Merger and Acquisition Activity, and Size.

Table A.2.7 Panel data logistic regression with crossed effects estimation output, FY09

M3 - LOG. CROSSED EFF.: FY09			
Crossed-effects logistic regression	Number of obs = 14132		
No. of Group / Observations per Group / Integration	Variable	Groups	Average
	_all	11	1284.7
	id	2516	5.6
Log likelihood = -2238.0709 Prob > chi2 = .	Wald chi2(9) = .		
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.155	0.104	0.134
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.010	0.006	0.101
ASX300 Dummy	0.566	0.128	0.000
Log (Total Assets)	0.252	0.029	0.000
Market Capitalisation	0.000	0.000	0.001
_cons	-7.992	0.535	0.000
Random-effects Parameters		Estimate	Std. Err.
_all: Identity var(R.sector)		0.033	0.164
id: Identity var(_cons)		0.823	0.130
LR test vs. logistic regression: chi2(2) = 13.64 Prob > chi2 = 0.0011			

Table A.2.8 Panel data logistic regression with crossed effects estimation output, FY10

M3 - LOG. CROSSED EFF.: FY10			
Crossed-effects logistic regression	Number of obs = 16080		
No. of Group / Observations per Group / Integration	Variable	Groups	Average
	_all	11	1461.8
	id	2612	6.2
Log likelihood = -2490.544 Prob > chi2 = .	Wald chi2(9) = .		
tkvr	Coef.	Std. Err.	P>|z|
Growth of 3 year Total Assets	-0.170	0.098	0.082
Quick Assets	0.000	0.000	0.016
Dividend per share / Earnings per share	-0.011	0.006	0.088
ASX300 Dummy	0.559	0.126	0.000
Log (Total Assets)	0.249	0.028	0.000
Market Capitalisation	0.000	0.000	0.000
_cons	-8.005	0.526	0.000

M3 - LOG. CROSSED EFF.: FY10		
Random-effects Parameters	Estimate	Std. Err.
_all: Identity var(R.sector)	0.047	0.111
id: Identity var(_cons)	0.922	0.115
LR test vs. logistic regression: chi2(2) = 24.30 Prob > chi2 = 0.0000		

Table A.2.9 Panel data logistic regression with crossed effects estimation output, FY11

M3 - LOG. CROSSED EFF.: FY11			
Crossed-effects logistic regression	Number of obs = 18004		
No. of Group / Observations per Group / Integration	Variable	Groups	Average
	_all	11	16080
	id	2612	6.2
Log likelihood = -2491.3354	Prob > chi2 = .	Wald chi2(9) = .	
tkvr	Coef.	Std. Err.	P>|z|
ROA	0.009	0.009	0.296
Growth of 1 year Total Assets	-0.018	0.017	0.307
Inventory/Working Capital	0.001	0.001	0.068
Quick Assets	0.000	0.000	0.018
ASX300 Dummy	1.116	0.103	0.000
Market Capitalisation	0.000	0.000	0.261
_cons	-3.665	0.089	0.000
Random-effects Parameters		Estimate	Std. Err.
_all: Identity var(R.sector)		0.012	0.019
id: Identity var(_cons)		0.668	0.176
LR test vs. logistic regression: chi2(2) = 22.38 Prob > chi2 = .0000			

The simple change in model structure is reflected in the estimation. Distinct from the previous models, there is an impressive substitution of significant variables from the estimation of the first sample in Table A.2.7 to the last sample in Table A.2.9. The variables ROA, Growth of 1 year Total Assets and Inventory/Working Capital replaced the variables Quick Assets, Growth of 3 year Total Assets and Dividend per Share/Earnings per Share from the previous two samples.

Appendix A

In general all models demonstrated consistent results and solid statistics for each sample. That allows them to proceed to the next stage, that is, the actual prediction of the takeover targets one year ahead. The change in variables from year-to-year noticed on the three model specifications provides the first hint on why the same model does not produce the same results every time it is applied to a different market. Actually, the failure to replicate the same methodology with success in other markets or periods is one of the great criticisms on the takeover prediction literature. This can be mostly explained by the change in economic environment. The market dynamics change from year-to-year and can present extensive structural breaks after periods of crisis. A model needs to be robust enough to take into account the change in the non-linear relationships among variables and accurate to provide stable forecasts based on new fundamentals.

Different from the logistic models, the neural network models do not attribute coefficients to the variables. Due to its structure, the feed-forward neural network uses a parallel processing method that constantly updates the weights so that the network starts to mimic the desirable input-output behaviour. However, the technical computing software MATLAB used to train and validate the neural network do not report which variables are more important for prediction.

The preliminary conclusion from this stage is that there is no best model. Each year will have a model that best fits the data and guessing which model will be better in the future is not a solution to the problem. The use of a combination of model to minimize the problem of stability and generate more accurate forecasts is presented on Tables A.2.10, A.2.11 and A.2.12. It contains the estimation from the logistic regression that uses the probability output from the single models as regressors. The method will attribute coefficients (weights) for each input (model). The use of such methodology eliminates substantial volatility in the process and the model takes care of selecting the optimal weights automatically. The advantage in using such a variety of models is to indirectly capture the different non-linear relationships among the variables to improve the forecast accuracy at a later stage.

The significance of the inputs in the following tables still changes from year to year, but also does the weights in the combined output. In the first two samples on Tables A.2.10 and A.2.11 just the output from the models Logistic with Mixed Effects, Logistic with Crossed Effects and the neural network with 1 layer and 4 neurons are significant on the estimation. However, the estimation for the last period in Table A.2.12 has all inputs significant.

Table A.2.10 Logistic regression estimation output from Weights Combination, FY09

C1 - Weights Combination: FY09			
Logistic regression	Number of obs = 14132		
LR chi2(6) = 1739.10			
Prob > chi2 = 0.0000			
Log likelihood = -1506.1223	Pseudo R2 = 0.3660		
tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	-2.429	8.393	0.772
M2 - LOG. MIXED EFFECTS	-67.509	13.330	0.000
M3 - LOG. HIERARCHICAL EFFECTS	73.173	6.325	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	3.532	3.158	0.263
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	-0.867	3.417	0.800
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	9.115	3.647	0.012
_cons	-4.359	0.113	0.000

Table A.2.11 Logistic regression estimation output from Weights Combination, FY10

C1 - Weights Combination: FY10			
Logistic regression	Number of obs = 16080		
LR chi2(6) = 1910.28			
Prob > chi2 = 0.0000			
Log likelihood = -1680.873	Pseudo R2 = 0.3623		
tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	4.871	6.828	0.476
M2 - LOG. MIXED EFFECTS	-96.505	12.813	0.000
M3 - LOG. HIERARCHICAL EFFECTS	92.607	7.115	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	5.110	3.003	0.089
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	8.363	9.478	0.378
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	7.657	3.342	0.022
_cons	-4.755	0.298	0.000

Table A.2.12 Logistic regression estimation output from Weights Combination, FY11

C1 - Weights Combination: FY11			
Logistic regression	Number of obs = 18004		
LR chi2(6) = 1864.81			
Prob > chi2 = 0.0000			
Log likelihood = -2014.8145	Pseudo R2 = 0.3164		
tkvr	Coef.	Std. Err.	P>|z|
M1 - LOGISTIC REGRESSION	-39.025	5.677	0.000
M2 - LOG. MIXED EFFECTS	32.070	5.316	0.000
M3 - LOG. HIERARCHICAL EFFECTS	19.091	2.984	0.000
M4 - NN: 1 LAYER; 10NEURONS, LOG.FUNC.	-15.645	5.949	0.009
M5 - NN: 1 LAYER; 3NEURONS, TAN.FUNC.	6.888	0.847	0.000
M6 - NN: 1 LAYER; 4NEURONS, TAN.FUNC.	7.231	3.180	0.023
_cons	-3.945	0.098	0.000

A.3 Test Results from Chapter 3

Table A.3.1 presents the results for the test for equality of proportions (unequal variances) among the accuracy rates presented in Tables 3.4.1 to 3.4.6 (H0: Accuracy KK Combination = Accuracy Models and Benchmarks). It confirms that the results are statistically significant.

Table A.3.1 Test for equality of proportions

Test for equality of proportions Sample 1999-2009		*Out-of-sample: 2009*		*In-sample: 1999-2008*	
		Z-Statistics	***P-Value***	*Z-Statistics*	***P-Value***
Logistic Models	***KK=M1***	0.251	**0.401**	-0.704	**0.759**
	KK=M2	0.120	**0.452**	1.055	**0.146**
	KK=M3	0.358	**0.360**	1.497	**0.067**
Neural Network Models	***KK=M4***	0.821	**0.206**	4.773	**0.000**
	KK=M5	0.858	**0.195**	3.985	**0.000**
	KK=M6	0.203	**0.420**	0.974	**0.165**
Benchmark	***KK=Linear Combination***	1.437	**0.075**	12.335	**0.000**
	KK=Chance Criterion	1.536	**0.062**	14.960	**0.000**
Test for equality of proportions Sample 1999-2010		*Out-of-sample: 2010*		*In-sample: 1999-2009*	
		Z-Statistics	***P-Value***	*Z-Statistics*	***P-Value***
Logistic Models	***KK=M1***	1.133	**0.129**	0.510	**0.305**
	KK=M2	2.033	**0.021**	3.945	**0.000**
	KK=M3	1.797	**0.036**	3.504	**0.000**
Neural Network Models	***KK=M4***	1.321	**0.093**	8.543	**0.000**
	KK=M5	1.039	**0.149**	8.310	**0.000**
	KK=M6	1.209	**0.113**	10.793	**0.000**
Benchmark	***KK=Linear Combination***	1.948	**0.026**	13.029	**0.000**
	KK=Chance Criterion	2.739	**0.003**	13.914	**0.000**

Appendix A

Test for equality of proportions Sample 1999-2011		*Out-of-sample: 2011*		*In-sample: 1999-2010*	
		Z-Statistics	***P-Value***	*Z-Statistics*	***P-Value***
Logistic Models	***KK=M1***	1.738	**0.041**	3.257	**0.001**
	KK=M2	2.201	**0.014**	3.239	**0.001**
	KK=M3	2.312	**0.010**	3.525	**0.000**
Neural Network Models	***KK=M4***	1.332	**0.091**	6.196	**0.000**
	KK=M5	1.167	**0.122**	1.573	**0.058**
	KK=M6	1.697	**0.045**	5.425	**0.000**
Benchmark	***KK=Linear Combination***	2.657	**0.004**	6.949	**0.000**
	KK=Chance Criterion	2.563	**0.005**	7.402	**0.000**

Appendix B

B.1 Weibull Distribution

The Weibull distribution is a continuous probability distribution with the probability density function given by:

$$f(x;\gamma,\varphi) = \begin{cases} \dfrac{\gamma}{\varphi} x^{\gamma-1} \exp\left\{-\dfrac{x^{\varphi}}{\varphi}\right\} & \text{for } x > 0 \\ 0, x \leq 0 \end{cases} \tag{B.1}$$

where $\gamma > 0$ is the shape parameter and $\varphi > 0$ is the scale parameter of the distribution.

As previously discussed, ACD models impose the restriction $E(\varepsilon_i) = 1$ and accordingly, create a constraint on the parameters. In the multiplicative error model, the positive duration process X is assumed to be the product of a scale factor (conditionally autoregressive) and a standardized innovation disturbance ε_i.[1] Thus, the distribution of the error becomes:

---

[1] For further explanation see De Luca and Gallo (2004).

Appendix B

$$\varepsilon_i \sim Weibull\left(\left[\Gamma\left(1+\frac{1}{\gamma}\right)\right]^{\gamma}, \gamma\right) \tag{B.2}$$

Hence, the conditional density function of x_i can be rewritten as:

$$f(x_i|I_{i-1}) = \frac{\gamma}{x_i}\left[\frac{x_i\Gamma\left(1+\frac{1}{\gamma}\right)}{\psi_i}\right]^{\gamma} \exp\left\{-\left[\frac{x_i\Gamma\left(1+\frac{1}{\gamma}\right)}{\psi_i}\right]\right\} \tag{B.3}$$

That is:

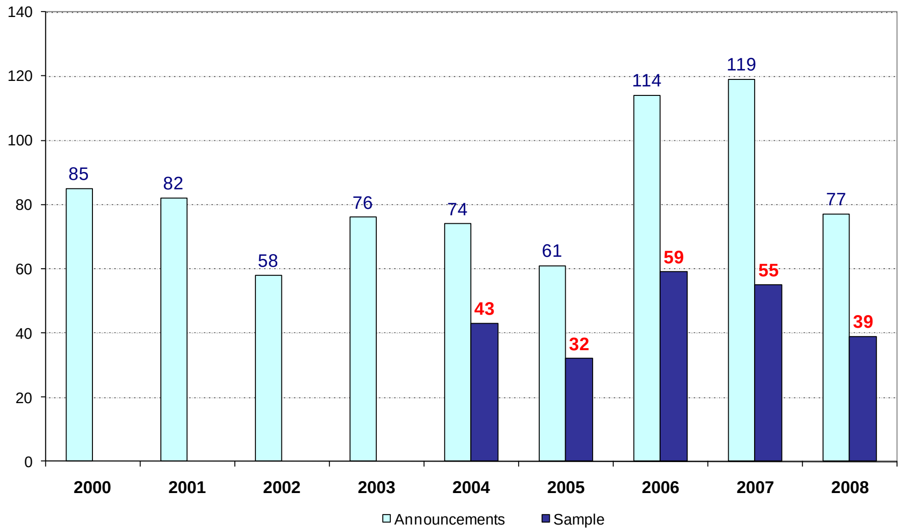
$$x_i|I_{i-1} \sim Weibull\left(\left[\frac{\Gamma\left(1+\frac{1}{\gamma}\right)}{\psi_i}\right]^{-\gamma}, \gamma\right). \tag{B.4}$$

De Luca and Gallo (2004) argue that the Weibull density usually achieves better results than the Exponential distribution, although the fitting in the tails is far from satisfactory. Many authors suggest the use of the Burr distribution (which contains the Weibull and the Log-logistic as special cases) to eliminate the problem of excess dispersion pointed out by Engle and Russell (1998). However, it could result in poor modelling of the higher moments of durations because it is not able to calculate all the moments of the distribution [see Bauwens, *et al.* (2003)].

B.2 Australian Takeover Market

Australia had a healthy and vigorous mergers and acquisitions market in the past decade. The country regularly featured in the world's most attractive merger and acquisition market, with huge deals involved. There are many factors that contributed to heat up the Australian market in the last decade. First, the recent revision of laws regulating deals. The increase in transparency and the introduction of policies to attract foreign investors played an important role in the market. Second, most of the last decade is characterized by a period of recovery after the Asian crisis at the end of the last century. In Figure B.2.1 there is the number of companies in the selected sample and the total of announcements in the Australian market.

Figure B.2.1 Announcement and sample per year



The selected sample maintains roughly the same proportion of the total announcements over the years and captures the cycles from the original population. From Table B.2.1 is possible to observe that the sample reflects the most important sectors of the market and the broader Australian economy. From the sample breakdown by industry sector in Table B.2.1, it is noted that Australia has a diversified economy with a particularly strong primary industries base. In the past few years, the most important industries that have undergone significant merger and investment activity include materials, energy, real estate, consumer services and diversified financials. Actually, the materials sector is heavily influenced by the mining companies that are the core of the Australian economy and has attracted many investments during the sample period.

Table B.2.1 Sample announcements by industry sector

Industry	**TARGETS** (Announcements)	**%**
Materials	66	28.95
Energy	24	10.53
Real Estate	19	8.33
Consumer Services	16	7.02
Capital Goods	14	6.14
Software & Services	14	6.14
Health Care Equipment & Services	13	5.70
Diversified Financials	9	3.95
Transportation	9	3.95
Pharmaceuticals & Biotechnology & Life Sciences	8	3.51
Food Beverage & Tobacco	7	3.07
Media	5	2.19
Retailing	5	2.19
Utilities	5	2.19
Telecommunication Services	4	1.75
Insurance	3	1.32
Automobiles & Components	2	0.88
Banks	2	0.88

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Industry	**TARGETS** (Announcements)	**%**
Consumer Durables & Apparel	1	0.44
Food & Staples Retailing	1	0.44
Technology Hardware & Equipment	1	0.44
Total	228	100

For reference, the composition of each GICS industry sector is in Table B.2.2 next.

Appendix B

Table B.2.2 GICS industry classification

Industry Sector	Industry Group	Industry						
Energy	Energy	Energy						
Materials	Materials	Chemicals	Construction Materials	Containers & Packaging	Metals & Mining	Paper & Forest Products		
Industrials	Capital Goods	Aerospace & Defense	Building Products	Construction & Engineering	Electrical Equipment	Industrial Conglomerates	Machinery	Trading Companies & Distributors
	Commercial & Professional Services	Commercial Services & Supplies	Professional Services					
	Transportation	Air Freight & Logistics	Airlines	Marine	Road & Rail	Transportation Infrastructure		
Consumer Discretionary	Automobiles & Components	Auto Components	Automobiles					
	Consumer Durables & Apparel	Household Durables	Leisure Equipment & Products	Textiles, Apparel & Luxury Goods				
	Consumer Services	Hotels, Restaurants & Leisure	Diversified Consumer Services					
	Media	Media						
	Retailing	Distributors	Internet & Catalog Retail	Multiline Retail	Specialty Retail			
Consumer Staples	Food & Staples Retailing	Food & Staples Retailing						
	Food, Beverage & Tobacco	Beverages	Food Products	Tobacco				
	Household & Personal Products	Household Products	Personal Products					
Health Care	Health Care Equipment & Services	Health Care Equipment & Supplies	Health Care Providers & Services	Health Care Technology				
	Pharmaceuticals, Biotechnology & Life Sciences	Biotechnology	Pharmaceuticals	Life Sciences Tools & Services				
Financials	Banks	Commercial Banks	Thrifts & Mortgage Finance					
	Diversified Financials	Diversified Financial Services	Consumer Finance	Capital Markets				
	Insurance	Insurance						
	Real Estate	Real Estate Investment Trusts	Real Estate Management & Development					
Information Technology	Software & Services	Internet Software & Services	IT Services	Software				
	Technology Hardware & Equipment	Communications Equipment	Computers & Peripherals	Electronic Equipment, Instruments & Components	Office Electronics			
	Semiconductors & Semiconductor Equipment	Semiconductors & Semiconductor Equipment						
Telecommunication Services	Telecommunication Services	Diversified Telecommunication Services	Wireless Telecommunication Services					
Utilities	Utilities	Electric Utilities	Gas Utilities	Multi-Utilities	Water Utilities	Independent Power Producers & Energy Traders		

Appendix B

B.3 Marketplace

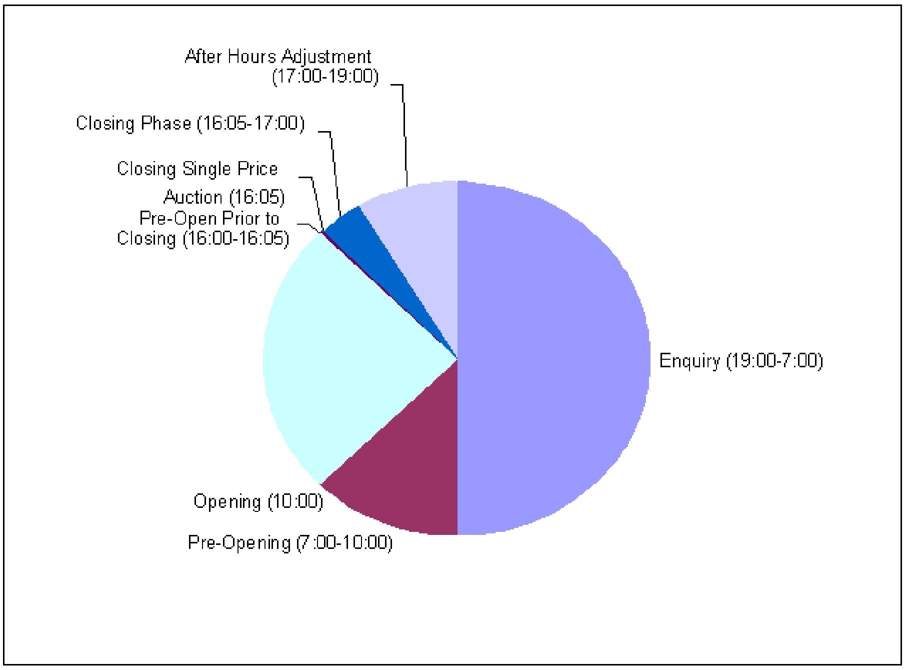
This part of Appendix B covers where the data for this study comes from and how the trades are generated. The marketplace where shares are traded in Australia is the Australia Securities Exchange (ASX). The ASX is a relatively new market. It was created on 1 April 1987 when six separate exchanges, spread around the country in the big cities merged to become one entity. At that time an electronic system, known as Stock Exchange Automated Trading System (SEATS), was introduced to consolidate the trading floors around Australia. The introduction of SEATS completely changed the dynamics of trading on the ASX. It enabled geographically dispersed brokers to be connected in the system and execute transactions online.

The ASX market is completely electronic without interventions, such as market makers. The equities are traded on an electronic order market and the trades enter the system as they arrive. As Bauwens and Giot (2000) report, an order driven market is where trading participants, or securities companies licensed by the exchange, may enter two types of orders: limit orders and market orders. Each type can be a buy or a sell order. All orders that enter the system specifies a quantity and a minimum price for sale (called ask price or offer price), or a quantity to buy and a given maximum price (called the bid price). The whole set of orders constitute the order book and, usually, the lowest ask price is strictly larger than the highest bid price. The trader who needs to buy or sell immediately places a market order for a given quantity, meaning that the order will be executed to buy or to sell up to a specified volume at the best available price.

The database selected for this study includes all trades executed on the market for a selected company in the normal trading hours. As Frino *et al.* (2004) explain, the SEATS process involves many phases; it starts at 7 am and finishes at 7 pm. The pre-opening period, starts at

7 am each morning. This is when the brokers can enter orders on SEATS. It precedes the opening period and is where orders may be adjusted or cancelled after being entered. Apart from overlapping buy and sell orders, the trades are settled in the opening call auction with no execution of orders until the opening phase for each stock. The Figure B.3.1 shows the market phases and the operating hours.

Figure B.3.1 Equity trading hours at the ASX



The figure above depicts the intraday trading schedule for the ASX. The opening auction stars at 10 am with ‘batches’ of stocks opening, over a period of approximately ten minutes. The order of opening for individual stocks depends on the first letter of the stock code. After the opening phase has occurred, normal trading begins. During normal trading, orders may execute immediately after being entered into the system, if price and volume conditions matches the demand. The closing time auction, which randomly runs between 4:05

and 4:06, allows brokers to enter new orders and retain unexecuted orders from normal trading. It operates similar to the opening call. After that, comes the closing period, from 4:06 to 5 pm, with after-hours market adjustments from 5 to 7 pm.

The calculation of the opening price on SEATS follows an algorithm that considers all orders placed in the pre-opening time and those carried over from the previous trading day. Price and time priority still applies to those orders. The current algorithm establishes the opening price during the opening phase. It utilizes a four step approach that uses some conditional decision rules that are applied only if there are overlapping orders. Otherwise, the opening price is set by the first trade during continuous trading on the opening call auction. The first of these decision rules is the maximum executable volume. It is the price that maximizes the volume to trade. If there are more than one price that maximizes the volume then the principle of minimum surplus is applied. That is the difference between the cumulative buy and sell quantities price that results in each price of the previous principle. If more than one price holds for these criteria, the third principle of market pressure is applied. It indentifies whether market pressure of potential auction price exists as to buy or to sell, by observing the signs that indicate the pressure in the market at the end of the opening auction.

B.4 Selected Sample and Dates

The Table B.4.1 next contains the ASX code of each target, bidder and control companies selected to participate in the study, including the respective dates for samples A and B.

Appendix B

Table B.4.1 Selected companies and dates for both samples

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
NVS		TAP	20/07/2003	19/10/2003	20/10/2003	19/01/2004
TAB	TAH	UTB	24/08/2003	23/11/2003	24/11/2003	23/02/2004
RBL		PLA	26/08/2003	25/11/2003	26/11/2003	25/02/2004
AFF		TAN	1/09/2003	1/12/2003	2/12/2003	2/03/2004
BHL		AWB	7/09/2003	7/12/2003	8/12/2003	8/03/2004
EMP	DRD	TRY	7/09/2003	7/12/2003	8/12/2003	8/03/2004
ABX		TOR	15/09/2003	15/12/2003	16/12/2003	16/03/2004
AXN		UNI	22/09/2003	22/12/2003	23/12/2003	23/03/2004
KAZ	TLS	IIN	7/10/2003	6/01/2004	7/01/2004	7/04/2004
CAI		BCL	22/10/2003	21/01/2004	22/01/2004	22/04/2004
WSF		SGP	22/10/2003	21/01/2004	22/01/2004	22/04/2004
BIR	PBL	ALH	27/10/2003	26/01/2004	27/01/2004	27/04/2004
AGX	PTD	PSD	3/11/2003	2/02/2004	3/02/2004	4/05/2004
NOL		CND	10/11/2003	9/02/2004	10/02/2004	11/05/2004
UEC	SGT	UNW	20/11/2003	19/02/2004	20/02/2004	21/05/2004
GPT	LLC	SGP	24/11/2003	23/02/2004	24/02/2004	25/05/2004
REG	MBL		4/12/2003	4/03/2004	5/03/2004	4/06/2004
MIA	DVC	PRY	7/12/2003	7/03/2004	8/03/2004	7/06/2004
ALH		ALL	7/01/2004	7/04/2004	8/04/2004	8/07/2004
SEL	CIY	ACF	13/01/2004	13/04/2004	14/04/2004	14/07/2004
CEP	PRX	GAN	26/01/2004	26/04/2004	27/04/2004	27/07/2004
PAO	MOF	JFM	27/01/2004	27/04/2004	28/04/2004	28/07/2004
DDF		ALZ	4/02/2004	5/05/2004	6/05/2004	5/08/2004
DIT		BWP	4/02/2004	5/05/2004	6/05/2004	5/08/2004
DOT		MOF	4/02/2004	5/05/2004	6/05/2004	5/08/2004
PSI	BKI	FPS	8/02/2004	9/05/2004	10/05/2004	9/08/2004
CDC	ABS	WDP	11/03/2004	10/06/2004	11/06/2004	10/09/2004
PMG	ABS	PRG	11/03/2004	10/06/2004	11/06/2004	10/09/2004
RPH		MCW	28/03/2004	27/06/2004	28/06/2004	27/09/2004
JFG	MGR	ABP	13/04/2004	13/07/2004	14/07/2004	13/10/2004
MPM		BDG	18/04/2004	18/07/2004	19/07/2004	18/10/2004
MGI		GAN	19/04/2004	19/07/2004	20/07/2004	19/10/2004
MGM		PAO	19/04/2004	19/07/2004	20/07/2004	19/10/2004
GGL	HSP	IVC	20/04/2004	20/07/2004	21/07/2004	20/10/2004

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
TER	CIY	LCP	27/04/2004	27/07/2004	28/07/2004	27/10/2004
NFD		BPC	28/04/2004	28/07/2004	29/07/2004	28/10/2004
HCN	IBA	ITD	4/05/2004	3/08/2004	4/08/2004	3/11/2004
MNR	OXR	SMC	10/05/2004	9/08/2004	10/08/2004	9/11/2004
SPC	CCL	SHV	13/05/2004	12/08/2004	13/08/2004	12/11/2004
WDP	CHY	CND	20/05/2004	19/08/2004	20/08/2004	19/11/2004
OPS		VCR	27/05/2004	26/08/2004	27/08/2004	26/11/2004
FOA	MTT	AWB	6/06/2004	5/09/2004	6/09/2004	6/12/2004
TEM		IWF	22/06/2004	21/09/2004	22/09/2004	22/12/2004
REM	CSM		7/07/2004	6/10/2004	7/10/2004	6/01/2005
PMM		TIM	13/07/2004	12/10/2004	13/10/2004	12/01/2005
SRP	FGL	LNN	18/07/2004	17/10/2004	18/10/2004	17/01/2005
BRK	MFS	RCT	28/07/2004	27/10/2004	28/10/2004	27/01/2005
HLY	TCL	PIF	1/08/2004	31/10/2004	1/11/2004	31/01/2005
CRD		TTT	11/08/2004	10/11/2004	11/11/2004	10/02/2005
JDV	IWL		23/08/2004	22/11/2004	23/11/2004	22/02/2005
AUO	CEY		24/08/2004	23/11/2004	24/11/2004	23/02/2005
WMR	BHP	RIN	6/09/2004	6/12/2004	7/12/2004	8/03/2005
PHY		ENE	27/09/2004	27/12/2004	28/12/2004	29/03/2005
NHL	HSP	CLV	28/09/2004	28/12/2004	29/12/2004	30/03/2005
TYC		IGL	22/11/2004	21/02/2005	22/02/2005	24/05/2005
TOR		CPB	29/11/2004	28/02/2005	1/03/2005	31/05/2005
TTT	SRL	LRL	2/12/2004	3/03/2005	4/03/2005	3/06/2005
VOY	ARQ	INP	20/12/2004	21/03/2005	22/03/2005	21/06/2005
FCO	COF	LCO	21/12/2004	22/03/2005	23/03/2005	22/06/2005
ALW	SGT	PAA	19/01/2005	20/04/2005	21/04/2005	21/07/2005
BCA		MYO	23/01/2005	24/04/2005	25/04/2005	25/07/2005
REA	NWS	UXC	30/01/2005	1/05/2005	2/05/2005	1/08/2005
PRK	TOL	MAP	20/02/2005	22/05/2005	23/05/2005	22/08/2005
SIG	AWP	COH	22/02/2005	24/05/2005	25/05/2005	24/08/2005
BKA		CKL	27/04/2005	27/07/2005	28/07/2005	27/10/2005
PDG		AWC	12/05/2005	11/08/2005	12/08/2005	11/11/2005
SGS		AGI	16/05/2005	15/08/2005	16/08/2005	15/11/2005
BIL		DOW	30/05/2005	29/08/2005	30/08/2005	29/11/2005
GGN		HIG	7/06/2005	6/09/2005	7/09/2005	7/12/2005
TBC		WBA	7/06/2005	6/09/2005	7/09/2005	7/12/2005

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
RBS	RHL	VTI	14/06/2005	13/09/2005	14/09/2005	14/12/2005
PSN		PRK	21/06/2005	20/09/2005	21/09/2005	21/12/2005
WYL		ITF	22/06/2005	21/09/2005	22/09/2005	22/12/2005
AEN			23/06/2005	22/09/2005	23/09/2005	23/12/2005
VGL	CDR	TNE	23/06/2005	22/09/2005	23/09/2005	23/12/2005
SEM	AUW	TRU	20/07/2005	19/10/2005	20/10/2005	19/01/2006
SGL	QGC		21/07/2005	20/10/2005	21/10/2005	20/01/2006
TYC		LAF	16/08/2005	15/11/2005	16/11/2005	15/02/2006
AND	KCN	EMP	23/08/2005	22/11/2005	23/11/2005	22/02/2006
TNS	SEL	JET	4/09/2005	4/12/2005	5/12/2005	6/03/2006
MTR	ACL	SBP	7/09/2005	7/12/2005	8/12/2005	9/03/2006
ALN	AGL		11/09/2005	11/12/2005	12/12/2005	13/03/2006
KDS	ABS	TBC	13/09/2005	13/12/2005	14/12/2005	15/03/2006
NXS	AZA	AOE	18/09/2005	18/12/2005	19/12/2005	20/03/2006
SFE	ASX	RCD	25/09/2005	25/12/2005	26/12/2005	27/03/2006
UTB	TTS	SKC	25/09/2005	25/12/2005	26/12/2005	27/03/2006
WNZ	TPI	PMP	18/09/2005	18/12/2005	19/12/2005	20/03/2006
MTX	BTX	AGS	30/10/2005	29/01/2006	30/01/2006	1/05/2006
TTT	SRL	ADN	31/10/2005	30/01/2006	31/01/2006	2/05/2006
CHX	AOE	KAR	2/11/2005	1/02/2006	2/02/2006	4/05/2006
ITF	FCL	LSG	9/11/2005	8/02/2006	9/02/2006	11/05/2006
TKR	CBH	RRL	16/11/2005	15/02/2006	16/02/2006	18/05/2006
WCG	MLB	JMB	20/11/2005	19/02/2006	20/02/2006	22/05/2006
GLS	SEL	TNS	27/11/2005	26/02/2006	27/02/2006	29/05/2006
VWD	MFT	BEC	29/11/2005	28/02/2006	1/03/2006	31/05/2006
CHL	CPB		8/12/2005	9/03/2006	10/03/2006	9/06/2006
SSX	OST	FMG	25/12/2005	26/03/2006	27/03/2006	26/06/2006
ADZ		KSC	1/01/2006	2/04/2006	3/04/2006	3/07/2006
EXL		CEY	4/01/2006	5/04/2006	6/04/2006	6/07/2006
MTN		SBS	4/01/2006	5/04/2006	6/04/2006	6/07/2006
HCC	ABS	KME	5/01/2006	6/04/2006	7/04/2006	7/07/2006
RPT		RRL	5/01/2006	6/04/2006	7/04/2006	7/07/2006
SED	AUS	CAZ	12/01/2006	13/04/2006	14/04/2006	14/07/2006
ZTL	CSL	MSB	15/01/2006	16/04/2006	17/04/2006	17/07/2006
CDO		MRL	16/01/2006	17/04/2006	18/04/2006	18/07/2006
AZR	MGX	AND	22/01/2006	23/04/2006	24/04/2006	24/07/2006

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
STR	TCI	CLT	25/01/2006	26/04/2006	27/04/2006	27/07/2006
VCM	SLM	CTI	25/01/2006	26/04/2006	27/04/2006	27/07/2006
TLC	MFS		7/02/2006	9/05/2006	10/05/2006	9/08/2006
VSL		CDR	9/02/2006	11/05/2006	12/05/2006	11/08/2006
GAS	CBA	HDF	13/02/2006	15/05/2006	16/05/2006	15/08/2006
BPC		GFF	20/02/2006	22/05/2006	23/05/2006	22/08/2006
SEL	MFS	APZ	5/03/2006	4/06/2006	5/06/2006	4/09/2006
OMP	WES	TWR	6/03/2006	5/06/2006	6/06/2006	5/09/2006
VLL	SCV	VOF	9/03/2006	8/06/2006	9/06/2006	8/09/2006
MYP		SIP	22/03/2006	21/06/2006	22/06/2006	21/09/2006
BBB	SOT	HTA	26/03/2006	25/06/2006	26/06/2006	25/09/2006
DVC		ANN	26/03/2006	25/06/2006	26/06/2006	25/09/2006
HDR		EXL	22/03/2006	21/06/2006	22/06/2006	21/09/2006
OPL		NZO	2/04/2006	2/07/2006	3/07/2006	2/10/2006
QGC	STO	NZO	5/04/2006	5/07/2006	6/07/2006	5/10/2006
API	SIP	BKL	6/04/2006	6/07/2006	7/07/2006	6/10/2006
LVR	PSV	AVO	9/04/2006	9/07/2006	10/07/2006	9/10/2006
PMN	SUN	TWR	12/04/2006	12/07/2006	13/07/2006	12/10/2006
BGF	LHG	BSG	17/04/2006	17/07/2006	18/07/2006	17/10/2006
PBB		CYG	18/04/2006	18/07/2006	19/07/2006	18/10/2006
FLT		IVC	26/04/2006	26/07/2006	27/07/2006	26/10/2006
RIN			30/04/2006	30/07/2006	31/07/2006	30/10/2006
BAX	TPI	CCP	3/05/2006	2/08/2006	3/08/2006	2/11/2006
BRZ		HWI	4/05/2006	3/08/2006	4/08/2006	3/11/2006
REB		ARP	9/05/2006	8/08/2006	9/08/2006	8/11/2006
RUP	FXJ	AUN	6/06/2006	5/09/2006	6/09/2006	6/12/2006
DBS	PGA	MLB	11/06/2006	10/09/2006	11/09/2006	11/12/2006
RCL		JBH	12/06/2006	11/09/2006	12/09/2006	12/12/2006
QAN		VBA	13/06/2006	12/09/2006	13/09/2006	13/12/2006
SRG	TCL	CEU	14/06/2006	13/09/2006	14/09/2006	14/12/2006
APN		WAN	26/07/2006	25/10/2006	26/10/2006	25/01/2007
AGC	OXR	GBG	30/07/2006	29/10/2006	30/10/2006	29/01/2007
PWT	TEL	SOT	1/08/2006	31/10/2006	1/11/2006	31/01/2007
LSG		IMA	2/08/2006	1/11/2006	2/11/2006	1/02/2007
IWF	PRG		13/08/2006	12/11/2006	13/11/2006	12/02/2007
ETR	ANZ	DUI	20/08/2006	19/11/2006	20/11/2006	19/02/2007

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
SMM	PDN	CMR	28/08/2006	27/11/2006	28/11/2006	27/02/2007
IBR	TMR	BRW	29/08/2006	28/11/2006	29/11/2006	28/02/2007
BEN	BOQ	ADB	17/09/2006	17/12/2006	18/12/2006	19/03/2007
SSX	OST	PPX	20/09/2006	20/12/2006	21/12/2006	22/03/2007
LIM		MRE	25/09/2006	25/12/2006	26/12/2006	27/03/2007
MPH	DES		28/09/2006	28/12/2006	29/12/2006	30/03/2007
VEA		MYO	1/10/2006	31/12/2006	1/01/2007	2/04/2007
GCL		RIV	9/10/2006	8/01/2007	9/01/2007	10/04/2007
OMC		GRR	12/10/2006	11/01/2007	12/01/2007	13/04/2007
MPR	LLC	GSA	16/10/2006	15/01/2007	16/01/2007	17/04/2007
BSG		ABY	2/11/2006	1/02/2007	2/02/2007	4/05/2007
CDO		SUL	6/11/2006	5/02/2007	6/02/2007	8/05/2007
EGX	PTD	ACL	2/11/2006	1/02/2007	2/02/2007	4/05/2007
ANE	GNS	KMN	13/11/2006	12/02/2007	13/02/2007	15/05/2007
SYB	HSP	RHC	27/11/2006	26/02/2007	27/02/2007	29/05/2007
IPG		MXG	29/11/2006	28/02/2007	1/03/2007	31/05/2007
MXG		DRT	11/12/2006	12/03/2007	13/03/2007	12/06/2007
GRD		WTP	26/12/2006	27/03/2007	28/03/2007	27/06/2007
SBC	MMG	AHD	1/01/2007	2/04/2007	3/04/2007	3/07/2007
HPX	SLM	DWS	16/01/2007	17/04/2007	18/04/2007	18/07/2007
KIM		ALB	17/01/2007	18/04/2007	19/04/2007	19/07/2007
AIA		CEU	21/01/2007	22/04/2007	23/04/2007	23/07/2007
NEL	TOE		4/02/2007	6/05/2007	7/05/2007	6/08/2007
GCX	SGX	MCO	8/02/2007	10/05/2007	11/05/2007	10/08/2007
PEP		LFE	8/02/2007	10/05/2007	11/05/2007	10/08/2007
CSF	CER		25/02/2007	27/05/2007	28/05/2007	27/08/2007
GUJ		AAO	1/03/2007	31/05/2007	1/06/2007	31/08/2007
HME	BOQ	WBB	1/03/2007	31/05/2007	1/06/2007	31/08/2007
GWR	FAS	SDL	5/03/2007	4/06/2007	5/06/2007	4/09/2007
SAQ	VRL	AGI	6/03/2007	5/06/2007	6/06/2007	5/09/2007
TVL	WEB		7/03/2007	6/06/2007	7/06/2007	6/09/2007
PCG		LYL	14/03/2007	13/06/2007	14/06/2007	13/09/2007
SDL	GBG	MMN	25/03/2007	24/06/2007	25/06/2007	24/09/2007
RSP	NHC	RIV	27/03/2007	26/06/2007	27/06/2007	26/09/2007
UNW	SEV	FRE	28/03/2007	27/06/2007	28/06/2007	27/09/2007
COA		UGL	2/04/2007	2/07/2007	3/07/2007	2/10/2007

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
VKI		REX	2/04/2007	2/07/2007	3/07/2007	2/10/2007
NPH	MFG	CFI	5/04/2007	5/07/2007	6/07/2007	5/10/2007
PBO		SLA	8/04/2007	8/07/2007	9/07/2007	8/10/2007
MIS	MMX	GRR	10/04/2007	10/07/2007	11/07/2007	10/10/2007
UKL	MRO	CUY	11/04/2007	11/07/2007	12/07/2007	11/10/2007
AZA	ARQ	DYL	24/04/2007	24/07/2007	25/07/2007	24/10/2007
JBM		DXL	29/04/2007	29/07/2007	30/07/2007	29/10/2007
PSV		ASL	30/04/2007	30/07/2007	31/07/2007	30/10/2007
NUF		IPL	6/05/2007	5/08/2007	6/08/2007	5/11/2007
AIA		CEU	8/05/2007	7/08/2007	8/08/2007	7/11/2007
SYB	PRY	FPH	9/05/2007	8/08/2007	9/08/2007	8/11/2007
ELL		SVM	23/05/2007	22/08/2007	23/08/2007	22/11/2007
HWG	MCG		7/06/2007	6/09/2007	7/09/2007	7/12/2007
HER		LYC	12/06/2007	11/09/2007	12/09/2007	12/12/2007
BEI	BNB	CHD	18/06/2007	17/09/2007	18/09/2007	18/12/2007
MXX	CUO	HIC	30/07/2007	29/10/2007	30/10/2007	29/01/2008
QMT	CPU	IRI	7/08/2007	6/11/2007	7/11/2007	6/02/2008
ZFX	OXR	OST	2/09/2007	2/12/2007	3/12/2007	3/03/2008
CIF		BBW	10/09/2007	10/12/2007	11/12/2007	11/03/2008
DXL	IPL	BKW	2/09/2007	2/12/2007	3/12/2007	3/03/2008
EQI	LGL	AGG	19/09/2007	19/12/2007	20/12/2007	20/03/2008
LST	IRN	CUO	19/09/2007	19/12/2007	20/12/2007	20/03/2008
CBH	PEM	OMH	25/09/2007	25/12/2007	26/12/2007	26/03/2008
PRG	SPT	SAI	26/09/2007	26/12/2007	27/12/2007	27/03/2008
JST	PMV	AHE	30/09/2007	30/12/2007	31/12/2007	31/03/2008
TWR	GPG	NHF	1/11/2007	31/01/2008	1/02/2008	2/05/2008
BVA		ESV	4/11/2007	3/02/2008	4/02/2008	5/05/2008
SGB	WBC	BEN	11/11/2007	10/02/2008	11/02/2008	12/05/2008
IRN		ALD	14/11/2007	13/02/2008	14/02/2008	15/05/2008
RIC	GNC	SHV	15/11/2007	14/02/2008	15/02/2008	16/05/2008
ASL	MAH	BOC	20/11/2007	19/02/2008	20/02/2008	21/05/2008
FUN			20/11/2007	19/02/2008	20/02/2008	21/05/2008
BMX		HRR	25/11/2007	24/02/2008	25/02/2008	26/05/2008
BMM	NGF	MOX	28/11/2007	27/02/2008	28/02/2008	29/05/2008
IPN	SHL	VGH	12/12/2007	12/03/2008	13/03/2008	12/06/2008
SXP	LNC	TEX	12/12/2007	12/03/2008	13/03/2008	12/06/2008

Appendix B

ASX code			SAMPLE A		SAMPLE B	
TARGET	**BIDDER**	**CONTROL**	**From**	**To**	**From**	**To (Bid date)**
MCQ		BCM	16/12/2007	16/03/2008	17/03/2008	16/06/2008
ORG		STO	24/12/2007	24/03/2008	25/03/2008	24/06/2008
ARH		GRR	5/02/2008	6/05/2008	7/05/2008	6/08/2008
SHG	QGC	KAR	19/02/2008	20/05/2008	21/05/2008	20/08/2008
BBC	PTN	PTN	5/03/2008	4/06/2008	5/06/2008	4/09/2008
EXT		PVE	6/03/2008	5/06/2008	6/06/2008	5/09/2008
IPM	COE	STX	9/03/2008	8/06/2008	9/06/2008	8/09/2008
PMM		BKW	12/03/2008	11/06/2008	12/06/2008	11/09/2008
MML		GWR	20/03/2008	19/06/2008	20/06/2008	19/09/2008
PEM	CBH	CDU	2/04/2008	2/07/2008	3/07/2008	2/10/2008
AVA			22/04/2008	22/07/2008	23/07/2008	22/10/2008
QGC		PDN	28/04/2008	28/07/2008	29/07/2008	28/10/2008
IGG	UXC		29/04/2008	29/07/2008	30/07/2008	29/10/2008
MYO		PBG	30/04/2008	30/07/2008	31/07/2008	30/10/2008
AUW	IFL	HGI	25/05/2008	24/08/2008	25/08/2008	24/11/2008
FSN	PDN		2/06/2008	1/09/2008	2/09/2008	2/12/2008
AVX	PGL	ACR	22/06/2008	21/09/2008	22/09/2008	22/12/2008
PES	AOE	ADI	22/06/2008	21/09/2008	22/09/2008	22/12/2008
SGL		OEL	24/06/2008	23/09/2008	24/09/2008	24/12/2008

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C.1 FRS Representation

The sequence of graphs in Figure C.1.1 contains an example of the FRS implementation, including details about the rolling window of observations and the triggering of the timing rules. It involves three steps:

Step 1 – Estimation of the model on the first in-sample month of observations and forecasting one trade ahead;

Step 2 – Compare if the actual value for the series comes inside the prediction range and appropriately follow the set of timing rules;

Step 3 – Roll the window of observations one trade ahead and forecast the next trade;

Repeat steps 2 and 3 until the end of the series/investment horizon.

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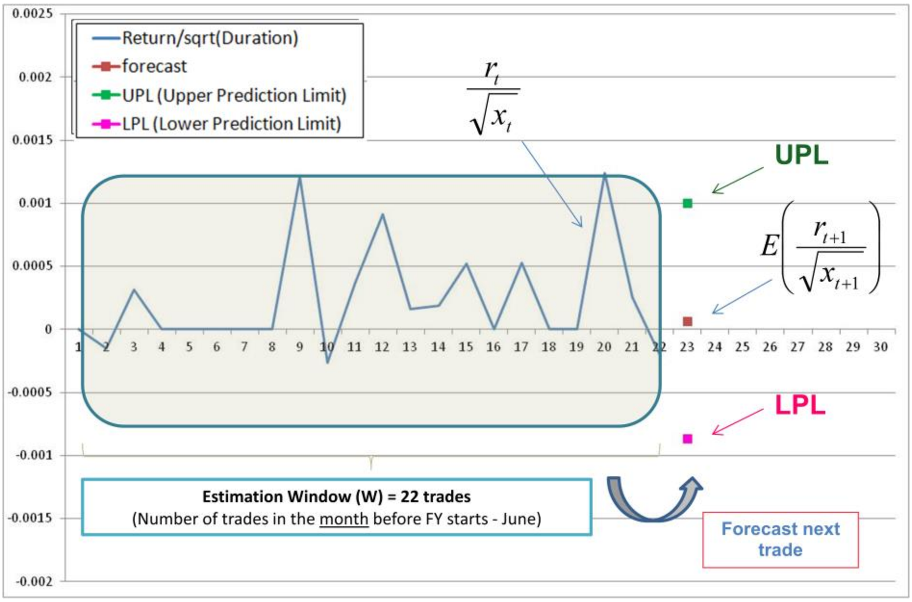
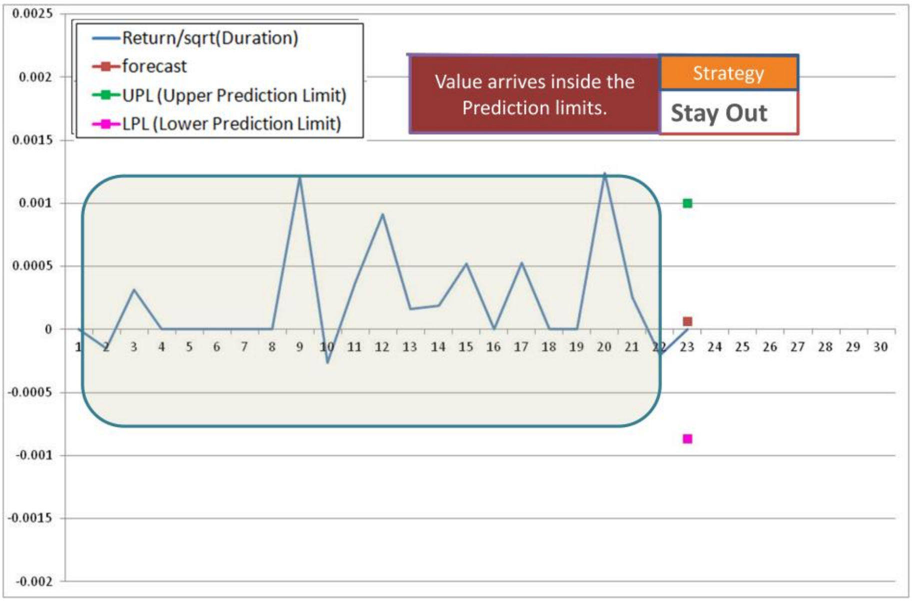
Figure C.1.1 Detailed example of the FRS implementation





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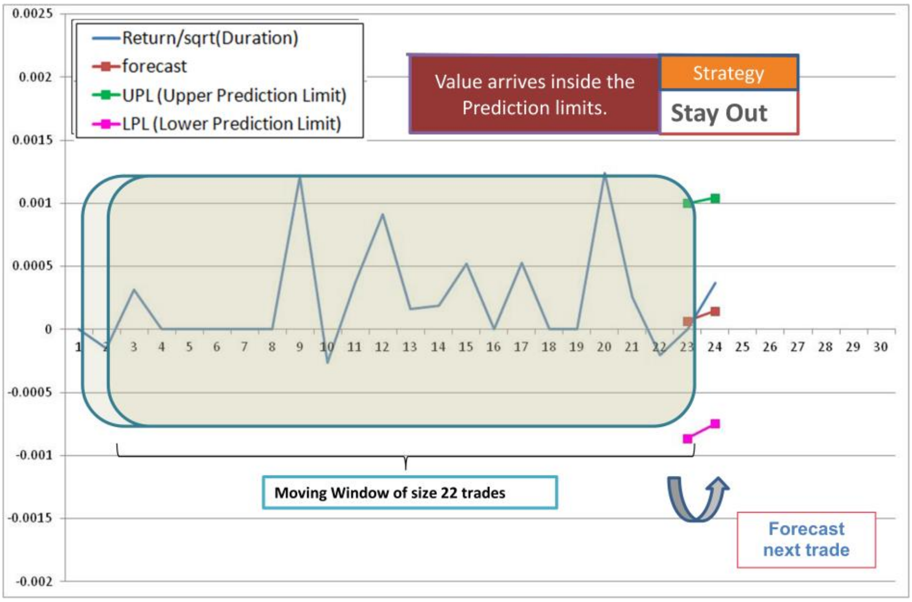
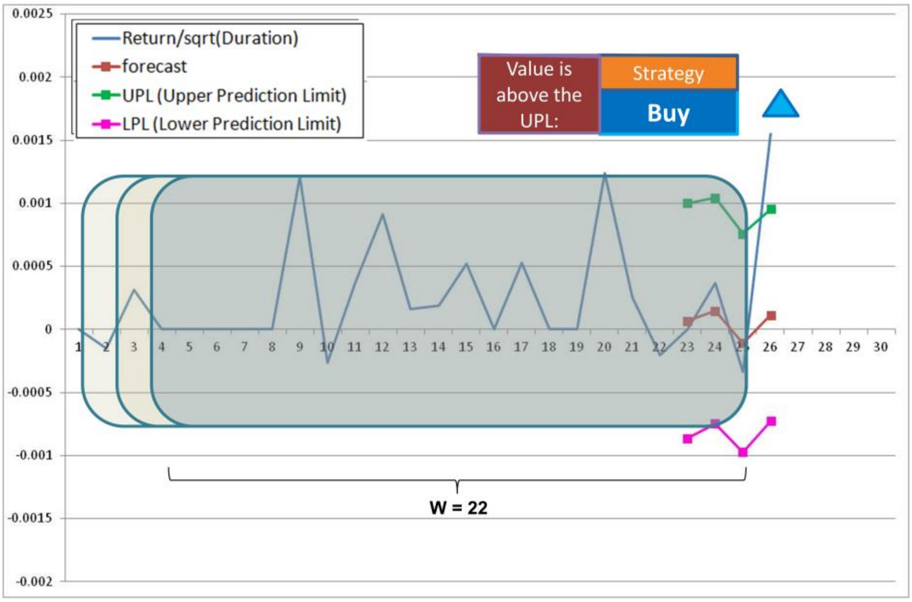


Return/sqrt(Duration)
forecast
UPL (Upper Prediction Limit)
LPL (Lower Prediction Limit)
Value arrives inside the Prediction limits.
Strategy
Stay Out
Moving Window of size 22 trades
Forecast next trade



Return/sqrt(Duration)
forecast
UPL (Upper Prediction Limit)
LPL (Lower Prediction Limit)
Value is above the UPL:
Strategy
Buy
W = 22

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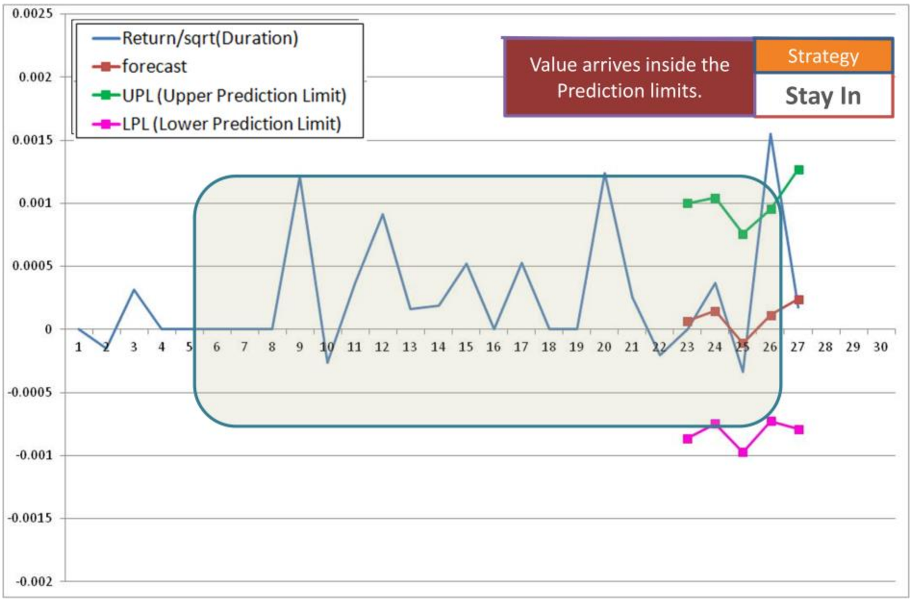
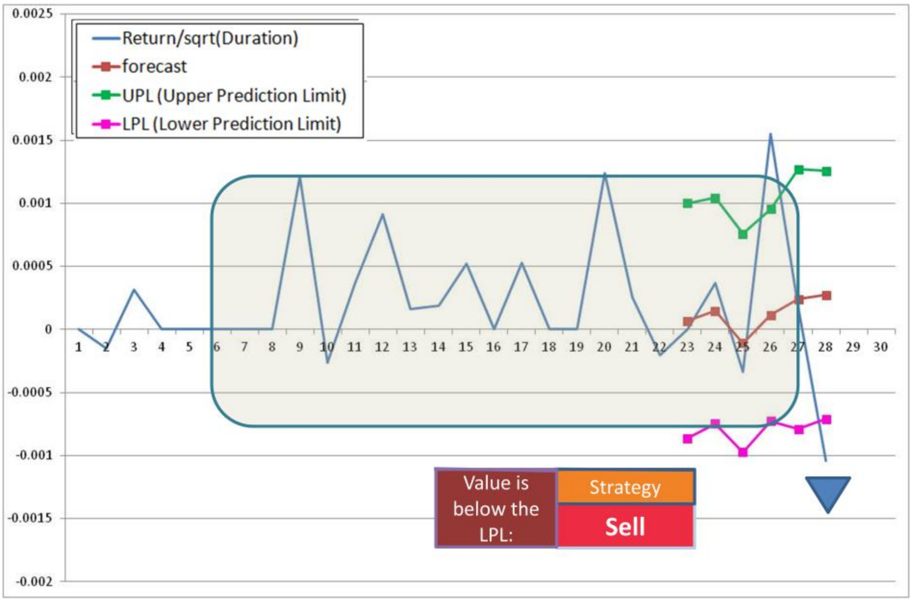
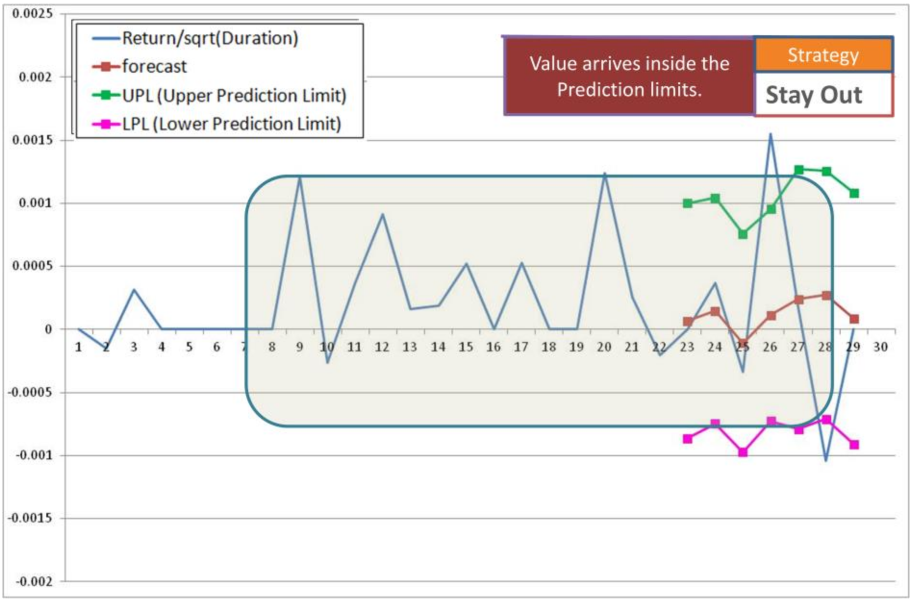

Return/sqrt(Duration)
forecast
UPL (Upper Prediction Limit)
LPL (Lower Prediction Limit)
Value arrives inside the Prediction limits.
Strategy
Stay In


Return/sqrt(Duration)
forecast
UPL (Upper Prediction Limit)
LPL (Lower Prediction Limit)
Value is below the LPL:
Strategy
Sell



C.2 Sample Size, Trading Costs and Risk-Free Rate

The cost associated with trading stocks can have a non-negligible impact on portfolio return. The calculation of these costs includes not only the broker commission but also the costs related with the spread. The trading costs associated to each company in Chapter 5 is calculated based on the average spread, the average price and the brokerage fee. The costs per trade related to the spread are calculated as half the average spread as a percentage of the price for each company independently. Since the mid-quote is used to calculate the price, the use of the full spread to calculate the cost of each trade would overestimate the real costs. In a "round trip" trade an investor would still pay the full spread, half when buying and another half when selling, but at different points in time and possibly at different price levels. The brokerage fee in Australia varies depending on the broker, but is reasonable to assume that a regular investor can find an institution that will charge 0.1% of the capital invested in order to execute each trade. The total cost of each trade is the sum of the spread costs and the broker fees. The equation C.1 is used to calculate the trading costs for each trade:

$$Costs_{PerTrade} = \frac{Average\ Spread\ /2}{Average\ Price} + \ 0.001 \tag{C.1}$$

The capital that is not being used by the FRS is assumed to be re-invested and receiving the risk-free rate. The rate used is the 30 day Bank-Bill Reference Rate (BBSW). The BBSW is the wholesale interbank rate within Australia and is published by the Australian Financial Markets Association (AFMA). It is the borrowing rate among the country's top market makers, and is widely used as the benchmark interest rate for financial instruments. The rate associated with each year is the daily average of the 30 day BBSW over the financial year. The average 30 day BBSW for FY09 was 4.6%, for FY10 it was 3.86%, while 4.76% for FY11.

The constituents of the trading costs and the risk-free rate are given in Tables C.2.1, C.2.2 and C.2.3. Additionally the tables contain the number of trades for each company and the size of the windows of observations.

Table C.2.1 Sample and window sizes, trading costs and risk-free rate: FY09

FY 2009							
Predicted Targets 19 Companies		Observations (trades)	Window Size (trades)	Average Price	Average Spread	Costs per Trade (fees + spread)	Risk Free Rate (BBSW)
TARGET	**LST**	1980	228	1.29	0.02	0.76%	4.60%
	QGC	15220	2129	4.34	0.02	0.29%	4.60%
	TPX	129	14	3.75	0.17	2.43%	4.60%

FY 2009							
Predicted Targets 19 Companies		Observations (trades)	Window Size (trades)	Average Price	Average Spread	Costs per Trade (fees + spread)	Risk Free Rate (BBSW)
NON-TARGET	**BEN**	30297	1805	9.83	0.03	0.25%	4.60%
	CBH	1774	135	0.09	0.00	1.68%	4.60%
	CHQ	100	10	0.93	0.13	6.81%	4.60%
	CIF	4447	307	2.02	0.02	0.69%	4.60%
	CNP	4762	230	0.12	0.00	1.15%	4.60%
	FLT	31686	2011	11.32	0.04	0.28%	4.60%
	GPT	27415	1542	1.37	0.01	0.37%	4.60%
	IPN	8	0	0.26	0.02	3.81%	4.60%
	MMX	18861	1115	1.70	0.01	0.43%	4.60%
	NXS	11943	103	1.00	0.01	0.46%	4.60%
	QAN	21101	945	2.54	0.01	0.31%	4.60%
	REA	1635	52	4.78	0.07	0.84%	4.60%
	SBM	3851	230	0.31	0.01	1.00%	4.60%
	SGB	17037	1944	28.39	0.05	0.18%	4.60%
	SST	340	30	12.34	0.88	3.66%	4.60%
	VBA	5439	311	0.49	0.01	0.76%	4.60%
AVERAGE		**10402**	**689**			**1.38%**	**4.60%**

Table C.2.2 Sample and window sizes, trading costs and risk-free rate: FY10

FY 2010							
Predicted Targets 40 Companies		Observations (trades)	Window Size (trades)	Average Price	Average Spread	Costs per Trade (fees + spread)	Risk Free Rate (BBSW)
TARGET	AOE	25567	2331	4.16	0.01	0.26%	3.86%
	CKT	343	42	0.65	0.02	1.86%	3.86%
	ERC	2182	617	1.16	0.01	0.58%	3.86%
	FLX	7929	3173	15.03	0.04	0.23%	3.86%

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FY 2010							
Predicted Targets 40 Companies		Observations (trades)	Window Size (trades)	Average Price	Average Spread	Costs per Trade (fees + spread)	Risk Free Rate (BBSW)
	LGL	11867	862	3.32	0.01	0.27%	3.86%
	LLP	444	94	0.15	0.01	1.76%	3.86%
	PLI	405	104	0.71	0.01	0.99%	3.86%
	SSI	197	19	0.59	0.06	5.27%	3.86%
	TKA	114	59	0.49	0.01	1.55%	3.86%
NON-TARGET	AAY	23	4	0.18	0.03	7.00%	3.86%
	AEM	169	11	0.02	0.00	6.26%	3.86%
	ANZ	18236	1893	21.03	0.02	0.14%	3.86%
	AQF	5	0	6.00	0.06	0.60%	3.86%
	AZO	842	204	0.61	0.02	1.36%	3.86%
	CBZ	169	62	0.39	0.02	2.51%	3.86%
	CDU	21050	1078	4.54	0.02	0.29%	3.86%
	CFE	3111	131	0.46	0.01	0.77%	3.86%
	CSL	12024	894	32.55	0.02	0.13%	3.86%
	CWK	1023	69	0.36	0.01	1.44%	3.86%
	CXC	2499	305	19.09	0.14	0.46%	3.86%
	EQX	517	33	0.04	0.00	3.85%	3.86%
	HDI	0	0	0.46	0.04	4.12%	3.86%
	KMD	3274	480	1.68	0.01	0.36%	3.86%
	MDL	5826	336	0.89	0.01	0.54%	3.86%
	MOO	112	12	0.01	0.00	6.28%	3.86%
	MQA	3315	1213	0.84	0.01	0.59%	3.86%
	PTN	550	62	0.11	0.01	2.60%	3.86%
	RMR	284	15	0.03	0.00	5.21%	3.86%
	ROB	88	8	0.01	0.00	12.27%	3.86%
	RUL	879	26	0.77	0.02	1.31%	3.86%
	RVE	127	10	0.16	0.01	4.68%	3.86%
	SHU	11	0	0.52	0.05	4.44%	3.86%

FY 2010							
Predicted Targets 40 Companies		**Observations (trades)**	**Window Size (trades)**	**Average Price**	**Average Spread**	**Costs per Trade (fees + spread)**	**Risk Free Rate (BBSW)**
	SNE	55	20	0.01	0.00	6.43%	3.86%
	SOI	57	14	0.01	0.00	7.89%	3.86%
	TBI	7	0	0.45	0.01	1.32%	3.86%
	VGM	67	23	0.16	0.01	4.11%	3.86%
	VIP	0	0	0.15	0.01	4.14%	3.86%
	WBC	18284	2113	23.56	0.01	0.13%	3.86%
	WCR	9	0	0.19	0.01	2.24%	3.86%
	WIG	234	15	1.59	0.09	2.82%	3.86%
AVERAGE		**3547**	**408**			**2.73%**	**3.86%**

Table C.2.3 Sample and window sizes, trading costs and risk-free rate: FY11

FY 2011							
Predicted Targets 18 Companies		**Observations (trades)**	**Window Size (trades)**	**Average Price**	**Average Spread**	**Costs per Trade (fees + spread)**	**Risk Free Rate (BBSW)**
TARGET	AKR	39	7	0.77	0.08	5.15%	4.76%
	ASX	10940	824	33.05	0.03	0.14%	4.76%
	CRG	10065	941	8.71	0.02	0.19%	4.76%
	DKN	188	18	0.63	0.04	3.01%	4.76%
	IIF	407	52	0.45	0.01	0.69%	4.76%
	JML	8739	82	0.65	0.01	0.63%	4.76%
NON-TARGET	API	1678	156	0.43	0.01	0.96%	4.76%
	CER	1149	31	0.29	0.01	1.12%	4.76%
	CNP	1107	39	0.11	0.00	1.41%	4.76%
	DUE	8627	717	1.69	0.01	0.28%	4.76%

FY 2011

Predicted Targets 18 Companies	Observations (trades)	Window Size (trades)	Average Price	Average Spread	Costs per Trade (fees + spread)	Risk Free Rate (BBSW)
DXS	2506	39	0.84	0.01	0.42%	4.76%
EXT	20632	712	8.02	0.01	0.19%	4.76%
MDL	9339	470	0.78	0.00	0.40%	4.76%
OMH	8394	721	1.43	0.01	0.35%	4.76%
RIO	7291	781	78.04	0.02	0.11%	4.76%
SPN	2857	158	0.88	0.01	0.43%	4.76%
TAP	3813	182	0.95	0.01	0.48%	4.76%
TPM	9463	675	1.68	0.01	0.34%	4.76%
AVERAGE	**5957**	**367**			**0.91%**	**4.76%**

C.3 Announcement Dates and Time Invested

Tables C.3.1, C.3.2 and C.3.3 contain the overall trading time in seconds for each company and the time invested under the FRS. In addition, the announcement dates and the dates associated companies were delisted are also available. This information complements the Tables 5.6.4, 5.6.5 and 5.6.6 in Chapter 5. The overall trading time, that is virtually the same as the time invested in the buy-and-hold strategy, is the number of seconds available to trade on each stock in the financial year. It is calculated by multiplying the number of trading days in the financial year by the six hours that the stock market stays open to trade on each day.

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Table C.3.1 Time Invested and Announcement Dates: FY09

FY 2009					
Predicted Targets 19 Companies		**Takeover Announcement**	**Delisted on:**	**Overall Trading Time (seconds)**	**Time Invested on FRS (seconds)**
TARGET	**LST**	24/06/2009		5,443,200	1,912,100
	QGC	28/10/2008	3/04/2009	4,168,800	1,569,300
	TPX	10/10/2008		5,443,200	0
NON-TARGET	**BEN**			5,443,200	1,873,000
	CBH			5,443,200	951,410
	CHQ			5,443,200	0
	CIF			5,443,200	0
	CNP			5,443,200	4,766,800
	FLT			5,443,200	1,424,400
	GPT			5,443,200	0
	IPN			5,443,200	0
	MMX			5,443,200	740,870
	NXS			5,443,200	0
	QAN			5,443,200	0
	REA			5,443,200	4,845,500
	SBM			5,443,200	1,101,900
	SGB			5,443,200	488,350
	SST			5,443,200	0
	VBA			5,443,200	518,060
AVERAGE				**5,376,126**	**1,062,721**

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Table C.3.2 Time Invested and Announcement Dates: FY10

	FY 2010				
	Predicted Targets 40 Companies	**Takeover Announcement**	**Delisted on:**	**Overall Trading Time (seconds)**	**Time Invested on FRS (seconds)**
TARGET	AOE	22/03/2010		5,443,200	2,753,500
	CKT	9/12/2009	9/02/2010	3,326,400	2,227,100
	ERC	14/09/2009	5/01/2010	2,808,000	63,371
	FLX	14/08/2009	30/12/2009	2,743,200	532,790
	LGL	29/03/2010		5,443,200	521,950
	LLP	28/09/2009	24/12/2009	2,700,000	809,580
	PLI	3/09/2009	30/11/2009	2,311,200	929,000
	SSI	1/09/2009		5,443,200	355,740
	TKA	8/02/2010		5,443,200	304,890
NON-TARGET	AAY			5,443,200	0
	AEM			5,443,200	14,999
	ANZ			5,443,200	1,480,000
	AQF			5,443,200	0
	AZO			5,443,200	1,523,700
	CBZ			5,443,200	0
	CDU			5,443,200	5,138,500
	CFE			5,443,200	3,552,200
	CSL			5,443,200	4,086,900
	CWK			5,443,200	317,170
	CXC			5,443,200	4,619,400
	EQX			5,443,200	0
	HDI			5,443,200	0
	KMD			5,443,200	1,199,300
	MDL			5,443,200	3,706,500
	MOO			5,443,200	1,913,100

FY 2010					
Predicted Targets 40 Companies		**Takeover Announcement**	**Delisted on:**	**Overall Trading Time (seconds)**	**Time Invested on FRS (seconds)**
	MQA			5,443,200	1,210,600
	PTN			5,443,200	428,680
	RMR			5,443,200	3,778,300
	ROB			5,443,200	0
	RUL			5,443,200	2,491,500
	RVE			5,443,200	3,528,300
	SHU			5,443,200	0
	SNE			5,443,200	0
	SOI			5,443,200	0
	TBI			5,443,200	0
	VGM			5,443,200	1,720,200
	VIP			5,443,200	0
	WBC			5,443,200	4,346,800
	WCR			5,443,200	0
	WIG			5,443,200	4,320,100
AVERAGE				**5,110,020**	**1,446,854**

Table C.3.3 Time Invested and Announcement Dates: FY11

FY 2011					
Predicted Targets 18 Companies		**Takeover Announcement**	**Delisted on:**	**Overall Trading Time (seconds)**	**Time Invested on FRS (seconds)**
TARGET	AKR	22/11/2010	21/02/2011	3,067,200	1,034,300
	ASX	25/10/2010		5,421,600	1,643,000
	CRG	15/12/2010	6/05/2011	4,600,800	1,606,900

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FY 2011					
Predicted Targets 18 Companies		**Takeover Announcement**	**Delisted on:**	**Overall Trading Time (seconds)**	**Time Invested on FRS (seconds)**
	DKN	27/06/2011		5,421,600	3,906,500
	IIF	23/12/2010	1/04/2011	4,125,600	2,045,400
	JML	9/02/2011	22/06/2011	5,292,000	1,366,600
NON-TARGET	API			5,421,600	1,006,500
	CER			5,421,600	4,994,900
	CNP			5,421,600	291,500
	DUE			5,421,600	2,150,100
	DXS			5,421,600	4,351,000
	EXT			5,421,600	1,384,100
	MDL			5,421,600	262,600
	OMH			5,421,600	1,258,600
	RIO			5,421,600	3,309,000
	SPN			5,421,600	4,893,000
	TAP			5,421,600	4,873,600
	TPM			5,421,600	5,096,500
AVERAGE				**5,166,000**	**2,526,339**