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Australian Takeover Waves: A Re-examination of Patterns, Causes and Consequences

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BCom (Hons)

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To

my loving husband, Sonny,

and

my little angel, Tammy.

Statement of Candidate Contribution

A paper based on Chapter 4 of this thesis is under review for a publication in *Accounting and Finance*. All co-authors have given the permission for the work to be included in this thesis.

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgment has been made.

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Abstract

This thesis provides more precise characterisation of patterns, causes and consequences of takeover activity in Australia over three decades spanning from 1972 to 2004. The first contribution of the thesis is to characterise the time series behaviour of takeover activity. It is found that linear models do not adequately capture the structure of merger activity; a non-linear two-state Markov switching model works better. A key contribution of the thesis is, therefore, to propose an approach of combining a State-Space model with the Markov switching regime model in describing takeover activity. Experimental results based on our approach show an improvement over other existing approaches. We find four waves, one in the 1980s, two in the 1990s, and one in the 2000s, with an expected duration of each wave state of approximately two years.

The second contribution is an investigation of the extent to which financial and macro-economic factors predict takeover activity after controlling for the probability of takeover waves. A main finding is that while stock market boom periods are empirically associated with takeover waves, the underlying driver is interest rate level. A low interest rate environment is associated with higher aggregate takeover activity. This relationship is consistent with Shleifer and Vishny (1992)'s liquidity argument that takeover waves are symptoms of lower cost of capital. Replicating the analysis to the biggest takeover market in the world, the US, reveals a remarkable consistency of results. In short, the Australian findings are not idiosyncratic.

Finally, the implications for target and bidder firm shareholders are explored via

investigation of takeover bid premiums and long-term abnormal returns separately between the wave and non-wave periods. This represents the third contribution to the literature of takeover waves. Findings reveal that target shareholders earn abnormally positive returns in takeover bids and bid premiums are slightly lower in the wave periods. Analysis of the returns to bidding firm shareholders suggests that the lower premiums earned by target shareholders in the wave periods may simply reflect lower total economic gains, at the margin, to takeovers made in the wave periods. It is found that bidding firms earn normal post-takeover returns (relative to a portfolio of firms matched in size and survival) if their bids are made in the non-wave periods. However, bidders who announce their takeover bids during the wave periods exhibit significant under-performance.

For mergers that took place within waves, there is no difference in bid premiums and nor is there a difference in the long-run returns of bidders involved in the first half and second half of the waves. We find that none of theories of merger waves (managerial, mis-valuation and neoclassical) can fully account for the Australian takeover waves and their effects. Instead, our results suggest that a combination of these theories may provide better explanation. Given that normal returns are observed for acquiring firms, taken as a whole, we are more likely to uphold the neoclassical argument for merger activity. However, the evidence is not entirely consistent with neo-classical rational models, the under-performance effect during the wave states is consistent with the herding behaviour by firms.

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Chapter 1

Introduction

1.1 Aims and objectives

This thesis advances our understanding of the behaviour, causes and consequences of takeover activity in Australia by using more comprehensive data than earlier studies and applying new refined methods. The thesis aims to:

- model the behaviour of aggregate takeover activity and detect takeover waves,
- identify the reasons for takeover waves,
- analyse the outcomes of takeover waves for market participants (i.e. for the shareholders of target and acquiring firms).

These objectives are investigated with reference to three prominent theories of merger waves (managerial, mis-valuation and neoclassical).

1.2 Motivation

Several reasons motivate this study of the behaviour, causes and consequences of takeover activity in Australia.

Firstly, takeover activity is a significant part of the Australian corporate market landscape, as demonstrated by the frequency and value of takeover transactions. For instance, the Bureau of Industry Economics (1990) reports that an average of 8.13% of exchange-listed Australian firms were subject to a takeover bid for each year between 1960 and 1988. In 2004 alone Australia had 1,440 merger and acquisition (M&A) deals totalling $116 billions,[1] equivalent to over 10% of the share market value of all publicly listed companies on the Australian Stock Exchange (ASX). The total value of Australian M&A activity for the first quarter of 2005 accounted for half of the total deals recorded in the Asia-Pacific region with 225 deals worth $A27.4 billions.[2] In addition, M&As are transactions of great significance, not only to shareholders, but also to other stakeholders, such as workers, managers, competitors, the general community and the economy since corporations often undergo extensive internal restructuring of assets and personnel following takeovers (Shleifer and Vishny (1988)).[3] These attributes affirm that understanding the characteristics of the takeover market is a non-trivial and worthy exercise.

Secondly, a comprehensive Australian-based empirical investigation into the behaviour, motives and outcomes of takeover activity will likely have a significant influence on the Australian Competition and Consumer Commission (ACCC) in its implementation of takeover policy. In Australia, takeover deals have been scrutinized by the ACCC to ensure the enforcement of Section 50 of the Trade Practices Act (Commonwealth). Section 50 prevents takeovers if they result, or will likely result in a corporation being a position to dominate a substantial mar-

[1] *"The Australian"* newspaper, 5th January 2005.

[2] *"Australian Associated Press Financial News Wire"*, 30th March 2005.

[3] Shareholders may lose their investment because of the imprudent acquisitions made by their companies. Target directors may have difficulty in the managerial labour market later (Harford (2003b) finds that target directors hold fewer directorships in the future than a control group). Acquiring companies are often motivated by the need to make efficiency savings in production and other activities. These are often achieved at considerable cost to workers in the form of job losses and communities in the form of terminated economic activity from the closing down of plants and factories. For example, after winning control of WMC Resources in early June 2005, BHP Billiton has announced that there would be hundreds of job losses at WMC's corporate headquarters in Melbourne (*Source: "BHP parachutes board into WMC"*, http://www.timesonline.co.uk, 6th June 2005).

ket in Australia or increase dominance.[4]

Thirdly, while takeovers are long-standing and significant features of the corporate landscape, many aspects remain perplexing. For instance, Brealey et al. (2000) include the timing of merger activity and its occurrence in waves in their list of ten major unsolved questions in finance. While the literature has acknowledged the incidence of takeovers fluctuating over time with high frequency periods being shorter, there is no consensus on how to characterise the behaviour of merger waves. This dissertation, hence, addresses this issue directly.

Fourthly, given the substantial volume of takeover activity and its economic significance, it is desirable to examine which factors drive merger waves. Although takeover waves are broadly discussed in the literature, research on their motives has employed single-state models with no justification for the existence of takeover waves. Takeover waves are referred to periods of intensive activity, so the motives during wave periods should be different from non-wave periods. This thesis thus intends to fill this gap in the literature by proposing a two-state regression model to incorporate the probability of being in a wave and non-wave period.

Finally, although takeovers occur intensively in both number and value, the question whether acquiring shareholders gain in the long run remains unclear. Previous Australian takeover research has focused on share returns without controlling for takeover waves (e.g. da Silva Rosa (1994), Brown and da Silva Rosa (1998), Simmonds (2004)). When Australian research has investigated takeover waves, the focus has primarily been on the announcement effect of takeovers (Kendig (1997)). Therefore, this thesis adds into the literature of takeover waves by investigating their effects on acquiring firms' stock performance in the long run using a method of return calculation that controls for firm size and survival as

[4] For example, Woolworths' proposal of \$969 million takeover of hotel and liquor group Australian Leisure & Hospitality was under scrutinized by the ACCC because there might be some issues, in their opinion, with "reduction of competition in some regional markets". *Source:* "*Watchdog may bite at takeover*", *Herald Sun* newspaper, 12th July 2004.

documented in Brown and da Silva Rosa (1998).

1.3 Research questions

This thesis examines the following research questions on takeover activity:

1. Does the Australian aggregate takeover activity follow a wave process? If so, how it can be statistically characterised?

2. What macro-economic and financial factors influence the incidence of takeover waves?

3. What are the effects of takeover waves on shareholder value?

1.4 Thesis contributions

The answers to the above-mentioned research questions are among the original contributions made in this dissertation. The specific contributions include the following:

1. The development of a new model to detect takeover waves by combining a State-Space model with a Markov switching regime model. The innovative aspect of this model is a refined method to improve goodness-of-fit and to cover for more generalised time series.

2. A two-state regression model is introduced when examining effects of macro-economic and financial factors on takeover waves. This shows that the liquidity hypothesis, advanced by Shleifer and Vishny (1992), has empirical support in both Australian and the US markets.

3. This thesis fills the gap in Australian literature about the effects of takeover waves on the long-term stock performance of acquiring firms.

4. This thesis also tests economic implications of three theories of merger waves (managerial, mis-valuation and neoclassical) on the shareholders of target and acquiring firms. An explanation for the takeover wave effect in the Australian market is also provided.

5. This thesis develops a more comprehensive and recent database of takeover activity by considering all types of takeover bids. Previous research on Australian takeover waves by Kendig (1997) only consider successful takeovers as measured by the number of delistings, and does not account for effective control.

6. Findings from this thesis will be of particular interest to a range of investors, managers and regulators because it provides evidence on predicting takeover waves, given the economic disturbance for acquiring firms participated during the wave periods.

1.5 Scope and overview

The remaining chapters are organised as follows. **Chapter 2** reviews related literature and highlights gaps in the knowledge of takeover waves. In particular, it focuses on research about the existence of takeover waves, macro-economic factors driving takeover activity (and takeover waves), and the economic consequences to shareholders in takeover waves.

Chapter 3 addresses the first research question on modelling aggregate Australian takeover activity. First, the thesis investigates whether linear models can capture all the structure of the takeover data. Then, the proposed model of combining a State-Space model with the Markov switching regime model is developed and applied. Finally, empirical results of our approach and other existing approaches in the literature are compared and discussed.

Chapter 4 investigates the second research question on the influence of financial and macro-economic factors on takeover waves. In this chapter, a two-state model, which has been found to be more effective in describing the incidence of takeover waves, is proposed in order to control for the probability of takeover waves. In addition, the liquidity hypothesis, advanced by Shleifer and Vishny (1992), in explaining takeover activity is tested. After confirming the validity of the liquidity hypothesis on the Australian market, the investigation is extended to the biggest takeover market in the world, the US. Results for the US are also consistent with the liquidity hypothesis.

Chapter 5 investigates the last research question on the economic consequences of takeover activity and takeover waves. Specifically, the focus is on the post-bid stock performance of acquiring firms since estimates of the value created for shareholders from takeover activity are subject to debate. Following the literature, it is hypothesized that takeover waves can influence the long-horizon performance of acquiring firms. This investigation also takes into account bid premiums as it is often claimed that the long-term adverse effects to acquiring firms are as a result of large premiums paid to target firms. The results are presented separately for the total period of examination, the wave and non-wave periods, the first half and second half of takeover waves. Based on the empirical findings, we examine the implications from three different theories of merger waves (managerial, misvaluation and neoclassical) and advance our explanations for the wave effects in the Australian market.

Chapter 6 presents concluding remarks of earlier chapters and highlights their major findings. It also identifies unresolved issues and directions for future research.

Chapter 2

Related Literature on Takeover Waves

2.1 Introduction

This chapter provides a review of relevant literature on takeover activity and takeover waves. The structure is as follows. Section 2.2 describes research on the existence of takeover waves. Section 2.3 documents the work done to date about influences of macro-economic and financial factors on the level of takeover activity (and takeover waves). Section 2.4 reviews the literature on the implications of takeover activity (and takeover waves) for the share market performance of bidding and target firms. Section 2.5 concludes the review.

2.2 Existence of takeover waves

It has been commonly observed that takeover activity fluctuates and clusters in periods of time. Time with high levels of takeover activity are often referred to as "merger wave" periods. While the notion of takeovers occurring in waves is widely acknowledged, there is no corresponding consensus on the statistical characterisation of the waves. Three distinct approaches have been presented in the literature to model time series behaviour of takeover activity.

In one approach, Golbe and White (1993) adopt curve estimation methodology to describe the cyclic pattern of M&As. They examine US annual takeover data for the period of 1985-1989 by merging three takeover series with different inclusion criteria, and argue that sine curve estimation is a “reasonable” way to illustrate the takeover activity. However, their method is not an obviously optimal or accurate way to describe takeover time-series behaviour. The actual “peaks” and “troughs” in the sine curve model occur at regular intervals that match the actual merger activity with substantial errors.

Another popular approach is to assume that linear time series models (autoregressive processes) are capable of modelling merger wave behaviour. Shughart and Tollison (1984) investigate both the count and dollar values of annual takeovers for the period 1897-1979, and conclude that merger levels are best characterised by either a white-noise process or a stable first-order autoregressive model. Their results raise doubts about the existence of takeover waves, and indicate that levels of merger activity provide no information beyond their relative frequency. These findings also imply that there is no need to develop predictive models of takeover activity. However, Shughart and Tollison (1984) admit that their results might not be conclusive because of the small number of observations in some of their sample periods. Moreover, their data series of merger activity is a compilation of three separate sources with different inclusion criteria which raises doubts whether their sample data are adequate for their investigation.

Chowdhury (1993) improves Shughart and Tollison (1984)’s work by using higher frequency (quarterly) data with unit root tests, and he confirms the aggregate takeover data series (1973-1987) contain a unit root, and that the change in the merger series is random. One implication of Chowdhury (1993)’s result is that economic variables do not affect the level of merger activity over time. However, as he points out, “various components of the data series do not behave uniformly; the conglomerate merger series appear to be stationary while both the horizontal and the vertical series have a unit root”.

Barkoulas et al. (2001) argue the dynamic structure in M&A activity exhibits a "strongly autocorrelated process". They note that the observation of high levels and low levels of merger activity over time can be attributed to the presence of dependent or long-memory dynamics. They present a model of an autoregressive fractionally integrated moving average (ARFIMA) which is set with the maximum order allowed in the AR and MA polynomials being three. Gaussian semi-parametric and exact maximum likelihood methods are used to estimate the long-memory or fractional-differencing parameter. The advantage of this method is that it provides insights into the persistence of shocks to the merger time-series.

Finally, many researchers use non-linear time series models with regime switching to characterise takeover wave behaviour. Both Town (1992) and Linn and Zhu (1997) employ Hamilton (1989)'s wave model of GDP to analyse the US takeover waves for the period of 1895-1989 and 1895-1994, respectively. A two-state Markov switching regime between high and low levels of takeover activity is used to capture the wave structure. Diagnostic tests of linear and non-linear models suggest the switching-regime model fitted the data very well. M&A activity alternate between two states: a high mean and high variance state (i.e. wave state), and a low mean and low variance state (i.e. non-wave state). One of the great advantages of this model is that it enables the prediction of waves, and potentially provides an insight into exogenous factors motivating the takeover regime shifts.

Following Town (1992) and Linn and Zhu (1997), Gartner and Halbheer (2006) use a two-state Markov switching model to characterise the stochastic behaviour of merger activity in the US and UK markets. Town (1992) and Linn and Zhu (1997) use the classical approach to make an inference based on the Markov switching model by estimating the model's unknown parameters, then making inferences on the unobserved variables, conditional on the parameter estimates. Gartner and Halbheer (2006), on the other hand, employ a Bayesian framework with Gibbs-sampling techniques that treat both the model parameters and Markov-switching state variable as random variables and conduct inferences on a joint probability distribution of parameters and states rather on a conditional probability distribution of the classical approach. However, in this thesis the former approach is preferred since Gartner and Halbheer (2006)'s approach is computationally expensive and the Gibbs sampler may fail to converge or the variance over different runs can be too large to be statistically meaningful. Furthermore, as this method collapses two variables into one, the predictive power (in terms of predicting unseen waves) could be limited due to the ignorance of the generative information.

Australian research on modelling takeover wave behaviour is relatively limited. Bishop et al. (1987) and the Bureau of Industry Economics (1990) only casually observe the activity of M&As by graphing association between takeover bids and share market performance. Both analyses document a positive relationship between changes in the share market index and the incidence of takeovers. A similar finding is made by Easton (1994) when he uses a simple regression technique to quantify the relationship between share market and takeover activity for the period 1946-1986. All authors conclude that such a relationship provides evidence consistent with the existence of takeover waves. Nevertheless, no research has provided clear reasons for reaching this conclusion nor do they acknowledge that a positive relationship between share returns and takeover activity could occur without takeover waves. In short, there is no attempt in these studies to use quantitative statistics to uncover the time-series structure of takeover activity that characterise waves.

To fill this gap, Kendig (1997) applies Hamilton (1989)'s approach to Australian merger data with a modification to the first-order autoregressive process (AR(1)) where a Poisson distribution is used in place of a Gaussian distribution[5] because merger data are positive and take discrete values. However, discrete values of the observations can be accounted for by negligible quantization noise in a standard

[5] At each state in Hamilton (1989)'s two-state Markov switching model, the time-series behaviour is described by an AR process. The original approach by Hamilton (1989) is formulated for a Gaussian case, i.e. the noise term is considered Gaussian.

model and thus need not be a point of concern. In addition, there are several shortcomings in Kendig (1997)'s methodology. Firstly, being an AR modelling approach, it is still unable to capture other characteristics of a general nonlinear time series model which is more accurately described by a general autoregressive moving average (ARMA) process. Secondly, the underlying assumption of the two-state Markov switching regime is that a higher mean and higher variance would be observed in a wave state than in a normal state, while the Poisson distribution assumes that the mean and variance of a Markov state are equal which makes it potentially too restrictive when characterising wave behaviour.

In Chapter 3, existing methods of detecting takeover waves will be reviewed, and this thesis' preferred model will be developed and justified. The preferred model is an extension of Hamilton (1989)'s approach for an ARMA process under the Gaussian distribution.

2.3 Drivers of takeover waves

If the takeover activity follows a wave process, which factors drive it? This section reviews a number of economic and financial factors that can affect the level of takeover activity and its clusters.

Several earlier studies (for example Nelson (1959), Melicher et al. (1983)) have linked the level of merger activity to specific variables that reflect economic activity and financial conditions. While it is generally accepted in the US literature that stock prices are positively related to takeover activity, there is less consensus on the effects of interest rates and industrial production on such activity. Nelson (1959) studies the US takeover market over the period 1895 to 1956 and finds that industrial production and stock prices are positively related to the level of takeover activity, though a negative relationship is found in some sub-periods. Weston (1961) finds that only stock prices are significantly related to the US merger activity, but not industrial production. Steiner (1975) concludes that the number of M&As is positively associated with changes in stock prices and GNP level, suggesting that economic conditions are responsible for increases in M&A activity. His results are similar when the dollar value of acquiring assets is used as the dependent variable. Both Beckentein (1979) and Benzing (1991) report that stock prices and interest rates are positively related to merger activity, while the opposite result for interest rates is observed in Melicher et al. (1983). In the latter study, they examine the relationship between the acquisition level and changes in the expected level of economic growth and capital market conditions for the period of 1947-1977. They find that increases in stock market prices together with decreases in interest rates are followed by increases in takeover activity.

Adopting a slightly different approach, Polonchek and Sushka (1987) view M&As as capital budgeting decisions but still use information about economic conditions in their regression model. Analysing mergers of mining and manufacturing firms with assets over $10 millions during the period of 1956-1978, they find that factors representing the strength of the economy such as the unemployment rate and potential business output, are important in explaining merger activity. Golbe and White (1988) examine the link between the number of US takeovers over the period 1948-1979 and the economic situation in the preceding periods. Their results suggest that GNP is positively related to acquisition activity while real interest rates are negatively linked to takeovers.

The finding of a significantly positive relationship between stock market performance and takeover activity is also present in some Australian empirical studies. Bishop et al. (1987) and the Bureau of Industry Economics (1990) document a positive relationship between share market index and takeover activity. A similar conclusion is reached by Easton (1994) in his study of the relationship between share market performance and Australian takeover activity over the period 1946-1986. In addition, Kendig (1997) claims that takeover waves are caused by general over-reactions during periods of economic prosperity when she examines the number of takeovers from 1955 to 1995. Although Kendig (1997) builds a model detecting waves in the Australian market[6], she ignores the existence of takeover waves in the regression of takeover activity against macroeconomic influences.

Recent theoretical models have also been developed to demonstrate how stock market mis-valuations can drive M&A activity. Shleifer and Vishny (2003) offer a speculative takeover model in which the share market is inefficient and routinely overprices stocks. Managers are assumed to be completely rational, and actively attempt to exploit what they perceive to be temporary valuation inefficiencies in the market by using their over-valued stocks to purchase relatively undervalued assets. Target managers accept over-valued bidder stocks because they have "short-time horizons" and they are willing to cash out their shares to generate private gains.

Based on similar ideas of the relative mis-valuations of the merging firms and the market's mis-perception of synergies from the combination, Rhodes-Kropf and Viswanathan (2004) propose another explanation to account for the positive correlation between stock market performance and merger waves. Their model is different from Shleifer and Vishny (2003) in that target managers rationally accept over-valued bidders' equity not due to shorter time horizons but due to errors in valuing potential takeover synergies. Both models explain that aggregate merger wave is a result of over-valuation and increased dispersion of valuation of firms. Various empirical studies in the US provide evidence consistent with the behavioural explanation of takeover activity (e.g. Rhodes-Kropf et al. (2005), Dong et al. (2006), Ang and Cheng (2006)).

However, Finn and Hodgson (2005) challenge this common belief of the stock market driving the level of takeover activity when investigating takeover announcements for ASX-listed target firms over the period 1972 to 1996. Using time-series techniques, they conclude that takeover and stock prices share a common trend

[6] Further details about Kendig (1997)'s Poisson Markov switching model for AR(1) processes are in Section 3.3.2 of the next chapter (Chapter 3).

and that Australian aggregate merger activity is driven by fundamental economic factors rather than by speculative share market activity or managerial optimism. They find that economic shocks, proxied by the growth in industrial production over the last four previous quarters, are the main factor that explains Australian M&A activity.

Building on studies of capital liquidity, we suggest a role for capital liquidity in explaining the clusters of the aggregate takeover activity. Shleifer and Vishny (1992), in a work on asset liquidity and debt capacity, posit that in order for the selling transactions to occur, buyers must be relatively unconstrained because if they are financially constrained, they cannot pay the fundamental values and sellers would delay sales until the market becomes more liquid. As a result, they claim takeover waves will occur in periods with high corporate cash flows and less financial constraints in the market; enhanced liquidity makes debt financing more attractive for firms to finance their acquisitions. The underlying feature in their argument is that "the ability to borrow increases liquidity, which in turn raises the ability to borrow" and "not only does liquidity create debt capacity, but debt capacity creates liquidity". It is often observed that borrowing capacity is more accessible in a low interest rate environment. Therefore, in our study we refer to periods of low interest rates as periods of high capital liquidity and vice versa.

The topic of capital liquidity has also been addressed in the corporate restructuring literature. For instance, Schlingemann et al. (2002) make a similar argument in their study of divestitures and asset liquidity, showing that firms are more likely to sell corporate assets in the most liquid market. Harford (2005) illustrates that sufficient capital liquidity must be present to accommodate the asset reallocation, and a merger wave can be explained by a macro-level expansion in liquidity. Martynova and Renneboog (2008), when graphically viewing takeover activity across the US, Europe and Asia-Pacific regions, notice that all merger waves usually coincide with periods of rapid credit expansion.

In a recent study of unlisted US companies that are subject to a takeover offer, Officer (2007) finds strong support for the contention of the relationship between acquisition discounts and aggregate debt market liquidity; acquisition discounts for unlisted targets are significantly higher when debt capital is difficult or relatively more expensive to obtain. Officer (2007) states "Selling part, or the whole of an unlisted firm is a last-resort source of liquidity for owners that need sources of cash when borrowing additional funds is unappealing". The results from his paper imply that firms should not sell their unlisted assets, as a part (divestiture) or as a whole (M&A), when the aggregate debt market liquidity condition is tighter since the sale price will be discounted more heavily.

Past papers (reviewed above) only use single-state models to study the relationship between the aggregate takeovers and economic variables. Using single-state regressions are not sufficient when studying takeover motives since they might be different because of the higher level of takeover activity in the wave periods than in the non-wave periods. Chapter 4 will address this issue by using a two-state method by controlling for the probability of takeover waves.

2.4 Consequences of takeover waves

If takeover waves exist, what are the economic consequences for firms participating in wave as opposed to non-wave periods? In this section, we review the effects of takeover activity (and takeover waves) on the share market performance of target and bidding firms. It is generally accepted that target shareholders enjoy large positive average abnormal returns, and acquiring firms experience smaller but still positive abnormal returns over the announcement periods. However, it remains controversial whether acquiring firms retain the value in the long run (e.g., Agrawal and Jeffe (2000), Andrade et al. (2001), Bruner (2004), Martynova and Renneboog (2008)). Hence, in this thesis, we concentrate on the post-bid stock performance of acquiring firms. In addition, takeover premiums (representing gains to target shareholders) are also considered since it is often argued that poor returns to acquiring firms in the long run is a direct consequence of over-payment to target firms.

2.4.1 Post-takeover returns to acquiring firms

Jensen and Ruback (1983) summarise six studies on long-term post-merger bidding firms performance and show that acquiring firms systematically under-perform after mergers. However, this finding is controversial. Table 2.1 presents a summary of studies on post-acquisition performance of acquiring firms that are conducted after Jensen and Ruback (1983)'s review.

As evident from Table 2.1, some studies do not find significant under-performance by bidding firms in the long run. Franks et al. (1991) examine mergers announced in the US from 1975 to 1984 and do not find significant under-performance of acquiring firms, two or three years after the acquisition. Their results are robust when using either CAPM or the calendar-time portfolio method to calculate excess returns. Longhran and Vijh (1997) report an insignificantly negative abnormal return (-6.5%) after five years for mergers announced from 1970 to 1989. Moeller et al. (2004) also do not find evidence of significant three-year post-merger performance of firms made acquisitions over the 1980-2001 period. In Australia, Walter (1984), using the market model, finds insignificant abnormal returns of 2% for all takeover bids announced in 1966-1972. da Silva Rosa (1994), in a comprehensive study of successful takeover bids[7] over the period 1974-1990, does not find post-merger under-performance of bidding firms when comparing raw returns of merger firms with 1,001 control portfolios matched in size and survival. Brown and da Silva Rosa (1998) reach similar conclusions when they extend da Silva Rosa (1994)'s period of study to 1996.

[7] In da Silva Rosa (1994)'s study, successful takeover bids are defined as all bids in which the offerer acquired more than 50% of the target's shares.

Table 2.1: Summary of studies analysing post-merger abnormal stock returns for acquiring firms

Event date is the first public announcement date unless otherwise indicated (superscript ^{o} refers to the date when outcome of the bid is announced; and superscript ^{d} refers to delisting date). Superscript ^{bt} indicates bootstrapping approach to assess statistical significance. * above the figures represents statistical significance level at least 10%.

Study	**Sample period**	**Method**	**AR cal.**	**Return series**	**Return window**	**Abnormal returns (%)**
Walter (1984)	1966-1972 (Australia)	Market model	CARs	Weekly	[+1;+100]	2.00 (all); -1.50* (successful); 21.30* (unsuccessful)
Ducan et al. (1989)	1976-1985 (NZ)	Market model	CARs	Monthly	[+1;+24]	-14.30*
Franks and Harris (1989)	1960-1985 (UK)	(0,1) Market model, Market model, CAPM	CARs	Monthly	[+1;+24]	4.60* (successful) -11.70* (successful) 4.40* (successful)
Franks et al. (1991)	1975-1984 (US)	CAPM Calendar-time portfolio	CARs	Monthly	[0,+36]	-3.96 (8-portfolio benchmark) 1.80 (8-portfolio benchmark)
Limmack (1991)	1977-1986 (UK)	(0,1) Market model Market model	CARs	Monthly	[+1, +24]^{o}	-4.47* (completed); -20.23* (abandoned) 0.80 (completed); -4.30 (abandoned)
Agrawal et al. (1992)	1955-1987 (US)	Market model with size control	CARs	Monthly	[1;+12]^{d} [1;+24]^{d}	-1.53 -4.94*
da Silva Rosa (1994)	1974-1990 (Australia)	Size, survival control portfolios	CARs	Monthly	[+7,+24]	5.55%
Longhran and Vijh (1997)	1970-1989 (US)	Size & B/M control firms	BHARs	Monthly	[0,+60]	-6.50 (all); -24.2* (stock); 18.5 (cash)
Rau and Vermaelen (1998)	1980-1991 (US)	Size & B/M control portfolios	CARs^{bt}	Monthly	[+1;+12] [+1;+36]	-1.76* (all); -6.25* (glamour); 1.83* (growth) -4.04* (all); -17.26* (glamour); 7.64* (growth)
Brown and da Silva Rosa (1998)	1974-1996 (Australia)	Size, survival control portfolios	Cf. BHRs^{bt}	Monthly	[+6;+36]	Poor performance: not significant
da Silva Rosa et al. (2000)	1988-1996 (Australia)	Size, survival control portfolios	Cf. BHRs^{bt}	Monthly	[0;+24]	Stock bidders: significantly < cash bidders
Mitchell and Stafford (2000)	1960-1993 (US)	Size & B/M control Calendar-time portfolio	BHARs^{bt} CARs	Monthly	[0;+36]	EW: -1.00 (all); -8.40* (stock); 6.4* (non-stock) EW: -7.20* (all); -11.88* (stock); -3.24 (non-stock)
Moeller et al. (2004)	1980-2001 (US)	Calendar-time portfolio	CARs	Monthly	[0;+36]	0.65 (all), 2.74 (large firms), 1.12 (small firms)
Moeller et al. (2005)	1998-2002 (US)	Calendar-time portfolio Market model	CARs BHARs	Monthly	[0;+60]	-51.00* (large loss deals) -48.00 (large loss deals, no significance level given)
Harford (2005)	1981-2000 (US)	Calendar-time portfolio	CARs	Monthly	[0;+36]	VW: -14.20* (stock); 25.40 (cash)
Betton et al. (2008a)	1980-2003 (US)	Matched firm control Calendar-time portfolio	BHARs CARs	Monthly Monthly	[0;+60] [0,+60]	-21.9%* (EW), -17.1%* (VW) 4.8% (EW), 1.2% (VW)

In contrast, some studies find that bidders do experience significant negative abnormal returns in the first few years after the merger. Agrawal et al. (1992), in a study from 1955 to 1987, document negative abnormal returns for acquiring firms for up to five years following merger announcements.[8] Rau and Vermaelen (1998) find significantly negative abnormal performance (-4.04%), three years after mergers during the period 1980 to 1991. Using a comprehensive sample of mergers for 1960-1993 period, Mitchell and Stafford (2000) also find significantly negative abnormal returns of -7.2% for 3 years following mergers.[9] In a recent US study, Betton et al. (2008a) compare five-year post-merger buy-and-hold returns between merging and non-merging firms (matched in size and book-to-market ratio) over the period 1980-2003. They find that merged firms, on average, significantly under-perform their matched firms. The post-takeover under-performance of bidding firms is also presented in New Zealand and the UK market. Ducan et al. (1989) report a negative average return to New Zealand bidders of -14.30% over two years after the announcement date. Similarly, both Franks and Harris (1989) and Limmack (1991) report negative abnormal returns for a subset of successful UK bidders.

In brief, the mixed results on post-merger stock performance of acquiring firms could be attributed to differences in their research methods. The next section will present possible explanations for the inconsistent results in relation to acquiring firms' returns after takeovers.

2.4.1.1 Explanations for post-takeover under-performance

A number of explanations have been proposed for why returns to acquiring firms are lower in the long-term post-acquisition periods.

[8] Agrawal et al. (1992) actually report significantly negative abnormal returns to acquiring firms since the second year after mergers.

[9] This significantly negative abnormal return is found when Mitchell and Stafford (2000) using the calendar-time portfolio approach. However, if they use BHAR measure with control for size and book-to-market value, an insignificantly negative return of -1.0% is reported over the same period. Different models used in computing long-run abnormal returns will be discussed in the next section (Section 2.4.1.1).

Firm size effect

A prominent likely contributing factor is the well-documented negative relationship between firm size and stock return. Acquiring firms are typically larger in size so their negative share market performance may be a function of the "firm-size effect". For instance, da Silva Rosa (1994) compares returns of successful bidders (over window [+7,+24] months relative to bid announcement month) to two different benchmarks: value-weighted market portfolio and their size-decile portfolio. He finds that acquiring firms suffer negative abnormal returns (-2.96%) in the former benchmark, but earn positive abnormal returns (3.44%) in the latter. In a study of recent mergers from 1998 to 2002, Moeller et al. (2005) find significantly negative abnormal returns to portfolios of "large loss deal" bidders for five years following mergers. Harford (2005) documents some evidence of relatively poor post-merger performance for the largest bidders.

Book-to-market ratio explanation

In addition to firm size, book-to-market (B/M) ratio has also been found to be a relevant factor in explaining post-acquisition performance.[10] Rau and Vermaelen (1998) find significantly positive abnormal returns of 7.64% for "value acquirers" (i.e. firms with a high B/M ratio) and significantly negative results of -17.26% for "glamour acquirers" (i.e. firms with a low B/M ratio) up to three years after mergers. They conclude that "the long-term under-performance of acquiring firms in mergers is predominantly caused by the poor post-acquisition performance of low book-to-market "glamour" firms".

Survivorship bias

Survivorship bias in event studies is first mentioned in Brown et al. (1992). In

[10] Fama and French (1992, 1993) find that the B/M equity ratio is systematically associated with cross-sectional variation in long-term stock returns. Their regression results show the cross-sectional relation between average returns and B/M equity is stronger than the relation between size and average returns. However, the B/M effect seems to be inconclusive in explaining stock returns in Australia since different studies report different findings. For instance, some research (e.g., Anderson et al. (1990), Halliwell et al. (1999), Durack et al. (2004), Durand et al. (2006)) find that the B/M relation with average returns virtually disappear once firm size is controlled. Conversely, other research (e.g., Faff (2001, 2004), Gaunt (2004), O'Brien (2007)) indicate that returns in Australia are positively related to B/M values.

general, survivorship bias refers to the situation when the returns of samples of firms selected ex-post are adjusted by the returns to portfolios comprising firms selected ex-ante. da Silva Rosa (1994) is the first Australian study to examine the effect of survivorship bias on the anomalous returns to acquiring firms in the post-merger periods. His study controls for survivorship bias by ensuring that both the sample of merger firms and the control portfolios comprise firms that have survived over the given event window. In his sample of takeover bids from 1974 to 1990, he finds that the value-weighted abnormal returns of successful bidders over period [+7,+36] months relative to the bid announcement month are, on average, much higher in their survivor sample than that of non-survivor sample (12.48% and -2.96% respectively). The results from da Silva Rosa (1994)'s study indicate that the effect of survivorship bias can be quite severe in calculating post-takeover performance of bidding firms.

Method of payment explanation

Various researchers have suggested that failure to control for method of payment might explain the mixed results across studies that investigate long-run returns to bidding firms. In line with other research showing a negative relationship between equity issuance and firm performance,[11] Longhran and Vijh (1997) find the post-acquisition stock returns to acquirers are systematically related to the form of payment. They report a significantly negative average abnormal return of -24.2% for stock acquirers whereas cash acquirers earn a positive average long-term abnormal return of 18.5%. In a later study, Mitchell and Stafford (2000) show that abnormal post-acquisition average returns are limited to mergers financed with stock; the negative abnormal returns to acquiring firms in the post-acquisition period disappear when mergers are financed without issuing stock. In an Australian study of takeover bids announced over the period 1988-1996, da Silva Rosa

[11] The negative relationship is found in literature of long-run stock returns following stock issues and repurchases. Longhran and Ritter (1995), Spiess and Affleck-Graves (1995), Spiess and Affleck-Graves (1999) show that firms making seasoned stock issues under-perform for a period of five years. Stock repurchases are the opposite of stock issues, and firms buy back their stocks over-perform for a period of four years (Ikenberry et al. (1995) and Ikenberry et al. (2000)).

et al. (2000) also confirm the association of long-term abnormal returns to bidding firms with the medium of exchange. Consistent with earlier research, they find that ASX-listed bidding firms who offer shares significantly under-perform in the post-acquisition periods.

Takeover wave effect

Given that takeover waves are defined in terms of high incidence of takeovers, it is reasonable to posit that the motivation and consequences of takeover bids undertaken during wave periods are different to those undertaken in other periods. Therefore, value creation (or destruction) to acquiring firms may be different for takeovers undertaken during wave periods. To understand how they might be different it is helpful to review the theories that attempt to explain why takeovers might occur in waves.

Takeover waves can occur because of managerial problems such as hubris or herding (Roll (1986), Scharfstein and Stein (1990)) (managerial hypothesis), or due to mis-valuation of the stock market (Shleifer and Vishny (2003)), or the relative mis-valuations of the merging firms and the market's mis-perception of synergies from the combination (Rhodes-Kropf and Viswanathan (2004)) (mis-valuation hypothesis), or as a response to economic shocks (Mitchell and Mulherin (1996), Harford (2005)) (neoclassical hypothesis).

We posit that merger waves make it easier for managers to pursue their own-self interest at the expense of shareholders since investors and other stakeholders have a more difficult time in analysing acquiring firms in periods of merger intensity. Previous research has shown that the accuracy of analysts' forecasts is reduced substantially when the analysts deal with a number of companies and industries (e.g. Clement and Tse (2005)). In addition, as evidence in Sah (1991) and Huang et al. (2004), criminals are less likely to be caught during periods of high crime rates. Therefore, it may induce self-serving managers to make more inefficient mergers during merger wave periods.

Under the first two explanations, acquiring firm managers are more likely to make valuation errors and attempt to pursue their personal interest at the expense of shareholders during takeover waves. Hence, according to these two theories, the returns to acquiring firms are relatively lower if the merger takes place during the wave state than in the non-wave state. Alternatively, if the wave is an efficient response to economic shocks, it is associated with more rational behaviour. Therefore, under the neoclassical hypothesis, we would expect the value creation to acquiring firms in the wave period to be equal to or greater than that in the non-wave period.

There is evidence that bidders in merger waves earn, on average, lower long-term abnormal returns. Rosen (2006), in a study of mergers announced between 1982 and 2001, shows evidence that firms announcing their acquisition decisions in "hot merger markets"[12] earn lower post-merger stock performance[13] than those in "cold merger markets". A caveat is in order here: "hot merger markets" are related to, but not necessarily the same as merger waves since hot markets are defined by reference to the market's reaction[14] to merger announcements, while merger waves are defined by concentration of mergers (by number or value). Rosen (2006) does not identify wave periods, however, when he controls for the number of mergers, as a measure of waves, in the regression. He finds the coefficient on merger waves is negative and significant.[15] Rosen (2006), thus, concludes that mergers announced during waves perform worse in terms of long-run stock performance than mergers announced at other times.

[12]The notion of "hot" market theory is also used in the context of Initial Public Offerings (IPOs). For examples, Loughran and Ritter (2002) suggest that large mis-pricing (underpricing) occurs in hot IPO markets.

[13]The post-merger abnormal return in Rosen (2006)'s study is calculated using buy-and-hold measure with return window from 3 days after an announcement to 3 years after the announcement.

[14]Rosen (2006) argues that there are two main components of market's reaction: the new information contained in a merger announcement, and the way market react to that information.

[15]The buy-and-hold returns of acquiring firms in Rosen (2006) samples are compared against three different benchmarks: the CRSP value-weighted index, an industry-based index, and an index based on one of 25 M-B/M quintiles. The significant coefficient of the number of mergers variable is only found in the last two indexes.

In a similar study, Gugler et al. (2006) demonstrate that stock performance of acquirers that undertook M&As during wave periods is, on average, significantly worse than those that took place outside the wave periods (the mean (median) abnormal returns after three years is 10% (11%) lower). Harford (2003a), using a bootstrapping method for identifying industry merger waves over the period 1981 to 2000,[16] finds that the median abnormal returns of acquiring firms is lower over three years following the end of the wave.[17] Following Harford (2003a)'s method of wave identification, Duchin and Schmidt (2008) document that acquiring firms that announced their takeover bids during wave periods perform worse than "non-wave" acquiring firms three years following the effective date of the mergers. Their results are robust across two different groups of long-term performance measure: stock performance and operating performance (return on assets).

There may also be a difference in bidder's returns if bidding firms participate in the first half (in time) versus the second half of takeover waves. Roll (1986)'s hubris hypothesis combined with the herding approach of Scharfstein and Stein (1990) suggest that a merger wave occurs because hubris managers make acquisition bids, and other managers mimic the leader's actions. So herding behaviour is expected to be observed mainly in the latter stages of takeover waves, suggesting a potential first-mover advantage for firms that initiate their bids early in the wave. Consequently, it is expected that acquiring firms that announce their takeover bids in the first half of the wave will have higher long-run abnormal returns than those in the second half of the wave. In line with this expectation, Harford (2003a) finds that the later in the wave that a firm bids, the worse its three-year post-bid performance. Bhagat et al. (2005) reveal that the highest M&A gains are realised at the beginning of takeover waves. Martynova and Renneboog (2008) conclude that "takeover towards the end of each wave are usually driven by non-rational, frequently self-interested managerial decision-making".

[16] M&A activity of each of 28 industries over a rolling period of 24 months in each decade will be used to identify merger waves. A bootstrap procedure is then implemented in order to record an industry-wave year.

[17] However, Harford (2003a) finds a positive effect for "in-wave" mergers on expected long-term earnings when he compares specialists' forecasts right before and right after the merger.

Measurement of post-takeover stock performance

Long-term event studies are sensitive to models used for computing abnormal returns, which may partially explain the conflicting findings of past research on the long-run performance of acquirers. The long-term return anomalies tend to become marginal or even disappear depending on which models are used to calculate returns or what statistical tests are used to measure them. Recent literature has attributed post-merger under-performance to flaws in measurement and statistical tests of long-run share market performance.

Two common methods for measuring long-run abnormal stock performance in the literature are cumulative abnormal returns (CARs) and buy-and-hold abnormal returns (BHARs). Fama (1998) argues that CARs should be used to draw inferences about long-horizon returns rather than BHARs. The reason for this argument is that the calculation of BHARs relies on compounding single period returns which can magnify long-term under-performance (over-performance) even though it might occur in only one period early in the sequence. Sharing the same view with Fama (1998), Mitchell and Stafford (2000) also oppose the use of BHARs. In contrast, Barber and Lyon (1997), Lyon et al. (1999) and Loughran and Ritter (2000) prefer the BHARs methodology since it accurately captures the wealth effects of a long-term investor. They argue that CARs are subject to more severe measurement bias.[18]

On the question of which measure of performance is better, Lyon et al. (1999) suggest that the BHARs measure is preferred "if a researcher is interested in answering the question of whether sample firms earned abnormal stock returns over a particular horizon of analysis". In contrast, if the research objective is to find out whether sample firms "persistently earn abnormal monthly returns" then the CARs measure should be used.

[18] Measurement bias is a problem particularly when discrete returns are averaged across firms and then cumulated over time.

In relation to tests of statistical significance of long-horizon abnormal returns, some recent studies (Barber and Lyon (1997), Kothari and Warner (1997), Fama (1998), Lyon et al. (1999), Brav (2000)) have questioned the validity of standard parametric tests (for both the CARs and BHARs methods[19]). Both Barber and Lyon (1997) and Kothari and Warner (1997) document the skewness of long-term abnormal returns, suggesting that statistical tests of the significance of these returns may be mis-specified. Barber and Lyon (1997) demonstrate that long-run traditional t-statistics are negatively biased (positively biased) in BHARs (CARs) methodology, detecting significant abnormal performance in many instances when none is present.

In addition, abnormal returns calculated using reference portfolios do not yield well-specified test statistics due to the existence of a new listing and rebalancing bias (Barber and Lyon (1997)). Furthermore, some researchers (e.g., Fama (1998), Mitchell and Stafford (2000)) believe that one of the problems with the power of traditional statistical test is the violation of an important underlying statistical assumption, i.e. that abnormal returns are independent across event firms. Mitchell and Mulherin (1996) contend that major corporate events like mergers often cluster through time by industry, and they are not random events. Therefore, samples of merger firms may not represent independent observations which in turn may lead to cross-correlation of abnormal returns calculated for these firms. According to Mitchell and Stafford (2000), the problem of cross-sectional dependence in merger sample observations will lead to a positive cross-correlation in abnormal returns and the test statistics that assume independence are overstated.

The new listing bias and the rebalancing bias can be controlled for by careful con-

[19]CARs are effected by sampling biases (e.g., calendar clustering, industry clustering, and overlapping returns) in analogous ways to BHARs. Kothari and Warner (1997) empirically find that CARs may pose fewer statistical problems than BHARs since CARs distribution is relatively closer to a normal distribution than that of BHARs. However, Lyon et al. (1999) prove that test statistics based on CARs are no less reliable than those based on BHARs.

struction of reference portfolios.[20] To eliminate the skewness bias, the bootstrapping method for statistical inference, as first suggested by Brock et al. (1992) and Ikenberry et al. (1995), can be implemented. Kothari and Warner (1997) argue the bootstrap procedure represents a state-of-the-art procedure for recognizing and attempting to adjust for systematic biases in assessing statistical significance. Lyon et al. (1999) prove that the bootstrap method not only yields well-specified test statistics but is also more powerful than the control firm method, one that has also been used to detect abnormal performance in some recent long-horizon studies. The advantage of the bootstrap approach is that the statistical significance is evaluated from an empirically generated distribution.[21] Thus, there are no concerns for the skewness bias or violation of parametric assumptions. However, the bootstrapping method is unable to control for an additional source of misspecification: the lack of independence generated by overlapping returns. Brav (2000) suggests that while BHARs can yield an abnormal return measure that accurately represent investor experience, this method is more sensitive to the problem of cross-sectional dependence among sample firms since it assumes independence of all observations, including those that are overlapping in calendar time.

Fama (1998) and Mitchell and Stafford (2000) propose that the calendar-time portfolio method[22] can address the problem of cross-sectional dependency. Under this method, a portfolio is formed monthly to include all merger firms within the last n periods. Calendar-time abnormal returns[23] is calculated for sample firms

[20]Consequently, these reference portfolios yield a zero mean abnormal return, therefore, reduce the mis-specification of test statistics population mean. Further details regarding construction of reference portfolios is in Section 5.2.1.

[21]We generate the empirical distribution of mean long-run abnormal returns under the null hypothesis: the mean long-run abnormal returns of the takeover sample equals the mean long-run abnormal returns for the control portfolios. On the contrary, the conventional t-statistic is tested on the null hypothesis that the mean long-run abnormal returns of the takeover sample is zero.

[22]The calendar-time portfolio approach was first used by Jaffe (1974) and Mandelker (1974).

[23]Calendar-time abnormal returns are calculated as the difference between return on the portfolio of event firms and expected return on the event portfolio. The expected return on the event portfolio that is proxied by the Fama-French three-factor model (Mitchell and Stafford (2000)).

and inference is based on a t-statistic derived from the time-series of average monthly calendar-time portfolio abnormal returns. Mitchell and Stafford (2000) contend this approach eliminates the problem of cross-sectional dependency since the cross-sectional correlations of returns of the individual merger firm are automatically accounted for in the portfolio variance at each point in calendar time.

However, both Fama (1998) and Mitchell and Stafford (2000) point out that the calendar-time portfolio method is not without its flaws. Firstly, the abnormal return obtained under the calendar-time method does not precisely measure investor experience. Secondly, this method can also lead to biased estimates since it violates one of the assumptions that the factor loading is constant through time. Mitchell and Stafford (2000) show that this assumption is unlikely to be realistic since the composition of the calendar-time portfolio changes each month, which means the true slopes on the risk factors in time-series regressions are time-varying. Thirdly, the number of firms in the portfolio changes through time, creating residual heteroskedasticity[24] since the variance is related to the portfolio composition. Obviously, this can affect inferences about the intercept as the ordinary least squares estimator may be inefficient, although it does not lead to biased estimates. Finally, Loughran and Ritter (2000) argue that the calendar-time portfolio approach has low power to detect abnormal performance because it weights each month equally, so months of high activity are treated the same as months with low activity. In the other words, this approach may not be able to identify significant abnormal returns if abnormal performance is mainly found in months of concentration of merger activity.[25]

In conclusion, Lyon et al. (1999) maintain that either the calendar-time portfolio approach or modified BHARs approach[26] should be considered in tests of long-

[24]Mitchell and Stafford (2000) empirically shows that the potential problem of heteroskedasticity can be overcome by using a non-parametric bootstrap procedure of Horowitz (1996).

[25]Even Mitchell and Stafford (2000) perform the calendar-time regression with two dummy variables for being in periods of heavy and low merger activity, no statistical significance is found on these two dummy variables' coefficients.

[26]The modified BHARs involve a careful construction of reference portfolio and use bootstrapping method for statistical inference.

term abnormal returns.[27] In this thesis, we focus on the modified BHARs since our study is concerned with relative wealth creation in the wave versus non-wave states of merger activity[28] which the calendar-time portfolio approach has lower power to detect. As documented earlier, the BHARs measure may be subject to measurement bias, but our results should not be affected by this bias as long as the bias is consistent inside and outside merger waves since we concentrate on differences in performance between the wave and non-wave periods.

2.4.1.2 Summary on long-run stock performance of acquiring firms

In short, the evidence indicates that bidding firm shareholders are not so fortunate in the takeover game. At best, these shareholders are no better off (in the sense that acquiring firms earn, on average, normal returns), or even they lose (earn negative abnormal returns) in the long run.

The seemingly systematic loss in value by acquiring firms, particularly those offering equity as consideration, in the long-run not only contradicts the neo-classical assumption that large scale transactions are, on average, value increasing to both parties but the prolonged manifestation of the loss in returns contradicts reasonable characterisations of market efficiency. One possible explanation for both puzzles (which they are from a neo-classical perspective) is that long-run returns to acquiring firms have been measured with a systematic downward bias. Indeed, it is well documented that the measurement of long-run performance is fraught with difficulties (e.g. Barber and Lyon (1997), Kothari and Warner (1997), Fama (1998), Lyon et al. (1999), Mitchell and Stafford (2000)).

However, an increasing number of financial economists acknowledge that the find-

[27]Even though Lyon et al. (1999) believe that "the analysis of long-run abnormal returns is treacherous" given the measurement and statistical issues relating to long-run share market abnormal returns.

[28]In Chapter 3, we show that takeover activity can be characterised in two distinct states (wave and non-wave). Wave state is referred to period of takeover concentration, and non-wave state is the period of low merger activity.

ing of long-run under-performance by acquiring firms offering shares as consideration is both economically significant and confirmed by so many studies across countries and periods that it seems reasonable to accept it as being accurate. In light of this, one plausible explanation is that poor returns to acquiring firms in the long run is a direct consequence of overpayment to target firms and the slow adjustment of stock prices reflects the gradual recognition of this outcome by the market. After all, if over-valuation takes a period of time to occur it is reasonable to assume that the correction will be prolonged by a similar magnitude. If we accept this model, then takeover waves are likely to be associated with over-payment and consequent long-run poor performance.

We posit that M&As that take place during takeover wave periods can be another potential factor influencing the long-term stock performance of bidding firms. Previous research is mostly conducted on the US market and to exclusively adopt Harford (2005)'s bootstrapping method of wave detection. Our contribution is to use a more systematic approach to identify Australian merger waves (details in Chapter 3) and then to see whether the findings from earlier studies on the impact of merger waves on post-acquisition performance remains robust. We will examine this issue in Chapter 5 of this thesis.

2.4.2 Effects of M&As on target firms

When one firm takes over another, the acquiring firm typically offers to buy the target's common stock at a premium, i.e. at a price per share in excess of its previous trading price. There are two ways of measuring target shareholders' gains in takeovers: target cumulative returns or takeover premiums. While the first is to use target cumulative abnormal stock returns (CARs) around the announcement date, the second is to employ offer price, and then compare it with target stock price before the takeover information is impounded. Despite the differences in methodology, the most consistent result across takeover studies is that target firm shareholders gain significant abnormal returns on the announcement of the

Table 2.2: Summary of studies analysing M&A effects on returns to target shareholders

This table presents studies of takeover effects on target firms. Wealth effect to target shareholders is calculated by either cumulative abnormal return method or bid premiums between offer price and target stock price some period before the announcement date (*Target price date*).

Study	**Sample period**	**Event window**	**CARs**	**Target price date**	**Average bid premiums**
Dodd (1976)	1960-1970 (Australia)	[-1,0] month	25%*		
Walter (1984)	1966-1972 (Australia)	[-10,0] weeks	28%*		
Bishop et al. (1987)	1972-1985 (Australia)	[-3,+3] months	20%*		
Lang et al. (1989)	1968-1986 (US)	[-5,+5] days	40.3%*		
Jarrell and Poulsen (1989)	1963-1986 (US)	[-20,+10] days	28.99%*		
Franks et al. (1991)	1975-1984 (US)	[-5,+5] days	28.04%*		
Kaplan and Weisbach (1992)	1971-1982 (US)	[-5,+5] days	26.9%*		
Healy et al. (1992)	1979-1984 (US)	[-5,+5] days	45.6%*		
Smith and Kim (1994)	1980-1986 (US)	[-5.+5] days [-1,0] days	30.19%* 15.84%*		
da Silva Rosa (1994)	1974-19990 (Australia)	[-3,+3] months	24.74%*		
Kendig (1997)	1955-1995 (Australia)			month -2	40% (annual average)
Mulherin and Boone (2000)	1990-1999 (US)	[-1,+1] days	21.2%*		
Houston et al. (2001)	1985-1996 (US)	[-4,+1] days	20.8%*		
Officer (2003)	1988-2000 (US)			day -43	48.65%
Maheswaran and Pinder (2005)	1992-2001 (Australia)			week -4	32.65%
Billett et al. (2008)	1979-1997 (US)	[-1,0] month	22.15%*		
Betton et al. (2008b)	1973-1989 (US)			day -41	46.1%
Betton et al. (2008a)	1980-2003 (US)	[-1,+1] days	14.61%*	day -42	48%
Levi et al. (2008)	1997-2006 (US)	[-1,+1] days	22.4%*	week -4	41.3%

takeover offer. This is evident in Table 2.2 which presents studies after Jensen and Ruback (1983)'s landmark review.

Jensen and Ruback (1983), in a review 13 studies of M&As in the US market, conclude that targets of successful tender offers made before 1980 earn cumulative abnormal returns ranging from 16% to 30%. Later research has shown consistent results with these early studies. For example, Jarrell and Poulsen (1989) estimate targets' CARs for 526 successful takeovers from 1963 to 1986, and find an average CAR of 28.99%, measured from 20 days before to 10 days after the bid. Other research (Franks et al. (1991), Kaplan and Weisbach (1992), Smith and Kim (1994), Mulherin and Boone (2000), Houston et al. (2001), Billett et al. (2008), and Levi et al. (2008)) document similar figures when calculating CARs for target shareholders. The highest CARs for targets is found in Healy et al. (1992)'s study of 382 mergers over the period 1979-1984. They report an average value of 45.6% to shareholders of target firms, measured five days from the first offer announced to the date target is delisted from trading.

The takeover premiums for the US acquisitions are, on average, more than 40% in two months prior to the bid announcement. For instance, Officer (2003) documents the average bid premiums of 48.65% relative to 43 days before the initial bid announced. His study covers 2,511 takeover bids over the period from 1988 to 2000. Similarly, Betton et al. (2008a) calculate offer premiums for 4,889 targets in the period 1980-2002. They report the mean (median) value of 48% (39%) when comparing the final offer price to target stock price 42 days before the announcement. The most recent study is found in Levi et al. (2008) that cover 403 takeover bids for the period 1997-2006. They document the average offer premiums of 41.3%, relative to 4 weeks before announcement.

Evidence of target cumulative abnormal gains in the Australian takeover market can be found in Dodd (1976), Walter (1984), Bishop et al. (1987), and da Silva Rosa (1994). Consistent with the US findings, Dodd (1976), in an analysis of 58 takeovers in the period 1960-1970, documents an average abnormal return of 25% in the month of announcement. Similarly, Walter (1984) reports an average increase of 28% for 383 target firms successfully acquired between 1966 and 1972 in their CARs in the ten-week period before and including the announcement weeks. Bishop et al. (1987) find that CARs of successful targets are 20% on average over the window [-3,+3] months relative to the bid announcement month.

Using a similar event window to Bishop et al. (1987), da Silva Rosa (1994) reports an average target CAR of 24.74% for takeover bids announced from 1974 to 1990.

Like the US market, Australian studies also report higher target gains if the takeover bid premiums are used rather than the CARs. Kendig (1997), in a comprehensive study of 1,980 mergers from 1955 to 1995, documents the average takeover premiums of 40%. In her analysis, takeover premiums are measured using share price two months prior. Maheswaran and Pinder (2005) recently report an average of 33% in takeover premiums, relative to four weeks prior to the announcement date. Their sample covers 133 takeover announcements made to exchange-listed targets over the period between January 1992 and June 2001.

In short, the gains experienced by target firm shareholders can be calculated by using either the CARs method or the bid premium method. As can be seen from Table 2.2 and the earlier studies reviewed in Jensen and Ruback (1983), the majority of the empirical studies on takeovers are content to use target CARs around the takeover bid as a proxy for the actual offer premiums. However, as Betton et al. (2008a) argue, target CARs "present noisy estimates of offer premiums because they incorporate the probability of bid competition at the initial offer date, and they must be estimated over a long event window to capture the final premiums". Our study will employ offer price data directly to calculate takeover premiums.

The literature has shown that a number of factors can affect offer premiums. They can be the existence of a target termination agreement (Officer (2003)), powerful entrenched target CEOs (Moeller (2005)), gender composition of the board (Levi et al. (2008)), toehold level (Betton and Eckbo (2000)), method of payment (Schwert (1996)), competing bids (Comment and Schwert (1995)), target hostility to the initial bid (Schwert (2000)), business cycle (Nathan and Terrence (1989)), or public status of acquiring firms (Bargeron et al. (2008)). In this study, we hypothesize that takeover waves can be another factor influencing bid premiums. The literature on the effect of takeover waves on stock returns of acquiring firms is fruitful (see the previous section (Section 2.4.1)), however, the literature on their influences on offer premiums is quite limited. We are only aware of Kendig (1997)'s study, but she reports only the annual average figures which exclude the variation of premiums within each year.

The previous section (Section 2.4.1) has demonstrated that there are three main theory groups to explain the incidence of merger waves: the managerial hypothesis (Roll (1986), Scharfstein and Stein (1990)), mis-valuation hypothesis (Shleifer and Vishny (2003), Rhodes-Kropf and Viswanathan (2004)), and neoclassical hypothesis (Mitchell and Mulherin (1996), Harford (2005)). According to the first hypothesis, takeover waves are driven by hubris and herding behaviour. So inefficient mergers are higher during the waves, and takeover premiums, as a consequence, are higher in the wave periods than in the non-wave periods. In addition, the bid premiums are lower in the early stages of the waves than the latter stages since the final stages of the waves consist of more mergers that are likely to be motivated by management herding behaviour.

The mis-valuation theory hypothesizes that takeover waves are caused by the timing of stock market over-valuation, and stock bids are the dominant method of payment in the wave periods. Therefore, it is expected that higher takeover premiums are more likely for “in-wave” takeovers than “non-wave” ones. In contrast to the first two theories, the neoclassical hypothesis claims that acquiring firms’ managers act in the best interest of their shareholders, and always make “good” acquisitions that increase their shareholders’ value. Takeover waves are caused by firms’ efficient responses to industry and economy-wide shocks. Hence, it is implied that “in-wave” takeover premiums should not be any different to “non-wave” premiums, and could be potentially be lower.

To sum up, M&As have been seen as beneficial to the shareholders of target firms. The gains to target shareholders can be measured either as cumulative abnormal returns (CARs) around the takeover bid, or takeover premiums by employing offer price data directly. The latter approach will be used in this study. Various research has documented a range of factors affecting bid premiums, we hypothesize that takeover waves can also potentially be another factor (see Chapter 5 for empirical testing).

2.4.3 Summary on effects of M&As to target and bidding firms

In summary, extensive empirical evidence supports the view that takeovers are beneficial to the shareholders of target firms. The long-term wealth effects on shareholders of acquiring firms, however, are much more puzzling. Researchers measuring these wealth effects have found them, on average, to be close to zero or even negative. The literature has advanced various factors that can influence returns to target and acquiring firms. We propose that takeover waves can potentially be one determinant[29] by drawing on the implications of three theories of merger waves (managerial hypothesis, mis-valuation hypothesis, and neo-classical). According to these three hypotheses, a significant takeover premium may reflect a range of features of the takeover, from the potential gains to over-payment by bidding firm's management. Therefore, in Chapter 5 of this dissertation, we analyse the impact of merger waves on both the takeover premiums, as well as, the long-run returns to acquiring firms.

2.5 Summary

The existence of takeover waves is generally accepted in the literature. However, there are still some interesting unanswered questions in relation to takeover waves. Firstly, it is the question of how to model the time-series behaviour of takeover

[29] As mentioned earlier, although previous studies have examined the effects of merger waves on post-acquisition performance, their method of wave identification is to replicate Harford (2005)'s bootstrapping method. We re-examine this issue by using a more systematic method of wave detection. Further details about our model are in Chapter 3.

activity, i.e. how to detect merger waves. Secondly, what drives takeover waves? The existing literature almost exclusively uses single-state models without accounting for the existence of takeover waves. Finally, can takeover waves affect the long-run stock market performance of acquiring firms? These issues will be investigated in the next three chapters (Chapter 3 for modelling takeover activity, Chapter 4 for causes of takeover waves, and Chapter 5 for the consequences of participating in the waves).

Chapter 3

Modelling of Time-Series Takeover Activity

3.1 Introduction

This chapter investigates and presents the results from testing the research question one. The key purpose of this question is to examine whether takeover activity follows a wave process and whether its time series can be statistically characterised.

It has been widely observed that takeover activity varies episodically, with high frequency periods being shorter. Episodes with high incidence of takeover activity are commonly termed "merger waves" in the literature. The precise timing of wave and non-wave dates of merger activity is a prerequisite for any investigation of possible underlying causes and consequences of merger waves.

As detailed in Section 2.2 of Chapter 2, while the notion that takeovers vary in incidence over time is undisputed, there is no consensus on how to describe "merger waves" in a time-series context. For example, Chowdhury (1993)) contends that M&A activity is random and hence unpredictable while other authors argue that the takeover series can be modelled. Amongst the latter group, there is disagreement as to how best to model this behaviour. Some authors (Shughart and Tollison (1984), Barkoulas et al. (2001)) claim that M&A activity can be best described by a linear process (namely, an autoregressive process), as a result of which, merger waves do not exist. Other authors (Town (1992), Linn and Zhu (1997), Kendig (1997), Gartner and Halbheer (2006)) argue that a non-linear model, specifically a two-state Markov switching model, should be used to characterise M&A time series. The advantages of using a Markov regime switching model include the possibility of drawing inferences about future probabilities of being in a wave state or a normal state, and the possibility of estimating the expected duration of each state. These possibilities are very important for market participants given the wealth creation and potential economic redistribution effects from takeover activity.

This chapter re-examines the case of modelling merger waves by using more recent Australian takeover data, extending from 1972 to 2004. It is believed that the two-state Markov switching model alone does not optimise wave locality and may not be sufficient to describe transient behaviour. Therefore, we employ a methodology advanced by Kim (1994) which combines a State-Space model with a Markov regime switching model to cover more generalised time series. To the best of our knowledge, this is the first paper which successfully applies this refined method in analysing takeover activity time series to improve the model's goodness-of-fit. In our approach, a more general autoregressive moving average (ARMA) modelling is used to describe the wave and normal states. The AR processes used in the existing approaches are only special cases of our proposed approach. As Hamilton (1989)'s approach was formulated for AR processes, it cannot be easily modified to accommodate ARMA processes. Hence, we shall use the procedure described in Kim (1994) to analyse the time-series behaviour of merger activity and verify the existence and extent of merger waves.[30] In this algorithm, an ARMA modelling of a Markov state is represented by the State-Space model. By using the Kalman filter to track the variation of the parameters in the State-Space model, it is possible to obtain an approximate estimation of the Markov state.

[30] Kim (1994)'s algorithm is an extension of Hamilton approach.

Our proposed model is then compared with a range of different Markov switching models in the literature, specifically Hamilton (1989)'s Markov switching model for AR(1) processes, and Kendig (1997)'s Poisson Markov switching model for AR(1) processes,[31] to demonstrate that our model provides a best fit. Diagnostics tests also suggest our model fits the data well. Experiments are run for both quarterly and annual takeover time series for the period from January 1972 to December 2004.

This chapter is structured as follows. Section 3.2 describes the collection procedure for our takeover data. Section 3.3 outlines the methodology of our model, and other Markov switching models in the literature are also briefly mentioned. Experimental results are discussed in Section 3.4 and conclusions in Section 3.5.

3.2 Data

Takeover data in Kendig (1997)'s study is obtained by reviewing ASX Delistings[32] and identifying which of those delistings are the result of a takeover. There are hence a few problems with this takeover data series. First, the reference date of the takeover bids is the completion date (the actual delisting date from the ASX), not the announcement date.[33] The time lag between the announcement date and the delisting date is obviously not consistent for each takeover bid.[34]

[31] As detailed in Section 2.2 of Chapter 3, Kendig (1997) has adopted Hamilton (1989)'s approach with a replacement of the original Gaussian distribution by the Poisson distribution. Kendig (1997) argues that the Poisson distribution is necessary because takeover data are positive and discrete. However, negligible quantization noise in a standard model can easily account for discrete values of the observations, it thus should not be of concern. Importantly, the Poisson-based model restricts the mean and variance of both wave and non-wave states to be the same. This makes it less flexible to describe wave behaviour when being applied to actual data. Therefore, in our proposed model, we still use the Gaussian distribution and extend the AR(1) processes by a more general ARMA modelling.

[32] This procedure is similar to that describe in another Australian study, Bureau of Industry Economics (1990)'s report.

[33] This thesis will follow the literature in using the announcement date rather than the completion date when examining takeover clustering.

[34] It is also not consistent among different studies of Australian takeovers. Kendig (1997) notes the average time lag between the announcement and delisting date for her sample is approximately 4 months, while Argus and Finn (1991) reveal it should be 7 months.

Secondly, Kendig (1997)'s data include only successful takeovers as measured by the number of delistings, and does not account for effective control. Moreover, Kendig (1997)'s data series contain only completed takeover deals. It is argued that broader range of acquisitions should be included in order to better explain the takeover phenomenon in the aggregate.[35]

Our data incorporate all takeover announcements for Australian listed targets, cover the period from January 1972 to December 2004 and are from several different sources but with same inclusion criteria. In order to minimise the number of missing observations from any one source, the population of takeover offers come from three separate, often overlapping sources.

- **Bishop et al. (1987)'s study**: cover takeover information between January 1972 and June 1985.[36] Their database includes all bids to listed target companies reported by the ASX.

- **Australian Financial Review (AFR) newspaper**: Data[37] are manually collected by reviewing the AFR newspaper to find takeover offer announcements[38] for ASX-listed target companies from June 1985 to June 1995.

- **Thompson Financial's Securities Data Company (SDC) Platinum database**: SDC is a commercial database that includes information on takeover offers for all Australian targets. The selection criteria are that each takeover offer is announced between January 1980 and December 2004 and has an ASX-listed company as a target. We cover all merger bids reported by SDC as acquisition of stocks (i.e. merger, acquisition, acquisition of

[35]Kendig (1997)'s data, for instance, does not cover the situations when majority interest (deals in which the acquirer must have held less than 50% and be seeking to acquire greater than 50% but less than 100% of the target company's stock) and partial interest (deals in which the acquirer holds less than 50% and is seeking to acquire less than 50%, or the acquirer holds over 50% and is seeking less than 100% of the target company's stock) are acquired.

[36]The Centre of Independent Studies granted access to their data file, and Dr Simmonds (Australian Graduate School of Management (AGSM)) kindly provided electronic copy of the database. Their assistance is gratefully acknowledged.

[37]Data were collected for an Australian Research Council (ARC) project of Professor da Silva Rosa (the University of Western Australia).

[38]Announcement date is always taken from the ASX files.

partial interest, acquisition of majority interest, acquisition of remaining interest).

Information from each data source is combined. Any bid appearing in only one data source is added to the final sample. Any bid appearing in multiple sources is compared to ensure agreement on appropriate offer details. In total, 5,407 takeover bids are announced for ASX-listed targets during the period January 1972 to December 2004. The reference date for takeover activity is always taken as the announcement date of the bid. Table 3.1 documents the number of Australian takeover bids identified each year from each of three data sources. As can be seen from this table, the level of Australian takeover activity fluctuates over the year with its clusters in some particular periods.

3.3 Methodology

In order to test for the wave hypothesis, the first part is to model the data to detect the presence of a linear structure by using the autoregressive process. Next, a wave process using methods developed by Hamilton (1989), Kendig (1997) and our approach is applied and goodness-of-fit is compared. The above-mentioned analytical procedures are all constructed and run in Matlab.

Tests for the existence of linear structure contain two parts. First, we test if the data and various levels of differencing exhibit white noise characteristics. The tests used are Ljung-Box test (Ljung and Box (1978)) and Brock, Dechert, Scheinkman & LeBaron (BDSL) test (Brock et al. (1996)). Next, we test if there is any linear structure inside the data, we fit an AR model and test the residuals for white noise characteristics using the tests above.

The literature has shown that the rejection of the linear AR model could be traced to structural shifts in the mean of the takeover series. The two-state Markov switching process accommodates such shifts. A review of existing meth-

Table 3.1: Australian takeover data - Number of takeover bids - 1972-2004

This table presents number of takeover bids to exchange-listed target companies. Data comes from three different sources: The Centre Independent Studies (CIS), Australian Financial Review newspaper (AFR), and Thompson Financial's Securities Data Company (SDC) Platinum database.

	Number of takeover bids			
Year	**CIS source**	**AFR source**	**SDC source**	**Total sample**
1972	198			198
1973	117			117
1974	65			65
1975	74			74
1976	91			91
1977	80			80
1978	107			107
1979	105			105
1980	132			132
1981	126		1	127
1982	70			70
1983	94			94
1984	119		1	120
1985	65	36	2	103
1986		114	11	125
1987		175	16	191
1988		246	36	282
1989		167	56	223
1990		94	56	150
1991		90	139	229
1992		58	50	108
1993		58	106	164
1994		35	148	183
1995		24	208	232
1996			240	240
1997			181	181
1998			176	176
1999			136	136
2000			182	182
2001			181	181
2002			190	190
2003			438	438
2004			313	313
Total	1,443	1,097	2,867	5,407

ods of wave processes developed by Hamilton (1989) (Gaussian Markov Switching Model for AR(1) processes), and Kendig (1997) (Poisson Markov Switching

Model for AR(1) process) is provided in the next section. Our method of combining the State-Space model with Gaussian Markov switching-regime model using ARMA(1,1) processes (Kim (1994)) is then discussed.

3.3.1 Hamilton's Markov switching model (HGMS) for AR processes

Merger data are observed to exhibit a clear distinction between high-level and low-level activities during different time periods. High-level activities occur over shorter periods than low-level activities. Hamilton (1989) proposes a two-state Markov switching approach to describe these differences (the discrete shifts in regime between a wave state and a non-wave (normal) state).[39] These regime shifts which are governed by the outcome of a Markov process are illustrated by a large, discrete, and unsustainable increase in the mean and variance of the time series, making it non-linear. At each state, the time-series behaviour is described by a linear ARMA model. The original approach by Hamilton is formulated for a Gaussian case, i.e. the noise term was considered Gaussian. This approach is also valid only for AR processes, which are a special case of a more general ARMA framework.

The two-state Hamilton's Markov switching model for AR(1) process can be mathematically represented by the following equation:

$$y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t \tag{3.1}$$

where

- y_t is time series of the aggregate number of takeover bids
- e_t - the error term - is normal, independently and identical distributed with $\mathrm{E}(e_t) = 0$

[39]Hamilton (1989)'s model has been used to test regime changes in structure of some financial time series such as GDP (Hamilton (1989)), interest rates (Hamilton (1988)), foreign exchange rates (Engel and Hamilton (1990)), inflation (Evans and Wachtel (1993)), and takeovers (Town (1992)).

- ϕ - the AR lag coefficient. The two-state Markov-switching process is composed of two distinct AR(1) processes which have unequal intercepts but equal lag coefficients.

- S_t describes the Markov state at time t and can take a value of 0 (normal state) or 1 (wave state)

$$\begin{cases} \text{If} & S_t = 1: \quad \mu_{S_t} = \mu_1, e_t \sim \mathcal{N}(0, \sigma_1^2) \\ \text{If} & S_t = 0: \quad \mu_{S_t} = \mu_0, e_t \sim \mathcal{N}(0, \sigma_0^2) \\ \text{where} & \mu_1 > \mu_0, \quad \sigma_1 > \sigma_0 \end{cases}$$

- μ_{S_t} refers to mean of the state

Each state is governed by a first-order Markov process with constant transition probabilities, so that the probability of being in any given state is dependent on the state in the previous time period. This introduces two other parameters, p_{00} and p_{11}, which respectively represent the probability of remaining in a normal state and in a wave state in the next period.

$$\begin{aligned} \text{Prob}[S_t = 1|S_{t-1} = 1] &= p_{11} \\ \text{Prob}[S_t = 0|S_{t-1} = 1] &= 1 - p_{11} \\ \text{Prob}[S_t = 0|S_{t-1} = 0] &= p_{00} \\ \text{Prob}[S_t = 1|S_{t-1} = 0] &= 1 - p_{00} \end{aligned}$$

These transition probabilities can be put in the following matrix notation:

$$P = \begin{bmatrix} p_{00} & 1 - p_{00} \\ 1 - p_{11} & p_{11} \end{bmatrix} \tag{3.2}$$

3.3.2 Kendig's Poisson Markov switching (KPMS) model for AR(1) processes

Kendig (1997) modifies Hamilton's AR(1) process by replacing the Gaussian distribution by a Poisson distribution due to the conceptual reason that merger data are positive and take discrete values. The two-state Kendig's Poisson Markov switching model for AR(1) process can be represented by the following system:

$$y_t \sim Pn(\lambda_t) \tag{3.3}$$

$$\begin{cases} \text{If} \quad S_t = 1: & \lambda_t = \alpha_1 + \phi y_{t-1} \\ \text{If} \quad S_t = 0: & \lambda_t = \alpha_0 + \phi y_{t-1} \end{cases}$$

where $\alpha_1 > \alpha_0$. The parameter ϕ indicates persistence in a particular state.

3.3.3 Proposed State-Space and Markov switching model for ARMA processes

The assumption of equal mean and variance under the Poisson distribution is a disadvantage of Kendig (1997)'s approach. It is expected that variance in a wave state is higher, and consequently this assumption is highly restrictive and the underlying approach may not provide a good empirical fit. The reason for Kendig (1997)'s use of the Poisson distribution is because of positive and discrete values of the merger data. However, discrete values of the observations can be simply accounted for by negligible quantization noise in a standard model and hence it should not be of great concern in this analysis.

Consequently, we propose to use the Kim (1994)'s methodology which combines the State-Space model with Hamilton's Markov switching model in order to cover more generalised time series. In our approach, a more general ARMA modelling is used with the AR approach being only a special case of the proposed approach. In Kim's algorithm, an ARMA modelling of a Markov state is represented by the State-Space model.[40] By using the Kalman filter to track the variation of

[40]The so-called "state" in the State-Space model has nothing to do with the Markov state in

the parameters in the State-Space model, it is possible to obtain an approximate estimation of the Markov state and model the time-series behaviour. The two-state Markov switching-regime model for ARMA(1,1) process can be represented by the following equation:

$$y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t + \gamma e_{t-1} \tag{3.4}$$

All parameters are the same as those defined in the HGMS Model, except for the new parameter γ, the MA lag coefficient which is identical in both wave state and normal state.

The above equation could be expressed in the following State-Space form:

$$\begin{cases} y_t &= \mathbf{H}\boldsymbol{\beta}_t + \mu_{S_t} \\ \boldsymbol{\beta}_t &= \mathbf{F}\boldsymbol{\beta}_{t-1} + \mathbf{v}_t \end{cases} \tag{3.5}$$

where the subscript S_t denotes Markov state-dependent quantities and:

$$\mathbf{H} = [1 \;\; \gamma]$$

$$\mathbf{F} = \begin{bmatrix} \phi & 0 \\ 1 & 0 \end{bmatrix}$$

$$\mathbf{v}_t = \begin{bmatrix} e_t \\ 0 \end{bmatrix}$$

$$e_t \sim \mathcal{N}(0, \sigma^2_{S_t})$$

This model can be reduced to the HGMS model by setting $\gamma = 0$. Hence, it is clearly more general. The algorithm for obtaining the Markov state conditional probabilities is given in Kim and Nelson (1999). It is much more complicated than the algorithm for AR processes and it involves approximations for the algorithm to be practically feasible.

Hamilton's formulation.

3.3.4 Estimation techniques of proposed State-Space and Markov switching model for ARMA processes

Estimation of the model involves computing the maximum likelihood estimates of its coefficients along with the transition probabilities. The algorithm consists of several steps. First, the Kalman filter update is used to obtain the conditional parameters of the State-Space model corresponding to each possible path of state transitions. Then the Hamilton filter is employed to update the state values. The final estimates at each time step are obtained via an approximation method to reduce the prohibitive computational cost. We give a highlight of the algorithms in what follows. Our notations mostly follow Kim and Nelson (1999).

3.3.4.1 Initialization

The initialization step specifies the following quantities

- Likelihood

$$l(\boldsymbol{\theta}) = 0$$

- Estimates of the state vector and covariance matrix at $t = 0$

$$\begin{aligned} \boldsymbol{\beta}^j_{0|0} &= (\mathbf{I} - \mathbf{F}_j)^{-1}\,\mathbf{0} = \mathbf{0}, \quad j = 0, 1 \\ \mathsf{vec}\left[\mathbf{P}^j_{0|0}\right] &= (\mathbf{I} - \mathbf{F}_j \otimes \mathbf{F}_j)^{-1}\,\mathsf{vec}\left[\mathbf{Q}_j\right], \end{aligned}$$

  where $\mathsf{vec}\,[.]$ is the operator that converts a matrix into a column vector, $\otimes$ is the Kronecker product, and $\mathbf{Q}_j$ is the covariance matrix of $\mathbf{v}_t$ corresponding to the Markov state $S_t = j,\ j = 0, 1$

$$\mathbf{Q}_j = \begin{bmatrix} \sigma_j^2 & 0 \\ 0 & 0 \end{bmatrix}, \quad j = 0, 1.$$

- Estimates of the Markov state probabilities

$$\begin{aligned}\Pr[S_t = 0] &= \pi_0 = \frac{1 - p_{11}}{2 - p_{00} - p_{11}}\\ \Pr[S_t = 1] &= \pi_1 = \frac{1 - p_{00}}{2 - p_{00} - p_{11}}.\end{aligned}$$

3.3.4.2 Kalman filter

At time t we need to consider all possible transitions of Markov state $S_{t-1} = i$ to $S_t = j$ where $i, j = 0, 1$. There are four possible transitions $(0, 0), (0, 1), (1, 0), (1, 1)$. The Kalman filter update calculates the prediction and estimation of the state vector and covariance matrix over every possible transition (i, j).

- Prediction:

$$\begin{aligned}\boldsymbol{\beta}_{t|t-1}^{(i,j)} &= \mathbf{F}_j \boldsymbol{\beta}_{t-1|t-1}^{i}\\ \mathbf{P}_{t|t-1}^{(i,j)} &= \mathbf{F}_j \mathbf{P}_{t|t-1}^{i} + \mathbf{Q}_j.\end{aligned}$$

  Note that $\boldsymbol{\beta}_{t-1|t-1}^{i}$ and $\mathbf{P}_{t|t-1}^{i}$ are the (final) estimates of the state vector and covariance matrix corresponding to the state $S_{t-1} = i$ *only* which are available after the previous step.

  The prediction error and its variance are given by

$$\begin{aligned}z_{t|t-1}^{(i,j)} &= y_t - \mathbf{H}_j \boldsymbol{\beta}_{t|t-1}^{(i,j)}\\ R_{t|t-1}^{(i,j)} &= \mathbf{H}_j \mathbf{P}_{t|t-1}^{(i,j)} \mathbf{H}_j^T.\end{aligned}$$

- Estimation:

$$\begin{aligned}\boldsymbol{\beta}_{t|t}^{(i,j)} &= \boldsymbol{\beta}_{t|t-1}^{(i,j)} + \mathbf{P}_{t|t-1}^{(i,j)} \mathbf{H}_j^T \left(R_{t|t-1}^{(i,j)}\right)^{-1} z_{t|t-1}^{(i,j)}\\ \mathbf{P}_{t|t}^{(i,j)} &= \left(\mathbf{I} - \mathbf{P}_{t|t-1}^{(i,j)} \mathbf{H}_j^T \left(R_{t|t-1}^{(i,j)}\right)^{-1} \mathbf{H}_j\right) \mathbf{P}_{t|t-1}^{(i,j)}\end{aligned}$$

3.3.4.3 Hamilton filter

Upon the availability of state vector and covariance estimates, the Hamilton filter is used to obtain the estimates of Markov state probabilities $\Pr[S_t = j \mid \Psi_t], j = 0, 1$ where $\Psi_t = [y_0, \ldots, y_t]$ denotes the information available up to time t.

First, we compute over each possible transition $S_{t-1} = i, S_t = j$:

$$\Pr(S_t, S_{t-1}|\Psi_{t-1}) = \Pr(S_t|S_{t-1}) \Pr(S_{t-1}|\Psi_{t-1}).$$

Note that $\Pr(S_t|S_{t-1}) = p_{ij}$ is from the Markov transition matrix while $\Pr(S_{t-1}|\Psi_{t-1})$ is available from the previous step. The fit of the observation y_t to the model obtained up to time $t-1$ is given by

$$f(y_t|\Psi_{t-1}) = \sum_{S_t} \sum_{S_{t-1}} f(y_t|S_t, S_{t-1}, \Psi_{t-1}) \Pr(S_t, S_{t-1}|\Psi_{t-1}),$$

where $f(y_t|S_t, S_{t-1}, \Psi_{t-1})$ is completely specified given the Markov model (3.4):

$$f(y_t|S_t, S_{t-1}, \Psi_{t-1}) = \frac{1}{\sqrt{2\pi \, |R^{(i,j)}_{t|t-1}|}} \exp\left\{ -\frac{1}{2} \frac{\left(z^{i,j}_{t|t-1}\right)^2}{R^{(i,j)}_{t|t-1}} \right\}.$$

Next, the probability of the transition given the new observation is

$$\Pr[S_t, S_{t-1}|\Psi_t] = \frac{f(y_t|S_t, S_{t-1}, \Psi_{t-1}) \Pr(S_t, S_{t-1}|\Psi_{t-1})}{f(y_t|\Psi_{t-1})},$$

from which one can derive

$$\Pr[S_t|\Psi_t] = \sum_{S_{t-1}} \Pr[S_t, S_{t-1}|\Psi_t].$$

It is also noted that the log-likelihood function is updated via

$$l(\boldsymbol{\theta}) \to l(\boldsymbol{\theta}) + \ln(f(y_t|\Psi_{t-1})).$$

3.3.4.4 Approximation

In the Kalman filter part, we have only obtained estimates of the state vector and covariance matrix of every possible transition path. To make the algorithm work recursively, we need to obtain the estimate of the state vector and covariance matrix for the state S_t *only*. An exact inference method would require prohibitive computational cost when the number of observations becomes large. To overcome this problem, Kim and Nelson (1999) suggest the following approximation:

$$\boldsymbol{\beta}^j_{t|t} = \frac{\sum_{i=0}^{1} \Pr[S_{t-1} = i, S_t = j|\Psi_t]\boldsymbol{\beta}^{(i,j)}_{t|t}}{\Pr[S_t = j|\Psi_t]}$$

$$\mathbf{P}^j_{t|t} = \frac{\sum_{i=0}^{1} \Pr[S_{t-1} = i, S_t = j|\Psi_t]\left(\mathbf{P}^{(i,j)}_{t|t} + (\boldsymbol{\beta}^j_{t|t} - \boldsymbol{\beta}^{(i,j)}_{t|t})(\boldsymbol{\beta}^j_{t|t} - \boldsymbol{\beta}^{(i,j)}_{t|t})^T\right)}{\Pr[S_t = j|\Psi_t]]}.$$

3.3.4.5 Related issues

The above three steps complete the algorithm. For every observation y_t, one needs to run the Kalman filter, the Hamilton filter, and the approximation procedure. This recursive update is repeated until the last observation y_N. In theory, one can run another backward procedure, which is called smoothing which is hoped to further improve the estimates at each time index taking into account the whole information set Ψ_T rather than only the information Ψ_t available up to time t. However, we notice that for the State-Space model, this would require a number of approximations for which the accuracy appears rather poor and no gain seems to be attained. Hence, we do not consider smoothing.

Now, for each set of parameters $\boldsymbol{\theta} = [p_{00}, p_{11}, \mu_0, \sigma_0, \mu_1, \sigma_1, \phi, \gamma]$ we can obtain the log-likelihood over the observed data Ψ_T. The maximum likelihood estimate of $\boldsymbol{\theta}$ is therefore the value of $\hat{\boldsymbol{\theta}}$ that solve the following problem

$$\hat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \; l(\boldsymbol{\theta}).$$

Note that the above problem is not an unconstrained optimisation problem as the parameters of $\boldsymbol{\theta}$ must satisfy

$$0 < p_{00}, p_{11} < 1 \tag{3.6}$$

$$0 < \mu_0 < \mu_1 \tag{3.7}$$

$$0 < \sigma_0 < \sigma_1. \tag{3.8}$$

To solve this problem, we first obtain an initial estimate from a coarse grid search. Then we use the function `fmincon` in Matlab to find the final estimate that satisfies the above constraints.

3.3.5 Model Selection

This section sets out the mathematical analysis to determine the "best" model from the set of three models described above. According to Burnham and Anderson (2002), a good model selection technique will balance goodness of fit with simplicity. More complex models will be better able to adapt their shape to fit the data, but the additional parameters may not represent anything useful. Goodness of fit is generally determined using a likelihood ratio approach. The likelihood ration test is employed by some researchers (e.g. Hamilton and Susmel (1994), and Simon (1996)) to test the fit of different Markov model specifications. This is possible since their Markov models have consistently adopted the underlying normal distribution. However, in the case being considered here, the candidates for the model selection problem have different model complexity and distributions.[41] The likelihood ratio test is thus impractical to implement due to the difficulty in obtaining the distribution of the test statistic under the null hypothesis.

Nevertheless, the likelihood ratio test is not the only approach for model selection. For the problem of interest, Bayesian information criterion (BIC) method

[41] Three different Markov switching models are tested in this thesis: Hamilton Gaussian Markov AR(1), Kendig Poisson Markov AR(1), and our proposed model Gaussian Markov ARMA(1,1). The Gaussian (normal) distribution is used in the first and the third model, while the underlying distribution for the second model is Poisson.

can cater for the different model complexity and underlying distributions. The method selects the suitable model that gives the minimum score of

$$\mathrm{BIC} = -2\ln L + k\ln n \tag{3.9}$$

where $\ln L$ is the log likelihood estimated from the above section (Section 3.3.4.5), k is the number of parameters in the model, and n is the number of observations.

3.3.6 Wave identification

Following the current literature, we classify the high mean, high variance regime as the "wave" period, and the low mean, low variance regime as the "non-wave" (normal) period. The probability of being in a wave state, Pr $[S_t = 1|\Psi_t]$ where $\Psi_t = [y_0, \ldots, y_t]$, is determined from the above procedure. Merger wave periods are identified when Pr $[S_t = 1|\Psi_t] \geq 0.5$ (We adopt the traditional definition employed by previous studies so that the waves detected from our model can be compared with the previous ones).

3.3.7 Predicting states and duration

One of the advantages of the Markov regime switching model, as Hamilton (1989, 1994) have pointed out, is its ability to make inferences about which state is in force for each date t in the sample period. These inferences are in the form of conditional probabilities calculated from the history of the takeover data series and the maximum likelihood estimates of the model's parameters. That is, assuming that the model is correctly specified, the future probabilities of being in the wave state (state 1) or the normal state (state 0) can be predicted by using the transition probability matrix implied by equation (3.2) in the earlier section (Section 3.3.1).

To determine the probability of being a state in k years in the future (k=1,2,3,...,n), we multiply the current state by the probability transition matrix:

$$[\text{Initial state}][\text{P}]^k = [\text{Final state}].$$

Another important feature of the Markov regime switching model is its ability to calculate the expected duration of the wave and non-wave states from the maximum likelihood parameter estimates. This expected duration then can be compared with the historical average. The diagonal elements of the matrix of the transition probabilities (3.2) (in Section 3.3.1) contain important information on the expected duration of a state or regime. Given we are currently in regime j, the relevant question is how long, on average, will the regime j last? It can be mathematically derived that the expected duration of regime j is $(1\text{-}p_{jj})^{-1}$.

Conditional on being a normal state (state 0), the expected duration of a normal state is $(1\text{-}p_{00})^{-1}$. The expected duration of being in a wave state is likewise $(1\text{-}p_{11})^{-1}$.

3.4 Experimental results

3.4.1 Quarterly data

The M&A quarterly data is collected over the period from January 1972 to December 2004 for Australian market. Figure 3.1 presents the time series plot of the quarterly number of takeover bids. It is evident that Australian takeover activity fluctuates over time with significantly high levels of activity occurring once in each decade.

3.4.1.1 Testing for White Noise

The results of the Ljung-Box test are given in Table 3.2. Rejection of white noise is observed up to the third level of differencing, i.e. the raw series and their differences do not show white noise characteristics. The other test for white noise (BDSL test) is not required as strong rejection is encountered. Therefore,

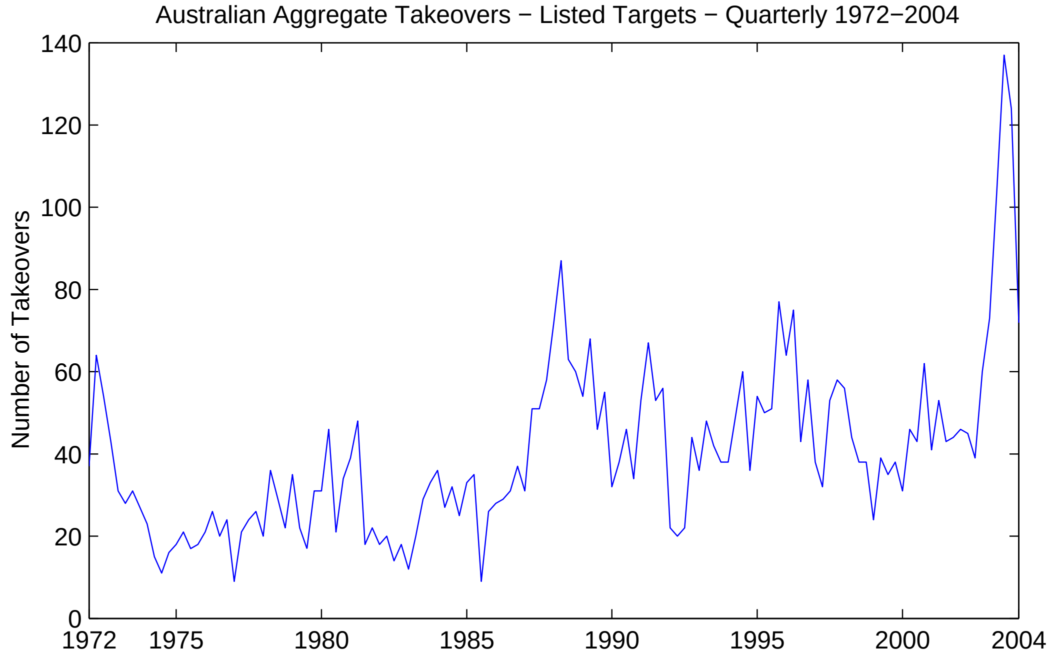

Figure 3.1: Australian M&A quarterly time-series data 1972-2004

Table 3.2: Ljung-Box test result of white noise characteristics - Quarterly data

This table presents the result of Ljung-Box test for white noise characteristics on quarterly takeover data (1972-2004). y represents the original data, with $y1$, $y2$, $y3$ refer to the level of differencing. Q(20) denotes the Ljung-Box statistic where 20 autocorrelation coefficients are computed in the statistic. Significance level of the test is 10%.

	y	$y1$	$y2$	$y3$
Q(20)	277.2021	62.2872	165.8405	254.6846
Critical Value (at 10%)	31.4104	31.4104	31.4104	31.4104
p-value	0	0	0	0
Ljung-Box decision	Reject	Reject	Reject	Reject

the next step is to carry out tests for the presence of a linear structure in the takeover data series.

3.4.1.2 Testing for Linear Model - Autoregressive

Before applying non-linear models to analyse wave behaviour of takeover activity, it is essential to test whether a simple linear model can adequately describe it. Therefore, the next step is to fit an AR model to the data and examine estimated errors of the fitted model. We estimate the AR parameters via the Yule-Walker method, then we compute the residuals. Tests are conducted for AR(1) up to AR(6). If the merger data are truly generated from a fitted linear model, the forecast errors should be white noise. If the merger data are generated from a non-linear model, the fitted linear model should leave extra structure in the residuals. Therefore, the residuals are then tested for white noise behaviour as above, i.e. by applying the Ljung-Box test. The BDSL test is further carried out as it is sensitive to deviation from independent and identically distributed (i.i.d.). This is to verify the conclusion made by the Ljung-Box test. The results are given in Table 3.3.

As can be seen from Table 3.3, at the level of significance of 10%, the Ljung-Box test only rejects AR(1) and AR(2) whilst AR(4) seems to be the best candidate. The BDSL test, on the other hand, is very conservative and rejects all models. The rejection is very strong for the high-orders. The rejection of AR models suggests that the time series of M&A activity may be best described by non-linear models. As can be seen from Figure 3.1, Australian takeover time series display a clear difference between periods of high-level and low-level activity. This could be traced to structural shifts in the mean of the takeover series. Therefore, the option of using a non-linear model, specifically the two-state Markov switching-regime model, in which there are two states with different means and variances, to characterise the wave behaviour of merger activity will be explored in the next section.

Table 3.3: Diagnostic tests for fit of the autoregressive (AR) residuals - Quarterly data

This table presents diagnostic tests for linear model on quarterly takeover data (1972-2004). AR models (up to level 6) are fitted into the quarterly takeover data, and the estimated errors of the fitted models are examined by using two tests (Ljung-Box and Brock et al. (1996)'s test). Q(20) is the Ljung-Box statistic for residual autocorrelation for 20 lags. BDSL(2) denotes the BDSL statistic (Brock et al. (1996)) with dimension 2. Significance level of the test is 10%.

	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)
Panel A: Ljung-Box test						
Q(20)	51.5847	29.7641	27.3600	17.2449	17.4697	19.1903
Critical Value (at 10%)	28.4120	28.4120	28.4120	28.4120	28.4120	28.4120
p-value	0.0001	0.0738	0.1254	0.6370	0.6223	0.5095
Ljung-Box decision	Reject	Reject	Fail to reject the null hypothesis			
Panel B: Brock et al. (1996)'s test						
BDSL(2)	2.3143	1.7585	1.7858	2.0926	2.1406	2.1942
p-value	0.0207	0.0787	0.0741	0.0364	0.0323	0.0282
BDSL decision	Reject	Reject	Reject	Reject	Reject	Reject

3.4.1.3 Results

Experiments are conducted for: Poisson Markov Switching model - AR(1); Gaussian Markov Switching model - AR(1); and State-Space Markov Switching model - ARMA(1,1) using quarterly takeover data. The results are displayed in Figure 3.2, Figure 3.3 and Figure 3.4 respectively with the actual and predicted takeovers in the top panel, the bottom panel represents the probability of being in a wave state. The maximum-likelihood parameter estimates are presented in Table 3.4.

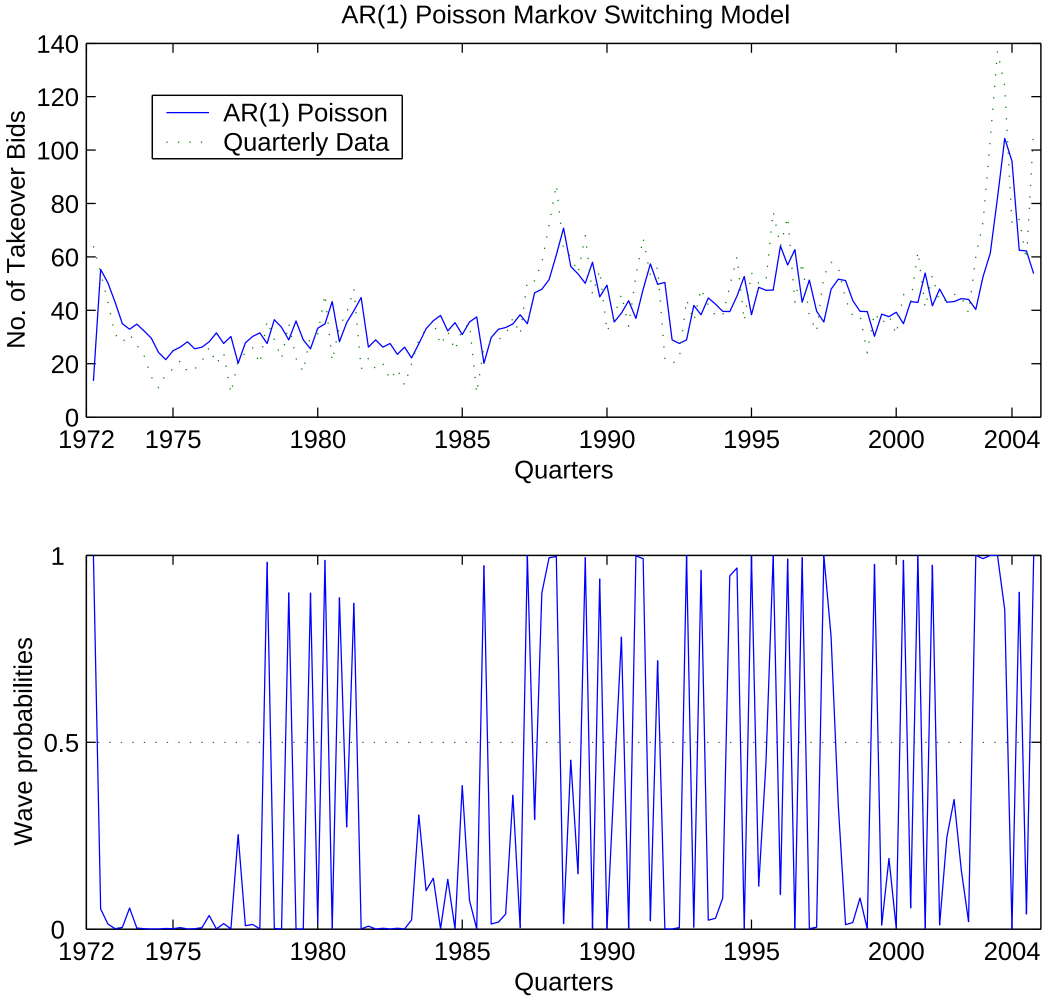

Figure 3.2: AR(1) Poisson Markov switching model on quarterly takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

Under the Bayesian information criterion (BIC) (see Section 3.3.5 of this chapter) for model selection, the State-Space ARMA(1,1) approach has the best fit with the lowest BIC score of 1,035.71. The Poisson model has low p_{00} (probability of remaining in normal state) which indicates the normal state being unstable. This is clearly depicted in Figure 3.2. In all models, the AR parameters are significant. The parameter γ is also significant which indicates that our proposed State-Space and Markov switching model for ARMA(1,1) process gives further improvement on the original Hamilton AR processes.

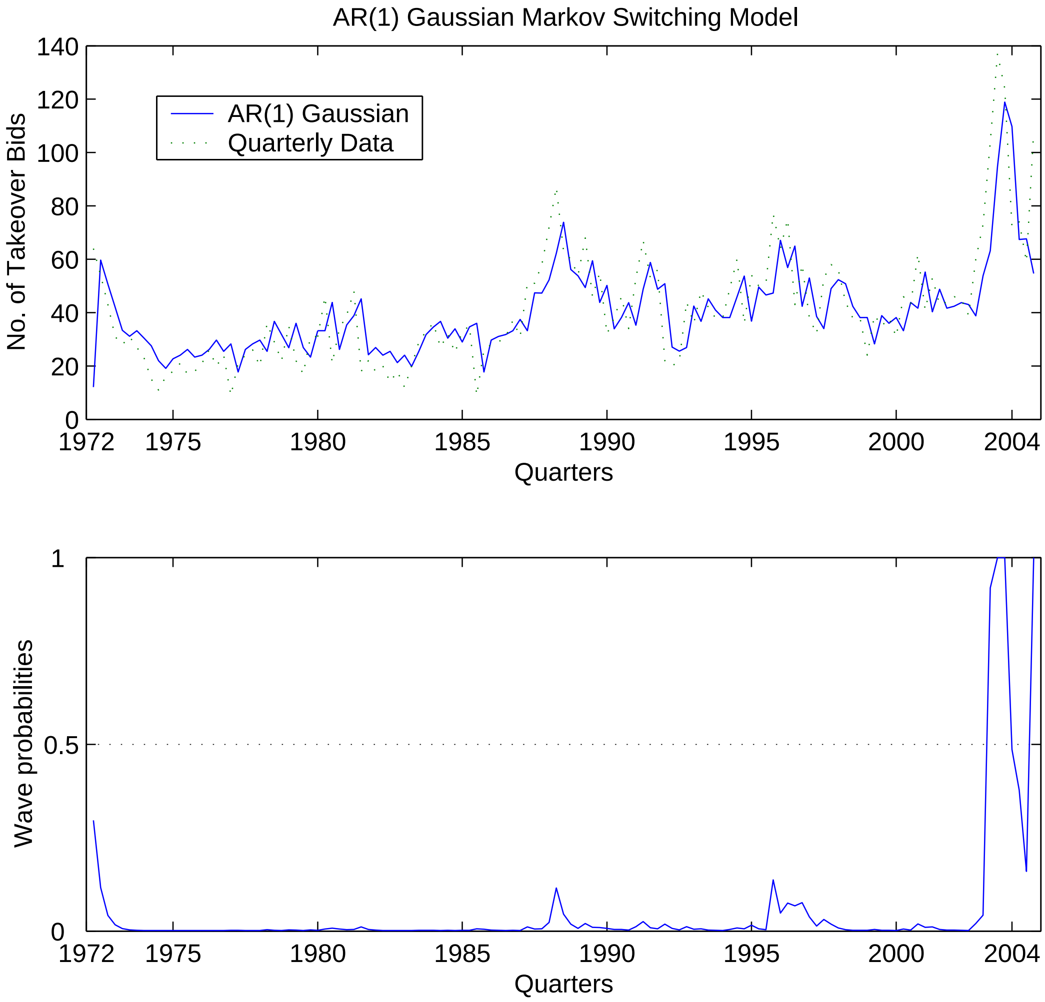

Figure 3.3: AR(1) Gaussian Markov switching model on quarterly takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

All models recognised that the last two waves (2003 & 2004) are significant. The waves in the 1980s and the 1990s were not strongly recognised by the State-Space approach and the AR(1) Gaussian Markov Switching model. Similarly, the wave in the early 1970s was only remotely noticeable in the AR(1) Gaussian approach. The main reason is perhaps these waves are not as strong as the last waves. Hence, if there are only two states: wave and non-wave, then the weaker waves can be statistically classified as the normal state.

All the above results are for quarterly takeover data. Since the quarterly data

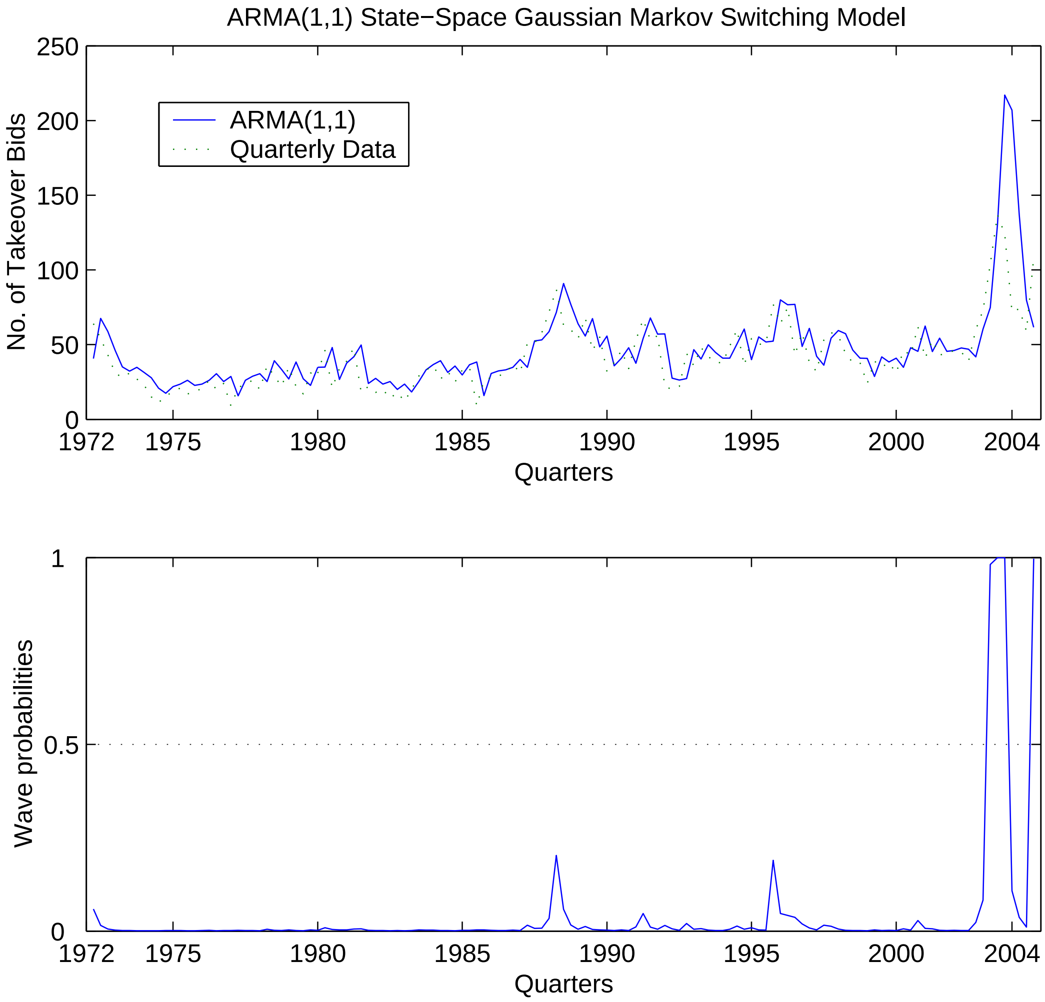

Figure 3.4: ARMA(1,1) State-Space Markov switching model on quarterly takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

is noisy, similar models will be fitted into the annual takeover data in order to provide better indication of the beginning and the end of the waves.

Table 3.4: Parameter estimates for different two-state Markov models - Quarterly data

This table presents parameter estimates for three different two-state Markov switching models on quarterly takeover data: AR(1) Poisson Markov model, AR(1) Gaussian Markov model, and ARMA(1,1) State-Space Markov Model. These models can be mathematically represented as:

AR(1) Poisson Markov model: $y_t \sim Pn(\lambda_t)$

$$\begin{cases} \text{If} \quad S_t = 1: & \lambda_t = \alpha_1 + \phi y_{t-1} \\ \text{If} \quad S_t = 0: & \lambda_t = \alpha_0 + \phi y_{t-1} \end{cases}$$

AR(1) Gaussian Markov model: $y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t$

ARMA(1,1) State-Space Markov Model: $y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t + \gamma e_{t-1}$

Across all models, S_t is to describe the Markov state at time t and can take a value of 0 (normal state) or 1 (wave state); μ_{S_t} refers to mean of the state; p_{00} and p_{11} are the probability of remaining in a normal state and a wave state, respectively. *BIC* is the score of Bayesian information criterion.

Parameters	**AR(1) Poisson Markov Model**	**AR(1) Gaussian Markov Model**	**ARMA(1,1) State-Space Markov Model**
α_0	7		
α_1	27		
μ_0		37.88	38.60
μ_1		82.43	85.25
σ_0		11.29	10.70
σ_1		27.26	23.82
ϕ	0.67	0.70	0.87
γ			-0.31
p_{00}	0.65	0.99	0.98
p_{11}	0.26	0.86	0.61
Log Likelihood	-543.19	-517.45	-508.09
BIC	1,096.15	1,049.55	1,035.71

3.4.2 Annual data

The Australian M&A annual data over the period from 1972 to 2004 is graphically shown in Figure 3.5. High levels of merger activity include the year 1972, the period 1987-1989, the year 1991, the period 1995-1996, and the period 2003-2004.

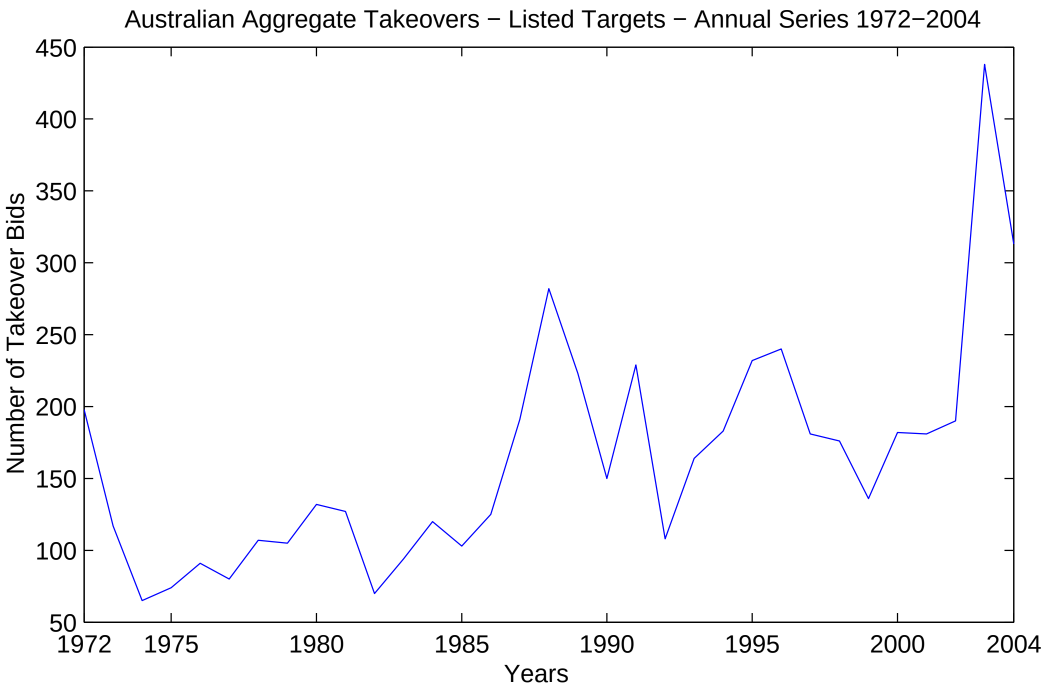

Figure 3.5: Australian M&A annual time-series data 1972-2004

Experiments are again conducted for: Poisson Markov Switching model - AR(1); Gaussian Markov Switching model - AR(1); and State-Space Markov Switching model - ARMA(1,1) using annual takeover data. Figure 3.6, Figure 3.7 and Figure 3.8 present the results of the experiments with the actual and predicted takeovers in the first panel, the second panel represents the probability of being in a wave state.

The maximum-likelihood parameter estimates are presented in Table 3.5. As can be seen from the table, the estimates of μ_1 and σ_1 are significantly larger than μ_0 and σ_0 in all models. In the other words, the periods of high level M&A activity

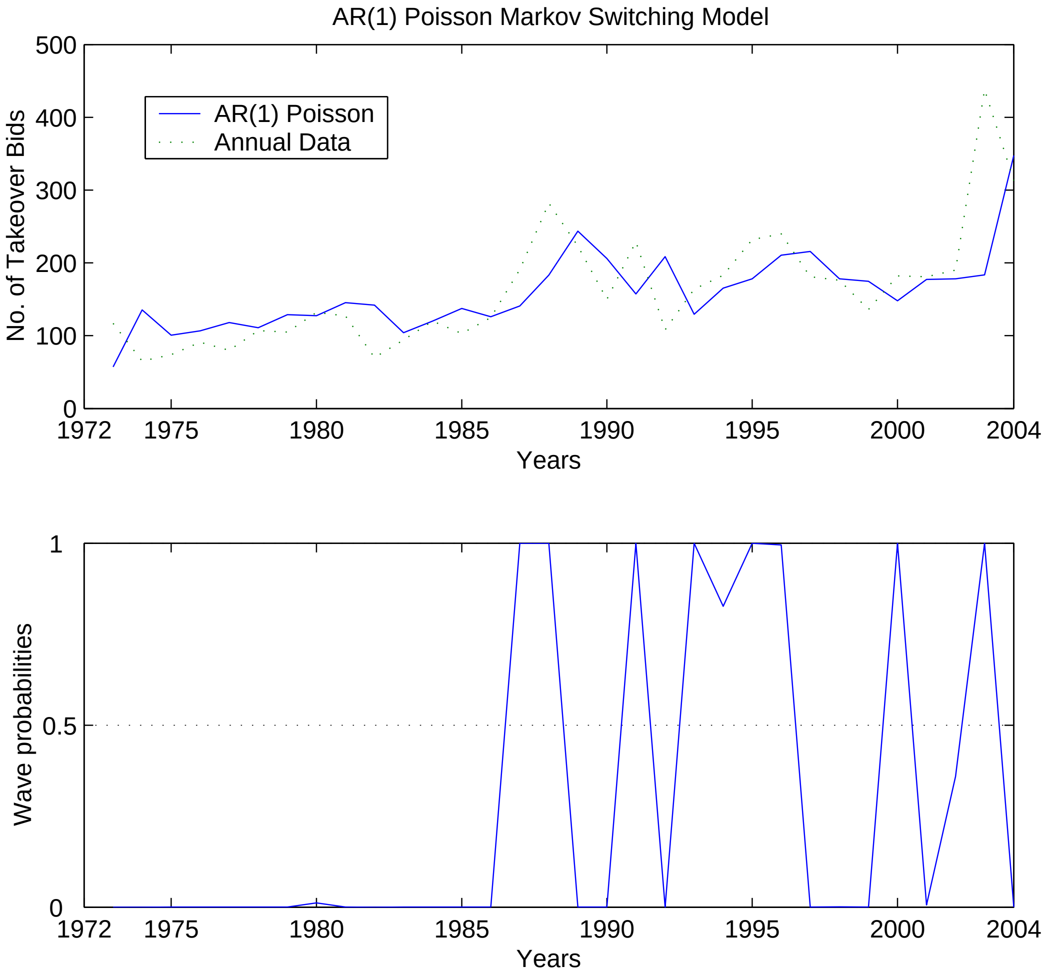

Figure 3.6: AR(1) Poisson Markov switching model on annual takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

are also the periods of increasing M&A volatility. This indicates that mergers and acquisitions seem to experience regime shifts characterised by large increases in the mean and variance of the series.

Under the Bayesian information criterion (BIC), the State-Space ARMA(1,1) approach has the best fit with the lowest BIC score of 346.67. In all models, the AR parameters are significant. The parameter γ is also significant which indicates that our proposed State-Space and Markov switching model has further improvement from the original Hamilton AR processes. All models recognised waves in

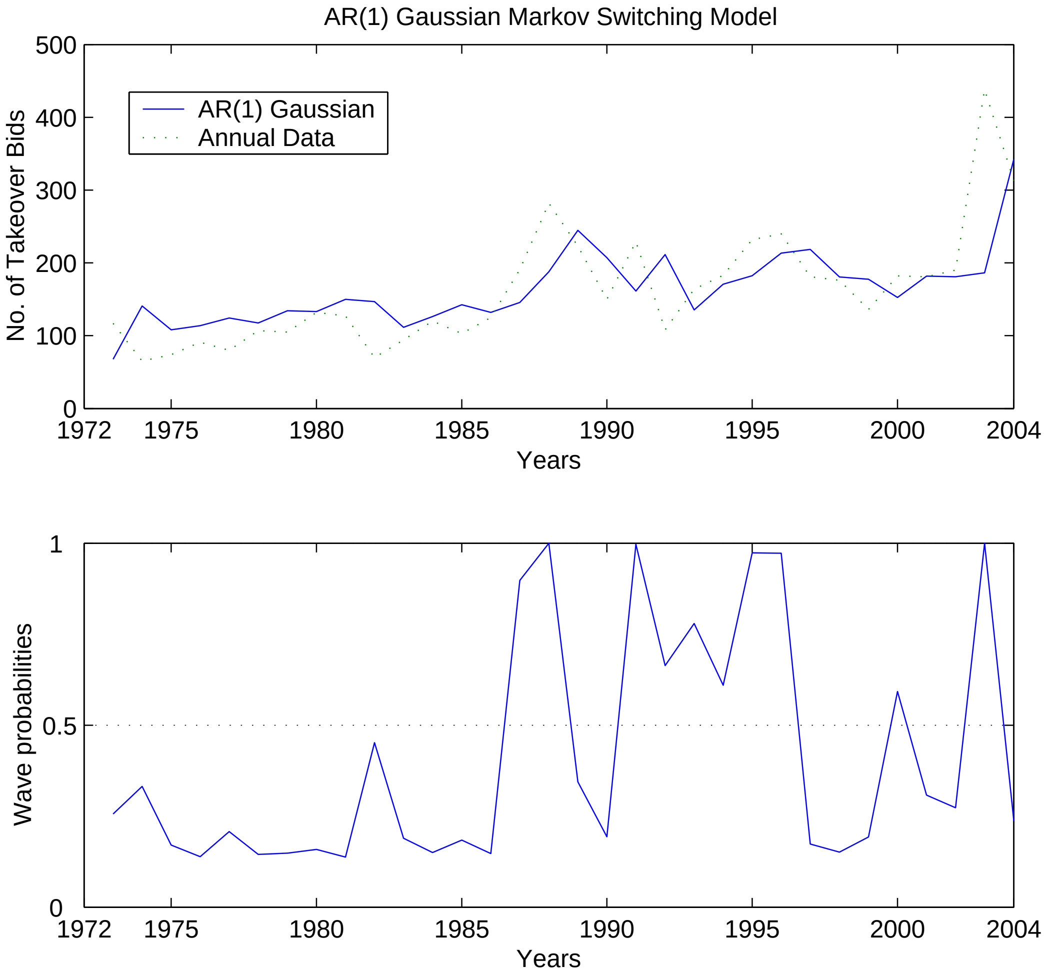

Figure 3.7: AR(1) Gaussian Markov switching model on annual takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

the late 1980s, the early and middle of 1990s, and the early 2000s. There is no wave reported in the 1970s. The reason for this is perhaps this wave is not as strong as other waves in the later decades. If there are only two states in the model: wave and non-wave, then the weaker wave in the 1970s is likely to be statistically classified as the normal state.

We place more weight on the results of the annual data set than that of the quarterly data since its results are more intuitive and seem to have the better fit in terms of wave recognition. Later discussions will be based on the results

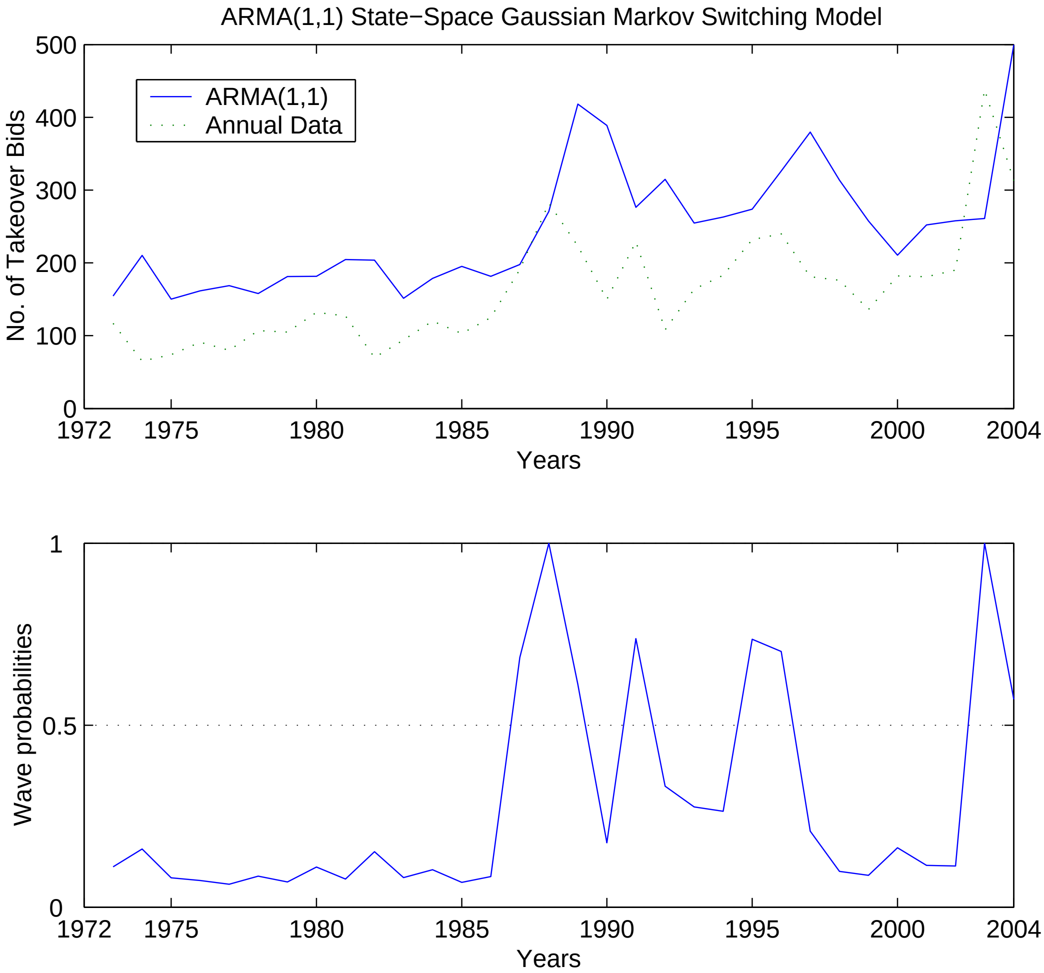

Figure 3.8: ARMA(1,1) State-Space Markov switching model on annual takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

obtained from modelling annual takeover data.

Since the State-Space ARMA(1,1) provides the best fit, diagnostic check on this model is carried out to examine whether the original specification was correct by analyzing the residuals of the model. We have assumed that the random error term e_t in the actual process are normally distributed and independent. Then if the model has been specified correctly, the residuals e_t should resemble a white noise process (i.e. serially uncorrelated and conditionally homoscedastic). Standardised diagnostic tools such as Ljung-Box test (Ljung and Box (1978)) and

Table 3.5: Parameter estimates for different two-state Markov models - Annual data

This table presents parameter estimates for three different two-state Markov switching models on quarterly takeover data: AR(1) Poisson Markov model, AR(1) Gaussian Markov model, and ARMA(1,1) State-Space Markov Model. These models can be mathematically represented as:

AR(1) Poisson Markov model: $y_t \sim Pn(\lambda_t)$

$$\begin{cases} \text{If} \quad S_t = 1: & \lambda_t = \alpha_1 + \phi y_{t-1} \\ \text{If} \quad S_t = 0: & \lambda_t = \alpha_0 + \phi y_{t-1} \end{cases}$$

AR(1) Gaussian Markov model: $y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t$

ARMA(1,1) State-Space Markov Model: $y_t - \mu_{S_t} = \phi(y_{t-1} - \mu_{S_{t-1}}) + e_t + \gamma e_{t-1}$

Across all models, S_t is to describe the Markov state at time t and can take a value of 0 (normal state) or 1 (wave state); μ_{S_t} refers to mean of the state; p_{00} and p_{11} are the probability of remaining in a normal state and a wave state, respectively. *BIC* is the score of Bayesian information criterion.

Parameters	**AR(1) Poisson Markov Model**	**AR(1) Gaussian Markov Model**	**ARMA(1,1) State-Space Markov Model**
α_0	29		
α_1	116		
μ_0		154.33	138.19
μ_1		217.76	201.09
σ_0		20.22	28.19
σ_1		72.75	73.36
ϕ	0.67	0.63	0.89
γ			-0.4
p_{00}	0.67	0.60	0.83
p_{11}	0.31	0.44	0.50
Log Likelihood	-280.73	-174.88	-166.34
BIC	568.45	360.25	346.67

Table 3.6: Diagnostic tests on residuals of State-Space ARMA(1,1) model - Annual data

This table presents diagnostic tests on residuals of State-Space ARMA(1,1) model when fitting into annual takeover data (1972-2004). Q(20) is the Ljung-Box statistic for residual autocorrelation for 20 lags. ARCH is Engle (1982)'s test for heteroscedasticity. Significance level of the tests is 10%.

	Ljung-Box Test	ARCH Test
Q(20)	24.6781	
ARCH Statistic		0.7669
Critical Value (at 10%)	25.9894	2.7055
p-value	0.1340	0.3812
Decision	Fail to reject null hypothesis	Fail to reject null hypothesis

ARCH test (Engle (1982)) can be used for this purpose. As can be seen from Table 3.6, the Ljung-Box test statistic indicates that the residuals are serially uncorrelated and our model also captures the changes in variance, as evidenced by the lack of heteroscedasticity identified by the ARCH test. Hence, it is confirmed that our State-Space ARMA(1,1) model is properly identified and estimated.

Another interesting point is to compare Australian takeover waves of our model with those found by previous studies from the early 1970s to 2003.[42] Table 3.7 provides a summary of takeover waves recognised under our proposed State-Space Markov switching model ARMA(1,1). Town (1992) documents a US takeover wave in late 1986, but no wave is found in the 1970s. Linn and Zhu (1997) record a high level of merger activity in the US for the period 1986-1993 and again no wave is found during the 1970s. Gartner and Halbheer (2006) confirm no waves in the 1970s and the 1980s for the US market, but evidence a merger peak since late 1995 to 2003. They also study the UK takeover market and find merger

[42] The previous studies of takeover waves only cover period up to 2003.

Table 3.7: Dates of being in a wave state (under ARMA(1,1) model - Annual data)

Wave Number	**Year Start (Inclusive)**	**Year End (Inclusive)**
1	1987	1989
2	1991	1991
3	1995	1996
4	2003	2004

waves in 1971-1973, and 1986-1989. Kendig (1997) recognises Australian waves in 1969-1973, 1979-1980, 1988-1990. As with these US studies, there is no merger wave detected during the 1970s in the Australian market under our study, though it is visible in UK market. The wave in the late 1980s is apparent in all Australian, UK and the US studies.[43] Our last two waves 1995-1996 and 2003-2004 correspond with waves identified the US market.

Under the ARMA(1,1) model, the dominant state is clearly state 0 (non-wave state). When the series is in state 0 (non-wave state), it is most likely to remain in that regime (83% probability) because the probability of the series jumping to state 1 (wave state) is only 17%. However, if the series is in state 1 (wave state), it can either remain in that regime or move to state 0 (non-wave state) since they have the equal probability (50%).

The final inference from the model is on the duration and expected timing of the waves. As pointed out in an earlier section, the expected duration of a normal state is (1-p_{00})$^{-1}$, and the expected duration of a wave state is (1-p_{11})$^{-1}$. Using figures in the State-Space Markov Switching ARMA(1,1) model, it is calculated that the expected duration of a wave state and a normal state equates to 2 years

[43] This 1980s wave is apparent in Town (1992) but not in Gartner and Halbheer (2006).

and 5.88 years, respectively. The durations confirm the information supplied by the transition probabilities. The expected duration of a non-wave state is considerably longer than the duration of a wave state. This suggests that on average the Australian takeover market maintains low-level activity for about six years, and then jumps into high-level activity for around two years.

3.5 Summary

In this chapter, we have characterised the univariate behaviour of Australian takeover time series by using recent data (from 1972 to 2004) and refined methods of inference. We analyse the data using both linear and non-linear models, and found that linear models do not adequately capture the structure of the takeover data, and that aggregate merger data are best operationalised by a non-linear, two-state Markov switching model. Takeover activity alternates between two states: high mean and high variance state (wave state), and low mean and low variance state (normal state).

Our proposed model is different from other Markov switching models in the literature since we combine the State-Space model with the Markov switching regime model to provide a more generalised time series model. In our approach, a definition of waves is defined by switches in the two unobserved states which are characterised by two distinct ARMA(1,1) processes governed by a transition probability law. We also study two other Markov switching models in the literature to confirm that our model provides a best fit based on the Bayesian information criterion.

Using annual data, our model detects four waves, one in the late 1980s (1987-1989), a second in the early 1990s (1991), a third in the middle 1990s (1995-1996) and a forth in the early 2000s (2003-2004). There is no merger wave identified in the 1970s under our model.[44] The expected duration of a wave period is two years

[44] Our findings are consistent with previous studies in the US market.

while that of non-wave period is six years. When the series is in a non-wave state, it is most likely to remain in that regime (83% probability) since the probability of the series jumping to a wave state is only 17%. However, if the series is in a wave state, it can either stay in that regime or shift into a non-wave state with equal probability (50%).

In the next two chapters, we will combine these inferences about merger waves with an analysis of macro-economic and financial factors to identify possible causes of merger waves (Chapter 4), and the consequences for firms participating in merger waves (Chapter 5).

Chapter 4

Takeover Waves and Influences of Financial and Economic Factors

4.1 Introduction

This chapter examines and presents the results from testing the second research question. Given the existence of takeover waves (in Chapter 3), the aim of this research question is to identify factors driving these waves.

Although there is a substantial literature that focuses on the reasons why mergers take place, the majority of empirical studies investigate takeover motives at the micro or individual firm level.[45] There are few publications on the factors that explain the fluctuations in aggregate merger activity.[46] This chapter focuses on the investigation of financial and economic factors generating clusters of aggregate takeover activity in periods identified as belonging to wave and non-wave states.

Takeover waves are widely recognised in the literature (see Chapter 3) but empirical research on takeover motives has almost exclusively used single-state models without accounting for their existence. In this chapter, we propose a model which

[45] Literature has mostly focused on the effects on stockholder wealth and what types of firms are most likely to engage in merger activity (e.g. Andrade et al. (2001), Rau and Vermaelen (1998), Schwert (2000)).

[46] The exceptions are Nelson (1959), Melicher et al. (1983), Polonchek and Sushka (1987), Golbe and White (1988) for the US market, and Easton (1994), Kendig (1997), Finn and Hodgson (2005) for Australian market. A summary of these studies is found in Section 2.3 of Chapter 2.

incorporates the two distinct states (wave and non-wave) of takeover activity identified in Chapter 3. We also test the liquidity hypothesis, advanced by Shleifer and Vishny (1992), in explaining takeover activity that states that takeover waves will occur in periods of high liquidity in the debt market, corresponding with a low interest rate environment.

We start our analysis by examining the number of takeover bids to targets listed on the Australian Stock Exchange (ASX) over the period 1980-2004. We then change our measure of takeover activity from the number of takeover bids to the proportion of bids relative to the number of ASX-listed companies to take into account the growth in the number of listed companies. In addition, the time series of aggregate takeover bids is decomposed by method of payment to further test for the liquidity hypothesis.

Our analysis is, furthermore, extended to the biggest takeover market in the world, the US market. The Australian and the US takeover environments have some similarities and differences[47] which make it interesting to see if the liquidity explanation observed in Australia also applies in the US.[48] One example of the differences is found in the method of payment of the takeover offers. In an examination of the stock market mis-valuation hypothesis in Australia, da Silva Rosa et al. (2006) document that a large majority of takeover bids in Australia since 1971 are cash-based bids. This is in contrast to the US market where 70% of all takeover deals in the 1990s included stocks as part of the consideration offered, with 58% entirely stock-financed (Andrade et al. (2001)).

The plan of this chapter is as follows. Section 4.2 outlines the methodology of

[47]As outlined in da Silva Rosa et al. (2006)'s study, similarities between the two countries include a shareholders' interest oriented corporate culture, a common law framework and an active market for corporate control characterised by temporal surges in M&A activity. They also point out methods for accounting for an acquisition (purchase or pooling), and M&A provisions of the *Corporation Act* and the *William Act* on their list of key differences in M&A regulatory regimes of the two countries.

[48]Shleifer and Vishny (1992) argue that asset liquidity helps account for the evidence of the 1980s takeover wave in the US. However, their theory has not been empirically tested. Our work will extend the period of examination to 2004 to cover for the recent merger waves.

our two-state regression model. Section 4.3 describes the data collection. Section 4.4 presents empirical findings for the Australian market and a quick summary of evidence from the US market (full details about the US analysis are in Appendix 4.A at the end of this chapter). Finally, conclusions are in Section 4.5.

4.2 Methodology

The objective of this chapter is to derive a model to explain which factors drive future merger movements, we thus restrict our attention to modelling the relationship between takeovers and independent variables in previous quarters. We estimate the following specification using a two-state Markov switching regression model:

$$y_t = \alpha_{S_t} + \mathbf{A_{n,S_t}} \mathbf{Z_{t-1}} + e_t \tag{4.1}$$

Depending on each test requirement, y_t can be the number of total takeover bids, or proportion of total takeover bids (or cash-funded bids, or shares-based bids) to the number of listed companies. $\mathbf{Z_{t-1}}$ is a vector of n macro-economic and financial market predictors in previous quarter; and $\mathbf{A_{n,S_t}}$ are estimated parameters of these predictors on each state (the wave and non-wave state).

S_t refers to the non-wave state ($S_{t=0}$) or the wave state ($S_{t=1}$) of takeover time series. In Chapter 3, we develop a model to describe the behaviour of takeover activity by combining a State-Space model with a Gaussian Markov switching regime model. A definition of waves is defined by switches in the two unobserved states (wave state and non-wave state) which are characterised by two distinct autoregressive moving-average processes of orders 1 and 1 (ARMA(1,1)) governed by a constant transition probability law.

- We denote P_1 and P_0 are the probabilities of being in the wave state and the non-wave state respectively when modelling the takeover time series ($0 \leq P_1, P_0 \leq 1$). P_1 (when modelling the number of annual takeover bids) is graphically presented in the second panel of Figure 3.8 in Chapter 3.[49]

- $P_0 = 1 - P_1$
- Merger wave periods are identified when $P_1 \geq 0.5$ (the criterion is discussed in Section 3.3.4.5 of Chapter 3)

Given information on the probability of being in a wave state (P_1) and a Gaussian assumption, the above equation (5.1) is reduced to the Least Squares estimates of the following model:

$$y_t = (\alpha_{S_{t=1}} P_1 + \alpha_{S_{t=0}} P_0) + (A_{n,S_{t=1}} P_1 + A_{n,S_{t=0}} P_0) Z_{t-1} + e_t \tag{4.2}$$

Each parameter is estimated for the wave state and the non-wave state separately. Standard errors and t-statistics are calculated for each parameter estimate. In our analysis below, variables which are statistically significant at the level of 10% or better are presented in bold form.

As the wave state is the period of takeover concentration, we expect that the effects of the macro-economic and financial market variables (if have) in the wave state would be stronger. That is, the coefficient estimates of each parameter would be different across the sates, with higher magnitudes for the wave state than for the non-wave state.

4.3 Data

4.3.1 Source of data collection

Takeover data for the Australian market are collected over the period from 1980 to 2004, giving a total of 100 quarterly observations. In our previous chapter (Chapter 3) which incorporates takeover time-series from 1972 to 2004, takeover

[49] In the result section of this chapter (Section 4.4), in addition to the examination of the number of takeover bids, further analysis is also performed for different time series of takeover activity (i.e. proportion of takeover bids (and cash/stock bids) to the number of listed companies). The State-space Markov switching model ARMA(1,1) (as specified in Chapter 3) is applied to each of these time series in order to have the new set P_1 and P_0.

waves are only detected in the 1980s, 1990s and 2000s. As data for some macro-economic variables are only available for periods in the late 1970s, this chapter only examines the influences of macro-economic and financial market variables on takeover waves during the period 1980-2004.

In total 4,570 takeover bids (denoted by TAK) are announced for ASX-listed targets during the period 1980-2004,[50] of which 3,199 bids (account for 70% of total bids) are purely cash-funded (denoted as TAK_c), and 461 bids (account for approximately 10% of total bids) are purely share-based (denoted as TAK_{sh}).

The number of companies listed on ASX is obtained from combining two sources: Finn and Hodgson (2005), for the period 1980-1996, and Share Price and Price Relative database (SPPR), for the period 1997-2004.[51] The number of total bids, cash-funded bids and shares-fund bids are also normalised by the number of ASX listed companies (denoted as $\%TAK$, $\%TAK_c$, and $\%TAK_{sh}$ respectively).

Following the literature, we incorporate in our analysis variables that represent macro-economic indicators, long-term interest rates and stock market returns. Macro-economic indicators included in our model are the growth rates of industrial production and of private capital expenditure. The level of long-term interest rate[52] (10-year Treasury Bond) is chosen as proxy for the availability of liquidity in the debt market since the cost of obtaining liquidity via a bond issue or a bank loan should increase if the level of interest rate rises.[53] In addition to aggregate

[50] In Chapter 3, the number of Australian takeover bids to exchange-listed targets over the period 1972 to 2004 is 5,407 (see Table 3.1 in Chapter 3). This number of takeover bids in the period 1980-2004 is reduced to 4,570.

[51] There is a discrepancy between Finn and Hodgson (2005)'s data (which came from various ASX fact files) and SPPR source over the period 1987-1991, SPPR reports much higher number. After some discussions and checking with ASX source, we decide to use Finn and Hodgson (2005)'s data for earlier period.

[52] Later analysis also incorporates the level of short-term interest rate (proxy as the rate of 90-day bank bill) to confirm the robustness of our results.

[53] Using Australian interest rate clearly can only explain domestic debt market liquidity. However, as foreign bidders do not account for a big proportion in our sample (approximately 22%), it is reasonable to assume that their borrowing capacity from foreign markets does not have a big impact on our results.

stock market return,[54] we add one new variable to capture industry return in the Australian market.[55] We choose to include only the most active industry (in terms of incorporating the highest number of takeover bids) to proxy for the industry return as M&As tend to cluster around particular industries (Mitchell and Mulherin (1996), Harford (2005)). We classify all targets in our sample according to Standards & Poors Global Industry Classification Standard (GICS)[56] and find that the most active industry is Metals & Mining (1,069 bids out of 4,570 total bids in our sample). Including both the aggregate and industry share market performance allow us to measure the additional impact for the industry over and above the aggregate market.

Macro-economic variables are obtained from the Australian Bureau of Statistics (ABS). Data on private new capital expenditure (non-dwelling construction and equipment) are taken from ABS Catalogue 5206.0, Table 5. Total industrial production comes from ABS Catalogue 5206.0, Table 37. We calculate quarterly growth rates on total industrial production and private new capital expenditure, which are denoted by TIP and CAE respectively. The annual yield on 10-year Australian treasury bonds, proxy for long-term interest rate (denoted by INT), is obtained directly from the Reserve Bank of Australia (RBA) website (Table F1 and F2), and converted to the effective quarterly rate.[57]

The return on ASX All Ordinaries Accumulation Index[58] in excess of the 90-

[54] Calculated as the aggregate stock market return in excess of 90-day bank bill rate.

[55] For Australia, this variable is calculated as the [most active] industry stock market return in excess of 90-day bank bill rate.

[56] As mentioned earlier, our sample of Australian takeover bids cover for the period of 1980-2004. For the Australian market, the industry classification system was previously based on the ASX scheme which was replaced by Standard & Poors GICS in September 2002. Therefore, we need to reclassify all target companies according to the new GICS standards. For companies have the deals announced in the 1990s and later, we obtain their financial reports via Aspect Financial database and classify them by mapping their business operation to the GICS guide (obtained from the ASX website). For companies whose deals announced in the 1980s, we refer to the business operation section in *Jobson's Year Book of Public Companies* which is available in hard copies in the Department of Accounting and Finance, the University of Western Australia.

[57] The formula for changing from an annual percentage rate to a quarterly one is:

$$\text{Quarterly Rate} = (1 + \text{Annual Rate})^{1/4} - 1$$

[58] Historical data on the index is supplied by Standard & Poors.

Table 4.1: Source of data - Australian market

Variables	**Measures**	**Source**	**Symbol**
Number of takeover bids	A total number of takeover bids announced to target companies listed on the ASX from January 1980 to December 2004.	Combination from 3 sources: • Centre of Independent Studies: Bishop et al. (1987)'s study • Australian Financial Review newspaper • Thompson Financial's Securities Data Company (SDC) Platinum database	TAK
Aggregate stock market performance	The return on ASX All Ordinaries Accumulation Index in excess of the 90-day bank bill rate	From 2 sources • Standard & Poors • The Reserve Bank of Australia (RBA)	AOI
Metals & Mining industry stock performance	The excess return on GICS Metals & Mining industry, measured as the residuals from the regression of this industry excess return (the GICS Metals & Mining industry return in excess of 90-day bank bill rate) on the excess return of All Ordinaries Accumulation Index	From 2 sources: • Standard & Poors • Share Price & Price Relative (SPPR) database	IND_M
Long-term interest rate	The yield on 10-year Treasury Bond	RBA table "Interest Rates and Yields: Money Market and Commonwealth Government Securities"	INT
Macroeconomic variable	Growth rate of industrial production	ABS Catalogue 5206.0, Table 37 Indexes of Industrial Production.	TIP
Macroeconomic variable	Growth rate of private new capital expenditure (non-dwelling construction plus machinery and equipment)	ABS Catalogue 5206.0, Table 5 Expenditure on Gross Domestic Product (GDP), Australia: Implicit price deflator	CAE

day bank bill rate is a proxy for the aggregate market return (denoted by AOI). The abnormal excess return on the GICS Metals & Mining industry (denoted by IND_M) is derived as the residuals from the regression of this industry excess return[59] on the excess return of All Ordinaries Accumulation Index. This en-

[59]The excess industry return is measured by the GICS Metals & Mining industry return (data is obtained in Share Price and Price Relative (SPPR) database) in excess of the 90-day bank bill rate

sures that the Metals & Mining excess return is orthogonal to the All Ordinaries Accumulation excess return and measures the additional impact for the industry other and above the aggregate market.

4.3.2 Data summary

A summary of data collection and data sources are listed in Table 4.1. Table 4.2 provides basic summary statistics for the variables used in subsequent analysis[60] with descriptive statistics in Panel A, and correlation of variables (Pearson's correlation coefficient) in Panel B. As evidenced in Panel A of Table 4.2, over our sample period, the quarterly average number of takeover bids in the Australian takeover market is around 46 bids, accounting for 3.74% of all ASX-listed companies. Companies use cash as the dominant source of finance for takeovers. On average, the excess return on ASX All Ordinaries Accumulation Index is 1.28% per quarter. In Australia, the excess return on Metal & Mining industry (orthogonal index) has a negative mean of -0.35% per quarter.[61] Australian long-term interest rate is, on average, 2.38% per quarter. The average growth rate of industrial production and private capital expenditure in Australia over our 25-year sample period is approximately 0.53% and 0.69% per quarter, respectively. Panel B of Table 4.2 shows that interest rate variable has the strongest relationship to takeover activity (compared with other macro-economic variables) with its Pearson's correlation coefficient being -0.45.

While Table 4.2 (Panel A) shows all of the variables have substantial variation in each of the time periods (the standard deviations are large), it also indicates that some of the variables, especially for long-term interest rate (INT), are highly

[60] Table 4.2 reports descriptive statistics for the variables as a whole. The variables are not decomposed into the wave versus non-wave periods (which are identified in Chapter 3) since we are using the probability of being in the wave and non-wave state in the two-state regression model, not the actual wave and non-wave environment.

[61] By definition, this series should have expected mean of zero (since they are regression residuals). We have run the regression (to obtain the orthogonal index) over the period from 1979 to 2004 so that we can have lagged values for our examination period of 1980-2004. The full series from 1979 to 2004 has average excess return of zero. This negative mean reports here is from the truncated series from 1980 to 2004.

Table 4.2: Summary statistics - Australian market

The table presents summary statistics of the variables used in the econometric analysis in the Australian market. Descriptive statistics are in Panel A, Panel B shows correlation of variables (Pearson's correlation coefficient). All variables are measured from the quarterly series 1980-2004. TAK is total number of takeover bids of ASX-listed target companies; TAK_c and TAK_{sh} are the number of cash-based bids and share-based bids. Those three numbers are normalised by the number of listed companies on ASX, denoted by $\%TAK$, $\%TAK_c$ and TAK_{sh}. AOI is the excess return on ASX All Ordinaries Accumulation Index, a proxy for the aggregate stock market return. IND_M is the excess return on Metals & Mining industry, measured as the residuals from the regression of the excess industry return (GICS Metals & Mining Industry) on the excess market return (ASX All Ordinaries Accumulation Index). INT is the yield on 10-year Treasury Bond, a proxy for long-term interest rate. TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure. All data (except TAK, TAK_c and TAK_{sh}) are in quarterly percentage points.

Panel A: Descriptive statistics

Variables	Quarters	Mean	Median	Standard Deviation	Max	Min	Autocorrelation Lag 1	Lag 2	Lag 3	Lag 4
TAK	100	45.70	43	21.99	137	9	0.93	0.89	0.86	0.84
TAK_c	100	31.99	27.5	16.34	100	7	0.92	0.88	0.82	0.79
TAK_{sh}	100	4.61	4	3.19	15	0	0.85	0.83	0.84	0.81
$\%TAK$	100	3.74	3.49	1.47	9.71	0.91	0.93	0.9	0.86	0.85
$\%TAK_c$	100	2.65	2.55	1.16	7.09	0.71	0.92	0.88	0.83	0.8
$\%TAK_{sh}$	100	0.37	0.33	0.24	1.04	0	0.83	0.82	0.83	0.8
AOI	100	1.28	1.39	9.21	25.21	-43.41	-0.05	0.09	0.03	-0.11
IND_M	100	-0.35	-0.14	7.23	26.75	-21.06	-0.15	-0.11	0.13	-0.12
INT	100	2.38	2.38	0.81	3.87	1.23	0.99	0.98	0.97	0.96
TIP	100	0.53	0.48	1.6	4.35	-5.38	0.14	0.11	0.09	0
CAE	100	0.69	0.57	1.29	3.57	-1.62	0.7	0.63	0.57	0.45

Panel B: Correlation of variables

	TAK	AOI	IND_M	INT	TIP	CAE
TAK	—	0.0768	0.1541	-0.4463	-0.0052	-0.3778
AOI	0.0768	—	-0.0518	-0.0849	-0.0150	0.0577
IND_M	0.1541	-0.0518	—	-0.1432	0.0545	-0.0305
INT	-0.4463	-0.0849	-0.1432	—	0.0239	0.5430
TIP	-0.0052	-0.0150	0.0545	0.0239	—	-0.0864
CAE	-0.3778	0.0577	-0.0305	0.5430	-0.0864	—

persistent (in the presence of high autocorrelation coefficients). Because the high autocorrelation coefficients suggest unit roots may be present in the data, and non-stationary variables can introduce econometric complexities, we conduct the augmented Dickey-Fuller (ADF) test for unit roots. The test is run for all orders of time polynomial.[62] We omit the tables of results for the sake of brevity,[63] but

[62] We examine all possible combinations: no deterministic part, for constant term, for constant plus time-trend, and for higher order polynomial.

[63] The full results of the test are available on request.

the upshot from the test is that all data series, except for long-term interest rate (INT) generate test statistics that clearly reject the null at a 99% confidence level. In the other words, all data series are stationary, except for long-term interest rate which is non-stationary and integrated of order one (I(1)).

Unit roots present difficulties because in many econometric settings, including the classical regression framework, the standard asymptotic results may not be valid when the data are non-stationary. In the extreme, regressions involving non-stationary variables can yield spurious results, as Granger and Newbold (1974) demonstrated. Following Granger and Newbold (1974), we interpret a spurious regression as one in which the usual significance tests on the coefficients are not valid. The problem may come from either the numerator or the denominator of the t-ratio: the coefficient or the standard error. Ferson et al. (2003) find the problem is with the biased standard errors.[64] They further demonstrate that if the regression residuals have no persistence, even if a highly autocorrelated regressor is used, the spurious regression phenomenon is not a concern since the standard errors are well-behaved. We will prove that the residuals from our two-state model show no level of persistence in the later part of diagnostic check for the model specification (Section 4.4.1).

4.4 Empirical evidence

4.4.1 Number of takeover bids

We start our analysis by examining the influence of variables in the past quarter (Z_{t-1}) to the number of takeover bids. The second panel of Figure 3.8 in Chapter 3 shows the probability of being in a wave state (P_1) when modelling annual time series of the number of Australian takeover bids with the State-space Markov switching model ARMA(1,1). We have used quarterly series in our regression,

[64] While Granger and Newbold (1974) do not study the slopes and standard errors to separate the effects, Ferson et al. (2003) replicate their study, and design the simulations to examine the source of errors. They confirm that the slopes are well-behaved, but the standard errors are biased.

therefore, it is assumed that the probability of four quarters in a given year remains the same.[65]

The results of various two-state regressions that establish the predictive ability of takeover activity are presented in Table 4.3. In Column (1) to Column (4), we run a two-state regression of takeover activity on the lagged value of each individual variable, namely share market performance (AOI and IND_M), long-term interest rate (INT), growth rate of industrial production (TIP) and of private capital expenditure (CAE). The Metal & Mining (M&M) industry share market performance and private capital expenditure variables are only statistically significant in the wave state while interest rate and industrial production variables are significant in both the wave and non-wave states. Examining each independent variable separately reveals that interest rate and stock market variables are compliments, not substitutes. This is shown in Table 4.3 (Column (1) and Column (2)) that their coefficient estimates are different in terms of sign and statistical significance, and the adjusted R-squared figures are not the same. Similar results are also observed for interest rate and industrial production.

To explore which variable remains statistically significant in multivariate models, we augment the specification in Column (1) by adding macro-economic predictors such as TIP and CAE (Column (5)), and long-term interest rate INT (Column (6)). Interestingly, the M&M industry share market performance variable is no longer significant when the long-term interest is included.[66] Interest rate is the

[65] In Chapter 3, we have modelled both annual and quarterly time series of number of Australian bids. Waves are not recognised under the quarterly time series data.

[66] Our results suggest that movements in the stock market do not appear to play a significant role in explaining the concentration of takeover activity, but interest rate does. This is somewhat different to Martynova and Renneboog (2008)'s conclusion that takeover waves "coincide with rapid credit expansion, which in turn results from burgeoning external capital markets accompanied by stock market booms". The difference is probably due to the fact that our method of identifying merger waves is more systematic (refer to the previous chapter, Chapter 3), while Martynova and Renneboog (2008) recognise takeover waves by graphically viewing the peaks in the level of takeover activity. In addition, when assessing the drivers of takeover activity, we adopt the two-state regression controlling for takeover waves probability, whereas Martynova and Renneboog (2008) just name events coinciding with the beginning and the end of merger waves.

Table 4.3: Predictive regressions of Australian takeover bids (number) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $TAK_t = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-1} + e_t$. The table presents the results from forecasting takeover activity in quarter t using all macro-economic and financial market variables lagged by one quarter. TAK is total number of takeover bids of ASX-listed target companies. P_1 and P_0 are probability of being in a wave state and in a non-wave state when modeling TAK annual time series by ARMA(1,1) State-space Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (AOI is excess returns of All Ordinaries Accumulation Index; IND_M is excess returns on Metals & Mining industry (orthogonal index); INT is 10-year Government Bond rate; TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure). The sample period is from 1980 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Number of Australian takeover bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept, Non-wave	**28.28^a**	**41.6^a**	**26.8^a**	**30.56^a**	**29.71^a**	**41.93^a**	**39.72^a**	**40.82^a**
	(2.27)	**(5.39)**	**(2.33)**	**(2.72)**	**(2.65)**	**(5.39)**	**(5.77)**	**(5.81)**
Intercept, Wave	**79.08^a**	**133.72^a**	**82.65^a**	**81.12^a**	**83.03^a**	**131.71^a**	**138.04^a**	**131.65^a**
	(3.61)	**(9.52)**	**(3.88)**	**(3.71)**	**(3.76)**	**(9.62)**	**(10.73)**	**(11.77)**
AOI_{t-1}, Non-wave	-0.21				-0.22	-0.17		-0.22
	(0.26)				(0.24)	(0.21)		(0.21)
AOI_{t-1}, Wave	0.53				0.57	0.22		0.21
	(0.35)				(0.37)	(0.28)		(0.33)
$IND_{M_{t-1}}$, Non-wave	0.17				0.03	0.03		0.07
	(0.3)				(0.28)	(0.24)		(0.24)
$IND_{M_{t-1}}$, Wave	**0.83^c**				**1.53^a**	0.58		0.59
	(0.49)				**(0.48)**	(0.39)		(0.46)
INT_{t-1}, Non-wave		**-5.41^a**				**-5.42^b**	**-4.63^c**	**-5.21^b**
		(2.08)				**(2.08)**	**(2.58)**	**(2.60)**
INT_{t-1}, Wave		**-23.53^a**				**-22.89^a**	**-25.97^a**	**-22.79^a**
		(3.93)				**(3.95)**	**(4.88)**	**(5.38)**
TIP_{t-1}, Non-wave			**2.15^c**		2.00		1.12	1.51
			(1.27)		(1.23)		(1.02)	(1.06)
TIP_{t-1}, Wave			**-4.45^b**		-4.33		0.58	-0.38
			(2.46)		(2.94)		(2.15)	(2.66)
CAE_{t-1}, Non-wave				-2.13	-1.50		-0.65	-0.04
				(1.64)	(1.59)		(1.68)	(1.71)
CAE_{t-1}, Wave				**-7.16^b**	**-10.22^b**		2.71	0.07
				(3.81)	**(4.03)**		(3.70)	(4.29)
Adjusted R^2	0.53	0.70	0.54	0.56	0.59	0.70	0.70	0.69
No. of observations	100	100	100	100	100	100	100	100
Regression residuals								
- Serial correlation	Yes	No	Yes	Yes	Yes	No	No	No
- Heteroscedasticity	Yes	No	Yes	Yes	Yes	No	No	No

only variable which is negatively significant in both the wave and non-wave states, and with a larger magnitude in the wave state. Our findings are robust even after we control for all macro-economic variables (Column (8))[67] and replace the share

[67] Finn and Hodgson (2005) also find that share market activity is independent of takeover

market performance variables by the macro-variables (Column (7)). Similar results still hold if we replicate Table 4.3 by replacing the long-term interest rate (i.e. 10-year Treasury bond) by short-term interest rate (proxy by 90-day bank bill rate).[68]

Further analysis confirms the significance of the interest rate variable when explaining variations in the level of takeover activity. If the interest rate is an important variable in our regression model, we would expect no regression residuals left or higher adjusted R-squared when it is included in the model. The residuals from regressions in Table 4.3 Column (2), (6), (7) and (8) (which include interest rate variable) follow a purely white-noise process,[69] while the residuals in Column (1), (3), (4) and (5) (which do not include interest rate variable) are serially correlated and conditionally heteroscedastic. Furthermore, when the interest rate variable is incorporated in the regression model, the adjusted R-squared is nearly 70% whereas this figure reduces to below 60% when it is left out.

In summary, we have found that takeover activity is higher following a low interest rate environment in the previous quarter. An interesting empirical question is whether interest rates lead the takeover market by more than one quarter. We conduct a similar analysis using different lags for the independent variables: two quarter previous, three quarter previous, and four quarter previous. For brevity, we do not present the results[70] but a crucial upshot from the tests is that the level of interest rate is statistically significant for all regressions up to 4 lags. The significance is observed in both the wave state and the non-wave sate with a larger magnitude in the wave state.

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activity. They note the negative relationship between the past level of interest rate to the current takeover activity, but this relationship is not statistically significant at conventional levels.

[68]For brevity, we do not present results when we change the measure of liquidity in the debt market from long-term interest rates to short-term ones. The results will be available upon request.

[69]Ljung-Box test and ARCH test are carried to check for serial correlation and conditional homoscedasticity.

[70]The results for various combinations of variables at each lag (from two to four) like Table 4.3 are available upon request.

The negative sign on the interest rate coefficient can be explained intuitively. Interest rate reflects inflationary expectations.[71] A higher inflation rate associated with higher interest rate is a negative signal to businesses. Higher inflation is generally associated with an increase in business uncertainty, a loss of confidence and a decrease in profit margins, all of which would dampen expectations and merger activity. In addition, it is widely accepted in the literature that asset liquidity plays an important role in the corporate restructuring process as it allows assets to be priced close to their fundamental values. For example, Shleifer and Vishny (1992) claim that a high volume of takeover transactions will occur in a liquid market with high cash flows and less financial constraints. They also believe that "the ability to borrow increases liquidity" which implies a relationship between the interest rates and capital liquidity since borrowing capacity is more available in the low interest environment. Their argument has been used by Harford (2005) to show that a macro-level expansion in liquidity can explain the clustering of merger waves in the aggregate.[72] We assert that the level of interest rates can be used as a proxy for the availability of liquidity in the debt market since the cost of obtaining liquidity via a bond issue or a bank loan increases if the level of interest rate increases. A low interest rate environment provides a low cost of debt and reduces financial constraints in the market, and subsequently increases the volume of takeover transactions.

Our results are also consistent with recent developments in the Australian takeover market which has seen an unprecedented increase in M&A activity funded by private equity.[73] According to the Reserve Bank of Australia (RBA), the staggering

[71] The argument of positive relationship between inflation and interest rate has been generally supported by economists. For example, Rory Robertson, an economist at Macquarie Bank has recently mentioned that "There's a pattern here. Over the past 18 months the Reserve Bank has had four disturbing inflationary reports and two comforting inflationary reports. Each of the disturbing inflationary reports was followed by a rate hike, so the pattern has been if there was a disturbing inflationary report at the end of October then you would be right to expect a move in November." Cited in "RBA hints at further rates rise" by S. Long, ABC News, 13th August 2007, http://www.abc.net.au/news/stories/2007/08/13/2004030.htm?section=business.

[72] Please refer to the literature review in Chapter 2 (Section 2.3) for a comprehensive argument.

[73] For examples, foreign private equity firms aimed massive takeover bids at some big Australian companies like Qantas and Coles in 2007.

Table 4.4: Predictive regressions of Australian takeover bids (number) on explanatory variables lagged by one quarter - Single-state model

Regressions take the form: $TAK_t = \alpha + A_n.Z_{t-i} + e_t$. The table presents the results from forecasting takeover activity in quarter t using all macro-economic and financial market variables lagged by one quarter. TAK is total number of takeover bids of ASX-listed target companies. Z_{t-1} contains the independent variables in previous quarter (AOI is excess returns of All Ordinaries Accumulation Index; IND_M is excess returns on Metals & Mining industry (orthogonal index); INT is 10-year Government Bond rate; TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure). The sample period is from 1980 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Number of Australian takeover bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	**45.73^a**	**74.93^a**	**44.89^a**	**50.26^a**	**50.06^a**	**74.45^a**	**69.78^a**	**68.85^a**
	(2.2)	**(6.23)**	**(2.32)**	**(2.38)**	**(2.41)**	**(6.3)**	**(6.63)**	**(6.75)**
AOI_{t-1}	0.04				0.09	-0.05		0.01
	(0.24)				(0.22)	(0.22)		(0.21)
$IND_{M_{t-1}}$	0.41				0.39	0.23		0.26
	(0.3)				(0.27)	(0.27)		(0.26)
INT_{t-1}		**-12.21^a**				**-11.96^a**	**-9.23^a**	**-8.77^a**
		(2.47)				**(2.49)**	**(2.91)**	**(2.96)**
TIP_{t-1}			1.43		0.31		0.7	0.64
			(1.38)		(1.27)		(1.22)	(1.22)
CAE_{t-1}				**-6.04^a**	**-6.61^a**		**-3.39^c**	**-3.53^c**
				(1.59)	**(1.57)**		**(1.82)**	**(1.83)**
Adjusted R^2	0.01	0.2	0.01	0.13	0.14	0.19	0.21	0.21
No. of observations	100	100	100	100	100	100	100	100
Regression residuals								
- Serial correlation	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
- Heteroscedasticity	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

rate of growth in this investment sector is driven by "unusual circumstances, including a very low cost of debt".[74] The RBA also believes that the current drop in liquidity caused by the prospect of higher interest rates is likely to result in far fewer takeover deals going ahead.[75]

For comparative purposes, we also perform a regression analysis without taking

[74] A Senate Committee was inquiry into private equity investment in Australia, in the wake of the failed $11 billion private equity bid for Qantas. Citation is from Mr. Battellino's (RBA deputy governor) speech when he gave evidence to the Senate inquiry on 25th July 2007 in Sydney.

[75] E. Alberici, "Private Equity Value Plummeting, Inquiry Hears", 25th July 2007, ABC news, http://www.abc.net.au/news/stories/2007/07/25/1988452.

into account takeover wave probabilities. Table 4.4 shows the results of single-state regressions. Compared with Table 4.3 (which reports the results of two-state regressions), it is clear that estimates of the single-state model tend to lie between the corresponding estimates for the two-state model. Since the coefficient estimates of our Markov switching model are very different across two states, assuming a constant coefficient model (i.e. single-state model) is thus insufficient. In addition, on average 69% of variation in takeover activity can be explained by the multiple two-state regression equation (refer to Table 4.3), while this proportion is only approximately 21% in the case of the single-state regression equation (refer to Table 4.4). The higher adjusted R-squared suggests that our two-state regression model explains better the variations in takeover activity.

An examination of the regression residuals of both the single-state and two-state models also draw a further important inference. Ljung-Box test and ARCH test are performed to check for serial correlation and conditional heteroscedasticity in the residuals. These tests reveal that there is no extra structure left in the residuals in the case of the two-state model (see Table 4.3), while the single-state model's residuals show some persistence (see Table 4.4). Therefore, it can be concluded that our two-state regression model fits the data better than the single-state regression model.

4.4.2 Proportion of takeover bids to number of listed companies

The number of companies listed on the ASX has changed over time. In order to account for the growth in the number of listed companies, we change the dependent variable from the number of takeover bids to the proportion of bids relative to the number of companies listed on the ASX. We apply the ARMA(1,1) State-Space Markov switching model (as detailed in Section 3.3.3 of Chapter 3) to this time series. The wave state probabilities of this time series is presented in Figure 4.1 (second panel), and predictive regressions are shown in Table 4.5.

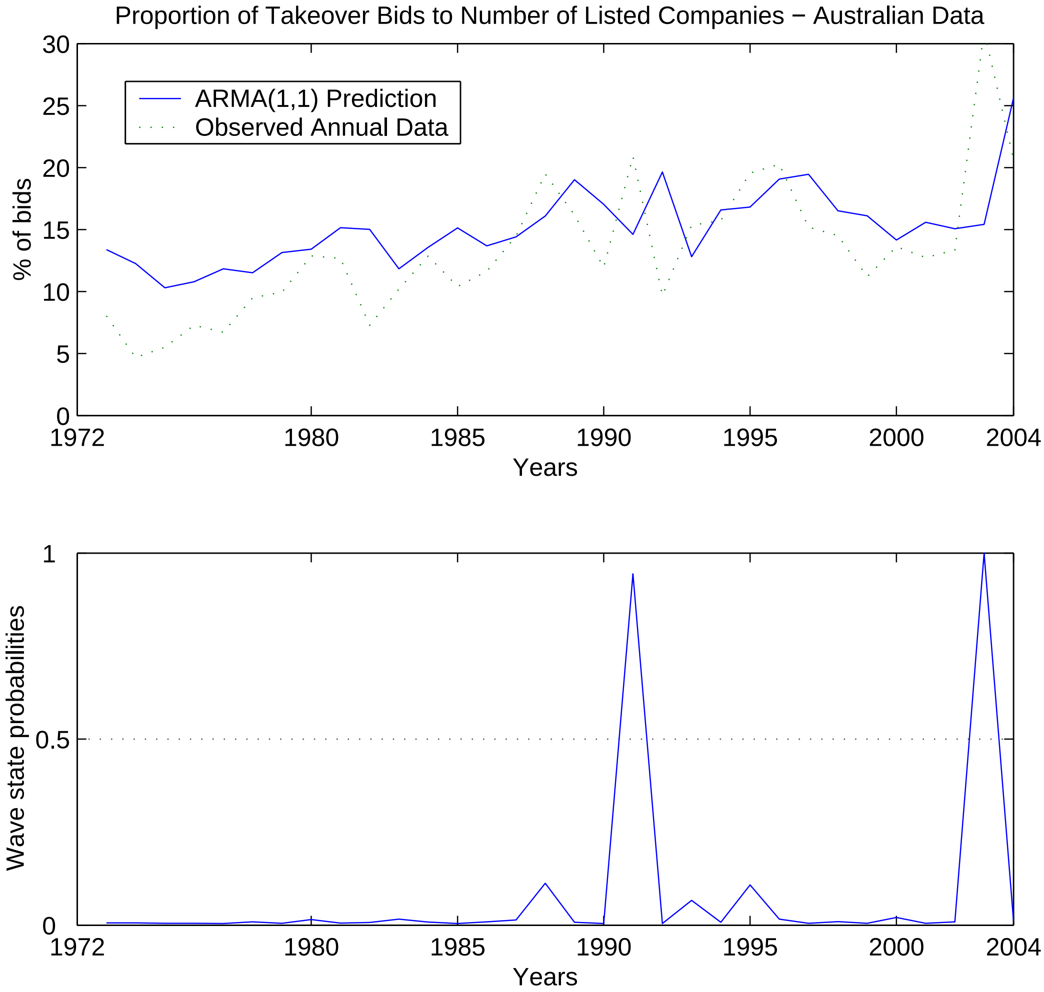

Figure 4.1: ARMA(1,1) State-Space Markov switching model on Australian annual takeover data - Proportion of takeover bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

As can be seen from Table 4.5, similar results are still obtained: the interest rate coefficient is negative in both the wave and non-wave states, and statistically significant in the wave state. In addition, industrial production and private capital expenditure variables are also significant (at the 5% level) in the non-wave state. However, when we increase the confidence level to 99% (i.e. being equivalent to significance level of 1%), interest rate becomes the only significant variable remained. This further confirms the significance of interest rate amongst other

Table 4.5: Predictive regressions Australian takeover bids (as a proportion to number of listed companies) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $\%TAK_t = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-i} + e_t$. The table presents the results from forecasting takeover activity in quarter t using all macro-economic and financial market variables lagged by one quarter. %TAK is the percentage of Australian takeover bids to the number of companies listed on the ASX. P_1 and P_0 are probability of being in a wave state and in non-wave state when modelling $\%TAK$ annual time series by ARMA(1,1) State-space Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (AOI is excess returns of All Ordinaries Accumulation Index; IND_M is excess returns on Metals & Mining industry (orthogonal index); INT is 10-year Australian Government Bond rate; TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure). The sample period is from 1980 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Proportion of Australian Takeover Bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept, Non-wave	**3.42^a**	**4.44^a**	**3.33^a**	**3.65^a**	**3.58^a**	**4.41^a**	**4.06^a**	**4.01^a**
	(0.13)	**(0.37)**	**(0.13)**	**(0.14)**	**(0.14)**	**(0.37)**	**(0.37)**	**(0.38)**
Intercept, Wave	**6.6^a**	**9.71^a**	**6.52^a**	**6.72^a**	**6.23^a**	**9.89^a**	**9.79^a**	**10.39^a**
	(0.45)	**(1.16)**	**(0.44)**	**(0.4)**	**(0.45)**	**(1.23)**	**(1.14)**	**(1.58)**
AOI_{t-1}, Non-wave	-0.0002				0.006	-0.004		-0.003
	(0.01)				(0.01)	(0.01)		(0.01)
AOI_{t-1}, Wave	0.09				-0.02	0.09		0.07
	(0.08)				(0.09)	(0.07)		(0.1)
$IND_{M_{t-1}}$, Non-wave	0.01				0.01	0.01		0.01
	(0.02)				(0.02)	(0.02)		(0.02)
$IND_{M_{t-1}}$, Wave	-0.02				0.14	-0.07		-0.08
	(0.08)				(0.11)	(0.08)		(0.13)
INT_{t-1}, Non-wave		**-0.41^a**				**-0.4^a**	-0.23	-0.21
		(0.15)				**(0.15)**	(0.16)	(0.17)
INT_{t-1}, Wave		**-1.51^a**				**-1.63^a**	**-1.71^a**	**-1.98^a**
		(0.56)				**(0.58)**	**(0.56)**	**(0.72)**
TIP_{t-1}, Non-wave			**0.18^b**		**0.16^b**		**0.17^b**	**0.17^b**
			(0.08)		**(0.07)**		**(0.07)**	**(0.07)**
TIP_{t-1}, Wave			-0.88		**-1.18^c**		**-1.14^b**	-0.87
			(0.58)		**(0.7)**		**(0.54)**	(0.68)
CAE_{t-1}, Non-wave				**-0.29^a**	**-0.27^a**		**-0.2^b**	**-0.21^b**
				(0.09)	**(0.09)**		**(0.1)**	**(0.1)**
CAE_{t-1}, Wave				-0.94	-1.76		-0.01	0.69
				(0.83)	(1.08)		(0.82)	(1.37)
Adjusted R^2	0.35	0.44	0.39	0.42	0.44	0.43	0.49	0.47
No, of observations	100	100	100	100	100	100	100	100

variables in explaining takeover activity.

4.4.3 Proportion of cash/shares-based bids to number of listed companies

Although the tests in the previous sections provide a useful first cut at the question of what drives merger activity, the takeover data employed are highly aggregated, and do not identify the method of payment in a merger. Faccio and Masulis (2005) argue that cash offers generally require debt financing since most bidders have limited cash and liquid assets. In making a M&A decision, a bidder is consequently faced with a choice between using debt, equity financing, or some combination of both. In general, Faccio and Masulis (2005) contend that debt would dominate stock as the funding source for a cash payment due to lower debt flotation costs. Given this view, if the liquidity theory can explain merger activity, firms should have easier access to the credit market to finance acquisitions at times when liquidity is high (i.e. interest rate is low). Accordingly, we would expect to see in the time series a higher negative correlation between cash-funded mergers and the level of interest rate.

For our sample period from 1980-2004, there were 3,199 cash-based takeover bids accounting for 70% of all bids, while there were only 461 stock-based bids equivalent to 10% of all bids. We first normalise each time series by the number of companies listed on the ASX, and then apply ARMA(1,1) State-space Markov Switching approach. Figure 4.2 and 4.3 (bottom panel) represent the wave state probabilities for the annual data of cash-funded bids and stock-funded bids, respectively.

The results for cash deal regressions, reported in Table 4.6, indicate clearly that a low level of interest rate significantly leads to a higher proportion of cash bids in the wave state. In contrast to the case of total bids, the interest rate coefficient for the cash bids in the non-wave state is positive but very small in magnitude (only 0.04), and statistically insignificant. At the 5% significance level, both industrial production (in the non-wave state) and interest rate (in the wave state) are significant but higher t-statistic is observed for interest rate variable.

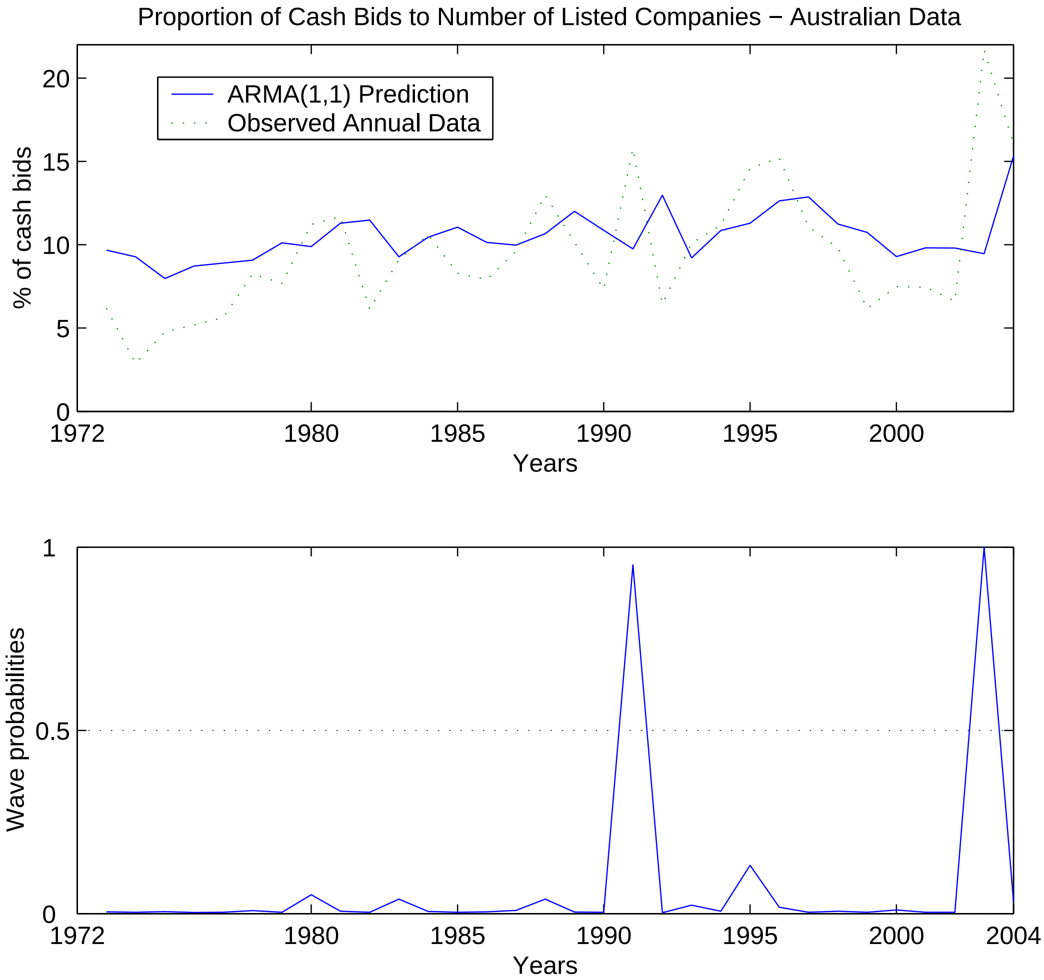

Figure 4.2: ARMA(1,1) State-Space Markov switching model on Australian annual takeover data - Proportion of cash bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

Compared with cash deals, the results for stock-funded bids presented in Table 4.7 are consistent with the liquidity theory's expectation. Interest rate has no impact in the non-wave state, and reports a significant negative relationship (in much smaller magnitude) in the wave state. The interest rate coefficient for stock deals (Table 4.7) is nearly three times smaller than that of cash deals (Table 4.6). In terms of the statistical significance level, the interest rate coefficient for cash bids is significant at the 5% level while it stays at the 10% level for stock bids. The influence of share market performance to the proportion of stock deals is

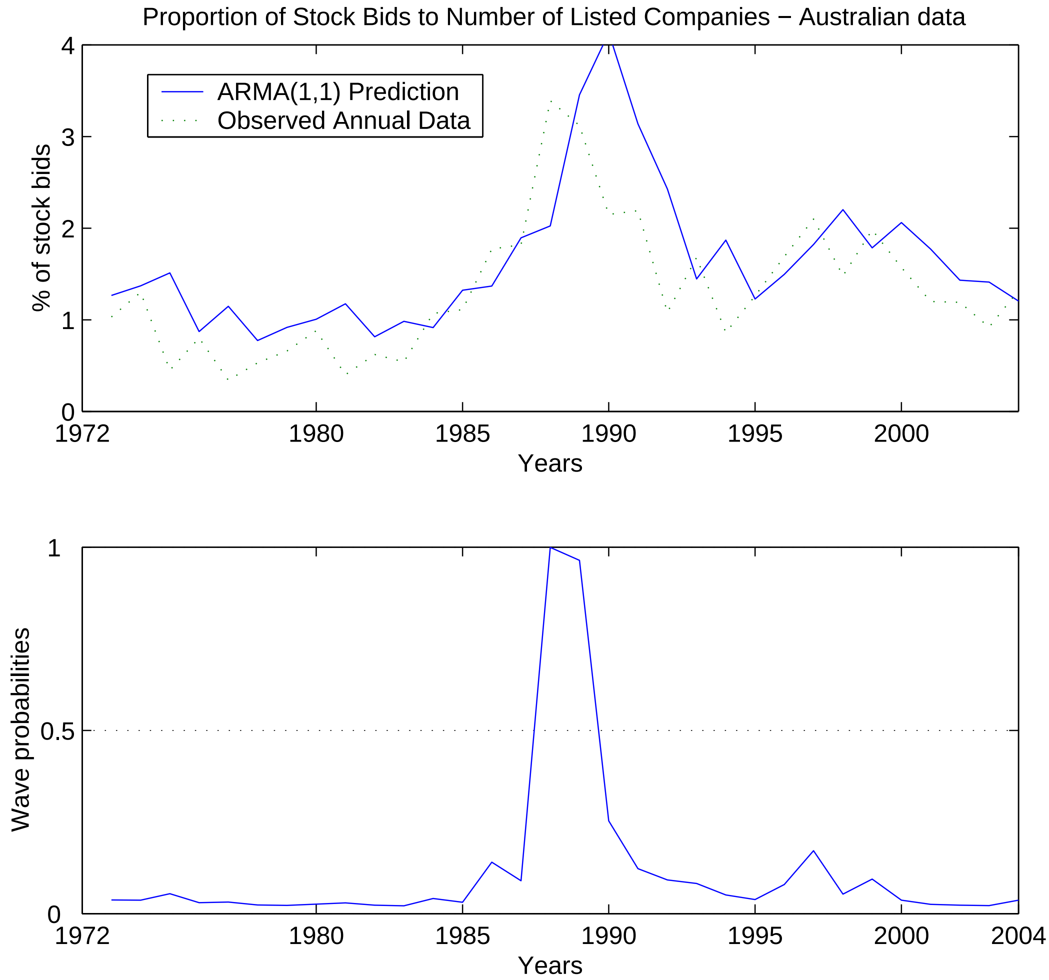

Figure 4.3: ARMA(1,1) State-Space Markov switching model on Australian annual takeover data - Proportion of stock bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

nearly zero.

The method of payment decomposition, as illustrated in Table 4.6 and 4.7, cast takeover activity behaviour in a light that strongly supports the liquidity argument. It indicates the co-movement between takeover bids and the level of interest rate is largely due to the behaviour of the cash deal component of takeover activity. This result is driven by the fact that cash bids in Australia account for approximately 70% of the total bids whereas this proportion is only 10% in case of stock bids. In addition, the proportion of cash bids (to total bids) in the wave

Table 4.6: Predictive regressions of Australian cash bids (as a proportion to number of listed companies) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $\%TAK_{c_t} = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-i} + e_t$. The table presents the results from forecasting cash-based bids in quarter t using all macro-economic and financial market variables lagged by one quarter. $\%TAK_c$ is the percentage of Australian cash-based bids to the number of companies listed on the ASX. P_1 and P_0 are probability of being in a wave state and in a non-wave state when modelling $\%TAK_c$ annual time series by ARMA(1,1) State-space Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (AOI is excess returns of All Ordinaries Accumulation Index; IND_M is excess returns on Metals & Mining industry (orthogonal index); INT is 10-year Australian Government Bond rate; TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure). The sample period is from 1980 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Proportion of Australian Cash-funded Takeover Bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept, Non-wave	**2.41^a**	**2.65^a**	**2.35^a**	**2.53^a**	**2.46^a**	**2.63^a**	**2.4^a**	**2.36^a**
	(0.1)	**(0.32)**	**(0.11)**	**(0.11)**	**(0.12)**	**(0.32)**	**(0.33)**	**(0.33)**
Intercept, Wave	**4.69^a**	**6.67^a**	**4.62^a**	**4.84^a**	**4.41^a**	**6.77^a**	**6.66^a**	**7.05^a**
	(0.36)	**(0.99)**	**(0.36)**	**(0.34)**	**(0.38)**	**(1.05)**	**(0.99)**	**(1.37)**
AOI_{t-1}, Non-wave	0.0003				0.004	-0.0005		0.002
	(0.01)				(0.01)	(0.01)		(0.01)
AOI_{t-1}, Wave	**0.12^c**				0.03	**0.13^b**		0.1
	(0.06)				(0.08)	**(0.06)**		(0.09)
$IND_{M_{t-1}}$, Non-wave	0.005				0.0002	0.004		0.004
	(0.01)				(0.01)	(0.01)		(0.01)
$IND_{M_{t-1}}$, Wave	-0.04				0.08	-0.08		-0.07
	(0.06)				(0.09)	(0.07)		(0.12)
INT_{t-1}, Non-wave		-0.09				-0.08	0.03	0.04
		(0.12)				(0.12)	(0.14)	(0.14)
INT_{t-1}, Wave		**-0.92^c**				**-1.04^b**	**-1.07^b**	**-1.26^b**
		(0.48)				**(0.49)**	**(0.48)**	**(0.63)**
TIP_{t-1}, Non-wave			**0.13^b**		**0.12^b**		**0.12^b**	**0.12^b**
			(0.06)		**(0.06)**		**(0.06)**	**(0.06)**
TIP_{t-1}, Wave			**-0.95^b**		**-0.98^c**		**-1.14^b**	-0.79
			(0.48)		**(0.58)**		**(0.48)**	(0.58)
CAE_{t-1}, Non-wave				**-0.13^c**	-0.12		-0.13	-0.14
				(0.08)	(0.07)		(0.09)	(0.09)
CAE_{t-1}, Wave				-0.83	-1.15		-0.2	0.42
				(0.7)	(0.91)		(0.7)	(1.19)
Adjusted R^2	0.31	0.33	0.35	0.34	0.35	0.33	0.38	0.36
No. of observations	100	100	100	100	100	100	100	100

period is higher than in the non-wave period (70.23% versus 68.91%) while the opposite situation is observed in the case of stock bids' proportion (9.68% in the wave state and 10.45% in the non-wave state).

Table 4.7: Predictive regressions of Australian shares-based bids (as a proportion to number of listed companies) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $\%TAK_{sh_t} = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-i} + e_t$. The table presents the results from forecasting shares-based bids in quarter t using all macro-economic and financial market variables lagged by one quarter. $\%TAK_{sh}$ is the percentage of Australian shares-based bids to the number of companies listed on the ASX. P_1 and P_0 are probability of being in a wave state and in non-wave state when modelling $\%TAK_{sh}$ annual time series by ARMA(1,1) State-space Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (AOI is excess returns of All Ordinaries Accumulation Index; IND_M is excess returns on Metals & Mining industry (orthogonal index); INT is 10-year Australian Government Bond rate; TIP and CAE represent the growth rate of total industrial production and of private new capital expenditure). The sample period is from 1980 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Proportion of Australian Shares-based Takeover Bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept, Non-wave	**0.29**^{a}	**0.32** ^{a}	**0.28**^{a}	**0.32**^{a}	**0.3**^{a}	**0.32**^{a}	**0.29**^{a}	**0.26**^{a}
	(0.02)	**(0.08)**	**(0.02)**	**(0.02)**	**(0.03)**	**(0.08)**	**(0.08)**	**(0.08)**
Intercept, Wave	**0.89**^{a}	**2.44**^{a}	**0.95**^{a}	**0.83**^{a}	**0.91**^{a}	**2.37**^{a}	**2.4**^{a}	**2.51**^{a}
	(0.07)	**(0.85)**	**(0.09)**	**(0.09)**	**(0.16)**	**(0.85)**	**(0.85)**	**(0.87)**
AOI_{t-1}, Non-wave	0.002				0.003	0.002		0.003
	(0.003)				(0.003)	(0.002)		(0.003)
AOI_{t-1}, Wave	0.006				-0.002	0.004		-0.005
	(0.006)				(0.01)	(0.006)		(0.01)
$IND_{M_{t-1}}$, Non-wave	0.002				0.002	0.002		0.002
	(0.003)				(0.003)	(0.003)		(0.003)
$IND_{M_{t-1}}$, Wave	0.003				-0.002	0.002		-0.001
	(0.009)				(0.02)	(0.008)		(0.02)
INT_{t-1}, Non-wave		-0.02				-0.02	-0.005	0.003
		(0.03)				(0.03)	(0.03)	(0.03)
INT_{t-1}, Wave		**-0.52**^{c}				**-0.49**^{c}	**-0.48**^{b}	**-0.51**^{b}
		(0.28)				**(0.28)**	**(0.27)**	**(0.28)**
TIP_{t-1}, Non-wave			0.02		0.02		0.02	0.02
			(0.01)		(0.01)		(0.01)	(0.01)
TIP_{t-1}, Wave			-0.06		-0.07		-0.06	-0.09
			(0.04)		(0.07)		(0.04)	(0.07)
CAE_{t-1}, Non-wave				**-0.04**^{b}	**-0.04**^{b}		-0.02	-0.03
				(0.02)	**(0.02)**		(0.02)	(0.02)
CAE_{t-1}, Wave				0.05	0.06		0.03	0.05
				(0.09)	(0.18)		(0.08)	(0.18)
Adjusted R^2	0.39	0.43	0.41	0.42	0.42	0.42	0.44	0.43
No. of observations	100	100	100	100	100	100	100	100

4.4.4 Summary on evidence of the Australian market

In short, when the probability of takeover waves is controlled for, it is found that the concentration of aggregate takeover activity in Australia is driven by interest rates rather than the speculation in the share market. The level of interest rate is generally the only variable significantly associated with variations in the rate of takeover activity. Historical aggregate takeover activity appears to move with the state of the debt market: a low level of the interest rate (i.e. high liquidity in the debt market) leads to a concentration of takeover bids, especially in the wave state. Our findings are consistent with Shleifer and Vishny (1992)'s liquidity argument that accounts for the clustering of takeover activity.

We also extend our analysis to the biggest takeover market in the world, the US. The results are presented in Appendix 4.A at the end of this chapter. It is found that the US takeover market shows similar results with the coefficient for the interest rate variable being negative and statistically significant in the wave state.

4.5 Summary

This chapter investigates the extent to which macro-economic and financial factors influence the concentration of takeover activity in Australia and the US market. Our innovation is to incorporate the probability of takeover waves into the regression analysis.

In Australia, we collect the number of takeover bids for ASX-listed targets over the period of 25 years from 1980 to 2004. We have found that share market performance does not explain the concentration of activity in the takeover market. Instead, interest rates significantly predict subsequent changes in aggregate takeover activity. Our analysis also suggests that our two-state model is significantly better than the single-state regression in which the existence of waves is ignored. Our findings indicate that the liquidity hypothesis advanced by Shleifer and Vishny (1992) can explain takeover clusters. Historical aggregate takeover activity is intimately tied to the level of the debt market: low levels of interest rates (i.e. high liquidity in the debt market) ultimately lead to concentration of takeover bids.

Our analysis is also broadened to the biggest takeover market in the world, the US market. However, we use data for only 23 years (from 1982 to 2004), and we are unable to obtain the same set of controls (e.g. returns to the most active industry (in terms of receiving highest number of takeover bids), and the growth rate of private capital expenditure). With these caveats in mind, we have found that the US takeover market shows remarkably similar patterns.

Appendix 4.A: Analysis of the US market

In this Appendix, we conduct a similar analysis to the US takeover market. As mentioned in the introduction part (Section 4.1), the underlying reason for this is to see if the liquidity argument can be extended beyond the Australian context to the largest takeover market in the world since both countries have some similarities and differences in terms of corporate culture, M&A regulatory regimes, and takeover activity varying episodically (da Silva Rosa et al. (2006)).

1. Methodology

In the previous chapter (Chapter 3), we propose a methodology of detecting takeover waves which combines a State-Space and two-state Markov switching regime ARMA(1,1) to describe the discrete shifts in regime between the wave state (high frequency of M&As) and the non-wave state (low frequency of M&As). For Australian data, the use of general ARMA(1,1) seems to capture the most interesting merger wave characteristics using annual data (see Section 3.4.2 of Chapter 3).

We therefore test to see whether a similar methodology applies to the US data. Figure 4.4 shows the results of applying the ARMA(1,1) State-Space Markov switching model to the number of US takeover bids (annual time series). As can be seen from Figure 4.4, there are three waves recognised in the US market under the ARMA(1,1) State-Space Markov switching model. They are in the year 1988, 1994 and 1996 with the wave probability of 0.6, 0.68 and 0.65 respectively.

The US literature (e.g. Town (1992), Linn and Zhu (1997)) has used the AR(1) Markov switching model[76] to characterise wave behaviour. We hence employ this approach and compare it to our ARMA(1,1) State-Space Markov switching

[76]The AR(1) Gaussian Markov switching model is a special case of the ARMA(1,1) State-Space Markov switching model. Details about these two models are found in Section 3.3 of Chapter 3.

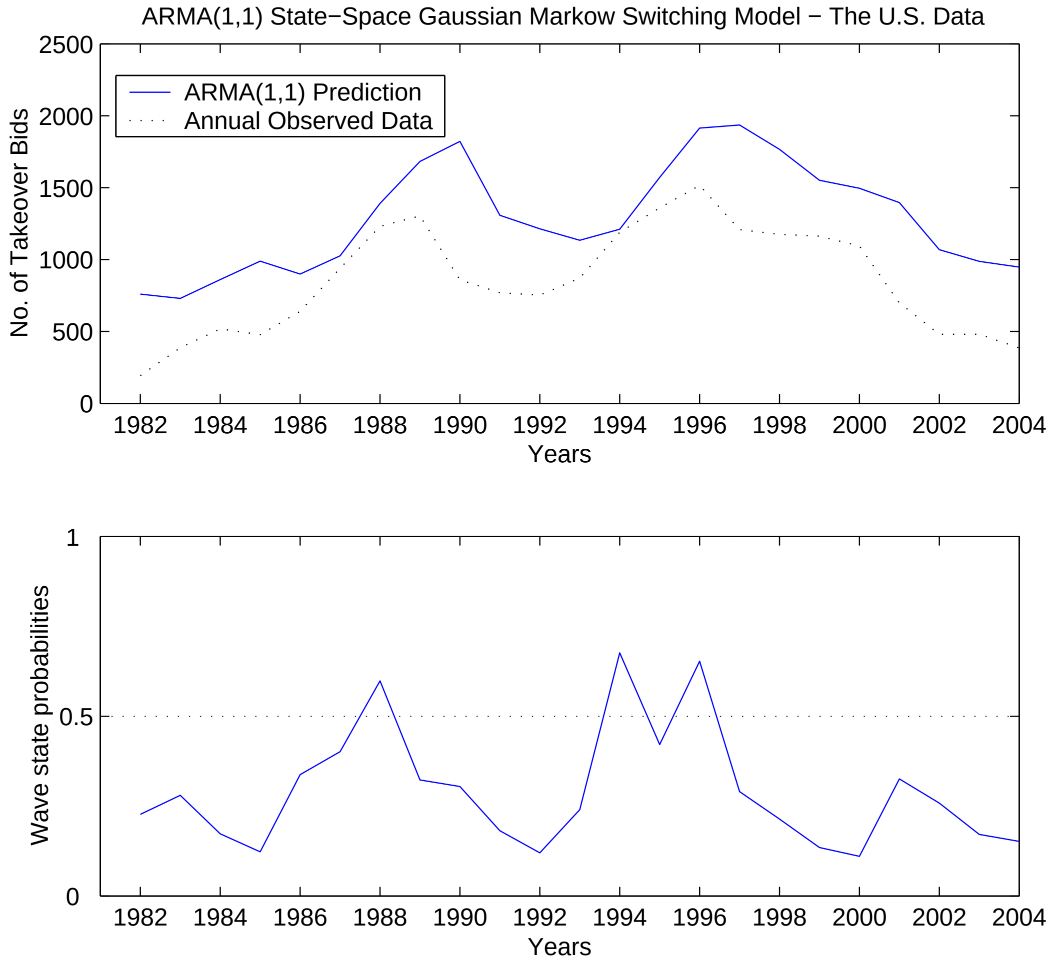

Figure 4.4: ARMA(1,1) State-Space Markov switching model on the US annual takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

approach to investigate which one gives the best fit for the US takeover data. Figure 4.5 represents the simulation results of applying the AR(1) Gaussian Markov switching model to the number of US takeover bids. As indicated in Figure 4.5, takeover waves detected using annual data are seen larger and clearer than those using quarterly data. Specifically, there are two big wave periods, the first one is from 1987 to 1989 and the second one is from 1994 to 1996. In each year of these two wave periods, the probability of being in a wave state nearly reaches 1.0.

In addition, as discussed in Section 3.3.5 of Chapter 3, another factor to look for

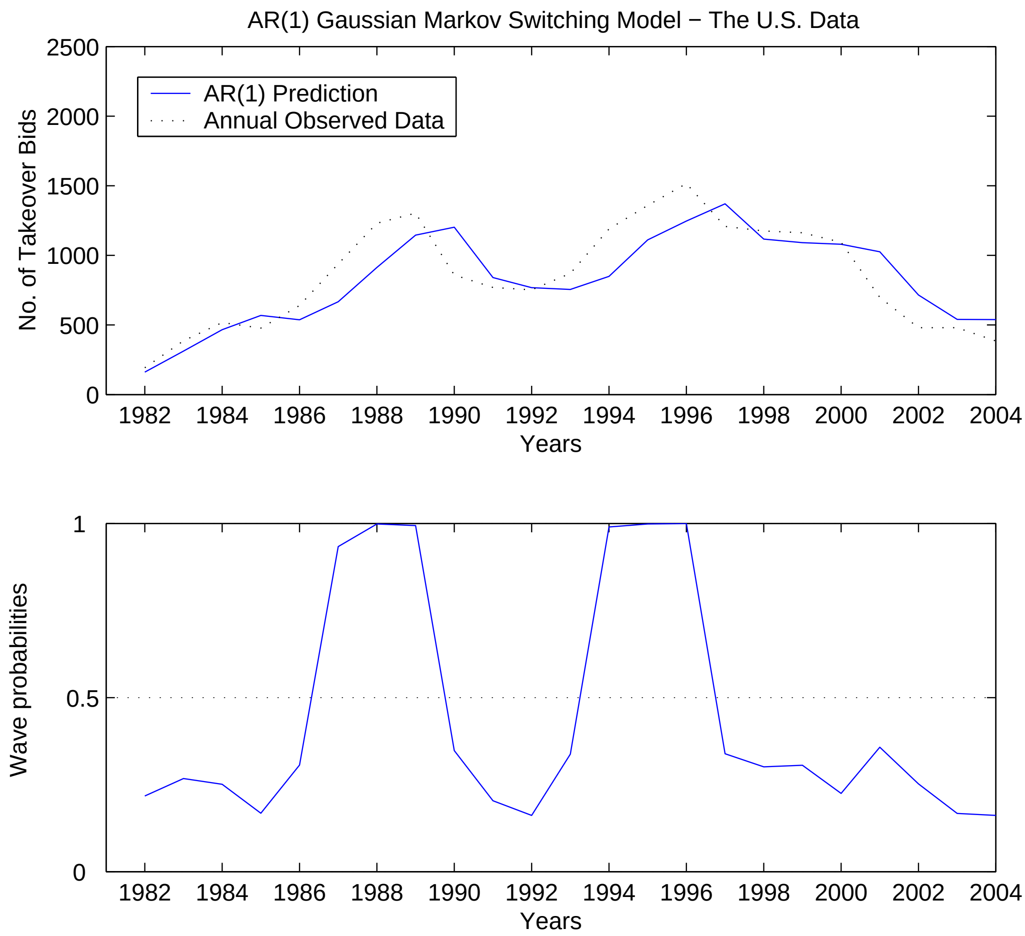

Figure 4.5: AR(1) Gaussian Markov switching model on the US annual takeover data - Number of takeover bids (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

a suitable model is the Bayesian information criterion (BIC). In the US takeover time series (for the number of bids), the BIC score under the ARMA(1,1) State-Space Markov switching model is slightly larger than that of AR(1) Gaussian Markov model (304 for the former model and 303 for the latter model). As evidenced in Table 3.5 of Chapter 3, the relevant figure for the Australian market is much higher under the ARMA(1,1) State-Space Markov switching approach (347 and 360 respectively).

To sum up, the State-Space model with a Gaussian Markov switching regime ARMA(1,1) seems to capture the most interesting M&A wave characteristics of the Australian market (see Chapter 3).[77] However, its use in the US context may not provide intuitive explanation of the market movements as our preliminary investigation leads to the conjecture that the US takeover time series do not favour a complicated model and are more likely to lead to an over-fitting and unstable problem. As such, when using the Gaussian Markov switching AR(1) model, which is a special case of the ARMA(1,1) model, the prediction of waves appears more intuitive and the result is more stable. We are then motivated to use the AR(1) Markov switching model for the US data. Therefore, for the US data, S_t are detected by using the Gaussian Markov switching model AR(1). For the US market, P_1 (when modelling the number of annual takeover bids) is shown in the bottom panel of Figure 4.5.

In addition to the analysis of the number of takeover bids, we apply the AR(1) Gaussian Markov switching model to three time series: proportion of takeover bids, proportion of cash bids, and proportion of stock bids to the number of the US exchange-listed companies. Figure 4.6, Figure 4.7 and Figure 4.8 show the results for these time series, respectively.

[77]In Chapter 3, we actually compare 3 models to see which one give the best fit: Hamilton (1989) Markov switching model AR(1), Kendig (1997) Poisson Markov switching model AR(1), and our proposed State-Space model with a Gaussian Markov switching regime ARMA(1,1). The first model is a special case of a more general ARMA framework.

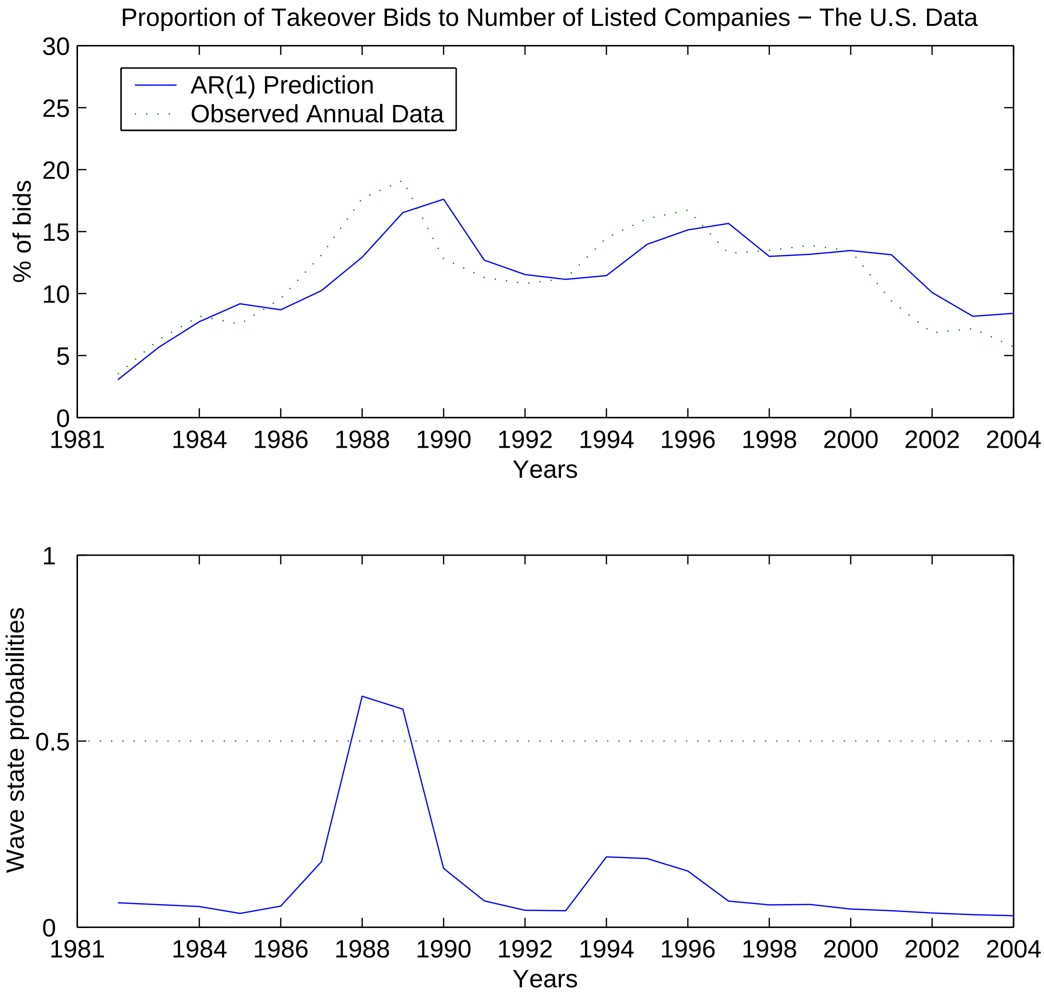

Figure 4.6: AR(1) Gaussian Markov switching model on the US annual takeover data - Proportion of takeover bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

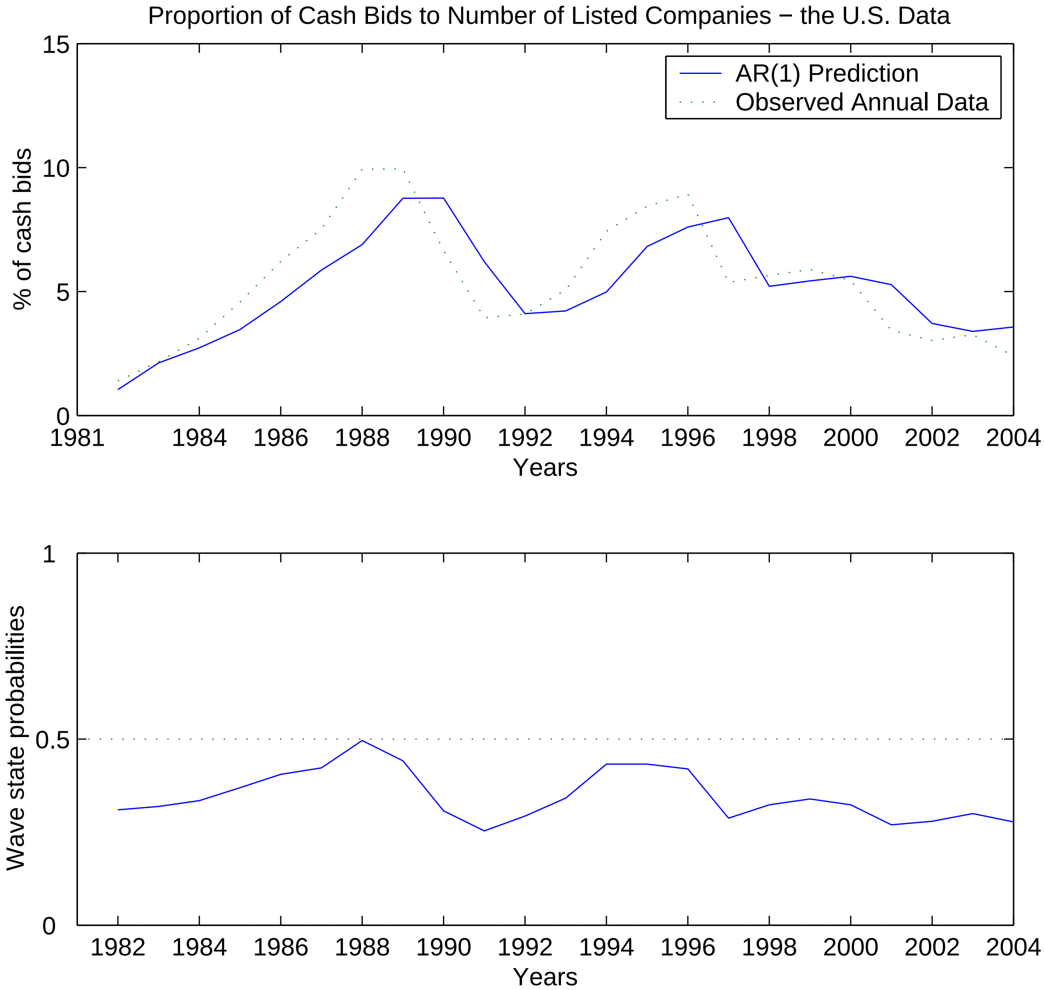

Figure 4.7: AR(1) Gaussian Markov switching model on the US annual takeover data - Proportion of cash bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

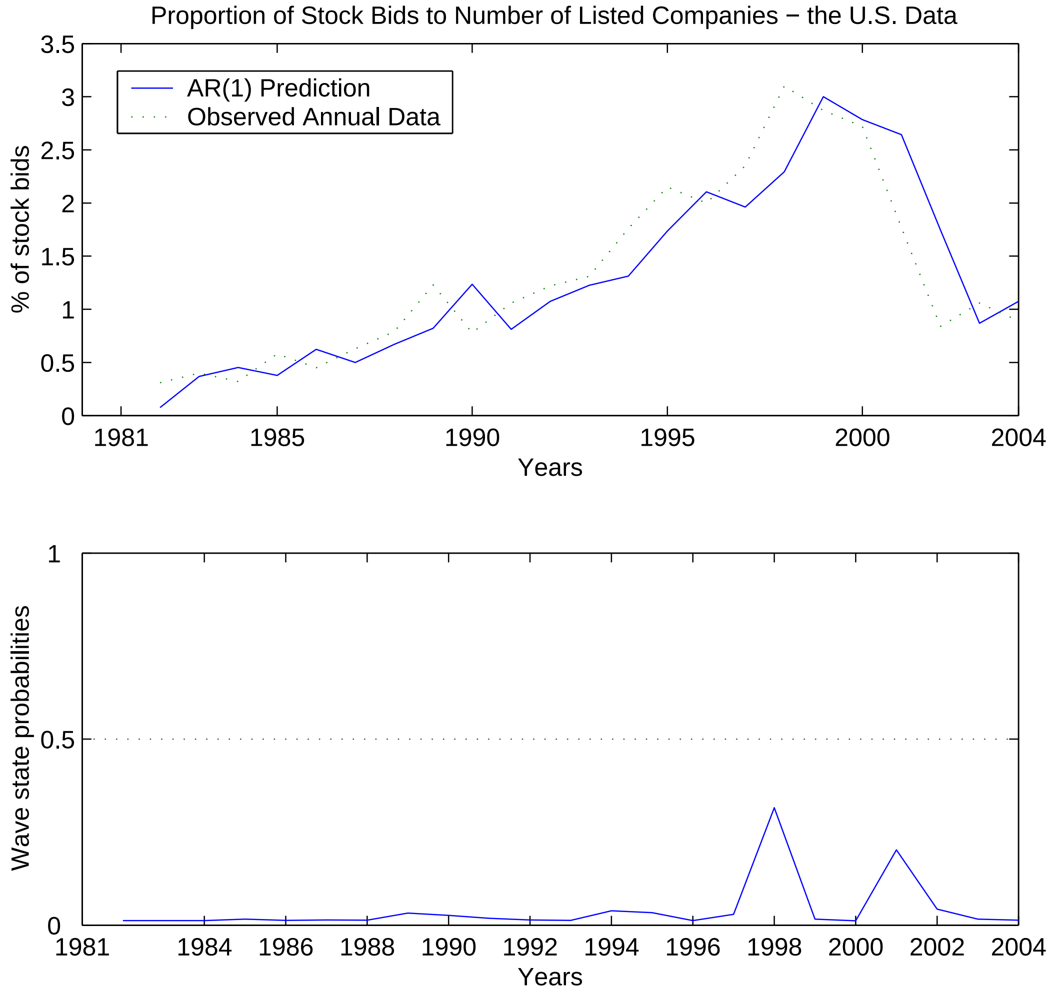

Figure 4.8: AR(1) Gaussian Markov switching model on the US annual takeover data - Proportion of stock bids to number of listed companies (the actual and predicted takeovers are shown in the top panel, the bottom panel represents the probability of being in a wave state)

Table 4.8: Source of data - the US market

Variables	**Measures**	**Source**	**Symbol**
Number of takeover bids	A total number of takeover bids announced to target companies listed on the US stock exchanges (namely, Nasdaq, New York and American stock exchange) from January 1982 to December 2004.	Thompson Financial's Securities Data Company (SDC) Platinum database	TAK
Aggregate stock market performance	The return on S&P 500 Accumulation Index in excess of 3-month the US Treasury bill rate	From 2 sources: • Standard & Poors • Datastream	S&P500
Long-term interest rate	The yield on 10-year Government Bond (Treasury Constant Maturities Nominal 10 years (TCM))	The Federal Reserve Board website	INT
Macroeconomic variable	Growth rate of industrial production	Datastream.	TIP

2. Data

For the US market, we use M&A data from 1982 to 2004,[78] obtained from several sources. The number of takeover bids to listed targets on the US stock exchanges[79] is sourced from SDC database. Similar to the Australian market, our inclusion criteria of the US merger bids are for deals classified by SDC as acquisition of stocks (i.e. merger, acquisition, acquisition of partial interest, acquisition of majority interest, acquisition of remaining interest).

The number of companies listed on the US Stock Exchanges comes from the Center for Research in Security Prices (CRSP)[80]. Data on industrial production and 3-month US Treasury Bill rates are from Datastream; data on 10-year US Treasury Bond rates come directly from the Federal Reserve Board website. The return on S&P 500 Accumulation Index in excess of 3-month the US Treasury bill rate is a proxy for aggregate stock market performance. We do not include the

[78]We can only obtain data for the US takeover bids since 1981. AR(1) Gaussian Markov Switching model requires 1 period for initialization. Therefore, our period of examining is limited to 1982-2004.

[79]Namely, Nasdaq, New York and American stock exchange.

[80]provided by Wharton Research Data Services (WRDS).

Table 4.9: Summary statistics - the US market

The table presents summary statistics of the variables used in the econometric analysis for the US market. Descriptive statistics are in Panel A, Panel B shows correlation of variables (Pearson's correlation coefficient) All variables are measured from the quarterly series 1982-2004. TAK is total number of takeover bids of the US exchange-listed target companies; TAK_c and TAK_{sh} are the number of cash-based bids and share-based bids. Those three numbers are normalised by the number of listed companies on the US (Nasdaq, New York and American stock exchange), denoted by $\%TAK$, $\%TAK_c$ and TAK_{sh}. S&P500 is returns on S&P500 Accumulation Index in excess of 3-month the US Treasury Bill rate. INT is the yield on 10-year the US Government Bond, a proxy for long-term interest rate. TIP represents the growth rate of total industrial production. All data (except TAK, TAK_c and TAK_{sh}) are in quarterly percentage points.

Panel A: Descriptive statistics

Variables	Quarters	Mean	Median	Standard Deviation	Max	Min	Autocorrelation Lag 1	Lag 2	Lag 3	Lag 4
TAK	92	213.98	205	94.29	441	46	0.99	0.98	0.97	0.96
TAK_c	92	101.23	95	52.89	233	19	0.98	0.97	0.95	0.94
TAK_{sh}	92	26.07	18	20.03	78	3	0.96	0.95	0.94	0.92
$\%TAK$	92	2.84	2.91	1.06	5.39	0.83	0.99	0.98	0.97	0.96
$\%TAK_c$	92	1.35	1.28	0.64	3.01	0.34	0.98	0.97	0.95	0.94
$\%TAK_{sh}$	92	0.33	0.26	0.22	0.9	0.05	0.96	0.95	0.94	0.92
S&P500	92	2.27	3.42	8.13	20.22	-23.93	0.07	0.08	0.03	0.08
INT	92	1.79	1.71	0.59	3.4	0.82	0.98	0.96	0.94	0.92
TIP	92	0.73	0.94	1.99	5.22	-5.3	0.17	-0.11	0.05	0.59

Panel B: Correlation of variables

	TAK	S&P500	INT	TIP
TAK	—	0.0855	-0.1664	0.0765
S&P500	0.0805	—	-0.0293	-0.1068
INT	-0.1664	-0.0293	—	0.0496
TIP	0.0765	-0.1068	0.0496	—

returns of the most active industry and the growth rate of private capital expenditure variables as we did for Australia as equivalent variables are not available. However, those two variables are not significant for the test using Australian data, so we omit them in our US sample. Table 4.8 shows a summary of data collection and the sources of data, Table 4.9 presents the descriptive statistics for the variables used in the later analysis with descriptive statistics in Panel A and Pearson's correlation of variables in Panel B.

As evidenced in Panel A of both Table 4.2 (for Australian market) and Table 4.9 (for the US market), the Australian takeover market is much smaller than the US counterpart with the average number of takeover bids for each quarter approximately five times lower (45.70 bids versus 213.98 bids). Similar figures are observed for cash bids (three times lower) and stock bids (six times lower). However, when these numbers are normalised by the number of exchange-listed companies, Australia accounts for a bigger proportion with 3.74% for total bids, 2.65% for cash bids, and 0.37% for stock bids. The equivalent figures for the US market are 2.84%, 1.35% and 0.33% respectively. On average, the quarterly excess return on ASX All Ordinaries Accumulation Index is lower than that of the US S&P 500 Accumulation Index (1.28% per quarter versus 2.27%). Australian long-term interest rate is, on average, higher than the US (2.38% per quarter versus 1.79%). Industrial production grows at the faster rate in the US than in Australia (0.73% per quarter versus 0.53%). However, like the Australian market, the US takeover activity is highly correlated to its domestic interest rate, with a Pearson correlation coefficient of -0.17 (Panel B of Table 4.9).

3. Empirical evidence from the US market

In this section, we extend the empirical analysis documented in Section 4.4 (for the Australian market) to the largest takeover market in the world, the US market. As explained in the previous part of data collection, our analysis for the US market is limited to the period from 1982 to 2004 only. We are unable to control for two predictors (i.e. the most active industry return and the growth rate of private capital expenditure) used in the Australian market sample due to lack of data. Therefore, our predictive regressions in Table 4.10 and 4.11 control for only three variables: the aggregate share market return, the level of interest rate, and the growth rate of industrial production.

The Gaussian Markov switching model AR(1) is applied to each of the annual time series of takeover activity (i.e. the number of US bids and its proportion to the number of listed companies). Figures 4.5 and 4.6 (the second panel) graphically represents the wave state probabilities for the two series, respectively. Similar to

Table 4.10: Predictive regressions of the US takeover bids (number) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $TAK_t = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-1} + e_t$. The table presents the results from forecasting shares-based bids in quarter t using all macro-economic and financial market variables lagged by one quarter. TAK is total number of takeover bids of the US listed target companies. P_1 and P_0 are probability of being in a wave state and in a non-wave state when modelling TAK annual time series by AR(1) Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (S&P500 is returns of S&P500 Accumulation Index in excess of the US 3-month Treasury bill rate; INT is 10-year the US Government Bond rate; TIP represents the growth rate of total industrial production). The sample period is from 1982 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Number of the US takeover bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept, Non-wave	**123.33^a**	**189.48^a**	**120.53^a**	**183.44^a**	**117.06^a**	**182.85^a**	**171.99^a**
	(12.56)	**(37.49)**	**(12.32)**	**(38.44)**	**(12.92)**	**(36.85)**	**(37.64)**
Intercept, Wave	**326.65^a**	**460.31^a**	**320.66^a**	**475.8^a**	**323.19^a**	**460.21^a**	**482.97^a**
	(15.03)	**(83.08)**	**(16.7)**	**(85.89)**	**(17.02)**	**(81.64)**	**(83.53)**
$S\&P500_{t-1}$, Non-wave	0.49			0.71	1.35		1.6
	(1.56)			(1.43)	(1.56)		(1.42)
$S\&P500_{t-1}$, Wave	-0.72			-1.17	-1.14		-1.66
	(1.92)			(1.78)	(1.91)		(1.76)
INT_{t-1}, Non-wave		**-35.98^c**		**-33.75^c**		**-34.48^c**	-30.83
		(19.48)		**(19.7)**		**(18.96)**	(19.07)
INT_{t-1}, Wave		**-74.2^c**		**-80.75^c**		**-76.32^c**	**-86.72^b**
		(44.69)		**(45.57)**		**(43.47)**	**(44.1)**
TIP_{t-1}, Non-wave			**9.57^c**		**10.29^c**	**9.18^c**	**9.92^c**
			(5.62)^c		**(5.75)**	**(5.09)**	**(5.2)**
TIP_{t-1}, Wave			3.06		3.82	3.19	4.34
			(8.67)		(8.83)	(7.86)	(7.96)
Adjusted R^2	0.48	0.57	0.5	0.56	0.5	0.58	0.58
No. of observations	92	92	92	92	92	92	92

the Australian analysis, we have used quarterly series in our regressions. It is thus assumed that the probability for four quarters in a given year remains the same. The predictive two-state regressions for each of the above-mentioned time series are presented in Table 4.10 and Table 4.11, respectively.

The regression results for the number of takeover bids, reported in Table 4.10, show clearly that interest rate coefficients are negative in both states, but the statistical significance is only observed in the wave state. Industrial production (in the non-wave state) and interest rate (in the wave state) are both significant at the 5% level, with higher t-statistic for the interest rate variable.

Table 4.11: Predictive regressions of the US takeover bids (as a proportion to number of listed companies) on explanatory variables lagged by one quarter - Two-state model

Regressions take the form: $\%TAK_t = (\alpha_{S_t=1}P_1 + \alpha_{S_t=0}P_0) + (A_{n,S_t=1}P_1 + A_{n,S_t=0}P_0)Z_{t-i} + e_t$. The table presents the results from forecasting proportion of the US takeover bids in quarter t using all macro-economic and financial market variables lagged by one quarter. %TAK is the proportion of the US takeover bids to the number of listed companies. P_1 and P_0 are probability of being in a wave state and in a non-wave state when modelling %TAK annual time series by AR(1) Markov Switching model. Z_{t-1} contains the independent variables in previous quarter (S&P500 is returns of S&P500 Accumulation Index in excess of the US 3-month Treasury bill rate; INT is 10-year the US Government Bond rate; TIP represents the growth rate of total industrial production). The sample period is from 1982 to 2004 (quarterly series). Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are significant at 10% or better, with superscript ^{a}, ^{b}, or ^{c} indicate significance level of 1%, 5%, or 10%.

Dependent variable: Proportion of the US takeover bids at time t

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept, Non-wave	**2.29**^{a}	**1.95**^{a}	**2.22**^{a}	**1.9**^{a}	**2.21**^{a}	**1.94**^{a}	**1.9**^{a}
	(0.11)	**(0.37)**	**(0.11)**	**(0.38)**	**(0.11)**	**(0.36)**	**(0.37)**
Intercept, Wave	**6.69**^{a}	**28.7**^{a}	**6.58**^{a}	**29.71**^{a}	**6.61**^{a}	**27.8**^{a}	**28.39**^{a}
	(0.48)	**(4.82)**	**(0.52)**	**(5.02)**	**(0.52)**	**(4.8)**	**(4.94)**
$S\&P500_{t-1}$, Non-wave	-0.003			-0.004	0.003		0.001
	(0.01)			(0.01)	(0.01)		(0.01)
$S\&P500_{t-1}$, Wave	0.03			-0.02	0.02		-0.02
	(0.05)			(0.04)	(0.05)		(0.04)
INT_{t-1}, Non-wave		0.06		0.08		0.03	0.05
		(0.18)		(0.19)		(0.18)	(0.18)
INT_{t-1}, Wave		**-10.44**^{a}		**-10.92**^{a}		**-9.98**^{a}	**-10.26**^{a}
		(2.3)		**(2.39)**		**(2.27)**	**(2.34)**
TIP_{t-1}, Non-wave			**0.11**^{b}		**0.11**^{b}	**0.11**^{b}	**0.11**^{b}
			(0.05)		**(0.05)**	**(0.04)**	**(0.04)**
TIP_{t-1}, Wave			0.1		0.05	-0.18	-0.14
			(0.36)		(0.37)	(0.3)	(0.31)
Adjusted R^2	0.42	0.6	0.47	0.59	0.46	0.62	0.61
No. of observations	92	92	92	92	92	92	92

The results for the proportion of takeover bids in Table 4.11 are similar. The impact of interest rate in the non-wave state is nearly nil, but reports a significantly negative (at the 10% level) relationship in the wave state. The industrial production variable again shows its significance in the non-wave state but this disappears when the confidence level of the test is increased to 99% (i.e. equivalent to significance level of 1%). At this confidence level, only the interest rate variable retains its statistical significance.

We are not able to perform a comparison between cash deals and stock deals for the US market as no obvious wave is recognised when modelling the time series of the proportion of stock bids.[81] If we conduct the two-state regressions on the proportion of cash bids,[82] no significant variables are found, but the interest rate coefficient is still negative in the wave state. When the US aggregate takeover bids are decomposed by method of payment, the liquidity argument is somewhat weakened. Differences in findings for the US and Australia markets could be due to differences in the method of payment in M&As. Stock and cash deals are evenly opened in the US takeovers whereas cash deals are dominant in Australia. In our sample, cash-only deals account for roughly 70% of all bids in Australia, whilst this proportion is almost halved (only 47%) in the US.

The results presented in Table 4.10 and Table 4.11 have clearly demonstrated that a low level of interest rate significantly lead to a larger proportion of takeover bids in the wave state. We therefore conclude that the basic finding that the level of interest rate can predict the concentration of takeover activity extend beyond the Australian market to the US takeover market as well.

[81] We have defined a wave is recognised when the wave state probability is 0.5 or higher (see Chapter 3). For the time series of the proportion of stock bids, there are only two spikes in 1998 and 2001 with probability of 0.32 and 0.2 respectively. For the time series of the proportion of cash bids, there is a minor wave recognised in 1988 with the probability of 0.5. See Figure 4.7 and Figure 4.8 for the time series of the proportion of cash bids and stock bids, respectively.

[82] For the time series of the proportion of cash bids, the probability of being in a wave state is shown in the second panel of Figure 4.7 in the Appendix 4.B at the end of this chapter.

Chapter 5

Consequences of Riding Takeover Waves

5.1 Introduction

This chapter presents the analysis and results from testing the third research question on the outcomes of takeover waves. The main objective of this research question is to investigate whether takeover waves, given their existence (see Chapter 3), can affect the value creation (or destruction) for the bidding and target firm shareholders.

Andrade et al. (2001), in a review of companies' financial performance following mergers and acquisitions, report large positive average abnormal returns to targets and small abnormal returns to bidders over the announcement periods. However, they point out that the question of whether mergers create value on behalf of shareholders of acquiring firms in the long run is still debatable. Therefore, we will re-examine the post-bid stock performance, from the perspective of acquiring firms' shareholders, to see whether takeovers create or destroy value in the Australian context. Furthermore, as it is often argued that the long-horizon adverse effects to acquiring firms' shareholders are a direct consequence of large premiums paid in takeovers (representing takeover gains to target shareholders). So in this chapter, takeover premiums will be analysed in conjunction with long-run abnormal returns to acquiring firms.

It is, on the one hand, often claimed that takeover waves are triggered by managerial problems like hubris or herding (Roll (1986), Scharfstein and Stein (1990)), or by stock market over-valuation (Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004)). On the other hand, neoclassical supporters argue that merger waves occur as a result of a combination of industry shocks (Mitchell and Mulherin (1996)) and sufficient capital liquidity to accommodate the asset reallocation (Harford (2005)). Therefore, we also analyse implications of the above-mentioned theories of merger waves on the shareholders of target and acquiring firms since each theory predicts different outcomes.

Specifically, in this chapter, we examine the influence of merger waves on post-takeover stock performance of bidding firms together with takeover premiums (calculated using target share price one month and two months prior to the announcement). Takeover waves are recognised under the State-space Markov switching ARMA(1,1) model (details in Chapter 3).[83] We compare takeover premiums and post-bid (12 months and 18 months following the bid announcement month) stock returns of acquiring firms that initiated their bids inside and outside of the waves, and in the first half and second half of the waves. Our sample covers all takeover bids between ASX-listed firms over the period of 1980-2004. To our best knowledge, this is the first Australian work on the effects of takeover waves to post-takeover stock performance of bidding firms.[84]

The remainder of chapter five is organised as follows. Section 5.2 outlines our research design with details of assessing abnormal performance for acquiring firms

[83] Our wave detection method is a systematic way of identifying takeover waves. Current studies on merger waves' effects are almost always based on Harford (2005)'s bootstrapping method of wave identification. Our method of wave identification not only allows us to identify wave periods (as Harford (2005)'s method), but also to predict when the next wave will happen.

[84] Recently, there are three major works on stock returns to bidding firms in the Australian takeover market. da Silva Rosa (1994) examines pre-bid period, bid-announcement period, and post-bid period returns to bidding firms. However, there is no control for a takeover wave effect when calculating these returns. Kendig (1997) only investigates the announcement effect of takeover waves on acquiring firms for mergers that took place inside and outside of the waves, and her work is limited to univariate evidence. Simmonds (2004) comprehensively studies only the announcement effect to bidding shareholders' returns with no reference to takeover waves.

and takeover premiums, and data collection for the analysis. Section 5.3 presents empirical findings, and provides an explanation for the wave effect in the Australian takeover market. Finally, conclusions are in Section 5.4.

5.2 Research Design

5.2.1 Assessing abnormal performance

This study uses [0,+12] and [0,+18] event window [85] to measure acquiring firms' abnormal returns where month zero is the first public announcement date of the takeover.[86] Following da Silva Rosa (1994), abnormal returns are calculated with control for size and survival condition. In particular, we calculate post-bid 12-month and 18-month buy-and-hold return (BHR) for each acquiring firm in our sample that survives for the next 18 months after the announcement month. These BHRs are then compared against two benchmarks: (a) the return to the sample firm's respective size decile, and (b) the return to the market portfolio. Those two benchmarks include all firms in the decile (market) portfolio for which data on share prices over the event window [0,+18] are available. The empirical distribution of 1,000 control portfolios is used to assess the significance of the abnormal returns calculated. Further details regarding the measures of decile and market adjusted returns are as below.

[85] Our method of controlling for survivorship bias introduces the "look-ahead" period (i.e., to check for companies that survive after a certain period). Our sample covers the period from 1980 to 2004, SPPR data is available to the end of 2007. Therefore, 18 months after the takeover announcement date is the maximum buy-and-hold return period that we can cover.

[86] Some early event studies of takeovers (e.g., Mandelker (1974), Walter (1984)) use the effective date of merger (the date of final approval by target shareholders) as the event date. The problem with using this type of date is that the event date makes it difficult to identify changes in security prices that are due to the takeover event itself (Dodd and Ruback (1977)). Therefore, we use the first public announcement of a takeover as the event date.

5.2.1.1 Calculation of abnormal returns

We calculate long-run buy-and-hold abnormal returns of each bidding firm for 12 months and 18 months after the end of the announcement month as:

$$BHAR_{iT} = R_{iT} - E(R_{iT}) \tag{5.1}$$

with

$$\mathrm{R}_{iT} = \prod_{t=1}^{T}(1 + r_{it}) - 1 \tag{5.2}$$

$$\mathrm{E}(R_{iT}) = \prod_{t=1}^{T}(1 + E(r_{it})) - 1 \tag{5.3}$$

where

- T is the holding month under a buy-and-hold strategy (T=12 or 18);
- r_{it} is simple return[87] of firm i in month t, adjusted for dividends and any capital changes (e.g., stock splits and right offerings);
- R_{iT} is the buy-and-hold return for firm i over T months (T=12 or 18) from the takeover announcement month;
- $\mathrm{E}(r_{it})$ is the expected return for firm in month t. In this research, we use the size (or market) reference portfolio. It is calculated as the average return of all firms on a market portfolio or a size-decile portfolio in which the sample firm belongs to;
- $\mathrm{E}(R_{iT})$ is the expected return for firm i over T months (T=12 or 18) under the buy-and-hold strategy;
- $BHAR_{iT}$ is the size-decile (or market) adjusted buy-and-hold abnormal return for firm i over T months (T=12 or 18), defined as the difference

[87] As demonstrated in Barber and Lyon (1997), continuously compounded returns yield inherently negatively biased estimates of long-run abnormal returns. The negative bias occurs because there is a considerable cross-sectional variation in the return of common stocks. As a result of that, they recommend the use of simple returns, not continuously compounded returns for analysing long-run return performance.

between the BHRs for sample takeover firms and the BHRs to the decile to which sample firms belong (or market portfolio).

The mean BHAR is the equally-weighted average of the individual BHARs (where N is the number of acquiring companies in the sample):

$$\text{BHAR} = \frac{1}{N}\sum_{i=1}^{N} BHAR_{iT} \tag{5.4}$$

5.2.1.2 Reference portfolios

Following Brown and da Silva Rosa (1998), we use the size-decile portfolio with control for survivorship bias as the benchmark for calculating abnormal returns.[88] The procedures in obtaining the size-decile return for each firm in the takeover sample are as below:

1. Identify all firms listed on the ASX that have survived and had sufficient share price data available for calculating BHRs over the [0;+18] months relative to the sample firm's bid announcement month,[89] denoted as set [S].

2. Calculate market capitalisation of all firms in set [S] as at the beginning of the announcement month (month 0).

3. Sort all firms in set [S] into 10 size deciles with decile one comprising the smallest 10% of firms and decile ten comprising the biggest 10% of firms.

4. Identify the size decile of the experimental firm.

5. Calculate the buy-and-hold return over 12 months (or 18 months) for the decile that experimental firm belong to (the monthly return for each of the ten size-decile portfolios is calculated by averaging the monthly returns across all firms in a particular size decile).

Step 4 and 5 in the above process are repeated for every firm in our takeover sample. A positive (or negative) value of BHAR indicates that the takeover firm

[88] This controls for a systematic association between firm size and share returns.
[89] This procedure is to minimise the impact of survival bias.

outperforms (or under-performs) a portfolio of control firms matched on size and survival status. The calculation of the size-benchmark return is equivalent to a strategy of investing in a size-decile portfolio which contains only survived companies over the event period. Therefore, the advantage of using size-decile adjusted returns is that both the firm size effect and survival bias are controlled for (Brown and da Silva Rosa (1998)).

For the market portfolio benchmark, a similar procedure is repeated without steps of sorting firms into ten size deciles.

Since the decile and market adjusted returns are generated conditioning on survival, these return estimates have a "look-ahead" bias component (Brown and da Silva Rosa (1998), da Silva Rosa et al. (2004)). Although these estimates cannot be attributable to a feasible investment strategy, it is not our particular concern because our goal is not a measure of the magnitude of abnormal performance attributable to acquisitions but to assess relative performance of the experimental sample firms and the control portfolios (da Silva Rosa et al. (2004)). The next section will document procedures of forming 1,000 control portfolios.

5.2.1.3 Forming of Control Portfolios

The use of the above-mentioned reference portfolio to calculate BHARs is subject to the skewness biases (see Barber and Lyon (1997)). This can reduce the statistical power of long-run performance measures because the positive skewness of abnormal returns can lead to biased and inefficient inference (Barber and Lyon (1997), Kothari and Warner (1997)).

Following Barber and Lyon (1997) and Lyon et al. (1999),[90] as a control for the skewness bias in tests of long-run abnormal returns, we apply standard statistical methods recommended for when the underlying distribution is positively skewed:

[90] The method used by Barber and Lyon (1997) and Lyon et al. (1999) are originally based on empirical methods of Brock et al. (1992) and Ikenberry et al. (1995).

empirical p-values calculated form the simulated distribution of mean long-run abnormal returns estimated from 1,000 control portfolios. We generate the empirical distribution of mean long-run abnormal returns under the null hypothesis that the mean long-run abnormal returns of the takeover sample equals the mean long-run abnormal returns for the 1,000 control portfolios and the difference observed is a coincidence of random sampling.[91] The statistical significance of the sample mean is evaluated based on this empirically generated distribution.

The procedures for size and survival matching the 1,000 control portfolios are as follows:

1. We repeat step 1 to 3 in the process of forming size-decile portfolios in previous procedure in Section 5.2.1.2 (that is, identify the 10 size-decile portfolios on all ASX firms that have survived over the [0;+18] months event window).

2. For each experimental firm in our takeover sample, we randomly select with replacement a firm that is in the same size-decile portfolio.

3. This process continues until each firm in our original takeover sample is represented by a control firm in this control portfolio.

4. After forming a single control portfolio, we estimate its long-run performance using the buy-and-hold size reference portfolio as was done for the original sample. This yields one observation of the abnormal performance obtained from randomly forming a portfolio with the same size as our original sample.

5. This entire process (from step 1 to step 4) is repeated until we have 1,000 control portfolios, and thus 1,000 mean abnormal returns observations. These 1,000 mean abnormal returns observations are used to approximate the empirical distribution of mean long-run abnormal returns.

[91] The conventional t-statistic is tested on the null hypothesis that the mean long-run abnormal returns of the takeover sample is zero.

In the case of forming 1,000 control portfolios when the market benchmark is used, we follow a similar procedure but this time firms are not sorted into deciles.

5.2.2 Control factors

Besides merger waves, the prior literature has shown the potential effects of other factors on the acquiring firm's shareholder wealth. In order to make more reliable inferences, we study the impact of takeover waves in a multivariate regression model, where other factors such as firm and bid characteristics are controlled for. Specifically, included variables are: relative size of target to bidding firm, takeover premium, industry-related bids, method of payment of the bid, and outcome of the bid.[92] The rationale for the inclusion of these variables is briefly discussed below.

Relative size

The relative size of target to acquirer variable is used since the performance of bidders can be influenced by the relative size of targets. The literature on the effect of relative size on an acquiring firm's stock performance is quite divided. On the one hand, it is expected that larger bidder abnormal returns are associated with greater target relative size, as stipulated by Asquith et al. (1983), Franks and Harris (1989), Eckbo and Thorburn (2000) and Hackbarth and Morellec (2008). They believe that unless the investment in the target is sufficiently large relative to the bidder, the expected value improvements from the merger will lead to insignificant changes in the bidder's share price. On the other hand, some researchers (e.g., Kuehn (1975), Travlos (1987)) argue that acquiring smaller target relative size involves lower acquisition and incorporation costs, resulting in higher bidder gains from takeovers.

[92] As discussed in Section 2.4.1.1 of Chapter 2, book-to-market equity ratio is also a relevant factor in explaining the post-acquisition performance of acquiring firms. However, we have to ignore this variable as book equity is unable to obtain for the early years under our total period of examination (i.e. 1980-2004).

Takeover premium

Shareholders in the target companies normally require certain premiums to capture perceived incremental value created from takeovers (Hart and Grossman (1980)). For example, Walkling (1985) indicates that bid premiums measured prior to market receipt of relevant offer information do appear as a significant determinant of tender offer success. A high premium suggests that an acquiring firm is paying more than the current market valuation in acquiring a target, and is an indicator of overpayment. Paying a high premium consequently means that the acquiring firm's future expected return could be lower.

Industry relatedness

Some of the managerial theories of conglomerate takeovers argue that diversification will destroy value. It is often claimed that conglomerate mergers are less likely to succeed, because managers of acquiring firms are not familiar with the target industry (Jensen (1986)). Also, when poor performance of the firm threatens a manager's job, he has an incentive to enter into a new line of business (Shleifer and Vishny (2003)). In all cases, managers may be willing to overpay for targets outside the bidding firm's industry, reducing the wealth of shareholders. Following this view, Singh and Montgomery (1987) argue that if acquiring and target firms operate in related industries, the gains for bidder shareholders will be larger due to the potential for economies of scale, greater synergy and complementary resources. Supporting evidence of acquiring firms having lower abnormal returns for diversifying acquisitions is found in Morck et al. (1990), Walker (2000), and Doukas et al. (2002). Therefore, it is expected that industry-related takeovers will result in higher abnormal returns for the acquiring firms.

Method of Payment

Myers and Majluf (1984) with their signalling hypothesis suggest that the method of payment can have an impact on bidder shareholder wealth effect. Under their hypothesis, if managers are better informed about the long-term prospects of their firms than is the market, they will tend to pay for their acquisitions with shares when they believe their stock to be overvalued and use cash otherwise. Hence, the signalling hypothesis predicts that, on average, long-horizon abnormal returns of bidding firms will be lower in stock-financed acquisitions.

Offer Outcome

Unsuccessful offers are not costless since the management of both the bidding and target firms dissipate resources in the offer (Bradley et al. (1988)). Berkovitch and Narayanan (1993) argue that unsuccessful offers should result in bidder shareholder wealth losses due to the costly takeover process. When the real assets of two firms are under the same management control, there are gains from takeovers arising from increased productivity efficiency. Consistent with this, a number of US studies document significantly larger abnormal returns for successful bidding firms compared to those that are unsuccessful (Asquith et al. (1983), Dodd and Ruback (1977), Bradley et al. (1988)). Consequently, it is expected that higher abnormal returns of acquiring firms will be associated with successful bids.

5.2.3 Data

We start our analysis using all Australian takeover bids from 1980 to 2004 as identified in Chapter 4 of this thesis[93] and impose the further data requirements:

- Acquiring companies, like target firms, are also publicly traded on the ASX.
- The offer price of each deal must be available for computation. In stock-financed deals and hybrid deals, the offer price is determined by using acquirer's share price of the last trading day before announcement.
- Both acquirers and targets have common stock data available on the Share Price and Price Relative (SPPR) database at the time of announcement, and two months before the announcement month.

[93]The base data in Chapter 4 consists of 4,570 takeover bids announced to ASX-listed targets during the period 1980-2004. In this sample, all bidding firms are considered regardless of their listing status.

- The acquirers have valid price relative in SPPR database for 18 months after the announcement month.

Our final sample consists of 1,184 takeover bids of ASX-listed companies for the period from 1980 and 2004. Figure 5.1 graphically shows the original sample of takeover bids used in Chapter 4 and the final sample used in this chapter. As evident from Figure 5.1, the peaks and troughs in the original sample of all bidders are still followed in the final sample used in this chapter (which contains only exchange-listed bidders with all above-mentioned selection conditions). Therefore, it is appropriate to examine the consequences of riding takeover waves for a subset of listed bidders by using takeover waves detected from the original time series in Chapter 3.

Wave periods are referred to as periods with high levels of takeover activity and identified in Chapter 3 using our State-space and Markov Switching ARMA(1,1) model. The first wave consists of three years in the 1980s (1987-1989), the second wave is in the year of 1991, the third wave contains two years in the 1990s (1995 and 1996), and the forth wave includes two years in the 2000s (2003 and 2004). In our sample, the wave periods include the above-mentioned four individual waves (8 years), and the non-wave periods contain 17 years. Bid announcements within the takeover waves are further classified as the first half or the second half of the waves, depending on whether they take place in the first half (in time) or the second half (in time) of the waves.

Each bidder and target is classified into one industry group according to Standards & Poors Global Industry Classification Standard (GICS).[94] We define a takeover bid as the industry-related bid if the acquiring and target firms share the same four-digit GICS industry code, whereas a conglomerate bid is determined if the acquiring firm's four-digit GICS industry code is different to the target's. The relative size variable is measured as the ratio of the target to the acquiring

[94]In Chapter 4, we have reclassified industry codes of target firms according to the GICS standard. A similar procedure is now repeated for bidding firms so that we can later decide whether a takeover bid is made within or outside the acquiring firm's industry.

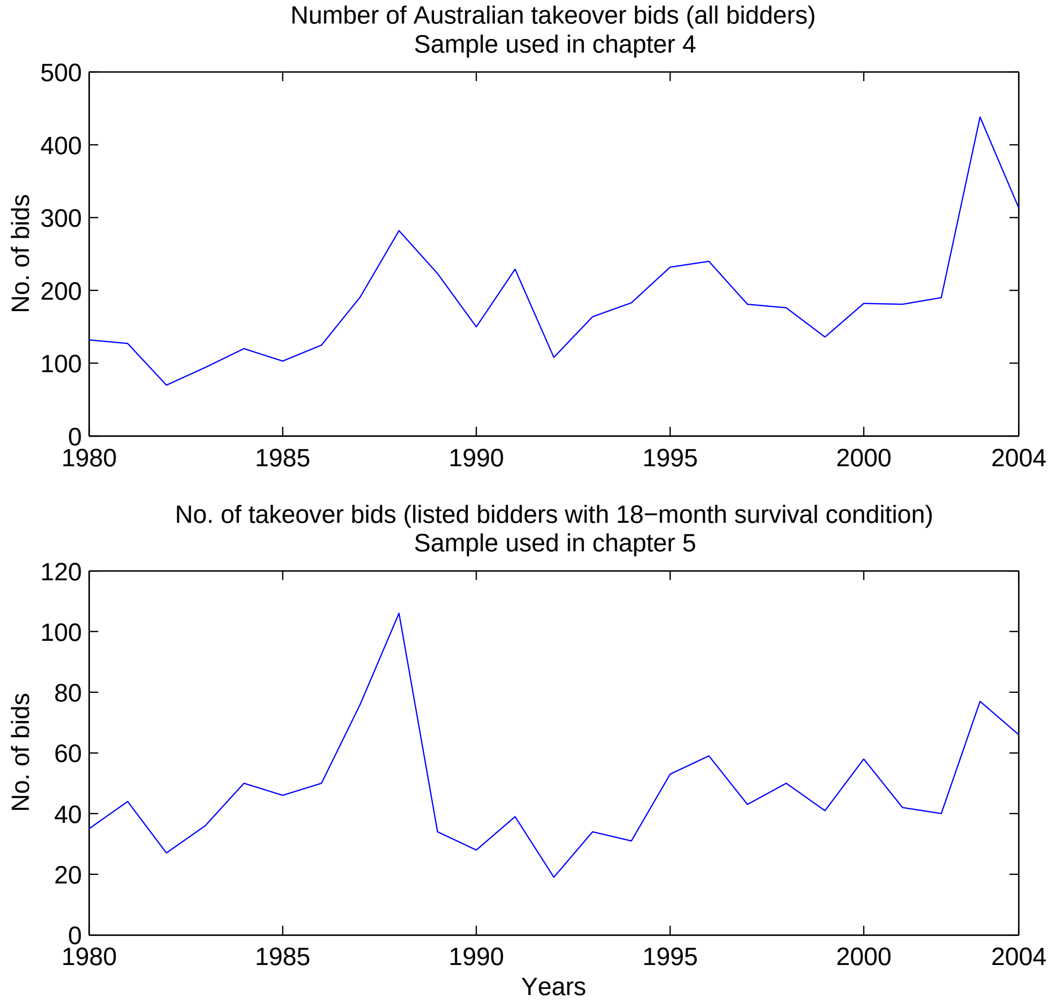

Figure 5.1: Australian number of takeover bids 1980-2004 - Comparison between original sample used in Chapter 4 (all bidders) and the final sample used in Chapter 5 (ASX-listed bidders with 18-month survival condition)

firm's market capitalisation two months prior to the announcement month. A bid is defined as successful if the acquirer aims at majority control, i.e. the offer is not withdrawn and the bidder holds at least 50% of target's shares after the closing date, and less than 50% of shares in target prior to the bid. The bid premiums are calculated as the difference between the final offer price and target share price one month (or two months) before the announcement, expressed in percentage form.

5.3 Empirical results

5.3.1 Takeover premiums

Given the large premiums paid in takeovers, it is often argued by managerial theory that the adverse effect for acquiring firms during the wave periods is a consequence of over-payment to target shareholders. Some studies (e.g., Berkovitch and Narayanan (1993), Kendig (1997)) have partly supported this claim. In this section, we analyse takeover premiums in all periods under examination and the differences in takeover premiums during different stages of merger waves.

Panel A of Table 5.1 presents summary statistics for target premiums which are calculated as the percentage difference between offer price and target share price one month (or two months) prior to the announcement month.[95] Over our total sample period of 1980-2004, the takeover premiums, on average, are approximately 29% (or 24%) when measured relative to two months (or one month) prior to the announcement date. The similar figures for median premiums are about 19% and 16%, respectively.

We do not find supporting evidence for the overpayment hypothesis since both the mean and median figures based on our two-month offer premiums are smaller during the merger waves compared to the non-wave periods. Although "in-wave" average premiums, based on share price one month before the announcement date, are slightly larger than the "non-wave" average premiums, the median premiums do not show any sign of overpayment. Panel B and C of Table 5.1 reports results from tests of differences in the mean and median of takeover premiums between the wave and non-wave periods. The parametric test (t-test) in Panel B indicates that there is no difference in mean premiums in the wave and non-wave periods for both measures of bid premiums. However, the non-parametric

[95] Due to difficulty in getting actual offer prices, the majority of empirical studies on takeover premiums use target abnormal stock returns around the takeover bid as a proxy for the actual takeover premiums. Clearly, this is a noisy estimate of takeover premiums since "they incorporate the probability of bid competition at the initial offer date, and they must be estimated over a long event window to capture the final premiums" (Betton et al. (2008a)).

Table 5.1: Takeover premiums

This table presents a summary of takeover premiums, calculated using target share price 2 months and 1 month before the announcement month. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *Wave* consists of 4 individual waves (Wave 1 (1987-1989), Wave 2 (1991), Wave 3 (1995-1996), and Wave 4 (2003-2004)). *First-half Wave* and *Second-half Wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively.

Panel A: Descriptive statistics

	2 months pre-announcement		**1 month pre-announcement**	
	Mean	**Median**	**Mean**	**Median**
Wave	27.44%	16.30%	24.84%	14.91%
First-half Wave	26.87%	16.51%	24.31%	15.06%
Second-half Wave	28.17%	15.79%	25.04%	14.58%
Non-wave	29.34%	20.14%	22.69%	17.27%
Total	28.52%	18.59%	23.62%	16.04%

Panel B: Parametric test (*t*-test)

	2 months pre-announcement		**1 month pre-announcement**	
	***t*-stat**	***p*-value**	***t*-stat**	***p*-value**
Wave vs. Non-wave	-7.0031	0.5400	-2.3543	0.4330
First-half vs. Second-half wave	–9.0926	0.7837	-9.5569	0.8138

Panel C: Non-parametric test (Mann-Whitney)

	2 months pre-announcement		**1 month pre-announcement**	
	***Z*-stat**	***p*-value**	***Z*-stat**	***p*-value**
Wave vs. Non-wave	-1.6670	0.0955	-0.8322	0.4053
First-half vs. Second-half wave	-0.3389	0.7347	-0.0194	0.9845

Mann-Whitney test in Panel C shows that “in-wave” premiums are significantly smaller than “non-wave” premiums when the bid premiums are measured using the prevailing price two months before the announcement date. Given the stricter assumption of normal distribution under the parametric test, we place more weight on the non-parametric test.

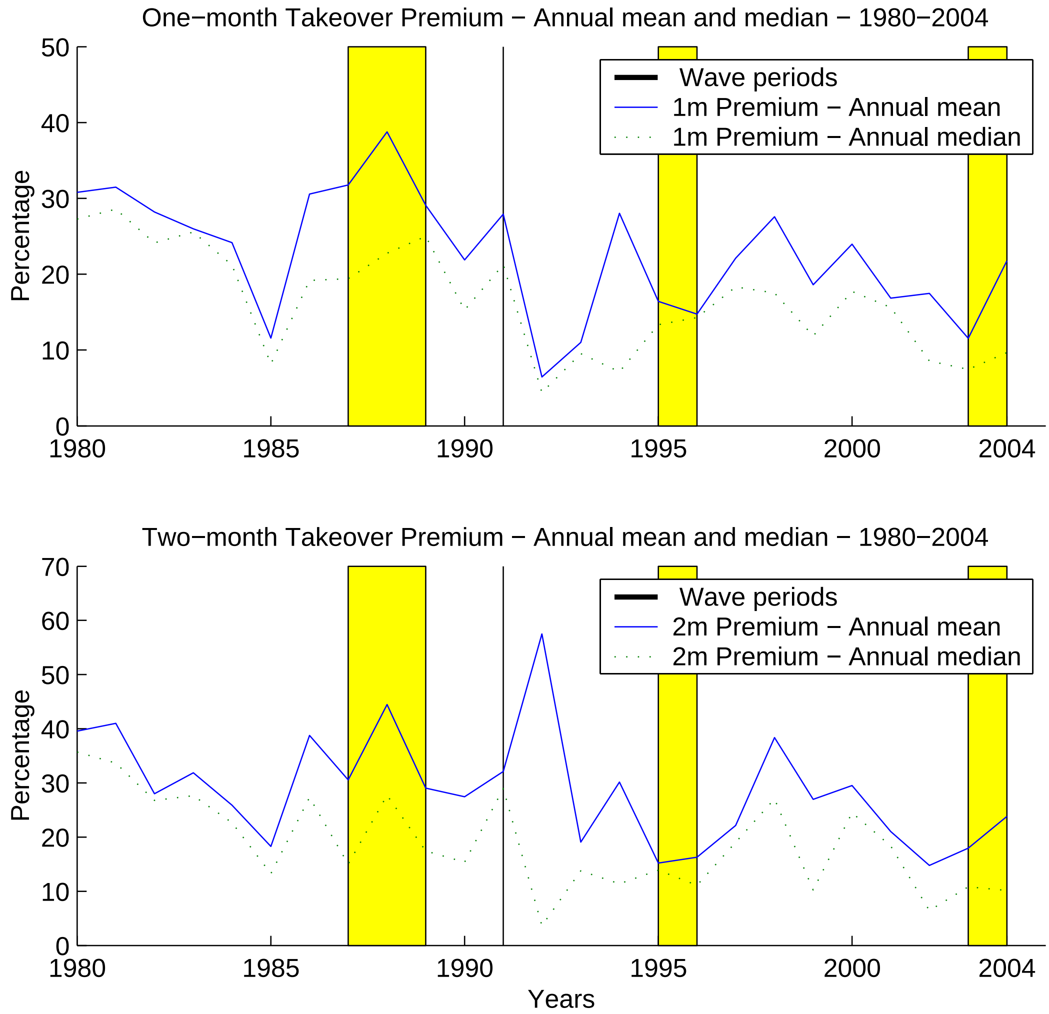

Figure 5.2: Takeover premiums paid to targets one month and two months pre-announcement - Annual average and annual median series - 1980-2004

In relation to dynamics within the wave periods (as indicated in Panel A of Table 5.1), the takeover premiums in the first-half wave are, on average, slightly smaller than those in the second-half wave. However, the opposite results are observed for median values with higher bid premiums in the first-half of the waves. Despite this, p-values from the parametric (t-test) and non-parametric (Mann-Whitney) tests (Panel B and C of Table 5.1) suggest that there is no difference between the two periods in terms of the mean and median premiums.

Figure 5.2 presents the annual average and the annual median takeover premium series together with the wave periods. The first panel and the second panel show the time series of takeover premiums measured by using the share price one month and two months prior to announcement, respectively. The straight line and vertical bars in each panel represents the wave periods. Like the individual premium series, it is observed that premiums of takeover bids announced in the wave periods are lower than that outside the wave periods.[96]

The above evidence is for the case of acquiring firms that survive over the next 18 months after takeover bids. Similar results are still obtained if the survival condition is reduced to 12 months (see Table 5.9 in Appendix 5.A at the end of this chapter for takeover premium analysis under the new survival condition).

To sum up, our empirical evidence indicates that Australian takeover premiums in the wave periods are lower (when measured relative to two months before announcement) or equal to (when measured relative to one month before announcement) than those in the non-wave periods. However, no significant difference is found for bid premiums in the first and final stages of the waves.

5.3.2 Post-bid stock performance of acquiring firms

5.3.2.1 Univariate analysis

We report the results for acquiring firms which initiated bids in the wave versus non-wave periods (Table 5.2), in the first half versus second half of the waves (Table 5.4). In each table, the results for acquiring firms' returns of 12 months and 18 months after takeovers are documented in Panel A and Panel B, respectively. Comparisons are based on both sample mean and median statistics. All tables are presented in the same format. In addition to raw (buy-and-hold) returns and decile adjusted returns, market adjusted returns are also reported, where the

[96]For the annual average (and median) premium series, both parametric (t-test) and non-parametric (Mann-Whitney) tests have indicated that there is no difference in annual mean (and median) premiums between the wave and non-wave states. T-statistics for one-month and two-month premiums are -4.14 (p-value 0.6) and -11.97 (p-value 0.4) respectively, while z-statistic figures are 0.15 (p-value 0.88) and -0.61 (p-value 0.54).

market portfolio includes all firms that survive and have the share price available for calculating BHRs over the window [0,+18] months relative to the announcement month.

As can be seen from these tables, the biases associated with market adjusted returns are more severe (in the sense that they indicate more under-performance in the post-merger period),[97] we consequently place more weight on decile adjusted returns. All discussions later refer to the size-decile adjusted returns, unless explicitly stated otherwise. The number in square brackets under each return figure is the number of 1,000 control portfolios that have a mean/median return higher than the mean/median return to our experimental sample firms.

Wave vs. non-wave period

Table 5.2 reports the summary statistics for the post-bid stock performance of acquiring firms which announced their bids in the wave versus non-wave periods. As evident from this table, both 12-month and 18-month post-bid performance of acquiring firms varies systematically between the wave and non-wave periods. "In-wave" acquiring firms perform worse than "non-wave" acquiring firms. These results are persistent across mean and median statistics, and across decile and market benchmarks. For example, the buy-and-hold returns of all acquirers in the next 12 months following takeovers are on average 0.89% higher when benchmarked against their (equally-weighted) decile; while they are 5.12% higher for "non-wave" acquirers and 4.70% lower for "in-wave" acquirers. The median returns show a similar pattern with 3.88% lower for all acquirers, 2.32% lower for "non-wave" acquirers and 4.74% lower for "in-wave" acquirers.

In terms of assessing the significance of differences in mean/median returns between our sample and control portfolios, "in-wave" acquirers significantly underperform relative to similar companies matched in size and survival. In contrast,

[97] The biases with market adjusted returns (relative to decile adjusted returns) are also found in studying the post-performance of acquirers of substantial assets (da Silva Rosa et al. (2004)) and post-IPO firms (Lin (2006)).

Table 5.2: Post-bid stock performance of acquiring firms - Wave vs. non-wave periods - Univariate evidence

This table presents mean and median statistics of stock returns to acquiring firms initiated in the wave and non-wave periods over the window [0,+18] months since the end of announcement month. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *Raw BHRs* is the buy-and-hold returns to sample of acquiring firms. *BHAR EW Decile* and *BHAR VW Decile* are the equal-weighted and value-weighted decile adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs to the decile to which sample firms belong. *BHAR EW Mkt* and *BHAR VW Mkt* are the equal-weighted and value-weighted market adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs of market portfolio. The benchmark (decile and market) portfolios include all firms that have the share price available for calculating the BHRs over the period [0,+18] months. *Obs No* is the number of observations in the sample of interest. The number of firms with higher mean/median BHARs from the 1,000 control portfolios than the original mean/median BHARs are in square brackets.

	Raw BHRs	**BHAR EW Decile**	**BHAR VW Decile**	**BHAR EW Market**	**BHAR VW Market**	**Obs No**
Panel A: 12-month post-takeover returns						
Mean						
Wave	5.62%	-4.70%	-3.58%	-12.26%	-5.33%	510
	$[966]^d$, $[936]^m$	[966]	[966]	[922]	[936]	
Non-wave	25.15%	5.12%	7.08%	-3.88%	10.91%	674
	$[292]^d$, $[263]^m$	[290]	[289]	[262]	[263]	
Total	16.74%	0.89%	2.48%	-7.65%	3.92%	1,184
	$[708]^d$, $[685]^m$	[708]	[709]	[685]	[684]	
Median						
Wave	7.53%	-4.74%	-4.39%	-14.60%	-6.04%	510
	$[924]^d$, $[920]^m$	[924]	[924]	[920]	[919]	
Non-wave	9.33%	-2.32%	-1.09%	-14.27%	-0.72%	674
	$[229]^d$, $[216]^m$	[229]	[228]	[217]	[216]	
Total	8.96%	-3.88%	-2.06%	-14.47%	-2.22%	1,184
	$[661]^d$, $[650]^m$	[660]	[660]	[651]	[650]	
Panel B: 18-month post-takeover returns						
Mean						
Wave	13.27%	-5.25%	-3.12%	-15.22%	-5.86%	510
	$[921]^d$, $[901]^m$	[921]	[922]	[902]	[901]	
Non-wave	35.33%	-1.34%	4.94%	-12.20%	13.35%	674
	$[400]^d$, $[461]^m$	[400]	[400]	[461]	[461]	
Total	25.83%	-3.02%	1.47%	-13.50%	5.08%	1,184
	$[767]^d$, $[770]^m$	[767]	[767]	[770]	[770]	
Median						
Wave	11.00%	-6.69%	-5.58%	-21.97%	-12.11%	510
	$[903]^d$, $[900]^m$	[903]	[903]	[899]	[900]	
Non-wave	16.24%	-3.36%	-2.19%	-25.75%	-1.30%	674
	$[377]^d$, $[350]^m$	[377]	[377]	[350]	[350]	
Total	15.39%	-5.05%	-3.49%	-23.80%	-5.46%	1,184
	$[740]^d$, $[726]^m$	[740]	[739]	[725]	[725]	

Table 5.3: Parametric and non-parametric tests

This table presents a summary of parametric (t-test) and non-parametric (Mann-Whitney) test statistics to compare the distribution between 2 groups (wave vs. non-wave, and first-half vs. second-half of the waves) of acquiring firms' returns. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *1st-half wave* and *2nd-half wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively. *Raw BHRs* is the BHRs to sample of acquiring firms over the window [0;+18] months from the announcement month. *BHAR EW Decile (Market)* and *BHAR VW Decile (Market)* are the equal-weighted and value-weighted decile (market) adjusted returns, respectively.

Panel A: Parametric test (t-test)

	Wave vs. Non-wave		**1st-half vs. 2nd-half wave**	
	t-stat	**p-value**	**t-stat**	**p-value**
12-month post-takeover returns				
BHARs				
Equally-weighted Decile	-0.1770	0.0408	-0.0686	0.6848
Value-weighted Decile	-0.1790	0.0155	-0.0606	0.7198
18-month post-takeover returns				
BHARs				
Equally-weighted Decile	-0.1847	0.6583	-0.0393	0.2220
Value-weighted Decile	-0.1767	0.1679	-0.0252	0.1981

Panel B: Non-parametric test (Mann-Whitney)

	Wave vs. Non-wave		**1st-half vs. 2nd-half wave**	
	Z-stat	**p-value**	**Z-stat**	**p-value**
12-month post-takeover returns				
BHARs				
Equally-weighted Decile	-1.3671	0.1716	-0.5837	0.5594
Value-weighted Decile	-1.4579	0.1449	-0.8530	0.3937
18-month post-takeover returns				
BHARs				
Equally-weighted Decile	-1.2351	0.2168	-1.0993	0.2717
Value-weighted Decile	-1.3831	0.1666	-1.4509	0.1468

"non-wave" acquirers and all acquirers do not show empirical evidence of under-performance.[98] These observations are consistent across mean and median statis-

[98]Our results do not report the under-performance of all acquiring in the post-bid periods. These are consistent with previous findings in Brown and da Silva Rosa (1998) in which they state that "the long-term performance of the acquiring firms in the post-merger period is consistent with the proposition that the market for corporate control is informationally efficient".

tics. Specifically, when assessing the 12-month post-takeover returns, 96.6% of "in-wave" control portfolios (966 out of the 1,000 control portfolios) have higher average decile adjusted returns than the average return of -4.70% of our sample "in-wave" acquiring firms. On the contrary, the percentage of control portfolios outperforming the experimental sample is only 29% for "non-wave" acquirers and 70.8% for all acquirers. Similar figures are also observed if abnormal returns are calculated in the next 18 months following takeovers: 92.1% for "in-wave" acquirers, 40% for "non-wave" firms, and 76.7% for all acquiring firms.

We conduct the parametric *t*-test and non-parametric Mann-Whitney test to examine the null hypotheses of having equal mean/median returns between "in-wave" and "non-wave" acquirers. For the case of 12-month post-bid returns, the difference between "in-wave" and "non-wave" acquirers' mean returns is significant at the 5% level (Panel A of Table 5.3), but there is no difference between the two groups in terms of the median figure (Panel B of Table 5.3). For the case of 18-month post-takeover returns, the null hypotheses of having equal mean/median returns between "in-wave" and "non-wave" acquiring firms cannot be rejected at the significance level of 10%.

First-half vs. second-half within the wave period

Table 5.4 shows the 12-month and 18-month post-bid stock performance of acquiring firms that announced bids in the first half and second half of the waves. As can be seen from this table, acquiring firms that participated in the first half of wave periods have higher abnormal returns (in both mean and median figures) than firms initiated their bids in the second half of waves. This result is observed for both the 12-month and 18-month post-bid returns (Panel A and B of Table 5.4). For example, in the case of equally-weighted decile adjusted returns for a period of 18 months following the bid announcement, the mean (median) decile adjusted returns to "first-half wave" acquiring firms are -0.26% (-3.66%), while they are -11.57% (-10.56%) for "second-half wave" bidders. Similar figures in the case of 12-month post-takeover returns are -3.71% (-3.21%) for "first-half wave"

Table 5.4: Post-bid stock performance of acquiring firms in wave periods - First-half vs. second-half wave - Univariate evidence

This table presents mean and median statistics of stock returns to acquiring firms initiated in the wave and non-wave periods over the window [0,+18] months since the end of announcement month. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *Wave* consists of 4 individual waves (Wave 1 (1987-1989), Wave 2 (1991), Wave 3 (1995-1996), and Wave 4 (2003-2004)). *1st-half wave* and *2nd-half wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively. *Raw BHRs* is the buy-and-hold returns to sample of acquiring firms. *BHAR EW Decile* and *BHAR VW Decile* are the equal-weighted and value-weighted decile adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs to the decile to which sample firms belong. *BHAR EW Mkt* and *BHAR VW Mkt* are the equal-weighted and value-weighted market adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs of market portfolio. The benchmark (decile and market) portfolios include all firms that have the share price available for calculating the BHRs over the period [0,+18] months. *Obs No* is the number of observations in the sample of interest. The number of firms with higher mean/median BHARs from the 1,000 control portfolios than the original mean/median BHARs are in square brackets.

	Raw BHRs	**BHAR EW Decile**	**BHAR VW Decile**	**BHAR EW Market**	**BHAR VW Market**	**Obs No**
Panel A: 12-month post-takeover returns						
Mean						
1st half wave	6.29%	-3.71%	-2.84%	-14.35%	-1.95%	285
	$[933]^d$, $[921]^m$	[933]	[933]	[921]	[920]	
2nd half wave	4.79%	-5.95%	-4.53%	-10.43%	-9.61%	225
	$[925]^d$, $[911]^m$	[925]	[926]	[911]	[910]	
Median						
1st half wave	12.72%	-3.21%	-0.83%	-14.60%	0.27%	285
	$[929]^d$, $[908]^m$	[929]	[929]	[908]	[908]	
2nd half wave	1.87%	-6.48%	-6.28%	-13.90%	-11.68%	225
	$[914]^d$, $[902]^m$	[914]	[914]	[902]	[902]	
Panel B: 18-month post-takeover returns						
Mean						
1st half wave	18.87%	-0.26%	0.87%	-14.08%	1.01%	285
	$[918]^d$, $[909]^m$	[918]	[919]	[909]	[909]	
2nd half wave	6.17%	-11.57%	-8.17%	-16.65%	-14.56%	225
	$[924]^d$, $[917]^m$	[924]	[924]	[917]	[917]	
Median						
1st half wave	22.34%	-3.66%	0.28%	-18.01%	-1.85%	285
	$[913]^d$, $[900]^m$	[913]	[913]	[900]	[900]	
2nd half wave	2.29%	-10.56%	-13.56%	-25.26%	-22.51%	225
	$[912]^d$, $[906]^m$	[912]	[912]	[906]	[904]	

acquirers, and -5.95% (-6.48%) for "second-half wave" acquirers. However, the parametric and non-parametric tests (Table 5.3) indicate that the difference in mean/median returns between the "first-half wave" and the "second-half wave" acquiring firms are not statistically significant at the 10% level.

Based on the application of the bootstrapping method for assessing statistical significance, both the “first-half wave” and the “second-half wave” acquirers experience significant under-performance at the 10% significance level under both the mean and median category. As demonstrated in Table 5.4, 93.3% of “first-half wave” control portfolios and 92.5% of “second-half wave” control portfolios on average outperform our experimental sample when returns of acquiring firms are assessed in a period of 12 months following takeovers. Similar figures are reported when returns are measured 18 months after takeover bids.

Annual average series

The above analysis use the original time series of all individual acquiring firms. We now take the annual mean and annual median from decile (equally-weighted) adjusted returns and graphically represent these time series in Figure 5.3. The 12-month and 18-month post-takeover returns are represented in the top panel and the bottom panel of Figure 5.3. The straight line and vertical bars denote the wave periods. As can be seen from Figure 5.3, the annual average return series exhibit similar patterns to the individual return series, with acquiring firms that announced bids in the “non-wave” periods reporting higher average (and median) annual returns than those announced during the “in-wave”’ periods.[99]

5.3.2.2 Multivariate analysis

The previous section (Section 5.3.2.1) compares the post-bid abnormal returns of acquiring firms that undertook M&As during the wave and non-wave periods, and in the first half or second half of waves. In this section, a multivariate model is estimated to control for other factors that can also influence the performance of acquiring firms other than the wave effect. Our control variables, as discussed in Section 5.2.2, are based on previous findings in the literature, which are takeover

[99] However, this difference is not statistically significant as indicated by both parametric (t-test) and non-parametric (Mann-Whitney) tests. T-statistics for the case of 12-month and 18-month post-takeover returns are -0.26 (p-value 0.26) and -0.37 (p-value 0.91) respectively, while z-statistic figures are -0.73 (p-value 0.47) and -0.79 (p-value 0.43)

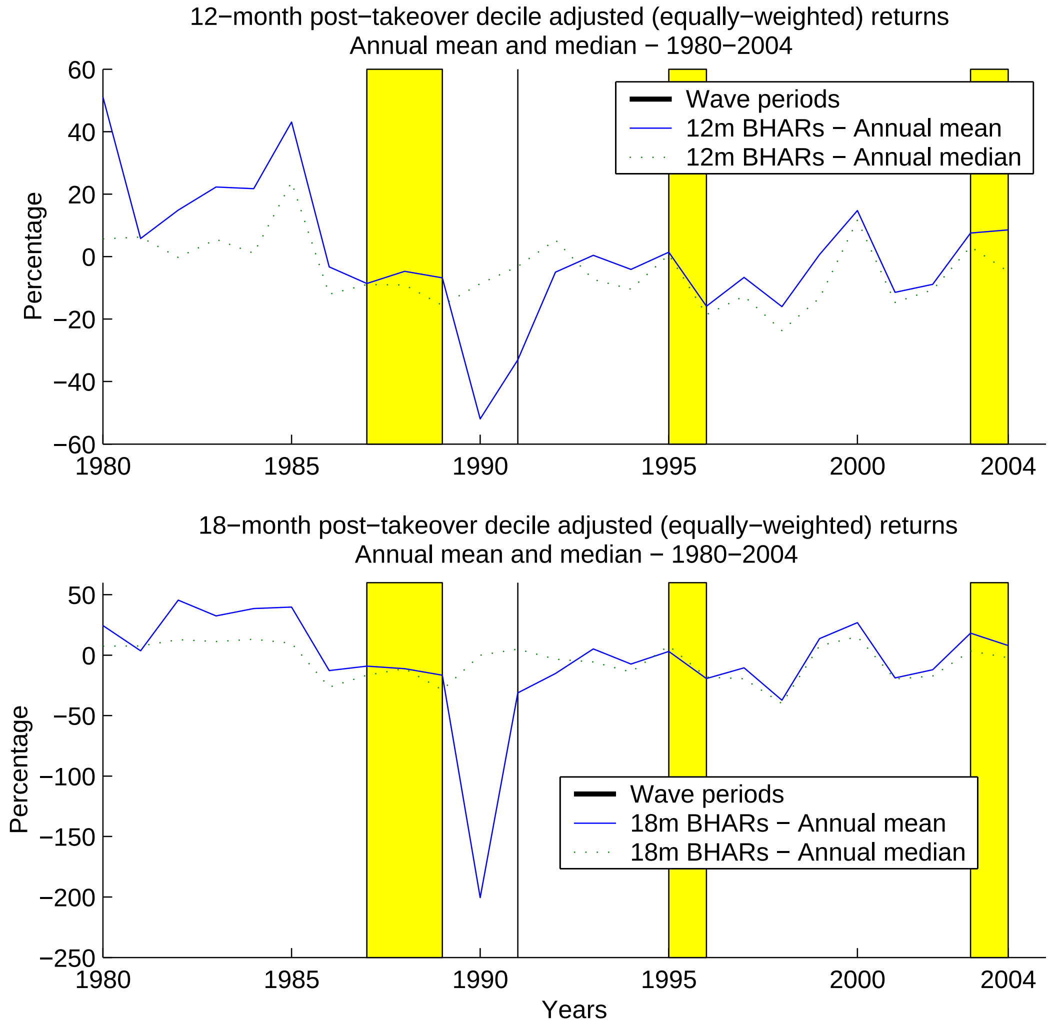

Figure 5.3: Equally-weighted decile adjusted returns to acquiring firms 12 months and 18 months after announcement month - Annual average and annual median series - 1980-2004

premium,[100] relative size of target to acquirer, industry relatedness, method of payment, and outcome of the bid.

Wave vs. non-wave period

Table 5.5 reports results when the long-run performance measure of acquiring firms is regressed against the set of control variables. The results are reported

[100]The takeover premium variable employed in the later regression analysis is calculated with reference to target share price two months before the announcement. The use of takeover premium relative to one month prior to the announcement date produces results that are exactly the same in terms of the sign of estimated coefficients and their statistical significance.

Table 5.5: Post-bid stock performance of acquiring firms - Wave vs. non-wave - Multivariate regression

This table presents the results of regressions of post-bid performance on merger waves and other control variables. *Premium* is the takeover premiums using target share price 2 months prior to the announcement month. *Relative size* is the ratio of target to acquiring firm's market capitalisation 2 months before the bid. *Industry relatedness* is a dummy variable for bids where both acquirer and target share the same 4-digit GICS industry code. *Stock payment* dummy refers to script-based only bids. *Successful bids* is a dummy variable where acquirer aims at majority control of target firm (acquiring firm holds less than 50% before the bid and greater than or equal 50% after the bid). *Wave periods* dummy identify takeovers taking place inside merger waves. The total period of examination is 1980-2004 with wave periods consisting of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004). Dependent variables are decile adjusted returns in all periods with columns headed EW use equally-weighted returns and those headed VW use value-weighted returns. Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are statistically significant at 10% level or better with superscript ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables: 12-month and 18-month post-takeover decile-adjusted returns in Total periods

	12-month post-takeover returns		**18-month post-takeover returns**	
	EW	**VW**	**EW**	**VW**
	(1)	**(2)**	**(3)**	**(4)**
Intercept	**0.1202**^{a}	**0.1165**^{a}	0.1246	**0.1340**^{b}
	(0.0466)	**(0.0432)**	(0.0859)	**(0.0570)**
Premium	-0.0440	-0.0449	0.0038	-0.0115
	(0.0442)	(0.0409)	(0.0813)	(0.0540)
Relative size	**-0.0482**^{a}	**-0.0318**^{a}	**-0.0906**^{a}	**-0.0502**^{a}
	(0.0077)	**(0.0071)**	**(0.0142)**	**(0.0094)**
Industry relatedness	-0.0286	-0.0155	-0.0301	-0.0060
	(0.0476)	(0.0441)	(0.0877)	(0.0583)
Stock payment	**-0.1405**^{b}	**-0.1171**^{b}	**-0.3707**^{a}	**-0.2442**^{a}
	(0.0601)	**(0.0556)**	**(0.1106)**	**(0.0735)**
Successful bids	0.0736	0.0658	0.0745	0.0370
	(0.0483)	(0.0447)	(0.0890)	(0.0591)
Wave periods	**-0.0969**^{b}	**-0.1051**^{b}	-0.0406	-0.0826
	(0.0472)	**(0.0437)**	(0.0869)	(0.0577)
Adjusted R^2 (%)	3.98	2.44	4.05	3.09
N	1,184	1,184	1,184	1,184

separately for each case of 12-month and 18-month post-bid returns, and for equally-weighted and value-weighted specifications.

Column (1) and (2) of Table 5.5 present the results for acquiring firms' returns in the next 12 months following takeover bids. As can be seen from these two columns, only three control variables, i.e. relative size, stock payment, and wave periods, significantly affect the post-takeover stock performance of acquirers. The coefficient on the wave dummy variable is negative and statistically significant at 5% level. Abnormal returns to "in-wave" acquirers would be 9.69% lower than that of "non-wave" acquirers in the case of equally-weighted portfolios, and 10.51% lower in case of value-weighted portfolios. This is consistent with the univariate result (Section 5.3.2.1) that "in-wave" acquiring firms have lower 12-month post-takeover stock performance than "non-wave" firms.

The estimated coefficient of the relative size variable is significantly negative at the 1% level in both cases of equally-weighted and value-weighted decile adjusted returns (Column (1) and (2) in Table 5.5). It shows the relationship between acquiring firm's relative size and its long-term abnormal returns is negative; the smaller is the firm's relative size, the larger is the BHAR for the acquiring firm later. For instance, the estimate of -0.0482 in the regression using equally-weighted decile adjusted returns (in Column (1) of Table 5.5) means that a takeover bid for a target that is about half the bidder's size produces an estimated bidder's BHAR 12 months after the announcement that is 1.93% lower than a bid for a target that is one-tenth the bidder's size.[101]

In the literature, the relative size variable is often significant, but the sign of its coefficient varies across studies. For instance, the relative size coefficient is positive in Asquith et al. (1983), but negative in Travlos (1987). It is often documented in the literature that smaller deals tend to outperform larger deals. For example, Moeller et al. (2005) find significantly negative abnormal returns to portfolios of "large loss deal" bidders for five years following mergers. The reason may be because the post-merger integration process is much easier for smaller deals - a less significant resource drain, more manageable assimilation logistics, and greater speed of execution. Bargaining power is more likely to favour the buyer in cases where the deal is less significant to the seller. Therefore, the risk

[101] Over the period of 12 months post-announcement, the bidder's BHAR of a bid for a target that is about half the bidders is -2.41% (-4.82%*0.50); the BHAR of a bid for a target that is one-tenth the bidder's size is -0.48% (-4.82%*0.10). So the difference would be -1.93% (-2.41% - (-0.48%)).

of overpayment is lower for smaller targets.

The statistically significant negative coefficient for the stock payment dummy variable indicates that our finding is also consistent with Myers and Majluf (1984)'s signalling hypothesis and previous studies on stock acquirers (Longhran and Vijh (1997), da Silva Rosa et al. (2000)). One year after the takeover bids are announced, firms using shares to finance their acquisitions experience (equally-weighted) adjusted returns that are 14.05% lower than their peers which use cash. Long-run abnormal stock returns to bidding firms reflect information effects associated with the method of payment used to finance the acquisitions.

We do not find the takeover premium to be a significant indicator of long-run stock performance of acquiring firms. In a recent survey, Pettit (2005)[102] also document that bid premium is not indicative of either short-term or longer-term success. He argues that successful deals demand disciplined acquirers, and that the takeover premium is influenced by too many factors to be a reliable indicator of success, including historical market values, strategic considerations, and estimated synergies.

Similar results are observed for bids funded by stock and relative size variables in the case of 18-month post-bid acquiring firms' returns (Column (3) and (4) of Table 5.5). They are both negative and statistically significant at the 1% level. Although the abnormal returns to acquiring firms 18 months following takeovers are lower during the wave periods than that outside the waves, its difference is no longer statistically significant at the 5% level, but it is significant at the 10% level. This is consistent with the univariate evidence (Table 5.2) when the difference in abnormal returns between "in-wave" and "non-wave" acquirers is smaller in the case of 18 months following takeover bids compared with the case of 12 months after.

[102] Pettit (2005) studies M&A transactions in the US from January 1992 to July 2004, where target's revenue was greater than $100 millions.

Table 5.6: Post-bid stock performance of acquiring firms in wave periods - First half vs. second half wave - Multivariate regression

This table presents the results of regressions of post-bid performance of acquiring firms initiated bids in merger waves. *Premium* is the takeover premium using target share price 2 months prior to the announcement month. *Relative size* is the ratio of target to acquiring firm's market capitalisation 2 months before the bid. *Industry relatedness* is a dummy variable for bids where both acquirer and target share the same 4-digit GICS industry code. *Stock payment* dummy refers to script-based only bids. *Successful bids* is a dummy variable where acquirer aims at majority control of target firm (acquiring firm holds less than 50% before the bid and greater than or equal 50% after the bid). *First-half wave periods* dummy identify takeovers taking place in the first half of waves. The wave periods of examination consist of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004). Dependent variables are decile adjusted returns in wave periods with columns headed EW use equally-weighted returns and those headed VW use value-weighted returns. Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are statistically significant at 10% level or better with superscript ^{a}, ^{b}, or ^{c} indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables: 12-month and 18-month post-takeover decile-adjusted returns in Wave periods

	12-month post-takeover returns		**18-month post-takeover returns**	
	EW	**VW**	**EW**	**VW**
	(1)	(2)	(3)	(4)
Intercept	**0.2107**^{a}	**0.1642**^{a}	**0.3275**^{a}	**0.2054**^{a}
	(0.0492)	**(0.0449)**	**(0.0798)**	**(0.0679)**
Premium	-0.0455	-0.0406	-0.0553	-0.0327
	(0.0429)	(0.0392)	(0.0696)	(0.0592)
Relative size	**-0.1089**^{a}	**-0.0716**^{a}	**-0.2019**^{a}	**-0.1086**^{a}
	(0.0075)	**(0.0068)**	**(0.0122)**	**(0.0103)**
Industry relatedness	**-0.1005**^{b}	**-0.0755**^{c}	**-0.1405**^{c}	-0.0840
	(0.0471)	**(0.0429)**	**(0.0764)**	(0.0650)
Stock payment	**-0.2280**^{a}	**-0.2409**^{a}	**-0.2085**^{b}	**-0.2342**^{a}
	(0.0592)	**(0.0540)**	**(0.0961)**	**(0.0817)**
Successful bids	-0.0139	-0.0128	-0.1171	-0.1044
	(0.0481)	(0.0439)	(0.0780)	(0.0663)
First-half wave periods	**-0.0812**^{c}	-0.0594	-0.0546	-0.0083
	(0.0461)	(0.0420)	(0.0748)	(0.0635)
Adjusted R^2 (%)	30.86	20.36	35.21	18.59
N	510	510	510	510

First-half vs. second-half within the wave period

Table 5.6 presents the results when we consider whether the timing of the takeovers in the first half or second half of wave periods can effect the performance of "in-wave" acquiring firms. The format of this table is similar to Table 5.5 (when comparing wave and non-wave periods). Column (1) and (2) of Table 5.6 show the results for equally-weighted and value-weighted BHARs for a period of 12 months after takeover bids, Column (3) and (4) of this table report the results of 18-month post-bid returns.

Similar to the findings reported earlier for bidders' performance during "in-wave" and "non-wave" periods, we find significant negative coefficients on relative size and stock payment variables for both 12-month and 18-month post-takeover returns. This indicates that bidding firms' post-takeover abnormal returns during the wave periods are significantly lower if using stock as method of payment, or acquiring other firms with higher ratio of relative size (target to acquirer).

The coefficient of the industry-relatedness variable is significantly negative,[103] except in the case of value-weighted decile adjusted returns 18 months post the takeover. The relatively lower post-takeover returns of industry-related takeovers during the wave periods is contrary to popular belief that like-industry acquisitions are more likely to be among the winners in the longer term than unrelated transactions. It is, however, consistent with the US finding in Agrawal et al. (1992) that "the under-performance of acquirers is worse in industry-related mergers than in conglomerate mergers" over several years after the mergers. More studies have provided support for the value creation properties of conglomerate mergers (e.g. Kendig (1997), Lins and Servaes (1999), Graham et al. (2002)). In a recent US study, Yan (2007) also documents that horizontal mergers are followed by substantially worse performance when they occur during waves.

Consistent with the univariate evidence presented earlier (Section 5.3.2.1), we do not find significant differences in post-takeover abnormal returns between acquiring firms that initiated bids in the first half and the second half of wave periods, except for the case of equally-weighted 12-month post-takeover returns.[104] There is, thus, very weak evidence to support the early-mover advantage of acquiring

[103] When dependent variable is bidders' stock performance in all periods (Table 5.5), industry-relatedness variable has insignificantly negative coefficient.

[104] In the case of equally-weighted specification for acquiring firms' returns in the next 12 months after the announcement, this variable's coefficient is still negative but statistically significant at 10% level (see Column (1) of Table 5.6).

firms that made their bids during the first half of takeover waves.

As can be seen from Table 5.5 and Table 5.6, adjusted R-squared figures increase substantially if the dependent variable is changed from post-merger returns in the total period under examination to that in the wave periods. For example, in the case of the equally-weighted 12-month post-takeover returns, the relevant adjusted R-squared are 3.98% (Table 5.5) and 30.86% (Table 5.6), respectively. We conduct a similar analysis to investigate the relationship between the control variables and post-takeover returns in the non-wave periods. The table of results is omitted for the sake of brevity, but the outcome from the regression is that adjusted R-squared figures are very low during the non-wave periods, ranging only from 0.11% to 1.03%. Therefore, it is concluded that our control variables can explain the variations in post-takeover returns much better for bids made in the wave states.

5.3.2.3 12-month survivors sample

The previous results (12-month and 18-month post-bid returns) are presented for the case of acquiring firms that survive over the next 18 months after takeover bids. Similar results for 12-month post-takeover returns are also obtained if the survival condition is limited to 12 months after the takeover bid announcement (refer to Appendix 5.A at the end of this chapter for analysis under the new survival condition. Univariate evidence is documented in Table 5.10, Table 5.11 reports results from parametric and non-parametric tests, and multivariate evidence is shown in Table 5.12). The only difference is the coefficient on “first-half wave” variable in the case of equally-weighted decile adjusted returns is no longer statistically significant under the 12-month survivors sample.

Table 5.7: Summary - Empirical results of post-takeover stock performance of acquiring firms

This table presents a summary of empirical results for post-bid stock performance of acquiring firms. There are 1,184 observations in the sample containing acquiring firms that survive in the next 18 months after the takeover announcement month. In case of 12-month survivors sample, the number of observations is increased to 1,275. The test of significance is at 10% level or better.

	Wave vs. non-wave		**1st-half vs. 2nd-half wave**	
	Univariate evidence	**Multivariate evidence**	**Univariate evidence**	**Multivariate evidence**
12-month post-takeover returns				
12-month survivors sample	Wave: smaller	Wave: smaller	No difference	No difference
18-month survivors sample	Wave: smaller (mean).	Wave: smaller	No difference	1st-half: smaller (EW decile).
	No difference (median).			No difference (VW decile).
18-month post-takeover returns				
18-month survivors sample	No difference	No difference	No difference	No difference

5.3.2.4 Summary: evidence of post-takeover performance of acquiring firms

In summary, it is found that acquiring firms earn normal post-takeover returns (relative to a portfolio of firms matched in size and survival) if their bids are initiated in the non-wave periods or over our total period of examination. However, for acquirers with bids during the wave periods, their stock under-performance in the long run is significant. Table 5.7 provides a summary of our empirical findings on post-takeover performance of acquiring firms grouped according to whether the bids took place during the wave and non-wave periods, and during the first half and second half of takeover waves. The summary is presented for both samples where acquiring firms survive in the next 12 months and 18 months after takeover bids.

As evident from the table, “in-wave” acquirers experience lower abnormal returns than “non-wave” acquirers. This difference is only statistically significant when the returns are calculated 12 months after the takeovers, but not for the longer

18-month horizon. In addition, the early-mover advantage is not strongly found within the wave dynamics. There is no significant difference in terms of abnormal returns for "first-half wave" and "second-half wave" acquirers.

5.3.3 Discussion

The above analyses have found that during the wave periods, acquiring firms pay lower takeover premiums and their post-bid stock performance is also significantly lower than those that announced their bids in the non-wave periods. Moreover, acquiring firms that initiated bids in the wave periods significantly under-perform relative to a portfolio of other firms matched in size and survival, while normal returns are observed in the non-wave and total periods. Our findings contradict the over-payment hypothesis (Berkovitch and Narayanan (1993), Kendig (1997)) which claims the adverse economic consequences to acquiring firms are due to over-payment to target shareholders. Our results suggest that the lower "in-wave" takeover premiums may be a sign of lower total economic gains, at the margin, to takeovers made in the wave periods.

In addition, we do not find supporting evidence for early-mover advantage for firms that initiated their bids in the first half of takeover waves. How can we explain the observed patterns of abnormal returns to bidding firms and takeover premiums in merger waves? In this section, we analyse which of the hypotheses can explain the wave effect, then present a potential explanation for it. As mentioned before (Section 2.4.1.1 in Chapter 2), there are three main groups of proposed theories in explaining for the incidence of merger waves and merger value creation (or value destruction).

The first group of models (managerial hypothesis) suggests that takeover waves are driven by hubris, herding behaviour and empire building of management which often leads to poor acquisition. Jensen (1986) argues that self-interested managers use excessive funds (free cash flows) to build up their managerial empire instead of returning them to shareholders. Merger waves occur when the costs of empire building are lower and hence the number of inefficient mergers is higher. Gorton et al. (2005) show that merger waves can arise when managers engage in preemptive takeovers to avoid being taken over themselves. Roll (1986)'s theory of managerial hubris provides another explanation for value-destroying mergers. In his model, overconfident managers of bidding firm are likely to overestimate the creation of merger synergy. So the acquirer's share price will fall eventually, since the acquiring firm pays a premium for the target where there are no synergistic gains to justify.

Roll (1986)'s managerial hubris hypothesis in combination with herding behaviour can explain clustering of M&A activity. Herding predicts that firms tend to mimic actions of a leader (Charfstein and Stein (1990)), so the first takeovers in a wave encourage other companies to mimic their actions rather than take actions based on clear economic rationale. Hence, it predicts that inefficient takeovers follow efficient ones and the inefficient takeovers are dominant in takeover waves. As a consequence, long-term stock returns of acquiring firms are lower for "in-wave" mergers than "non-wave" ones, while takeover premiums are higher in the wave periods. Also post-takeover stock returns to firm initiated bids at the later stage of the takeover waves are lower than those at the early stage, and bid premiums are higher in the final stages of the waves.

The second group (market mis-valuation hypothesis) argues that merger clustering is a result of financial market over-valuation. Under this hypothesis, mergers are clustered due to mis-pricing of the market (Shleifer and Vishny (2003)) or mis-valuation of takeover synergies between the merging parties (Rhodes-Kropf and Viswanathan (2004)). Although both models assume that bidders use their over-valued stocks to pay for relatively undervalued ones, there is a difference between them. In Shleifer and Vishny (2003)'s model, target managers accept overvalued bidders' equity because of their shorter time horizon and their wish to cash out their private gains, while in Rhodes-Kropf and Viswanathan (2004)'s model it is due to an error in valuing potential synergies. Because mergers occur due to timing of over-valuation, this leads to a prediction that acquiring firms under-perform in the long run following takeovers. In addition, this under-performance is more severe for firms that announced their bids in the wave periods than those outside the wave periods (Gugler et al. (2006)). Furthermore, higher takeover premiums will be observed in the wave periods than in the non-wave periods since takeover waves, under this hypothesis, are caused by wide over-valuation and dispersion in the aggregate.

The third group (the neoclassical hypothesis) claims that merger waves are the result of adequate responses of firms to industry and economy-wide shocks (e.g., Mitchell and Mulherin (1996), Harford (2005)). The neoclassical hypothesis implies that firms, by acting in the best interest of shareholders, make only acquisitions that increase their value. Therefore, acquiring firms should achieve normal long-run stock returns. Moreover, if a takeover wave occurs as a response to such shocks, it is expected that post-takeover stock performance for "in-wave" mergers would be equal or even greater than those outside the wave,[105] and bid premiums during the wave periods should be lower or at least equal to that observed outside the wave periods. Also, takeover waves contain all efficient acquisitions, it is expected that there is no significant difference in terms of post-takeover acquiring firms' stock returns and bid premiums between the first half and second half of waves.

Table 5.8 summarises the predictions together with our empirical findings for bid premiums and post-takeover stock performance of the three above-mentioned hypotheses of merger waves. Our empirical evidence indicates that none of the above theories dominate in explaining Australian takeover waves and their effects. While the managerial hypothesis and the market mis-valuation hypothesis

[105] Gugler et al. (2006) argue that under the neoclassical approach, the long run stock performance of acquiring firms following mergers should be indistinguishable from non-merging firms. Therefore, they believe that normal returns should be expected over longer post-merger windows, and this observation should be consistent for acquiring firms undertaken takeovers in both "in-wave" and "non-wave" periods.

Table 5.8: Predictions of bid premiums and post-takeover stock performance of three different hypotheses for merger waves

	Managerial	**Mis-valuation**	**Neoclassical**	**Finding**
Bid premiums				
Wave vs. non-wave	Wave: bigger	Wave: bigger	Wave: smaller or equal	Wave: smaller (2m premiums). No difference (1m premiums).
1st-half vs. 2nd-half wave	1st-half: smaller	No prediction	No difference	No difference
Post-takeover returns				
Total periods	Lower, compared with firms matched in decile and survival	Lower, compared with firms matched in decile and survival	No difference, compared with firms matched in decile and survival	No difference, compared with firms matched in decile and survival
Wave vs. non-wave	Wave: smaller	Wave: smaller	Wave: bigger or equal	Wave: smaller (post 12m case) No difference (post 18m case)
1st-half vs. 2nd-half wave	1st-half: bigger	No prediction	No difference	No difference

are supported based on acquiring firms' wealth destruction in the wave periods, they are not able to explain why there is no overpayment in terms of takeover premiums for "in-wave" takeovers (compared with the "non-wave" ones). Also we do not find the early-mover advantage in the wave periods, and the stock under-performance after mergers of acquiring firms in all periods as suggested by these two hypotheses. Conversely, the neoclassical hypothesis can account for normal returns to all bidding firms over longer windows following mergers, lower or equal bid premiums in the wave periods, and no early-mover wave effect. However, we do not see higher post-takeover abnormal returns for "in-wave" acquiring firms. It thus seems that a combination of these theories may provide better explanation.

Banal-Estanol et al. (2006) develop a theoretical model, by combining the neoclassical theory with Rhodes-Kropf and Viswanathan (2004)'s mis-valuation model, to explain for merger clustering based on asymmetric information and screening. In their model, the target rationally screens the acquirer on the expected synergy gains, by setting the takeover price. In periods of favourable economic conditions, screening out relatively "bad" acquirers becomes less desirable as the one-off merging costs are lower and merging with the inefficient acquirer becomes relatively more attractive. Therefore, they propose that economic booms cause a lack of screening and lead to a spike in merger activity. Their model predicts that "in-wave" mergers are, on average, "less efficient and thus less profitable in the long run". In contrast, mergers during the non-wave periods should stay relatively more profitable in the long term because these are better filtered out by the target.

Banal-Estanol et al. (2006)'s model claims that positive economic shocks are the main driver of takeover waves; and their merger wave "is characterised by an exogenous shift in the economic environment - an upward shift in the market demand - that simultaneously makes all mergers attractive".[106] The implications of Banal-Estanol et al. (2006)'s screening model are persistently matched with the findings from our previous work (see Chapter 4) on factors influencing aggregate takeover waves. In Chapter 4, it is found that capital liquidity plays a significant role in explaining the clustering of takeover activity. Takeover waves occur in periods of high liquidity in the credit market, corresponding with a low interest rate environment. In addition to that, based on our finding of normal returns to all bidders, we are more likely to accept the neoclassical hypothesis for merger activity.[107]

[106]Recent literature has supported the notion of favourably economic environment leading to the concentration of M&A activity. For instance, Lambrecht (2004) argues that when merger synergies are an increasing function of a product market demand, then each firm's payoff from merging has features similar to call options. Firms, thus, have an incentive to merge (exercise their options) in periods of economic expansion. Similarly, Toxvaerd (2004) claims that if an increase in an economic fundamental increases the number of expected future mergers, this in turn can induce preemptive mergers today, leading to cluster effects.

[107]In a recent work on examining stock market mis-valuations as a driver of Australian takeover activity over the period 1993-2000, da Silva Rosa et al. (2006)'s empirical evidence is not supportive of the mis-valuation hypothesis for M&A activity in Australia. They conclude

The liquidity argument combined with herding behaviour can explain the disappointing long-term returns to acquiring firms involved in takeovers in wave periods. The high capital liquidity (an economy-wide shock) can motivate responsible management to spring into action resulting in large scale reallocation of assets. However, due to herding behaviour, many other companies also take such actions in an irresponsible way, especially during wave periods. Takeover waves contain both efficient and herding behaviour. This, consequently, results in long-term stock under-performance of acquiring firms involved in M&As in wave states, normal returns in non-waves states and in all periods, and no difference between the early and later stages of the waves.

Capital liquidity can also account for the smaller bid premiums in the wave periods. According to traditional corporate finance theory, company share price represents the present value of future economic benefits. During wave periods, a lower interest rate means a lower discount rate, leading to a higher intrinsic value of securities and it, in turn, results in higher market price of securities, *ceteris paribus*. We also find that the stock market positively leads takeover activity by one quarter, especially in the wave periods.[108] Bid premiums are calculated using target share price two months prior to the announcement which is higher in the wave periods than outside the waves. Therefore, bid premiums are smaller during the wave states.[109]

that "the Australian evidence does not support the proposition that managers exploit their informational advantage to benefit from over-valuation".

[108]In Chapter 4, the current level of takeover activity is regressed against the aggregate and (the most active) industry share market performance lagged by one quarter, with controlling for the probability of takeover waves. It is found that coefficient on industry share market performance is significantly positive during the wave state (though this significance is suppressed when interest rate variable is included in the regression). In addition, it is graphically shown that the aggregate stock market (represented by the quarterly All Ordinaries Accumulation Index) is on the way going up before takeover wave periods (see Figure 5.4) in Appendix 5.B at the end of this chapter.

[109]As mentioned in the literature review (Section 2.3 of Chapter 2), Officer (2007), in a study of unlisted targets in the US, concludes that sellers are very aware of the loss in value when selling in a credit constrained environment. So if we follow the findings of Officer (2007), it seems reasonable to presume that sellers get a premium over fair value when they sell in a highly liquid market. However, our result of slightly lower premiums in the wave state is somewhat contradictory with Officer (2007)'s findings and there are possible few reasons for this divergence. Firstly, our sample contains of all takeover bids to Australian exchange-listed targets while Officer (2007) examines US unlisted companies that receive takeover offers. There

5.4 Summary

In this chapter, we have investigated effects of takeover waves to the shareholders of target and bidding firms by analysing the implications of three major theories of merger waves (managerial, mis-valuation and neoclassical theories).

Our empirical evidence indicates that target firm shareholders benefit from takeovers, and bidding firm shareholders do not loose in the long run. On average, the shareholders of acquiring firms are no better off, but often they lose if takeover bids are made during wave periods. We do not find the evidence of overpayment since the relationship between bid premiums and acquiring firms' long-term returns is not negatively significant.

We have found that no single theory can fully account for the Australian takeover waves and their effects. While the managerial hypothesis and the market mis-valuation hypothesis can account for the stock under-performance of acquirers that undertook M&As in the wave periods, they are not able to explain why bid premiums for "in-wave" takeovers are equal or lower than that outside the wave periods. Moreover, the early-mover advantage within the takeover waves, and the stock under-performance after mergers of acquiring firms in all periods, as suggested by these two hypotheses, are not found in our sample. In contrast, the findings of normal returns to all bidding firms over longer windows following the merger, lower bid premiums in the wave periods, and no early-mover wave effect

is evidence that listing status of target firms significantly affects the returns to bidders (e.g. Fuller et al. (2002), Faccio et al. (2004)), so it is expected that it would also affect takeover premiums. Secondly, our method of premium computation (i.e. using offer price and share price data) is different from Officer (2007)'s one which adopts Kaplan and Ruback (1995)'s "comparable industry transaction method". This technique computes acquisition discounts by matching acquisitions of unlisted targets to comparable industry and size-matched acquisitions of publicly traded targets, using accounting multiples (e.g. market to book ratio, price to earnings ratio). As acknowledged by Officer (2007), the percent difference in *multiples* is not equal to that difference in *premiums* between unlisted and listed targets. Thirdly, according to Officer (2007), acquisitions of unlisted targets experience, on average, 15% to 30% discount relative to acquisitions of comparable publicly traded firms. As reported in Table 5.1 of this chapter, our one-month average premiums are approximately 24% under the total period of examination, 25% for the wave periods and 23% for the non-wave periods. Therefore, it is possible that Officer (2007)'s acquisition discounts and our takeover premiums are not of the same sign, and it makes our result, to some extent, diverge from his findings.

are consistent with the neoclassical implications. Nevertheless, we do not find higher post-takeover abnormal returns for acquiring firms that announced their bids during the wave periods. Our results suggest that a combination of these theories may provide a better explanation.

The finding of normal returns (relative to a portfolio of other firms matched in size and survival) for bidders in the total periods of examination provides more support for the neoclassical argument. Furthermore, in one of our previous analysis (Chapter 4), it is found that the capital liquidity environment is the main driver of Australian aggregate takeover activity. A low interest rate leads to a high concentration of takeover bids. The under-performance effect for acquirers with bids during the wave states can be explained as the presence of herding behaviour.

Appendix 5.A: Analysis of 12-month survivors sample

This Appendix presents analysis on the merger sample which contains acquiring firms that survive in the next 12 months after the bid announcement month. There are 1,275 firms in the final sample, with 555 firms announced their bids during the wave periods and 720 firms in the non-wave periods.

Table 5.9 reports the analysis of takeover premiums. Univariate evidence on acquiring firm's returns 12 months after the takeover is presented in Table 5.10 with the parametric and non-parametric tests are in Table 5.11. The results on multivariate regression are in Table 5.12.

Table 5.9: 12-month post-takeover survivors sample - Takeover premiums

This table presents a summary of takeover premiums, calculated using target share price 2 months and 1 month before the announcement month. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *Wave* consists of 4 individual waves (Wave 1 (1987-1989), Wave 2 (1991), Wave 3 (1995-1996), and Wave 4 (2003-2004)). *First-half Wave* and *Second-half Wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively.

Panel A: Descriptive statistics

	2 months pre-announcement		**1 month pre-announcement**	
	Mean	**Median**	**Mean**	**Median**
Wave	26.21%	15.38%	24.39%	14.58%
First-half Wave	25.48%	15.38%	23.99%	15.06%
Second-half Wave	27.10%	15.38%	24.90%	14.29%
Non-wave	30.57%	20.83%	23.75%	17.62%
Total	28.67%	18.57%	24.03%	16.28%

Panel B: Parametric test (t-test)

	2 months pre-announcement		**1 month pre-announcement**	
	t-stat	**p-value**	**t-stat**	**p-value**
Wave vs. Non-wave	-9.2383	0.1413	-3.6302	0.8033
First-half vs. Second-half wave	-8.9217	0.7155	-8.7055	0.8468

Panel C: Non-parametric test (Mann-Whitney)

	2 months pre-announcement		**1 month pre-announcement**	
	Z-stat	**p-value**	**Z-stat**	**p-value**
Wave vs. Non-wave	-2.6447	0.0082	-1.4656	0.1428
First-half vs. Second-half wave	-0.1816	0.8559	-0.0386	0.9692

Table 5.10: 12-month post-takeover survivors sample - Post-bid stock performance of acquiring firms - Univariate evidence

This table presents mean and median statistics of stock returns to acquiring firms initiated in the wave and non-wave periods over the window [0,12] months since the end of announcement month. The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *1st-half wave* and *2nd-half wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively. *Raw BHRs* is the buy-and-hold returns to sample of acquiring firms. *BHAR EW Decile* and *BHAR VW Decile* are the equal-weighted and value-weighted decile adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs to the decile to which sample firms belong. *BHAR EW Mkt* and *BHAR VW Mkt* are the equal-weighted and value-weighted market adjusted returns, defined as the difference between BHRs to sample of acquiring firms and BHRs of market portfolio. The benchmark (decile and market) portfolios include all firms that have the share price available for calculating the BHRs over the period [0,12] months. *Obs No* is the number of observations in the sample of interest. The number of firms with higher mean BHARs from the 1,000 control portfolios than the original mean BHAR are in square brackets.

	Raw BHRs	BHAR EW Decile	BHAR VW Decile	BHAR EW Market	BHAR VW Market	Obs No
Panel A: Wave vs. non-wave						
Mean						
Wave	3.28%	-5.73%	-5.22%	-13.42%	-7.24%	555
	$[994]^d$, $[988]^m$	[994]	[994]	[988]	[988]	
Non-wave	24.72%	3.56%	6.32%	-3.90%	11.01%	720
	$[295]^d$, $[315]^m$	[295]	[295]	[314]	[314]	
Total	15.38%	-0.48%	1.30%	-8.05%	3.07%	1,275
	$[815]^d$, $[834]^m$	[814]	[814]	[834]	[832]	
Median						
Wave	5.30%	-5.00%	-4.81%	-16.63%	-6.80%	555
	$[972]^d$, $[960]^m$	[972]	[972]	[960]	[960]	
Non-wave	9.63%	-1.72%	-0.32%	-14.49%	0.17%	720
	$[300]^d$, $[320]^m$	[300]	[300]	[320]	[321]	
Total	8.34%	-3.05%	-2.11%	-15.09%	-2.56%	1,275
	$[800]^d$, $[809]^m$	[800]	[801]	[808]	[809]	
Panel B: First half vs. second half of waves						
Mean						
1st half wave	4.24%	-6.53%	-5.13%	-14.34%	-3.12%	307
	$[966]^d$, $[958]^m$	[965]	[965]	[958]	[958]	
2nd half wave	2.08%	-4.75%	-5.33%	-12.29%	-12.33%	248
	$[930]^d$, $[919]^m$	[930]	[930]	[919]	[919]	
Median						
1st half wave	11.84%	-2.57%	-1.67%	-16.87%	-0.81%	307
	$[943]^d$, $[937]^m$	[943]	[943]	[937]	[937]	
2nd half wave	0.47%	-7.90%	-7.63%	-16.54%	-15.33%	248
	$[920]^d$, $[912]^m$	[920]	[920]	[912]	[912]	

Table 5.11: 12-month post-takeover survivors sample - Parametric and non-parametric tests

This table presents a summary of non-parametric Mann-Whitney test statistics to compare the distribution between 2 groups (wave vs. non-wave, first-half vs. second-half wave). The *Total* period of examination is 1980-2004 with *Wave* period consists of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004), and the remaining years refer to *Non-wave* period. *1st-half wave* and *2nd-half Wave* refer to bids occurring in the first half (according to time) and second half of each wave, respectively. *Raw BHRs* is the BHRS to sample of acquiring firms over the window [0;12] months from the announcement month. *BHAR EW Decile (Market)* and *BHAR VW Decile (Market)* are the equal-weighted and value-weighted decile (market) adjusted returns respectively.

Panel A: Parametric test (t-test)

	Wave vs. Non-wave		**1st-half vs. 2nd-half wave**	
	t-stat	**p-value**	**t-stat**	**p-value**
12-month post-takeover returns				
BHARs				
Equally-weighted Decile	-0.1700	0.0474	-0.1018	0.7270
Value-weighted Decile	-0.1844	0.0059	-0.0709	0.9645

Panel B: Non-parametric test (Mann-Whitney)

	Wave vs. Non-wave		**1st-half vs. 2nd-half wave**	
	Z-stat	**p-value**	**Z-stat**	**p-value**
12-month post-takeover returns				
BHARs				
Equally-weighted Decile	-1.8760	0.0606	-0.8780	0.3800
Value-weighted Decile	-2.2791	0.0227	-1.2826	0.1996

Table 5.12: 12-month post-takeover survivors sample - Post-bid stock performance of acquiring firms - Multivariate regression

This table presents the results of regressions of post-bid performance on merger waves and other control variables. *Premium* is the takeover premium using target share price 2 months prior to the announcement month. *Relative size* is the ratio of target to acquiring firm's market capitalisation 2 months before the bid. *Industry relatedness* is a dummy variable for bids where both acquirer and target share the same 4-digit GICS industry code. *Stock payment* dummy refers to script-based only bids. *Successful bids* is a dummy variable where acquirer aims at majority control of target firm (acquiring firm holds less than 50% before the bid and greater than or equal 50% after the bid). *First-half wave periods* dummy identify takeovers taking place in the first half of waves. *Wave periods* dummy identify takeovers taking place inside merger waves. The total period of examination is 1980-2004 with wave periods consisting of 8 years (1987-1989, 1991, 1995-1996 and 2003-2004). Dependent variables are decile adjusted returns in all periods with columns headed EW use equally-weighted returns and those headed VW use value-weighted returns. Standard errors appear in parentheses below the parameter estimates. Bold figures indicate that the coefficients are statistically significant at 10% level or better with superscript ^{a}, ^{b}, and ^{c} indicate statistical significance at the 1%, 5% and 10% level, respectively.

Dependent variables: 12-month post-takeover decile-adjusted returns in Total or Wave periods

	Wave vs. Non-wave		**1st-half vs. 2nd-half wave**	
	(1) EW	**(2) VW**	**(3) EW**	**(4) VW**
Intercept	**0.1250^a**	**0.1261^a**	**0.169^a**	**0.1165^a**
	(0.0458)	**(0.0413)**	**(0.0462)**	**(0.0427)**
Premium	-0.0449	-0.0509	-0.0516	-0.0447
	(0.0435)	(0.0392)	(0.0417)	(0.0386)
Relative size	**-0.0472^a**	**-0.0318^a**	**-0.1002^a**	**-0.0661^a**
	(0.0077)	**(0.0069)**	**(0.0073)**	**(0.0068)**
Industry relatedness	-0.0479	-0.0277	**-0.1012^b**	**-0.0742^c**
	(0.0465)	(0.0419)	**(0.0448)**	**(0.0414)**
Stock payment	**-0.1881^a**	**-0.1462^a**	**-0.2092^a**	**-0.2101^a**
	(0.0583)	**(0.0526)**	**(0.0561)**	**(0.0518)**
Successful bids	0.0706	0.0596	-0.0103	-0.013
	(0.0473)	(0.0427)	(0.046)	(0.0425)
Wave periods	**-0.0904^b**	**-0.114^a**		
	(0.0462)	**(0.0416)**		
First-half wave periods			-0.0433	-0.0212
			(0.0437)	(0.0404)
Adjusted R^2 (%)	3.98	2.77	27.01	17.17
N	1,275	1,275	555	555

Appendix 5.B: Takeover waves and the share market graph

Figure 5.4 shows the quarterly series of the All Ordinaries Accumulation Index together with our takeover wave periods over the period from 1980 to 2004.

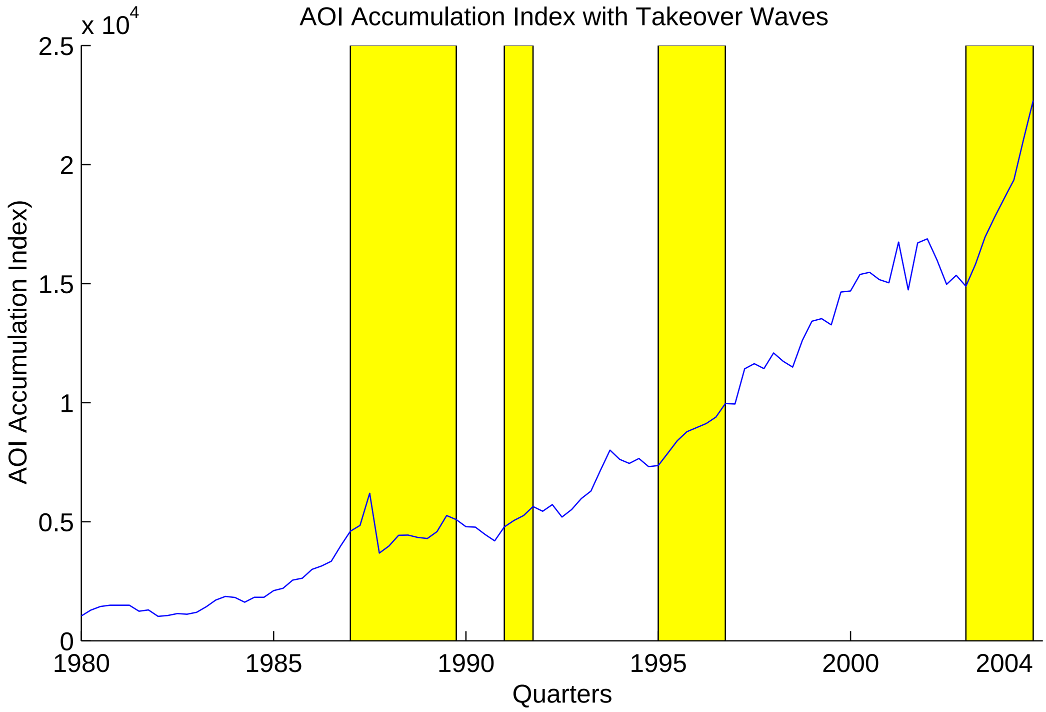

Figure 5.4: All ordinaries accumulation index with takeover waves - Quarterly series - 1980-2004

Chapter 6

Conclusions

6.1 Summary of findings and contributions

A number of aspects of Australian takeover waves have been considered in this dissertation. First, we study the time series behaviour of takeover activity, and propose a new model of detecting takeover waves (Chapter 3). We then apply the probability of being in a wave state to examine the influences of economic and financial factors to merger waves (Chapter 4). The last part deals with the effects of takeover waves to the shareholders of acquiring firms in the long run (Chapter 5). This is analysed together with takeover premiums paid to targets' shareholders.

6.1.1 Chapter 3 - Modelling of time-series of takeover activity

It is commonly observed that the intensity of takeover activity varies over time with concentrations occurring in particular time periods to generate merger waves. While the concept of merger waves is popular in the literature, there is no agreement on how best to describe them in a time-series context. On the one hand, it is often claimed that M&A activity is random and therefore unpredictable. On the other hand, it is contended that it is possible to model the time series behaviour of M&A activity. In Chapter 3, we investigate the behaviour of takeover activity in Australia by using a recent and comprehensive data set (by covering all takeover bids to ASX-listed target companies over the period from 1972 to 2004).

It is shown that linear models are not sufficient to capture all the structure of the takeover data, and aggregate takeover behaviour is better characterised by a non-linear two-state Markov switching model.

A model describing the takeover time series is then proposed by combining a State-Space model with a Markov switching regime model. The thesis' contribution is a refined method to cover more generalised time series and to improve the goodness-of-fit of the model. Under our new approach, two distinct ARMA(1,1) processes are used to describe the wave and non-wave states of takeover activity. The existing Markov switching models using AR processes are only special cases of our proposed model. Empirical results based on the approach adopted here have shown an improvement over other Markov switching models.

Four merger waves are detected over the annual period 1972-2004, one in the late 1980s (1987-1989), a second in the early 1990s (1991), a third in the middle 1990s (1995-1996) and a forth in the early 2000s (2003-2004). The expected duration of a wave state is considerably shorter than that of a non-wave state. On average, the Australian takeover market is characterised by the low level of M&A activity for about six years, and then jumps into its high level for around two years.

6.1.2 Chapter 4 - Takeover waves and influences of financial and economic factors

Although takeover waves are generally acknowledged in the literature, previous research on the reason why they take place has almost exclusively used single-state models without accounting for their existence. In Chapter 4, this issue is re-examined by proposing a two-state regression model in which the probability of takeover waves (as identified in Chapter 3) is controlled.

We start our analysis by examining the number of takeover bids for targets listed on the ASX over the period 1980-2004. We find that movements in the stock market do not play a significant role in explaining the concentration of takeover activity, but interest rate does. The level of interest rate is the only variable significantly associated with variations in the rate of takeover activity. Our findings are robust to both long-term and short-term interest rate measures. Interest rate is significantly negative in both the wave and the non-wave states with a higher coefficient observed in the wave state. We further show that the level of interest rate is an important and relevant variable as residuals (from the regression) are not persistent when the interest rate variable is included in the model. Our analysis suggests also that our two-state model is significantly better than the single-state regression in which the existence of merger waves is ignored.

Our results are robust to changing our measure of takeover activity from the number of takeover bids to the proportion of bids relative to the number of ASX-listed companies. Our findings are consistent with the argument advanced by Shleifer and Vishny (1992) that liquidity can account for the clustering of takeover activity. Historical aggregate takeover activity appears to move with the state of the debt market: the low level of the interest rate (i.e. high liquidity in the debt market) leads to a concentration of takeover bids.

Decomposition of the time series of aggregate takeover bids by method of payment also provides strong support for the liquidity hypothesis in the Australian market. Tests on the two series of cash-funded and stock-funded bids (normalised by the number of companies listed on the ASX) reveal that the interest rate variable is significantly negative in the wave state of the time series of cash deals, while its statistical significance is not discovered in the series of stock deals.

We also perform the analysis to the biggest takeover market in the world, the US market, to examine our findings can extend beyond the Australian market. We can only obtain data for 23 years (from 1982 to 2004) though we are unable to obtain the same set of controls as are used in the Australian analysis. However, a remarkably similar pattern is still observed: the level of interest rate is strongly associated with high concentration of bids in the US takeover market.

6.1.3 Chapter 5 - Consequences of riding takeover waves

Chapter 5 has two main objectives. Firstly, to assess the consequences of takeover waves to the shareholders of target and bidding firms. Secondly, to understand the economic implications of the three theories of merger waves (managerial, misvaluation and neoclassical theories) so that a justification for the wave effects in Australia can be accounted for.

Although it is usually reported that targets earn large positive abnormal returns, the question of whether acquiring shareholders benefit in the post-takeover periods is still unresolved. In addition, the literature on stock returns to Australian bidding firms either focuses on the returns without reference to the existence of takeover waves (e.g. da Silva Rosa (1994), Brown and da Silva Rosa (1998), Simmonds (2004)), or takes into account the existence of takeover waves but only considers the announcement effect using a simple method of return calculation (Kendig (1997)). To counteract this gap, the effects of takeover waves on acquiring firms' stock performance in the long run are explored in this chapter. Our method of return calculation is adopted from Brown and da Silva Rosa (1998) in which firm size and survival are controlled for. Additionally, takeover premiums are also analysed since it is often claimed that the long-term undesirable effect to acquiring firms is due to overpayment made to target shareholders.

Our empirical results have shown that shareholders of target firms are the winners in the takeover game with an average bid premium about 29% based on the share price taken two months prior to the bid announcement. However, acquiring firm shareholders earn only normal returns (relative to a portfolio of other firms matched in size and survival) in the long run post takeovers. Additionally, they experience long-term stock under-performance if the decision to acquire other firms were initiated in the wave periods. No evidence of overpayment has been found in our sample.

It is also found that none of the three hypotheses of merger waves can totally explain their presence in the Australian environment. The findings of normal returns to all bidding firms in the long run, of smaller or equal bid premium in the wave periods (compared with the non-wave periods), and of no early-mover advantage within the wave dynamics, are all consistent with the neoclassical predictions. However, the observation of lower or equal returns to “in-wave” acquiring firms provides evidence that supports the managerial and mis-valuation theories.

We lean towards the neoclassical argument since there is more evidence to support this theory in Chapter 5, and the results found in Chapter 4 further strengthen it. In Chapter 4, it is evident that the key driving force of takeover waves in Australia comes from the disturbance in the liquidity environment, not from speculative activity. However, besides the efficient market motivation, herding behaviour is also alternatively present during the wave periods. This is justified for the under-performance effect of “in-wave” acquiring firms.

6.2 Limitations and future research

Though some new methods are proposed and improvements are made, the thesis still has some limitations, and addressing them will be left to future research. In particular,

- There are number of data limitations in this thesis. The principal dataset (used in Chapter 3) only covers takeover bids to exchange-listed targets over the period 1972-2004. It excludes takeover bids made for private targets. Furthermore, the latter chapters of the thesis (Chapter 4 and Chapter 5) only use a truncated version (from 1980 to 2004) due to lack of data on other variables in the 1970s such as macro-economic variables and offer price of takeover deals.

- Although the use of two-state model is common in analysing takeover activity, this is not necessarily the optimal number of states (Hamilton (1989, 1994)). The quarterly data might well better suit a three-state model because of the relatively higher concentration of takeover bids in the 2003-2004 period.

- The thesis recognises the fact that it is desirable to identify more specific variables to proxy for the managerial, mis-valuation and neoclassical hypotheses. For example, deregulation has been identified to have been the dominant economic shock in US, at least during the 1990s. Australia has also experienced deregulation and similar M&A waves, so it is expected that deregulation can be proxied for economic shocks in the analysis. Also, possible variables for the managerial and mis-valuation theories could include bidding firm's previous takeover experience, the book-to-market (B/M) equity ratio, or net external financing by acquiring firms prior to takeovers.

- The result from Chapter 4 suggests that a low interest rate is associated with a high concentration of takeover activity, and more liquidity can contribute to merger waves. However, a low interest rate environment could be proxying for other effects that have some influence on M&A activity. An alternative explanation for the finding in Chapter 4 could be that the government lowers interest rate to stimulate the economy in a downward business cycle, when firms are more likely be to financial distressed and become targets. Firms with high cash reserves are more likely to be involved in takeovers because the price of the distressed firms is relatively low causing higher concentration of M&A activity.

- As acknowledged in Chapter 4 that our sample contains foreign bidders, but this chapter only looks at local interest rate as a proxy for local debt market liquidity. Future work could thus treat foreign bidders separately or incorporate a global interest rate.

- The underlying assumption in Chapter 4 is that firms choose debt rather than equity to fund their investments during low interest rate periods. This implicates the market timing hypothesis of capital structure (Baker and Wurgler (2002)). Therefore, future research could empirically investigate how market timing of alternative financing methods affect takeover activity.

- It is found in Chapter 4 that firms are more likely to engage in M&A activity when the debt market is more liquid. As an alternative choice, firms can also form alliances. Future work thus could examine how capital liquidity affects firm alliance decisions.

- There is evidence in the literature that acquiring private firms is more profitable than acquiring public firms. For instance, Fuller et al. (2002) show, for a sample of firms that make five or more acquisitions in the 1990s, that their abnormal returns are higher if acquiring private firms or subsidiaries than acquiring public firms. Hence, the conclusions in Chapter 5 may be more representative if private firms are in our inclusion criteria.

- The analysis in Chapter 5 only concentrates on stock performance of acquiring firms. It could include measures for operating performance such as the post-merger return on assets (ROA) for more comparative results.

- The post-bid returns to acquiring firms in Chapter 5 are controlled for size. Since there are different benchmarks in the literature, those returns can be compared against industry or non-merging firms.

- The returns to acquiring firms can only be calculated for a maximum period of 18 months following the takeover bids due to availability of SPPR data at the time of completing this thesis. A natural extension would be to analyse returns for a longer period post the takeover.

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