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Volatility, Price-Discovery and Trading Volume in Australian Equity
Index and Option Markets

A dissertation presented in partial fulfilment of the requirements for

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To

My dear wife Aileen and sons Michael and Thomas.

This dissertation is completed with their love and encouragement.

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Abstract

This dissertation investigates the information considerations of volatility, price-discovery and the relationship change in volume and volatility resulting from index derivatives transactions on financial markets in Australia.

The impact of information on volatility was investigated in the essay one, as volatility is a key factor for accurately pricing derivative securities. I assessed the forecast accuracy, unbiasedness and information content of volatility forecasts, based on implied volatility and conditional volatility models for the S&P/ASX 200 Index Options market in Australia. The conditional volatility models produce the most accurate forecasts and are robust when forecasting into short time horizons.

Essay two, investigates the information content of the index and option markets in the price-discovery process. Based on the above volatility results, the long-run equilibrium relationship between the share price index and the implied price of the share-price-index option was investigated. Causality was determined to show which market leads the other. Information share measures were used to gauge the contribution of the share price index and index option markets to the price-discovery process. Unambiguous evidence shows the index market leads the options market and the former contributes more to price-discovery than the latter.

In essay three, I investigate the dynamic relationship between the future price volatility of the S&P/ASX 200 Index and the trading volume of the S&P/ASX 200 Index Options to explore the informational role of option volume in predicting price volatility. I found the contemporaneous call options volume have a significant strong

positive feedback effect on the implied volatility, but the contemporaneous feedback effect of volume on the TARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call options volume are positive, significant and strong.

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1 Volatility, Price-discovery and Trading Volume in Australian Equity Index and Options Markets

1.1 Introduction

Financial markets are defined by the trading and settlement technologies which they employ, regulations, market participants, traded instruments information mechanisms and the information trading protocols which surround these technologies and mechanisms. These institutional details are important, as the trading systems and regulations affect the liquidity, transaction costs and efficiency of the market. In perfectly frictionless and rational markets, the prices of securities and security derivatives must simultaneously reflect the incorporation of information into prices, otherwise costless arbitrage profits would be possible.

The first objective of this dissertation is to investigate volatility as a measure of the amount by which an asset price is expected to fluctuate over a given period. Financial variables often exhibit quiet periods, followed by volatile periods, indicating that volatility is not constant, but varies over time. Therefore, it seems reasonable for risk-averse investors to require a time-varying risk premium as a reward for bearing financial risk over time. Volatility is also a key factor for accurately pricing derivative securities. Despite the key role that volatility plays in finance, there is no way to observe it directly in the market; rather, it must be estimated.

The second objective of this dissertation is to investigate the lead/lag relationship and price-discovery between the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options traded on the ASX. In perfect markets, perfect substitutes must have the

same price, since price discrepancies are instantly arbitrated away and no arbitrage opportunities should exist. Returns on derivative securities, such as stock index options and futures contracts with payoff structures, can be replicated by a portfolio of stocks, and bonds should not lead or lag returns on the spot index. Moreover, the returns should be perfectly correlated. Option markets provide a means of hedging positions held in underlying markets. Black (1975) suggested that informed traders utilise option markets, given the higher leverage they offer compared to the underlying market. Evidence that the options market leads the stock market provides some support for the notion that option markets are used by informed traders to make speculative profits. Conversely, evidence that the stock market leads the options market supports the notion that options are used primarily to hedge positions held in the underlying stocks. One aspect of the price-discovery function of the share market is establishing the value of companies and their shares, and any share market will have a number of indices designed to reflect changes in the value of listed securities (Hunt and Terry, 2005)

The third objective of this dissertation is to investigate the relationship between the future price volatility of the S&P/ASX 200 Share Price Index and the trading volume of S&P/ASX 200 Index Options to explore the informational role of option volume in predicting the price volatility. A limited number of studies have examined the direct links between the option-trading volume and the stock-price volatility expected in the future. The ability to predict price volatility is important for portfolio selection and asset management as well as for the pricing of derivative securities.

Understanding the way in which information is processed in financial markets is important for the general analysis of market efficiency. Shocks leading to higher

volatility should dissipate quickly and returns data should approximate a normal distribution, given a random flow of information. One aspect of the price-discovery function of the share market is establishing the value of companies and their shares, and any share market will have a number of indices designed to reflect changes in the value of listed securities (Hunt and Terry, 2005). The Australian options market changed in 1998 from floor trading to screen trading and the Australian Stock Exchange (ASX) changed its benchmark index in 2000, then in 2001 sold its index market business to Standard & Poor's. These changes in the microstructure of the share market, stock index and stock index options market motivated this study.

1.2 Outline of this Dissertation

I investigated the options market in Australia as index options can offer similar benefits to index futures contracts relating to hedging and leverage. Options have non-linear characteristics and offer contingent trading outcomes unavailable with futures contracts. This dissertation presents three essays on the information considerations of volatility, price-discovery and trading volume on index and options markets in Australia. Each essay (presented in Chapter 3, 4 and 5) deals with a separate research question. Thus the literature relevant to the question is discussed and reviewed separately within each chapter. An exploration is carried out of the market microstructure aspects of volatility, price-discovery and the role of option-trading volume on the S&P/ASX 200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX.

Australia has two exchanges, namely the Australian Stock Exchange (ASX) and the Sydney Futures Exchange (SFE). Apart from individual stocks, the ASX is also an

exchange for trading index options. The All Ordinaries Index was the main stock market index from 1980 to 2000. Before April 2000, the All Ordinaries Index was considered Australia's institutional benchmark index. The All Ordinaries combined stocks from these exchanges to calculate one return for the Australian equity market. The All Ordinaries was launched in January 1980, to act as an indicator for the Australian equity market.

As the Australian investment community became more sophisticated, the role of the All Ordinaries changed as investors began using the index to closely track or benchmark the performance of their investments. It was based on the top 300 shares listed on the ASX. In 2000, the ASX introduced new indices, the most important of which were the ASX 100, ASX 200 and ASX 300. These indices were based on the largest companies, measured by market capitalisation and the most actively traded shares listed on the ASX. The ASX sold its index business to Standard & Poor's and the indices are now known as the S&P/ASX 100, S&P/ASX 200 and S&P/ASX 300. With extensive use by institutional investment managers, mutual fund managers and professional advisers, an estimated A\$200 billion in funds under management is benchmarked to the S&P/ASX 200.

The optimal approach to estimate volatility is still an open issue. The existing literature provides conflicting evidence when studies conducted in different markets are compared. In Australia, we must also be cautious when applying volatility measures, because the various measures of realised volatility and forecasted volatility are subject to estimation errors and model misspecification.

Empirical research into lead/lag relations between stock indices and index derivatives has been inconclusive. Most of the research on stock and option markets has been focused on US markets (NYSE, AMEX, OTC, and CBOT) but these are dealer markets with less than full automation. The ASX is a competitive order-matching market with full automation, suggesting that different market structures may give rise to different spreads.

1.3 Organisation of this Dissertation

Chapter 2 gives an institutional overview of the ASX and the S&P/ASX Australian indices. A detailed discussion in terms of the products which I am using for the other chapters is included.

Chapter 3 investigates the forecast power of Autoregressive Conditional Heteroscedasticity (ARCH)-type models and the implied volatility for the Australian equity market. Volatility of the ASX has not received much attention and research into implied volatility characteristics of the Australian market after full automation could not be found. Forecast accuracy, unbiasedness and the information content of volatility forecasts are assessed, based on the implied volatility and ARCH-type models for the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options.

In Chapter 4, an assessment is made of the nature of the short-run and long-run equilibrium relationships between the stock prices implied by the S&P/ASX 200 Index Options prices and the S&P/ASX 200 Share Price Index, with a co-integration approach and an error-correction model being presented to test the causal relationships. The direction of this association is also determined (i.e., whether the S&P/ASX 200 Share

Price Index tends to lead changes in the S&P/ASX 200 Index Options, or vice versa). The asset price dynamics are extracted and applied to the findings from the previous chapter, which are implicit in the market prices of stock index options and the underlying stock index. Common-factor models are utilised to measure the contribution of the S&P/ASX 200 Share Price Index and S&P/ASX 200 Index Options markets to the price-discovery process, using information-sharing and permanent-transitory models.

In Chapter 5, the dynamic relationship between the future volatility of the S&P/ASX 200 Share Price Index and the trading volume of the S&P/ASX 200 Index Options are examined to explore the informational and hedging role of option volume in predicting the price volatility. The future volatility of the index are approximated alternatively by implied volatility and by Threshold Autoregressive Conditional Heteroscedasticity (TARCH) volatility. I will use a simultaneous equation model to capture the volume-volatility relations and investigate if contemporaneous feedbacks exist between the future price volatility and the trading volume of call options.

Chapter 6 summarises the contributions of this dissertation. Suggestions for future work conclude this work.

1.4 Contribution of this Dissertation

The literature is extended in at least two ways by this study. First, previous studies on forecasting volatility failed to perform the so-called Modified Diebold and Mariano (DM-LS) test in forecast evaluation and relied on visual inspections on the size of some accuracy measures. This work corrects this oversight. Second, previous studies focused on relatively large and liquid markets (such as those in the US and the UK). This

study investigates a relatively small and illiquid market, which may behave differently from larger markets.

The modified version of the Diebold and Mariano (1995) test proposed by Harvey, Leybourne et al., (1999) uses the squared prediction errors to make pair-wise comparisons of different models and its statistics are adjusted for the presence of ARCH in forecast errors. This work uses the modified Diebold and Mariano test. I did find the Threshold Autoregressive Conditional Heteroscedasticity (TARCH) model outperforms implied volatility in terms of forecast accuracy, indicating its better tracking of realised volatility.

Finally, little evidence is available concerning the lead/lag and price-discovery relationships on the index and option markets in Australia. To my knowledge, this is the first study of the lead/lag relationship and price-discovery function of the S&P/ASX 200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX. The results, contrary to other literature, indicate the index market plays the primary role in the price discovery in Australian markets. Unambiguous evidence shows the index market leads the options market and the former contributes more to price-discovery than the latter.

2 The Australian Index and Option Markets

2.1 Introduction

The Australian Stock Exchange (ASX)¹ can trace its roots back to the establishment of the Melbourne Stock Exchange in 1861. This was followed between 1871 and 1889 by exchanges in each of what were to become the future Australian federation's state capitals. In 1987, the national Australian Stock Exchange and National Guarantee Fund were formed as part of the process to amalgamate all the individual state stock exchanges along with their associated fidelity funds. The ASX was one of the pioneers in launching electronic trading with the introduction of SEATS for a restricted number of listed stocks. During the 1990s, the ASX introduced a range of new products. 1992 saw the introduction of the ASX Derivatives Board and in 1993, SEATS featured fixed-income trading. The ASX also began forging links with overseas exchanges including the Korea Stock Exchange and Kuala Lumpur Stock Exchange. This was followed in 2001 with the implementation of ASX World Link, allowing Australian investors to trade 200 counters on the NYSE, NASDAQ and AMEX. In the same year, a co-trading link was formalised between the ASX and the Singapore Exchange. In 1994, a fully electronic central clearing house, the Clearing House Electronic Sub-register System (CHESS), was established for all Australian equities, and in 1996 this was expanded to include settlement for overseas companies. The same year saw ASX members vote to de-mutualise. Following Government legislation, the ASX change of

¹ Information from <http://www.asx.com.au/markets>.

status took place on October 13, 1998. The next day, ASX shares were listed for trading. In 2006, the ASX achieved a long-standing ambition to take over the Sydney Futures Exchange.

The ASX provides a range of financial products, including equities, exchange-traded options, debt securities market, ASX futures, listed managed investments, and warrants. The ASX lists more than 1500 companies and is the 8th largest stock exchange in the world. Institutional business accounts for 50 per cent of all transactions. Currently, equities are traded via SEATS, which will be superseded by the derivatives CLICK XT terminal, thereby offering a single integrated trading platform across the ASX's products. The ASX and Standard & Poor's offer a range of indices calculated by S&P for the Australian equities markets, including the benchmark ASX/S&P All Ordinaries. The ASX launched exchange traded options (ETOs) to provide local investors with a hedge to reduce risk and generate additional revenue on their equity portfolios. The benchmark index is the S&P/ASX Buy Write Index. The ASX Debt Products provides markets in corporate bonds, floating-rate notes, convertible notes and hybrid products. The ASX offers futures contracts for the equity, interest rate, commodity currency and energy markets. The key products are Equity Index Futures, Mini Index Futures, S&P/ASX 50, S&P/ASX 200 Options Property Trust Futures, Commodity Futures, Options Grain Futures, Options Wool Futures, Energy Futures and Electricity Futures. The ASX offers six types of LMIs for trading, namely Listed Property Trusts (LPTs), Listed Investment Companies (LICs), Infrastructure Funds, Exchange Traded Funds (ETFs), Pooled Development Funds and Absolute Return Funds.

There are approximately 3489 exchange-traded warrants with both European and American ex-style issues. The ASX allows multiple types of warrants to be issued and traded. Like other exchanges, the ASX charges for its feeds. However, it itemises the content and charges are dependent upon the subscribed sub-set. Delayed and end-of-day data are available free of charge. In 2006, the ASX launched low-latency market data services based on the FIX protocol provided by the Cameron FIX Market Data Server Platform, which is being introduced as SEATS is migrated to CLICK. This will encompass all of the ASX's traded instruments. ASX feeds are widely available via Bloomberg, Reuters and Thomson, as well as a range of smaller specialist vendors.

2.2 The Australian Index Market²

The All Ordinaries Index was the main stock market index from 1980 to 2000. Before April 2000, the All Ordinaries was considered Australia's institutional benchmark index. It was Australia's first truly national index, and replaced the regional indices independently run on the Sydney and Melbourne exchanges. The All Ordinaries took stocks from these exchanges and combined them to calculate one return for the Australian equity market. The All Ordinaries was launched in January 1980 to act as an indicator for the Australian equity market. Over the years, the Australian investment community became more sophisticated and the role of the All Ordinaries changed as investors began using the index to closely track or benchmark the performance of their investments. It was based on the top

² Standard and Poor's: S&P/ASX Indices Overview from [http://www.asx.com.au/statistics/13/Index Description](http://www.asx.com.au/statistics/13/Index%20Description).

300 shares listed on the ASX. In 2000, the ASX introduced new indices, the most important of which were the ASX 100, ASX 200 and ASX 300. These indices were based on the largest companies, measured by market capitalisation and the most actively traded shares listed on the ASX. The ASX sold its index calculation business to Standard & Poor's and the indices are now known as the S&P/ASX 100, S&P/ASX 200 and S&P/ASX 300.

The S&P/ASX 200³ is recognised internationally as Australia's principal equity index. With extensive use by institutional investment managers, mutual fund managers and professional advisers, an estimated A\$200 billion in funds under management is benchmarked to the S&P/ASX 200. The S&P/ASX 200, together with the entire S&P/ASX index series, was launched in the Australian market in April 2000. The launch of these indices coincided with Standard & Poor's taking over the index business, formerly owned and managed by the ASX.

The introduction of the S&P/ASX series placed Australia's indices at the forefront of the global market, displaying the performance of the Australian equity market and putting it alongside other leading international indices, including the U.S. S&P 500, as one of the world's most transparent and investable equity benchmarks.

The new series of indices included the S&P/ASX 200 and S&P/ASX 300 and the renaming of the 20, 50, and 100 Leaders indices as the S&P/ASX 20, S&P/ASX 50 and S&P/ASX 100. The existing All Ordinaries Index was also broadened to include 500

³ The S&P/ASX 200 equity index: <http://www2.standardandpoors.com/spf/pdf/index/SPASXDirectory2006.pdf>

stocks, with no screening for liquidity, and the sector indices, based on the former 24 ASX industry-classification structure, were recalculated against the S&P/ASX 200 and S&P/ASX 300.

In conjunction with the introduction of the S&P/ASX indices in April 2000, index review periods changed from monthly to quarterly. The market welcomed this approach, because it reduced participant turnover in the indices, therefore reducing associated tracking costs.

In June 2001, Standard & Poor's introduced a new series of live industry sector indices. Derived from the Global Industry Classification Standard (GICS), these were launched over the S&P/ASX 200, while day-end GICS sector indices were launched over the S&P/ASX 300. These indices ran parallel to the traditional 24 ASX sector indices that also ran over the S&P/ASX 200 and S&P/ASX 300.

The traditional 24 ASX sector indices were discontinued in July 2002, with investors adopting GICS as the primary classification system for the Australian market. Investors realised that as well as facilitating comparisons between the overall performance of global market sectors and industry groups, Australians could invest in companies overseas with a greater understanding of their underlying business, and vice-versa for overseas investors interested in Australian companies.

2.3 Standard & Poor's Assumes Control of the Index Calculation Process

On November 26, 2001, Standard & Poor's assumed sole responsibility for the calculation of the S&P/ASX indices. The previous ASX index calculator had been calculating the indices, sending index values to the ASX SEATS trading platform and its

open-interface distribution system, generating index reports and storing historical data. Standard & Poor's replaced the ASX calculation engine with its own live index calculator, which began feeding index values to the ASX for circulation. SPICE (Standard & Poor's Index Calculation Engine), developed by Standard & Poor's and used for all of its global indices, also began calculating official day-end S&P/ASX index values.

From October 1, 2002, after extensive market consultation and feedback in favour of the change, Standard & Poor's integrated "free float" into the S&P/ASX methodology. The move was designed to enhance the transparency of the S&P/ASX indices, by standardising the methodology for selecting which portion of a company should be included in each index.

The previous liquidity-factor methodology had a level of uncertainty and was subject to a certain amount of interpretation. The use of an investable weight factor (IWF), based on the free float of a stock⁴, removed ambiguity, as substantial shareholder information is freely available to the market. It also reflects which shares are available to the broader investment community. The move to free float necessitated the use of a global standard in terms of allocation of index weight, which brought the Australian market more in line with global equity markets.

The change to a Standard & Poor's system affected the S&P/ASX indices in three broad areas:

⁴ Free float can be defined as the percentage of each company's shares that are freely available for trading in the market. A company's index market capitalisation is calculated by multiplying its price by the number of ordinary shares by an investable weight factor.

- Calculation methodology. The replacement of last price adjusted (by a higher bid or lower offer) with last price simplified the calculation process and subsequently provided greater transparency. Standard & Poor's also introduced the divisor in the calculation of indices. The divisor does not alter the outcome of the index value, but allows for quicker computation.
- Timing of index reports. The distribution of index reports was brought forward from midnight to 7 pm at the close of each trading day, allowing market members to verify their close-of-trade positions more efficiently.
- Changes to the daily management practices. Standard & Poor's assumed control over all inputs to the index process, including the number of constituent securities, security index price, shares and the proportion of each security included in each index. This allowed Standard & Poor's to implement methodology practices that have made it more efficient for institutions tracking the index by simplifying the treatment of corporate actions and reducing the frequency of share changes, which has, in turn, reduced index turnover.

The S&P/ASX 200 is designed to offer representation of a broad benchmark index, covering about 85 per cent of market capitalisation in the Australian equity market. It achieves this coverage while maintaining the liquidity characteristics of narrower indices. This unique combination makes the S&P/ASX 200 ideal for portfolio management and index replication. All Standard & Poor's indices are constructed with the aim of matching the economic sector distributions of the securities universe from which they are drawn. This allows comparison between Standard & Poor's sector weightings and actively managed portfolios, so that a plan sponsor or superannuation

fund consultant can determine exactly where a manager is adding or losing value in stock selection or trade execution. This procedure also works across all S&P/ASX equity indices, which together make a unified whole.

In maintaining the S&P/ASX 200, Standard & Poor's Australian index analysts are able to draw on the organisation's breadth of experience and practice. The S&P/ASX 200 methodology strikes the appropriate balance between quantitative and qualitative stock.

2.4 The Australian Options Market

The Australian Options Market (AOM) is a contemporary mixed market dealer structure. Like many international option exchanges, the AOM has undergone a significant transformation over time, evolving from a floor-traded dealer market structure to a dealer structure superimposed on an electronic limit order book. The market is characterised by a competitive dealer price structure that operates with an open electronic limit order book. ASX options are traded on a screen-based system over a range of leading shares and indices that are viewable to all market participants. These options are characterised by a standardised set of strike prices and expiry dates that occur on the Thursday before the last Friday of the settlement month.⁵ Trades are executed on a price-priority then time-priority basis and quotes represent firm orders. In the financial year ending June 30, 2007, nearly 23 million options contracts traded on the ASX market. This represents the equivalent of A\$27 billion in turnover.

⁵ Excessive product differentiation through a range of expiries and moneyness levels has the ability to foster market power. Requirements by the AOM for market makers to undertake obligations in identical combinations of moneyness and expiry are designed to prevent market failures.

Market makers play a pivotal role in the AOM. Market makers are charged with maintaining a regular market presence by quoting maximum bid-ask spreads and a minimum depth on a range of option series and maturities. These obligations are ascertained from the liquidity category that a security is designated to. This process demonstrably contributes to the price-discovery process by ensuring that option quotes are informative, binding and continuous throughout the trading day. Although the exchange compensates market makers for providing liquidity, market makers are not granted any special trading privileges over other market participants. Market makers in the AOM can operate in one of three capacities: making a market on a continuous basis only, or making a market in response to quote requests only, or making a market both on a continuous basis and in response to quote requests.⁶

The presence of market makers is, however, not the sole source of competition on the ASX Options market. Market makers may face direct competition for order flow from limit-order traders. Despite this direct competition, however, market makers are the primary providers of liquidity, representing approximately 80-85 percent of executed volume and a much greater percentage of overall quoting behaviour.⁷

2.5 S&P/ASX 200 Index Options

Options on the S&P/ASX 200 were first listed on the ASX in March 2000. The expiry day of ASX call options is the third Friday of the contract month, providing this is

⁶ A detailed outline of market maker obligations in the AOM is available from http://www.asx.com.au/investor/options/trading_information/market_makers.htm

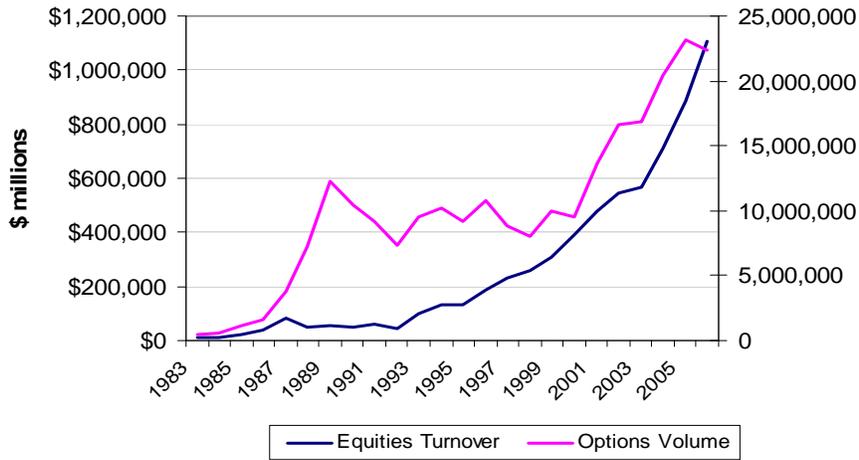
⁷ The AOM is primarily made up of institutional investors and therefore direct competition from smaller limit-order traders is limited.

a trading day, trading ceasing the day before. The options are settled in cash using the opening price index calculation on expiry day. In order to obtain a greater sample size, Share Price Index (SPI) options listed on the Sydney Futures Exchange were used as proxies for S&P/ASX 200 options prior to the year 2000.

The S&P/ASX 200 Index Options are traded on the ASX and written against the S&P/ASX 200 index. The first contracts had a listing date of March 31, 2001. These options contracts are European in exercise style and have a quarterly expiry cycle: March, June, September and December. The types of these contracts are call and put options (code XJO). The exercise prices are set at intervals of 25 index points and new exercise prices are automatically created as the underlying index oscillates. Index options are expressed in points and each point is worth \$10. The expiration day is the third Thursday⁸ of the expiry month or the following business day when the expiry Thursday happens to be a public holiday. Trading ceases at noon on expiry Thursday. This means trading will continue after the settlement price has been determined. The S&P/ASX 200 Index Options are settled in cash. The settlement amount is based on the opening prices of the stocks in the underlying index on the morning of the last trading date. The closing value of the index is determined on the opening prices of the stocks in the underlying index on the morning of the maturity date. As the stocks in the relevant index open, the first traded price of each stock is recorded. Once all stocks in the index have opened, an index calculation (Opening Price Index Calculation, OPIC) is made using these opening prices.

⁸ It was the first Friday before September 2004

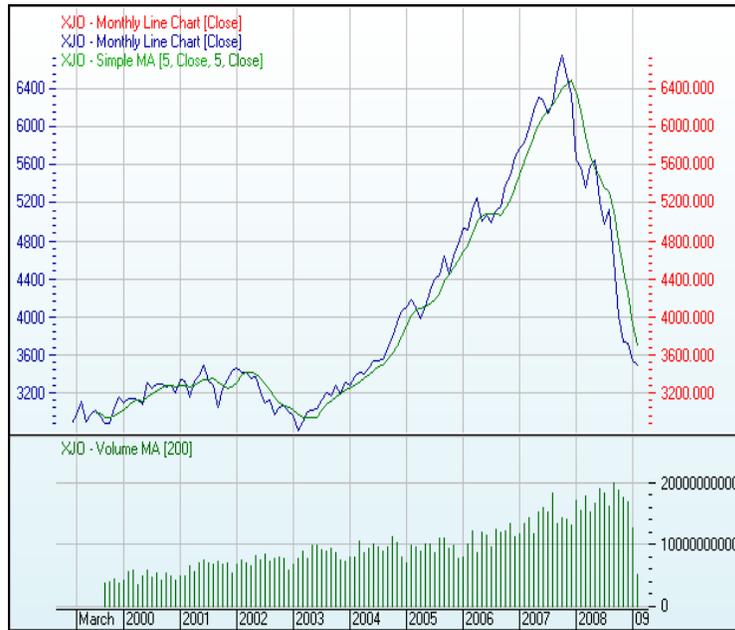
Figure 2-1 Turnover on ASX (Equities) and Volume in ASX Options



Source: Data supplied by ASX

Figure 2-2 Turnover and Volume of S&P/ASX 200 Index Options (XJO)

This figure represents the monthly prices over 10 years for S&P/ASX 200 Index Options. The blue line represents the price or value of the S&P/ASX 200 Index. The actual price or value is shown on the left axis. The green line represents the moving average for the S&P/ASX 200 Index Options. The green bars represent the turnover for the S&P/ASX 200 Index Options.



Source: Data supplied by ASX

These contracts can be traded during the normal trading hours between 6 am and 5 pm and night trading hours between 5.30 pm to 8 pm (Sydney local time). Unlike the ASX equities market where liquidity is provided by electronic orders, the options market uses market makers to provide liquidity. Each market maker is assigned one or more stocks in which they must meet certain obligations for certain percentages of time. This involves quoting buy and sell prices for a certain number of series, and/or responding to requests from other market participants for prices.

Table 2-1 Contract Specifications S&P/ASX 200 Index Options

Underlying asset	ASX approved indices (currently the S&P/ASX 200 Index).
Exchange	Australian Stock Exchange (ASX).
Exercise style	European.
Listing date	March 31, 2001.
Settlement	Cash settled based on the opening prices of the stocks in the underlying index on the morning of the last trading date.
Exercise intervals	25 index points.
Expiry day	The third Thursday of the month, unless otherwise specified by ASX.
Last trading day	Trading in expiring contracts will cease at 12 noon on expiry Thursday.
Premium	Expressed in points.
Contract month	March, June, September, December.
Strike price	Expressed in points.
Index multiplier	A specified number of dollars per index point, currently AUD \$10.
Contract value	The exercise price of the option multiplied by the index multiplier.
Trading hours	6am to 5pm and 5.30pm to 8pm Sydney local time.
Settlement day	The first business day following the last trading day.

Note: All the information in this table was obtained from the ASX website: www.asx.com.au

Turnover and volume from 2001 to 2008 of the S&P/ASX 200 Index Options (XJO) traded are depicted in Figure 2-2 and the contract specifications are summarised in Table 2-1. Following the introduction of index options in 1983, turnover in ASX equities increased from \$10.3 billion to \$1107 billion by the end of 2006. At the same time, trading in equity options, including index options, increased strongly to 22.3 million

contracts traded in 2006. The option volumes increased markedly in the years following the 1987 global stock market crash before stagnating for most of the 1990s. Following the 2000 dotcom crash and resulting recession, option turnover again began to increase rapidly, closely shadowing equities turnover through the resulting bull market.

3 Forecasting Stock Market Volatility and Assessing Information

Content Present in S&P/ASX 200 Index Options Prices

3.1 Introduction

This chapter seeks to improve the ability to price the S&P/ASX 200 Index Options by creating and testing a model for predicting the underlying options volatility, which is the most important component when pricing options. How information shocks impact on return volatility is the key ingredient in modelling volatility, and how information flows into a market place can have a major impact on volatility. Volatility is investigated as a measure of the amount by which an asset's price is expected to fluctuate over a given period. Many researchers have questioned the information content and forecast quality of implied volatility and realised volatility. I join the debate by examining the accuracy, unbiasedness and information content of volatility forecasts based on implied volatility and conditional volatility models for the S&P/ASX 200 Index Options market in Australia. As we have recently seen, financial variables often exhibit quiet periods followed by volatile periods, indicating that volatility is not constant but time varying. Therefore it seems reasonable for risk-averse investors to require a time-varying risk premium as a reward for bearing financial risk. Yet, despite the key role volatility plays in finance, there is no way to observe volatility directly in the market. Rather it must be estimated. Most existing studies have concentrated on the most actively traded options on the U.S. markets. Options traded on the Australian markets have seldom been examined, despite the growth in trading volume and availability of price data.

The optimal approach to estimating volatility is still an open issue. The existing literature provides conflicting evidence when comparing different markets. In 1988, the Australian Share Price Index used liquidity and market capitalisation as key qualifications for choosing and weighting companies included in the index (Aitken, Brown et al., 1995) (Carew, 2007). In April 2000, the All Ordinaries Index was changed from a benchmark index to a market indicator index. It now comprises the 500 largest companies in Australia by market capitalisation, representing 95 per cent of the market capitalisation of the Australian equity market. Criteria for selection also changed, as the liquidity of a company is no longer relevant for inclusion in the All Ordinaries Index. In 2000, the ASX introduced new indices and the most important were the ASX 100, ASX 200 and ASX 300. These indices are based on market capitalisation, liquidity and free float⁹. Previous Australian research used index data across the 20 Leaders, 50 Leaders, and All-Ordinaries indices when the options on the index were traded on an open outcry system before screen trading was introduced on October 31, 1997.

Basically there are two approaches to forecasting volatility. The first is to extract information about the volatility of future returns from their history. The simplest way to obtain this kind of volatility estimate is by computing the standard deviation of a financial asset's past returns. Black (1976) claims, however, that this approach is unreasonable as the relevant volatility is in the future and not in the past and the two will not necessarily be equal. In response, financial economists have developed more sophisticated models to extract volatility information from past asset returns. The most

⁹ Free float can be defined as the percentage of each company's shares that are freely available for trading in the market. A company's index market capitalisation is calculated by multiplying its price by the number of ordinary shares by an investable weight factor.

commonly used models are ARCH (Autoregressive Conditional Heteroscedasticity) and its generalised version, GARCH (Generalised Autoregressive Conditional Heteroscedasticity).

Alternatively, volatility can be estimated using implied volatility. If the options market is efficient, the instantaneous variance of return embedded in the option price can be interpreted as an ex ante forecast of the average volatility of the underlying asset over the life of the option (Hull and White, 1987). Christensen and Prabhala (1998) state that if option markets are efficient, implied volatility should be an efficient forecast of future volatility; i.e., implied volatility should subsume the information contained in all other variables in the market information set when explaining future volatility.

In this chapter, I first examine how information flows affect volatility in order to determine which of the available linear and non-linear GARCH models will theoretically yield the best results. Each of the models are tested by producing parameter estimations and goodness-of-fit statistics using market data to see if my theoretical predictions prove correct. The accuracy, unbiasedness and information content of volatility forecasts, based on the implied volatility and ARCH-type models at the 1-, 5-, 10- and 20-day forecast horizons for the S&P/ASX 200 index and the S&P/ASX 200 Index Options are assessed.^{10 11} Then, the models are applied to out-of-sample data to see if the results are robust. The analysis undertaken allows me to recommend the most appropriate models

¹⁰ Standard and Poor's: S&P/ASX Indices Overview from http://www.asx.com.au/statistics/l3/IndexDescription_MS3.shtm#S&P/ASX_200_Index

¹¹ Information from http://www.asx.com.au/markets/l4/IndexOptions_AM4.shtm

for predicting return volatility patterns for the S&P/ASX 200 Index Options hence solving a key element in the puzzle of how best to price S&P/ASX 200 index options.

I contribute to the literature around changes in the market microstructure of the Australian Stock Exchange (ASX), as the index composition changed when the ASX sold its index calculation business to Standard & Poor's. Insights are added into comparing the forecast accuracy, unbiasedness and information content of volatility forecasts, based on implied volatility and conditional volatility models for the S&P/ASX 200 Index Options market in Australia. The conditional volatility models produce the most accurate forecasts and are robust when forecasting into short time horizons.

3.2 Literature Review

Volatility refers to a statistical measure of the dispersion of a return distribution and is specified as the square root of the conditional variance, estimated on the basis of the information available at t , and projected τ periods ahead (Schwert, 1990). To model changes in the variance, I use the Autoregressive Conditional Heteroscedasticity (ARCH) pioneered by Engle (1982) or the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models developed by Bollerslev (1986). While the vast majority of earlier studies relied on ARCH and GARCH frameworks, there is now a large and diverse body of time-series literature on volatility modelling. Among the most popular techniques are those belonging to the family of ARCH models.

Since the 1980s, forecasting models, such as ARCH and GARCH, have been developed in order to predict volatility from historical return data. In relation to financial markets, these models have been developed to describe the returns-generating process. These

models are typically found to work well for in-sample fits and have begun to challenge the forecasting power of implied volatility. Hence, subsequent studies on implied volatility have focused more interest on the comparison of the forecast performance of these two approaches. Day and Lewis (1992) study the relative forecasting power of implied volatility versus a GARCH estimate, by adding implied volatility as an explanatory variable in the GARCH conditional variance equation. They find, for OEX options, that both implied volatility and historical data contain incremental information about future volatility. Xu and Taylor (1995) extend the same approach to currency options data.

The behaviour of volatility to good and bad news (the so-called leverage effect) is translated into asymmetric GARCH models, such as the Threshold ARCH model (Zakoian, 1994) and Threshold GARCH model (Glosten, Jagannathan et al., 1993). The TARARCH model is based on the assumption that unexpected (unforeseen) changes in the return of an asset, expressed in error terms, have a different effect on the conditional variance of returns. An unforeseen increase is presented as good news and contributes to the variance in the model through a multiplier. An unforeseen fall, which is a piece of bad news, generates an increase in volatility. The asymmetric nature of the returns is given by a positive, indicating a leverage effect.

A drawback of the GARCH-type models is the occurrence of negative variances for some parameters, which are meaningless. Therefore, non-negativity constraints have to be imposed on the parameters. Nelson (1991) claims the non-negativity constraints in the GARCH model are too restrictive to overcome this problem, so introduces the Exponential GARCH model instead. EGARCH models the logarithm of the conditional

variance where the co-efficient γ measures the asymmetric effect, which, if negative, indicates that negative shocks have a greater impact upon conditional volatility than positive shocks of equal magnitude.

EGARCH has certain advantages over GARCH. Using an exponential formulation, the restrictions of positive constraints on the estimated co-efficients in GARCH are no longer necessary. Further, the GARCH model fails to capture the negative asymmetry apparent in many financial time series. The EGARCH model solves this problem by allowing for the standardised residual as a moving average regressor in the variance equation, while preserving estimation of the magnitude effect.

Franses and van Dijk (1996) investigate whether ARCH and GARCH models could adequately describe stock price behaviour in European capital markets, which are generally much smaller and thinner than the US market. They compare standard GARCH, quadratic-GARCH, and TARARCH models for forecasting weekly volatility of various European stock market indices. They find the non-linear GARCH models are unable to outperform the standard GARCH model.

Tse (1991) and Tse and Tung (1992) investigate the performance of the GARCH model in the Japanese and Singaporean markets. Their results, however, question the superiority of the GARCH model, as they find strong evidence in favour of an exponentially weighted moving average (EWMA) model.

Canina and Figlewski (1993) find evidence against an efficient and unbiased hypothesis. By using a simple regression procedure, the S&P 100 Index Options from 1983 to 1987, and the Black-Scholes (1973) model, they report that implied volatility is a

poor forecast of subsequently realised volatility, compared to simple historical volatility. Lamoureux and Lastrapes (1993) make the first attempt to introduce the stochastic volatility option model into the study of implied volatility. Their tests on individual stock options reject the orthogonal restriction forecasts from time-series models and should not have predictive power in addition to implied volatility. These findings, based on stock index and individual stock options, are inconsistent with the hypothesis that implied volatility is the optimal predictor of future volatility. This contradiction has motivated further studies.

Outside the US and UK markets, limited research has been undertaken to test the predictability of ARCH-type models. Gwilym and Buckle (1999) focus on implied volatility from options, using the daily UK FTSE 100 index. They find that implied volatility contains more information about future realised volatility than historical volatility estimators do. They also indicate that implied volatility becomes more volatile around the maturity of the option, and in this period tends to overestimate realised volatility.

In Australia, a number of papers have sought to model volatility when the options were floor-traded. Brailsford and Faff (1993; 1996) find the GJR-GARCH models to be slightly superior to various simpler models in predicting Australian monthly stock index volatility and the GARCH (3,1) model is found to be favourable when the model is subjected to symmetry-based diagnostic tests. However, their results suggest it is unable to capture asymmetric responses in volatility to past innovations. They were seeking to fit a number of different models and assessed their predictive performance against different measures of prediction error but failed to conduct forecast-encompassing tests.

Walsh and Tsou (1998) make a comparison of volatility forecasting techniques on the Australian value-weighted indices to evaluate the trade-off between diversification and non-trading. They find the exponentially weighted moving average and GARCH models dominate for all the loss functions they use. But Walsh and Tsou fail to conduct forecast-encompassing tests, and measuring volatility over a narrow index leaves models open to errors caused by idiosyncratic risks.

Dowling and Muthuswamy (2005) construct a new measure of Australian stock market volatility based on the implied volatility of the S&P/ASX Index Options. They construct the Australian Market Volatility Index (AVIX) in a manner similar to the CBOE Market Volatility Index (VIX) in the United States. They examine the presence of any seasonalities before assessing the AVIX as a predictor of future volatility and find that large first-order autocorrelation is negatively correlated with lagged and contemporaneous S&P/ASX 200 index returns. As a predictor of future volatility, AVIX performed poorly compared to historical volatility.

In summary, the consensus is that implied volatility forecasts are more accurate than those derived using pure time-series analysis, but the latter still contains additional information not embedded in implied values. The same results may not apply to the Australian market. Previous studies have weaknesses due to methodological issues. The relatively smaller transaction volume of ASX options, compared to S&P options, may have an impact on market efficiency and, therefore, may favour time-series models.

3.3 Data and Methodology

3.3.1 Data Sample

This study uses daily closing prices (dividend-adjusted) of the S&P/ASX 200 index and daily closing prices for the S&P/ASX 200 call option contracts. The Securities Industry Research Centre of Asia-Pacific (SIRCA) on behalf of the ASX supplied data. The S&P/ASX 200 index sample data range is from January 1, 2000, to April 29, 2004. The study uses 847 observations. A total of 783 observations between January 1, 2001, and December 31, 2003, are used as the initial period, in order to estimate ARCH-type models. The remaining 64 observations from January 2, 2004, to April 29, 2004, are used in rolling windows to form an out-of-sample forecast series.

3.3.2 Methodology

First, the return series is obtained from the daily price series. Linear and non-linear ARCH and GARCH models, using the return series, are explained in detail in Appendix 3.7.1. The ability of each volatility estimator in accurately forecasting true volatility is evaluated according to error statistics measures. Finally, orthogonality tests address the question of whether implied volatility is an efficient forecast of future realised volatility.

Implied volatilities are computed from the S&P/ASX 200 index call option prices. All models are evaluated in a purely out-of-sample framework, and h -day-ahead out-of-sample volatility forecasts from the implied volatility can be calculated straightforwardly from the implied volatility calculated at time t . Therefore, prices for

options traded between December 31, 2003, and March 30, 2004, inclusive, are used to form the volatility forecast series.

Computing implied volatility involves several practical problems. Only options with three months to expiration are available, and trading on these options is inactive, as the volume is low. During the sample period, six days have no transactions on options whose maturity matches the filtering criteria. Therefore, the following rules are applied in order to filter the options from a population of 1715 call option transactions:

Only at-the-money and close at-the-money options (options that were less than 10 per cent in-the-money or out-of-the-money) are used, ignoring out-of-the-money and in-the-money options. The choice is made on the consideration that relative bid-ask spreads are especially large for out-of-the-money and in-the-money options, and they are generally less liquid compared to at-the-money options; and options with a remaining lifetime of less than 10 days or more than 180 days are excluded. Very short-term options contain little time value; hence, the estimation of volatility is extremely sensitive to possible measurement errors. Longer-term options are very illiquid (the number of no-transaction days is significant), with large bid-ask spreads.

Daily closing prices are used and the return series is obtained by taking the difference between t and $t-1$ of the natural log of the prices:

$$r_t = \log \frac{P_t}{P_{t-1}} \quad (3.1)$$

where P_t is the daily closing trading price of the S&P/ASX 200 Index.

3.3.3 Linear and Non-Linear GARCH Models

The forecasting models examined include GARCH, IGARCH, GARCH-M, TARCH, and EGARCH. Details of the models are discussed in Appendix 3.1. The model orders (p, q) are initially determined by application of the Akaike Information Criterion (Akaike, 1973), and the Schwarz Criterion (Schwarz, 1978). The error distribution is assumed to be a t distribution. Bollerslev and Wooldridge (1992) show that under the normality assumption, the quasi maximum likelihood estimator is consistent, where the conditional mean and the conditional variance are correctly specified. This estimator is, however, inefficient when the error distribution departs from normality. Further, as reported by Bollerslev (1987), Hsieh (1989) and Baillie and Bollerslev (1989), the use of a fat-tailed distribution performs better in capturing higher kurtosis. As the sample series in the current study is fat-tailed and has excess kurtosis, a fat-tailed distribution (Student- t distribution) is utilised in order to maximise the likelihood function.

Since literature presents a wide range of ARCH-type models, it is a challenge to choose suitable processes. To test for this finding, and for the purposes of forecast comparisons, the variance of the returns series is allowed to follow two stages of the ARCH process. The first part involves linear ARCH models, including ARCH (p) , GARCH $(1,1)$, and the GARCH-Mean process. The second part involves non-linear ARCH processes, including EGARCH and TARCH models, which allow asymmetry effects. To examine whether an IGARCH model fits the data, or if volatility is still mean reverting, the Wald co-efficient test is performed to test the null hypothesis $+\sum_{j=1}^p \beta_j = 1$.

The EGARCH model is an alternative way of accommodating the asymmetric

relationship between stock returns and volatility changes. Moreover, it releases the non-negative constraints on co-efficient estimates on the parameters. For these reasons, the EGARCH model is also utilised in order to examine the S&P/ASX 200 return series.

While expected volatility can be estimated using historical return information, it can also be derived from option prices. For example, in the framework of the Black-Scholes (1973) option-pricing model, if option prices and other variables are available, then the option-pricing formula can be inverted, such that the expected volatility over the life of the option is computed from the observed market prices of the call, or put, options. This yields the implied volatility, which equates the theoretical price of an option with its market price (Hull, 2006). The Black-Scholes model is utilised to derive implied volatility. As a proxy for the risk-free interest rate, the Australian 90-day Inter-bank Bill Rate is appropriate, as its maturity is close to the option expiration. The midpoint of the bid-ask quote is utilised as the option price, in order to avoid problems due to bid-ask bounce and thin trading.

Each model is estimated initially over a three-year in-sample period. Forecasts of the realised volatility are made for the next day, say day $t+1$, using the in-sample parameter estimates. The start and end dates for the parameter-estimation periods are then rolled forward one day, with model parameters being re-estimated in order to incorporate day $t+1$ information. These new estimates are utilised to forecast the day $t+2$ volatility. This procedure is repeated, with the estimation window rolled forward one day at a time until forecasts for the whole period are obtained.

Hence, the one-day-ahead forecast provides predictions for January 2, 2004, to March 31, 2004, inclusive and defines a time series of length sixty-four. To evaluate the

forecast accuracy of each volatility estimator, forecasts from each approach are assessed against the ex-post realised volatility. Unfortunately, the ex-post realised volatility is not directly observable from the market. A number of ways have been developed to estimate the ex-post realised volatility in the forecasting literature. A common approach is to use absolute daily returns, or daily standard deviation, to estimate daily volatility.

3.3.4 Forecast Error Statistics

The ability of each volatility estimator in accurately forecasting true volatility is evaluated according to error statistics measures. In order to evaluate and compare forecast errors a variety of statistics has been used. This study uses the root mean square error (RMSE), the mean absolute error (MAE), the mean absolute percentage error (MAPE), the Theil Inequality Co-efficient and the modified Diebold and Mariano test statistic of Harvey, Leybourne et al., (1999) (DM-LS).

The RMSE is a common criterion for evaluating forecast accuracy. It exaggerates the forecast error (the difference between prediction value and actual value) of each prediction and weights greater forecast errors more heavily by squaring them. The RMSE is scale-dependent and is often utilised to compare forecasts of a given series across different models, the smaller its value, the more accurate the forecast.

The MAE is another commonly used measure in testing the forecast power of a model. It averages the prediction errors and serves as an indicator in order to assess how far away from the actual series its forecasted counterpart is. The closer the MAE is to zero, the better its accuracy. It should be noted that when the value of the RMSE is

significantly greater than the MAE, prediction errors are indicated to exist at a significantly greater level than the average prediction error.

Despite the mathematical simplicity, both the RMSE and the MAE are not invariant to scale transformation. Hence, two additional, scale-dependent error measures are utilised. The first one is the MAPE statistic. It yields a relative indication of overall forecasting performance, since it expresses the magnitude of the mean absolute error in percentage terms of the actual series. The smaller the MAPE, the better the forecast.

The Theil Inequality Co-efficient is another scaled independent statistic. It is the ratio of the RMSE of a particular forecasting model to a no-change model. Hence, if this ratio is less than unity, then the forecast from a given model tends to be superior to the no-change-model forecast over the testing sample. This measure is invariant to scale transformation and lies in the range 0 to 1, with 0 indicating a perfect forecast.

However, these measurement models do not provide a formal statistical indication of whether one model is significantly better than another is. So this work uses forecast-encompassing tests. Diebold and Mariano (1995) proposed several methods to test the null hypothesis of equal forecast accuracy. The modified version of the Diebold and Mariano (1995) test proposed by Harvey, Leybourne et al., (1999) uses the squared prediction errors to make pair-wise comparisons of different models, with its statistics being adjusted for the presence of ARCH forecast errors.

Their underlying assumptions about the forecasting error distributions are non-Gaussian, nonzero, serially correlated and contemporaneously correlated. If two forecasts

have produced two sets of forecasting errors (ε_{1t} and ε_{2t} , $t=1,2,\dots,n$) then the forecasting accuracy could be tested by using the following null hypothesis.

$$E(\varepsilon_{1t} - \varepsilon_{2t}) = 0 \quad \text{and} \quad d_t = \varepsilon_{1t} - \varepsilon_{2t}$$

and the observed sample mean can be calculated as:

$$\bar{d} = \sum_{t=1}^n d_t / n \tag{3.2}$$

In Harvey, Leybourne et al., (1997), the series d_t is likely to be autocorrelated. It is also assumed that all autocorrelations of order h , or higher, of the d_t are zero for h -steps ahead forecasts and the variance of d_t will be asymptotically. They pointed out the Diebold-Mariano test could be oversized in the case of a two-steps-ahead prediction ($h=2$), getting worse when h increases.

The test compares a statistic (S) to a critical value drawn from a student t -distribution with $(n-1)$ degrees of freedom (n is the number of independent point forecasts in the out-of-sample period), where S is given by:

$$S = \left[\frac{n+1+2h+n-1h(h-1)}{n} \right]^{-\frac{1}{2}} \hat{V}(\bar{d})^{-\frac{1}{2}} \bar{d} \tag{3.3}$$

$$\bar{d} = \frac{1}{n} \sum_{t=1}^n d_t ; \quad d_t = g(e_{1,t}) - g(e_{2,t}) ; \quad \hat{V}(\bar{d}) = n^{-1} \left(\hat{\gamma}_0 + 2 \sum_{i=1}^{h-1} \hat{\gamma}_i \right) ; \tag{3.4}$$

where $\hat{\gamma}_i$ is the estimated auto-covariance of the series of squared prediction errors and h is the forecast horizon being considered.

3.3.5 The Information Content of Implied Volatility

The error measurement statistics presented in the previous section are ideal when examining the forecast accuracy of a particular method. For the purposes of evaluating the unbiasedness and efficiency of volatility forecasts, however, it is necessary to rely on other statistics. Canina and Figlewski (1993) and Christensen and Prabhala (1998) proposed a simple ordinary least square (OLS) regression procedure to analyse the information content of volatility forecasts.

$$\sigma_{REA,T+h} = \alpha + \beta\sigma_{for,T+h,t} + \varepsilon_t \quad (3.5)$$

where $\sigma_{REA,T+h}$ is the ex-post realised volatility over the h -day horizon, $\sigma_{for,T+h,t}$ is the volatility estimate based on the information set available in time t and forecasted h -days-ahead, and ε_t is the residual. Christensen and Prabhala (1998) also noted that by analysing the estimated co-efficients, t -statistics and R^2 of the regression, three hypotheses could be tested. If the forecast contains some information about actual volatility, β should be significantly different from zero. If the forecast is an unbiased estimate of realised volatility, then $\alpha = 0$ and $\beta = 1$ cannot be rejected. If the forecast is efficient, the residual ε_t should be white noise and orthogonal to any variable in the market's information set.

In practice, employing Equation (3.5) requires the use of non-overlapping realised, and forecast, volatility data to avoid an autocorrelation problem in the data series. As highlighted by Christensen and Prabhala (1998), if the data series have an overlapping structure, they automatically exhibit a large amount of autocorrelation.

Statistically, this can yield invalid statistical inferences for the regression co-efficients and spurious explanatory power. For the data series of the current research, the overlapping data problem obviously exists because the forecast horizons for the ARCH estimates are overlapped from day to day and the estimates of the realised volatility for two adjacent days share all information, with the exception of one day.

To address this problem, Fleming (1998) advocated subtracting the lagged independent variable from both sides of Equation (3.5), which gives:

$$\sigma_{REA,T+h} - \sigma_{for,T+h,t-1} = \alpha + \beta(\sigma_{for,T+h,t} - \sigma_{for,T+h,t-1}) + \varepsilon_t \quad (3.6)$$

In addition, Fleming (1998) suggested the use of Hansen's (1982) Generalised Method of Moments (GMM) for the estimation of the parameters, as the GMM method is robust to heteroscedasticity and autocorrelation of unknown forms in a time series. With the GMM method, the following vector is estimated:

$$\frac{1}{T} \sum_{t=1}^T [(\sigma_{REA,t} - \sigma_{f,t-1} - \alpha - \beta(\sigma_{f,t} - \sigma_{f,t-1}))](1, \sigma_{f,t} - \sigma_{f,t-1})' \quad (3.7)$$

Equation (3.7) has two instrumental variables and two parameters to be estimated. The GMM approach will select the parameter estimates, so the sample correlations between the instruments and the residuals defined by Equation (3.6) are as close as possible to zero. Fleming (1998) illustrates t , in estimating the moment vector, if $\sigma_{f,t}$ is unbiased for $\sigma_{REA,t}$, then α and β should be insignificantly different from zero and one, respectively. Therefore, Equation (3.7) is utilised in the current study to test the unbiasedness hypothesis of volatility forecasts.

The GMM approach is also useful for the purpose of the orthogonality test. The following vector is estimated:

$$\frac{1}{T} \sum_{t=1}^T (\sigma_{REA,t} - \alpha - \beta \sigma_{f,t}) (1, \sigma_{f,t}, \sigma_{h,t})' \quad (3.8)$$

where $\sigma_{h,t}$ is the alternative forecast of the realised volatility. Equation (3.8) is different from Equation (3.7), as it does not include the lagged independent variable to guard against spurious regression. As shown by Fleming (1998), however, statistical inference regarding orthogonality is not affected by this problem and Equation (3.7) seems to simplify the test. Best, the system in Equation (3.7) is over-identified, with two parameters and three instrumental variables. GMM tests the validity of over-identifying restrictions by measuring the closeness to zero of the correlation between the residuals from the regression and $\sigma_{h,t}$, so it is ideal for testing orthogonality.

Finally, orthogonality tests are utilised to address the question of whether or not implied volatility is an efficient forecast of future realised volatility. Theoretically, to be an efficient forecast, implied volatility must be subject to more rigorous tests and its forecast error must be orthogonal to any information set available in the marketplace.

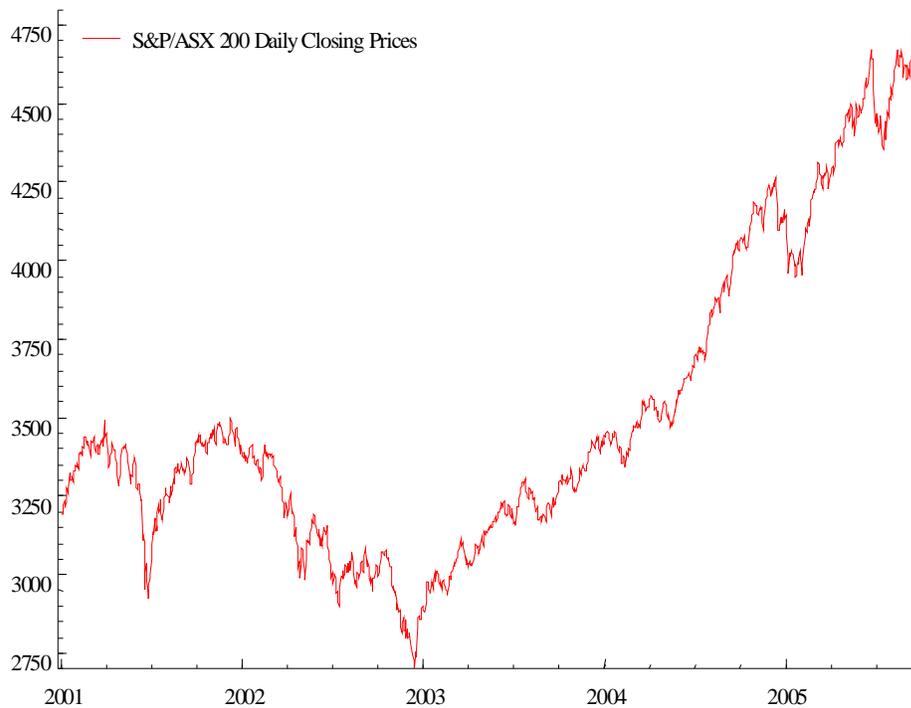
3.4 Results

3.4.1 Descriptive Statistics

Figure 3.1 overleaf displays the S&P/ASX 200 Index daily closing prices for the in-sample period used to estimate the ARCH-type models.

Figure 3-1 Patterns of Daily Closing Prices of the S&P/ASX 200 Index

The daily closing prices of the S&P/ASX 200 Index were used to estimate ARCH and GARCH models

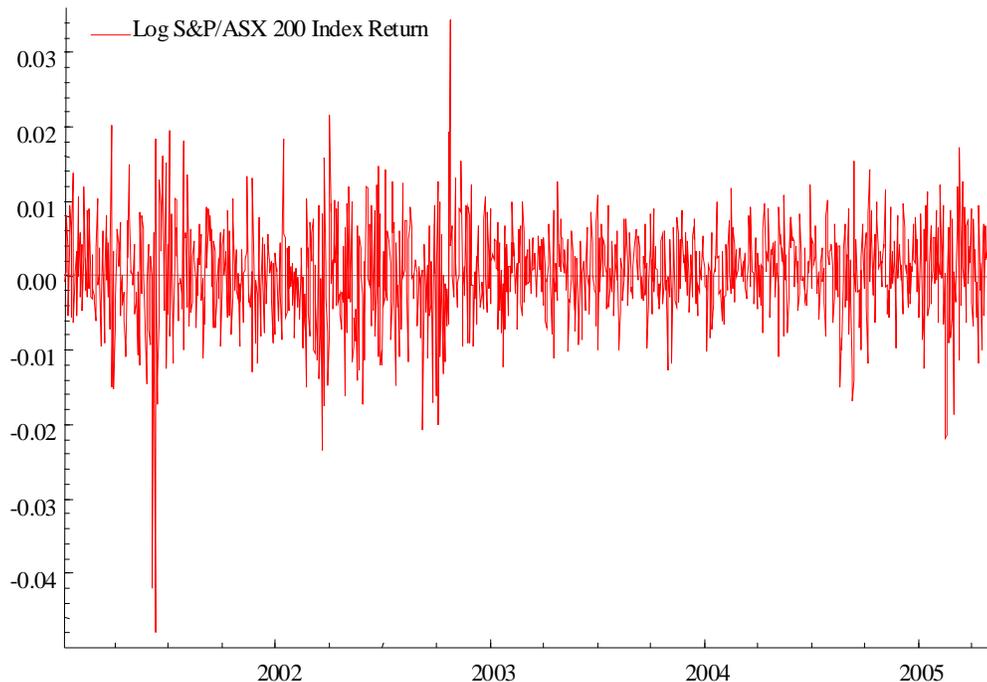


The series is a multiplicative time series with no linear deterministic trend. I observe that the index has fluctuated widely in the past couple of years, reaching its lowest level in the study period in February 2003. After that time, it climbed gradually and stands at its highest level at the end of the sample period.

The return series illustrated in Figure 3-2 below reveals volatility is not constant over time and tends to cluster. Periods with high volatility can be easily distinguished from periods of low volatility. For example, there are clusters of large, negative returns in September 2001, most likely due to the shock from the September 11 terrorist attacks

in the U.S. The return series for the S&P/ASX 200 index are obtained by taking the first difference of the natural log of the daily closing price. The conclusion as to whether, the clustering is statistically and economically significant is presented in the following section.

Figure 3-2 Patterns of Daily Closing Log S&P/ASX 200 Index Returns



Return volatility descriptive statistics are presented in Table 3-1 overleaf for the S&P/ASX 200 Index. The sample size, mean, standard deviation, skewness, kurtosis, Jarque-Berra normality test and the ARCH test are all listed in the table. The mean daily return of the S&P/ASX 200 index is 0.0183%. The standard deviation of the daily return is 0.07144. This is equivalent to an annualised volatility of 11.34% when using 252 days as the number of trading days as suggested by Hull (2006). The series has a negative skewness of -0.465 , implying its distribution has a long left tail. This confirms the

findings in the literature that stock returns often display asymmetry. Kurtosis of the series is 7.214, which exceeds 3 under a Gaussian distribution, indicating the series distribution is leptokurtic. The Jarque-Berra (1987) statistic of 606.9635, with a *p*-value of (0.000), suggests that the null hypothesis, of a normal distribution, should be strongly rejected.

Table 3-1 Descriptive Statistics for the S&P/ASX 200 Return Series

Table 3-1 shows descriptive statistics for the S&P/ASX 200 index return series. These include sample size, mean, standard deviation, skewness, kurtosis, Jarque-Berra normality test and ARCH test

Index	Sample Size	Mean (10 ⁻⁵)	Standard Deviation	Skewness	Kurtosis	Normality Test ^a	ARCH Test
S&P/ASX 200	2383	1.83	.007144	-.0465	7.214	606.9635**	5.2620*

^aJarque-Berra normality test,

*Significant at the 5% level,

**Significant at the 1% level

To provide a better description of the time-dependent pattern, which is important in modelling the series under study, it is necessary to test the stationarity of the return series and squared return series, which gives an approximation of the volatility process. The Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF) plots of the lagged series are first investigated. Appendices 3.7.2 and 3.7.3 present the ACF and PACF plots for the S&P/ASX 200 return series and the squared return series. The autocorrelation reflects how quickly and completely stock prices adjust to new information. There are no significant ACF and PACF spikes in the lagged return series. The Ljung-Box Q-statistics are not significant at any lags. Therefore, the hypothesis that there is no serial correlation in the return series, which means the residuals of the return series are not correlated with their own lagged values, cannot be rejected. As to the squared return series, while higher-order autocorrelations are in general diminishing, the first three autocorrelations are low, but not negligible. This is evidence of volatility clustering and suggests volatility is predictable.

3.4.2 Stationarity Testing

Formal testing for stationarity can be performed using the Augmented Dickey-Fuller (ADF) unit root test, with no constant and no lagged term. The ADF t -statistic for the return series is -29.14463 , which is less than the critical value of -2.567926 at the 1 per cent significance level.

Table 3-2 Augmented Dickey-Fuller Unit Root Tests¹² for the S&P/ASX 200 Implied Index

The Augmented Dickey-Fuller (ADF) test involves incorporating lagged values of the dependent variable into the following equation: $\Delta Y_t = \alpha_0 + \beta Y_{t-1} + \gamma T + \delta_1 \Delta Y_{t-1} + \dots + \delta_n \Delta Y_{t-n} + u_t$ with the number of lags being determined by the residuals which are free from autocorrelation. This could be tested for in the standard way, such as by the Lagrange Multiplier (LM) test. In practice, many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here, the AIC and SIC tests are used to test the optimal lag number.

Series	T-Statistic	P-Value ^a	R2	DW Stats	AIC	SIC
S&P/ASX 200 ^b	-29.1451**	0.0000	0.5216	1.9907	-7.0485	-7.0366
D(S&P/ASX 200) ^c	-10.5484**	0.0000	0.5355	2.0355	-15.2471	-15.2231

a MacKinnon (1996) one-sided p-values.

b This is the logarithm of the S&P/ASX 200 return series.

c This is the first difference of the series described in b.

** Significance at the 1% level.

Therefore, the unit root hypothesis of the return process can be rejected at a confidence level of more than 99%. Furthermore, the hypothesis of a unit root in the squared return process, where the ADF t -statistic is equal to -10.5484 when allowing for a constant and 2 lags, also can be rejected. Based on the above test results, it is concluded that the S&P/ASX 200 return series and the squared return series are stationary. So the series can be estimated.

¹² The lag value is determined by the Schwarz Criterion (SIC) (Schwarz, 1978) and the Akaike Information Criterion (AIC) (Akaike, 1973).

3.4.3 Volatility Model Estimation

Given the descriptive statistics in Table 3-1, I estimate return volatilities for the S&P/ASX 200 Index using linear GARCH and non-linear GARCH models. The linear GARCH models refer to the GARCH model suggested by Bollerslev (1986), the non-linear GARCH models refer to the Exponential GARCH model described by Nelson (1991), and the Threshold ARCH (TARCH) model refers to the model described by Zakoian (1994) and Glosten, Jagannathan et al.,(1993). I also apply the ARCH-In-Mean model, as suggested by Engle, Lilien et al., (1987), to linear and non-linear GARCH models.

At this stage it has been determined that the return series of the S&P/ASX 200 Index is stationary. However, this does not ensure the return variance is constant over time. In other words, ARCH effects may remain in the residuals. The results of the ARCH LM test for the return series on the S&P/ASX 200 indicate lag 1 and lag 2 AR terms are not significant in the ARCH LM test, whilst lag 3 and lag 4 terms are significant in the test. This indicates volatility displays a long memory, or long-term dependence. The ARCH LM test statistic is highly significant, with a *p*-value far below 0.001. It is concluded that ARCH effects exist, and the variance of the return series is non-constant over time.

In Table 3-3 I present the model selection process and parameters for the S&P/ASX 200 Index model. I fit various lower-order GARCH (p, q) models, and the GARCH (1,1) model was initially used.

Table 3-3 Model Selection and Parameter Estimation for the S&P/ASX 200 Index

This table presents the results of linear and non-linear GARCH models applied to measure S&P/ASX 200 return volatilities. The GARCH-In-Mean is also applied to all linear and non-linear GARCH (1,1) models.

Model	Estimated	Standard	<i>t</i> -statistic	<i>p</i> -value
GARCH (3,1)				
ω	0.0000	0.0000	1.9296	0.0537
α	0.0216**	0.0076	2.8260	0.0047
β_1	2.3654**	0.1747	13.5388	0.0000
β_2	-2.0740**	0.2990	-6.9368	0.0000
β_3	0.6751**	0.1373	4.9164	0.0000
GARCH (3,1) M				
ω	0.0000	0.0000	1.8995	0.0575
α	0.0207**	0.0073	2.8310	0.0046
β_1	2.3860**	0.1630	14.6336	0.0000
β_2	2.1096**	0.2792	-7.5558	0.0000
β_3	0.6912**	0.1285	5.3783	0.0000
EGARCH (1,1,1)				
ω	-0.2566**	0.0677	-3.7879	0.0002
α	0.0307	0.0264	1.1599	0.2461
γ	-0.1146**	0.0187	-6.1392	0.0000
β	0.9772**	0.0062	156.9627	0.0000
TARCH (3,1,1)				
ω	0.0000**	0.0000	3.0085	0.0026
α	-0.0137**	0.0045	-3.0495	0.0023
γ	0.0681**	0.0137	4.9523	0.0000
β_1	2.1595**	0.1108	19.4858	0.0000
β_2	-1.9376**	0.1838	-10.5443	0.0000
β_3	0.7412**	0.0876	8.4611	0.0000

* Significant at the 5% level.

** Significant at the 1% level.

However, the ACF and PACF of the standardised residuals squared from the GARCH (1,1) model are highly significant at lag 3, and indicate higher-order GARCH terms are required. The GARCH (3,1) model is found to be the most appropriate and adequate model. This is consistent with Brailsford and Faff's (1993) research and the GARCH (3,1) model is found to be the most appropriate of the standard GARCH models when explaining volatility in the Australian stock index return data. The co-efficients for

lagged GARCH terms violate the constraints $\beta_j \geq 0$. As Nelson and Cao (1992) have shown, however, the inequality $\alpha_i, \beta_i \geq 0$ need not hold, as long as $0 < \sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j < 1$ holds to ensure non-negativity of the conditional variance and the existence of a finite unconditional variance. The sum of $\alpha_i + \beta_j = 0.988094$ indicates that the volatility of returns is persistent and current information is relevant in predicting future volatility at a long horizon. In the GARCH (3,1) model, the sum of $\alpha_i + \beta_j$ is close to 1.0. The AIC and SC statistics are -7.189687 and -7.147957 , respectively. The log likelihood ratio statistics are large, which implies the GARCH model is successful in capturing the temporal dependence of volatility. I also conducted the residual test and found the Jarque-Berra statistic is still significant, suggesting the residuals are non-normally distributed. The ARCH LM test suggests that there is some remaining ARCH effect in the residuals.

In the GARCH (3,1) model, the sum of $\alpha_i + \beta_j$ is close to 1.0. To examine whether the model is an IGARCH one, or whether volatility is still mean reverting, the Wald-Co-efficient test is performed on co-efficients of the GARCH parameters to test the null hypothesis $\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j = 1$. The p -values of the F-statistic and Chi-square statistic suggest the IGARCH hypothesis should be rejected at the 90 per cent confidence level, but not at the 95 per cent confidence level. Although it is difficult to say that there is definitely an IGARCH model, the prudent conclusion can be drawn where the volatility of the returns appears to have quite a long memory and current information remains important for long horizons.

The GARCH (3,1)-M model is also employed to investigate the effect of volatility on the return-generation process. The conditional standard deviation is included in the mean equation (Appendix 3.7), so the conditional mean is allowed to vary, dependent on the volatility. The co-efficient for the conditional standard deviation is not significant, indicating the GARCH model estimates do not allow for the trade-off between risk and expected returns. In other words, it seems investors in the Australian stock market are not statistically significantly rewarded for their exposure to higher levels of volatility.

This finding is consistent with the results of Poon and Taylor (1992) for UK data and Baillie and DeGennaro (1990) for US data, where variables other than volatility are important in explaining expected returns.

An EGARCH model is an alternative way to accommodate the asymmetric relationship between stock returns and volatility changes. Moreover, it releases the non-negative constraints on co-efficient estimates on the parameters, so an EGARCH model is also used to model the S&P/ASX 200 return series. The EGARCH (3,1,1) is not an appropriate model for the sample series in this study, as the p -value for higher-order GARCH terms is not significant. An EGARCH (1,1,1) is chosen as the appropriate model for the return series and confirms the existence of an asymmetric effect. The measure of the asymmetric effect γ equals -0.1145861 is negative and has a p -value of (0.000). This indicates that negative shocks have a greater impact upon conditional volatility. Interestingly, when the impact from bad news is accounted for separately in the conditional variance equation, the parameter α (accounting for impacts from both bad news and good news) is no longer significant. This suggests negative shocks have

significant impacts on the conditional volatility of the Australian stock market, whereas positive shocks have no statistically significant impact on volatility. This result is consistent with many empirical studies (Pagan and Schwert, 1990), (Glosten, Jagannathan et al., 1993), who report only negative returns increase the conditional volatility in developed markets. The persistence measure of the EGARCH (1,1,1) model, which is given by $\sum_{j=1}^p \beta_j$, is 0.9772. The AIC and SC statistics are -7.2233 and -7.1875 , respectively. The residual tests, however, suggest the EGARCH (1,1,1) model is not fully capable of capturing the time-varying volatility pattern in the return series. The ARCH LM test indicates there is a remaining ARCH effect in the residuals, and the correlogram of the standardised residuals squared has significant p -values.¹³

Brailsford and Faff (1993) find the GARCH (3,1) model to be the most appropriate of the standard GARCH models when explaining volatility in the Australian stock index return data and give good explanations to symmetrically positive or negative residuals, but not asymmetric variance. Asymmetric models were tested, and the TARCH (3,1,1) model was found to be the best parameter. Consistent with Brailsford and Faff's research, TARCH (3,1,1) is also the best parameter order for the sample series. The sign of the shocks has a significant influence on the volatility of returns. The bad news parameter γ is clearly positive and highly significant, indicating a substantial leverage effect. The persistence of shocks, which is quantified by $\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j + (\gamma/2)$ when assuming returns have symmetric distributions, is equal to 0.9834731, indicating long

¹³ See Appendix 3.7.5 for correlogram.

memory volatility exists. The AIC and SC statistics are -7.218571 and -7.170879 , respectively, and the log-likelihood ratio is large. Residual diagnostics also support a leverage effect. Appendix 3-9 outlines the correlogram of the standardised residuals squared of the TARCH (3,1,1) model. No p -values are significant and the Ljung-Box Q-Statistic is only 20, at a lag of 34, and not significant. The results from the ARCH LM test, when 3 lags are included, provides little evidence of a remaining ARCH effect, indicating the TARCH (3,1,1) model is successful in capturing the dependence of volatility and asymmetric responses in volatility to past innovations.

3.5 Evaluation of Error Measurement Statistics

An examination of Table 3-4 reveals the TARCH (3,1,1) model is superior to the other two methods. It ranks first in terms of the RMSE and MAE statistics. This ranking is also robust in all test forecast horizons. The GARCH (3,1) method ranks second in the 1-, 5- and 10-day forecast horizons. Forecasting into the 20-day horizon, implied volatility performs better than the GARCH (3,1) estimate. This change in ranking is also robust between the RMSE and MAE statistics.

Table 3-4 Forecast Performance Evaluated by RMSE & MAE Statistics

The formulas of MAE, RMSE and Theil's U statistics can be expressed as follows:

$$MAE = \frac{1}{h+1} \sum_{t=s}^{s+h} |\hat{y}_t - y_t|, \quad RMSE = \sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} (\hat{y}_t - y_t)^2},$$

where, \hat{y}_t is the forecast value, y_t is the actual value, h is the forecast sample and $t = s$.

The MAE and RMSE statistics depend on the scale of the dependent variable.

	1 day ahead		5 days ahead		10 days ahead		20 days ahead	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
GARCH (3,1)	0.0030	0.0026	0.0041	0.0034	0.0052	0.0044	0.0077	0.0071
Rank	2	2	2	2	2	2	3	3
TARCH (3,1,1)	0.0029	0.0025	0.0039	0.0034	0.0048	0.0040	0.0068	0.0057
Rank	1	1	1	1	1	1	1	1
Imp. volatility	0.0032	0.0027	0.0043	0.0037	0.0052	0.0045	0.0072	0.0063
Rank	3	3	3	3	3	3	2	2

Table 3-5 Forecast Performance Evaluated by MAPE & Theil Statistics

The formula for Theil's U statistics can be expressed as follows:

$$\text{Theil's U} = \frac{\sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} (\hat{y}_t - y_t)^2}}{\sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} \hat{y}_t^2} \sqrt{\frac{1}{h+1} \sum_{t=s}^{s+h} y_t^2}}$$

$$MAPE = 100\% \times \frac{1}{h} \sum_{t=1}^h |(\sigma_t - \sigma_{REA}) / \sigma_{REA}|$$

The Theil's U statistics always lie between zero and one, where zero indicates a perfect fit. Both the RMSE and MAE are measures, which depend on the scale of the dependent variable. Table 3-5 presents RMSE and MAE statistics for 1-, 5-, 10- and 20-day horizons for the forecasting period: January 2, 2004, to March 31, 2004.

	1-day-ahead		5-days-ahead		10-days-ahead		20-days-ahead	
	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE
GARCH (3, 1)	0.0030	0.0026	0.0041	0.0034	0.0052	0.0044	0.0077	0.0071
Rank	2	2	2	2	2	2	3	3
TARCH (3,1,1)	0.0029	0.0025	0.0039	0.0034	0.0048	0.0040	0.0068	0.0057
Rank	1	1	1	1	1	1	1	1
Imp. volatility	0.0032	0.0027	0.0043	0.0037	0.0052	0.0045	0.0072	0.0063
Rank	3	3	3	3	3	3	2	2

Table 3-5 presents the results for the MAPE and Theil statistics. A common feature of these results is the greater accuracy across all methods for longer horizons, with the exception of the GARCH (3,1) volatility at the 20-day horizon. The TARCH (3,1,1) model remains the best performer in terms of the MAPE and Theil statistics, and its ranking is robust for all horizons. Between the GARCH (3,1) model and implied volatility, the general result is similar to that from the RMSE and MAE. MAPE and Theil statistics still favour the GARCH (3,1) estimate in shorter horizons, and favour implied volatility for longer horizons.

Table 3-6 presents the results for the (DM-LS) statistics. A common feature of these results is that the TARCH (3,1,1) model remains the best performer and its ranking is robust at all horizons. The results are statistically significant.

Table 3-6 Forecast Performance Evaluated by (DM-LS) Statistics

The formula for (DM-LS) statistics can be expressed as follows:

$$S = \left[\frac{n+1+2h+n-1h(h-1)}{n} \right]^{\frac{1}{2}} \hat{V}(\bar{d})^{\frac{1}{2}} \bar{d} = \frac{1}{n} \sum_{t=1}^n d_t$$

$$d_t = g(e_{1,t}) - g(e_{2,t})$$

$$\hat{V}(\bar{d}) = n^{-1} \left(\hat{\gamma}_0 + 2 \sum_{i=1}^{h-1} \hat{\gamma}_i \right)$$

This table presents the Modified Diebold and Mariano test statistic of Harvey, Leybourne et al., (1999) for each of the modelling techniques under comparison. Table 3-6 presents DM-LS* for 1-, 5-, 10- and 20-day horizons for the forecasting period January 2, 2004, to March 31, 2004.

	1 day ahead	5 days ahead	10 days ahead	20 days ahead
TARCH vs. GARCH	-2.23685*	-2.49331*	-4.72866**	-6.4129**
TARCH vs. IMPLIED	-4.28473**	-3.35813**	-2.47009*	-0.9564
IMPLIED vs. GARCH	3.82046**	2.69659**	0.90139	-1.10698

*Significant at the 5% level.

** Significant at the 1% level.

In conclusion, the TARCH (3,1,1) model produces the most accurate forecasts among the models. It always has the lowest value measured by the five error statistics,

and its superiority is robust over all test forecast horizons. The GARCH (3,1) model performs better than implied volatility over the 1- and 5-day horizons, but its model ranking is not robust over the 10- and 20-day horizons. In the 20-day horizon, implied volatility produces better results than GARCH (3,1) estimates, when measured by the five error statistics. The performance improvement of implied volatility as the forecast horizon increases is consistent with its definition as a measure of average volatility over the remaining life of the options, which is 90 days in this sample series.

3.5.1 Evaluation of Unbiasedness Test Results

The error measurement statistics presented in the previous section give some indications of forecast accuracy of each method. For the purpose of evaluating the unbiasedness and efficiency of volatility forecasts, I need to rely on other statistics. Canina and Figlewski (1993) and Christensen and Prabhala (1998) propose a simple OLS regression procedure to analyse the information content of volatility forecasts.

Table 3-7 overleaf displays the regression results for the unbiasedness test. The significance of the co-efficients is assessed according to the GMM t -statistics. R^2 is the co-efficient of determination and the Chi-square statistic is from the Wald Co-efficient test of the joint null that $\alpha = 0$ and $\beta = 1$ for each forecast. The intercept co-efficients for GARCH (3,1) in all horizons are negative and significantly different from zero. As interpreted by Fleming (1998), a significantly negative intercept co-efficient indicates an overestimation of any volatility forecast. The β co-efficients of the GARCH (3,1) estimates are all insignificantly different from one. The formal test of unbiasedness is rejected in the 1-day and 20-day horizons, as the Chi-square statistics are significant for

Table 3-7 Unbiasedness Tests of Volatility Forecasts

This table displays the regression results for the unbiasedness test. The significance of the co-efficients is assessed according to the GMM t -statistics. R^2 is the co-efficient of determination. The Chi-square statistic is from the Wald Co-efficient test of the joint null that $\alpha = 0$ and $\beta = 1$ for Panel A GARCH (3,1), Panel B TARARCH (3,1,1) and Panel C implied volatility forecast.

Statistics	1 day ahead	5 days ahead	10 days ahead	20 days ahead
Panel A: GARCH (3,1)				
α	-0.00167*	-0.00274**	-0.00426**	-0.00712*
β	0.57783	0.16010	0.06319	0.31079
R^2	0.00112	0.00045	0.00011	0.00347
χ^2	23.16327*	4.49997	5.30719	110.21325*
Panel B: TARARCH (3,1,1)				
α	-0.00151*	-0.00241	-0.00356*	-0.00576*
β	1.12180	0.50509	0.80682	0.58562
R^2	0.01438	0.00697	0.01885	0.01084
χ^2	19.82184*	3.76859	22.05804*	45.12142*
Panel C: Implied volatility				
α	-0.00200*	-0.00326*	-0.00440*	-0.00617*
β	0.18997	0.43849*	0.56391*	0.49305*
R^2	0.00339	0.07051	0.20451	0.18144
χ^2	42.89713*	53.94681*	55.86208*	100.48845*

*Significant at 1% level **Significant at 5% level

these two forecast horizons. Overall, the GARCH (3,1) forecasts have low R^2 values, and this result is consistent with previous research (Day and Lewis, 1992), (Fleming, 1998) and often contributes to the fact that the GARCH (3,1) estimate is much less variable and is unable to entirely capture the variation in actual volatility.

Test results for the TARARCH (3,1,1) model suggest an overestimation, as the intercept co-efficients are all negative and significantly different from zero in all horizons, except the 5-day-horizon. The β co-efficients are all insignificantly different from one. The Chi-square for the joint null that $\alpha = 0$ and $\beta = 1$ are rejected for the

1-, 10- and 20-day horizons. The R^2 is still low, but improved compared to the GARCH (3,1) estimate.

For the implied volatility model, the significant negative intercept co-efficients for all horizons suggest an overestimation of the realised volatility. The β co-efficients are significantly different from one, except for the 1-day horizon. The unbiasedness hypothesis is rejected in all horizons since the Wald test statistics are highly significant.

The considerably higher R^2 values indicate that, although implied volatility is biased, it contains significantly more information about ex-post realised volatility and exhibits a strong relationship with realised volatility.

The volatility forecasts overestimate the realised volatility. The unbiasedness hypothesis is rejected in most forecast horizons across all methods except the 5-day horizon with the GARCH (3,1) and TARCH (3,1,1) estimates, and the 10-day horizon by the GARCH (3,1) forecast. I find evidence that the implied volatilities from the S&P/ASX 200 option prices are considerably richer in information about ex-post realised volatility than are ARCH-type forecasts.

3.5.2 Evaluation of Efficiency Test Results

In Table 3-8, I present the results of the orthogonality test for all horizons. Panel A reports the orthogonality test of implied volatility when the GARCH (3,1) or TARCH (3,1,1) volatility forecasts are included as an instrument.

Table 3-8 Orthogonality Tests of Implied Volatility

This table presents the results of the orthogonality test for all horizons. Panel A shows the orthogonality test of implied volatility when the GARCH (3,1) or TARCH (3,1,1) volatility forecasts are included as an instrument. Panel B shows the orthogonality test when implied volatility is an instrument in the GARCH (3,1)/TARCH (3,1,1) regression. OI^2 is the test statistic for over-identifying restrictions, which is the asymptotically distributed χ^2 value for the null hypothesis of orthogonality. The p -values of the test statistics are also reported.

Statistics	1-day-ahead	5-days-ahead	10-days-ahead	20-days-ahead
Panel A: Orthogonality of implied volatility with GARCH & TARCH				
GARCH (3,1)				
OI^2	2.20569	3.10351	4.64163	3.68409
p -value	0.13750	0.07812	0.03121	0.05493
TARCH (3,1,1)				
OI^2	0.76020	1.75030	3.14412	4.88701
p -value	0.38326	0.18584	0.07620	0.02706
Panel B: Orthogonality of GARCH & TARCH with implied volatility				
GARCH (3,1)				
OI^2	1.17940	5.50974	5.77750	4.24566
p -value	0.27748	0.01891	0.01623	0.03935
TARCH (3,1,1)				
OI^2	0.383855	4.061293	5.005571	4.958303
p -value	0.535547	0.043877	0.025266	0.025966

Panel B reports the orthogonality test when implied volatility is an instrument in the GARCH (3,1) / TARCH (3,1,1) regression. OI^2 is the test statistic for over-identifying restrictions, which is the asymptotically distributed χ^2 value for the null hypothesis of orthogonality. The p -values of the test statistics are also reported.

Conversely, when implied volatility is performed as an instrument in the GARCH (3,1) and TARCH (3,1,1) regressions, the OI^2 statistics are highly significant in most forecast horizons, except for the 1-day horizon. The rejection of orthogonality suggests the conditional volatility, which is unexplained by GARCH (3,1) / TARCH (3,1,1) specifications, is explainable by implied volatility. In other words, implied volatility has

additional information about future volatility, which is not subsumed in the GARCH (3,1) / TARCH (3,1,1) forecasts. This conclusion displays a high level of confidence when forecasting into the longer horizon. The evidence is broadly consistent with the results of Fleming (1998).

Finally, the evidence I obtained from the orthogonality tests is far less likely to lead to the conclusion that implied volatility is an efficient forecast of future realised volatility. Theoretically, to be an efficient forecast, implied volatility must be subject to more rigorous testing and its forecast error must be orthogonal to any information available in the marketplace. This study indicates implied volatility from the S&P/ASX 200 option prices contains information about future volatility beyond that which is contained in ARCH-type specifications.

3.6 Conclusion

GARCH (3,1) and TARCH (3,1,1) models were found to be a better fit within linear and non-linear ARCH specifications. The implied volatility was derived from the daily S&P/ASX 200 option prices. Both loss functions and regressions were employed, in order to evaluate the forecast accuracy and information content of volatility forecasts. Based on RMSE, MAE, MAPE and Theil inequality co-efficient statistics and the modified DM-LS* test, it was found the TARCH (3,1,1) model provides the most accurate forecast across all forecasting horizons. The GARCH (3,1) model is superior to implied volatility in terms of forecast accuracy at the 1- and 5-day horizons. When forecasting into longer horizons, however, the GARCH (3,1) model was found to be inferior to implied volatility modelling. But, regression results suggest, overall, all the longer-term forecasts from each model appear to be biased and overstate the realised

volatility. The unbiasedness hypothesis is rejected in most forecast horizons, across all methods. Implied volatility is found to have a comparably higher R^2 value in the regression, indicating it is a highly informative predictor for future volatility.

To assess the information content of implied volatility, the orthogonality tests of implied volatility were performed, with GARCH (3,1) / TARCH (3,1,1) volatility as an instrument in the regression. The insignificant test statistics in most cases suggest the GARCH (3,1) / TARCH (3,1,1) specification has little incremental information beyond that contained in the implied volatility model. In the reverse test, when implied volatility is entered as an instrument in the GARCH (3,1) / TARCH (3,1,1) regression, orthogonality is strongly rejected in all horizons, excepting the 1-day horizon. This indicates implied volatility subsumes more information about ex-post realised volatility than its GARCH (3,1) / TARCH (3,1,1) counterparts. The result is especially strong over longer forecast horizons.

Overall, on the empirical evidence presented, I conclude that there is no single best volatility model in terms of all evaluating criteria. The TARCH (3,1,1) model outperforms implied volatility in terms of forecast accuracy, indicating its better tracking of realised volatility. The lower R^2 value suggests, however, that it is unable to entirely capture the variation in realised volatility. Implied volatility derived from option prices has more information content about future volatility than do historical forecasts, which are estimated using GARCH (3,1) / TARCH (3,1,1) models. This result is unexpected when considering the infrequent trading and low-volume features in the S&P/ASX 200 Index Options market. Implied volatility appears to be upward biased, however, which is consistent with the findings of Christensen and Prabhala (1998).

Caution must be used when applying these results, as the measures of realised volatility and forecasted volatility are all subject to estimation errors and model misspecification. A reasonable guideline is, in the short forecast horizon, implied volatility combined with ARCH-type volatility could be utilised as a reasonable proxy of conditional volatility when calculating option prices for the S&P/ASX 200 Index. When forecasting into the longer horizon, implied volatility is more valuable for estimating an option price for the S&P/ASX 200 Index.

Finally, the ARCH-type models examined in this paper all fall into the univariate time-series family. In the recent literature, multivariate models which incorporate other variables (such as trading volume, inflation rates, etc.) have been developed in order to forecast volatility. An empirical study of the forecast performance between implied volatility and multivariate models would be another direction for future research, but using out-of-sample data to calculate option prices.

The literature is extended in at least two ways by this study. First, previous studies on forecasting volatility failed to perform the so-called Modified Diebold and Mariano (DM-LS) test in forecast evaluation and relied on visual inspections on the size of some accuracy measures. This work corrects this oversight. Second, previous studies have focused on relatively large and liquid markets (such as those in the US and UK). This study investigates a relatively small and illiquid market, which may behave differently from larger markets.

The information impact on volatility was investigated in this chapter. I assessed the accuracy, unbiasedness and information content of volatility forecasts, based on implied volatility and conditional volatility models for the S&P/ASX 200 Index Options

market in Australia. This study has several implications for investors who wish to effectively trade, hedge or speculate with the S&P/ASX 200 Index Options markets as the underlying S&P/ASX 200 Index market volatility is an important component when pricing the S&P/ASX 200 Index Options. Quite often, the underlying markets may have significant influences on their derivative markets. The conditional volatility models have limitations, however, as they omit information on long-run behaviour and yield little information about short-run adjustment processes.

In the next chapter I investigate the relationship between the S&P/ASX 200 Index Options market and its underlying S&P/ASX 200 Index market by testing how information is transmitted between them. If there is a causal relationship between the S&P/ASX 200 Index market and the S&P/ASX 200 Index Options market it may be possible to use one market to predict the other. This may provide market participants with important information regarding when and how to execute trades in the S&P/ASX 200 Index Options market.

3.7 Appendices

3.7.1 Appendix: Linear and Non-Linear ARCH and GARCH Models

Linear and non-linear ARCH and GARCH models are examined and include GARCH, IGARCH, GARCH-M, TARCH and EGARCH models.

3.7.1.1 Linear GARCH

Linear GARCH models are capable of capturing the first two properties of the return series, but their distribution is symmetric and, therefore, fails to model the third property, namely the leverage effect. To solve this problem, many non-linear extensions of the GARCH model have been proposed in the last 20 years. Among the most widely utilised are the TARCH, or Threshold ARCH, and Threshold GARCH models, which were introduced independently by Zakoian (1994) and Glosten, Jagannathan et al., (1993), and the Exponential GARCH (EGARCH) of Nelson (1991).

3.7.1.2 The standard ARCH (q) and GARCH (p, q) Models

In a seminal paper, Engle (1982) proposes to model time-varying conditional variance with the Autoregressive Conditional Heteroscedasticity (ARCH) processes, which use past disturbances to model the variance of the series:

$$\varepsilon_t = z_t \sigma_t \tag{A3.1-1}$$

$$z_t \sim i.i.d.D(0,1) \tag{A3.1-2}$$

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 \tag{A3.1-3}$$

where, ε_t depicts the error term, or shocks, news, or innovations; σ_t^2 is the conditional variance of ε_t , and $D(\cdot)$ is a probability density function with mean zero and unit variance. This model is known as an ARCH (q) model. An ARCH model describes the conditional variance at time t as an increasing function of the square of the shocks occurred in $t-1$. Consequently, if ε_{t-1} was large in absolute value, then σ_t^2 and, thus, ε_t , are also expected to be large (in absolute value). This model structure captures the property returns with similar magnitudes that tend to cluster in time and can explain the non-normality feature of asset return distributions. Therefore, the ARCH model takes the first two properties of the return series into account.

As early empirical evidence shows, a high ARCH order has to be selected in order to catch the dynamic of the conditional variance. Bollerslev (1986) proposes the Generalised ARCH (GARCH) model in order to simplify the issue. The standard GARCH (p, q) model specifies the conditional mean and the conditional variance, respectively, as:

$$Y_t = X_t' \theta + \varepsilon_t \quad (\text{A3.1-4})$$

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (\text{A3.1-5})$$

The mean equation is a function of the exogenous variables and an error term. The constraint $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$ is applied to avoid negative variance and

$\sum_{i=1}^q \alpha_i + \sum_{j=1}^p \beta_j \leq 1$ represents a stationary variance process.

GARCH specification predicts the conditional variance as a combination of a long-term average (the constant ω), a weighted average of the variance expected for the last periods (the GARCH term), and information (shocks, news, etc.) about volatility observed in the previous periods expressed as square errors (the ARCH term). When an asset return has an unexpected increase or decrease at time t , the GARCH model will generate an increase in the variability predicted for the next period. This feature is consistent with the property of volatility clustering. Also, the GARCH model recognises the property of mean reversion by embedding a long-run average level of variance into the model specification, which equals to $\frac{\omega}{1-\alpha-\beta}$ in the GARCH (1,1) case.

3.7.1.3 Other Types of Linear GARCH Models

Since the seminal propositions of ARCH and GARCH models, variances in their extensions have been developed by researchers in order to overcome the weaknesses of the standard ARCH/GARCH models.

3.7.1.4 The IGARCH Model

Often in economics, or finance, shocks occur to the economy or to the stock market. It is possible to measure whether these shocks are permanent or temporary with the use of the Integrated GARCH (IGARCH) model of Engle and Bollerslev (1986). A simple numerical test is performed by adding up all the co-efficients in the conditional variance equation:

$$\sum_{j=1}^p \beta_j + \sum_{i=1}^q \alpha_i \tag{A3.1-6}$$

If the sum of these co-efficients is equal to one, an IGARCH model is present, meaning there is a unit root in the conditional variance. Past shocks will persist for very long periods of time and current information remains of importance when forecasting the volatility for all horizons. If the co-efficients add up to less than one, then the shocks will be temporary and the market will correct itself by reverting the volatility to its mean long-run level.

3.7.1.5 The GARCH-M Model

The GARCH-In-Mean model¹⁴ is often applied in financial time series when the expected return on an asset is related to the expected asset risk. The GARCH-In-Mean (GARCH-M) model, proposed by Engle, Lilien et al., (1987), placed the conditional variance σ^2 into the mean equation A3.1-1. The conditional variance is included in the conditional mean equation as:

$$Y_t = X_t' \theta + \lambda \sigma^2 + \varepsilon_t \tag{A3.1-7}$$

where, X_t' is an exogenous variable.

¹⁴ See Bollerslev, Ray et al., (1992) for a survey of GARCH and GARCH-In-Mean models.

The GARCH-M model includes the conditional variance in the mean equation¹⁵, allowing the mean return to depend partly on the conditional variance of the series. For risk-averse investors, the co-efficient λ of the conditional variance in the mean equation would be expected to be positive, which means investors require higher returns for increased risk, or there is a positive relationship between risk and return.

3.7.1.6 Non-linear GARCH Models

3.7.1.7 The TARARCH Model

The different behaviour of volatility to good and bad news (the so-called leverage effect) is translated into asymmetric GARCH models, such as the TARARCH model (Zakoian, 1994) and Glosten, Jagannathan et al.,(1993). The TARARCH specification for the conditional variance is:

$$\sigma_t^2 = \omega + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^r \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- + \sum_{j=1}^p \beta_j \sigma_{t-j}^2 \quad (\text{A3.1-8})$$

where, $I_t^- = 1$ if $\varepsilon_t < 0$, and 0 otherwise.

The TARARCH model is based on the assumption that unexpected (unforeseen) changes in the returns of the asset, expressed in terms of ε_t , have different effects on the conditional variance of returns. An unforeseen increase ($\varepsilon_t > 0$) is presented as good news and contributes to the variance in the model through the multiplier, α . An unforeseen

¹⁵ Some GARCH-M specifications include conditional standard deviation, instead of conditional variance, in the mean equation.

fall ($\varepsilon_t < 0$), which is a piece of bad news, generates an increase in volatility through the multiplier, $\alpha + \gamma$. The asymmetric nature of the returns is then given by the nonzero value of the co-efficient γ , while a positive value of γ indicates a leverage effect.

3.7.1.8 The EGARCH Model

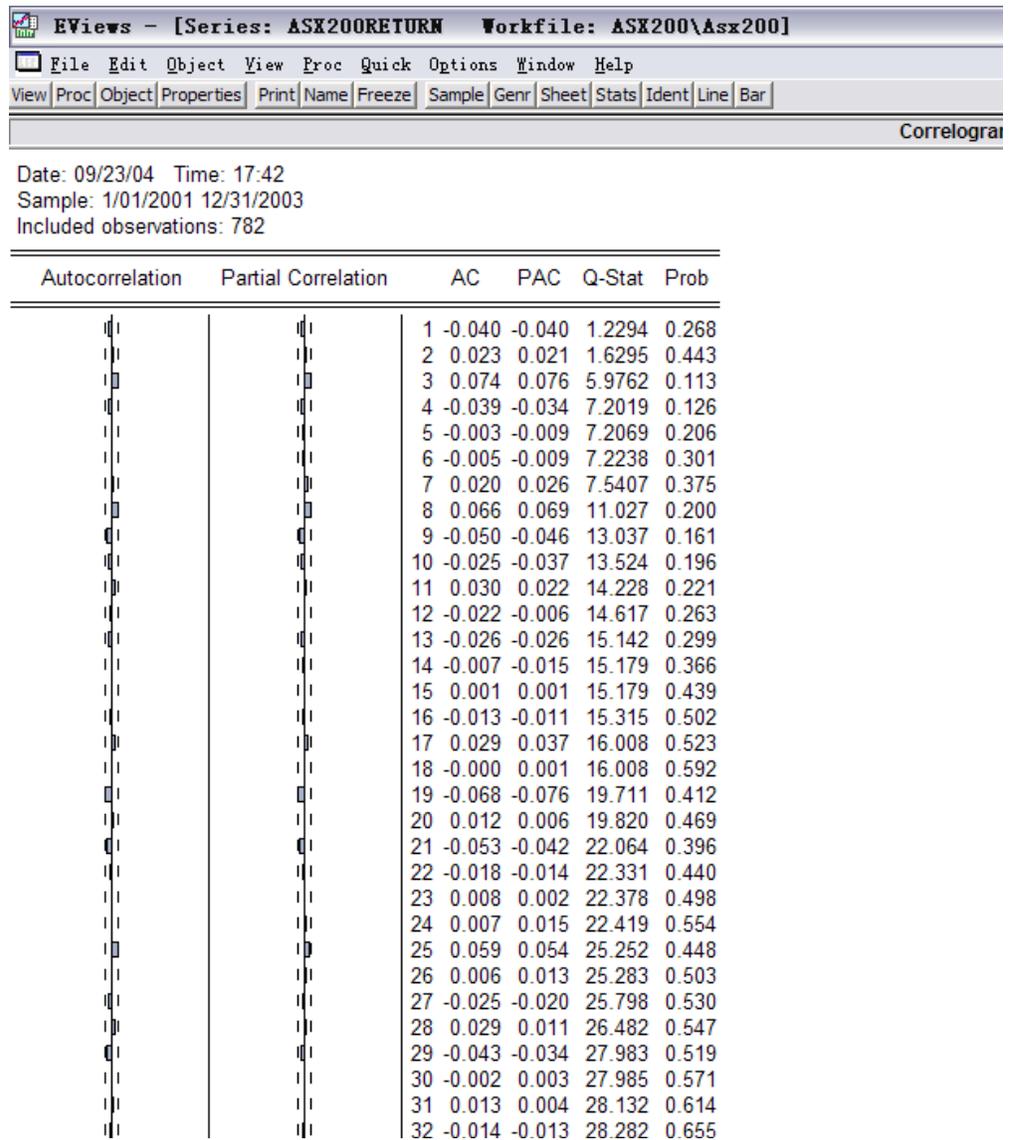
There is a potential problem with the linear GARCH model: A GARCH model can produce negative variances for some parameters, which is meaningless. Therefore, non-negativity constraints have been imposed on these parameters. Nelson (1991) claims the non-negativity constraints in the GARCH model are too restrictive. He introduces the Exponential GARCH (EGARCH) model to overcome this problem. EGARCH models the logarithm of the conditional variance:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^q \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right) \right| + \sum_{j=1}^p \beta_j \log(\sigma_{t-j}^2) + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} \quad (\text{A3.1-9})$$

where, the co-efficient γ measures the asymmetric effect, which, if negative, indicates negative shocks have a greater impact upon conditional volatility than positive shocks of equal magnitude.

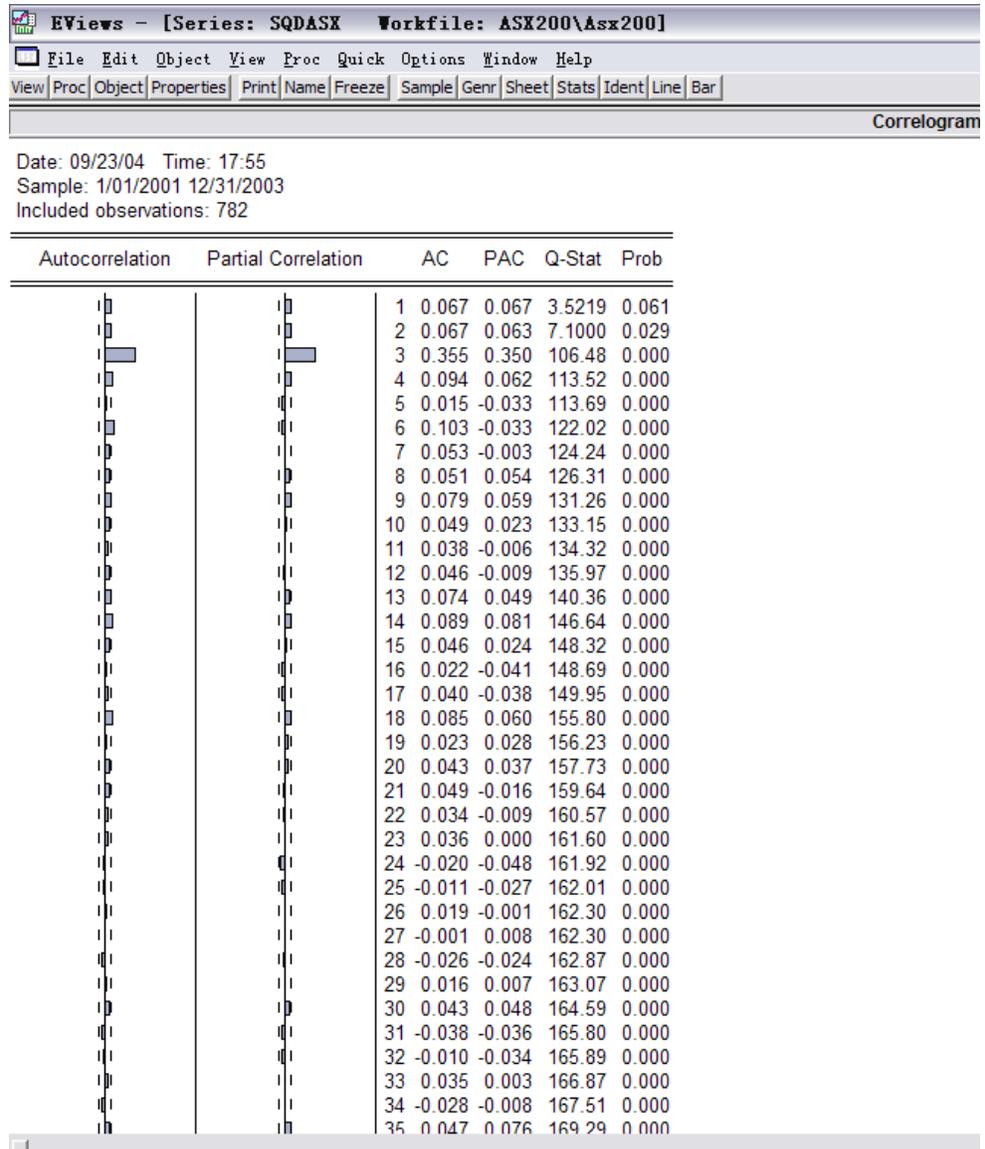
EGARCH has certain advantages over GARCH. Firstly, by using the exponential formulation, the restrictions of positive constraints on the estimated co-efficients in GARCH are no longer necessary. Secondly, GARCH fails to capture the negative asymmetry apparent in many financial time series. The EGARCH model solves this problem by allowing for the standardised residual as a moving average regressor in the variance equation, while preserving the estimation of the magnitude effect.

3.7.2 Appendix: Correlogram of ACF and PACF on S&P/ASX 200 Return Series



Sample range: January 1, 2001, to December 31, 2003.

3.7.3 Appendix: Correlogram of ACF and PACF of S&P/ASX 200 Squared Return Series



Sample range: January 1, 2001, to December 31, 2003

3.7.4 Appendix: ARCH LM Test on S&P/ASX 200 Return Series

ARCH Test:

F-statistic	40.14049	Probability	0.000000
Obs*R-squared	104.7644	Probability	0.000000

Test Equation:

Dependent Variable: RESID^2

Method: Least Squares

Sample (adjusted): May 1,2001 December 31, 2003

Included observations: 779 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.83E-05	5.05E-06	5.603929	0.0000
RESID^2(-1)	0.039515	0.033468	1.180690	0.2381
RESID^2(-2)	0.035429	0.033468	1.058571	0.2901
RESID^2(-3)	0.356014	0.033399	10.65959	0.0000
R-squared	0.134486	Mean dependent var	5.03E-05	
Adjusted R-squared	0.131135	S.D. dependent var	0.000127	
S.E. of regression	0.000118	Akaike info criterion	-15.24349	
Sum squared resid	1.08E-05	Schwarz criterion	-15.21957	
Log likelihood	5941.340	F-statistic	40.14049	
Durbin-Watson stat	2.037141	Prob (F-statistic)	0.000000	

Sample range: January 1, 2001, to December 31, 2003

Source: Author

*When lag 1 and lag 2 terms are included, the ARCH LM test is not significant. However, when lag 3 of AR term is included, the ARCH LM test statistic is highly significant, while the lag 1 and lag 2 terms are still not significant. So we have to dispose of the lag 1 and lag 2 terms and test ARCH effect manually. When lag 1 and lag 2 are deleted from the test equation, lag 3 and lag 4 give significant coefficients. The results are presented in the continuation of Appendix 3.7.4 overleaf.

Appendix 3.7.4 (continues)
 ARCH LM Test on S&P/ASX 200 Return Series

Dependent Variable: SQDRESIDASX

Method: Least Squares

Sample(adjusted): January 1, 2001 December 31, 2003

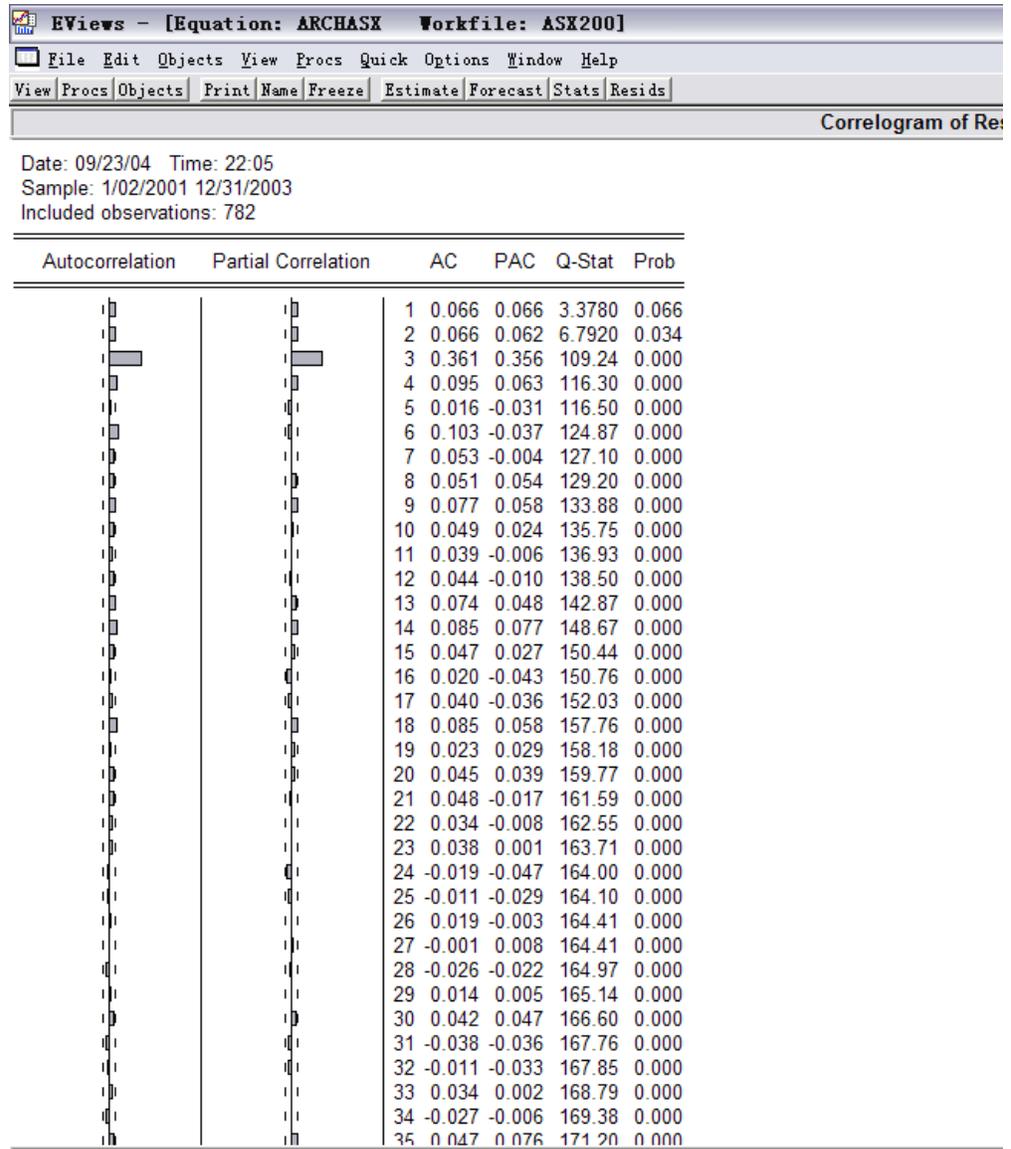
Included observations: 778 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.85E-05	4.82E-06	5.909515	0.0000
SQDRESIDASX(-3)	0.358685	0.033338	10.75891	0.0000
SQDRESIDASX(-4)	0.071293	0.033270	2.142837	0.0324
R-squared	0.137829	Mean dependent var	5.04E-05	
Adjusted R-squared	0.135604	S.D. dependent var	0.000127	
S.E. of regression	0.000118	Akaike info criterion	-15.24881	
Sum squared resid	1.08E-05	Schwarz criterion	-15.23086	
Log likelihood	5934.788	F-statistic	61.94674	
Durbin-Watson stat	1.953111	Prob (F-statistic)	0.000000	

Sample range: January 1, 2001, to December 31, 2003

Source: Author

3.7.5 Appendix: Correlogram of ACF and PACF of S&P/ASX 200 Residuals Squared



Sample range: January 1, 2001, to December 31, 2003

3.7.6 Appendix: GARCH (3, 1) Model on S&P/ASX 200 Return Series

Dependent Variable: ASX200RETURN

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1/02/2001 12/31/2003

Included observations: 782 after adjustments

Convergence achieved after 33 iterations

Variance backcast: ON

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1) + C(5)
*GARCH(-2) + C(6)*GARCH(-3)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000381	0.000220	1.731229	0.0834
Variance Equation				
C	5.55E-07	2.88E-07	1.929630	0.0537
RESID(-1)^2	0.021600	0.007643	2.825992	0.0047
GARCH(-1)	2.365387	0.174712	13.53876	0.0000
GARCH(-2)	-2.073980	0.298980	-6.936844	0.0000
GARCH(-3)	0.675087	0.137313	4.916405	0.0000
T-DIST. DOF	8.273115	1.805882	4.581205	0.0000
R-squared	-0.000770	Mean dependent var		0.000183
Adjusted R-squared	-0.008518	S.D. dependent var		0.007144
S.E. of regression	0.007175	Akaike info criterion		-7.189687
Sum squared resid	0.039896	Schwarz criterion		-7.147957
Log likelihood	2818.168	Durbin-Watson stat		2.070397

Sample range: January 2, 2001, to December 31st, 2003

Source: Author

3.7.7 Appendix: GARCH (3, 1) Model on S&P/ASX 200 Return Series

Dependent Variable: ASX200RETURN

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1/02/2001 12/31/2003

Included observations: 782 after adjustments

Convergence achieved after 33 iterations

Variance backcast: ON

GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1) + C(5)
*GARCH(-2) + C(6)*GARCH(-3)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000381	0.000220	1.731229	0.0834
Variance Equation				
C	5.55E-07	2.88E-07	1.929630	0.0537
RESID(-1)^2	0.021600	0.007643	2.825992	0.0047
GARCH(-1)	2.365387	0.174712	13.53876	0.0000
GARCH(-2)	-2.073980	0.298980	-6.936844	0.0000
GARCH(-3)	0.675087	0.137313	4.916405	0.0000
T-DIST. DOF	8.273115	1.805882	4.581205	0.0000
R-squared	-0.000770	Mean dependent var		0.000183
Adjusted R-squared	-0.008518	S.D. dependent var		0.007144
S.E. of regression	0.007175	Akaike info criterion		-7.189687
Sum squared resid	0.039896	Schwarz criterion		-7.147957
Log likelihood	2818.168	Durbin-Watson stat		2.070397

Sample range: January 1st, 2001, to December 31st, 2003

Source: Author

3.7.8 Appendix: GARCH (3, 1) - M Model on S&P/ASX 200 Return Series

Dependent Variable: ASX200RETURN

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1/02/2001 12/31/2003

Included observations: 782 after adjustments

Convergence achieved after 36 iterations

Variance backcast: ON

GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)
*GARCH(-2) + C(7)*GARCH(-3)

	Coefficient	Std. Error	z-Statistic	Prob.
@SQRT(GARCH)	0.191467	0.175671	1.089918	0.2757
C	-0.000827	0.001127	-0.733654	0.4632

Variance Equation				
C	5.40E-07	2.85E-07	1.899529	0.0575
RESID(-1)^2	0.020684	0.007306	2.830953	0.0046
GARCH(-1)	2.385962	0.163047	14.63357	0.0000
GARCH(-2)	-2.109560	0.279197	-7.555823	0.0000
GARCH(-3)	0.691203	0.128517	5.378282	0.0000
T-DIST. DOF	8.306861	1.815921	4.574461	0.0000

R-squared	-0.001751	Mean dependent var	0.000183
Adjusted R-squared	-0.010810	S.D. dependent var	0.007144
S.E. of regression	0.007183	Akaike info criterion	-7.188619
Sum squared resid	0.039935	Schwarz criterion	-7.140927
Log likelihood	2818.750	Durbin-Watson stat	2.067655

Sample range: January 1st, 2001, to December 31st, 2003

Source: Author

3.7.9 Appendix: TAR(3, 1) Model on S&P/ASX 200 Return Series

Dependent Variable: ASX200RETURN

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1/02/2001 12/31/2003

Included observations: 782 after adjustments

Convergence achieved after 20 iterations

Variance backcast: ON

$$\text{GARCH} = C(2) + C(3)*\text{RESID}(-1)^2 + C(4)*\text{RESID}(-1)^2*(\text{RESID}(-1)<0) \\ + C(5)*\text{GARCH}(-1) + C(6)*\text{GARCH}(-2) + C(7)*\text{GARCH}(-3)$$

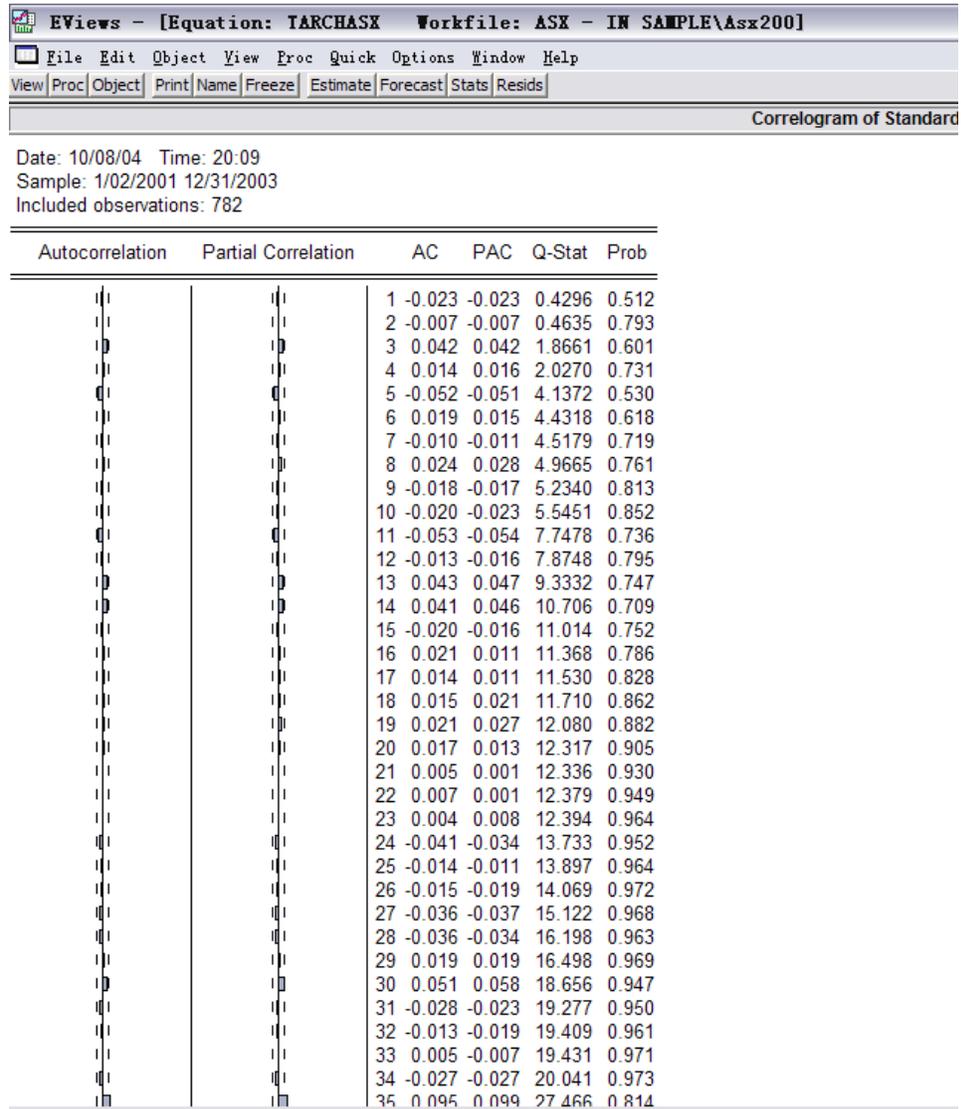
	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000199	0.000215	0.921675	0.3567
Variance Equation				
C	6.89E-07	2.29E-07	3.008480	0.0026
RESID(-1)^2	-0.013700	0.004493	-3.049545	0.0023
RESID(-1)^2*(RESID(-1)<0)	0.068083	0.013748	4.952290	0.0000
GARCH(-1)	2.159531	0.110826	19.48579	0.0000
GARCH(-2)	-1.937622	0.183760	-10.54431	0.0000
GARCH(-3)	0.741223	0.087604	8.461058	0.0000
T-DIST. DOF	9.920450	2.742659	3.617092	0.0003
R-squared	-0.000005	Mean dependent var		0.000183
Adjusted R-squared	-0.009049	S.D. dependent var		0.007144
S.E. of regression	0.007177	Akaike info criterion		-7.218571
Sum squared resid	0.039865	Schwarz criterion		-7.170879
Log likelihood	2830.461	Durbin-Watson stat		2.071981

Sample range: January 1st, 2001, to December 31st, 2003

Source: Author

3.7.10 Appendix: Correlogram of Standardised Residuals Squared of TARCH (3,1)

Model



Sample range: January 1st, 2001, to December 31st, 2003

3.7.11 Appendix: EGARCH (1, 1, 1) Model on S&P/ASX 200 Return Series

Dependent Variable: ASX200RETURN

Method: ML - ARCH (Marquardt) - Student's t distribution

Sample (adjusted): 1/02/2001 12/31/2003

Included observations: 782 after adjustments

Convergence achieved after 11 iterations

Variance backcast: ON

LOG(GARCH) = C(2) + C(3)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(4)*RESID(-1)/@SQRT(GARCH(-1)) + C(5)*LOG(GARCH(-1))

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000198	0.000216	0.915869	0.3597
Variance Equation				
C(2)	-0.256603	0.067743	-3.787866	0.0002
C(3)	0.030658	0.026431	1.159926	0.2461
C(4)	-0.114561	0.018661	-6.139156	0.0000
C(5)	0.977154	0.006225	156.9627	0.0000
T-DIST. DOF	10.55314	3.179986	3.318612	0.0009
R-squared	-0.000004	Mean dependent var		0.000183
Adjusted R-squared	-0.006448	S.D. dependent var		0.007144
S.E. of regression	0.007167	Akaike info criterion		-7.223270
Sum squared resid	0.039865	Schwarz criterion		-7.187501
Log likelihood	2830.299	Durbin-Watson stat		2.071982

Sample range: January 1st, 2001, to December 31st, 2003

Source: Author

4 Lead/lag Direction and Price-Discovery of the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options

4.1 Introduction

In Chapter 3 volatility, as a measure of the amount by which asset prices are expected to fluctuate over a given period, was investigated. The volatility of the S&P/ASX 200 Index Options are clustered and the GARCH (3,1) and TARCH (3,1,1) models were found to be the better-fitted models within the linear and non-linear ARCH specifications. Implied volatility was derived from the daily S&P/ASX 200 option prices, employing both loss functions and regression, to evaluate the accuracy and information content of the volatility forecasts. A reasonable guideline is, in the short forecast horizon, implied volatility combined with ARCH type volatility could be utilised as a reasonable proxy of conditional volatility when calculating option prices for the S&P/ASX 200 Index. When forecasting into the longer horizon, implied volatility is more valuable for estimating an option price for the S&P/ASX 200 Index.

In this Chapter I investigate the relationship between the S&P/ASX 200 Index Options market and its underlying S&P/ASX 200 Index market by testing how information is transmitted between them. If there is a causal relationship between the S&P/ASX 200 Index market and the S&P/ASX 200 Index Options market it might be possible to use one market to predict the other. This might provide market participants with important information regarding when and how to execute trades in the S&P/ASX 200 Index Options market. I examined the lead/lag relationship on the S&P/ASX 200 Share Price Index, as the underlying security of the S&P/ASX 200 Index Options traded on the ASX. Co-integration testing procedures are utilised as univariate and multivariate

approaches to test the causal relationship between the variables and vector error-correction modelling (VECM), in order to test for causality (Vogelvang, 2005). Price-discovery is defined as "*the dynamic process by which market prices incorporate new information*" (Yan and Zivot, 2007). The main object of the price-discovery analysis is to identify the primary venue where efficient price innovations occur. The quotes and trades submitted by informed traders contain vital information about securities, and the market with more informative quotes and trades contributes more to price discovery.

The financial industry has come to recognise the importance of derivative securities in providing unique investment opportunities and risk-management vehicles. Trading volume on derivatives has increased tremendously during the past few years. Accompanying this expansion in derivatives have been rapid expansions and transformations in the options market. Option prices provide information about the underlying security which is not readily available from the primary security market. The price quote of a stock represents a mean valuation of the stock, but the prices of options underlying this stock at the whole spectrum of strike prices and maturities present a complete picture on the conditional distribution of the stock value at different possible realisations and conditioning horizons. Therefore, it is important to understand the information flow in the options and index markets.

If an investor obtains information regarding a firm's future returns, he can trade in stock and/or option markets to take advantage of that information. The ideal strategy for him will be to trade in all markets until the marginal profits from all markets are equivalent and thereafter to trade with equal probability in all markets. However, it is also possible that an informed trader prefers trading in one specific market due to a

relatively favourable trading environment or his familiarity with the market. Informed traders may prefer trading in the stock market due to its relatively high liquidity. In this case, I will observe that most price-discovery occurs in the stock market rather than in the option market. If informed traders choose to trade in the options market for its higher leverage, I will observe that most of the price-discovery occurs in the option market.

The purpose of this study is threefold. The first is to assess the nature of short- and long-run equilibrium relationships between prices, implied by the S&P/ASX 200 Index Options prices and the S&P/ASX 200 Share Price Index, utilising a co-integration approach and error-correction model in order to test the causal relationships. The second aim is to determine the direction of this association, whether or not the S&P/ASX 200 Share Price Index tends to lead changes in the S&P/ASX 200 Index Options, or vice versa. The asset price dynamics will be extracted and applied to the findings from the previous chapter in order to determine whether, or not, volatility is implicit in the market prices of stock index options and the underlying stock index. The third aim is to use common factor models to measure the contribution of the S&P/ASX 200 Share Price Index and S&P/ASX 200 Index Options markets to the price-discovery process. An estimate will be made of how much price-discovery occurs in the index and option markets, using information-sharing and permanent-transitory models. I will estimate how much price-discovery occurs in the index and option markets, using the information shares approach of Hasbrouck (1995) and a factor weight based on the (Gonzalo and Granger, 1995) decomposition first applied to financial markets by Booth, So et al., (1999).

Empirical research into lead/lag relations between stock indices and index derivatives has been inconclusive. Several researchers find stock markets lead, others find option markets lead and one study finds the lead/lag relationship between stock and option markets is spurious. Most of the research on stock and option markets was focused on US markets (NYSE, AMEX, OTC and CBOT) and these are all dealer markets with less-than-full automation. The ASX is a competitive order matching market with full automation suggesting different market structures give rise to different spreads (Aitken and Frino, 1996).

The fundamental role of option markets is recognised as being the provision of a risk-management tool for investors in underlying securities. Options are redundant securities in the marketplace, since their payoffs can be replicated using shares and bonds. Option markets provide a means of hedging positions held in underlying markets. Black (1975) suggested informed traders utilise option markets, given the higher leverage which they offer compared to the underlying market. Evidence that the options market leads the stock market provides some support for the notion option markets are used by informed traders to make speculative profits. Similarly, evidence that the stock market leads the options market supports the notion options are primarily used to hedge positions held in the underlying stocks.

My analysis is motivated by the debate and discussion about the interpretation of Gonzalo and Granger's (1995) method and Hasbrouck's (1995) information share approach. As illustrated by various papers in the special issue on price-discovery of the *Journal of Financial Markets* (Issue 3, 2002), there has been substantial confusion in the literature over what the information share and permanent-transitory model imply for

price-discovery measurement. The fundamental cause of this confusion is that both measures are defined in terms of the reduced form-forecasting errors of individual markets from an empirical vector-error-correction model.

Lehmann (2002) states:

“This muddled state is unsurprising because the error-correction model is a reduced form and the role of each market in price-discovery depends on the parameters of the structural model.”

I contribute to the literature relating to changes in the market microstructure of the ASX, as the index composition changed when the ASX sold its index calculation business to Standard & Poor's. To my knowledge, this is the first study of the lead/lag relationship and price-discovery function of the S&P/ASX 200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX. The direction of causality from the index market to the options market is strong, but a much weaker effect exists from the options market to the index market. The results, contrary to other literature, indicate the index market plays the primary role in price discovery. Unambiguous evidence shows the index market leads the options market and the former contributes more to price-discovery than the latter.

4.2 Literature Review

Three major approaches towards the study of price-discovery of assets have been identified in the literature. The first approach focuses on the sparse theoretical research and is predominantly based on a framework for addressing issues related to the adjustment of prices to information. The second direction examines the role of lead/lag relationships

between the prices of national markets, or between different securities. The third direction examines price-discovery of how information is transmitted among different markets. The empirical price-discovery literature is comprehensive in considering different informationally linked markets and securities. While many studies compare stock and options markets, others focus on spot, futures and options/futures markets, as well as the securities traded on different domestic and international exchanges. Despite the wealth of literature, the general findings suffer from a lack of consensus.

O'Hara (1999) states:

"The microstructure literature analyses how specific trading mechanisms affect the price formation process and the process by which markets become efficient." The theoretical research is predominantly based on "the sequential trade models of Glosten, Milgrom and Easley and O'Hara who provide a framework for addressing issues related to the adjustment of prices to information".

The efficient market hypothesis (EMH) does not explicitly consider the price-formation process and does not explain a persistent price-quantity relationship, which contradicts the size effect of trades which is theoretically documented in Easley and O'Hara (1987) and empirically documented in Hasbrouck (1991a),(1991b). Information models stipulate that when informed investors communicate their trade intentions, they inevitably reveal their more-precise value perception to the market. Market makers and less-informed traders are able to infer the value perception of more-informed investors indirectly from observed trading parameters, such that the trading process itself plays a part in price discovery. Grossman and Stiglitz (1980) suggest that if the only uncertainty concerns the value of an informed investor's private information, competitive trading

might cause prices to be fully revealing, such that one price formation would be sufficient to reveal a security's true value. Copeland and Galai (1983) consider information costs to market makers from trading against informed investors. The model assumes that any private signal is fully revealed after each trade. This precludes a market maker from dynamically adjusting his quotes over a series of trades. Trading parameters constitute indirect evidence of value, and unlike private signals, these trading parameters may arise from transitory liquidity effects. As such, the history of trading parameters may offer more revelations on an asset's value than currently observed trading parameters.

Theoretical extensions on information models based on the preceding ground form the basis for sequential trade models. Kyle (1985) models the strategic behavior of an informed trader under different trading mechanisms, including batch, sequential auction, and continuous auction. Glosten and Milgrom (1985) apply Bayesian learning models to consider multiple rounds of trading and quote adjustments. In such models, although price adjustment is modeled over a series of trades, signals are drawn from the price of each trade rather than from a sequence of prices over a series of trades. In the Glosten and Milgrom (1985) framework, market makers set bid and ask quotes such that resulting transaction prices reflect the information possessed by investors with which they trade. Market makers achieve that by setting the bid quote conditional on the next trader wanting to sell and the ask quote conditional on the next trader wanting to buy. Bid and ask quotes reflect a market maker's assessment of the value of the stock as well as his assessment of the probability of informed trading. A variant class of sequential trade models by Brown and Jennings (1989) and Grundy and McNichols (1989) allow the price formation to be influenced by either information or liquidity effect. Traders in

such models have to distinguish one effect from the other and this requires the observation of price changes since the price level at a point in time may not be fully revealing. This gives rise to the informational relevance of an observed price sequence.

Grossman (1988) argues that even when options can be synthetically replicated by dynamic trading strategies, their absence can prevent the transmittal of information to market participants and lead to more volatile stock prices. Back (1993) presents a model with asymmetrically informed traders and shows that the introduction of an option causes the volatility of the underlying stock to become stochastic. Biais and Hillion (1994) examine the impact of option trading on an incomplete market. They show that even though options' trading mitigates the market-breakdown problem caused by asymmetric information and market incompleteness, its impact on the informational efficiency of the market is ambiguous. Brennan and Cao (1996) use a noisy rational expectations model to demonstrate that gains which accrue to informed and uninformed traders from multiple rounds of trading in a risky asset can be achieved in a single round of trading by introducing trading in a quadratic option. Easley, O'Hara et al., (1998) use this intuition to develop and test a market microstructure model of informed traders who can trade the stock or the option and show how certain options trades could contain information about future stock price movements.

The temporal relationship between derivative security markets and their underlying markets are of interest to researchers for a variety of reasons. As described by Wahab and Lashgari (1993) and De Jong and Donders (1998), the issues are linked to a central notion in fundamental financial theory of market efficiency and arbitrage theory. In perfectly efficient markets, profitable arbitrage should not exist, as prices would adjust

instantaneously and fully to all relevant information and new information coming into the market should be immediately reflected in all of the markets simultaneously. There should be no systematic lagged responses long enough, or large enough, to be economically exploited, when transaction costs are taken into consideration. Investors have to examine the potential volatility-spillover effects on the underlying markets from the derivative securities trading. Specifically, the derivative markets have been suspected of exerting a destabilising influence on the underlying securities markets. There is some evidence that trade in the derivative markets will increase the underlying markets' volatility (Harris, 1989).

John, Koticha, et al., (2000) model the traders' decision on whether to trade in the stock or option market. They argue that a common shortfall of the studies involving the stock and options markets is that they ignore the presence of the margin requirements when trading options versus stocks. The authors then go on to show that, in the presence of wealth constraints, the differential margin requirements on stocks versus options can affect traders' strategies in these two securities and the resulting equilibrium market prices. Informed traders may be more sensitive to trading costs than uninformed traders and more likely to switch trading venues in response to changing margin requirements.

Capelle-Blancard (2001) develop a multimarket sequential trades model with asymmetric information in which directional traders and volatility traders interact strategically. He considers a sequential model where risk-neutral market makers serve market orders placed either by informed or liquidity traders. To exploit their private information, while avoiding full revelation, directional-traders split their trades between spot and options markets as volatility traders cannot trade in the spot market. The major

finding is that volatility traders evict directional traders from the option markets. There are conditions under which volatility trades have a positive impact on options bid/ask spread so that directional traders choose the spot market, despite the leverage effect of the options. When market makers are not subject to volatility trading, options markets play an important role in optimal trading strategies of directional traders, but where traders do face volatility traders, directional traders do not use options markets.

Past evidence of the lead/lag relationship between stock and option prices has been mainly US-based, and conflicting results have been reported in regards to which markets lead or lag. Table 4.1 provides a summary of empirical research in this field.

Manaster and Rendleman (1982) investigated close-to-close returns of portfolios based on the relative difference between stock and option prices. They concluded option prices lead stock prices and it takes up to one day for stock prices to adjust. This implies option prices contain information which is not reflected by the stock prices. The results of this study are undermined, as the CBOE closes 10 minutes after the stock market and information contained in the option prices may have been information which has been disseminated into the market place after the stock market has closed for the day.

Table 4-1 Annotated Bibliography of Empirical Studies on Lead/Lag Relations between Equity Index and Options Markets

Author/Year	Market/Database Interval Size	Leading Market	Main Findings
Manaster and Rendleman (1982)	CBOE CRPS Option Tape (Daily)	Derivative (1 Day)	Closing option prices contain information that is not contained in closing stock prices and it takes one day for stock prices to adjust.
Bhattacharya (1987)	CBOE, Berkeley Options Database (15, 30, 45 minutes, 1, 2 hour and overnight)	Derivative	Option prices lead stock prices but are insufficient to overcome transaction costs.
Anthony (1988)	CBOE Call/Put (Daily)	Derivative (1 Day)	Trading in call options leads underlying shares by one day.
Stephan and Whaley (1990)	CBOE Call (Intraday 5 minutes)	Equity (15 minutes)	Price changes in the stock market lead the options market by 15 minutes.
Chan, Chung and Johnson (1993)	CBOE Call/Put (Intraday 5 minutes)	Derivative	The stock price lead disappears when the average bid/ask prices are used instead of transaction prices. Neither market leads the other.
Diltz and Kim (1996)	CBOE Call (Daily)	Derivative (2 Days)	Trading in call options leads underlying shares by two days.
Fleming, Ostdiek and Whaley (1996)	CBOE, CME Options and Futures (Intraday 5 minutes)	Derivative/Equity (10 minutes)	The index futures market leads the index options market. Index options lead cash index by five minutes.
Easley, O'Hara and Srinivas (1998)	CBOE, Berkeley Options Database (Intraday 5 minutes)	Derivative	Options markets are preferred for information-based trading.
O'Connor (1999)	CBOE, Berkeley Options Database (Intraday 5 minutes)	Equity	The stock market leads the options market, but the relationship depends on trading costs.
Booth, So and Tse (1999)	DAX, from DTB for FDAX, ODAX (Intraday 15 minutes)	Equity/Derivative (1 minute)	DAX index spot and futures share most of the price-discovery and the options market the least.
Finucane (1999)	CBOE, Berkeley Options Database (Intraday 5 minutes)	Equity (6 minute)	Stock quotes lead option quotes from a few seconds to six minutes.
Gwilym and Buckle (2001)	FTSE100 index futures and options (Intraday Hourly intervals across the day)	Derivative (60 minutes)	Index futures and index options contracts lead the cash index. Call options market marginally leads index futures and put options.
Hatch (2003)	CBOE, Berkeley Options Database (Intraday 5 minutes)	Equity (30 minutes)	Stock market returns lead the options market returns by at least 30 minutes.
Chakravarty, Gulen and Mathew (2004)	CBOE, Berkeley Options Database (Intraday 1,30,60 minutes)	Derivative	Options market leads stock market.
Nam , Oh , Kim H, Kim B (2006)	KOSPI 200 stock index, futures and options markets Intraday 1, 5, 10, 60 mins)	Derivative (5-9 minutes)	Index futures and index options lead the cash index.

Bhattacharya (1987) used intraday data to measure the lead/lag effect. Using a sorting technique, he attempts to separate the option trades into those occurring at the bid and those occurring at the ask price. He finds that the implied prices do contain information not in the actual price, but not enough to overcome the bid-ask spread. His sample selection includes both announcements that are consistent with expectations as well as those that are abnormal. Including the announcements that simply confirm prior expectations dilutes the strength of any informationally-based lead/lag relation. Bhattacharya's test design, however, suffers in that it only detects whether the options market leads the stock market and not vice versa. Although Bhattacharya recognises this as a problem, the reverse simulations are not performed.

Anthony (1988) used daily data to examine whether, or not, trading in options markets causes trading in stock markets, and vice versa. He uses causality tests, derived from Granger (1969), to determine the timing and direction of information flows between the stock and options markets and concludes trading in call options leads underlying shares by one day. Volume may not be the best proxy for the rate of information arrival, if price change-data is also available.

Stephan and Whaley (1990) investigated the intraday price change and trading volume relationship between stocks and options for a sample of firms trading on the CBOE. They used Sims (1972) style causality tests of observed and implied stock prices. The implied stock prices were calculated using Roll's (1977) American call option pricing formula. Stephan and Whaley (1990) found price changes in the stock market lead the options market by 15 minutes. They used a single-equation specification and not a vector autoregression (VAR). A time shock is likely to affect both the actual and

implied returns. Since the actual return is an explanatory variable, correlation with the error term could result in inconsistent parameter estimates. No formal causality test of lead/lag behaviour was conducted and their interpretation of their results relied on the economic interpretation of the estimated co-efficients.

Chan, Chung et al.,(1993) confirmed Stephan and Whaley's results for the same period and showed non-synchronous trading induced their results. They found that by analysing transaction prices, there is a lead of fifteen minutes of the stock market over the options market. Furthermore, they show by analysing bid-ask quotes rather than transaction prices, the result disappears, and state that the lead may be a spurious result caused by the different tick sizes in the two securities. They used a non-linear multivariate model to compute implied stock prices, rather than an option-pricing model. No formal causality test of lead/lag behaviour was conducted and their interpretation of their results relied on the economic interpretation of the estimated co-efficients Hatch (2003) indicated using trade prices will favour any results towards the stock market lead.

Diltz and Kim (1996) investigated the conflicting results regarding the price-change relationship between options and their underlying stocks. They used bi-directional causality testing, and found the problem of non-synchronicity and bid/ask bounce is overcome by the use of observed bid/ask spread data. They implemented an error-correction model to investigate the lead/lag relationships in daily stock and options market data. Diltz and Kim (1996) did not conduct formal causality tests of the lead/lag relationship, but relied on the significance of the individual regression co-efficients. They found that trading in call options leads the underlying shares by two days.

Fleming, Ostdiek, et al., (1996) consider the relation between the S&P 100, the S&P 500, S&P 500 futures, and S&P 100 options. They formalise the trading cost hypothesis and argue that information-based trades result in maximum net profits when they are executed in the lowest-cost market where price-discovery occurs more quickly. The empirical approach follows Stoll and Whaley (1990), with the pair wise relation between the markets examined in single-equation regressions of one return series on lead, lag, and contemporaneous returns of another series. Fleming, Ostdiek, et al., (1996) primary hypothesis that leads and lags are induced by relative trading costs in the different markets is supported by their results. The results indicate that both derivatives markets tend to lead the equity market and the futures market tends to slightly lead the options market, although there is considerable feedback between the two derivatives markets. They used a single-equation specification and not a vector autoregression (VAR). A time shock is likely to affect both the actual and implied returns. Since the actual return is an explanatory variable, correlation with the error term could result in inconsistent parameter estimates.

Easley, O'Hara et al., (1998) develop an asymmetric information model to describe the impact of informed traders on spread and volume of stocks and options. They show that in a multi-market setting, there is a trade-off between liquidity and leverage. They also suggest that stock and option markets are in a pooling equilibrium, where informed traders will trade in one or both markets until their profit margin becomes equivalent. Their empirical result shows that signed option volume contains information about future stock prices. They find that information flows are bi-directional between stock and option markets, but the degree of relative informativeness of the options market is uncertain.

O'Connor (1999) investigates the relationship between cross-sectional differences in trading costs and intraday lead/lag effects in stock and options markets. This study uses an error-correction model framework to investigate the lead/lag effects. This approach provides information on both the long-run equilibrating process and the short-term interactions between stock and options markets. All models are estimated with quote data and are constructed to eliminate overnight effects. He shows that overall the stock market leads the options market and that the lead is related to options' trading costs, but the study covers a two-month trading period only.

Booth, So et al., (1999) employ the common-factor-weight approach to study price-discovery in German equity derivative markets. They investigate information sharing among the spot index, index futures, and index options based on the Germany DAX index securities for the period from 1992 to 1994. Using at-the-money options in 15-minute intervals, Booth, So et al., (1999) find that index futures lead the spot index by 30 minutes and a feedback relationship exists between the futures and spot markets. Both the DAX futures and spot react to information faster than the DAX options. The DAX index options contribute only two percent to price discovery.

Finucane (1999) uses ordered quote changes in the stock and options markets to construct variable-length price-change intervals as a way of controlling the biases from using fixed length intervals, and finds that neither the stock market nor the options market leads when five-minute intervals are constructed using bid-ask quotes, but using variable intervals, shows that stock market leads are present. He argues that these results could be due to aggregation of price and volume data over fixed length time intervals ranging from five minutes to a day. By employing variable length time intervals, he avoids the

problems associated with aggregation and finds that stocks exhibit a short lead of five minutes or less.

Gwilym and Buckle (2001) examine the lead/lag relationships between the FTSE100 stock market index and its related futures and options contracts, and also the interrelationship between the derivatives markets. Hansen's (1982) generalised method of moments is used to account for possible inefficient OLS standard errors.

Chan, Chung et al., (2002) examine the intraday interdependence of order flows and price movements for actively traded NYSE stocks and their CBOE-traded options. They find that informed investors initiate trades in the stock market, not in the options market, but that stock and option quote revisions have predictive ability for one another. This suggests that while information in the stock market is contained in both quote revisions and trading prices, information in the options market is contained only in quote revisions. One interpretation is that option quotes affect the level of information asymmetry in the stock market.

Hatch (2003) employs a vector error-correction model of stock prices and option-implied stock prices, but aggregates the data over five-minute intervals. He then constructs a GARCH model for the volatility, also with aggregated data, and concludes that there is bi-directional causality, with stocks exhibiting a longer lead. However, the assumptions for an admissible error-correction representation of these time series preclude GARCH behaviour in the residuals. The observed heteroscedasticity may be a result of data aggregation.

Chakravarty, Gulen et al., (2004) use a procedure suggested by Hasbrouck (1995) to estimate how much price-discovery occurs in the options market and how much occurs in the underlying stock market. This methodology measures the information share of price-discovery by the proportion of innovations to the efficient price occurring in each market. They find that some price-discovery occurs in the options market, where the information share averages 17 percent when option volume is elevated and stock volume is lower and when option effective spreads are narrower and stock effective spreads are wider. While they report average annual information shares ranging from 12 to 23 percent for daily firm-level option trades, there is no indication that the average is representative of the distributions, nor is it clear that the individual averages are significantly different from zero. Their results are based on stock prices rather than using stock returns.

Nam, Oh et al., (2006) investigate the Korean financial markets, price-discovery and pricing bias associated with stock index, futures and options. First, the lead/lag relationships among the KOSPI 200 stock index, the index futures, and the index options markets are explored based on minute-to-minute price data. The empirical approach follows Fleming, Ostdiek, et al., (1996). The results explain that the KOSPI 200 stock index futures lead the index and the at-the-money options lead the stock index. The pricing bias between the observed KOSPI stock index and implied stock index from at-the-money options is affected by market inefficiency, moneyness and implied volatility. They used a single-equation specification and not a vector autoregression (VAR). A time shock is likely to affect both the actual and implied returns. Since the actual return is an explanatory variable, correlation with the error term could result in inconsistent parameter estimates.

Capelle–Blancard, (2001) model explains why options markets should not lead the spot market, which is consistent with empirical findings of Easley, O’Hara et al., (1998). The model predicts also that the informational role of stock price is great when uncertainty about future volatility is high, which has been confirmed by Chakravarty, Gulen et al., (2004), and their results are consistent with theoretical arguments that informed investors trade in both stock and option markets. He suggests that when there is greater uncertainty, there is likely to be more price-discovery in the stock market and less in the option market.

Gonzalo and Granger (1995) investigated price-discovery using a permanent-transitory model, while Hasbrouck (1995) used an information-shares model. Hasbrouck (1995) defines price-discovery in terms of the variance of the innovations to the common factor. Thus the information-shares model measures each market’s relative contribution to this variance. Gonzalo and Granger (1995) are concerned with only the error-correction process. This process involves only permanent (as opposed to transitory) shocks that result in a disequilibrium. In the price-discovery context, disequilibria occur because markets process news at different rates. The permanent-transitory model measures each market’s contribution to the common factor, where the contribution is defined to be a function of the market’s error-correction co-efficients.

Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988), Stephan and Whaley (1990), Chan, Chung et al., (1993), Diltz and Kim (1996), Fleming, Ostdiek, et al., (1996), Easley, O’Hara et al., (1998), O’Connor (1999), Finucane (1999), Gwilym and Buckle (2001) and Hatch (2003) utilize the lead/lag approach in their studies. Using the lead/lag approach in price-discovery between stock and option markets is

inconclusive. The lead/lag regression between stock and option markets depends on a multivariate time series of prices, returns, volume, and/or spreads of stocks and options. Researchers, studying the lead/lag regression, test whether a co-efficient or set of co-efficients of each variable is significant. With this approach, I have to acknowledge only one market's price leadership and cannot examine relative roles of stock and options markets in the price-discovery process.

Baillie, Booth et al., (2002), De Jong (2002) and Lehmann (2002) derived the relationship between the information-share and permanent-transitory models from Hasbrouck (1995). Harris, McInish et al., (2002a), (2002b) and Hasbrouck (2002) compared the differences between the two models. Although both Gonzalo and Granger (1995) and Hasbrouck (1995) offer a measure for the informativeness of a market on the efficient price process, De Jong (2002) shows that "*only information share takes into account the variability of the innovations in each market's price*". He proves that with the Gonzalo and Granger method, the total variance of innovation is not considered. On the other hand, the information-share approach provides a relative measure of how much variation in the efficient-price process is explained. The variation in the efficient price can be interpreted as new information injected into the efficient-price process. Yan and Zivot (2007) also prove that only the information share approach provides the relative informativeness, whereas Gonzalo and Granger's method "*does not reflect a market's price response to new information at all*". Hasbrouck (2002) pointed out this violates the condition the efficient price should be a martingale.

Booth, So et al., (1999), Chu, Hsieh et al., (1999) and Harris, McInish et al., (2002b) use Gonzalo and Granger's (1995) method in their studies. Chakravarty, Gulen et

al., (2004), Collver (2005) and Upper and Werner (2007) employ Hasbrouck's information-share approach. Booth, Lin et al., (2002) use both models to examine the Finnish upstairs and downstairs stock markets.

4.3 Data and Methodology

4.3.1 Data

Daily closing values (dividend-adjusted) of the S&P/ASX 200 Index and daily closing prices for the S&P/ASX 200 call option contracts are used in this study. Data was supplied by SIRCA, the ASX and DataStream. The S&P/ASX 200 Index sample data range covers the period from March 1, 2001, to December 31, 2005, inclusive. The dates were chosen due to the fact the S&P/ASX 200 and other index series were launched by Standard and Poor's in 2000. This launch coincided with Standard and Poor's taking over the index business, which was formerly owned and managed by the Australian Stock Exchange.¹⁶

Daily closing prices are used and the return series is obtained by taking the difference between t and $t-1$ of the natural log of prices of the return series and the implied return series:

$$\text{Return Series: } r_t = \log \frac{P_t}{P_{t-1}} \quad \text{Implied Return Series: } \hat{r}_t = \log \frac{\hat{P}_t}{\hat{P}_{t-1}} \quad (4.1)$$

where P_t and \hat{P}_t are the time-weighted average daily trading price.

¹⁶ S&P/ASX 200 2006 Directory.

Implied index prices are used, as the raw call option prices cannot be directly used to draw inferences. Implied stock index prices may be estimated, either independently or jointly, with the implied stock price volatility. The implied stock price is estimated independently. By converting option prices to implied stock index prices, the non-linearity problem between index and option prices is resolved. Following Diltz and Kim (1996), O'Connor (1999) and Hatch (2003), the implied stock index ask prices are obtained by solving a modified¹⁷ Black-Scholes formula for the implied stock ask price¹⁸. Roll's (1977) compounded option pricing formula is used, as the options on the S&P/ASX 200 Index are European-style options.

$$C_t = S_t N(d) - Ke^{-rt} N(d - \sigma\sqrt{\tau}), \quad (4.2)$$

$$\text{where } d = \frac{\log(S_t / K) + (r + \sigma^2 / 2)\tau}{\sigma\sqrt{\tau}},$$

$$\text{and } N(d) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^d e^{-\frac{x^2}{2}} dx.$$

$$\text{Min}_{\sigma} Q = \left(\sum_{i=1}^N (C_{a,i} - f(S_a, K_i, T_i, \sigma)) \right)^2 \quad (4.3)$$

where C_t is the Black-Scholes price for the call option, S_t is the price of the stock index (dividend-adjusted), K is the exercise price, K_i is the call option, I is the strike price, T is the time to expiration, T_i is the call option z time to expiration, N is the total

¹⁷ The σ^2 of the stock index return variance is calculated using the GARCH (3, 1) specification. using a rolling window.

¹⁸ For detailed analysis on the mathematics underlying the Black Scholes Model, see Hull, J. (2006).

number of qualifying calls written on the stock and r is the risk-free interest rate sourced from Treasury bills. Data for the 30-day, 60-day and 90-day bills were obtained from DataStream, and the yield on the bill having the expiry closest to that of the option was used as the risk-free rate. The σ^2 of the stock index return variance is calculated using the GARCH (3, 1) specification. A rolling window was used to calculate the volatility. The volatility proxy was found to be the better-fitting model within the linear and non-linear ARCH specifications. Only those options which were close at the money were selected, to mitigate volatility smile effect.

The option price is found by taking the midpoint of the bid and ask quotes for the option under consideration (Chan, Chung et al., 1993). This has advantages over using the actual trading price. Using the midpoint prices removes any spurious negative autocorrelation, resulting from bid/ask bounce (Lo and MacKinlay, 1990). Also, bid and ask quotes are more often reported than are actual trade prices (O'Connor, 1999). This is important in minimising the impact of infrequent and non-synchronous trading, and the use of stale prices.¹⁹ Trading in the options and stock index markets is based on bid and ask quotes, but every quote does not result in a trade.

4.3.2 Methodology

There are three widely used techniques in the price-discovery literature, the lead/lag approach, the Hasbrouck's (1995) information-share approach and the Gonzalo and Granger (1995) approach. I employ all these techniques to measure the relative

¹⁹ Lo and Mackinlay (1988); (1990) examined the non-synchronous problem. Miller, Muthuswamy et al., (1994) showed that, under reasonable assumptions about infrequent trading of index portfolio stocks, strong negative first-order autocorrelation could be expected.

contribution of the options market on the evolution of efficient stock index prices. These techniques are explained in detail in Appendix 4.6.1

4.3.2.1 Lead/lag Approach

Before the lead/lag relationship between the S&P/ASX 200 Index and the S&P/ASX 200 options is examined in a causality framework of several simultaneous equation models, it is important to test the unit roots prior to testing the causal relationships, as Granger causality tests require the data to be stationary. A series is said to be integrated of order one if it has to be differentiated once before becoming stationary (Vogelvang, 2005). Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF), Dickey and Fuller, (1979), (1981) unit root test and the Phillips-Perron, (Perron, 1988), (Phillips and Perron, 1988) nonparametric tests (Enders, 2004). Instead of choosing between either one of these test methods, Enders (2004) considers a safe choice is to use both types of unit roots tests, since they reinforce each other.

Following the unit root test procedures gives the first step in the Engle-Granger (1987) methodology in testing for co-integration. Granger (1981) introduced the concept of co-integration when he wrote two variables may move together, although individually they are non-stationary. Co-integration is based on the long-run relationship between the variables. In the short run the variables may diverge from each other. This step would involve estimating the long-run equilibrium equation and conducting an ADF test on the residual sequence from this equation. If the residual sequence is found to be stationary, then X and Y are co-integrated.

The Engle and Granger technique allows identification of only a single co-integration vector within a system. This automatically raises the possibility more than one co-integrating relationship may exist between the variables, so the property of uniqueness is lost. In general, if there are q $I(1)$ variables, then there are a maximum of $q-1$ co-integrating vectors. Johansen (1991), (1995) introduced this approach, enabling the researcher to identify the maximum number of co-integrating vectors existing between a set of variables. The Johansen co-integration test checks whether, or not, there is any co-integration between the variables and is, therefore, an alternative, or supplementary, test to those previously described. This approach also gives the maximum likelihood estimates for the co-integrating vectors. These estimates can be compared with those obtained through the application of ordinary least squares using the Engle and Granger two-step method.

Co-integration analysis is important, because if two non-stationary variables are co-integrated, a vector auto regression (VAR) model in the first difference is misspecified, due to the effect of a common trend. If a co-integration relationship is identified, the model should include residuals from the vectors, lagged at one period, in a dynamic vector error-correction mechanism (VECM). Granger (1986) and Engle and Granger (1987) have demonstrated, if Y and X are both $I(1)$ variables and are co-integrated, an error-correction model exists. The error-correction model can be interpreted as showing there often exists a long-run equilibrium relationship between two economic variables, but in the short run, however, there may be disequilibrium. With the error-correction mechanism, a proportional disequilibrium in one period is corrected in the next period. The testing procedure for causal relationships between variables uses VAR and VECM modelling. The VECM allows the simultaneous estimation of short-

term and long-term inter-market adjustments. The VECM will be used, as sources of causality cannot be detected by the VAR technique (Li, 2001); (O'Connor, 1999). The VECM equation requires the time series to be non-stationary or integrated of an order bigger than zero, as well as being co-integrated. To assess the adequacy of the ECM model, Enders (2004) performed diagnostic tests to determine whether, or not, the residuals approximate white noise. If the residuals are serially correlated, lag lengths are to be short and need to be extended until they yield serially uncorrelated errors.

I denote ΔR_t^{IND} to the return series of the S&P/ASX 200 Index, and ΔR_t^{OPT} to the S&P/ASX 200 options. An error-correction model can be estimated as identifying the direction of causality between ΔR_t^{IND} and ΔR_t^{OPT} where:

$$\Delta R_t^{IND} = \alpha_0^{IND} + \beta_1^{IND} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{IND} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{OPT} + \varepsilon_t^{IND} \quad (4.4)$$

$$\Delta R_t^{OPT} = \alpha_0^{OPT} + \beta_1^{OPT} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{OPT} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{IND} + \varepsilon_t^{OPT} \quad (4.5)$$

where u_{t-1} is the lagged residual from the co-integrating regression, with ε_t^{IND} and ε_t^{OPT} being random error terms. Equation 4.4 postulates the current ΔR_t^{IND} is related to the previous periods' lagged residual and lagged values of ΔR_t^{OPT} , as well as the lagged values of ΔR_t^{IND} . The co-efficient β in Equation 4.4 measures the single period response of ΔR_t^{IND} to departures from equilibrium. A small β indicates the ΔR_t^{IND} adjusts only fractionally to correct the disequilibrium situation, so most of the adjustment is accomplished by ΔR_t^{OPT} . Similarly, Equation 4.5 states the current ΔR_t^{OPT} is related to

the previous periods' equilibrium error; the lagged values of ΔR_t^{IND} ; as well as the lagged values of ΔR_t^{OPT} . A small β in Equation 4.5 indicates the ΔR_t^{OPT} responds very little to correcting the disequilibrium situation, so most of the adjustment is accomplished by ΔR_t^{IND} . It has been stated that if ΔR_t^{IND} and ΔR_t^{OPT} are co-integrated, then there must be Granger causality in at least one direction. In the Granger causality framework, ΔR_t^{OPT} is said to cause ΔR_t^{IND} , if some of the δ_i in Equation 4.4 are nonzero, while all the δ_i in Equation 4.5 are equal to zero, and/or the error-correction co-efficient β is nonzero at conventional significance levels. In the same way, ΔR_t^{IND} is said to cause ΔR_t^{OPT} , if some of the δ_i in Equation 4.5 are nonzero while all the δ_i in Equation 4.4 are equal to zero and/or the error-correction co-efficient β is nonzero. If both of these events occur, there is feedback and the test for causality (Malliaris and Urrutia, 1992); (Li, 2001)), is based on a standard Wald F statistic, which is calculated by estimating Equations 4.4 and 4.5 in both the unconstrained, and constrained, forms:

$$F_c = \frac{(ESSR - ESSU)/n}{ESSU/(T - m - n)} \quad (4.6)$$

where T is the number of observations used in the unrestricted model, ESSR and ESSU are the residual sum squares of the reduced and full models, and m and n is the optimal order of lags.

The Wald test deals with hypotheses involving restrictions on the co-efficients of the explanatory variables. The restrictions may be linear, or non-linear, and two or more restrictions may be tested jointly. The output from the Wald test depends on the linearity

of the restriction. The F test is carried out for the null hypothesis of no Granger causality ($H_0 : \lambda_{i1} = \lambda_{i2} = \lambda_{ik} = 0, i = 1, 2$), where the F statistic is the Wald statistic for the null hypothesis.

4.3.2.2 Price-discovery Process

Price-discovery is the process by which new information is revealed by market participants and incorporated into observable asset prices. Arbitrage activities should keep prices in the index and options markets from diverging. The prices of the two markets should be co-integrated and be driven by one common factor, which is also known as the “implicit efficient price”.²⁰ I investigate the common driving force mechanics in price-discovery for the index and options market and adapt two approaches to investigate the mechanics of price discovery. Both are based on a decomposition of transaction prices into a permanent component associated with efficient price of the asset and a transitory component which reflects noise. The efficient price should be identical in both the index and option markets, while the transitory component may differ. I want to establish which market information is first incorporated into the efficient price.

The first approach to price-discovery I use is the permanent-transitory model discussed by Gonzalo and Granger (1995) and the second is the information-shares model developed by Hasbrouck (1995). Hasbrouck (1995) uses a Stock Watson (1988) common stochastic trend decomposition to decompose transaction prices into random

²⁰Co-integration describes the presence of a stationary relationship among non-stationary series. See Engle and Granger (1987) and Appendix 4.1.

walk, which Hasbrouck interprets as the efficient price and noise and measures the contribution of each market to the variance of the former. The information shares are not uniquely defined if the price innovations in the index and option markets are correlated and one has to compute upper and lower bounds for the information shares by attributing as much information to each market. The approach by Gonzalo and Granger's (1995) contributions to each market is uniquely defined and decomposes transaction prices into a permanent component which is integrated of order 1 and the transitory component is stationary.

These two models complement each other and provide different views of the price-discovery process between markets. The Gonzalo and Granger model focuses on the components of the common factor and the error-correction process, while the Hasbrouck model considers each market's contribution to the variance of the innovations to the common factor. Both models use the vector error-correction model (VECM) as their basis, and Hasbrouck (1995) points out that the VECM is consistent with several market microstructure models in the extant literature. Despite this initial similarity, the information-shares and permanent-transitory models use different definitions of price discovery. Hasbrouck (1995) defines price-discovery in terms of the variance of the innovations to the common factor. Thus the information-shares model measures each market's relative contribution to this variance. Gonzalo and Granger (1995), however, are concerned with only the error-correction process. This process involves only permanent (as opposed to transitory) shocks that result in a disequilibrium. In the price-discovery context, disequilibria occur because markets process news at different rates. The permanent-transitory model measures each market's contribution to the common

factor, where the contribution is defined to be a function of the market's error-correction co-efficients.

Although the information-sharing and the permanent-transitory models study the same economic phenomenon, the two techniques provide different views on the price-discovery process. The Hasbrouck (1995) model extracts the price-discovery process using the variance of innovations to the common factor. The Gonzalo and Granger (1995) approach focuses on the components of the common factor and the error-correction process. This method involves only permanent (as opposed to transitory) shocks which result in disequilibrium.

I will use the Hasbrouck (1995) and Gonzalo and Granger (1995) methodology extended to financial markets by Harris, McInish et al., (2002a) and Booth, So et al., (1999), Chu,Hsieh et al., (1999), Roope and Zurbreugg (2002), Baillie, Booth et al., (2002), Chakravarty, Gulen et al., (2004) , Su and Chong (2007) to measure the index and options markets relative contribution to price discovery. In the empirical test of Chakravarty, Gulen et al., (2004), they use a binomial option-pricing model to derive a variable. However, like the Black-Scholes option-pricing model, the binomial option-pricing model assumes log normality of stock prices. The conflict between the structural model and the empirical method cannot satisfy the stationary assumption in a vector autoregression model, which they utilise in their empirical processes. We resolve the inconsistency found in their paper by using stock returns rather than stock prices.

4.3.2.3 Impulse-response Functions

The information transmission can also be measured on the basis of variance structure with innovation accounting method. Impulse-response functions or variance decomposition indicate the extent a shock on one variable is transitory in terms of its effect on other variables. An impulse-response function traces the effect of a one-standard-deviation shock to one of the innovations on the current and future values of the endogenous variables.

Yan and Zivot (2006) and Lutkepohl and Reimers (1992) show impulse responses and variance decomposition analysis help us to analyse the dynamics of a VAR model in its vector moving average representation (VMA). My application, with a two-dimensional system, describes two response functions through time. I denote the return series of the index as R_t^{IND} and the return series of the implied index as R_t^{OPT} . This involves switching to a VMA representation to investigate the impact of exogenous shocks to the different markets and trace out the responses to shocks in each market. The ordering of the contemporaneous correlations, based on a Cholesky decomposition of the estimated residual covariance matrix, must be used to orthogonalise the innovations. The impulse-response confirms the speed of this procedure and the variance decomposition confirms the degree of change of the variance structure.

4.4 Results

In this section I first report descriptive characteristics for my series. The ADF and PP tests are applied to test stationarity of the return series for the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options Implied Index. Engle-Granger and

Johansen co-integration tests are presented in order to test if the S&P/ASX 200 Share Price Index is co-integrated with the S&P/ASX 200 Index Options Implied Index price. I use the error-correction models I have formed in equation (4.4) and (4.5) to find the causal relationships between the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options Implied Index price to determine the lead/lag relationship between the index and options markets. Finally, I will estimate how much price-discovery occurs in the index and options markets, using information-sharing and permanent-transitory models.

4.4.1 Descriptive Statistics

Descriptive characteristics are presented for my series before proceeding to model estimations. Figure 4.1 displays the S&P/ASX 200 Index prices and the S&P/ASX 200 Implied Index. Both series rise and fall in tandem, hence a possible strong linear relationship. The two series indicate the existence of co-movements between the security prices. This co-movement indicates the possible existence of co-integration between the markets. Co-integration between these markets means that they share a common stochastic trend. This implies one market will be useful in predicting the other market's returns and a valid error-correcting presentation will exist. The series tend to drift together and are not far apart over time.

Figure 4-1 Patterns of Daily Closing Prices of the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

The daily closing prices of the S&P/ASX 200 Index and the S&P/ASX 200 Implied Index were used to estimate the lead/lag relationship

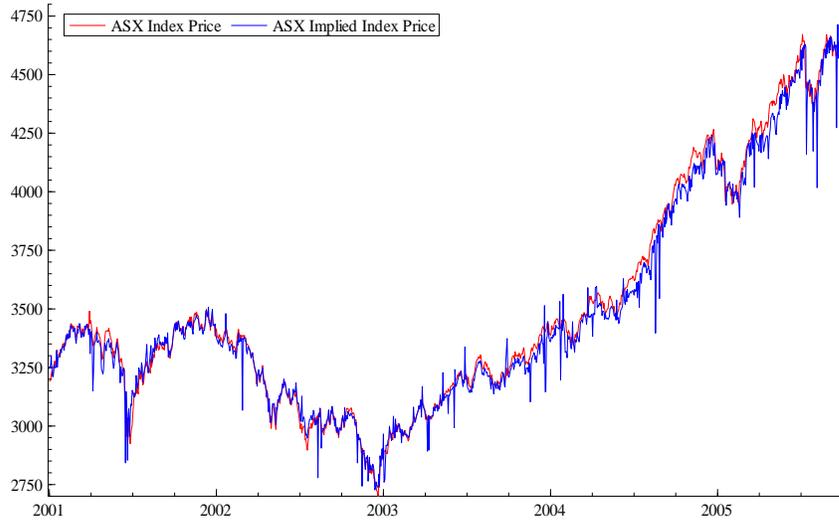
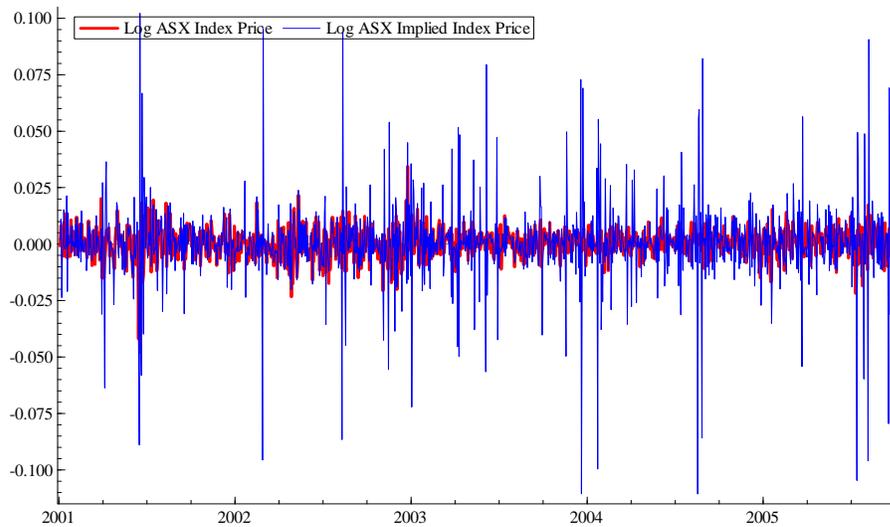


Figure 4-2 Patterns of Daily Closing Prices of the LOG S&P/ASX 200 Index and the Log S&P/ASX 200 Implied Index

The series for the log S&P/ASX 200 Index and the log S&P/ASX 200 Implied Index are obtained by taking the first difference of the natural log of the daily closing price.



4.4.2 Stationarity Testing

Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) (Dickey and Fuller 1979, 1981) unit root test and the Phillips-Perron (Perron, 1988, Phillips and Perron 1988) nonparametric tests. I run the ADF test with a linear trend on level and first differences of spreads of up to five lags in order to control for serial correlation. The Akaike Information Criterion (AIC) was used to determine the optimal number of lags for both the tests. I also run the PP test diagnostic corrected by the Newey-West autocorrelation consistent variance estimator. For both tests I employ MacKinnon (1996) critical values for rejection of the unit root null hypothesis. I further test for statistically significant residual autoregressive effects on the basis of the Ljung-Box Q statistic. Table 4.2 presents the ADF test results and Table 4.3 presents the PP test results. Results indicate the return series are not stationary at levels, but they are stationary after the first difference is taken as the MacKinnon one-sided p -values are significant at the 1% level. These results provide strong evidence the index and implied index return series are integrated in order one $I(1)$. In all cases the results of the ADF and PP tests reinforce each other.

Table 4-2 Augmented Dickey-Fuller Unit Root Tests²¹ for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This table presents the results of the Augmented Dickey-Fuller unit root test. The Augmented Dickey-Fuller (ADF) test involves incorporating lagged values of the dependent variable into the following equation: $\Delta Y_t = \alpha_0 + \beta Y_{t-1} + \gamma T + \delta_1 \Delta Y_{t-1} + \dots + \delta_n \Delta Y_{t-n} + u_t$ with the number of lags being determined by the residuals free from autocorrelation. This could be tested for in the standard way such as by Lagrange Multiplier (LM) test. In practice many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here I am going to use the AIC and SIC to test the optimal lag number.

Series	t-Statistic	P-Value ^a	AIC	SIC
S&P/ASX 200 ^b	1.0494	0.9971	-7.3548	-7.345
D(S&P/ASX 200) ^c	-32.0821	0.0000**	-7.3544	-7.3446
S&P/ASX 200 Imp ^d	0.9946	0.9966	-5.4321	-5.3977
D(S&P/ASX 200Imp) ^e	-21.1403	0.000**	-5.4332	-5.4036

a MacKinnon (1996) one-sided *p*-values.

b This is the logarithm of the S&P/ASX 200 Series.

c This is the first difference of the series described in b.

d This is the logarithm of the S&P/ASX 200 Implied Series.

e This is the first difference of the series described in d.

** Significance at the 1% level.

Table 4-3 Phillips-Perron Unit Root Tests²² for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This table presents the results of the Phillips-Perron nonparametric test. The Phillips-Perron (PP) test involves incorporating lagged values of the dependent variable into the following equation: $\Delta Y_t = \alpha + \rho Y_{t-1} + u_t$ with the number of lags being determined by the residuals free from autocorrelation. In practice many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here I am going to use the AIC and SIC to test the optimal lag number.

Series	t-Statistic	P-Value ^a	AIC	SIC
S&P/ASX 200 ^b	1.0707	0.9971	-7.3548	-7.345
D(S&P/ASX 200) ^c	-32.0791	0.0000**	-7.3544	-7.3446
S&P/ASX 200 Imp ^d	0.1357	0.9683	-5.1217	-5.1119
D(S&P/ASX 200Imp) ^e	-69.9367	0.0001**	10.9745	10.9843

a MacKinnon (1996) one-sided *p*-values.

b This is the logarithm of the S&P/ASX 200 Series.

c This is the first difference of the series described in b.

d This is the logarithm of the S&P/ASX 200 Implied Series.

e This is the first difference of the series described in d.

** Significance at the 1% level.

²¹The lag value is determined by the Schwarz Criterion (SIC) (Schwarz, 1978) and the Akaike Information Criterion(AIC) (Akaike, 1973).

²² The lag value is determined by the Schwarz Criterion (SIC) (Schwarz, 1978) and the Akaike Information Criterion(AIC) (Akaike, 1973).

4.4.3 Co-Integration Tests

4.4.4 Engle-Granger Co-integration

A necessary condition for co-integration is each of the time series integrates in the same order greater than zero and conducted the Engle-Granger co-integration test to determine if the return series of the S&P/ASX 200 Index and the S&P/ASX 200 Implied index are co-integrated of order one. Table 4.4 reports the co-integration

Table 4-4 Engle-Granger Co-integration Tests and Co-integration Vectors Results for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This table presents the results of the Engle-Granger co-integration residual-based tests and co-integration vectors for the logarithm of the index return series (Y) and the option-implied index return series (X).

$$Y_t = \beta x_t + \varepsilon_t \text{ or } (1-\beta) \begin{pmatrix} Y_t \\ x_t \end{pmatrix} = \varepsilon_t \text{ with } (1-\beta) \text{ the co-integrating vector}$$

Y&X: Dependent variable: Index

Tau (τ)	-7.5130
P-value	0000
Optimal number of lags	9
Co-integrating vector	1.0, -0.9982

X&Y: Dependent variable: Implied index

Tau (τ)	-7.70711
P-value	0000
Optimal number of lags	9
Co-integrating vector	1.0, -0.9902

vectors and Engle-Granger tests and reject the null hypothesis the two series cannot be co-integrated. Since both the series are co-integrated with co-integration vector (1.0,-0.9982), I conclude that invoking the OLS regression in Equation A4.1-2 is not

subject to the risk of spurious regression, the errors of the regression will be stationary and an error-correction model can be estimated in section 4.4.6.

4.4.5 Johansen Co-integration

Johansen's co-integration test differs from the Engle-Granger co-integration. Johansen is carried out in the context of a VECM representation. The lag length used in the co-integration tests is the same as in their corresponding VECM representation and so is determined on the consideration that it is the most parsimonious provided the residuals from the VECMs are free of serial correlation. Given these lag lengths, the trace and λ -max statistics allow us to reject the null of no co-integration relation in favour of the alternative of one co-integration vector, at the 5% level or above.

Table 4-5 presents results from the Johansen co-integration test and reports the number of co-integrating relations among the variables. There are two types of test statistics reported. The first is trace statistics and the second is Eigen value statistics. The first column in Table 4-5 is the number of co-integrating relations under the null hypothesis (if the null hypothesis is stated, no co-integrating relationship exists). The second column is the ordered Eigen values of the Π matrix. The third column is the trace statistic and the last column is the 5% and 1% critical values. Both the trace test and the Eigen value tests indicate there is one co-integrating relationship among the variables at 5% significant level. Both the series are co-integrated with co-integration vector of (1,-1.0096).

Table 4-5 Johansen Co-integration Test for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This table presents results from the Johansen co-integration test and reports the number of co-integrating relations among the variables. Following Johansen (1991, 1995) the following equation is used to test the co-integration relationship on a VAR of order p , and generating Y as: $y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t$, where y_t is a vector of k (I(1)) variables of interest, x_t is a vector of deterministic variables, p is the maximum lag and ε is a vector of error terms. I can rewrite the above equation as: $\Delta y_t = \Pi y_{t-1} + \sum \Gamma_i y_{t-i} + Bx_t + \varepsilon_t$. The equilibrium relationship or co-integration vector is given by: $\Pi = \sum A_i - I \Gamma_i = - \sum A_j$, where $i = 1, 2, \dots, p, j = i + 1, \dots, p$, and the rank of the matrix Π gives the number of distinct co-integrating vectors amongst the variables. It is then possible to define two further $k \times r$ matrices α and β such that: $\Pi = \alpha\beta'$ where rows of the matrix β provide the rows of the r distinct co-integrating vectors, i.e. co-integration relations.

Series: LOGIMPINDEX LOGRAWINDEX			
Lags interval (in first differences): No lags			
Unrestricted Co-integration Rank Test			
Hypothesized No. of CE(s)	Eigen value	Trace Statistic	5 Percent Critical Value
None **	0.4928	680.5325	15.41
At most 1 **	0.0011	1.0757	3.76
*(**) denotes rejection of the hypothesis at the 5% level			
Trace test indicates 1 co-integrating equation(s) at 5% level			
Hypothesized No. of CE(s)	Eigen value	Max-Eigen Statistic	5 Percent Critical Value
None **	0.4928	679.4568	14.07
At most 1 **	0.0011	1.0757	3.76
*(**) denotes rejection of the hypothesis at the 5% (1%) level			
Max-Eigen value test indicates 1 co-integrating equation(s) at 5% level			
Unrestricted Adjustment Coefficients (alpha):			
D(LOGIMPINDEX)	0.0165	0.0001	
D(LOGRAWINDEX)	-0.0173	0.0002	
Normalised co-integrating co-efficients:			
(LOGIMPINDEX)	1.0000		
(LOGRAWINDEX)	-0.9905		
Standard error	(0.0039)		

The (nonstandard) critical values are taken from Osterwald-Lenum (1992), which is slightly different from those reported in Johansen and Juselius (1990).

4.4.6 Vector Error-Correction Model and Granger Causality

The Engle Granger and Johansen co-integration tests evaluate long-run relationships between variables. Granger suggests the use of ECM to examine the dynamic short-run relation and long-run equilibrium relation. The framework of ECM is also able to examine the Granger-causality relationship between variables. The causation analyses between the time series supply short-run dynamic adjustments needed by each variable to reach positions of long-run equilibrium.

Table 4-6 reports the estimation results of the VECM and causality. My method of estimation was the OLS and used Ljung-Box Q statistics to test for serial correlation in the residuals. I found no serial correlation in the residuals for up to 20 lags. The number of lagged changes was restricted to two as co-efficients for lagged changes greater than two are insignificant in diagnostic model checking. I checked the residuals are independent and found no further lags needed to be added.

Estimation of the VECM shows the influence of the index returns on the option returns. Of particular interest are the estimates of error-correction co-efficients. As shown in Table 4-6, the error-correction co-efficients for the index market are calculated using Equation 4.4, and Equation 4.5 is used to calculate the error-correction co-efficients for the option market. The co-efficient estimates of the index market are negative (-0.0208) and not statistically significant ($p=.3680$), but the error-correction term for the options market (0.7913) is statistically significant at the 1% level or higher ($p=0.000$) and is

Table 4-6 Vector Error-correction Results for the S&P/ASX 200 Index and S&P/ASX 200 Index

Options

This table presents the results of the vector error-correction model for the change in the index and the option-implied index returns. This model specification has been employed by Diltz and Kim (1996), Li (2001) and others in order to examine causality between the two time series. The error-correction term is u_{t-1} and is obtained as a lagged residual from the co-integration regression of p on p . The first column shows the regressor, where Δ Index and Δ Option stand for S&P/ASX Index return and S&P/ASX Index Option (implied index return). Lags are denoted as (-1), (-2). For both index and implied index return equations, the table shows the regression co-efficients and the figures in parentheses (.) and in squared brackets [.] indicate t-statistics and exact significance levels, respectively. The constant C is the intercept of the regression.

$$\Delta R_t^{IND} = \alpha_0^{IND} + \beta_1^{IND} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{IND} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{OPT} + \varepsilon_t^{IND}$$

$$\Delta R_t^{OPT} = \alpha_0^{OPT} + \beta_1^{OPT} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{OPT} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{IND} + \varepsilon_t^{OPT}$$

Dependent variable: Δ Index				Dependent variable: Δ Option			
Regressor	Estimated Co-efficient	t-statistic	P-value	Regressor	Estimated Co-efficient	t-statistic	P-value
Δ Index (t-1)	0.0094	(0.2296)	[.8180]	Δ Index (t-1)	0.2124	(1.9573)	[.0510]
Δ Index (t-2)	0.0693	(1.6296)	[.1030]	Δ Index (t-2)	-0.0464	(-0.5386)	[.5900]
Δ Option (t-1)	-0.0170	(-0.846)	[.3980]	Δ Option (t-1)	-0.1162	(-2.4065)	[.0160]
Δ Option (t-2)	-0.0324	(-2.1281)	[.0340]	Δ Option (t-2)	-0.0563	(-1.5141)	[.1300]
ECT(-1)	-0.0208	(-0.867)	[.3860]	ECT(-1)	0.7913	(13.2625)	[.0000]
F1	2.8509		[.0583]	F2	3.5357		[.02950]
R ²	0.0074			R ²	0.4248		

ECM of the index market is:

$$\Delta Index = -0.0208(Index_{t-1} + 0.0764 - 1.0097 Option_{t-1}) + 0.0094 \Delta Index_{t-1} + 0.0693 \Delta Index_{t-2} - 0.0170 \Delta Option_{t-1} - 0.0324 \Delta Option_{t-2} + \varepsilon_t$$

ECM of the option market is:

$$\Delta Option = 0.7913(Option_{t-1} - 0.0756 - 0.9905 Index_{t-1}) + 0.2124 \Delta Index_{t-1} - 0.0464 \Delta Index_{t-2} - 0.1162 \Delta Option_{t-1} - 0.0563 \Delta Option_{t-2} + \varepsilon_t$$

positive. This implies that adjustments to the disequilibrium take place mainly in one market. Noticeable differences in the adjustment process are observed between the index

market and the options market. The options market is responsive to the departures of the index market but not vice versa. This indicates that an information shock to the index market would have a significant effect on the options market but an information shock to the options market would not influence the index market significantly.

To test whether the index market leads the options market or the options market leads the index market, the Granger causality test was performed. Causality tests may provide insights into the nature of lead/lag behavior in index and index option markets. If the hypothesis that the index market data do not Granger cause index options market, the data is rejected, then current index market information is relevant to forecasting future index options market prices. At the same time, suppose the hypothesis that index options market data do not Granger cause index market the data fails to reject. Then index options market data do not help forecast index market prices. In this case, index market data appear to forecast index options market values while index options market data cannot forecast index market values. Hence, the index market may be considered the informational leading market, as it appears to reflect information more rapidly. The Wald F test statistic from Equation 4.6 is carried out for the null hypothesis of no Granger causality ($H_0 : \lambda_{i1} = \lambda_{i2} = \lambda_{ik} = 0, i = 1, 2$), where the F statistic is the Wald statistic for the null hypothesis. The null hypothesis that lagged values of the co-efficients for the adjustment is rejected by the Wald F test statistic are shown in Table 4-6. The Wald F test statistic for the index market is 2.8509 and is statistically significant at the 10% level ($p=0.0583$). The Wald F test statistic for the options market is 3.5357 and is statistically significant at the 5% level ($p=0.0295$). This implies that there is a bi-directional Granger causality between the index market and the option market. The direction of causality from the index market to the options market is strong, but a much weaker effect exists

from the options market to the index market. An information shock to the index market would have a significant effect on the options market but an information shock to the options market would not influence the index market significantly.

Overall, my results contrast with Manaster and Rendleman (1982), Anthony (1988) and Diltz and Kim (1996), who find options market leads using error-correction models estimated with daily data. The results also contrast with Bhattacharya (1987) and Easley, O'Hara, et al., (1998), who find the options market leads using intraday data to measure the lead/lag effect. Easley, O'Hara, et al., (1998) state that option markets are primarily used for informational trading. Fleming, Ostdiek et al.,(1996) find that index options lead the cash index by about five minutes, even after controlling for infrequent trading in the cash index. They conclude that causality runs from the options market to the cash market. These results of Fleming, Ostdiek et al., (1996) are in contrast with my results, as they conclude that causality runs from the options market to the cash market. My results further contrast with Gwilym and Buckle (2001) and Nam, Oh et al., (2006) who find the index options market leads using intraday data.

My results are consistent with O'Connor (1999), who finds that overall the stock market leads the options market and that the lead is related to options' trading costs. Finucane (1999) uses quote revision data and variable-length time intervals and finds the stock market leads the option market. Hatch (2003) finds the stock market leads the option market.

Finally, my results do not support the finding of Chan, Chung et al., (1993) in Hatch (2003) of a spurious stock market lead. They conclude that neither market leads

the other and that new information appears to be impounded in both markets simultaneously.

4.4.7 Price Discovery

In Table 4-7 Panel A the return series in each market are co-integrated with one common stochastic factor. The co-integrating vector is (1,-1.0096), indicating the index market and the options market value the same underlying information differently over the long run. Results of the VECM using Johansen's (1991) maximum likelihood procedures are also presented in Panel A.

In Table 4-7 Panel B, presents the price-discovery results of the index market and the option market. The common factor weights are 97.43% for the index market and 2.57% for the option market, suggesting that the index market contributes the most to the price-discovery process. The factor weights are a measure of the markets' contribution to permanent information, and the greater a factor weight assigned to a market, the slower its speed of adjustment to equilibrium and the bigger its role in discovering equilibrium prices.

In Table 4-7 Panel B, reports the lower bound, upper bound and average of all permutations of the Cholesky factorisation of information shares. The index market dominates with an information share of 90.92% and the options market yields an information share of 9.08%. The lower and the upper bounds differ considerably, but Martens (1998), Baillie, Booth et al., (2002) and Booth, Lin et al., (2002) also report a substantial difference in their Hasbrouck (1995) upper and lower bounds of information shares. Baillie, Booth et al., (2002) show in a bivariate case, using various examples, that

the average of the information shares given by the two permutations is a reasonable estimate of the markets' role in price discovery. Both the Hasbrouck (1995) and Gonzalo and Granger (1995) results indicate the index market plays the primary role in price discovery. The information share is significantly larger than the options market and the price-discovery is predominately in the index market.

Table 4-7 Results for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This table presents the results of the vector error-correction model using Johansen's (1991) maximum likelihood procedures and co-integration vectors for the logarithm of the index return series (Y) and the option-implied index return series (X). For both index and implied index return equations, the table shows the regression co-efficients and the figures in parentheses (.) and in squared brackets [.] indicate t-statistics and exact significance levels, respectively.

Panel A		(1,-1.0096)	
Co-integration relationship		Index Market	Option Market
Error-correction co-eff	α_i	-0.0208 (-0.9044) [0.3860]	0.7913 (14.7589) [0.0000]
Lag t		ΔR_{t-1}^{IND}	ΔR_{t-1}^{OPT}
Lag 1		0.0094 (0.2524) [0.8010]	-0.0170 (-0.8586) [0.3910]
Lag 2		0.0693 (2.0007) [0.0460]	-0.0324 (-2.2198) [0.0270]
		ΔR_{t-1}^{IND}	ΔR_t^{OPT}
		0.2124 (2.4459) [0.0150]	-0.1162 (-2.5188) [0.0120]
		-0.0464 (-0.5758) [0.5650]	-0.0563 (-1.6571) [0.0980]
Panel B			
Common Factor			
Relative factor weight		0.9743	0.0257
Information share			
Upper Bound		0.9969	0.0031
Lower Bound		0.8215	0.1785
Average		0.9092	0.0908

My results of price-discovery are consistent with Booth, So et al., (1999). They used the common factor weight approach analysing the German DAX index spot, futures,

and options markets. The price-discovery role is shared about equally by the spot and futures markets, with no role for the options market. The DAX index options only contribute two percent to price discovery.

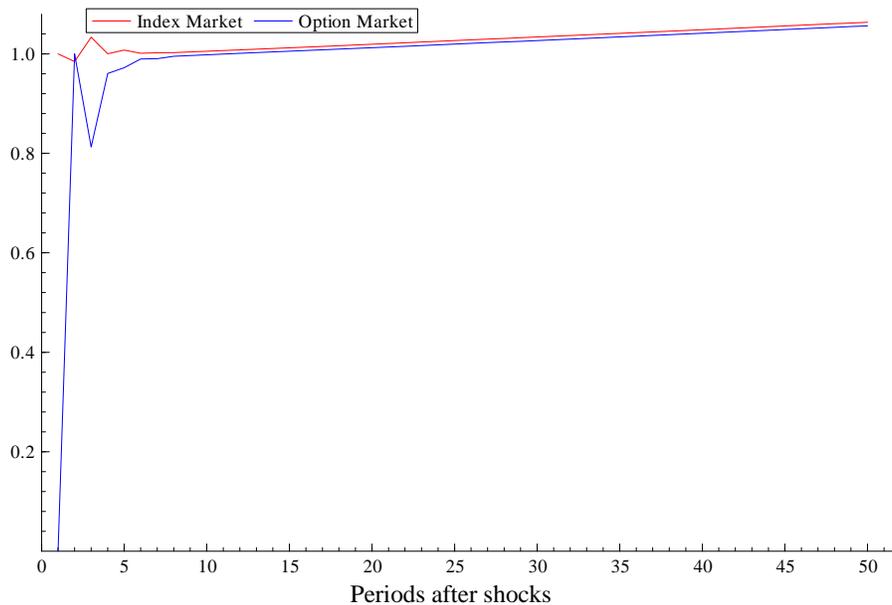
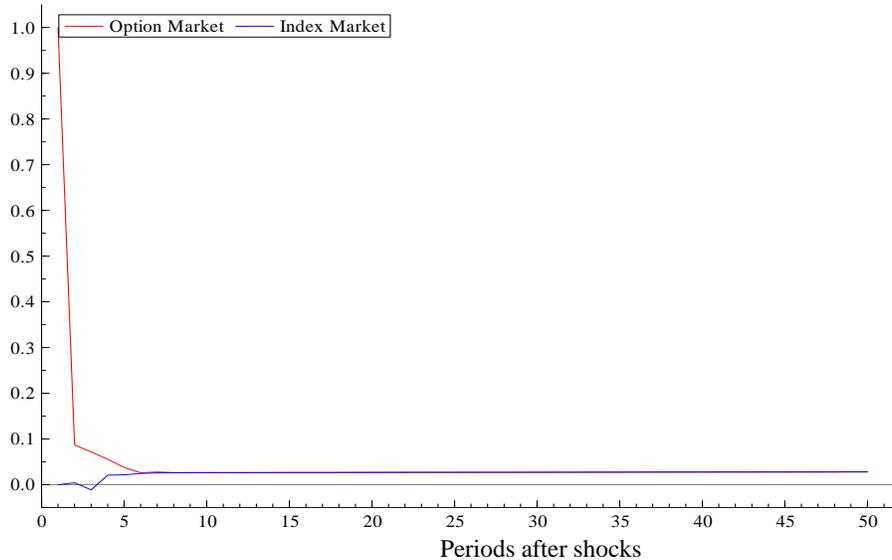
My results of price-discovery contrast with Chakravarty, Gulen et al., (2004). They show that the contribution of stock options market to price-discovery is, on average, about 17% among 60 stock options traded in the Chicago Board Options Exchange. They find evidence that is more supportive of the option market's ability to contribute to price discovery.

4.4.8 Impulse-Response Analysis

In this section I apply impulse-response analysis which outlines the dynamic response of each variable to innovations from other individual variables in the system. The impulse-response function traces the impact of a one-time, unit standard deviation, positive shock to one variable on the current and future values of the endogenous variables. Since innovations are correlated, they need to be orthogonalised. They are computed using standard Cholesky decompositions of the VAR residuals and assuming that innovations in the variables placed earlier in the VAR have greater effects on the following variables. For each variable a unit shock is applied to the error, and the persistence of the effects upon the VAR system over time is noted. A shock to a stable system should gradually die out in the long-run (Brooks, 2002). A fast adjustment to the previous equilibrium indicates strong co-integration relationships between the two markets in the long run, as deviations from the equilibrium are short lived.

Figure 4-3 Shocks to daily closing prices of the S&P/ASX 200 Index and S&P/ASX 200 Implied Index

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables in the VAR to shocks from all the explanatory variables. The purpose of the VAR is mainly to examine the dynamic adjustments of each of the involved variables to exogenous stochastic structural shocks. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 options market indicates that the S&P/ASX 200 Index market does not respond strongly. A shock to the S&P/ASX 200 Index market indicates the S&P/ASX 200 Options market responds strongly.



I investigate the response path of the index and option prices to a large (one standard deviation) shock. Impulse-response paths associated with the VECM are presented in Figure 4-3 with the option markets as the first variable in the ordering of the decomposition of the contemporaneous covariance of the residuals. A shock to the option market indicates the index market does not respond strongly and only has a weak response. A shock to the index markets triggers a strong response from the option market. The impulse-response paths indicate the options market contributes less to discovering information about the underlying asset but investors overreact to its innovations while discounting the more informative index market events.

4.4.9 Robustness of the Results

To add robustness to my findings above, I investigate the sensitivity of my results to empirical design choices. In my main analysis, implied stock index prices are computed with GARCH (3,1) specifications. In section 4.3.1 the implied stock index ask prices were obtained by solving a modified Black-Scholes formula for the implied stock ask price. The σ^2 of the stock index return variance was calculated using the GARCH (3,1) specification. In my robustness check I use implied volatility to calculate the implied option price to further investigate the contribution of the S&P/ASX 200 Share Price Index and S&P/ASX 200 Index Option markets to the price-discovery process.

The justification for the use of implied volatility comes from several previous studies. Fleming, Ostdiek et al., (1996) find that implied volatilities from S&P 100 index options yield efficient forecasts of month-ahead S&P index volatility. Further studies of the performance of the S&P 100 implied volatility index were conducted by Fleming (1998) and Christensen and Strunk-Hansen (2002). They find that implied volatility

forecasts are upwardly biased, but are superior to historical volatility in terms of ex ante forecasting power. Corrado and Miller (2005) focus on three volatility indices from the S&P 100, S&P 500 and NASDAQ 100 and conclude that the forecast qualities of these implied volatility indices easily outperform historical volatility as predictors of future volatility. Corrado and Miller (2006) test the relationship between expected and realised excess returns for the S&P 500 Index. When risk is measured by option-implied volatility, they find a positive and significant relationship between expected and realised excess returns.

To test the sensitivity of my measures to the implied volatility, I re-estimate the Johansson's co-integration test, vector error-correction model and the price-discovery process. In Table 4-8 both the trace test and the Eigen value tests indicate there is one co-integrating relationship among the variables at 5% significant level. Both the series are co-integrated with co-integration vector (1,-0.995).

The framework of ECM is also able to examine the Granger-causality relationship between variables. The causation analyses between the time series supply short-run dynamic adjustments needed by each variable to reach positions of long-run equilibrium. Estimation of the VECM shows the influence of the index returns on the the option returns. Of particular interest are the estimates of error-correction co-efficients

Table 4-8 Johansen Co-integration Test for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index ²³

This table presents results from the Johansen co-integration test and reports the number of co-integrating relations among the variables. Following Johansen (1991, 1995) the following equation is used to test the co-integration relationship on a VAR of order p , and generating Y as: $y_t = A_1 y_{t-1} + \dots + A_p y_{t-p} + Bx_t + \varepsilon_t$, where y_t is a vector of k ($I(1)$) variables of interest, x_t is a vector of deterministic variables, p is the maximum lag and ε is a vector of error terms. I can rewrite the above equation as: $\Delta y_t = \Pi y_{t-1} + \sum \Gamma_i Y_{t-i} + Bx_t + \varepsilon_t$. The equilibrium relationship or co-integration vector is given by: $\Pi = \sum A_i - I \Gamma_i = - \sum A_j$, where $i = 1, 2, \dots, p, j = i + 1, \dots, p$, and the rank of the matrix Π gives the number of distinct co-integrating vectors amongst the variables. It is then possible to define two further $k \times r$ matrices α and β such that: $\Pi = \alpha\beta'$ where rows of the matrix β provide the rows of the r distinct co-integrating vectors, i.e. co-integration relations.

Series: LOGIMPINDEX LOGRAWINDEX

Lags interval (in first differences): No lags

Unrestricted Co-integration Rank Test

Hypothesized No. of CE(s)	Eigen value	Trace Statistic	5 Percent Critical Value
None **	0.4928	680.5325	15.41
At most 1 **	0.0011	1.0757	3.76

*(**) denotes rejection of the hypothesis at the 5% level
Trace test indicates 1 co-integrating equation(s) at 5% level

Hypothesized No. of CE(s)	Eigen value	Max-Eigen Statistic	5 Percent Critical Value
None **	0.4928	679.4568	14.07
At most 1 **	0.0011	1.0757	3.76

*(**) denotes rejection of the hypothesis at the 5% (1%) level
Max-Eigen value test indicates 1 co-integrating equation(s) at 5% level

Unrestricted Adjustment Coefficients (alpha):

D(LOGIMPINDEX)	-0.0002	0.0002
D(LOGRAWINDEX)	-0.0165	0.0001

Normalised co-integrating co-efficients:

(LOGIMPINDEX)	1.0000
(LOGRAWINDEX)	-1.0096
Standard error	(0.0039)

The (nonstandard) critical values are taken from Osterwald-Lenum (1992), which is slightly different from those reported in Johansen and Juselius (1990).

²³ The σ^2 of the stock index return variance is calculated using implied volatility specification.

Table 4-9 Vector Error-correction Results for the S&P/ASX 200 Index and S&P/ASX 200 Index Options²⁴

This table presents the results of the vector error-correction model for the change in the index and the option-implied index returns. This model specification has been employed by Diltz and Kim (1996), Li (2001) and others in order to examine causality between the two time series. The error-correction term is u_{t-1} , and is obtained as a lagged residual from the co-integration regression of p on p . The first column shows the regressor, where Δ Index and Δ Option stand for S&P/ASX Index return and S&P/ASX Index Option (implied index return). Lags are denoted as (-1), (-2). For both index and implied index return equations, the table shows the regression co-efficients and the figures in parentheses (.) and in squared brackets [.] indicate t-statistics and exact significance levels, respectively. The constant C is the intercept of the regression.

$$\Delta R_t^{IND} = \alpha_0^{IND} + \beta_1^{IND} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{IND} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{OPT} + \varepsilon_t^{IND}$$

$$\Delta R_t^{OPT} = \alpha_0^{OPT} + \beta_1^{OPT} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{OPT} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{IND} + \varepsilon_t^{OPT}$$

Dependent variable: Δ Index				Dependent variable: Δ Option			
Regressor	Estimated Co-	t-statistic	P-value	Regressor	Estimated Co-efficient	t-statistic	P-value
Δ Index (t-1)	-0.0534	(-1.2818)	[.2000]	Δ Index (t-1)	0.2688	(3.3369)	[.0010]
Δ Index (t-2)	-0.0054	(-0.0143)	[.9890]	Δ Index (t-2)	0.2459	(3.3562)	[.0010]
Δ Option (t-1)	0.0409	(1.5867)	[.1130]	Δ Option (t-1)	-0.2467	(-4.9495)	[.0000]
Δ Option (t-2)	0.0398	(1.9981)	[.0460]	Δ Option (t-2)	-0.1077	(-2.8016)	[.0050]
ECT(-1)	0.0367	(1.2664)	[.2020]	ECT(-1)	0.6292	(11.2424)	[.0000]
F1	2.0694		[.1270]	F2	9.1662		[.0000]
R ²	0.058			R ²	0.3381		

ECM of the index market is:

$$\Delta Index = 0.0367(Index_{t-1} + 0.0764 - 0.9905Option_{t-1}) - 0.0534\Delta Index_{t-1} - 0.0054\Delta Index_{t-2} + 0.0409\Delta Option_{t-1} + 0.0398\Delta Option_{t-2} + \varepsilon_t$$

ECM of the option market is:

$$\Delta Option = 0.6292(Option_{t-1} - 0.0756 - 0.98Index_{t-1}) + 0.2688\Delta Index_{t-1} - 0.2459\Delta Index_{t-2} - 0.2467\Delta Option_{t-1} - 0.1077\Delta Option_{t-2} + \varepsilon_t$$

²⁴ The σ^2 of the stock index return variance is calculated using implied volatility specification.

As shown in Table 4-9, the error-correction co-efficients for the index market is calculated using Equation 4.4, and Equation 4.5 is used to calculate the error-correction co-efficients for the option market. The co-efficient estimates of the index market are positive (0.0367) and not statistically significant ($p=0.2020$), but the error-correction term for the options market (0.6292) is statistically significant at the 1% level or higher ($p=0.000$) and is positive.

The options market is responsive to the departures of the index market but not vice versa. This indicates that an information shock to the index market would have a significant effect on the options market but an information shock to the options market would not influence the index market significantly.

To test whether the index market leads the options market or the options market leads the index market, the Granger causality test was performed. The Wald F test statistic from Equation 4.6 is carried out for the null hypothesis of no Granger causality ($H_0 : \lambda_{i1} = \lambda_{i2} = \lambda_{ik} = 0, i = 1,2$), where the F statistic is the Wald statistic for the null hypothesis. The null hypothesis that lagged values of the co-efficients for the adjustment is rejected by the Wald F test statistic are shown in Table 4-9. The Wald F test statistic for the index market is 2.0694 and is not statistically significant ($p=0.1270$). The Wald F test statistic for the options market is 9.1662 and is statistically significant at the 1% level ($p=0.0000$). The direction of causality from the index market to the options market is strong, but a much weaker effect exists from the options market to the index market. An information shock to the index market would have a significant effect on the options market but an information shock to the options market would not influence the index market significantly.

Table 4-10 Results for the S&P/ASX 200 Index and S&P/ASX 200 Implied Index²⁵

This table presents the results of the vector error-correction model using Johansen's (1991) maximum likelihood procedures and co-integration vectors for the logarithm of the index return series (Y) and the option-implied index return series (X). For both index and implied index return equations, the table shows the regression co-efficients and the figures in parentheses (.) and in squared brackets [.] indicate t-statistics and exact significance levels, respectively.

Panel A					
Cointegration relationship		1-0.9905			
		Index Market	Option Market		
Error correction coeff	α_i	0.0367 (1.2764)	0.6292 (11.2424)		
		[0.2020]	[0.0000]		
Lag t		ΔR_{t-1}^{IND}	ΔR_{t-1}^{OPT}	ΔR_{t-1}^{IND}	ΔR_t^{OPT}
Lag 1		-0.0534 -1.2818 [0.2000]	0.4093 1.5867 [0.1130]	0.2688 3.3369 [0.0010]	-0.2467 (-4.9495) [0.0000]
Lag 2		-0.0054 -0.0143 [0.9890]	0.0398 (1.9981) [0.0460]	0.2459 3.3562 [0.0010]	-0.1077 (-2.8016) [0.0050]
Panel B					
Common Factor					
Relative factor weight		0.9445	0.0555		
Information share					
Upper Bound		0.9903	0.0097		
Lower Bound		0.7505	0.2495		
Average		0.8704	0.1296		

In Table 4-10 Panel A the return series in each market are co-integrated with one common stochastic factor. The co-integrating vector is (1,-0.9905), indicating the index market and the options market value the same underlying information differently over the

²⁵ The σ^2 of the stock index return variance is calculated using implied volatility specification.

long run. Results of the VECM using Johansen's (1991) maximum likelihood procedures are also presented in Panel A.

In Table 4-10 Panel B, I present the price-discovery results of the index market and the option market. The common factor weights are 94.45% for the index market and 5.55% for the option market, suggesting that the index market contributes the most to the price-discovery process. The factor weights are a measure of the markets' contribution to permanent information, and the greater a factor weight assigned to a market, the slower its speed of adjustment to equilibrium and the bigger its role in discovering equilibrium prices.

In Table 4-10 Panel B, I report the lower bound, upper bound and average of all permutations of the Cholesky factorisation of information shares. The index market dominates with an information share of 87.04% and the options market yields an information share of 12.96%. I find the results also indicate the index market plays the primary role in price discovery. The information share is significantly larger than the options market and the price-discovery is predominately in the index market.

In my robustness check I used implied volatility to calculate the implied option price to further investigate the contribution of the S&P/ASX 200 Share Price Index and S&P/ASX 200 Index Option markets to the price-discovery process. Overall I found my results are comparable with my main results and the use of implied volatility does not alter my main findings.

4.5 Conclusion

Little evidence is available concerning the lead/lag and price-discovery relationship on the index and option markets in Australia. This chapter examined the lead/lag relationship and the price-discovery relationship between the S&P/ASX 200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX.

While the VEC model has been claimed to be able to account for the dynamics of the relationship within a temporal causal framework, the use of this analytical tool is constrained by the requirements that variables must be $I(1)$ and share long-run co-movements. My first task was to investigate the time-series properties of my data, testing for unit roots and co-integration with application of ADF and PP methods. Once the co-integration relationship were identified, error-correction terms were extracted in a bivariate VAR system to constitute a VEC model in first differences. This enabled the examination of causal relationships through which any long-run information about the dynamics of the co-integrated variables can be exposed, while preserving the short-run causal effects on the behaviour of the dependent variables. I found my data to be stationary and co-integrated using Engle-Granger and Johansen tests. I embedded the residuals from these vectors in a VECM in order to gauge short- and long-run Granger causality, which allows formal classification of lead/lag behaviour. I found evidence the index market leads the option market.

I further measured the contributions of the index and option markets to price-discovery using the information-shares approach of Hasbrouck (1995) and a factor weight decomposition approach of Gonzalo and Granger (1995). The analysis was then

extended to decomposition of variance and impulse-response functions to explain shocks to the index and option markets. The price-discovery process was shown to be dominated by the index market and found evidence of significant price-discovery in the index market. My robustness tests confirmed my findings.

In this chapter I investigated the information content of the index and option markets in the price-discovery process. The long-run equilibrium relationship between the share price index and the implied price of the share-price-index option was investigated. Causality was determined to show which market leads the other. Information-share measures were used to gauge the contribution of the share price index and index option markets to the price-discovery process. Unambiguous evidence showed the index market leads the options market and the former contributes more to price-discovery than the latter. In the next chapter I examine the dynamic relations between future price volatility of the S&P/ASX 200 Index and trading volume of the S&P/ASX 200 Index Option to explore the informational role of option volume in predicting the price volatility. I use the implied volatility of the S&P/ASX 200 Index Option as a proxy for the future price volatility.

4.6 Appendices

The lead/lag approach is often called the Granger (1969) causality method, since it is based on Granger (1969). Granger (1969) defines that X causes Y if the past value of X can predict Y. He was very careful about the definition of "granger causality." He notes that X causes Y does not necessarily mean that controlling X will influence Y, since the innovation to Y and the innovation to X can be correlated. If both innovations are correlated, then the causality will be bi-directional. Therefore, a Granger causality test should be conducted in both directions to confirm an absolute lead/lag relationship

4.6.1 Appendix: Stationarity and Unit Root Tests

Before the lead/lag relationship between the S&P/ASX 200 Index and the S&P/ASX 200 options is examined in a causality framework of several simultaneous equation models, it is important to test the unit roots prior to testing the causal relationships, as Granger causality tests require the data to be stationary.

It is necessary to examine the univariate stochastic properties of the prices in the study data, as the data could either exhibit mean reversion or conform to a random walk process with a constant forecast value, conditional on time and time varying auto covariance with first order integration yielding a stationary difference series.

"A series is said to be stationary if displacement over time does not alter the characteristics of a series in a sense the probability distribution remains constant over time" (Engle and Granger, 1991). This means the fundamental form of the data-generating process remains the same over time. A stationary series exhibits mean

reversion, as it fluctuates in terms of a constant long-run mean, and has a finite variance which is time-invariant. The first step to determine the order of integration of each series is to apply the unit root test.

As most economic time series are non-stationary, however, the data need to be transformed by using log transformation and/or differencing, in order to obtain stationarity. If the transformed series is stationary, or $I(0)$, this implies the original series is integrated of order 1, or $I(1)$, which is an example of a random walk series. For a series to be stationary, the mean, variance and co-variance of the series should be constant over time. In a non-stationary series the mean and/or the variance are time-dependent and there is no long-run mean to which the series returns. The variance is time-dependent and approaches infinity as time approaches infinity. The important part, which is closely related with stationarity, is the series degree of integration.

A series is said to be integrated of order 1 (or to be $I(1)$) if it has to be differentiated once before becoming stationary (Vogelvang, 2005). Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979, 1981) unit root test and the Phillips-Perron (Perron, 1988, Phillips and Perron, 1988) nonparametric tests (Enders 2004). Instead of choosing between either one of these test methods, Enders (2004) considers a safe choice is to use both types of unit roots tests, since they reinforce each other.

Since most financial data contain stochastic trends, these trends need to be detected and detrended if, and as, necessary (Wilkinson, Rose et al., 1999). The test statistics can be based on the ordinary least squares (OLS) to determine a suitable specified regression equation for a time series Y_t for the ADF test for each series:

$$\Delta Y_t = \alpha_0 + \beta_1 Y_{t-1} + \sum_{i=1}^n \beta_i \Delta Y_{t-i} + \varepsilon_t \quad (\text{A4.1-1})$$

with the number of lags being determined by the residuals free from autocorrelation. This could be tested using the Lagrange Multiplier (LM) test. In practice, many researchers have used a model-selection procedure (such as AIC), or have alternatively assumed a fixed number of lags. The AIC method is used to test the optimal lag number in this study.

The Phillips-Perron test uses a method designed to overcome the problem that the error term is serially correlated, without including a lagged difference error term as in the ADF tests. The difference between the tests is the PP test allows for mild assumptions concerning the distribution of the errors, as they can be weekly dependent and heterogeneously distributed. The PP test statistic is adjusted to take into account the potential autocorrelation pattern in the errors. Enders (2004), Li (2001) and Wilkinson, Rose et al., (1999) found it appropriate to use both types of unit root tests, since they reinforced each other and added confidence to the results. The test is based on the ordinary least squares for a suitable, specified regression equation for a time series ΔY_t for each series:

$$Y_t = \alpha_0 + \beta_1 Y_{t-1} + \varepsilon_t \quad (\text{A4.1-2})$$

where ε_t = white noise.

These tests are based on a linear AR (p) model with p number of lags, which considers all combinations of price sensitivity γ to the past mean prices and the significance of some resilient price level as drift.

4.6.2 Appendix: Co-integration

The concept of co-integration was first introduced by Granger (1981) and elaborated further by Engle and Granger (1987), Engle and Yoo (1987), Phillips and Ouliaris (1990), Stock and Watson (1988) and Johansen (1991), (1995), among others.

Following the unit root test procedures gives the first step in the Engle-Granger methodology in testing for co-integration. Granger (1981) introduced the concept of co-integration when he wrote two variables may move together, although individually they are non-stationary. Co-integration is based on the long-run relationship between the variables. In the short run the variables may diverge from each other. The theory arises from considering equilibrium relationships, where equilibrium is a stationary point characterised by forces which tend to push the variables back towards equilibrium whenever they move away. If it is assumed two variables, say X and Y , are both $I(1)$, then it is normally true that a linear combination of the two variables will also be $I(1)$. Nevertheless, in some circumstances a linear combination of two $I(1)$ variables will result in a variable which is $I(0)$. In this instance, the two variables are said to be co-integrated (Enders, 2004).

This step would involve estimating the long-run equilibrium equation and conducting an ADF test on the residual sequence from this equation. If the residual sequence is found to be stationary, then X and Y are co-integrated.

The discussion has so far centered on the two-variable case, in which the co-integrating equation is unique. The Engle and Granger (1987) technique allows identification of only a single co-integration vector within a system. This automatically raises the possibility more than one co-integrating relationship may exist between the variables, so the property of uniqueness is lost. In general, if there are q $I(1)$ variables, then there are a maximum of $q-1$ co-integrating vectors (i.e., co-integrating relationships). Johansen (1991; 1995) introduced this approach, enabling the researcher to identify the maximum number of co-integrating vectors existing between a set of variables. The approach suggested by Johansen (1991; 1995) can be used for two purposes: (i) Determining the maximum number of co-integration vectors for the variables of interest; and (ii) obtaining maximum likelihood estimates of the co-integrating vector and the adjustment parameters. This is achieved by employing canonical correction methods and by utilising the Eigen values and Eigen vectors revealed by the matrix of correlation co-efficients. The Johansen (1991; 1995) procedure uses the trace statistics and the maximum Eigen value statistics to determine the number of co-integrating relationships. The maximum Eigen value statistic tests the null hypothesis of r co-integrating relationships, against the alternative of $r+1$ co-integrating relationships.

In fact, the Johansen co-integration test checks whether, or not, there is any co-integration between the variables and is, therefore, an alternative, or supplementary, test to those previously described (i.e., stationarity test; co-integration test). This approach also gives the maximum likelihood estimates for the co-integrating vectors. These estimates can be compared with those obtained through the application of ordinary least squares using the Engle and Granger two-step method.

4.6.3 Appendix: Error-Correction Model (ECM) and Causality

Co-integration analysis is important, because if two non-stationary variables are co-integrated, a vector autoregression (VAR) model in the first difference is misspecified, due to the effect of a common trend. If a co-integration relationship is identified, the model should include residuals from the vectors, lagged at one period, in a dynamic vector error-correction mechanism (VECM). Granger (1986) and Engle and Granger (1987) have demonstrated, if Y and X are both $I(1)$ variables and are co-integrated, an error-correction model exists. The error-correction model can be interpreted as showing there often exists a long-run equilibrium relationship between two economic variables, but in the short run, however, there may be disequilibrium. With the error-correction mechanism, a proportional disequilibrium in one period is corrected in the next period. The testing procedure for causal relationships between variables uses VAR and VECM modelling. The VECM will be used, as sources of causality cannot be detected by the VAR technique (Li, 2001; O'Connor, 1999). The VECM equation requires the time series to be non-stationary or integrated of an order bigger than zero, as well as being co-integrated.

The error-correction model may exist in the following form for two variables:

$$\Delta Y_t = -\rho_1 u_{t-1} + \text{lagged}(\Delta Y, \Delta X) + \varepsilon_{1t} \quad (\text{A4.1-3})$$

$$\Delta X_t = -\rho_2 u_{t-1} + \text{lagged}(\Delta Y, \Delta X) + \varepsilon_{2t} \quad (\text{A4.1-4})$$

with $|\rho_1| + |\rho_2| \neq 0$

where u_{t-1} is the error lagged one period, which is derived from the co-integrating regression given by Equation (A4.1-2), and ε_{it} are the two error terms which may be correlated, or exhibit autocorrelation. Additional lags should be added into the analysis until the residuals are independent. An estimate will be made regarding an ECM for each variable, where the lagged residuals from the equilibrium regression are included.

To assess the adequacy of the ECM model, Enders (2004) performs diagnostic tests to determine whether, or not, the residuals approximate white noise. If the residuals are serially correlated, lag lengths are to be short and need to be extended until they yield serially uncorrelated errors.

If it is not known which of the variables are exogenous, or endogenous, a VAR model allows for the treatment of variables which are stationary, as being symmetrical, where past values of all the variables can influence each variable (Ramanathan, 1998). The relationship between the variables can then be investigated simultaneously. A VAR model in the first difference for my bivariate time series is:

$$\begin{bmatrix} \Delta y_t \\ \Delta x_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ \Delta x_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{bmatrix} \quad (\text{A4.1-5})$$

where Δ is the first difference operator, a_{10} and a_{20} are intercept terms and ε_{yt} and ε_{xt} are the residuals. The link between co-integration and causality stems from the fact that if two variables are co-integrated, then causality must exist in at least one direction, and possibly in both directions as in Granger (1986). Since co-integration implies each series can be represented by an error-correction model, which includes the last period's equilibrium error, as well as the lagged values of the first differences of the variable,

temporal causality can be assessed by examining the statistical significance and relative magnitudes of error-correction co-efficients and co-efficients on the lagged variables. Significant causal relationships would be incompatible with market efficiency because they would imply forecast accuracy of one variable's subsequent performance, but this can be improved upon by using past information from the other variable. Adding an ECM to the VAR gives us the following VECM:

$$\begin{bmatrix} \Delta y_t \\ \Delta x_t \end{bmatrix} = \begin{bmatrix} a_{10} \\ a_{20} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} \Delta y_{t-1} \\ \Delta x_{t-1} \end{bmatrix} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} [y_{t-1} - \beta x_{t-1}] + \begin{bmatrix} \varepsilon_{yt} \\ \varepsilon_{xt} \end{bmatrix} \quad (\text{A4.1-6})$$

where α_1 and α_2 is the speed of the adjustment parameters. The larger α_1 is the greater result of the response of y_t to the previous period's deviation from long-run equilibrium. Small values of α_1 imply y_t is unresponsive to the last period's equilibrium error.

The ΔR_t^{IND} is denoted to the return series of the S&P/ASX 200 Index, and ΔR_t^{OPT} to the S&P/ASX 200 options. An error-correction model can be estimated as identifying the direction of causality between ΔR_t^{IND} and ΔR_t^{OPT} where:

$$\Delta R_t^{IND} = \alpha_0^{IND} + \beta_1^{IND} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{IND} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{OPT} + \varepsilon_t^{IND} \quad (\text{A4.1-7})$$

$$\Delta R_t^{OPT} = \alpha_0^{OPT} + \beta_1^{OPT} u_{t-1} + \sum_{i=1}^n \delta_i \Delta R_{t-i}^{OPT} + \sum_{i=1}^n \lambda_i \Delta R_{t-i}^{IND} + \varepsilon_t^{OPT} \quad (\text{A4.1-8})$$

where u_{t-1} is the lagged residual from the co-integrating regression, with ε_t^{IND} and ε_t^{OPT} being random error terms. Equation A4.1-7 postulates the current ΔR_t^{IND} is related to the

previous periods, lagged residual and lagged values of ΔR_t^{OPT} , as well as the lagged values of ΔR_t^{IND} . The co-efficient β in Equation A4.1-7 measures the single period response of ΔR_t^{IND} to departures from equilibrium. A small β indicates the ΔR_t^{IND} adjusts only fractionally to correct the disequilibrium situation, so most of the adjustment is accomplished by ΔR_t^{OPT} . Similarly, Equation A4.1-8 states the current ΔR_t^{OPT} is related to the previous period's equilibrium error; the lagged values of ΔR_t^{IND} ; as well as the lagged values of ΔR_t^{OPT} . A small β in Equation A4.1-8 indicates the ΔR_t^{OPT} responds very little to correcting the disequilibrium situation, so most of the adjustment is accomplished by ΔR_t^{IND} . It has been stated that if ΔR_t^{IND} and ΔR_t^{OPT} are co-integrated, then there must be Granger causality in at least one direction. In the Granger causality framework, ΔR_t^{OPT} is said to cause ΔR_t^{IND} , if some of the δ_i in Equation A4.1-7 are nonzero, while all the δ_i in Equation A4.1-8 are equal to zero, and/or the error-correction co-efficient β is nonzero at conventional significance levels. In the same way, ΔR_t^{IND} is said to cause ΔR_t^{OPT} , if some of the δ_i in Equation A4.1-8 are nonzero while all the δ_i in Equation A4.1-7 are equal to zero and/or the error-correction co-efficient β is nonzero. If both of these events occur, there is feedback and the test for causality (Malliaris and Urrutia, 1992), (Li, 2001) is based on a standard Wald F statistic, which is calculated by estimating Equations A4.1-7 and A4.1-8 in both the unconstrained, and constrained, forms:

$$F_c = \frac{(ESSR - ESSU) / n}{ESSU / (T - m - n)} \quad (A4.1-9)$$

where T is the number of observations used in the unrestricted model, ESSR and ESSU is the residual sum squares of the reduced and full models, and m and n is the optimal order of lags.

The Wald test deals with hypotheses involving restrictions on the co-efficients of the explanatory variables. The restrictions may be linear, or non-linear, and two or more restrictions may be tested jointly. The output from the Wald test depends on the linearity of the restriction. The F test is carried out for the null hypothesis of no Granger causality ($H_0 : \lambda_{i1} = \lambda_{i2} = \lambda_{ik} = 0, i = 1, 2$), where the F statistic is the Wald statistic for the null hypothesis.

4.6.4 Appendix: Price-discovery Process

Price-discovery is the process by which new information is revealed by markets, participants and incorporated into observable asset prices. Arbitrage activities should keep prices in the index and option markets from diverging. The prices of the two markets should be co-integrated and be driven by one common factor, which is also known as the “implicit efficient price”.²⁶ I investigate the common-driving force mechanics in price-discovery for the index and option markets and adapt two approaches to investigate the mechanics of price discovery. Both are based on a decomposition of transaction prices into a permanent component associated with an efficient price of the

²⁶Co-integration describes the presence of a stationary relationship among non-stationary series. See Engle and Granger (1987).

asset and a transitory component which reflects noise. The efficient price should be identical in both the index and option markets, while the transitory component may differ. I want to establish which market information is first incorporated into the efficient price.

The first approach to price-discovery I will use is the permanent-transitory model discussed by Gonzalo and Granger (1995) and the second is the information- shares model developed by Hasbrouck (1995). Hasbrouck (1995) uses a Stock-Watson (1988) common stochastic trend decomposition to decompose transaction prices into random walk, which Hasbrouck interprets as the efficient price and noise and measures the contribution of each market to the variance of the former. The information shares are not uniquely defined if the price innovations in the index and option markets are correlated and one has to compute upper and lower bounds for the information shares by attributing as much information to each market. The approach by the Gonzalo and Granger (1995) contributions to each market is uniquely defined and decomposes transaction prices into a permanent component which is integrated of order 1 and the transitory component is stationary.

Although the information-sharing and the permanent-transitory models study the same economic phenomenon, the two techniques provide different views on the price-discovery process. The Hasbrouck (1995) model extracts the price-discovery process using the variance of innovations to the common factor. The Gonzalo and Granger (1995) approach, however, focuses on the components of the common factor and the error-correction process. This method involves only permanent (as opposed to transitory) shocks which result in disequilibrium.

I will use Hasbrouck (1995) and Gonzalo and Granger (1995) methodology extended to financial markets by Harris, McNish et al., (2002a), Booth, So et al., (1999), Chu, Hsieh et al., (1999), Roope and Zurbreugg (2002), Baillie, Booth et al., (2002), Chakravarty, Gulen et al., (2004) and Su and Chong (2007) to measure the index and option markets' relative contribution to price discovery. Both the information-sharing and permanent-transitory models are derived based on the vector error-correction model. Let R_t be a (2x1) vector containing index return (ΔR_t^{IND}) and an option return (ΔR_t^{OPT}) then;

$$R_t = \begin{bmatrix} R_t^{IND} \\ R_t^{OPT} \end{bmatrix} \quad (\text{A4.1-10})$$

If the R_t has co-integrating vector(s) with the co-integration vector $\beta = (1, -1)'$ both the information-share and permanent-transient models start from the following VECM:

$$\Delta R_t = \alpha \beta R_{t-1} + \sum_{i=1}^k \Gamma_i(L) \Delta R_{t-i} + \varepsilon_t, \quad (\text{A4.1-11})$$

where ΔR_t is an 2×1 return vector, α is the error-correction vector, β is the co-integrating vector, βR_{t-1} describes the equilibrium error between the two prices, and ε_t is a zero mean vector of serially uncorrelated innovations with covariance matrix Ω such that:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix} \quad (\text{A4.112})$$

where $\sigma_1^2(\sigma_2^2)$ is the variance of $\varepsilon_{1t}(\varepsilon_{2t})$. The βR_{t-1} term describes the long-run equilibrium dynamics between the price series and $\sum_{i=1}^k \Gamma_i(L)\Delta R_{t-i}$ depicts the short-run dynamics induced by market imperfections and α is the error-correction co-efficient vector which measures the speed each market eliminates short-run price disequilibrium. Hasbrouck (1995) transforms Equation A4.1-11 into a vector moving average (VMA)

$$\Delta R_t = \Psi(L)\varepsilon_t \quad (\text{A4.1-13})$$

and its integrated form

$$R_t = l\Psi \sum_{s=1}^t \varepsilon_s + \Psi^*(L)\varepsilon_t \quad (\text{A4.1-14})$$

If I denote the equilibrium price vector associated with ε_t as r^* then the long-run version of A4.1-13 is:

$$r^* - R_{t-1} = \Psi(1)\varepsilon_t \quad (\text{A4.1-15})$$

where $l = (1,1)'$ is a column vector of ones, $\psi = (\psi_1, \psi_2)$ is a row vector and $\psi^*(L)$ is a matrix of polynomials in the lag operator, L. Equation A4.1-14 is related to the common factor representation of Stock and Watson (1988), in which

$$X_t = \omega_t + G_t, \quad (\text{A4.1-16})$$

where ω_t is the common factor component and G_t is the transitory component which does not have a permanent impact on X_t .

Engle and Granger (1987) show the long-run multiplier in A4.1-15, long-run shocks on returns are:

$$\Psi(1) = \sum_{i=0}^{\infty} \Psi_i = \theta\psi \quad (\text{A4.1-17})$$

where 2×1 θ and 1×2 $\psi = (\psi^{IND} \psi^{OPT})$ are the orthogonal complement of β and α' so $\beta'\theta = 0$ and $\psi\alpha = 0$. Substituting A4.1-17 into A4.1-15 gives us:

$$r^* = R_{t-1} + \theta\psi\varepsilon_t \quad (\text{A4.1-18})$$

Equation A4.1-18 defines a scalar shock instead of a vector shock to $\psi\varepsilon_t$, whose impact on r^* is measured by the co-efficient vector θ . The elements of ψ represent weights used to combine information innovations from each market to form the permanent information series $\psi\varepsilon_t$ and size of weights indicates each market's innovation in forming the long-run equilibrium price.

Gonzalo and Granger (1995) present the $\psi\varepsilon_t$ in equation A4.1-18 as a scalar permanent factor x_t in co-integrated prices as:

$$R_t = \theta x_t + y_t \quad (\text{A4.1-19})$$

where R_t is a 2×1 price vector, θ has the same loading vector as in A4.1-18, and y_t is the 2×1 transitory price components. The common factor is a weighted sum of the original prices as:

$$x_t = \psi R_t \quad (\text{A4.1-20})$$

with the common factor component weights as $\psi = (\psi_{IND} \psi_{OPT})$ as in A4.1-17.

The measure of the markets' contribution to permanent information is calculated by the size of component weights (factor weights) and because $\beta' \theta = 0$ and $\psi \alpha = 0$ the weights are related to the relative sizes of the error-correction co-efficients by:

$$\phi_{IND} = \frac{|\alpha_{OPT}|}{|\alpha_{IND}| + |\alpha_{OPT}|} \text{ and } \phi_{OPT} = \frac{|\alpha_{IND}|}{|\alpha_{IND}| + |\alpha_{OPT}|} \quad (\text{A4.1-21})$$

The greater the factor weights of a market, the slower its speed of adjustment to equilibrium and the bigger its role in discovering equilibrium prices. Hasbrouck's (1995) measure of a market's contribution to price-discovery hinges on the decomposing of the variance of the individual in the 2×1 $\theta \psi \varepsilon_t$, which measures the long-run impact of innovations on the two prices. If the index market and the options market value the scalar permanent information equally in the long run, I have to decompose $Var(\psi \varepsilon_t) = \psi \Sigma \psi'$ by obtaining the Cholesky decomposition Σ as F , then:

$$Var(\psi \varepsilon_t) = \psi \Sigma \psi' = \psi F F' \psi' = v_{IND}^2 + v_{OPT}^2 \quad (\text{A4.1-22})$$

This provides us with a way to break down the permanent information variance into parts attributable to the index and the options market with v_i^2 , and i is for the index and the option markets. The information share of market i by Hasbrouck is:

$$s_i = \frac{v_i^2}{\psi' \Sigma \psi} \tag{A4.1-23}$$

If the index market and the options market value $\psi \varepsilon_t$ differently in the long-run both still have information share as in Equation A4.1-23.

4.6.5 Appendix: Impulse-Response Functions

The information transmission can also be measured on the basis of variance structure with the innovation accounting method. Impulse-response functions or variance decomposition indicates the extent a shock on one variable is transitory in terms of its effect on other variables. An impulse-response function traces the effect of a one standard deviation shock to one of the innovations on the current and future values of the endogenous variables.

Yan and Zivot (2006) and Lutkepohl and Reimers (1992) show impulse responses and variance decomposition analysis help us to analyse the dynamics of a VAR model in its vector moving average representation (VMA). My application, with a two-dimensional system, describes two response functions through time. I denote the return series of the index as R_t^{IND} and the return series of the implied index as R_t^{OPT} . This involves switching to a VMA representation to investigate the impact of exogenous shocks to the different markets and trace out the responses to shocks in each market. The ordering of the contemporaneous correlations, based on a Cholesky decomposition of the estimated residual covariance matrix, must be used to orthogonalise the innovations. The impulse-response confirms the speed of this procedure and the variance decomposition confirms the degree of change of the variance structure.

5 The Informational Role of Options Trading Volume in the Australian Index Options Markets

5.1 Introduction

The previous chapter investigates the information content of the index and option markets in the lead-lag and price-discovery process. The long-run equilibrium relationship between the share price index and the implied price of the share-price-index option was investigated. Causality was determined to show which market leads the other. Information-share measures were used to gauge the contribution of the share price index and index option markets to the price-discovery process. Unambiguous evidence shows the index market leads the options market and the former contributes more to price-discovery than the latter.

This chapter expands on the role trading volume plays in financial markets. Abnormal returns and abnormal trading volume are widely used in the literature to reflect the changes in the expectations of the market in terms of price changes and changes in trading activity. It facilitates the price-discovery process, enables investors to share financial risks, and ensures that corporations can raise funds needed for investment.

Hedging and speculative uses of options arise from an asset's price volatility, and one may argue that the option trading volume should follow the price volatility. This assumes that perfect markets and symmetric information about option markets and trading volume do not influence the trading process. Options markets are more attractive to informed traders than are the index markets because of the higher leverage available in the options markets. Option trades may first reflect the information on the future price

volatility as option-pricing formulas need this volatility to determine the option price (Easley, O'Hara et al., 1998). Option trading volume may precede the future price volatility if the option trades are largely initiated by informed traders. Hedging-based uses of options suggest that the option trading volume should follow the future price volatility because higher future price volatility leads to a greater use of options and thus a higher option trading volume.

In this chapter the implied volatility of the S&P/ASX 200 Index Options is used as a proxy for the future price volatility. Easley, O'Hara et al., (1998) demonstrate that the option trading volume may actually contain information about the future asset prices and thus the future price volatility. The dynamic relationship between future volatility, trading volume and the future volatility and the options market activity of the S&P/ASX 200 Index Options is examined to explore the informational role of option volume in predicting the price volatility. The measure for options market activity is the daily closing volume of options, standardised by open interest (Chatrath, Kamath et al., 1995a), (Chatrath, Ramchander et al., 1996).

I find the contemporaneous call options volume have a significant strong positive feedback effect on the implied volatility, but the contemporaneous feedback effect of volume on the TARARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARARCH volatility to the call options volume are positive, significant and strong. My results indicate that market forces, such as speculation and arbitrage, in the S&P/ASX 200 call options market operate effectively to produce quick and strong interactions between call options volume and volatility. I find bi-directional causality (or feedback) between call options volume and implied volatility

or TARCH volatility. The direction of causality from implied volatility or TARCH volatility to call options volume is significant, implying lagged volatilities cause current volume to change. The causality from call options volume to implied volatility or TARCH volatility exists but is relatively weak. My results indicate that lagged volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of implied volatility and TARCH volatility values.

Since the implied price volatility appears to change with the call options moneyness, the relationship between call options volume and volatility may also change with the options moneyness. The predictive ability of call options market activity for price volatility is more pronounced in call options market activity near-the-money and in-the-money. I find options volume and options market activity for price volatility in call options out-of-the-money have very little or no predictive ability.

5.2 Literature Review

Information models I reviewed in the previous chapter did not address the role of trading volume in price formation and the role of lead/lag relationships between the prices of various markets, or between different securities. In Copeland and Galai (1983) and Glosten and Milgrom (1985), trade size is assumed constant. The informed trader in the Kyle (1985) model always adjusts order size to maintain a constant fraction of trade, such that trade size does not influence price adjustments. Schwert (1989) identifies variability in trading activity as a key explanation for variability in market volatility. Gannon (1994) finds significant volume and volatility transmission effects between index and index futures in a system of simultaneous equations. Chng and Gannon (2003) document similar findings in extended work on simultaneous volatility models. In

subsequent theoretical work, researchers pursue the view of volume playing a supporting role during price adjustment. Easley and O'Hara (1987) extend the Glosten and Milgrom (1985) findings by considering the price formations of large versus small trades. Their extension is based on the presumption that an informed investor who decides to trade will trade in large quantity in order to maximize trading profits. Blume, Easley et al., (1994) examine price-discovery contribution by price and volume. In their model, an information event has two dimensions. While the observed price series indicates the direction of an information effect, trade size indicates the quality of that information effect.

Another strand of the literature discuss the dynamic effects of trading volume on future volatility. Shalen (1993) examines a noisy rational expectations model. The model predicts a positive correlation between trading volume and future absolute price changes because of the dispersion of the future price expectations. Gallant, Rossi et al., (1992) find that large price movements are followed by high volume by applying a semi-nonparametric estimation of the joint process of price changes and volume. Lee and Rui (2002) examine the dynamic causal relationship between stock market returns, trading volume and volatility. They find that there is a positive feedback effect between volume and volatility while volume does not help predict the level of returns. This finding suggests that information in returns is contained in trading volume indirectly through its predictability of return volatility. If this is the case, trading volume might be used as a proxy for information flow in the stochastic process generating volatility.

Anthony (1988) investigates whether trades in the stock and/or options market lead trades in the other market. He uses Granger (1969) causality tests to examine daily

closing data. He finds that trades in the call options market lead trades in the stock market by one day. However, using stock and option volume, he finds that for only 14 out of 25 firms, option volume leads stock volume. For four firms, stock volume leads option volume. For eight firms, the causality is not clear.

Lamoureux and Lastrapes (1990) were the first to apply stochastic time series models of conditional heteroscedasticity (GARCH-type) to explore the contemporaneous relationship between volatility and volume data. They find the persistence in stock return variance mostly vanishes when trading volume is included in the conditional variance equation. If trading volume is considered to be an appropriate measure for the flow of information into the market, this finding is consistent with the mixture of distributions hypothesis (MDH). The observation by Lamoureux and Lastrapes (1990) is indicating that trading volume and return volatility are driven by identical factors, leaving the question of the source of the joint process largely unresolved.

Numerous empirical studies address the informational role of options markets. The earliest work on option-equity market linkages includes Manaster and Rendleman (1982), Bhattacharya (1987), and Anthony (1988). They use daily data and present evidence that the options market leads the stock market in terms of both price movements and trading activity. Using transactions data, Stephan and Whaley (1990) find that stock price movements lead option price movements.

Chatrath, Ramchander et al., (1995b) examine option market activity versus cash market volatility on the S&P 100 index for the period February 1984 to November 1993 with Granger causality tests. Their evidence suggests that while increased cash market volatility is followed by an increase in the level of option market activity, an increase in

option market activity is followed by a decline in cash market volatility. They use a bivariate VAR with options trading volume and spot price volatility and execute conventional causality tests, providing evidence that there is strongly significant feedback between the two variables. An increase in cash market volatility seems to cause an increase in the level of options trading, whereas an increase in options trading is followed by a decrease in spot market volatility. They interpret their results as evidence that options trading reduces cash market volatility.

Amin and Lee (1997) document that the signed daily trading volumes of the calls and puts written on 147 NYSE-traded stocks from 1988 to 1989 increased by more than 10 percent at least four days before earnings announcements. They also show that the trading profit using mid-quotes is positively correlated with the proportion of long positions to short positions in the options market prior to earnings announcements. Their results confirm that the options market contributes to the price-discovery process of the underlying stocks.

Easley, O'Hara et al., (1998) focus on the informational role of options markets when investors are asymmetrically informed. They show that in a multi-market setting, there is a trade-off between liquidity and leverage. They also suggest that stock and options markets are in a pooling equilibrium, where informed traders will trade in one or both markets until their profit margin becomes equivalent. Their empirical result shows that signed options volume contains information about future stock prices. They find that information flows are bi-directional between stock and options markets, but the degree of relative informativeness of the options market is uncertain.

Chan, Chung et al., (2002) investigate stock and option volume using quotes and trades of options and analyse the intraday interdependence of order flows and price movements. They find that stock net trading volume (buyer-initiated trading volume minus seller-initiated trading volume) leads option net trading volume. They find that stock net-trade volume has strong predictive ability for stock and option quote revisions, but option net volume has no incremental predictive ability, suggesting that informed investors initiate trades in stock markets but not in options markets. They also find that quote revisions in the options market contain some information and conjecture that this happens because informed traders prefer limit-orders in options markets. Chan, Chung et al., (2002) show that both stock and option quote revisions predict each other. However, unlike the result in Easley, O'Hara et al., (1998), they find that signed option volume does not predict changes in stock prices.

In the Australian setting, Turkington and Walsh (2000) investigate the causal structure of price and volume in options and stock markets to determine whether a preferred market for informed trading exists. They test for co-integration, using the vector-error-correction (VEC) approach, and find that volume leads price in both markets but that option volume leads stock volume and stock price leads option price. Jarneic (1999) empirically analyses the intraday relations between trading volume of underlying stocks and stock options listed on the ASX using 15 minute intraday observations and finds that stocks typically lead stock options by as much as fifteen minutes. Adjusting the study to accommodate differences in trading, he removes all 15 minute interval observations that exhibit zero stock or option trading volumes. The Jarneic (1999) lead/lag relationship between stock and stock options suggests this to be “a phenomenon

induced by less frequent trading of options". His findings are consistent with Chan, Chung et al., (1993) and Finucane (1999).

Kyriacou and Sarno (1999) examine the relationship between derivatives trading activity and spot market volatility using daily data for the U.K. market. The dynamic relationship between spot market volatility, futures trading and options trading, using a trivariate simultaneous equations model to estimate Granger causality, was investigated. Their results provide strong evidence that significant simultaneity and feedback characterise the relationship between the spot market volatility and derivatives trading. Futures trading and options trading are found to affect spot market volatility in opposite directions in the structural model proposed. The results suggest that the failure to account for any contemporaneous interaction between the variables under consideration, as well as the omission of any of the derivatives trading activities examined in their study, may generate serious misspecification and ultimately produce misleading estimation results and statistical inferences.

Hagelin (2000) investigates the relationship between options market activity and cash market volatility on the OMX Index of Sweden. He uses a bivariate VAR, as in Chatrath, Ramchander et al., (1995b), with options trading volume and cash market volatility, and executes conventional causality tests. His study contributes by investigating empirical evidence relating to two periods with different market conditions. He finds that for the complete sample period there is unidirectional causality from cash market volatility to option market activity for calls and puts jointly, as well as for calls and puts respectively. While unidirectional causality from cash market volatility to call option market activity is documented for both the sub-periods, bilateral causality between

put option market activity and cash market volatility was found for one of the sub-periods.

Sarwar (2003) examines the relationship between future volatility of the U.S. dollar/British pound exchange rate and trading volume of currency options for the British pound in the context of a simultaneous equations model. The future volatility of the exchange rate is approximated by implied volatility and by IGARCH volatility. The results suggest the presence of strong contemporaneous positive feedbacks between the exchange rate volatility and the trading volume of call and put options. He finds previous option volumes have significant predictive power with respect to the expected future volatility of the dollar/pound exchange rate. The results support the hypothesis that the information-based trading explains more of the trading volume in currency options on the U.S. dollar/British pound exchange rate than hedging. Sarwar (2003) fails to investigate option market activity (open interest) of the currency options market, that is often interpreted as an indicator of the hedging activity (Hagelin, 2000).

Kim, Kim et al., (2004) examine the relationship between the trading activities of the Korea Stock Price Index 200 derivatives contracts and the underlying stock market volatility. They find a positive (negative) contemporaneous relationship between the stock market volatility and the volume (open interest) for both futures and options contracts. This confirms that the derivatives volume, which largely proxies speculative trading activities, tends to increase the underlying stock market volatility while the open interest, which mainly reflects hedging activities, tends to stabilise the cash market. They also find that the lagged futures (options) volume causes the current stock market volatility, and that the lagged cash volatility also causes the current volume. The lagged

cash volatility causes the current open interest in both the futures and options markets, but the causal relationship between the current cash volatility and the lagged open interest exists only in options market.

Sarwar (2005) examines the dynamic relationship between future price volatility of the S&P 500 index and trading volume of S&P 500 options in the context of a simultaneous equations model to explore the informational role of option volume in predicting the price volatility. The future volatility of the index is approximated by implied volatility and by EGARCH volatility. He uses a simultaneous equation model to capture the volume-volatility relations, and finds strong feedback exists between the future price volatility and the trading volume of call and put options. Sarwar (2005) fails to investigate option market activity (open interest) of the index options market, that is interpreted as an indicator of the hedging activity(Hagelin, 2000).

Pan and Poteshman (2006) use a data set from the CBOE covering 1990 to 2001 that contains information on investor classes and trade types in the option market. They find that the put-call volume ratio can predict future stock prices. They identify the source of this predictability as not publicly observable and that it is exclusive to only the options market. The categorised option volume to predict future stock returns and predictability becomes stronger with the presence of informed traders. They find option volume is more predictive on stocks with higher concentrations of informed investors and the volume of more levered options contains more information about future stock prices.

As noted by Koch (1993), the econometric strategies employed by various previous empirical literature may suffer from a misspecification problem inasmuch as

they do not allow for the plausible possibility that the variables under consideration are determined simultaneously. In summary, the consensus is that much of the previous empirical literature investigating the relationship between derivatives trading and spot market volatility in the context of structural VAR that omit any of the two derivatives trading activity or fail to account for simultaneous interactions between the variables should be interpreted with caution because it is based on misspecified models. The failure to account for simultaneity reduces the power of Granger causality tests, whereas omission of a relevant variable in the model tends to bias causality tests towards rejection of the null hypothesis of non-causality, generating potentially misleading results.

5.3 Data and Methodology

5.3.1 Data

Daily closing values (dividend adjusted) of the S&P/ASX 200 Index and daily closing prices for the S&P/ASX 200 Call options contracts are used in this chapter. The transaction data includes daily closing prices, exercise price, expiration date, trading volume, open interest, underlying index value, and high, low and last option prices. Data was supplied by SIRCA, the ASX and DataStream. The S&P/ASX 200 option sample data range covers the period from March 1, 2001, to December 31, 2008, inclusive. This launch coincided with Standard and Poor's taking over the index business, which was formerly owned and managed by the Australian Stock Exchange.

I use the implied volatility and conditional volatility of a Threshold Autoregressive Conditional Heteroscedasticity model (TARCH) of the S&P/ASX 200 Index Options as a proxy for the future price volatility. Easley, O'Hara et al., (1998) demonstrate that the options trading volume may actually contain information about the

future asset prices and thus the future price volatility. The implied volatility is obtained by solving a modified Black-Scholes formula. Roll's (1977) compounded option pricing formula is used, as the options on the S&P/ASX 200 Index are European-style options.

$$C_t = S_t N(d) - Ke^{-rt} N(d - \sigma\sqrt{\tau}), \quad (5.1)$$

$$\text{where } d = \frac{\log(S_t / K) + (r + \sigma^2 / 2)\tau}{\sigma\sqrt{\tau}},$$

$$\text{and } N(d) = \frac{1}{2\pi} \int_{-\infty}^d e^{-\frac{x^2}{2}} dx.$$

$$\text{Min}_{s_{u\sigma}} Q = \left(\sum_{i=1}^N (C_{a,i} - f(S_{a,i}, K_i, T_i, \sigma)) \right)^2 \quad (5.2)$$

where C_t is the Black-Scholes price for the call option, S_t is the price of the stock index (dividend adjusted), K is the exercise price, K_i is the call option, I is the strike price, T is the time to expiration, T_i is the call option z time to expiration, N is the total number of qualifying calls written on the stock and r is the risk-free interest rate sourced from Treasury bills. Data for the 30-day, 60-day and 90-day bills was obtained from DataStream, and the yield on the bill having the expiry closest to that of the option was used as the risk free rate. The option price is found by taking the midpoint of the bid and ask quotes for the option under consideration (Chan, Chung et al., 1993). This has advantages over using the actual trading price, as the midpoint prices removes any spurious negative autocorrelation as described in Roll (1984) resulting from bid/ask bounce (Lo and Mackinlay, 1990). Bid and ask quotes are more often reported than are actual trade prices (O'Connor 1999). This is important in minimising the impact of

infrequent and non-synchronous trading, and the use of stale prices.²⁷ Poteshman (2000) and Chernov (2002) argue that implied volatilities should theoretically provide the best forecasts of the expected future volatilities because option prices can impound all publicly available information. Corrado and Miller (2005) focus on three volatility indices from the S&P 100, S&P 500 and NASDAQ 100 and conclude that the forecast qualities of these implied volatility indices easily outperform historical volatility as predictors of future volatility. Corrado and Miller (2006) test the relationship between expected and realised excess returns for the S&P 500 Index. When risk is measured by option-implied volatility, they find a positive and significant relationship between expected and realised excess returns.

Computing implied volatility involves several practical problems. Only options with three months to expiration are available. The following rules are applied in order to filter the options from a population of 24,131 call option transactions. Options with time-to-maturity of less than a day, price less than \$0.125 and trading volume of less than three contracts are excluded. Aït-Sahalia and Lo (1998) argue that prices of options with a very low trading volume are notoriously unreliable. Very short-term options contain little time value and the estimation of volatility is extremely sensitive to possible measurement errors.

The TARARCH-based volatility of the S&P/ASX 200 Index Options as a proxy for the future price volatility is calculated using the TARARCH (3,1,1) specification. Buhr, Li et

²⁷ Lo and Mackinlay (1988; 1990) examine the non-synchronous problem. Miller, Muthuswamy et al., (1994) show that, under reasonable assumptions about infrequent trading of index portfolio stocks, strong negative first-order autocorrelation can be expected.

al., (2008) find that the TAR_{CH} (3,1,1) model provides the most accurate forecast across all forecasting horizons for the S&P/ASX 200 Index Options. The volatility proxy was found to be the better-fitting model within the linear and non-linear ARCH specifications.

5.3.2 Methodology

If trading activity is a valid proxy for information release, then inferences may be drawn by examining the comparative trading activity of index and options markets. There are two main measures of activity on options markets. The first, turnover (or volume) refers to the number of purchases/sales of the various contracts listed on an exchange during a given period of time. Since the exchange automatically matches a purchase with a corresponding sale, turnover gives an account of the total number of purchases or sales in the specified period. The basic unit of time on exchanges is the trading day, with the information on activity being reported in number of contracts traded. Turnover is a flow concept, which is generally used by market participants as an indicator of liquidity in a particular contract or as a measure of an exchange's success in attracting trading business.

The second main measure of activity on options markets, open interest, refers to the total number of contracts that have not yet been offset by an opposite transaction or fulfilled by delivery of the asset underlying a contract. Although each transaction has both a buyer and a seller, only one side of the transaction is included in open interest statistics. Open interest is a stock concept reflecting the net outcome of transactions on a given date. It is often interpreted as an indicator of the hedging or long-term commitment of traders to a particular contract. Open interest is generally smaller than turnover

because a large number of contracts that are bought or sold during the course of the day are reversed before the end of the trading day.

The relationship between price volatility and options trading volume and the relationship between price volatility and options market activity are investigated using variants of the causality testing approaches of Granger (1969) and Granger and Newbold (1977). Daily options market activity (OMA) is the daily closing volume of options, standardised by open interest. I use the daily OMA as proposed by Garcia, Leuthold et al., (1986), Chatrath, Ramchader et al., (1995b), (1996), Kyriacou and Sarno (1999) and Hagelin (2000) and is specified as:

$$OMA = \frac{V_t}{OI_t} \quad (5.3)$$

where V_t and OI_t denote the daily closing volume and open interest for options at day t . OMA has some advantages compared to using only the daily trading volume as a proxy for the options market activity. Garcia, Leuthold et al., (1986) point out that the daily trading volume and level of open interest are functions of time to expiration and by dividing the daily trading volume with the level of open interest, standardisation is achieved. In addition, Leuthold (1983), Garcia, Leuthold et al., (1986) and Chatrath, Ramchander et al., (1996) suggest that market activity defined in this way reflects the specific impact of speculative activity. The rationale for this is that daily trading volume is assumed largely to reflect speculation, as hedgers' transactions comprise relatively minor proportions of the total daily trading volume, whereas open interest largely captures hedging, since open interest reflects longer than intra-day positions. Options

market activity relating the two variables to each other is likely to reflect the relative level of speculation more accurately than only trading volume.

Ordinary least squares (OLS) estimation is the most widely used regression method in the literature (Greene, 2003), (Stock and Watson, 2007). If the least squares assumptions hold (Stock and Watson, 2007), (Wooldridge, 2006) and if errors are homoscedastic indicating the variance of the error term, conditional on the regressor, is constant, then OLS estimation is the best linear unbiased estimator. However, if the OLS estimation is inconsistent and the estimator does not converge to the population parameter and thus produces biased co-efficients then there is an endogeneity problem. Endogeneity arises when a regressor is correlated with the error term, thereby violating the most important OLS estimation assumption, the exogeneity condition (Wooldridge, 2006).

Many researchers conduct Granger causality tests by estimating a vector autoregressive (VAR) model and testing zero restrictions on the lagged parameters (Chan, Chung et al., 1993), (Chatrath, Ramchander et al., 1995b), (Chatrath, Ramchander et al., 1996). The VAR model specifies that each endogenous variable depends upon its own lagged values and the lagged values of the other endogenous variable involved. However, the VAR model omits the contemporaneous interaction among the variables, and thus ignores the possibility that the variables may be simultaneously determined. Easley, O'Hara et al., (1998) examine the Granger causality between stock prices and options trading volume by using a two-step regression method. They use the ordinary least square (OLS) procedure to estimate the parameters of the second-step regression. Koch (1993) argues that if the variables in question are structurally related within the

same time interval, then the VAR-based parameters yield biased and inconsistent estimates of the structural dynamic linkages and do not allow for simultaneity. He advocates the estimation of the parameters in the context of a simultaneous equations model that requires an instrumental variables (IV) estimator which provides consistent estimates.

Koch (1993) comments on this omission as follows:

“The interpretation of the simultaneous equation model is straightforward; the contemporaneous co-efficients reflect the simultaneous interaction among the four variables, whereas the lagged co-efficients reflect the lagged responses across variables after accounting for their contemporaneous interaction.”

I follow the Koch (1993), Kyriacou and Sarno (1999), Kim, Kim et al., (2004) and Sarwar (2005) procedures in testing the Granger causality between price volatility and options trading. I also extend the Sarwar (2005) procedure to include options trading activity in testing the Granger causality between the future price volatility and options market activity. Causality tests may provide insights into the nature of the relationship and predictive power of past values of price volatility on options volume. If the hypothesis that the implied volatility/TARCH volatility data does not Granger-cause options trading volume/options market activity and the data is rejected, then current price volatility has predictive power for options volume. At the same time, suppose the hypothesis that options trading volume/options market activity do not Granger-cause implied volatility/TARCH volatility, the data fails to reject. Then options trading volume/options market activity data does not have predictive power of the implied volatility/TARCH volatility data. If price volatility Granger-causes options trading but

options trading does not Granger-cause price volatility, then past values of price volatility should be able to help predict future values of options trading, but past values of options trading should not be helpful in forecasting price volatility.

The test for causality (Malliaris and Urrutia, 1992); (Li, 2001), is based on a standard Wald F statistic, which is calculated by estimating Equations 5.5, 5.6, 5.7 and 5.8 in both the unconstrained and constrained forms:

$$F_c = \frac{(ESSR - ESSU) / n}{ESSU / (T - m - n)} \quad (5.4)$$

where T is the number of observations used in the unrestricted models in Equations 5.5, 5.6, and 5.7, 5.8, $ESSU$ denotes the error sum of squares for Equations 5.5, 5.6 and 5.7, 5.8, $ESSR$ is the error sum of squares for the restricted models, and m and n is the optimal order of lags.

The Wald test deals with hypotheses involving restrictions on the co-efficients of the explanatory variables. The restrictions may be linear, or non-linear, and two or more restrictions may be tested jointly. The output from the Wald test depends on the linearity of the restriction. The F test is carried out for the null hypothesis of no Granger causality ($H_0 = \alpha_{1i} \dots \alpha_{1m} = 0$ in Equation 5.5 and $H_0 = \beta_{2i} \dots \beta_{2m} = 0$ in Equation 5.6), where the F statistic is the Wald statistic for the null hypothesis. If the null hypothesis in Equation 5.5 is rejected, the timing and direction of the predictive power of lagged volatility terms can be examined by testing the significance of individual lagged coefficients on the basis of a t test (Easley, O'Hara et al., 1998).

A simultaneous equations model for testing causality between the future price volatility and the options volume series can be specified as:

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} V_{t-i} + e_t \quad (5.5)$$

$$V_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} V_{t-i} + \varepsilon_t \quad (5.6)$$

where I_t denotes the future price volatility, V_t is the options trading volume, α and β denote the intercepts and e_t, ε_t are the disturbance term.

The options trading activity, denoted by OMA, is the daily closing volume of options, standardised by open interest, and is defined in accordance with Garcia, Leuthold et al., (1986). A simultaneous equations model for testing causality between the future price volatility and options market activity series can be specified as:

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} OMA_{t-i} + e_t \quad (5.7)$$

$$OMA_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} OMA_{t-i} + \varepsilon_t \quad (5.8)$$

where I_t denotes the future price volatility, OMA_t is the options trading activity, α and β denote the intercepts and e_t, ε_t are the disturbance term. Since most economic time series are non-stationary, the data needs to be transformed by using log transformation and/or differencing, in order to obtain stationarity. If the transformed series is stationary, or I

(0), this implies the original series is integrated of order 1, or $I(1)$, which is an example of a random walk series. For a series to be stationary, the mean, variance and co-variance of the series should be constant over time. In a non-stationary series the mean and/or the variance are time-dependent and there is no long-run mean to which the series returns. The variance is time-dependent and approaches infinity as time approaches infinity. The important part, which is closely related with stationarity, is the series degree of integration.

Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) (Dickey and Fuller, 1979; 1981) unit root test and the Phillips-Perron (Perron, 1988; Phillips and Perron, 1988) nonparametric tests (Enders 2004). Instead of choosing between either one of these test methods, Enders (2004) considers a safe choice is to use both types of unit roots tests, since they reinforce each other.

I use the impulse-response function (IRF) to trace the impact of a one-time, unit standard deviation, positive shock to one variable on the current and future values of the endogenous variables. The IRF are used to conduct simulations where one of the variables is shocked and the response of each of the other variables is traced over a given number of time periods. Further insight into the volatility and options volume relationship is provided by simulating the responses of the volatility and volume coefficients. The response is portrayed graphically, with horizon on the horizontal axis and response on the vertical axis.

5.4 Results

5.4.1 Summary Statistics

Summary statistics of the sample data on the S&P/ASX 200 Index Options are presented in Table 5-1. The implied volatility of the S&P/ASX 200 Index, a proxy for the expected future price volatility, is very unstable, varying from 1.2% to 29.17%. The TARCH volatility is also unstable and varying from 2.44% to 37.41%, but has a lower mean and standard deviation.

Table 5-1 Summary Statistics for the S&P/ASX 200 Index Options Data

This table provides summary statistics for the daily closing prices of call options on the S&P/ASX 200 Index for the period from March 1, 2001, to December 31, 2008.

Variable	Mean	Standard deviation	Minimum	Maximum
Option price (\$)	73.36	158.80	1.50	3299.00
TARCH volatility %	11.85	2.44	2.44	37.41
Implied volatility %	9.10	3.27	1.20	29.17
Exercise Price	3565.62	529.91	1.00	5100.00
Spot index value	3518.72	497.98	497.98	4773.00
Volume (Option contracts)	78.00	220.91	3.00	12870

5.4.2 Stationarity Testing

Formal testing for stationarity can be performed with the Augmented Dickey-Fuller (ADF) Dickey and Fuller (1979, 1981) unit root test and the Phillips-Perron (Perron, 1988; Phillips and Perron 1988) nonparametric tests. I run the ADF test with a linear trend on level up to six lags in order to control for serial correlation. The Akaike Information Criterion (AIC) is used to determine the optimal number of lags for both the tests. I also run the PP test diagnostic corrected by Newey-West autocorrelation consistent variance estimator. For both tests I employ MacKinnon (1996) critical values

for rejection of the unit root null hypothesis. I further test for statistically significant residual autoregressive effects on the basis of the Ljung-Box Q statistic. Table 5-2 presents the ADF results and Table 5-3 presents the PP results.

Results indicate the series are stationary at levels, as the MacKinnon one-sided p -values are significant at the 1% level. These results suggest all the series are integrated in order one (I (1)). In all cases the results of the ADF and PP tests reinforce each other and the series are modelled without differencing. My series need to be stationary to circumvent the problem of spurious regressions.

Table 5-2 Augmented Dickey-Fuller Unit Root Tests for the S&P/ASX 200 Index Options Volume and Volatility Series²⁸

This table shows the results of the Augmented Dickey-Fuller (ADF) unit root test for the trading volume, options market activity, TARARCH volatility, and implied volatility series of the S&P/ASX 200 Index Options. The Augmented Dickey-Fuller (ADF) test involves incorporating lagged values of the dependent variable into the following equation $\Delta Y_t = \alpha_0 + \beta Y_{t-1} + \gamma T + \delta_1 \Delta Y_{t-1} + \dots + \delta_n \Delta Y_{t-n} + u_t$, with the number of lags being determined by the residuals free from autocorrelation. This could be tested for in the standard way such as by Lagrange Multiplier (LM) test. In practice, many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here I am going to use the AIC and SIC to test the optimal lag number.

Series	t-Statistic	p-Value ^a	AIC	SIC
Volume	-19.3269	0.0000**	13.5376	13.5290
Options market activity	-23.5606	0.0000**	0.4303	0.4382
TARARCH volatility	-8.8722	0.0000**	-6.6599	-6.6367
Implied volatility	-4.8022	0.0000**	-5.5256	-5.5104

^a MacKinnon (1996) one-sided p -values.

** Significant at the 1% level.

²⁸ The lag value is determined by the Schwarz Criterion (SIC) (Schwarz, 1978) and the Akaike Information Criterion (AIC) (Akaike, 1973).

Table 5-3 Phillips-Perron Unit Root Tests for the S&P/ASX 200 Index Options Volume and Volatility Series²⁹

This table shows the results of the Phillips-Perron (PP) unit root test for the trading volume, options market activity, TARCH volatility, and implied volatility series of the S&P/ASX 200 index Options. The Phillips-Perron (PP) test involves incorporating lagged values of the dependent variable into the following equation: $\Delta Y_t = \alpha + \rho Y_{t-1} + u_t$, with the number of lags being determined by the residuals free from autocorrelation. In practice, many researchers use a model selection procedure (such as SIC, AIC) or, alternatively, assume a fixed number of lags. Here I am going to use the AIC and SIC to test the optimal lag number.

Series	t-Statistic	p-Value ^a	AIC	SIC
Volume	-110.4961	0.0000**	13.6769	13.6784
Options market activity	-115.8888	0.0000**	0.4563	0.4578
TARCH volatility	-18.9353	0.0000**	-6.6388	-6.6374
Implied volatility	-49.7695	0.0000**	-5.3412	-5.3397

^a MacKinnon (1996) one-sided p-values.

** Significant at the 1% level.

5.4.3 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series

My regression results of the relationship between call options volume and future price volatility and the relationship between future price volatility and call options volume from the three-stage least squares estimation are presented in Table 5.4. The Wald F test statistic for the causality from implied volatility to options volume is 7.61 and is statistically significant at the 1% level ($p=0.0000$). The Wald F test statistic for the causality from TARCH volatility to options volume is 3.80 and is statistically significant at the 1% level ($p=0.0009$). The Wald F test statistic for the causality from options volume to implied volatility is 2.70 and is statistically significant at the 5% level

²⁹The lag value is determined by the Schwarz Criterion (SIC) (Schwarz, 1978) and the Akaike Information Criterion (AIC) (Akaike, 1973).

($p=0.0129$), but the Wald F test statistic for the causality from options volume to TARCH volatility is 0.79 and is statistically insignificant ($p=0.5710$).

Table 5-4 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series

This table presents results of causality between volatility and options volume in call options. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options volume on future price volatility is determined from the three-stage least squares estimation. These are:

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} V_{t-i} + e_t$$

$$V_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} V_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported. The F-statistic tests the joint hypothesis that the six lagged co-efficients of V_t (I_t) are zero when the dependent variable is I_t (V_t). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume (V_t)				Dependent variable: Volatility (I_t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	85.206250	11.87 **	62.630430	0.00 **	-	-	-	-
I_{t-1}	451.943200	3.41 **	380.737600	0.11	0.586969	58.99 **	0.945892	0.00 **
I_{t-2}	-187.309700	-1.22	-184.722300	0.58	0.094673	8.20 **	0.011967	0.39
I_{t-3}	-33.587720	-0.22	-339.506700	0.30	0.052256	4.51 **	-0.009158	0.51
I_{t-4}	-211.208000	-1.38	131.837800	0.69	0.039396	3.40 **	0.003157	0.82
I_{t-5}	-171.867900	-1.12	196.430100	0.55	0.048415	4.19 **	-0.008628	0.53
I_{t-6}	-35.073800	-0.23	47.642200	0.89	0.112649	11.32 **	-0.015838	0.11
V_t	-	-	-	-	0.000003	3.41 **	0.000001	0.11
V_{t-1}	0.004744	0.48	0.007953	0.42	0.000001	0.92	0.000000	0.30
V_{t-2}	0.017791	1.79	0.020558	0.04 *	-0.000001	-0.74	0.000000	0.51
V_{t-3}	0.393511	39.56 **	0.395088	0.00 **	-0.000003	-3.17 **	0.000000	0.57
V_{t-4}	0.023933	2.41 *	0.024492	0.01 *	-0.000002	-2.75 **	0.000001	0.21
V_{t-5}	0.013158	1.32	0.014538	0.14	-0.000001	-1.00	0.000000	0.83
V_{t-6}	-0.113048	-11.36 **	-0.110517	0.00 **	0.000000	-0.24	0.000000	0.25
F-statistic	7.61 **		3.80 **		2.70 *		0.79	
System R^2	0.14		0.14		0.77		0.87	

* Significant at the 5% level

**Significant at the 1% level

My results indicate that the contemporaneous call options volume has a significant strong positive feedback effect on the implied volatility, but the contemporaneous feedback effect of volume on the TARCH volatility is insignificant.

The contemporaneous feedback effects from the implied volatility and the TARCH

volatility to the call options volume are positive, significant and strong. The results indicate that market forces, such as speculation and arbitrage, in the S&P/ASX 200 call options market operate effectively to produce quick and strong interactions between options volume and volatility.

My results contrast with Sarwar (2005) who find contemporaneous call options volume has a significant strong negative feedback effect on both volatility measures, and the contemporaneous feedback effects from the implied volatility and the EGARCH volatility to the call options volume are negative. My results are consistent with Sarwar (2003) who finds call options volume and exchange rate volatility, either implied or IGARCH, show significant positive contemporaneous feedbacks. My results are also consistent with Kim, Kim et al., (2004) who find the contemporaneous relationship is positive for stock market volatility and option volume.

Past implied volatilities jointly have a significant negative effect on the options volume. The negative effect indicates that an increase in the expected future volatility is followed by a rise in the trading of the S&P/ASX 200 options. The lagged option volumes have significant negative influences on the implied volatility and the relationship is negative. This supports the expected hedge related uses of trading of S&P/ASX 200 options.

My results are consistent with Sarwar (2005) who finds the lagged implied volatility terms have a positive effect on call options volume. My results contrast with Sarwar (2005) who finds that lagged call volumes have positive predictive ability with respect to implied volatility. My results also contrast with Kim, Kim et al., (2004) who

find the lagged option volume has positive explanatory power over the current stock market volatility.

My results indicate bi-directional causality (or feedback) between call options volume and implied volatility or TARCH volatility. The direction of causality from implied volatility or TARCH volatility to call options volume is significant, implying lagged volatilities cause current volume to change. The causality from call options volume to implied volatility or TARCH volatility exists but is relatively weak. My results indicate that lagged volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of implied volatility and TARCH volatility values.

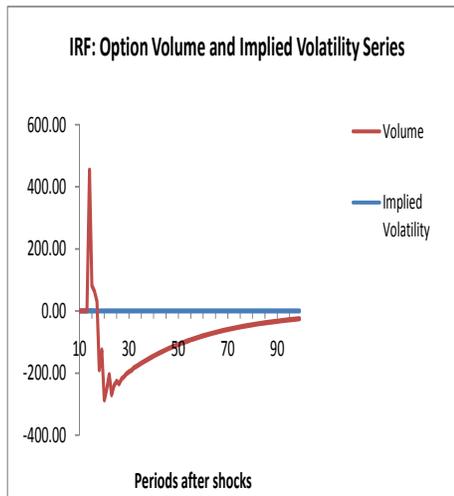
Further insight into the relationship between call options volume and volatility is provided by investigating the responses of a variable to an innovation (shock) to the other variable. Specifically, I use impulse-response functions (IRF) to indicate the magnitude and duration of the effect of a one unit shock to volatility (volume) and volume (volatility). The response is portrayed graphically, with duration on the horizontal axis and magnitude on the vertical axis.

In Figure 5-1 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on options volume. In Figure 5-1 Panel C and D presents the results from the IRF of a one unit shock to options volume to trace the effects on both volatility measures.

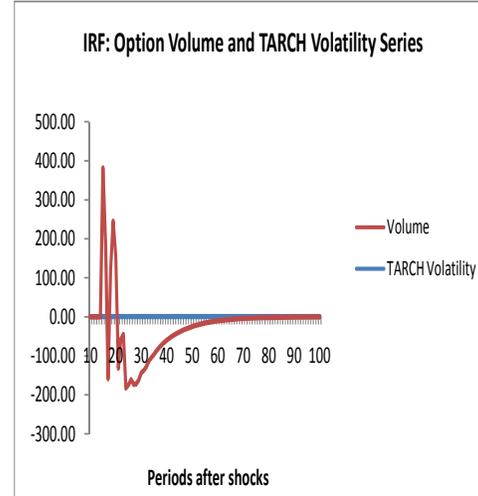
Figure 5-1 Impulse-Response Function of the S&P/ASX 200 Options Volume and Implied Volatility/TARCH Volatility Series

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options market volume indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options market volume responds strongly.

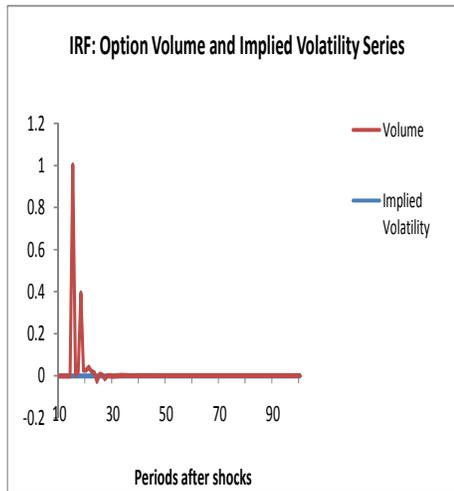
Panel A:
A shock of one unit to implied volatility only



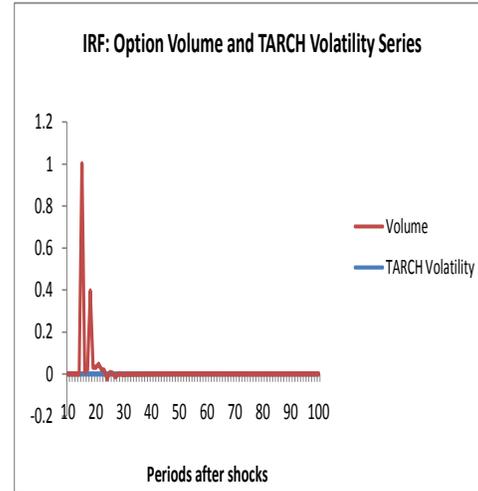
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to volume only.



Panel D:
A shock of one unit to volume only



In Panel A volume first overreacts strongly positively and then negatively to shocks but implied volatility is not affected significantly. The magnitude of the reaction of volume in Panel B for the TARCH volatility is similar to the implied volatility but the reaction is smaller in magnitude. The overreaction of volume to implied volatility and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude. The evidence of the IRF is consistent with my results in Table 5-4.

5.4.4 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series

The results of the relationship between options market activity (OMA) and future price volatility and the relationship between future price volatility and OMA from the three-stage least squares estimation are presented in Table 5-5. The Wald F test statistic for the causality from implied volatility to OMA is 6.84 and is statistically significant at the 1% level ($p=0.0000$). The Wald F test statistic for the causality from TARCH volatility to OMA is 3.21 and is statistically significant at the 1% level ($p=0.0038$), but the Wald F test statistic for the causality from OMA to implied volatility and TARCH volatility are both statistically insignificant.

The results indicate that the contemporaneous call options OMA has a significant strong negative feedback effect on the implied volatility, but a significant strong positive feedback effect on the TARCH volatility. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call OMA are significant strong

Table 5-5 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series

This table presents results of causality between volatility and options market activity in call options. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCh volatility. The regression of the relationship between options market activity on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} OMA_{t-i} + e_t$$

$$OMA_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} OMA_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported. The F-statistic tests the joint hypothesis that the six lagged co-efficients of OMA (I_t) are zero when the dependent variable is I_t (OMA). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume OMA (VOMA _t)				Dependent variable: Volatility (I _t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCh Volatility	Implied Volatility	TARCh Volatility	Implied Volatility	TARCh Volatility	Implied Volatility	TARCh Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	0.095079	9.46 **	0.040033	2.42 *	-	-	-	-
I_{t-1}	-1.433246	-7.53 **	2.007561	5.73 **	0.590542	59.23 **	0.942213	93.95 **
I_{t-2}	1.328667	6.04 **	-1.451611	-3.01 **	0.095471	8.24 **	0.012522	0.91
I_{t-3}	0.450044	2.04 *	-0.477379	-0.99	0.053427	4.60 **	-0.009607	-0.70
I_{t-4}	0.418611	1.90	0.438710	0.91	0.037446	3.22 **	0.003383	0.25
I_{t-5}	-0.447532	-2.03 *	0.019915	0.04	0.048450	4.18 **	-0.009475	-0.69
I_{t-6}	0.136400	0.62	0.137355	0.29	0.111107	11.14 **	-0.014915	-1.49
VOMA _t	-	-	-	-	-0.003973	-7.53 **	0.001643	5.73 **
VOMA _{t-1}	0.070805	7.08 **	0.069491	6.94 **	0.000613	1.16	0.000194	0.68
VOMA _{t-2}	0.048614	4.85 **	0.048087	4.79 **	-0.000225	-0.43	0.000144	0.50
VOMA _{t-3}	0.042501	4.25 **	0.038735	3.87 **	0.000494	0.94	0.000285	0.99
VOMA _{t-4}	0.061967	6.19 **	0.059036	5.89 **	0.001209	2.29 *	0.000236	0.82
VOMA _{t-5}	0.053875	5.38 **	0.050758	5.06 **	0.000804	1.52	0.000463	1.61
VOMA _{t-6}	0.037659	3.77 **	0.037410	3.74 **	0.000850	1.62	-0.000154	-0.54
F-statistic	6.84 **		3.21 **		1.56		1.77	
System R ²	0.03		0.03		0.87		0.87	

*Significant at the 5% level

**Significant at the 1% level

and positive. The results indicate that hedging, arbitrage and other market forces in the S&P/ASX options market operate effectively to produce quick and strong interactions between OMA and price volatility.

My results contrast with Kim, Kim et al., (2004) who find the contemporaneous relationship is negative for stock market volatility and open interest (OMA). My results

also contrast with Kyriacou and Sarno (1999) who find the contemporaneous relationship between spot market GARCH volatility and open interest (OMA) is negative.

My results indicate causality for implied volatility or TARCH volatility are significant, implying lagged volatilities cause current OMA to change. The causality from call OMA to implied volatility or TARCH volatility is weak. My results indicate that lagged implied volatility values are good predictors of OMA levels. The lagged implied volatility changes jointly and the individual implied volatilities at lags 1, 2, 3 and 5 have a significant effect on OMA. The influence suggests the lead of the future volatility over the call trading volume and is consistent with the hedging-based uses of the call options.

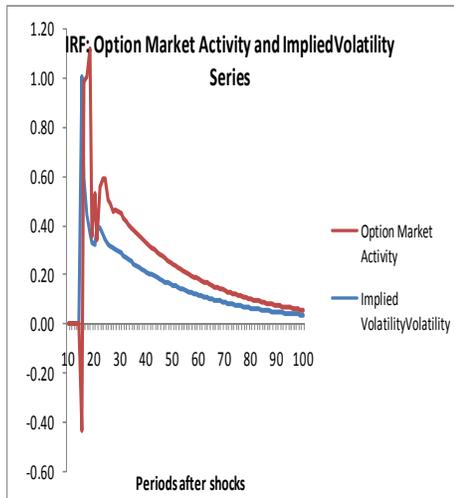
My results are consistent with Kim, Kim et al., (2004) who find the lagged open interest variables have significant negative influences on the current stock market volatility. My results are also consistent with their results that the lagged open interest variables terms have a positive effect on options volatility. My results contrast with Kyriacou and Sarno (1999) who find the lagged open interest variables have significant positive influences on the spot market volatility.

In Figure 5-2 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA. In Figure 5-2 Panel C and D presents the results from the IRF of a one unit shock to OMA to trace the effects on both volatility measures. In Panel A volume first overreacts negatively and then positively to shocks. The shock also effects implied volatility but not with the same magnitude. The magnitude of the reaction of volume in Panel B for the TARCH volatility is similar to the implied volatility but the reaction is significantly larger in

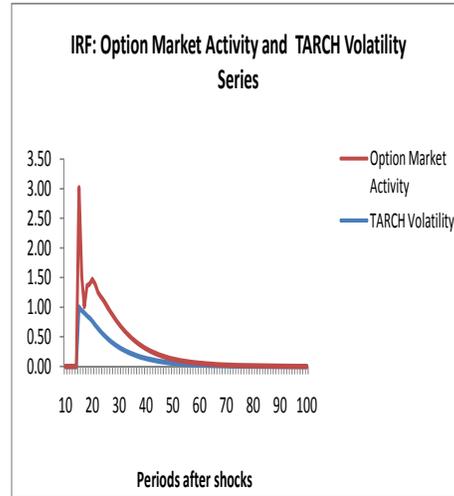
Figure 5-2 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Implied Volatility/TARCH Volatility Series

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options Market Activity indicates that the S&P/ASX 200 Options market volatility responds. A shock to the S&P/ASX 200 Options Market Activity indicates the S&P/ASX 200 Options market volume responds strongly.

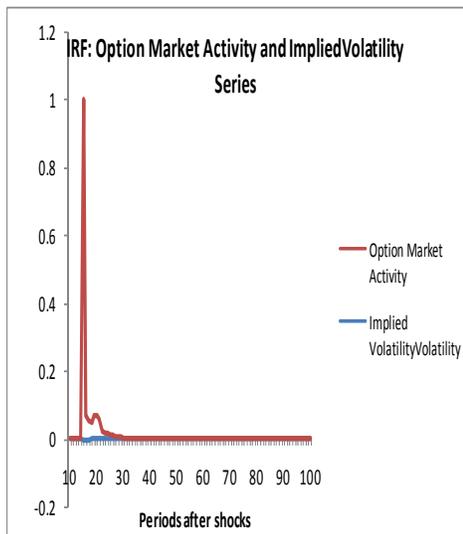
Panel A:
A shock of one unit to implied volatility only



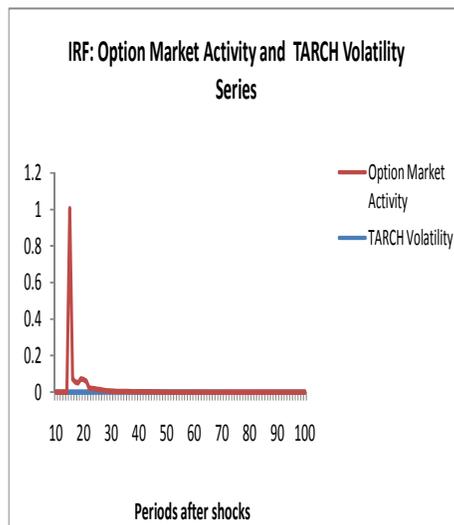
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to OMA only.



Panel D:
A shock of one unit to OMA only



magnitude. The overreaction of volume and implied volatility and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude and short in duration. The evidence of the IRF is consistent with my results in Table 5-5.

5.4.5 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Near-the-Money Options.

Since the implied price volatility appears to change with the call options moneyness, the relationship between call options volume and volatility may also change with the options moneyness.

My regression results of the relationship between options call volume (near-the-money) and future price volatility and the relationship between future price volatility and options call volume (near-the-money) from the three-stage least squares estimation are presented in Table 5.6. The Wald F test statistic for the causality from implied volatility to options volume (near-the-money) is 3.32 and is statistically significant at the 1% level ($p=0.0029$). The Wald F test statistic for the causality from TARCH volatility to options volume (near-the-money) is 0.00 but is statistically insignificant. The Wald F test statistic for the causality from implied volatility to options volume (near-the-money) is 1.70 but is statistically insignificant, but the Wald F test statistic for the causality from TARCH volatility to options volume (near-the-money) is 11.29 and is statistically significant at the 1% level ($p=0.0000$).

Table 5-6 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Near-the-Money Options

This table presents results of causality between volatility and options volume in call options near-the-money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options volume on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} V_{t-i} + e_t$$

$$V_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} V_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of V_t (I_t) are zero when the dependent variable is I_t (V_t). These are: $H_0 = \alpha_{1i} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable:Volume (V_t)				Dependent variable:Volatility (I_t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	122.270100	11.67 **	92.722220	4.86 **	-	-	-	-
I_{t-1}	726.203800	4.61 **	623.063100	2.34 **	0.177418	13.96 **	0.899820	70.23 **
I_{t-2}	-310.293100	-1.96	-647.228600	-1.81	0.257925	20.08 **	-0.034579	-2.01 *
I_{t-3}	-227.405800	-1.39	-10.597690	-0.03	0.136719	10.37 **	-0.016333	-0.95
I_{t-4}	-241.381700	-1.48	119.657200	0.33	0.117484	8.91 **	-0.009831	-0.57
I_{t-5}	-56.978530	-0.35	11.088870	0.03	0.102018	7.94 **	-0.014892	-0.86
I_{t-6}	-187.346200	-1.18	97.520130	0.27	0.133187	10.49 **	0.045889	3.58 **
V_t	-	-	-	-	0.000005	4.61 **	0.000001	2.34 *
V_{t-1}	0.016085	1.25	0.018767	1.46	-0.000003	-2.63 **	-0.000001	-0.87
V_{t-2}	0.019626	1.53	0.025076	1.96	0.000000	-0.17	0.000000	-0.76
V_{t-3}	0.029756	2.32 *	0.034217	2.67 **	-0.000001	-0.86	-0.000001	-1.12
V_{t-4}	0.049612	3.87 **	0.055202	4.31 **	-0.000001	-0.58	-0.000001	-1.37
V_{t-5}	0.018656	1.45	0.022082	1.72	-0.000001	-0.62	0.000001	1.12
V_{t-6}	0.034010	2.65 **	0.038078	2.97 **	-0.000002	-1.56	0.000000	-0.68
F-statistic	3.32 **		0.00		1.70		11.29 **	
System R ²	0.01		0.01		0.65		0.75	

*Significant at the 5% level

**Significant at the 1% level

The results indicate that the contemporaneous call options volume (near-the-money) has a significant strong positive feedback effect on both the implied volatility and TARCH volatility. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call options volume (near-the-money) are significant strong and positive. The results indicate that arbitrage and other market forces

in the S&P/ASX options market operate effectively to produce quick and strong interactions between OMA and price volatility.

My results indicate bi-directional causality (or feedback) between call options volume (near-the-money) and implied volatility. The direction of causality from implied volatility to call options volume (near-the-money) is significant, implying lagged volatilities cause current volume to change. The causality from call options volume (near-the-money) to TARCH volatility but is weak. My results indicate that lagged implied volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of TARCH volatility values.

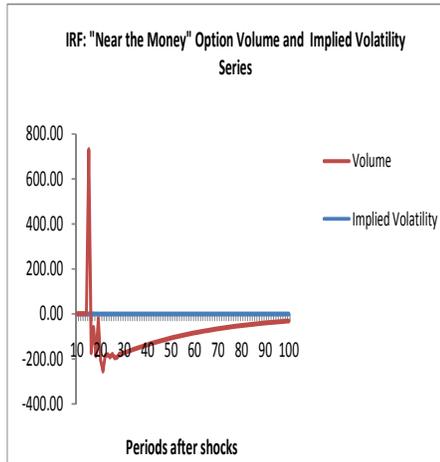
In Figure 5-3 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on options volume (near-the-money). In Figure 5.3 Panel C and D presents the results from the IRF of a one unit shock to options volume (near-the-money) to trace the effects on both volatility measures.

In Panel A volume first overreacts strongly positively and then negatively to shocks but implied volatility is not affected significantly. The magnitude of the reaction of volume in Panel B for the TARCH volatility is similar to the implied volatility but the reaction is smaller in magnitude. The overreaction of volume to implied volatility and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude and short in duration. The evidence of the IRF is consistent with my results in Table 5.6

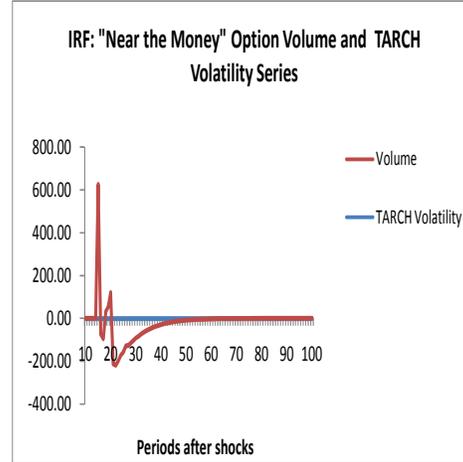
Figure 5-3 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Near-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options market volume indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options market volume responds strongly.

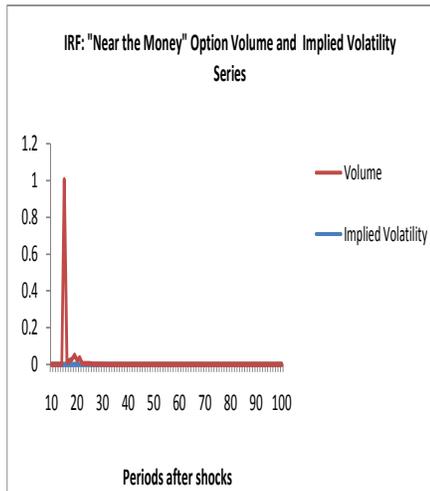
Panel A:
A shock of one unit to implied volatility only



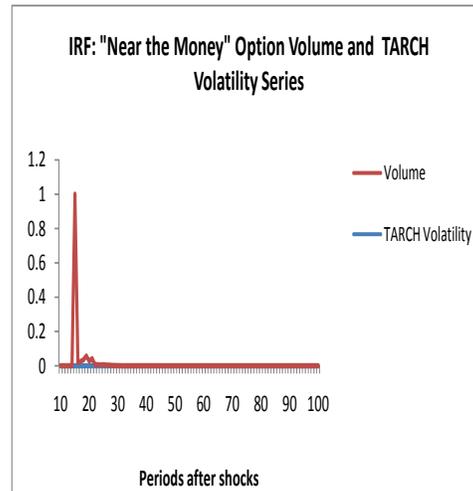
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to volume only.



Panel D:
A shock of one unit to volume only



5.4.6 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Near-the-Money Options

The regression results of the relationship between OMA of call options (near-the-money) and future price volatility and the relationship between future price volatility and OMA of call options (near-the-money) from the three-stage least squares estimation is presented in Table 5.7. The Wald F test statistic for the causality from implied volatility to OMA of call options (near-the money) is 6.85 and is statistically significant at the 1% level ($p=0.0000$). The Wald F test statistic for the causality from TARCH volatility to OMA of call options (near-the-money) is 2.04 and is statistically significant at the 5% level ($p=0.0500$). The Wald F test statistic for the causality between OMA of call options (near-the-money) and implied volatility is 1.88 and the causality between OMA of call options (near-the-money) to TARCH volatility is 0.97 but are both statistically insignificant.

The results indicate that the contemporaneous call OMA (near-the-money) has a significant strong negative feedback effect on the implied volatility, but significant strong positive feedback effect on TARCH volatility. The contemporaneous feedback effect from implied volatility to the call OMA (near-the-money) has a significant strong positive effect, but the contemporaneous feedback effect from the TARCH volatility is insignificant to the OMA (near-the-money). The results indicate that arbitrage and other market forces in the S&P/ASX options market operate effectively to produce quick and strong interactions between OMA and price volatility. The contemporaneous positive feedback from TARCH volatility to the call OMA is strong, but the lagged call OMA jointly have no predictive power with respect to the implied volatility.

Table 5-7 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Near-the-Money Options

This table presents results of causality between volatility and options market activity in call options near-the-money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options market activity on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} OMA_{t-i} + e_t$$

$$OMA_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} OMA_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of OMA (I_t) are zero when the dependent variable is I_t (OMA). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume OMA (VOMA _t)				Dependent variable: Volatility (I)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	0.093755	7.07 **	-0.002891	-0.11	-	-	-	-
I_{t-1}	-0.893169	-4.20 **	3.258049	9.10 **	0.174612	13.72 **	0.898201	70.05 **
I_{t-2}	-0.197156	-0.92	-2.768620	-5.75 **	0.262298	20.39 **	-0.034867	-2.02 *
I_{t-3}	1.123146	5.10 **	-0.026299	-0.05	0.138131	10.45 **	-0.018904	-1.10
I_{t-4}	0.912384	4.13 **	0.795052	1.65	0.116826	8.84 **	-0.006891	-0.40
I_{t-5}	-0.165560	-0.75	-0.665765	-1.38	0.102900	8.00 **	-0.017033	-0.99
I_{t-6}	-0.040464	-0.19	0.605497	1.25	0.131454	10.32 **	0.044909	3.50 **
VOMA _t					-0.003248	-4.20 **	0.004161	9.10 **
VOMA _{t-1}	0.066144	5.16 **	0.066752	5.21 **	0.000173	0.22	-0.000124	-0.27
VOMA _{t-2}	0.078255	6.10 **	0.071863	5.59 **	0.000743	0.96	0.000574	1.25
VOMA _{t-3}	0.041581	3.23 **	0.036658	2.85 **	-0.000880	-1.13	0.000203	0.44
VOMA _{t-4}	0.048208	3.75 **	0.047167	3.67 **	0.000659	0.85	-0.000193	-0.42
VOMA _{t-5}	0.029264	2.28 **	0.025825	2.01 *	0.002384	3.09 **	-0.000059	-0.13
VOMA _{t-6}	0.046134	3.61 **	0.044782	3.50 **	-0.000197	-0.26	0.000040	0.09
F-statistic	6.85 **		2.04 *		1.88		0.97	
System R ²	0.03		0.03		0.65		0.75	

*Significant at the 5% level

**Significant at the 1% level

The results indicate that hedging, arbitrage and other market forces operate effectively to produce quick and strong interactions between OMA and implied volatility.

My results indicate the direction of causality from implied volatility or TARCH volatility to call OMA (near-the-money) is significant, implying lagged volatilities cause current call OMA (near-the-money) to change. My results indicate that lagged volatility

values are good predictors of OMA levels, but lagged OMA levels are weak predictors of implied volatility and TARCH volatility values.

In Figure 5-4 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (near-the-money). In Figure 5.4 Panel C and D presents the results from the IRF of a one unit shock to OMA (near-the-money) to trace the effects on both volatility measures.

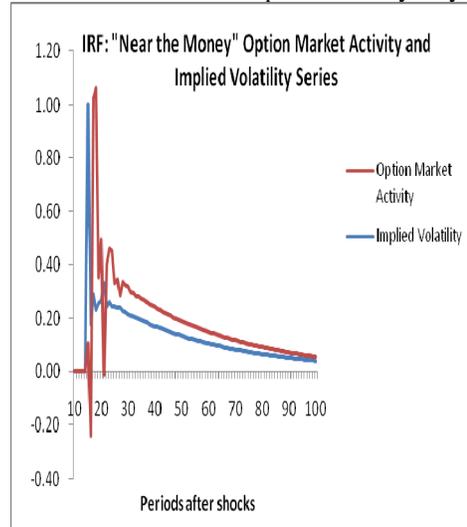
In Panel A OMA first overreacts negatively and then positively to shocks. The shock also effects implied volatility with the same magnitude. The magnitude of the reaction of OMA in Panel B to the TARCH volatility is similar to the implied volatility but the reaction is significantly larger in magnitude. The shock also effects TARCH volatility but the reaction less in magnitude. The overreaction of OMA and implied volatility and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to OMA, but small in magnitude. The evidence of the IRF is consistent with my results in Table 5-7.

Figure 5-4 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Near-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options Market Activity indicates that the S&P/ASX 200 Options market volatility does respond. A shock to the S&P/ASX 200 Options Market Activity indicates the S&P/ASX 200 Options market volume responds strongly.

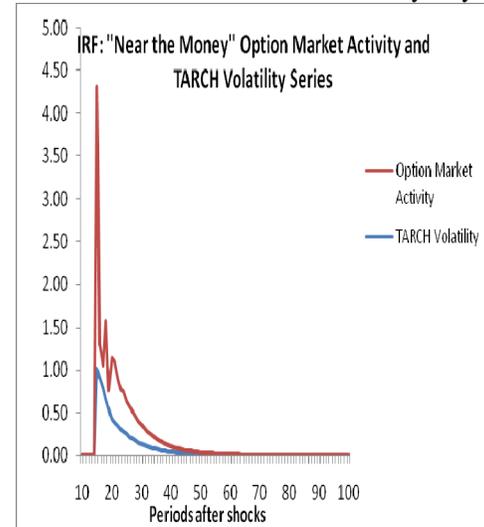
Panel A:

A shock of one unit to implied volatility only



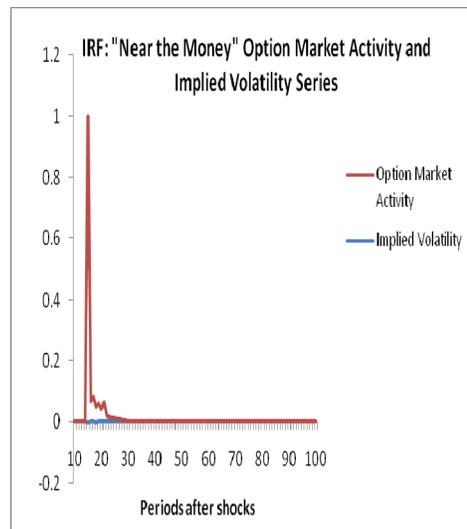
Panel B:

A shock of one unit to TARCH volatility only.



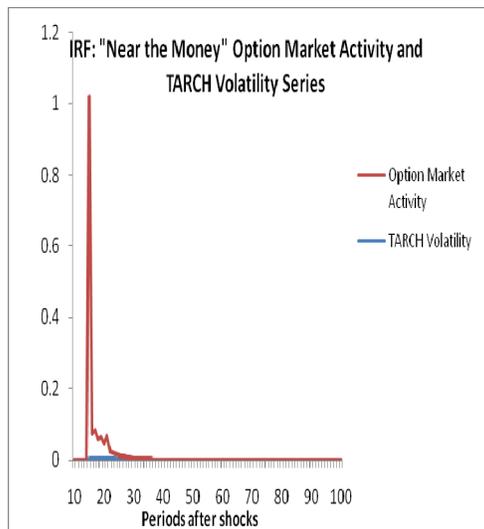
Panel C:

A shock of one unit to OMA only.



Panel D:

A shock of one unit to OMA only



5.4.7 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: In-the-Money Options

My regression results of the relationship between call options volume (in-the-money) and future price volatility and the relationship between future price volatility and call options volume (in-the-money) from the three-stage least squares estimation is presented in Table 5.8. The Wald F test statistic for the causality from implied volatility to call options volume (in-the-money) is 1.77, from TARCH volatility to call options volume (in-the-money) is 1.14 and from call options volume (in-the-money) to implied volatility is 0.33. They are all statistically insignificant, but the Wald F test statistic for the causality from call options volume (in-the-money) to TARCH volatility is 24.87 and is statistically significant at the 1% level ($p=0.0000$).

The results indicate that the contemporaneous call options volume (in-the-money) has a significant strong negative feedback effect on the implied volatility, but the contemporaneous feedback effect on the TARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call options volume (in-the-money) has a significant strong positive effect.

My results indicate causality between call options volume (near-the-money) and TARCH volatility is significant. The causality from call options volume TARCH volatility exists but is relatively weak. My results indicate that lagged volume levels are weak predictors of implied TARCH volatility values.

Table 5-8 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: In-the-Money Options

This table presents results of causality between volatility and options volume in call options in-the-money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options volume on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} V_{t-i} + e_t$$

$$V_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} V_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of V_t (I_t) are zero when the dependent variable is I_t (V_t). These are: $H_0 = \alpha_{1i} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable:Volume (V_t)				Dependent variable:Volatility (I_t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	45.973310	3.76 **	57.954190	2.30 *	-	-	-	-
I_{t-1}	-520.340800	-3.52 **	345.473400	1.71	0.414478	9.28 **	0.585189	13.05 **
I_{t-2}	207.274800	1.30	-143.781600	-0.62	0.121200	2.52 **	-0.030718	-0.59
I_{t-3}	30.299170	0.19	-204.349000	-0.88	0.073173	1.50	0.021914	0.43
I_{t-4}	354.929500	2.21 *	-100.881700	-0.44	0.021284	0.44	0.063825	1.36
I_{t-5}	75.938610	0.47	303.894100	1.45	0.132724	2.72 **	0.048269	1.06
I_{t-6}	-271.108500	-1.68	-178.278600	-0.87	0.115129	2.57 **	0.094258	2.32 *
V_t					-0.000048	-3.52 **	0.000017	1.71
V_{t-1}	0.111313	2.47 *	0.112441	2.50 *	0.000010	0.75	-0.000005	-0.49
V_{t-2}	0.005963	0.13	0.011112	0.24	0.000000	0.00	-0.000023	-2.29 *
V_{t-3}	0.035463	0.78	0.021106	0.46	0.000002	0.12	0.000003	0.25
V_{t-4}	0.073908	1.64	0.069452	1.53	-0.000011	-0.82	-0.000005	-0.48
V_{t-5}	0.004975	0.11	0.009810	0.22	-0.000008	-0.58	-0.000006	-0.62
V_{t-6}	-0.011790	-0.27	-0.002208	-0.05	-0.000001	-0.06	0.000006	0.57
F-statistic	1.77		1.14		0.33		24.87	**
System R^2	0.04		0.04		0.61		0.46	

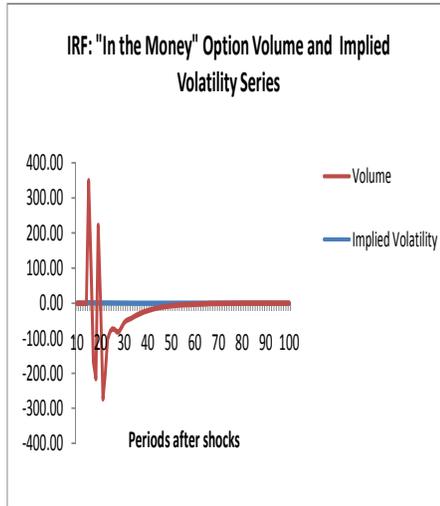
*Significant at the 5% level

**Significant at the 1% level

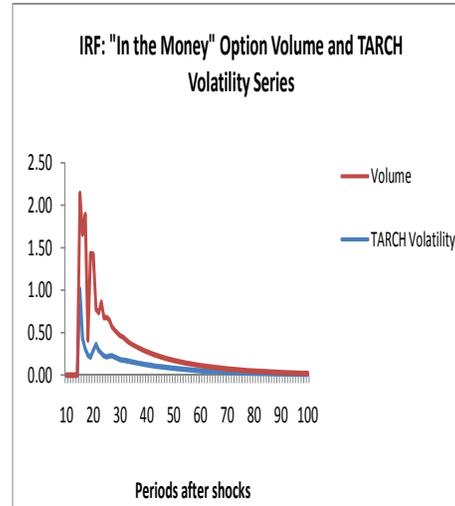
Figure 5-5 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: In-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options market volume indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options market volume responds strongly

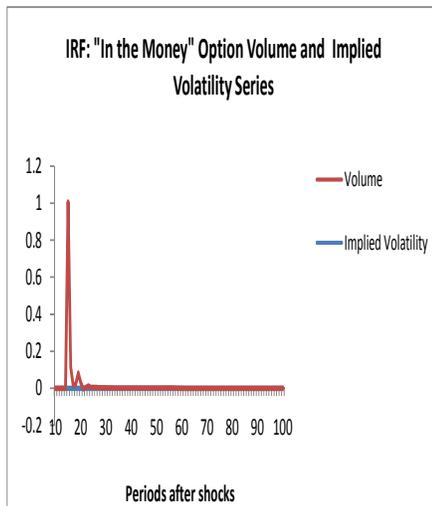
Panel A:
A shock of one unit to implied volatility only



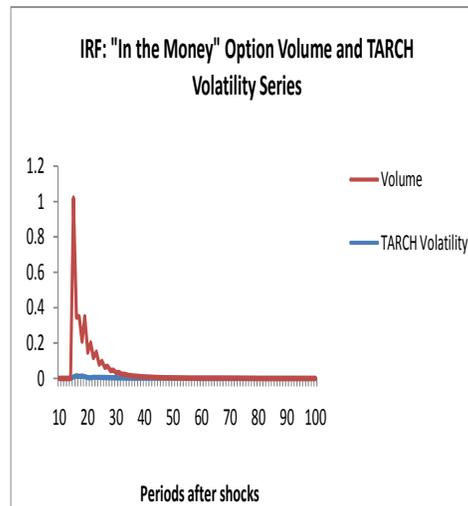
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to volume only.



Panel D:
A shock of one unit to volume only.



In Figure 5-5 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on options volume (in-the-money). In Figure 5.5 Panel C and D presents the results from the IRF of a one unit shock to options volume (in-the-money) to trace the effects on both volatility measures.

In Panel A volume first overreacts strongly positively and then negatively to shocks but implied volatility is not affected significantly. The magnitude of the reaction is significantly large. The magnitude of the reaction of volume in Panel B for the TARCH volatility effects both volume and volatility but the reaction is significantly smaller in magnitude. The overreaction of volume to implied volatility and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude. The evidence of the IRF is consistent with my results in Table 5-8.

5.4.8 Regression Results for the S&P/ASX 200 Options OMA and Volatility Series by Moneyness Classes: In-the-Money Options

My regression results of the relationship between OMA of call options (in-the-money) and future price volatility and the relationship between future price volatility and OMA of call options (in-the-money) from the three-stage least squares estimation is presented in Table 5.9. The Wald F test statistic for the causality from implied volatility to OMA of call options (in-the-money) is 1.92 and is statistically significant at the 5% level ($p=0.0453$). The Wald F test statistic for the causality from TARCH volatility to OMA of call options (in-the-money) is 4.97 and is statistically significant at the 1% level ($p=0.0001$). The Wald F test statistic for the causality from OMA of call options (in-the-

Table 5-9 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: In-the-Money Options

This table presents results of causality between volatility and options market activity in call options in-the-money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options market activity on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} OMA_{t-i} + e_t$$

$$OMA_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} OMA_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of OMA (I_t) are zero when the dependent variable is I_t (OMA). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume OMA ($VOMA_t$)				Dependent variable: Volatility (I_t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	0.010194	0.27	-0.373449	-4.01 **	-	-	-	-
I_{t-1}	1.121103	2.21 *	2.226058	3.28 **	0.401901	8.88 **	0.559968	11.87 **
I_{t-2}	0.398733	0.73	0.025949	0.03	0.108598	2.23 *	-0.025513	-0.47
I_{t-3}	0.456023	0.84	-1.148000	-1.41	0.047262	0.96	-0.044662	-0.83
I_{t-4}	-1.144121	-2.09 *	1.926553	2.42 *	0.051670	1.04	0.058130	1.20
I_{t-5}	0.625898	1.14	1.066294	1.49	0.128770	2.62 **	0.046219	0.98
I_{t-6}	0.132641	0.24	0.580179	0.83	0.141800	3.17 **	0.053361	1.25
$VOMA_t$		*			0.009072	2.21 *	0.010048	3.28 **
$VOMA_{t-1}$	0.308100	6.63 **	0.287893	6.23 **	0.008712	2.00 *	-0.003471	-1.08
$VOMA_{t-2}$	0.208647	4.29 **	0.210407	4.42 **	-0.001539	-0.35	-0.001939	-0.59
$VOMA_{t-3}$	0.008508	0.17	-0.010505	-0.22	0.002417	0.55	0.009555	2.97 **
$VOMA_{t-4}$	0.191133	3.92 **	0.160434	3.34 **	-0.002453	-0.55	-0.001687	-0.52
$VOMA_{t-5}$	-0.081944	-1.68	-0.094612	-1.99 *	-0.006666	-1.52	0.001017	0.32
$VOMA_{t-6}$	0.046190	0.99	-0.019693	-0.43	-0.003529	-0.84	0.005653	1.84
F-statistic	1.92 *		4.97 **		2.22 *		3.32 **	
System R^2	0.34		0.37		0.62		0.48	

*Significant at the 5% level

**Significant at the 1% level

money) to implied volatility is 2.22 and is statistically significant at the 5% level ($p=0.0399$), and the Wald F test statistic for the causality from OMA of call options (in-the-money) to TARCH volatility to is 3.32 and is statistically significant at the 1% level ($p=0.0033$).

My results indicate that the contemporaneous call OMA (in-the-money) has a significant positive feedback effect on the implied volatility, but significant strong positive feedback effect on the TARARCH volatility. The contemporaneous feedback effect from implied volatility to call OMA (in-the-money) is insignificant, but the contemporaneous feedback effect from the TARARCH volatility to the call OMA (in-the-money) has a significant strong negative effect.

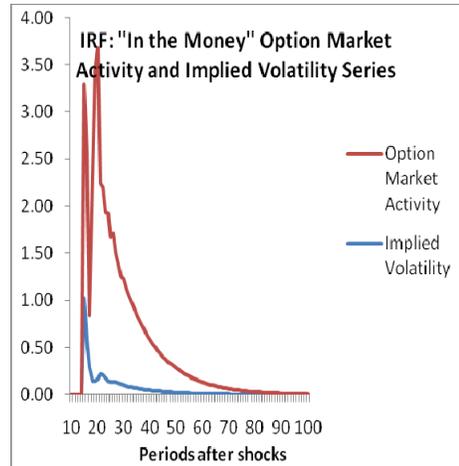
My results indicate bi-directional causality (or feedback) between call OMA (near-the-money) and implied volatility or TARARCH volatility. The direction of causality from implied volatility or TARARCH volatility to call options OMA (near-the-money) is significant, implying lagged volatilities cause current OMA (near-the-money) to change. The causality from call OMA (near-the-money) to implied volatility or TARARCH volatility is significant. My results indicate that lagged volatility values are good predictors of OMA (near-the-money) levels and lagged volume levels are good predictors of implied volatility and TARARCH volatility values. My results points to the hedging role of S&P/ASX 200 Index Options.

In Figure 5-6 Panel A and B presents the results from the IRF of a one unit shock to implied and TARARCH volatility to trace the effects on OMA (in-the-money). In Figure 5-6 Panel C and D presents the results from the IRF of a one unit shock to OMA (in-the-money) to trace the effects on both volatility measures. In Panel A OMA reacts positive to shocks and implied volatility also reacts positively but less in magnitude. In Panel B OMA first reacts strongly positive and then strongly negatively to shocks, but the magnitude of the TARARCH volatility is minimal. In Panel C and D the

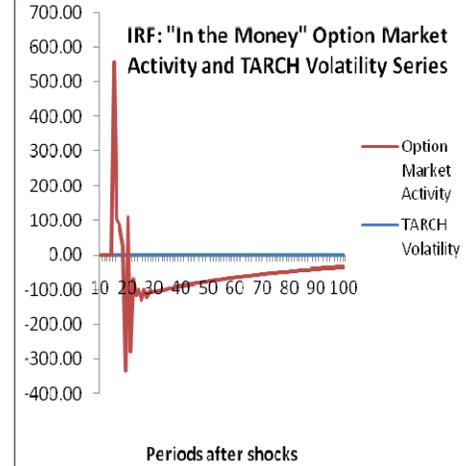
Figure 5-6 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: In-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options Market Activity indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options Market Activity responds strongly.

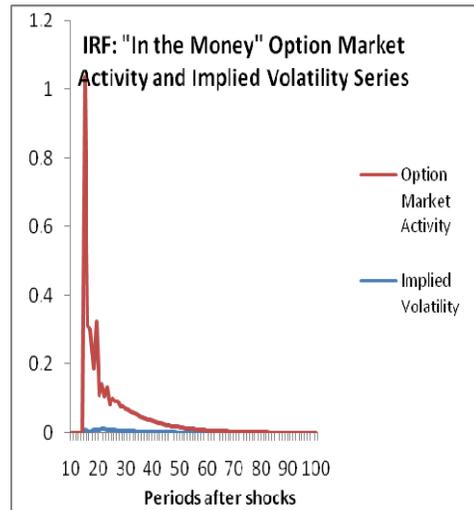
Panel A:
A shock of one unit to implied volatility only



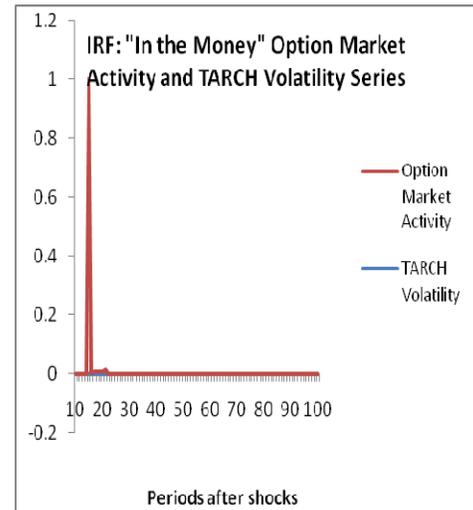
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to OMA only.



Panel D:
A shock of one unit to OMA only



magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude. The evidence of the IRF is consistent with my results in Table 5-9.

5.4.9 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Out-Of-the-Money Options

My regression results of the relationship between call options volume (out-of-the-money) and future price volatility and the relationship between future price volatility and call options volume (out-of-the-money) from the three-stage least squares estimation is presented in Table 5.10. The Wald F test statistic for the causality from implied volatility and TARCH volatility to call options volume (out-of-the-money) and between call options volume (out-of-the-money) to implied volatility and TARCH volatility are all statistically insignificant.

The results indicate that the contemporaneous call options volume (out-of-the-money) has a significant positive feedback effect on the implied volatility, but the contemporaneous feedback effect on the TARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call options volume (out-of-the-money) are significant strong and positive.

My results of the relationship of call options (out-of-the-money) have no predictive power. The lagged options call volumes jointly have no predictive power with respect to the implied volatility TARCH volatility and the lagged implied and TARCH volatility have no predictive power of the options call volume. Arbitrage and other market forces do not generate efficient daily interactions between options volume and

Table 5-10 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Out-of-the-Money Options

This table presents results of causality between volatility and options volume in call options out-of-the-money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options volume on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} V_{t-i} + e_t$$

$$V_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} V_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of V_t (I_t) are zero when the dependent variable is I_t (V_t). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume (V_t)				Dependent variable: Volatility (I_t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	90.453230	6.09 **	50.406600	2.35 *	-	-	-	-
I_{t-1}	554.571400	2.06 *	494.123800	1.68	0.291418	17.05 **	0.900016	52.40 **
I_{t-2}	-57.345510	-0.20	-424.888100	-1.07	0.233986	13.20 **	-0.136450	-5.91 **
I_{t-3}	-76.189120	-0.27	9.480815	0.02	0.092517	5.13 **	0.116946	5.04 **
I_{t-4}	-81.075640	-0.29	187.400600	0.47	0.133908	7.42 **	0.024723	1.07
I_{t-5}	-448.612800	-1.57	75.402600	0.19	0.103572	5.84 **	-0.041886	-1.82
I_{t-6}	119.950300	0.43	-72.635170	-0.18	0.100202	5.86 **	0.015547	0.91
V_t					0.000002	2.06 *	0.000002	1.68
V_{t-1}	0.001447	0.08	0.002660	0.15	0.000000	-0.08	0.000000	-0.15
V_{t-2}	0.007284	0.42	0.009438	0.55	0.000000	-0.33	-0.000001	-0.58
V_{t-3}	0.008621	0.50	0.008682	0.51	0.000000	-0.39	0.000002	2.32 *
V_{t-4}	0.008616	0.50	0.010029	0.58	0.000001	0.59	0.000000	-0.14
V_{t-5}	0.005933	0.35	0.008086	0.47	0.000001	0.69	0.000000	0.26
V_{t-6}	0.013942	0.81	0.014752	0.86	-0.000001	-0.71	0.000000	0.22
F-statistic	0.00		0.00		0.26		0.99	
System R^2	0.00		0.00		0.78		0.75	

*Significant at the 5% level

**Significant at the 1% level

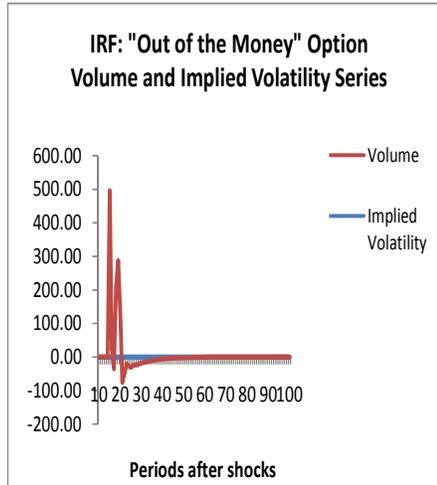
volatility for options out-of-the-money and are less likely sources of timely reliable information for active options traders. The results are statistical and economical unimportant.

In Figure 5-7 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (out-of-the-money)

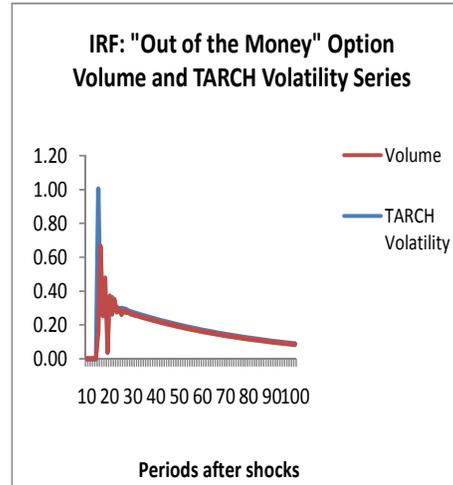
Figure 5-7 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Out-of-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options market volume indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options market volume responds strongly.

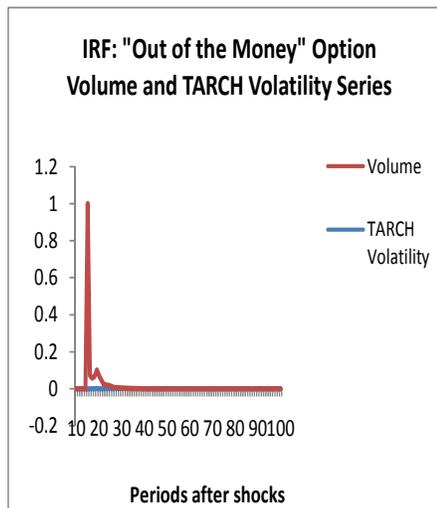
Panel A:
A shock of one unit to implied volatility only



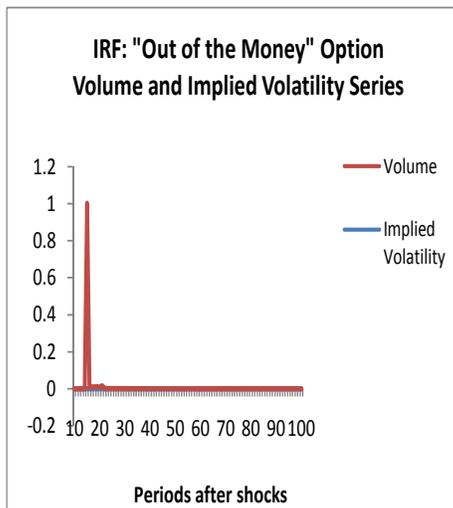
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to volume only.



Panel D:
A shock of one unit to volume only.



In Figure 5-7 Panel C and D presents the results from the IRF of a one unit shock to OMA (out-of-the-money) to trace the effects on both volatility measures.

In Panel A volume (out-of-the-money) first overreacts strongly positively in magnitude to shocks, but implied volatility is not affected significantly. A shock to both volume (out-of-the-money) and TARCH volatility in Panel B overreacts positively, but the reaction is small in magnitude. The overreaction of volume and TARCH volatility is followed by a decaying response pattern. In Panel C and D the magnitude to both implied volatility and TARCH volatility is minimal. There is a positive reaction to volume, but small in magnitude and short in duration. The evidence of the IRF is consistent with my results in Table 5-10.

5.4.10 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Out-Of-the-Money Options

My regression results of the relationship between OMA of call options (out-of-the money) and future price volatility and the relationship between future price volatility and OMA of call options (out-of-the money) from the three-stage least squares estimation is presented in Table 5.11. The Wald F test statistic for the causality from implied volatility and TARCH volatility to OMA of call options (out-of-the money) and between OMA of call options (out-of-the money) to implied volatility and TARCH volatility are all statistically insignificant.

The results indicate that the contemporaneous call OMA (out-of-the money) has a significant negative feedback effect on both the implied volatility and the TARCH volatility. The contemporaneous feedback effects from the implied volatility and the

Table 5-11 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Out-Of-the-Money Options

This table presents results of causality between volatility and options market activity in call options out-of-the money. In the regression future volatility (I_t) is alternatively estimated by implied volatility and by TARCH volatility. The regression of the relationship between options market activity on future price volatility is determined from the three-stage least squares estimation. These are :

$$I_t = \alpha + \sum_{j=1}^k \beta_{1j} I_{t-j} + \sum_{i=0}^m \alpha_{1i} OMA_{t-i} + e_t$$

$$OMA_t = \beta + \sum_{j=0}^k \beta_{2j} I_{t-j} + \sum_{i=1}^m \alpha_{2i} OMA_{t-i} + \varepsilon_t$$

The intercept is omitted for brevity. Absolute t-values for the co-efficients are reported . The F-statistic tests the joint hypothesis that the six lagged co-efficients of OMA (I_t) are zero when the dependent variable is I_t (OMA). These are: $H_0 = \alpha_{11} \dots \alpha_{1m} = 0$ and $H_0 = \beta_{21} \dots \beta_{2m} = 0$

Independent Variable	Dependent variable: Volume OMA (VOMA _t)				Dependent variable: Volatility (I _t)			
	Coefficient		Coefficient		Coefficient		Coefficient	
	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility	Implied Volatility	TARCH Volatility
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	0.132377	7.09 **	0.137472	5.07 **	-	-	-	-
I_{t-1}	-0.840870	-2.55 *	-0.708269	-1.97 *	0.294196	17.18 **	0.892899	51.02 **
I_{t-2}	0.680890	1.99 *	0.721006	1.48	0.232277	13.07 **	-0.142302	-6.07 **
I_{t-3}	0.021354	0.06	0.223180	0.45	0.091802	5.09 **	0.122234	5.19 **
I_{t-4}	0.247218	0.71	0.204148	0.41	0.135725	7.52 **	0.023131	0.98
I_{t-5}	-0.224617	-0.64	-0.054990	-0.11	0.101929	5.74 **	-0.041799	-1.78
I_{t-6}	0.109669	0.32	0.120573	0.25	0.099404	5.80 **	0.017295	0.99
VOMA _t					-0.002277	-2.55 *	-0.001622	-1.97 *
VOMA _{t-1}	0.074690	4.35 **	0.073296	4.27 **	0.000029	0.03	0.000690	0.84
VOMA _{t-2}	0.053373	3.10 **	0.052332	3.04 **	0.001108	1.24	-0.000428	-0.52
VOMA _{t-3}	0.057807	3.37 **	0.057989	3.38 **	0.000588	0.66	0.001181	1.44
VOMA _{t-4}	0.088780	5.17 **	0.088052	5.13 **	0.002218	2.47 *	0.000222	0.27
VOMA _{t-5}	0.047457	2.76 **	0.050128	2.91 **	-0.000313	-0.35	0.001431	1.74
VOMA _{t-6}	0.022895	1.33	0.021578	1.26	0.000349	0.39	-0.000520	-0.63
F-statistic	0.51		1.00		1.29		1.01	
System R ²	0.03		0.03		0.78		0.74	

*Significant at the 5% level

**Significant at the 1% level

TARCH volatility to the call options (out-of-the money) are significant strong and positive

My results of the relationship of OMA in call options (out-of-the money) have no predictive power. The lagged OMA in call options (out-of-the money) jointly have no predictive power with respect to the implied and TARCH volatility and the lagged

implied and TARCH volatility have no predictive power of the OMA in call options (out-of-the money). Arbitrage and other market forces do not generate efficient daily interactions between OMA in call options (out-of-the money) and volatility for OMA in call options (out-of-the money) and are less likely sources of timely reliable information for active options hedging activities. The results are statistical and economical unimportant. Portfolio managers and market participants involved in hedge-related trading are not attracted to OMA in call options (out-of-the money).

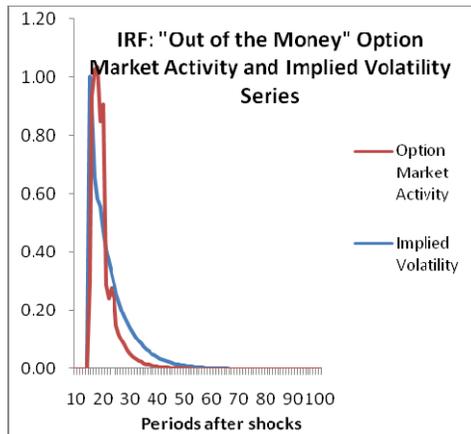
In Figure 5-8 Panel A and B presents the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (out-of-the money) In Figure 5-8 Panel C and D presents the results from the IRF of a one unit shock to OMA (out-of-the money) to trace the effects on both volatility measures.

In Panel A OMA and implied volatility reacts positively to shocks, but small in magnitude. The magnitude of the reaction of OMA in Panel B for the TARCH volatility is similar to the implied volatility but the reaction is larger in magnitude. The reaction of volume and implied volatility and TARCH volatility is followed by a decaying response pattern, but do not die out. In Panel C the magnitude to implied volatility is minimal. In Panel D the magnitude to TARCH volatility is present, but small in magnitude. There is a positive reaction to volume, but small in magnitude. The effect of both volume and TARCH volatility do not die out.

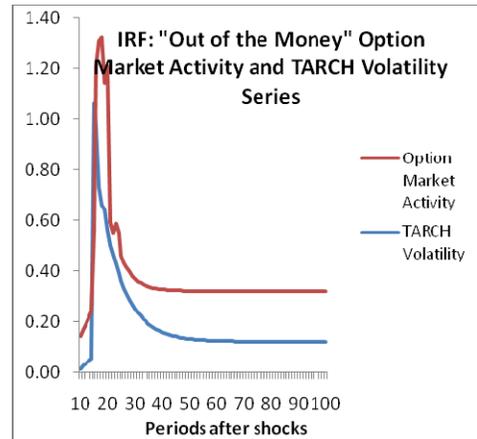
Figure 5-8 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Out-Of-the-Money Options

This figure presents the results from the impulse-response function. The impulse-response function can be used to produce the time path of the dependent variables parameters to shocks from all the explanatory variables. If the system of equations is stable, any shock should decline to zero. An unstable system would produce an explosive time path. A shock to the S&P/ASX 200 Options Market Activity indicates that the S&P/ASX 200 Options market volatility does not respond. A shock to the S&P/ASX 200 Options market volatility indicates the S&P/ASX 200 Options Market Activity responds strongly.

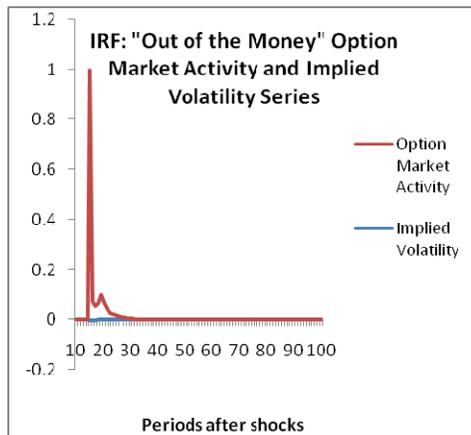
Panel A:
A shock of one unit to implied volatility only



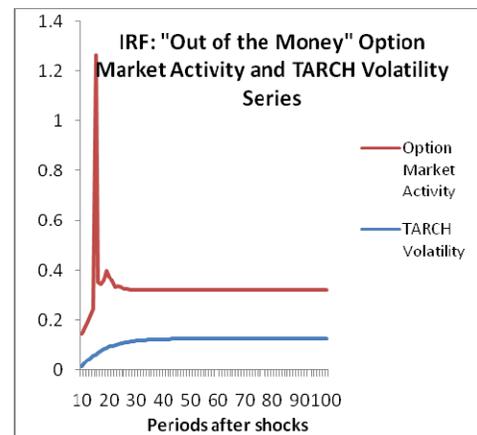
Panel B:
A shock of one unit to TARCH volatility only.



Panel C:
A shock of one unit to OMA only.



Panel D:
A shock of one unit to OMA only



5.5 Conclusion

Little evidence is available concerning the relationship between future volatility of the S&P/ASX 200 Index and trading volume of the S&P/ASX 200 Index Options in Australia. This chapter examines the dynamic relationship between future price volatility, trading volume and the future price volatility and the options market activity of the S&P/ASX 200 Index Options market. I used the implied volatility and TARARCH volatility as a proxy for the future price volatility.

The relationship between price volatility and options trading volume and the relationship between price volatility and options market activity were investigated for call options and different classes of call option's moneyness. I use variants of the causality testing approaches of Granger (1969) and Granger and Newbold (1977), using simultaneous equations model for testing causality between the future price volatility and the options volume and future price volatility and options market activity.

My results find the contemporaneous call options volume has a significant strong positive feedback effect on the implied volatility, but the contemporaneous feedback effect of volume on the TARARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARARCH volatility to the call options volume are positive, significant and strong. My results indicate that market forces, such as speculation and arbitrage, in the S&P/ASX 200 call options market operate effectively to produce quick and strong interactions between call options volume and volatility. I also find bi-directional causality (or feedback) between call options volume and implied volatility or TARARCH volatility. The direction of causality from implied volatility or TARARCH volatility to call options volume is significant, implying lagged volatilities cause

current volume to change. The causality from call options volume to implied volatility or TARCH volatility exists but is relatively weak. My results indicate that lagged volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of implied volatility and TARCH volatility values.

My results find that the contemporaneous call options market activity has a significant strong negative feedback effect on the implied volatility, but a significant strong positive feedback effect on the TARCH volatility. The contemporaneous feedback effects from the implied volatility and the TARCH volatility to the call options market activity are significant strong and positive. The results indicate that hedging, arbitrage and other market forces in the S&P/ASX options market operate effectively to produce quick and strong interactions between call options market activity and price volatility. The causality for implied volatility or TARCH volatility are significant, implying lagged volatilities cause current OMA to change. The causality from call options market activity to implied volatility or TARCH volatility is weak. My results indicate that lagged implied volatility values are good predictors of call options market activity levels. The influence suggests the lead of the future volatility over the call trading volume and is consistent with the hedging-based uses of the call options.

I find the predictive ability of options volume for price volatility is more pronounced in options trading near-the-money. The predictive ability of call options market activity for price volatility is more pronounced in call options market activity near-the-money and in the money. I find options volume and options market activity for price volatility in call options out-of-the-money have very little or no predictive ability.

Informed traders with bullish expectations wishing to gain leverage from the options market will buy calls or, with greater risk, sell puts. As market sentiment was bullish for most of the sample period examined, this could explain trading of the S&P/ASX 200 Index Options is driven by information-based trading and hedging based trading.

6 Conclusion

6.1 Major Findings and Implications

The chapter concludes this dissertation by briefly summarising the key findings. A discussion of the implications of these findings is presented followed by an examination of potential areas for further research.

Options can be used for hedging and investment purposes. Hedging mitigates both the negative and positive performance potential, but investment strategies with different motivations could be used. Investors would use long call options to participate in the appreciation of the underlying asset with downside protection if the asset price drops. Investors in call options on the S&P/ASX 200 Index permit the management of market risk. Institutional investors would use S&P/ASX 200 Index Options for hedging their portfolios against adverse market movements, but also to enhance their returns on investments.

I explored market microstructure aspects of the S&P/ASX 200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX. It provides important information about volatility, lead/lag information, price-discovery and the dynamic relationship between the informational role of options volume in predicting the price volatility of the S&P/ASX 200 Share Price Index and the S&P/ASX 200 Index Options in Australia.

The information impact on volatility was investigated in Chapter 3 as volatility is a key factor for accurately pricing derivative securities. I assessed the forecast accuracy, unbiasedness and the information content of volatility forecasts, based on the implied

volatility and conditional volatility models for the S&P/ASX 200 Index Options market in Australia. I presented estimations of volatilities quantitatively with linear and non-linear ARCH-GARCH models. Forecast accuracy, unbiasedness and the information content of volatility forecasts based on the implied volatility with ARCH-type models at different forecast horizons were assessed. Estimations from the models examined suggest that the GARCH (3, 1) and TARCH (3, 1, 1) were found to be the better-fitted models within linear and non-linear ARCH specifications. The implied volatility was derived from the daily S&P/ASX 200 options prices. Both loss functions and regressions were employed, in order to evaluate the forecast accuracy and information content of the volatility forecasts. The ability of each volatility estimator to accurately forecast true volatility was evaluated according to error statistics measures. Utilising RMSE, MAE, MAPE, Theil inequality co-efficient statistics and the so-called Modified Diebold and Mariano (DM-LS) forecast test, it was found that the TARCH (3, 1, 1) model provides the most accurate forecast across all forecasting horizons. The GARCH (3, 1) model is superior to implied volatility in terms of forecast accuracy at the 1- and 5-day horizons. To assess the information content of implied volatility, orthogonality tests of implied volatility were performed, with GARCH/TARCH volatility as an instrument in the regression. The insignificant test statistics in most cases suggest the GARCH/TARCH specification has little incremental information beyond that contained in the implied volatility. In the reverse test, when implied volatility is entered as an instrument in the GARCH/TARCH regression, orthogonality is strongly rejected in all horizons, except the 1-day horizon.

Lead/lag relations and price-discovery between stock index and stock index options have received little attention in the Australian market. Hence additional research

into lead/lag effects and price-discovery in the Australian stock index and stock index options markets warrants further research. In Chapter 4, I investigated the information content of the index and options markets in the price-discovery process. Based on the volatility results in Chapter 3, the long-run equilibrium relationship between the share price index and the implied price of the share-price-index options was investigated. Causality was determined to show which market leads the other. Information share measures were used to gauge the contribution of the share price index and index options markets to the price-discovery process.

I assessed the nature of the short- and long-run equilibrium relationships between the stock returns implied by the index options prices and the returns of index prices. My series are co-integrated, indicating that the index market and the options market value the same underlying information differently over the long run but do not wander far from each other. The direction of causality is from the index market to the options market. The index market has much higher information discovery ability and plays a more important role than the options market in determining the equilibrium prices. The average information share is 0.91 for the index market and 0.09 for the options market. The relative factor weights results are not qualitatively different. The results, contrary to other literature, indicate the index market plays the primary role in the price-discovery of Australian markets. Unambiguous evidence shows the index market leads the options market and the former contributes more to price-discovery than the latter

An understanding of lead/lag relations between stock and stock options markets can be used to infer whether one market learns from the other. In perfect markets, one market should not be able to learn from another as all information would be incorporated

into both markets simultaneously. Friction in these markets (transaction cost, taxes, and microstructure effects) causes price reactions and has implications for the types of traders attracted to one or other market and subsequently the purpose for which each market is used. Investors and speculators will use the causal relationship to predict the movement of one market to the other. Traders with bullish expectations wishing to gain leverage from the options market will buy call options or, with greater risk, sell put options. On the ASX, a change in the index market of less than 1 % can result in a change in the value of the options contract of 15 % or more. Therefore leverage does impact on traders and investors in the Australian options market.

In Chapter 5, the relationship between price volatility and options trading volume and the relationship between price volatility and options market activity were investigated for call options and different classes of call option's moneyness. I used a simultaneous equation model to capture the volume-volatility relations and investigated if contemporaneous feedbacks exist between the future price volatility and the trading volume of call options.

I found the contemporaneous call options volume have a significant strong positive feedback effect on the implied volatility, but the contemporaneous feedback effect of volume on the TARARCH volatility is insignificant. The contemporaneous feedback effects from the implied volatility and the TARARCH volatility to the call options volume are positive, significant and strong. My results indicate that market forces, such as speculation and arbitrage, in the S&P/ASX 200 call options market operate effectively to produce quick and strong interactions between call options volume and volatility. I found bi-directional causality (or feedback) between call options volume and implied

volatility or TARARCH volatility. The direction of causality from implied volatility or TARARCH volatility to call options volume is significant, implying lagged volatilities cause current volume to change. The causality from call options volume to implied volatility or TARARCH volatility exists but is relatively weak. My results indicate that lagged volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of implied volatility and TARARCH volatility values.

Since the implied price volatility appears to change with the call options moneyness, the relationship between call options volume and volatility may also change with the options moneyness. I found the predictive ability of options volume for price volatility is more pronounced in options trading near-the-money. The predictive ability of call options market activity for price volatility is more pronounced in call options market activity near-the-money and in-the-money. I found options volume and options market activity for price volatility in call options out-of-the-money have very little or no predictive ability.

In summary, this dissertation made several contributions. In Chapter 3 the contribution of this dissertation extends the literature in at least two ways. Firstly, previous studies on forecasting volatility failed to perform the so-called Modified Diebold and Mariano (DM-LS*) test in forecast evaluation and relied on visual inspections on the size of some accuracy measures. The modified version of the Diebold and Mariano (1995) test proposed by Harvey Leybourne and et al., (1999) uses the squared prediction errors to make pair-wise comparisons of different models and its statistics are adjusted for the presence of ARCH in forecast errors. This work uses the modified Diebold and Mariano test.

Secondly, previous studies have focused on relatively large and liquid markets (such as those in the US and UK). I investigated a relatively small and illiquid market, which may behave differently than larger markets. In fact, I did find the TARARCH model outperforms implied volatility in terms of forecast accuracy, indicating its better tracking of realised volatility.

The next contribution of this work is found in Chapter 4 on lead/lag relations between stock indexes and index derivatives. Empirical research into lead/lag relations between stock indexes and index derivatives has been inconclusive. Most of the research on stock and options markets was focused on US markets (NYSE, AMEX, OTC and CBOT) and these are all dealer markets with less than full automation. The ASX is a competitive order-matching market with full automation, suggesting different market structures give rise to different spreads. To my knowledge this is the first study of lead/lag relationships and price-discovery of the S&P/ASX200 Share Price Index as the underlying security of the S&P/ASX 200 Index Options traded on the ASX.

Little evidence is available concerning the relationship between future volatility of the S&P/ASX 200 Index and trading volume of the S&P/ASX 200 Index Options in Australia. To my knowledge this is the first study to examine the dynamic relationship between future price volatility, trading volume and the future price volatility and the options market activity of the S&P/ASX 200 Index Options market in Australia.

6.2 Future Areas of Research

The research contained in this dissertation highlights several areas of research that may prove fruitful. ARCH-type models examined falls in the univariate time series

family. In recent literature, multivariate models which incorporate other variables (such as trading volume and inflation rates) have been developed to forecast volatility. An empirical study of the forecast performance between implied volatility and multivariate models would be another opportunity for further study.

I found unambiguous evidence that the index market leads the options market and the former contributes more to price-discovery than the latter. I could extend this study by including futures contracts on the S&P/ASX 200 Share Price Index to determine which market dominates the price-discovery process. Informed traders with bullish expectations wishing to gain leverage from the options market will buy calls or, with greater risk, sell puts. As market sentiment was bullish for most of the sample period examined, this could explain the index market leads reported.

Figure 6-1 illustrates that market sentiment was bullish for most of the sample period of my study. Because interactions between trading volume and expected future price volatility may react differently in a market that is bearish may yield an opportunity for further study.

Figure 6-1 Key dates related to the S&P/ASX 200 Index Options (XJO)



Source: Data supplied by ASX

Legend:

Red line: Week of September 14, 2007 – run on Northern Rock, Bank of England loans it £ 24 Billion
Green line: October 8, 2007 – S&P/ASX - \$6,748.8999 (DJIA – October 9, 2007 – its highest 14,164.53)
Blue line: week of March 10, 2008 collapse of Bear Stearns March 16 sells to JP Morgan
Orange line: week of September 15, 2008 bankruptcy of Lehman Brothers

Finally, I assessed the forecast accuracy, unbiasedness and the information content of volatility forecasts, based on the implied volatility and conditional volatility models for the S&P/ASX 200 Index Options market in Australia. Volatility may react differently in a market that is bearish. This provides another opportunity for further study.

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