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

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Abstract:

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. Our 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. The 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. Our 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.

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

1.1 Introduction

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 paper we use the implied volatility 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 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).

We 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. Our 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. The 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. Our 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. We found options volume and options market activity for price volatility in call options out-of-the-money have very little or no predictive ability.

2 The Australian Index Market

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 1979 to 2000. Before April 2000, the All Ordinaries Index was considered Australia's institutional benchmark index. It was based on the top 300 shares listed on the ASX. In 1988, the Australian Share Price Index used liquidity and market capitalisation as key qualifications for picking and weighting companies that were included in the index (Carew, 2007). In April 2000, the All Ordinaries index was changed from a benchmark index to market indicator index. It now comprises the 500 largest companies in Australia by market capitalisation, representing 95% 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 were based on the market capitalisation, liquidity, and free float.[1] Previous Australian research used index data across the 20 Leaders, 50 Leaders, and All-Ordinaries when the options on the index were on an open outcry system. Screen trading was introduced on October 31, 1997.

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[1] 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 the company's price by the number of ordinary shares by an investable weight factor.

2.1 Literature Review

Information models we 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 discusses 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 found 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. Jarnecic (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 Jarnecic (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.

2.2 Data and Methodology

2.2.1 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.

We 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.

$$C_t = S_t N(d) - Ke^{-rT} N(d - \sigma\sqrt{\tau}), \tag{1.1}$$

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

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

$$\underset{s_{u\sigma}}{Min}\ Q = (\sum_{i=1}^{N} (C_{a,i} - f(S_{a,}, K_i, T_i, \sigma))^2 \tag{1.2}$$

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.[2] Poteshman (2000) and Chernov (2002) argue that implied volatilities should theoretically provide the best forecasts of the expected future volatilities because option

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

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 TARCH-based volatility of the S&P/ASX 200 Index Options as a proxy for the future price volatility is calculated using the TARCH (3,1,1) specification. Buhr, Li et al., (2008) found that the TARCH (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.

2.2.2 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 Newold (1977). Daily options market activity (OMA) is the daily closing volume of options, standardised by open interest. We 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:

$$OMA = \frac{V_t}{OI_t} \tag{1.3}$$

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."*

We 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. We 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 both the unconstrained and constrained forms:

$$F_c = \frac{(ESSR - ESSU)/n}{ESSU/(T-m-n)} \tag{1.4}$$

where T is the number of observations used in the unrestricted models, ESSU denotes the error sum of squares, 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 =

$\alpha_{1i} \ldots \alpha_{1m} = 0$ in Equation 1.5 and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$ in Equation 1.6), where the F statistic is the Wald statistic for the null hypothesis. If the null hypothesis in Equation 1.5 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:

$$I_t = \alpha + \sum_{j=1}^{k} \beta_{1j} I_{t-j} + \sum_{i=0}^{m} \alpha_{1i} V_{t-i} + e_t \qquad (1.5)$$

$$V_t = \beta + \sum_{j=0}^{k} \beta_{2j} I_{t-j} + \sum_{i=1}^{m} \alpha_{2i} V_{t-i} + \varepsilon_t \qquad (1.6)$$

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:

$$I_t = \alpha + \sum_{j=1}^{k} \beta_{1j} I_{t-j} + \sum_{i=0}^{m} \alpha_{1i} OMA_{t-i} + e_t \qquad (1.7)$$

$$OMA_t = \beta + \sum_{j=0}^{k} \beta_{2j} I_{t-j} + \sum_{i=1}^{m} \alpha_{2i} OMA_{t-i} + \varepsilon_t \qquad (1.8)$$

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.

We 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 co-efficients. The response is portrayed graphically, with horizon on the horizontal axis and response on the vertical axis.

2.3 Results

2.3.1 Summary Statistics

Summary statistics of the sample data on the S&P/ASX 200 Index Options are presented in Table 1-1. 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 2-1 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

2.3.2 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. We 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. We also run the PP test diagnostic corrected by Newey-West autocorrelation consistent variance estimator. For both tests we employ MacKinnon (1996) critical values for rejection of the unit root null hypothesis. We further test for statistically significant residual autoregressive effects on the basis of the Ljung-Box Q statistic. Table 1-2 presents the ADF results and Table 1-3 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. Our series need to be stationary to circumvent the problem of spurious regressions.

Table 2-2 Augmented Dickey-Fuller Unit Root Tests for the S&P/ASX 200 Index Options Volume and Volatility Series [3]

This table shows the results of the Augmented Dickey-Fuller (ADF) 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 Augmented Dickey-Fuller (ADF) test involves incorporating lagged values of the dependent variable into the following equation $\Delta Yt = \alpha 0+\beta Yt-1+\gamma T+\delta 1\Delta Yt-1+\ldots+\delta n\Delta Yt-n +ut$, 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 we are 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
TARCH volatility	-8.8722	0.000**	-6.6599	-6.6367
Implied volatility	-4.8022	0.000**	-5.5256	-5.5104

[a] MacKinnon (1996) one-sided p-values.
** Significant at the 1% level.

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

Table 2-3 Phillips-Perron Unit Root Tests for the S&P/ASX 200 Index Options Volume and Volatility Series[4]

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:$\Delta Yt = \alpha + pYt\text{-}1 + ut$, 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 we are 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	0.000**	-6.6388	-6.6374
Implied volatility	-49.7695	0.000**	-5.3412	-5.3397

[a] MacKinnon (1996) one-sided p-values.
** Significant at the 1% level.

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

Our 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 1.4. TheWald 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). TheWald 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). TheWald F test statistic for the causality from options volume to implied volatility is 2.70 and is statistically significant at the 5% level (*p*=0.0129), but theWald F test statistic for the causality from options volume to TARCH volatility is 0.79 and is statistically insignificant (*p*=0.5710).

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

Table 2-4 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 (It) 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: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

	Dependent variable:Volume (V_t)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	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

Our 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.

Our 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. Our results are consistant with Sarwar (2003) who finds call options volume and exchange rate volatility, either implied or IGARCH, show significant positive contemporaneous feedbacks. Our results are also consistant 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.

Our results are consistant with Sarwar (2005) who finds the lagged implied volatility terms have a positive effect on call options volume. Our results contrast with Sarwar (2005) who finds that lagged call volumes have positive predictive ability with respect to implied volatility. Our 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.

Our 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. Our 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.

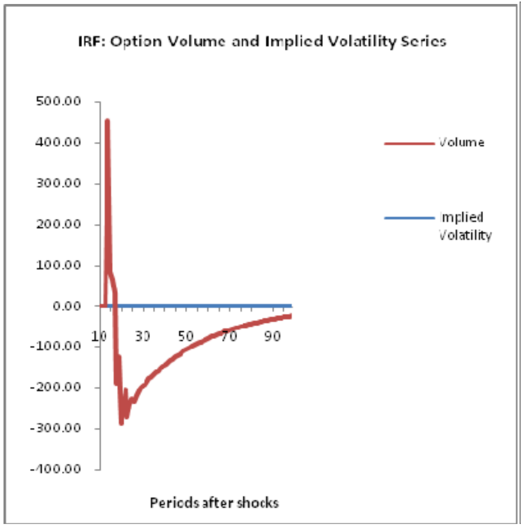
Further insight into the relationship between call options volume and volatility is provided by investigating the responses of a variable to an innovation (shock) to the other variable. Specifically, we use impulse-response functions (IRF) to indicate the magnitude and duration of the effect of a one 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 1-1 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on options volume. In Figure 1.1 Panel C and D we present the results from the IRF of a one unit shock to options volume to trace the effects on both volatility measures.

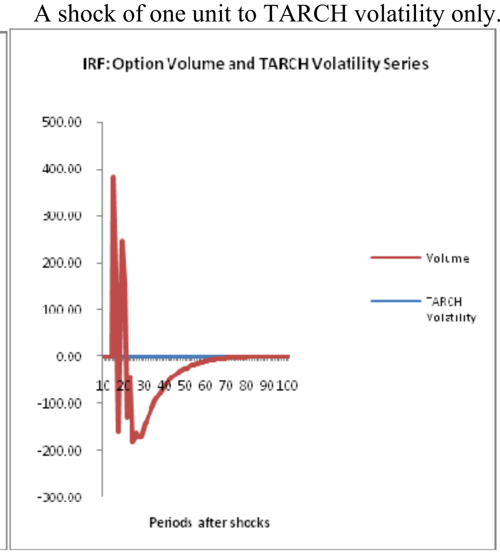
Figure 2-1 Impulse-Response Function of the S&P/ASX 200 Options Volume and Implied Volatility/TARCH Volatility Series

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.

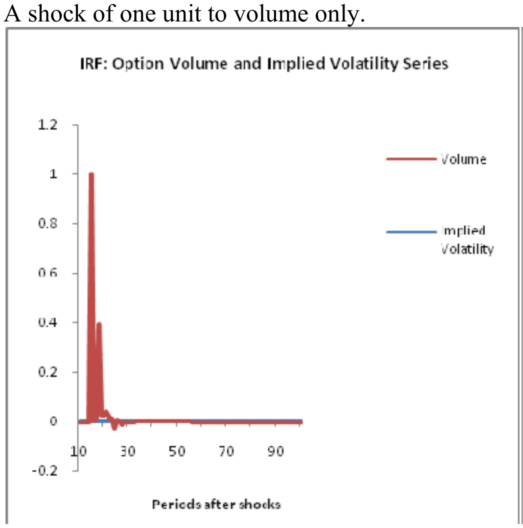
Panel A:
A shock of one unit to implied volatility only



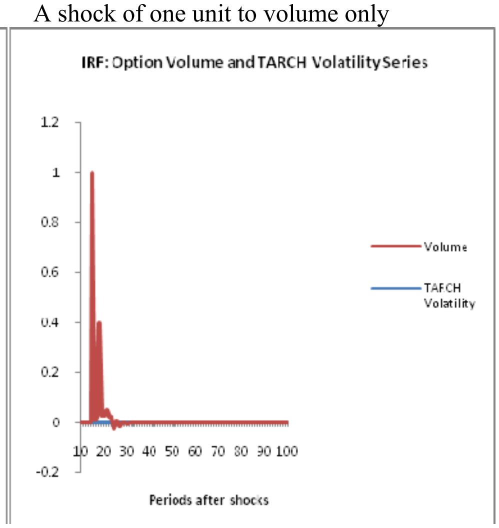
Panel B:
A shock of one unit to TARCH volatility only.



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 our results in Table 1-4.

2.3.4 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 is presented in Table 1-5. The Wald F test statistic statistic for the causality from implied volatility to OMA is 6.84 and is statistically significant at the 1% level (p=0.0000). TheWald 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 2-5 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: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

	Dependent variable:Volume OMA ($VOMA_t$)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	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.

Our results contrast with Kim, Kim et al., (2004) who find the contemporaneous relationship is negative for stock market volatility and open interest (OMA). Our results also contrast with Kyriacou and Sarno (1999) who find the contemporaneous relationship between spot market GARCH volatility and open interest (OMA) is negative.

Our 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. Our 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

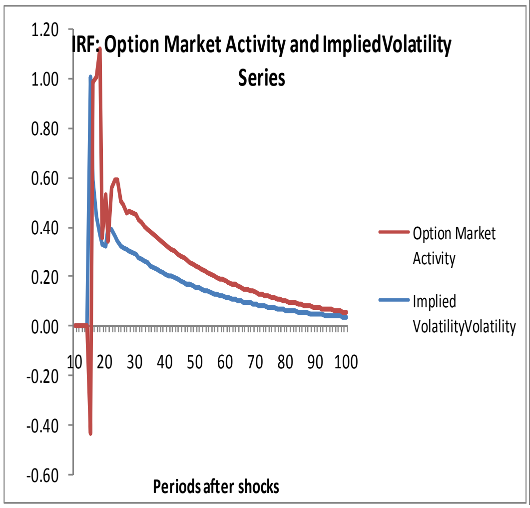
Our results are consistant with Kim, Kim et al., (2004) who find the lagged open interest variables have significant negative influences on the current stock market volatility. Our results are also consistant with their results that the lagged open interest variables terms have a positive effect on options volatility. Our 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 1-2 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA. In Figure 1-2 Panel C and D we present 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

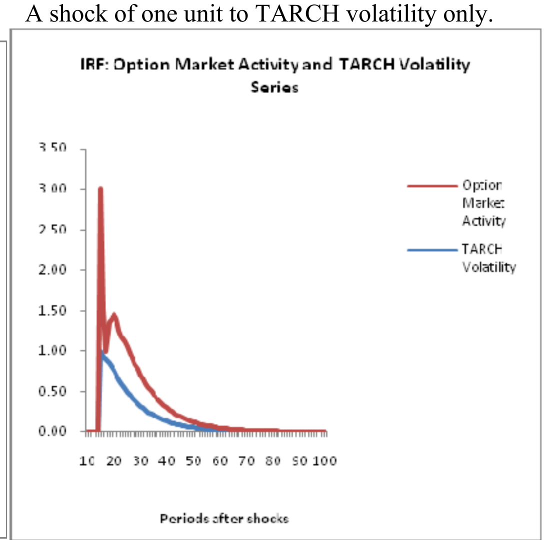
Figure 2-2 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Implied Volatility/TARCH Volatility Series

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.

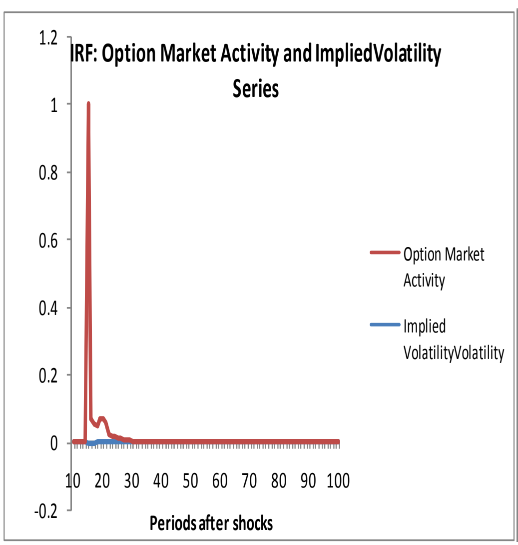
Panel A:
A shock of one unit to implied volatility only



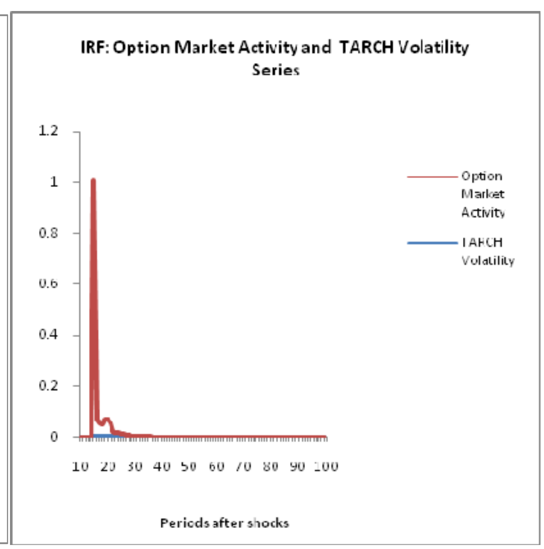
Panel B:
A shock of one unit to TARCH volatility only.



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 our results in Table 1-5.

2.3.5 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.

Our 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 is presented in Table 1.6. 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 2-6 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: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

	Dependent variable:Volume (V_t)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	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.

Our 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. Our results indicate that lagged implied volatility values are good predictors of volume levels, but lagged volume levels are weak predictors of TARCH volatility values.

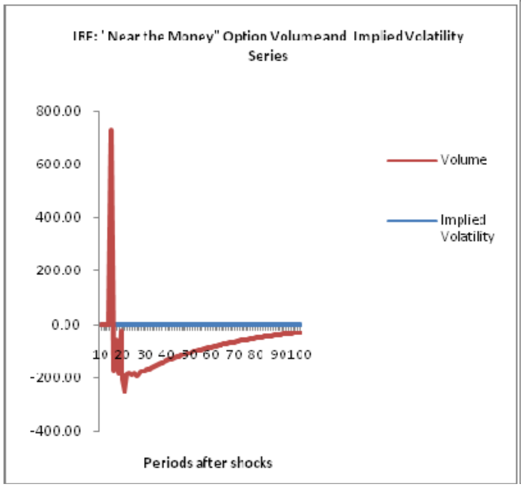
In Figure 1-3 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on options volume (near-the-money). In Figure 1.3 Panel C and D we present the results from the IRF of a one unit shock to options volume (near-the-money) to trace 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 our results in Table 1.6

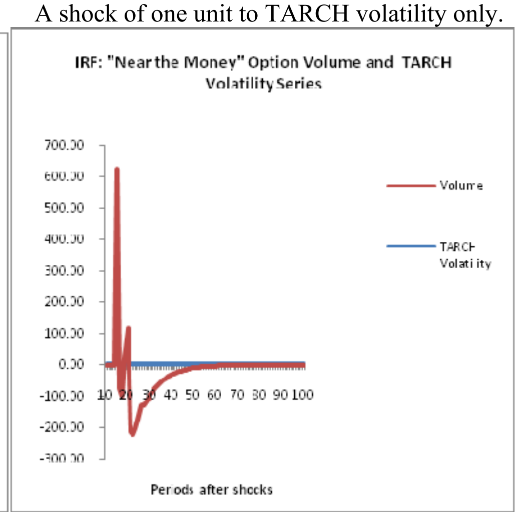
Figure 2-3 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Near-the–Money Options

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.

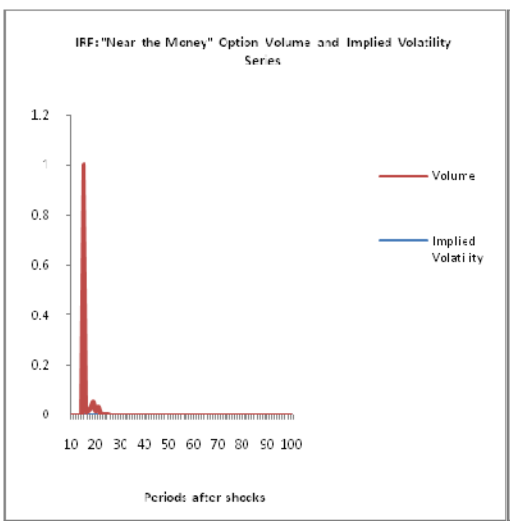
Panel A:
A shock of one unit to implied volatility only



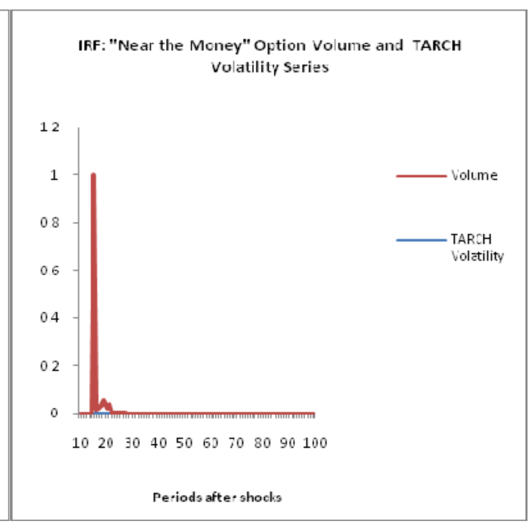
Panel B:
A shock of one unit to TARCH volatility only.



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



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



2.3.6 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 1.7. 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

Table 2-7 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 isI_t (OMA). These are: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

	Dependent variable:Volume OMA ($VOMA_t$)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	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

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

Our 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. Our 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.

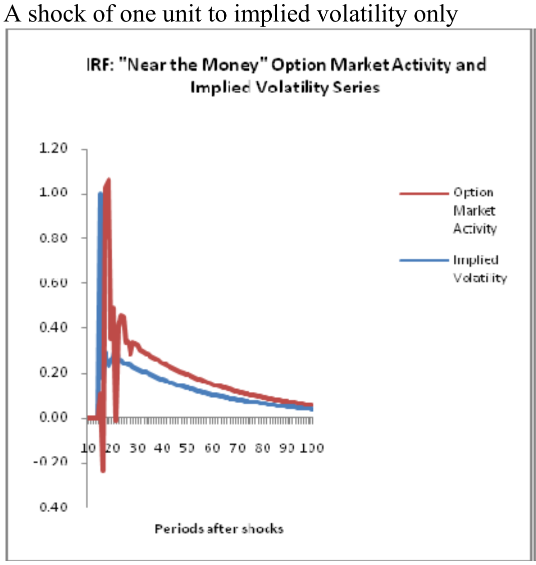
In Figure 1-4 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (near-the-money). In Figure 1.4 Panel C and D we present the results from the IRF of a one unit shock to OMA (near-the-money) to trace the effects on both volatility 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 our results in Table 1-7.

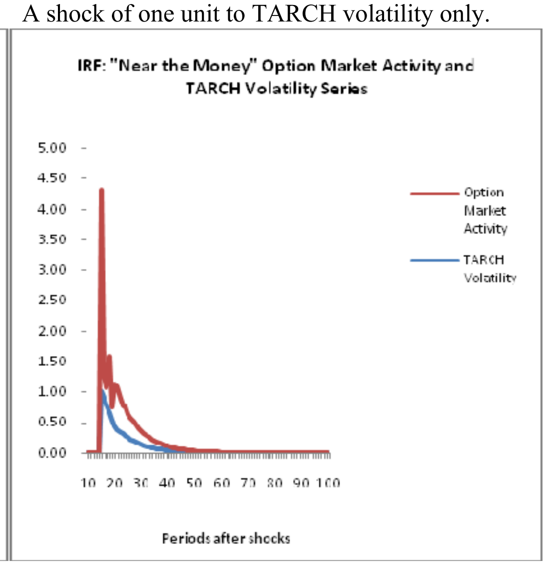
Figure 2-4 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Near-the–Money Options

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.

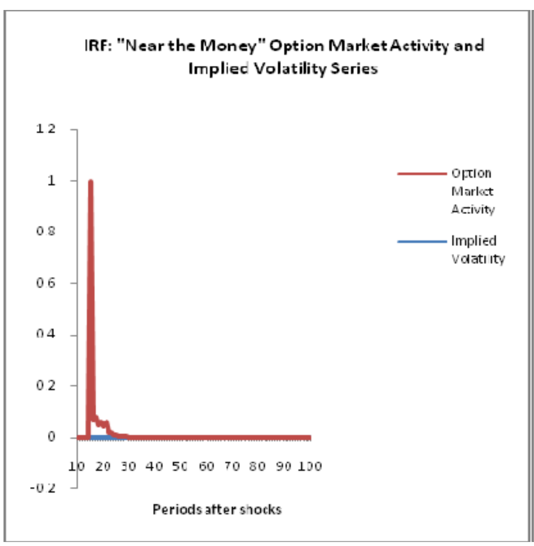
Panel A:
A shock of one unit to implied volatility only



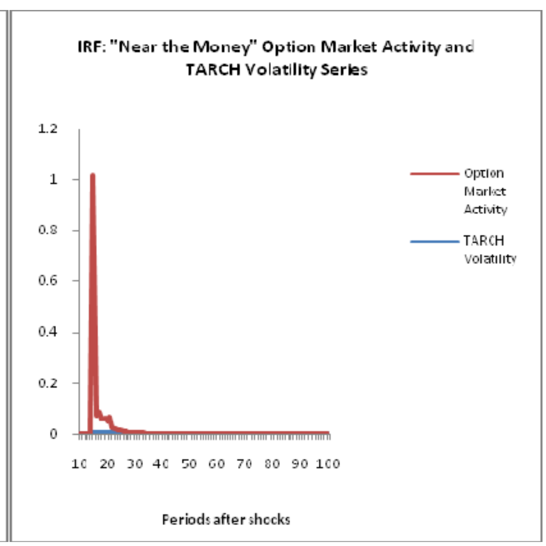
Panel B:
A shock of one unit to TARCH volatility only.



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



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



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

Our 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 1.8. 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.

Our 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. Our results indicate that lagged volume levels are weak predictors of implied TARCH volatility values.

Table 2-8 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: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

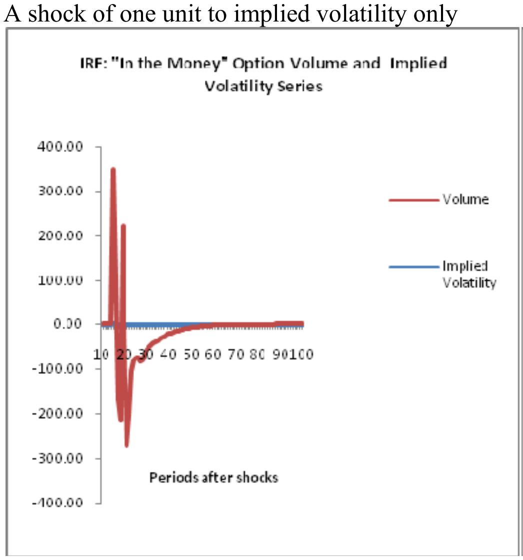
	Dependent variable:Volume (V_t)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	Implied Volatility		TARCH Volatility		Implied Volatility		TARCH Volatility	
	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat	Coefficient	t-Stat
I_t	45.973310	3.76 **	57.954190	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

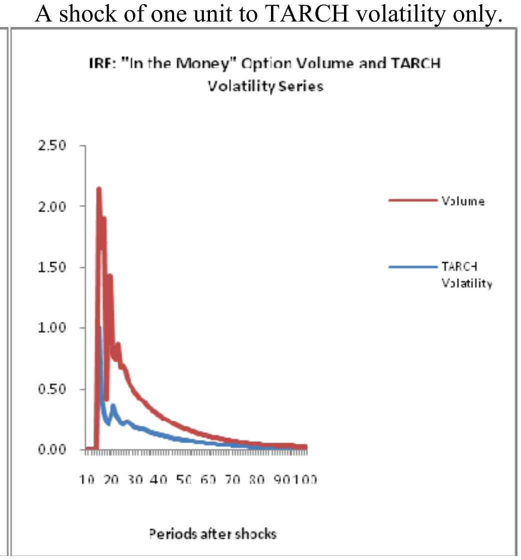
Figure 2-5 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: In-the–Money Options

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

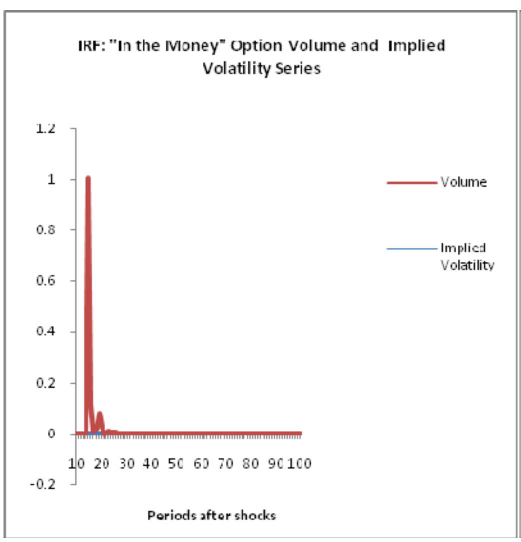
Panel A:
A shock of one unit to implied volatility only



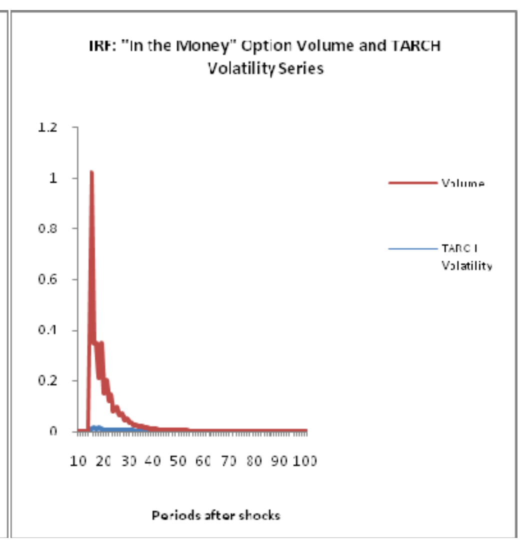
Panel B:
A shock of one unit to TARCH volatility only.



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



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



In Figure 1-5 Panel A and B we present 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 1.5 Panel C and D we present 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 our results in Table 1-8.

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

Our 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 1.9. 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 2-9 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 isI_t (OMA). These are: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

Independent Varible	Dependent variable:Volume OMA ($VOMA_t$) Coefficient: Implied Volatility Coefficient	t-Stat	TARCH Volatility Coefficient	t-Stat	Dependent variable:Volatility (I_t) Coefficient: Implied Volatility Coefficient	t-Stat	TARCH Volatility 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).

Our 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 TARCH volatility. The contemporaneous feedback effect from implied volatility to call OMA (in-the-money) is insignificant, but the contemporaneous feedback effect from the TARCH volatility to the call OMA (in-the-money) has a significant strong negative effect.

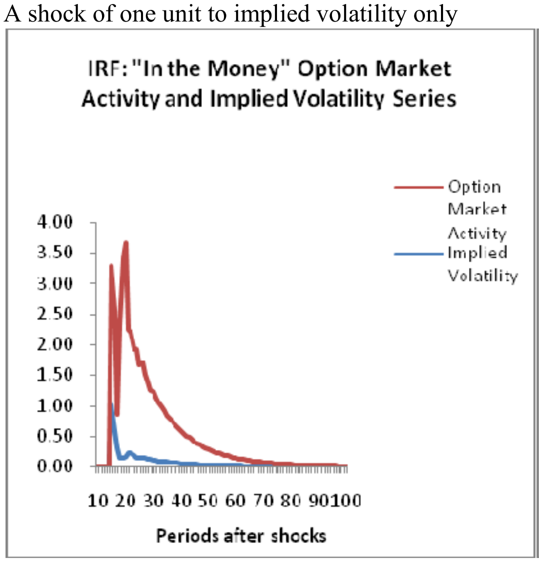
Our results indicate bi-directional causality (or feedback) between call OMA (near-the-money) and implied volatility or TARCH volatility. The direction of causality from implied volatility or TARCH volatility to call options OMA (near-the-money) is significant, implying lagged volatilities cause current OMA (near-the-money) to change. The causality from call OMA (near-the-money) to implied volatility or TARCH volatility is significant. Our 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 TARCH volatility values. Our results points to the hedging role of S&P/ASX 200 Index Options.

In Figure 1-6 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (in-the-money). In Figure 1-6 Panel C and D we present 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 TARCH volatility is minimal. In Panel C and D the

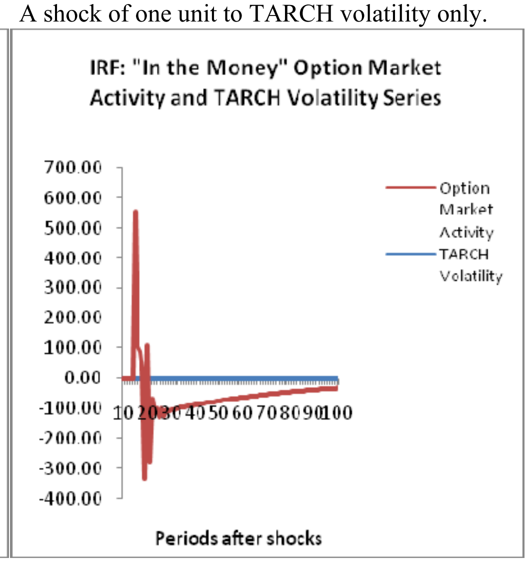
Figure 2-6 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: In-the–Money Options

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.

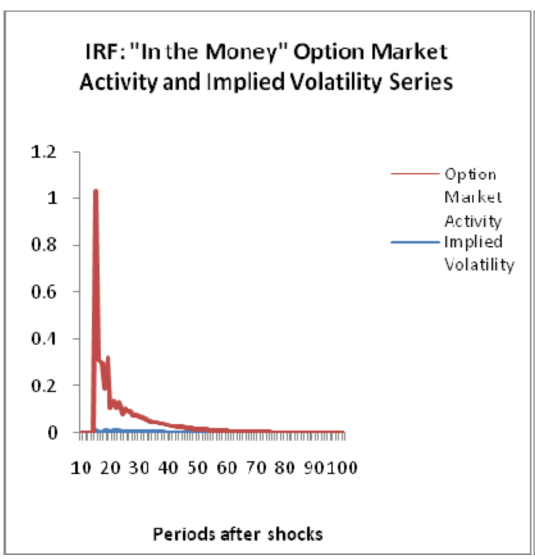
Panel A:
A shock of one unit to implied volatility only



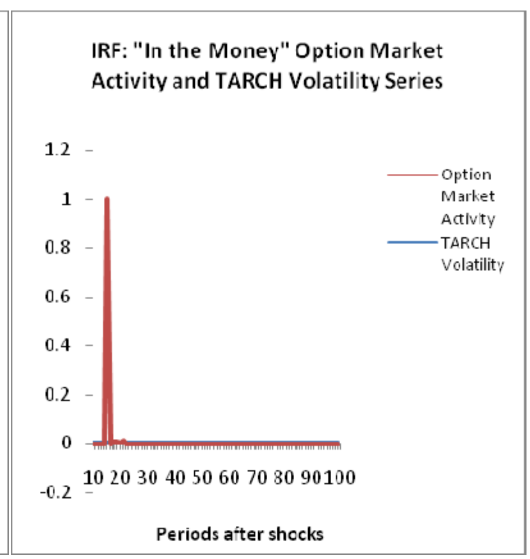
Panel B:
A shock of one unit to TARCH volatility only.



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 our results in Table 1-9.

2.3.9 Regression Results for the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Out-Of-the–Money Options

Our 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 1.10. 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.

Our 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 2-10 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: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

Independent Varible	Dependent variable:Volume (V_t) — Coefficient				Dependent variable:Volatility (I_t) — Coefficient			
	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

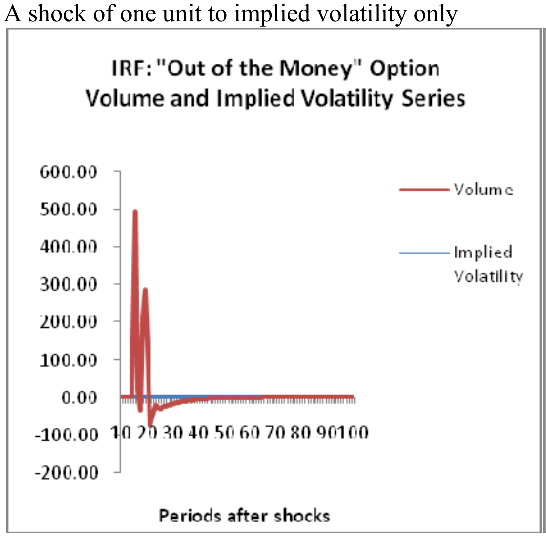
volatility for options out-of-the-money and are less likely sources of timely reliable information for active options traders. The results are statistical and economical unimportant.

In Figure 1-7 Panel A and B we present 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)

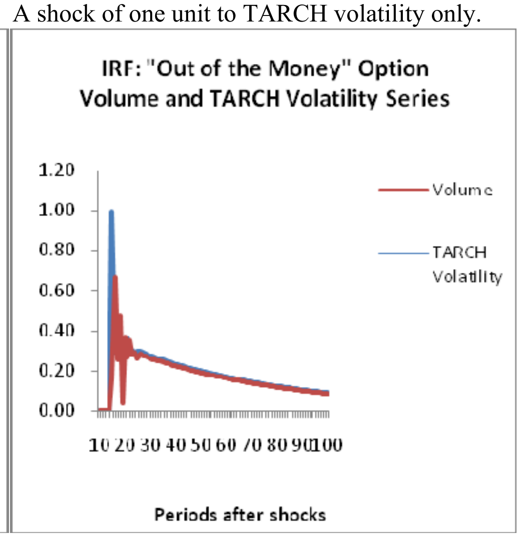
Figure 2-7 Impulse-Response Function of the S&P/ASX 200 Options Volume and Volatility Series by Moneyness Classes: Out-of-the–Money Options

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.

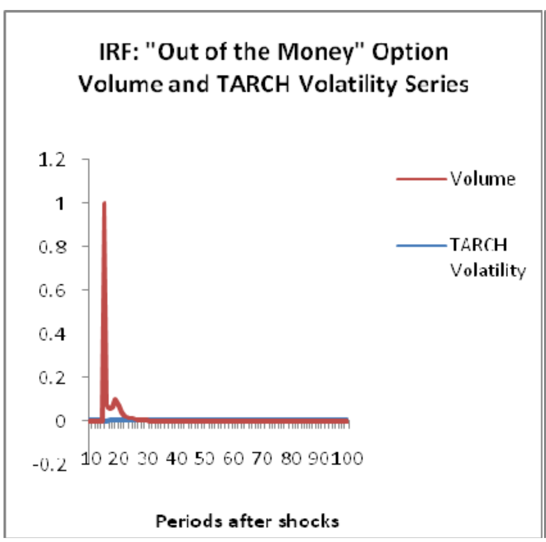
Panel A:
A shock of one unit to implied volatility only



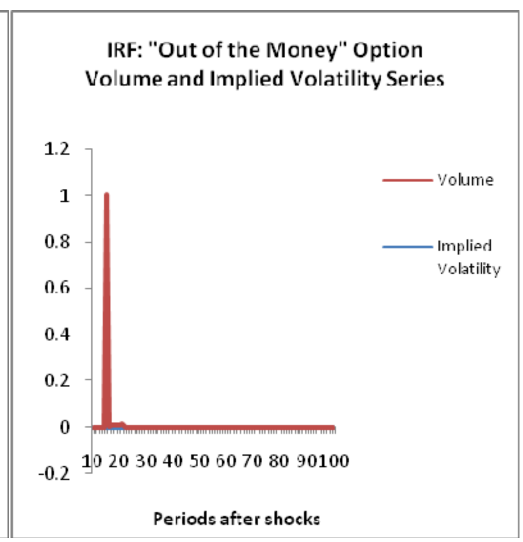
Panel B:
A shock of one unit to TARCH volatility only.



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



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



In Figure 1-7 Panel C and D we present 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 our results in Table 1-10.

2.3.10 Regression Results for the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Out-Of-the–Money Options

Our 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 1.11. 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 2-11 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 isI_t (OMA). These are: $H_0 = \alpha_{1i} \ldots \alpha_{1m} = 0$ and $H_0 = \beta_{2i} \ldots \beta_{2m} = 0$

	Dependent variable:Volume OMA ($VOMA_t$)				Dependent variable:Volatility (I_t)			
	Coefficient				Coefficient			
Independent Varible	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

Our 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).

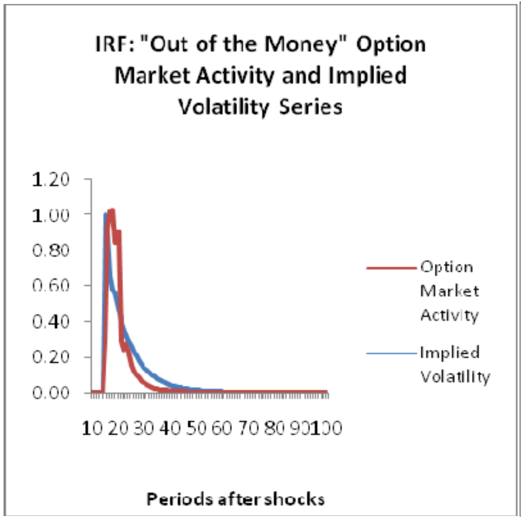
In Figure 1-8 Panel A and B we present the results from the IRF of a one unit shock to implied and TARCH volatility to trace the effects on OMA (out-of-the money) In Figure 1-8 Panel C and D we present the results from the IRF of a one unit shock to OMA (out-of-the money) to trace the effects on both 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.

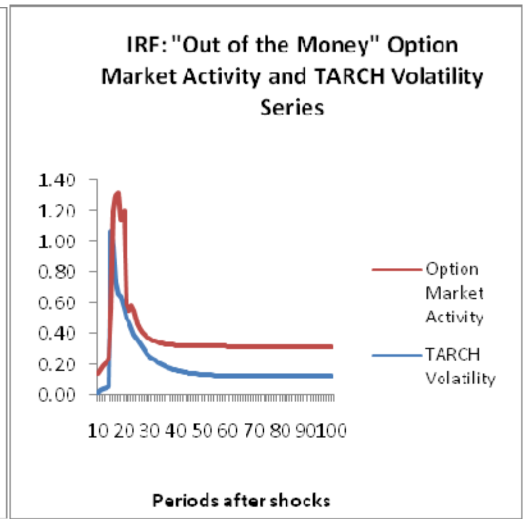
Figure 2-8 Impulse-Response Function of the S&P/ASX 200 Options Market Activity and Volatility Series by Moneyness Classes: Out-Of-the–Money Options

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.

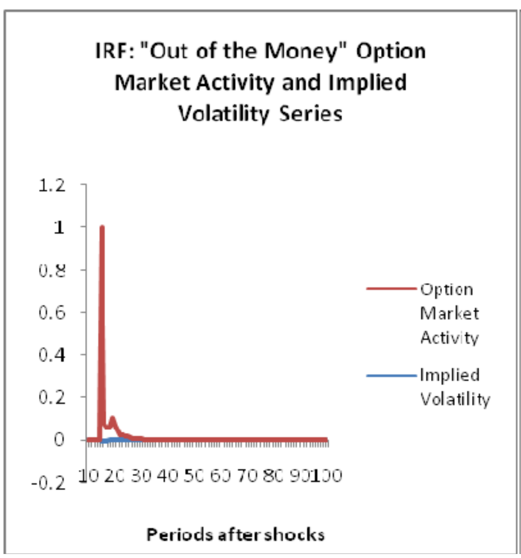
Panel A:
A shock of one unit to implied volatility only



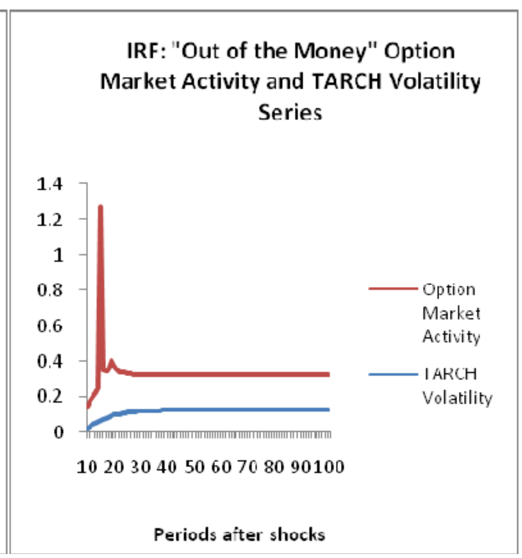
Panel B:
A shock of one unit to TARCH volatility only.



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



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



2.4 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 examined 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. We used the implied volatility and TARCH 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. We used variants of the causality testing approaches of Granger (1969) and Granger and Newold (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.

Our results found 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. Our 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. We also found 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. Our 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.

Our results found 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. Our 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.

We 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. We found 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.

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