

# Informed Traders and Their Market Preference: Empirical Evidence from Prices and Volumes of Options and Stock

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## ABSTRACT

The causal structure of price and volume in options and stock markets is examined to investigate whether a preferred market for informed trading exists. The possible trade-off of leverage on one hand and liquidity and transactions costs on the other, and the effect of different market mechanisms, are discussed in this context.

We test for cointegration and use the vector-error-correction (VEC) approach if we find it. Otherwise, causality tests are via the conventional vector-autoregression (VAR). We find that volume leads price in both markets, but that option volume leads stock volume, and stock price leads option price. These results differ from previous studies. Potential explanations are discussed.

***Keywords:* Causality; Australian options and stocks; Cointegration**

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## Introduction

What factors specific to a market influence the trading behaviour of informed investors and the rate of price discovery? This is a central question in market microstructure. Given a choice between markets, an informed trader may evaluate the trade-off between liquidity, leverage and transaction costs for these different markets. The trading mechanism (for example, automated compared to open outcry) may have some bearing on this trade-off and on price discovery and volume patterns.

The Australian market structure is unusual in that stocks are traded via an automated trading system called SEATS (Stock Exchange Automated Trading System) whilst the option market structure is traditional open outcry. Both are the conventional continuous double auction. Previous studies have analysed markets with similar trading systems (for example, in Stephan and Whaley (1990), neither market is electronic), so the Australian environment provides an interesting opportunity to further compare the effects of market mechanism on the nature of price discovery.<sup>1</sup>

Our study is constructed as follows. We first discuss the differences in liquidity, leverage and transaction costs between the stock market and the options market, to develop the idea that an underlying trade-off between these exists, and to suggest some tentative expectations of results or potential observed outcomes. We then outline what would appear to be the principal effects of the specific market mechanisms in Australia.

We study the causal structure of the price and volume of the Australian stock and options markets, using recent advances in cointegration theory that account for long run price tendency. Volume leads price in both markets, but option volume leads stock volume, and stock price leads option price. As we will see, it is possible to conclude from this that conditions are more favourable in the options market for informed traders, because we find that option volume leads stock volume. It also seems that electronic trading systems may enhance price discovery, because stock price leads option price.

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<sup>1</sup> An excellent example of a liquidity study of options on a different market is in Vijh (1990).

The layout of this paper is as follows. Section 1 briefly outlines relevant prior research. Section 2 provides an overview of the Australian market structure and the data we use. Section 3 outlines the methodology we use, while Section 4 documents and discusses the results, and a conclusion and directions for future research are offered in Section 5.

## 1 FACTORS AFFECTING MARKET PERFORMANCE

In efficient, frictionless capital markets, price discovery should be instantaneous and contemporaneous. While this would be true for an underlying security or for a derivative written on this security, recent empirical evidence has cast doubt on it. For example, many authors document a distinct lead/lag relation between the price adjustment behaviour of exchange-traded options and the underlying asset; examples include Stephan and Whaley (1990), Chan, Chung and Johnson (1993), and Fleming, Ost diek and Whaley (1996). There is also some evidence of a lead/lag relationship in volume between stock and options markets; see Stephan and Whaley (1990) and Anthony (1988). Theoretical arguments for this lead/lag relationship can be based in the market microstructure, the role of volume and the flow of information, like that examined in Easley, O'Hara and Srinivas (1998). These authors develop a theoretical model based on asymmetric information that shows that options volume can contain information that is relevant to future stock prices.

Table 1 provides a summary of previous empirical research in this field. The general consensus of these papers appears to suggest that the derivative market leads the asset market in terms of price discovery. Studies examining the relationship between trading activity measures appear to be less conclusive. Most of the studies listed explain the lead/lag relation they discover in terms of only one of the three possible inputs discussed here.

< INSERT TABLE 1 ABOUT HERE >

Observed lead/lag relationships with price or volume may be a consequence of market imperfections, of which market inefficiency is only one. (Market inefficiency is defined here to be an inability to process information into price in the absence of any other barriers.) Other imperfections might include lags in reporting, in communicating with traders or in entering of orders. This means that evidence of a finitely small adjustment time to news need not imply market inefficiency. If a systematic price discovery or volume lead/lag relationship is found, we might interpret this as evidence of where informed traders might choose to transact. This in turn allows us to consider possible reasons why informed traders choose one market rather than another. Intuitively, the factors that might drive an informed trader to choose one market over another are liquidity, leverage, and transaction costs, and the type of market mechanism.

## 1.1 Leverage

As initially noted by Black (1975), options provide the investor with higher leverage than for the underlying asset. (Leverage – for stock or options - is defined as expected return for a given price change  $\Delta S$ , which can be rewritten in terms of option delta, expected change in stock price and option price.<sup>2</sup>) We can show that in-the-money options have a lower ratio of  $\Delta C$  to  $C$  than out-of-the-money options, so lower delta options will have greater leverage than higher delta options. To maximise the leverage from the investment, an investor acting upon new information trades within the options market in preference to the stock market and chooses deeper out of the money options (those with lower delta).

Stephan and Whaley (1990) test this using samples of high and low delta options. Results suggest only a marginal difference between the samples in the strength of the causal relationship between stock and options. The authors do not consider possible differences due to higher transaction costs and lower liquidity in the options market.

Since trading by informed traders influences price, the benefits from leverage to traders holding private information about a known asset price change will reduce as time passes. This means that if there is a tendency for informed traders to choose the options market over the stock market, it will decrease as the information gets older.

## 1.2 Trading Costs

All else equal, we would expect that price discovery will occur in the market for which trading costs are the least, thus providing the highest net profits from information trading. Transaction costs have three dominant components; the bid ask spread, brokerage and related fees, and the price concession due to the trade's impact on price. This last "market impact" cost is a function of the trade size, market liquidity, depth and time of day. So, depending on the preferred trading size and timing of the informed trader and the depth of market, informed traders may have a preference for a market with lower trading costs.

Further, as argued by John, Koticha and Subramanyam (1991), if informed traders chose to trade only in derivatives, then the adverse selection component of the bid/ask spread would become very large. Thus the benefits of increased leverage in the options may be offset by additional costs of trading.

The brokerage costs per dollar invested are roughly the same in each market (in Australia), so it is only the bid ask spread and the market impact cost that need to be evaluated. Market impact costs are difficult to estimate, so little evidence exists on the different impacts in each market. However, we suggest that they are inversely related to market depth and liquidity. Vijh (1990) supports this view. Further, the options market percentage bid-ask spreads are usually much larger than for the stock market. This may also be a function of liquidity.

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<sup>2</sup> Since leverage for a call option =  $\frac{\Delta C}{C} = \frac{\Delta C}{\Delta S} \frac{\Delta S}{C} = \frac{(\text{option delta})}{C} \Delta S$  then the ratio of the call option delta to its price determines its leverage, for a given change in stock price  $\Delta S$ . It is easy to see that the deeper out of the money the call, the higher this ratio, hence the higher its leverage. The same argument applies for puts.

It seems that, on balance, transaction costs are larger in option markets than stock markets, so the leverage benefits discussed earlier will be traded off against the cost of transacting.

### 1.3 Liquidity

The ability of informed traders to hide their trades is important to them. In Australia, liquidity is much higher in the stock market (reflected in a smaller bid-ask spread) than in the options market. This is particularly true for the high leverage deep out-of-the-money options. Consequently, as suggested by Biais and Hillion (1990), if informed traders to trade in options, they may choose a more actively traded options series, even though it has lower leverage. Options series have greater liquidity and we would expect this to aid the anonymity of traders.

The market preference of informed traders is also likely to be a function of the relative market depths. Along this line, Garbade and Silber (1983) present a model which suggests that price discovery is a function of the relative size of the market measured by the number of market participants. This idea is supported by Admati and Pfleiderer (1988), whose trading model suggests that discretionary liquidity traders will band together to increase market liquidity and minimise the adverse affects of informed traders. In this model, the informed trader's optimal trading strategy is to trade where uninformed trading is highest, so informed participants will follow the pattern set by discretionary traders. Thus we might conclude that price discovery will occur in the more liquid market, which in Australia is the stock market.

Stephan and Whaley (1990) find that stock trading activity proxied by the number of transactions or volume leads trading activity on the options market. In conjunction with findings that stock prices lead options prices, this provides evidence that price discovery and trading activity are related. Chan (1992) further investigates this hypothesis using the number of trades as a proxy for trading activity and concludes that there is no compelling evidence to suggest a causal relationship between trading activity and the lead/lag relationship.

To help evaluate these conflicting views, our study concentrates on the causal structure of the option and stock markets and on the reaction time (lead/lag length) of this structure. If (as we might expect) reaction time is directly related to liquidity, the options market will react more slowly than the stock market.

## 1.4 Market Trading Mechanism

There has been a recent trend away from floor-based trading systems to electronic (screen) trading and settlement. The proponents of screen trading argue that it reduces the cost of transacting, improves market transparency and enhances the price discovery process. For example, Harris (1990) argues that electronic screen trading reduces the fixed costs of running an exchange, which in a competitive market could translate into lower transaction costs. Traders will find it profitable to trade on less significant information, accelerating the price discovery process. Grossman (1990) notes that screen trading accelerates the execution of portfolio trading strategies by “speeding up the process of information collection, demand execution and order execution”.

In addition to the actual speed of order execution it is possible that electronic markets disseminate price information more rapidly. Hasbrouck and Sosebee (1992) present evidence in this, showing that the average reporting lag on the NYSE is approximately 20 seconds and can be as long as two minutes. On a screen trading system, traders have access to most or all of the limit order book and thus may condition their trades on a more recent information set.

On the other hand, some critics argue that the elimination of the floor-based market comes at the cost of a reduction in market liquidity, a reduction in beneficial reputational effects and a decrease in market transparency. An example of this type of argument appears in Benveniste, Marcus and Wilhelm (1992), who take the example of the floor-based market maker. Further, an electronic screen trading market (with or without a market maker) may preserve anonymity of market participants and thus may not be as transparent as floor-trading markets in which pit traders can observe the identity and actions of all traders<sup>3</sup>. Harris (1990) and Grossman and Miller (1988) have examined the effect of market transparency of price determination and suggest that informed traders prefer to trade in markets that are opaque. This would suggest that informed traders are more likely to choose a more opaque market, which might deter uninformed traders and hence lower liquidity.

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<sup>3</sup> It must be noted that the SEATS system does not provide complete trader anonymity as all limit orders are accompanied by a broker identification number

In sum, we may expect screen trading markets to process information more rapidly than floor-trading markets. However, we are unsure about the impact this will have on liquidity due to the opposite effects of information asymmetry and speed and cost of transactions.

Three empirical studies in different markets are of particular interest in this comparison. Firstly, Shyy *et al* (1996) investigate the relationship between prices on the French stock market (Bourse, electronic trading) and the futures markets (Matif, open outcry). This combination is the only precedent literature with a comparable pair of market structures to our study. The authors conclude that the stock market leads futures trading, reversing previous studies findings. They reason that this result is either due to the trading mechanisms of the Bourse and the Matif or stale price data used in previous studies. An alternate explanation is the additional competition from the *quote driven* London SEAQ system.

Secondly, Grünbichler *et al* (1994) also test this automated trading hypothesis by examining the German DAX index for which DAX futures are traded in an electronic market.<sup>4</sup> They find that the futures market leads the spot by between 15 and 20 minutes and on the basis of these results conclude that electronic screen trading accelerates price discovery. This reported lead may be due to short selling restrictions in the German spot market.

Thirdly, Turkington and Walsh (1999) study the Australian futures market (Sydney futures exchange, open outcry) and the Australian stock exchange (electronic) and find that neither market has a discernible lead in price discovery.

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<sup>4</sup> For the sample period of this paper, the German spot equity market was a floor trading system. It has since changed to an electronic system.

## 2. MARKET STRUCTURE AND DATA

### 2.1 Market Structure

During our sample, the Australian options market is an open outcry trading system<sup>5</sup>. Competing market professionals called registered traders act as market makers to ensure the existence of a continuous, liquid market. This characteristic of the options market clearly differentiates it from the spot market, which operates in an electronic trading environment.

Member organisations of the Australian Stock Exchange (ASX) are the parties to options contracts, and individual investors trade through them. These members, on behalf of the option writers, lodge margins with the Options Clearing House to allow for profits/losses to be paid through marking to market. Note that buying a call (put) may be preferred given good news (bad news) due to a better payoff function compared that of writing a put (call). In this study, both put and call options are included in the analysis to capture all relevant informational trades in the sample.

### 2.2 Data

The data in this study covers the 244 trading days from January 3 1995 to December 21 1995. Both stock and options transactions data give the time, price, best bid/ask, volume and initiating party of each transaction.<sup>6,7</sup>

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<sup>5</sup> The ASX options market converted to a new integrated computerised system in early 1998.

<sup>6</sup> Our thanks to the Securities Industry Research Centre of the Asia-Pacific (SIRCA) for providing both data sets.

<sup>7</sup> However the options database only records the initiating party for about 37% of options transactions. To determine the initiator of the remaining transactions, we use the approach suggested by Lee and Ready (1991); trades occurring in the lower half of the spread are classified as sells and trades in the upper half of the spread are classified as buys. Trades occurring at the midpoint of the spread are classified using the “tick test”; if the current trade occurs on an up-tick (down-tick), it is classified as a buy (sell), while for a “zero tick” the tick test is applied to the last price change preceding this trade.

The trading activity of stock options is highly variable. The number of options trades per day ranges from an average of 290 for the most highly traded company (Broken Hill Proprietary Company Ltd, or BHP) to a company with only one option trade in the entire sample. The grand population daily trading average is 16.92.

To ensure that sufficient trading activity takes place, only seven companies with the most active options series (BHP, NAB, WMC, NCP, CRA, ANZ and MIM) are chosen for this study. Beyond these, volume drops off dramatically; there is a natural break in the trading volume. These companies comprise almost three-quarters of total dollar volume of the market, although the trading volume is still quite low compared with the stock volume. Note also that to ensure a meaningful analysis of information flows across markets, matched trading times of the markets (10am to 12:15pm and 2pm to 4pm) are chosen, separated into 15 minute intervals..

Verrecchia (1981) notes that informational effects may be obscured when trading is for non-informational purposes, and Phillips and Smith (1980) suggest that traders usually close out their position in the option by making a reversing trade just prior to the expiration of the option. Consequently, trades occurring during the expiry day of the option are excluded from the sample. Finally, overnight movements and the first fifteen minutes of trading have been excluded as well.

### 2.3 Trading Costs and Liquidity

Trading costs and market liquidity are important components in the trade-off decision faced by an informed investor. Table 2 examines the market liquidity (panels A, B and C) and the bid/ask spread measures (panels D, E and F) of stock options and the underlying stock for our sample of stock and options. Panels A, B and C also report the proportion of the total population that each category of options series comprises.

< INSERT TABLE 2 ABOUT HERE >

Table 2 shows the distribution of liquidity across option series. At-the-money options comprise between 50-60% of all trading activity in the sample. In fact, at-the-money options with under 3 months to maturity dominate trading, with about 41% of all trading

for both calls and puts. For these options, the average percentage spread is also slightly lower than the population value. For put options, the average percentage spread is slightly higher than for calls, perhaps reflecting the comparatively lower trading activity of puts.

In-the-money options are the least actively traded and the percentage bid-ask spread for these options is also markedly lower.<sup>8</sup> This may be due to a reduction in the adverse selection component of the spread due to informed traders being discouraged by low trading activity and low leverage (see John, Koticha and Subramanyam (1991)). Supporting this, the percentage bid/ask spread is highest for those series with the greatest leverage; deep out-of-the-money options with a short time to maturity have a much higher percentage spread than in-the-money options, even though dollar volume is also much higher in four of six cases, and uniformly higher for the other volume measures.

Another way of demonstrating this is to consider the “unlevered” spread (Panel F) which is the cost of obtaining one “delta” of exposure to the underlying asset. Although this reduces the effect of the “moneyness” of the option series, we still see a much larger value for out-of-the-money options.

Further, both the percentage and unlevered spreads are significantly lower on the stock market than the options market. Even the average unlevered spread on the most actively traded options series is very large compared to the average stock market spread.

The stock market has significantly higher trading volume than the options market. When using the number of trades as a measure of volume, the stock market has over four times the average daily trading activity of the options market. When we examine the dollar volume of trades, it is much larger again. While we are unable to quantify the difference, the market impact costs of trading on the options market are likely to be considerably larger than on the stock market.

Based on trading costs and liquidity, the stock market appears a less expensive trading alternative to the options market. We might suspect, consistent with Flemming *et al*

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<sup>8</sup> The *absolute* bid-ask spreads are higher for in-the-money options. However, it is not valid to compare options based on this as in-the-money option prices are higher too.

(1996), that stock will have an observable lead on options, proportional to the disparity in trading costs.

In summary, we can hypothesize that informed traders assess the direct trade-off of the benefits of leverage in the options market with the benefits of lower costs of trading and higher liquidity of the stock market. The result of this trade-off is an empirical question that we now address.

### **3 METHODOLOGY**

To examine the price discovery process and the causal structure linking stock and options markets, we construct a high frequency comparison of prices and volumes of the seven stocks and their option series. We sample at fifteen minute intervals, recording price as the bid/ask midpoint at the last transaction recorded in each 15 minute time partition. If no observation occurs in the interval then the previous period's price is recorded. The total number of trades and the total number of shares traded in each interval are also recorded. Each trading day comprises 17 fifteen minute time intervals (i.e., ignoring the first 15 minutes of each day) making a total of 4148 intervals/observations.<sup>9</sup>

Note that implied spot prices, not actual options prices, are used. Since derivative contracts regularly expire and may have different strike prices and maturity dates, the raw option price series cannot be used directly to draw inferences. Rather, we use the option price to *imply* a spot price, by inversion of the Boyle (1988) trinomial lattice approach modified to account for multiple dividends. This implied spot price (from the last option traded in each interval) is the option price "observation" that we use. Appendix 1 contains details of this calculation.

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<sup>9</sup> Removing the opening 15 minutes of trading avoids a period during which both price discovery and market mechanism are different to the rest of the trading day. (The equity market opens with a call market rather than the usual electronic trading system.)

## 3.1 Causality Tests

### 3.1.1 Price Discovery

Spot and derivatives markets are strongly linked to each other by complex arbitrage relationships which ensure long run price tendency towards an equilibrium constraint. The price series cannot diverge and instead follow paths that cannot drift too far apart. If the time paths of such variables are responsive to the previous period's pricing error, in that the variables adjust to correct for deviations from the long run equilibrium path, then the series are said to be cointegrated.

Formally, two series are cointegrated if they are integrated of the same order  $n$  (i.e., stationary after the  $n^{\text{th}}$  difference) but a linear combination of the two is stationary. Traditional causality tests such as that of Granger (1969) detect only whether past changes in the observed series of one random variable affect current movements of another random variable. However, Engle and Granger (1987) show that if two series are cointegrated then a standard bivariate dynamic model that uses only first differences is misspecified because it ignores interim short-run adjustments (error correction) to the long-run equilibrium. Lead-lag relationships reported in some previous studies may in fact be induced by an omitted error correction variable in the model specification, which causes parameter estimates to be biased, inconsistent and inefficient. Thus to properly account for the cointegration of price series, a more complete model must be implemented which allows for long run path-dependency. This model is the vector error correction model.

Vector error correction (VEC) models allow the simultaneous estimation of short term and long term inter-market adjustments. Examples of their use include Wahab and Lashgari (1993) and Ghosh (1993), who examine the performance of error correction models in the futures setting, and conclude that they are superior forecasting models, compared to both the naïve and VAR models. Estimation of these models is through the Johansen (1991) full information maximum likelihood (FIML) technique, which tests for cointegration in a system of equations while estimating the parameters of the VEC.

There are two steps in testing for cointegration; determining the order of integration, and then, if the series are of the same order, testing whether a single cointegrating vector

exists. For the first step we use the augmented Dickey-Fuller (ADF) test of a unit root null with the Mackinnon (1991) critical values. For the second test, we apply the Johansen likelihood ratio test statistics<sup>10</sup>. Johansen's first statistic ( $\lambda_{trace}$ ) tests whether the number of distinct cointegrating vectors is less than or equal to one. The second statistic ( $\lambda_{max}$ ) tests whether the null that the number of cointegrating vectors is one against a two-vector alternative.

If the series are indeed cointegrated then the following VEC representations are estimated and interpreted for causality:

$$\Delta S_t = \alpha_1 + \sum_{i=1}^n \beta_i \Delta S_{t-i} + \sum_{i=1}^n \phi_i \Delta O_{t-i} + \delta_1 r_{t-1} + \varepsilon_{1t} \quad (1)$$

$$\Delta O_t = \alpha_2 + \sum_{i=1}^n \theta_i \Delta S_{t-i} + \sum_{i=1}^n \varphi_i \Delta O_{t-i} + \delta_2 r_{t-1} + \varepsilon_{2t} \quad (2)$$

where  $S_t$  is the spot price at interval  $t$ .

$O_t$  is the spot price implied by option trading in interval  $t$ .

$r_{t-1}$  is the error correction term (single-lagged difference between spot and implied spot prices).

In order to conclude whether the results obtained from the VEC procedure are robust to microstructure effects and consistent with results obtained under the previous methodology, a second set of models is estimated, following the Stoll and Whaley (1990) procedure. Under this method, microstructure effects such as infrequent trading are filtered out of the (first-differenced) actual spot and implied spot series via an ARMA (p,q) specification. The residuals from this process represent series innovations which are then tested for causality using a conventional bivariate vector autoregression

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<sup>10</sup> To test if  $q$  cointegrating equations is the correct specification the following statistics are calculated:

$$\lambda_{trace}(q) = -T \sum_{i=q+1}^P \ln(1 - \hat{\lambda}_i)$$

$$\lambda_{max}(q, q+1) = -T \ln(1 - \hat{\lambda}_{q+1})$$

where:  $P$  is the number of series

$T$  is the number of useable observations

$\hat{\lambda}$  are the estimated eigenvalues obtained from the cointegrating matrix

Johansen and Juselius (1990) provide the critical values of these statistics.

(VAR), which has a similar structure to the VEC except that it excludes the error correction term in equations (1) and (2) (i.e.,  $\delta_1$  and  $\delta_2$  are constrained to be zero).

### 3.1.2 Trading Activity

As no formal equilibrium relationship appears to exist between trading activity and prices on stock and derivatives markets it is unlikely that these variables are cointegrated. Consequently, a standard Granger causality methodology may be employed to test the trading activity relationship, using a bivariate VAR.

Rather than use raw trading activity, we define and use a net trading activity measure equal to the aggregate number of buyer-initiated shares traded less the aggregate number of seller-initiated shares traded. (In the case of options, this meant simply differencing the buy and sell volume of *all* options traded.) This measure allows us to focus on the imbalance of order flow as our trading activity measure, in the same way as Brown, Walsh and Yuen (1997).<sup>11</sup>

To test the relationship between trading activity on stock and options markets the standard VAR system is estimated and interpreted for causality:<sup>12</sup>

$$SV_t = \alpha_1 + \sum_{i=1}^n \beta_i SV_{t-i} + \sum_{i=1}^n \phi_i OV_{t-i} + \varepsilon_{1t} \quad (3)$$

$$OV_t = \alpha_2 + \sum_{i=1}^n \theta_i SV_{t-i} + \sum_{i=1}^n \varphi_i OV_{t-i} + \varepsilon_{2t} \quad (4)$$

where  $SV_t$  is the proxy for net stock trading activity during interval  $t$

$OV_t$  is the proxy for net option trading activity.

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<sup>11</sup> We also use net number of trades and net dollar volume as alternate proxies of trading volume. However, the net number of shares traded yielded the clearest set of results.

<sup>12</sup> We also conduct “cross-causality” tests between trading activity and price, to draw conclusions about which of these causes the other. The method is VAR, in the same way as the trading activity VAR described here.

## 4 EMPIRICAL RESULTS

### 4.1 Price Discovery Causality Tests

#### 4.1.1 Testing for Cointegration

The observed values of the ADF test statistic for the levels series are reported in Table 3. The values of the statistic for BHP, MIM, NAB and NCP all strongly suggest that both the stock and option level series are stationary.<sup>13</sup> Thus by definition these series cannot be cointegrated and a standard Granger causality test is applied.

However, the ANZ, CRA and WMC series all contain a unit root in the levels series and are integrated of the same order, thus fulfilling the first condition for cointegration.<sup>14</sup> For these levels series, the Johansen test is then applied to determine the rank of the cointegrating matrix. The results of this test are in Table 4. Recall that for two series to be cointegrated, only one cointegrating equation (CE) must exist or (equivalently) the rank of the cointegrating matrix must be one. Following an exploration of the lag space to determine the appropriate lag length for the Johansen test, we find that the second cointegration condition is fulfilled for these three series.

**< INSERT TABLES 3 AND 4 ABOUT HERE >**

#### 4.1.2 Performing Causality Tests

The VEC and VAR models of price change for all of the series were estimated, but for brevity, only the results from “innovation VARs” are given. These are conducted as follows.

The implementation of the cointegration method requires that the multivariate time series are non-stationary. Consequently, any transformation of the series (for example, to purge microstructure effects) will generally remove cointegrating relationships. In

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<sup>13</sup> The alternate Phillips-Perron unit root test – not reported here - confirms these results.

<sup>14</sup> Susceptibility of these results to outliers, intercept and trend terms was tested and the results given here confirmed; the unit root cannot be rejected for any standard specification.

order to test the robustness of results to microstructure effects such as infrequent trading, a methodology similar to Stoll and Whaley (1990) is employed.

Presuming that information is randomly and independently revealed to the market, the returns process should in the absence of microstructure effects follow a similar (Markov) process. Any observed serial correlation is assumed to be non-informational and should be purged from the series. To achieve this, we estimate an ARMA process and use the residuals from this process - the price *innovations* - as solely a function of informational flows in the causality test.

The appropriate ARMA specification is fitted to the first-differenced series; an ARMA(1,1) process was appropriate in most cases. Diagnostic statistics indicated that the ARMA specifications were generally successful in purging the majority of serial correlation from the stock series, although it was less successful for the implied spot price series. A VAR containing the series *innovations* is then estimated.

Table 5 gives the results from this innovations VAR.<sup>15</sup> The parameter estimates for six of the seven series indicate that stock prices cause option prices. The  $\theta$  coefficients are significant and positive, indicating that the lagged stock prices affect current options price. However, the  $\phi$  coefficients are insignificant, so there is no effect in the opposite direction (option to stock). The insignificance of the  $\beta$  coefficients indicates no serial correlation in stock prices, but the significance of the  $\varphi$  coefficients shows strong serial correlation in the option prices, even after purging these effects.

< INSERT TABLE 5 ABOUT HERE >

It is important to realise that in a VAR, the signs of the individual coefficients are not necessarily indicative of a direction of causation. The entire system of equations needs to

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<sup>15</sup> To determine the appropriate lag length the Schwartz Bayesian Criterion (SBC) is used in preference to the Akaike information criterion (AIC) due to its superior large sample properties. In the absence of economic theory, a lag length of ten is initially tested and progressively shortened in accordance with the SBC. The multivariate generalisation of the SBC is given by:  $SBC = T \ln(|\Sigma|) + n \ln(T)$

where  $|\Sigma|$  is the determinant of the variance/covariance matrix of the residuals

$T$  is the number of usable observations

$n$  is the total number of parameters estimated in all equations.

be examined together, and for that conclusion a specification test is applied. This test (similar to the original idea of Granger causality) simply examines the explanatory power of the exogenous variables (in the stock equation, the lagged option price innovations, and in the option equation, the lagged stock price innovations). The resulting test, based on constrained and unconstrained residual sum of squares, is F-distributed. The results also appear in Table 5, and confirm the results discussed earlier; stock price innovations appear to lead option price innovations.<sup>16</sup>

(It is interesting to note that the results from the stock and option price innovation regressions are much more conclusive than those from the VEC models.<sup>17</sup> The lag length from the pre-whitened series is considerably shorter than for the raw series. This is as expected; removal of non-trading effects reduces the serial correlation in the price change series. However, while there are less lags, the causal relationship is much sharper.)

## 4.2 Trading Activity Causality Tests

If trading activity is a valid proxy for information release, then inferences may be drawn by examining the comparative trading activity of stock and options markets. Unit root tests on all series indicate that they are stationary and thus a classical VAR is estimated to test for causality between the trading activity series.

Results reported here use trading activity defined as net number of shares traded (buy volume less sell volume), since it produced the clearest results of the metrics we chose.<sup>18</sup>

We in fact conduct *three* sets of trading activity causality tests:

- The first tests causality between the two trading activity series. Results appear in Table 6, Panel A.

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<sup>16</sup> For robustness, we removed intervals in which no trading took place for either the stock or option markets. This procedure resulted in some 6650 intervals (23%) being removed from the sample. Following appropriate refitting of ARMA specifications and re-estimating VARs, identical inferences were drawn.

<sup>17</sup> Our thanks to an anonymous referee who drew our attention to this point.

<sup>18</sup> . We also investigated the use of net number of trades and net dollar value of trades, and although the direction of causality was similar, the results were less consistent.

- The second tests “cross-causality”, between stock price innovations and options trading activity. Results appear in Table 6, Panel B.
- The third tests the “cross-causality” as well, but this time between option price innovations and stock trading activity. Results appear in Table 6, Panel C.

Note that since the results are quite clear, Table 6 only reports direction of causality, the F-statistic and the time length. Actual coefficient estimates are not provided.

**< INSERT TABLE 6 ABOUT HERE >**

The evidence from Table 6, Panel A is clear; in all seven firms we *cannot* reject the null hypothesis that stock trading activity does not cause option trading activity. At the same time, for all seven firms, we *can* reject the opposite null, that option trading activity does not cause stocks trading activity. In other words, we have clear evidence of stock trading activity being caused by option trading activity. The inferences derived are quite consistent and indicate that the trading activity in the options market appears to lead that on the stock market, by between fifteen and thirty minutes.<sup>19</sup> This finding is not consistent with evidence reported by Anthony (1988) and Stephan and Whaley (1990).

Panel B shows a similar (although slightly less persuasive) story regarding the causal structure of stock price innovations and option trading activity. In four of the seven stocks, option trading activity leads stock price innovations. In the other three, we either observe bi-directional causality (feedback) or no causality at all. None of the cases examined shows causality from stock price innovations to option trading activity.

Panel C shows that stock trading activity leads option price innovations in five of the seven stocks under consideration. In the other two stocks, we either observe feedback or no causality at all. This seems to be relatively strong evidence in favour of a conclusion of causality running from stock trading activity to option price innovations.

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<sup>19</sup> Once again the robustness of these conclusions to infrequent trading is tested by removal of intervals in which no trading is observed and re-estimating. We also experimented with removing or including the lunch break from our data. The results in each case bear close resemblance to those tabulated here.

There is one final pair of results that need to be mentioned. While it was not the specific focus of this study, causality tests between option trading activity and option price innovations, and between stock trading activity and stock price innovations, were conducted. As expected from the above results, we found that tests of causality between option price innovations and option trading activity, and between stock price innovations and stock trading activity, both yield causality from trading activity to price. Option trading activity appeared to lead option prices by between 15 and 45 minutes, and although the F-statistics for the tests suggested that causality from volume to price was fairly clear, the number of lags was quite variable. Stock trading activity exhibited some feedback with stock prices but generally trading activity showed a small lead (one lag, about 15 minutes) over stock price.<sup>20</sup>

### 4.3 Discussion of Results

We can summarise the above set of results as follows:

- option trading activity leads stock trading activity, stock price innovations and option price innovations,
- stock trading activity leads stock price innovations and option price innovations,
- stock price innovations lead option price innovations.

While some of these conclusions are known, others suggest several distinct patterns that need explanation. These are:

- trading activity leads price innovations, in both markets,
- information arrives at the options market ahead of the stock market,
- the options market appears to respond more slowly to the news in trading than the stock market, to the extent that prices in the options market respond later than those in the stock market.

We can offer three partial explanations of these results. Firstly, the common empirical result that volume leads price is suggestive of traders reacting to private information

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<sup>20</sup> Detailed results on this tests have been omitted for the sake of brevity..

rather than to public information. This helps to confirm that our results are indeed driven by informed trading, and further that the lower transparency of the options market (i.e., lower than the electronically-traded stock market), may be enticing informed traders to the options market first.

Secondly, using our “trade-off” argument from section 1, the options market may be chosen by informed traders because of the leverage advantage it offers, even compared with the decreased liquidity and increased costs of trading. The stock market follows, perhaps because uninformed traders learn from the (unusual) trading activity on the options markets. However, the time between this reaction and the reaction on the stock market (15 to 30 minutes) may be too short for this to be true. Alternatively, if the expected advantage of leverage in the options market to informed traders erodes rapidly (widening of the bid-ask spread, or through price pressure) then the informed traders may switch from the options market to the stock market when the advantage to the options market disappears. In more liquid options markets, this effect is significantly less, perhaps suggesting that informed traders remain in the options market for longer. This might also explain the observed price lead of derivatives over stocks from some previous US studies.<sup>21</sup>

Thirdly, there are two possible reasons for the slow reaction of options market price. The first of these is based on the different market structures of stock and options markets. We have already noted that if the open outcry structure of the options market offers less transparency than the stock market, it may take longer for uninformed market participants to note the presence of informed trading, so price would take longer to reflect the influence of informed trading volume. The second reason, which does not exclude the first, is simply that liquidity is much lower in options markets, and it takes longer for the market to react in calendar time. In support, Walsh (1997) finds this to be true of Australian stocks; the time taken for order flow news to be incorporated in price is roughly the same in transaction time for all companies, even though the calendar time taken is directly related to the trading volume.

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<sup>21</sup> Another possible explanation for this, which is not easily proved, is that there is some kind of clientele effect present in the markets. If market participants tend to persist with one market or the other (perhaps for reputational reasons) we might explain this difference in lead/lag times purely as the reactions of a different set of investors.

## 5 CONCLUSIONS

This study aimed to examine the dynamics of the Australian stock and options markets in order to assess where information is initially incorporated into price. We suggest that both trading activity and price will reflect new information, and that the rate of price discovery is a function of market structure and the trade-off of the leverage, trading cost and liquidity characteristics of the individual markets.

By applying causality tests to price and volume series for options and stocks, we find that stock prices appear to lead option prices by 15 to 30 minutes, suggesting that information is incorporated into stock prices prior to option prices. However, using various proxies for trading activity, evidence suggests that information first arrives in the trading volume of the options markets, leading stock volume by at least 15 minutes. Further, volume leads price by about 15 minutes in the stock markets, but by at least 45 minutes in the options market.

We can briefly summarise our conclusions as follows. It is possible that informed trading is driving our results because volume leads price. It is also possible that the leverage offered to informed traders by the options market outweighs the costs of trading and the lower liquidity of that market, and switching of informed traders from options to stock is feasible given the short response time. Finally, open outcry markets may have slower incorporation of private information into price compared to the electronic stock market. It is also possible that the greater liquidity of the stocks market is driving this result.<sup>22</sup>

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<sup>22</sup> The Australian Options Market changed to an electronic market (known as CLICK) early in 1998, and future research into the change that this induces in the causal structure of the markets will help to improve our understanding of the results here.

## REFERENCES

Admati A. R., and P. Pfleiderer, 1988, A theory of intraday patterns: Volume and price variability, *Review of Financial Studies*, 1, 3- 40.

Anthony J.H., 1988, The interrelation of stock and options market trading-volume data, *Journal of Finance*, 43, 949-64.

Benveniste, L.M., A.J. Marcus and W.I. Wilhelm, 1992, What's special about the Specialist?, *Journal of Financial Economics*, 32, 61-86

Black F., 1975, Fact and fantasy in use of options, *Financial Analysts Journal*, 31, 36-41, 61-72.

Bhattacharya M., 1987, Price changes of related securities: The case of call options and stocks, *Journal of Financial and Quantitative Analysis*, 22, 1-15.

Biais, B. and P. Hillion, 1990, Option prices, insider trading, and inter-dealer competition, Working Paper, INSEAD.

Boyle P.P, 1988, A lattice framework for option pricing with two state variables, *Journal of Financial and Quantitative Analysis*, 23, 1-12.

Brailsford T. and B.R Oliver, 1994, Time-varying volatility estimates in option pricing, Working Paper, ANU.

Brown P., D.M. Walsh and A. Yuen, 1997, The interaction of order imbalance and stock price, *Pacific Basin Finance Journal*, 5, 539-557.

Brown R.L and T.J Shevlin, 1983, Option and stock market efficiency, *Australian Journal of Management*, 8, 71-87

Chan K., 1992, A further analysis of the lead-lag relationship between the cash market and stock index futures market, *Review of Financial Studies*, 5, 123-152.

- Chan K.Y, Chung P. and H. Johnson, 1993, Why option prices lag stock prices: A trading based explanation, *Journal of Finance*, 48, 1957-1968.
- Chiras, D.P and Manaster S., 1978, The information content of option prices and a test of market efficiency, *Journal of Financial Economics*, 6, 213-34.
- Easley D., O'Hara M. and Srinivas P., 1998, Option volume and stock prices: evidence of where informed traders trade, *Journal of Finance*, 53, 431-465.
- Engle R.F. and Granger G.W., 1987, Cointegration and error correction: Representation, estimation and testing, *Econometrica*, 55, 251-276.
- Flemming J., Ostdiek B and R.E Whaley, 1996, Trading costs and the relative rates of price discovery in stock, futures and options markets, *Journal of Futures Market*, 16, 353-387.
- Garbade K.D and W.L Silber, 1982, Price movement and price discovery in the futures and cash markets, *Review of Economics and Statistics*, 64, 289-297.
- Ghosh A., 1993, Cointegration and error correction models: Intertemporal causality between index and futures prices, *Journal of Futures Markets*, 13, 193-198.
- Granger C.W.J., 1969, Investigating causal relations by econometric models and cross-spectral models, *Econometrica*, 37, 424-38.
- Grossman S.J, 1990, Report for market volatility and investor confidence panel, New York Stock Exchange, G2-1-G2-17.
- Grossman S.J and M.H Miller, 1988, Liquidity and market structure, *Journal of Finance*, 43, 617-633.
- Grunblicher A., Longstaff F. and E. Schwartz, 1994, Electronic screen trading and the transmission of information: An empirical examination, *Journal of Financial Intermediation*, 3, 166-187.

Harris L.E, 1990, Liquidity, trading rules and electronic trading systems, New York University Salomon Centre Monograph series in Finance and Economics, Vol. 4.

Hasbrouck J. and D. Sosebee, 1992, Orders, trade, reports and quotes at the New York stock exchange, NYSE working paper, 92-01.

Hull J.C, 1997, Options, futures and other derivative securities (Prentice Hall, USA).

Johansen S., 1991, Estimation and hypothesis testing for cointegrating vectors in Gaussian vector autoregressive models, *Econometrica*, 59, 1551-1580.

John K., Koticha A and M. Subrahmanyam, 1991, The microstructure of options markets: Informed trading, liquidity, volatility and efficiency, Working Paper, New York University.

Lee C. and M. J. Ready, 1991, Inferring trade direction from intraday data, *Journal of Finance*, 42, 733-746.

MacKinnon, 1991, Critical values for cointegration tests, in: R. Engle and C. Granger, eds., *Long-run economic relationships: Readings in cointegration* (Oxford University Press, New York).

Phillips S.M and C.W Smith, 1980, Trading costs for listed options: The implications for market efficiency, *Journal of Financial Economics*, 8, 179-201.

Puttonen V., 1993, Short sales restrictions and the temporal relationship between the stock and index cash and derivatives markets, *Journal of Futures Markets*, 13, 645-664.

Shyy G., V. Vijayraghavan and B.S. Quinn, 1996, A further investigation of the lead-lag relationship between the cash market and the stock index futures market with the use of bid/ask quotes: The case of France, *Journal of Futures Markets*, 16, 405-240.

Stephan J.A and R.E. Whaley, 1990, Intraday price change and trading volume relations in the stock and option markets, *Journal of Finance*, 45, 191-220.

Stoll H.R. and R.E. Whaley, 1990, The dynamics of stock index and stock index futures returns, *Journal of Financial and Quantitative Analysis*, 25, 441-468.

Turkington, J. and D.M. Walsh, 1999, Price Discovery and Causality in the Australian Share Price Index Futures Markets, *Australian Journal of Management*, 24(2), 97-113.

Verrecchia R.E, 1981, On the relationship between volume reaction and consensus of investors: Implication for interpreting tests of information content, *Journal of Accounting Research*, 19, 271-83.

Vijh, A. M., 1990, Liquidity of the CBOE equity options, *Journal of Finance*, 45(4): 1157-1179.

Wahab, M. and M. Lashgari, 1993, Price dynamic and error correction in stock index and stock index futures: A cointegration approach, *Journal of Futures Markets*, 13, 711-742.

Walsh, D.M., 1997, Price reaction to order flow 'news' in Australian equities, *Pacific Basin Finance Journal*, 5, 1-23.

## Appendix 1. Calculation of Implied Spot Price from Options

The technique used in this study to obtain implied stock prices is a modification of the Boyle (1988) trinomial lattice approach that accounts for multiple dividends (see Hull 1997:194-206). A 250-step trinomial tree was constructed using the parameters specified below.

$$u = e^{\sigma\sqrt{3\Delta t}}$$

$$d = \frac{1}{u}$$

$$p_u = \sqrt{\frac{\Delta t}{12\sigma^2} \left( r - \frac{\sigma^2}{2} \right) + \frac{1}{6}}$$

$$p_m = \frac{2}{3}$$

$$p_d = -\sqrt{\frac{\Delta t}{12\sigma^2} \left( r - \frac{\sigma^2}{2} \right) + \frac{1}{6}}$$

where  $u$  is the up factor

$d$  is the down factor

$p_u, p_m, p_d$  are the probabilities of the stock price rising,  
remaining constant and falling respectively

$\Delta t$  is the time step of each branch

$r$  is the risk-free rate of interest

$\sigma$  is the estimated volatility of the underlying asset.

Brailsford and Oliver (1994) show that the previous day's implied volatility is a reasonable proxy for actual volatility on a day. We use the above trinomial tree technique to obtain an implied volatility estimate for each 15-minute interval during each day. The estimate of a day's volatility is then a weighted estimate of the previous day's implied volatilities. The weighting scheme used is similar to that of Chiras and Manaster (1978); we weight each option by its vega (also known as lambda). Since estimation errors are likely to be higher for options whose prices are insensitive to volatility, we place more weight on options with higher vegas.

The trinomial tree is also adjusted for dividends at each point when dividends are expected to be paid, using actual last period dividends as a proxy for expected dividends. To proxy for the risk-free rate, the results of the fortnightly tender auctions of 5, 13 and 26 week treasury notes are obtained from the Reserve Bank of Australia. The most recent yield on the note with term that best matches the time to maturity of the option contract is then used as the risk-free rate proxy.

To then obtain the implied stock price, a Newton-Raphson (NR) algorithm was implemented on the trinomial tree. The option contract which traded closest to the end of each 15 minute period was selected, and the NR algorithm converged quickly to an implied stock price in most cases. (Rarely did convergence fail. When it did, a different option from the 15-minute interval was chosen. Also, our implied stock prices were not very sensitive to the term or moneyness of the selected options contract.)

Note that implied stock prices from this technique are better than those generated by the Black-Scholes model because they allow for the proper incorporation of dividends.

Table 1  
Previous empirical research on the lead/lag relationship between options and stock

<b>Study</b>	<b>Data</b>	<b>Leading Market</b>	<b>Main Findings</b>
Manaster and Rendleman (1982)	CBOE Call (Daily)	Derivative (1 Day)	1) Price adjustment in derivative leads cash market
Brown and Shevlin (1983)	SFE Options (Daily)	Inconclusive	1) Severe thin trading
Bhattacharya (1987)	CBOE (Daily)	Derivative	1) Option prices lead stocks prices but insufficient to overcome transaction costs.
Anthony (1988)	CBOE Call/Put (Daily)	Derivative (1 Day)	1) Trading activity in derivative market leads cash.
Stephan and Whaley (1990)	CBOE Call (Intraday)	Equity (20 Min)	1) Trading activity and price adjustment in cash leads derivative market. 2) High delta options have slightly stronger leading relationship. 3) Stronger contemporaneous relation attributable to “good news”.
Chan Chung and Johnson (1993)	CBOE Put/ Call (Intraday)	Derivative	Stephan and Whaley (1990) price determination results reversed when average bid/ask spread used.
Puttonen (1993)	FOX <sup>1</sup> (Daily)	Derivative (2 Days)	1) Price adjustment in derivative leads cash market. 2) Derivatives markets better predictors on downticks than upticks. 3) Suggests cointegration should be considered when examining information flow between markets.
Flemming <i>et al</i> (1996)	CBOE/ S&P 500/ S&P 100 (Intraday)	Equity/ Derivative	1) Price adjustment in index futures leads index options which leads cash market. 2) Price adjustment in cash market leads stock options market. 3) Findings are consistent with trading cost hypothesis.

<sup>1</sup> Finnish market value-weighted index

Table 2.

Average trading activity and bid-ask spread across stock and options with different levels of moneyness and time to maturity. Panels A, B and C denote the proportion of the total population that each category of option comprises, while Panels D, E and F are absolute and relative bid-ask spread measures.

	Grand Average	Out of the Money <sup>1</sup>		At the Money		In the Money	
		Far	Near <sup>2</sup>	Far	Near	Far	Near
<i>Panel A: Daily Volume (number of shares or options)</i>							
Stocks	134.2						
Options	21.1	0.17	0.16	0.15	0.41	0.03	0.08
Calls	14.5	0.19	0.15	0.14	0.42	0.03	0.08
Puts	6.6	0.12	0.19	0.15	0.41	0.05	0.07
<i>Panel B: Daily \$ Volume (millions of dollars)</i>							
Stocks	\$125.78						
Options	\$8.78	0.09	0.08	0.14	0.51	0.05	0.14
Calls	\$6.61	0.09	0.07	0.12	0.52	0.04	0.16
Puts	\$2.16	0.08	0.11	0.17	0.49	0.07	0.07
<i>Panel C: Number Of Trades</i>							
Stocks	2304						
Options	558	0.13	0.13	0.14	0.47	0.05	0.08
Calls	372	0.13	0.15	0.12	0.48	0.04	0.08
Puts	187	0.12	0.11	0.18	0.47	0.07	0.06
<i>Panel D: Absolute Spread (ask price less bid price)</i>							
Stocks	0.02						
Options	0.33	0.30	0.19	0.42	0.30	0.50	0.50
Calls	0.33	0.30	0.18	0.44	0.30	0.61	0.53
Puts	0.32	0.29	0.20	0.40	0.30	0.38	0.44
<i>Panel E: Percentage Bid/Ask Spread<sup>3</sup></i>							
Stocks	0.2%						
Options	18.6%	19.8%	35.8%	11.4%	18.4%	7.9%	8.23%
Calls	18.2%	19.6%	34.4%	10.7%	17.5%	6.9%	7.3%
Puts	19.4%	20.0%	39.1%	12.2%	20.0%	9.1%	10.5%
<i>Panel F: Unlevered Spread<sup>4</sup></i>							
Stocks	0.02						
Option	0.09	0.13	0.13	0.11	0.07	0.11	0.07
Call	0.08	0.10	0.10	0.08	0.06	0.08	0.07
Put	0.12	0.21	0.19	0.14	0.09	0.13	0.06

<sup>1</sup>An at-the-money option is classified as an option with a strike price within 5% of the underlying spot.

<sup>2</sup>An option is classified as "near" maturity if the time to maturity is less than one quarter and "far" otherwise.

<sup>3</sup>Percentage spread is calculated by dividing absolute spread by the spread midpoint.

<sup>4</sup>The unlevered spread is calculated as  $\frac{\text{Price}}{\text{Delta}} \times \text{Percentage Spread}$

Table 3.  
ADF test for Unit Roots

Variable	Company	Degree of Augmentation ADF(J)	t-statistic	I(1)?
Stock	ANZ	ADF(1)	-0.561	Yes
	BHP	ADF(0)	-16.09*	No
	CRA	ADF(5)	-1.1690	Yes
	MIM	ADF(0)	-165.193*	No
	NAB	ADF(0)	-18.135*	No
	NCP	ADF(0)	-6.035*	No
	WMC	ADF(2)	-1.006	Yes
Option	ANZ	ADF(10)	-1.353	Yes
	BHP	ADF(7)	-16.110*	No
	CRA	ADF(5)	-1.169	Yes
	MIM	ADF(0)	-162.382*	No
	NAB	ADF(4)	-18.998*	No
	NCP	ADF(3)	-6.0724*	No
	WMC	ADF(10)	-1.592	Yes

\*Denotes rejection of the unit root null at the 1% level.

Table 4.  
Johansen Cointegration Test of Stock and Option Series

Company	Test Statistic	Likelihood Ratio	1 % Critical Value	Hypothesised No. of CE(s)	Cointegrating Rank
ANZ	$\lambda_{trace}$	419.56	20.04	None *	1
	$\lambda_{max}$	0.34	6.65	At most 1	
CRA	$\lambda_{trace}$	541.55	20.04	None *	1
	$\lambda_{max}$	1.34	6.65	At most 1	
WMC	$\lambda_{trace}$	571.98	20.04	None *	1
	$\lambda_{max}$	1.045	6.65	At most 1	

\*Denotes rejection at the 1% level.

Table 5 Causal Relationships between Changes ( $\Delta$ 's) in Stock and Option Price Innovations

$$\Delta S_t = \alpha_1 + \sum_{i=1}^n \beta_i \Delta S_{t-i} + \sum_{i=1}^n \phi_i \Delta O_{t-i} + \varepsilon_{1t}$$

$$\Delta O_t = \alpha_2 + \sum_{i=1}^n \theta_i \Delta S_{t-i} + \sum_{i=1}^n \varphi_i \Delta O_{t-i} + \varepsilon_{2t}$$

$\Delta S_t$  is the innovation in the change in spot price of stock at time t and  $\Delta O_t$  is the innovation in the change in spot price implied by option trading in time t.

Endogenous Coefficient	Company					
	ANZ		BHP		CRA	
	$\Delta S_t$	$\Delta O_t$	$\Delta S_t$	$\Delta O_t$	$\Delta S_t$	$\Delta O_t$
$\alpha_1 / \alpha_2$	-0.000 (-0.01)	0.000 (0.00)	-0.001 (-0.03)	-0.008 (-3.37)**	0.000 (0.03)	-0.000 (-0.03)
$\beta_1 / \theta_1$	-0.001 (-0.07)	0.365 (5.44)**	-0.023 (-1.50)	0.254 (5.90)**	-0.011 (-0.76)	0.126 (4.31)
$\beta_2 / \theta_2$	0.003 (0.25)	0.426 (6.32)**	-0.001 (-0.11)	0.243 (5.63)**	0.002 (0.14)	0.116 (3.99)**
$\beta_3 / \theta_3$	0.013 (0.87)	0.376 (5.56)**	-0.002 (-0.10)	0.212 (4.89)**	0.004 (0.27)	0.094 (3.22)**
$\beta_4 / \theta_4$	0.017 (1.11)	0.321 (4.72)**	0.005 (0.34)	0.190 (4.40)**	0.012 (0.78)	0.068 (2.33)*
$\beta_5 / \theta_5$	0.015 (0.95)	0.172 (2.52)*	0.020 (1.30)	0.133 (3.08)**		
$\beta_6 / \theta_6$			-0.000 (-0.16)	0.099 (2.37)*		
$\phi_1 / \varphi_1$	0.004 (1.18)	-0.051 (-3.32)**	-0.005 (-0.99)	-0.703 (-38.38)**	0.030 (3.69)**	-0.016 (-1.07)
$\phi_2 / \varphi_2$	-0.002 (-0.78)	0.034 (2.19)*	0.003 (0.50)	-0.630 (-34.50)**	0.022 (2.67)**	-0.000 (-0.03)
$\phi_3 / \varphi_3$	-0.004 (-0.78)	-0.008 (-0.55)	0.002 (0.38)	-0.431 (-20.97)**	-0.005 (0.71)	-0.012 (-0.80)
$\phi_4 / \varphi_4$	0.004 (1.19)	0.001 (0.10)	0.010 (1.35)	-0.211 (-10.30)**	0.016 (1.99)*	-0.012 (-0.78)
$\phi_5 / \varphi_5$	-0.000 (-0.05)	-0.028 (-1.84)	0.008 (1.22)	-0.111 (-6.12)**		
$\phi_6 / \varphi_6$			0.002 (0.47)	-0.122 (-7.84)**		
<b>F-Test<sup>‡</sup>:</b> $\Delta O_t$ Does Not Cause $\Delta S_t$	1.60 (Cannot reject)		0.63 (Cannot reject)		5.96 (Cannot reject)	
<b>F-Test:</b> $\Delta S_t$ Does Not Cause $\Delta O_t$	20.10** (Reject)		67.55** (Reject)		13.01 (Cannot reject)	
<i>Direction of Causality</i>	<i>Stock to Option</i>		<i>Stock to Option</i>		<i>No causality</i>	

Endogenous Coefficient	Company							
	MIM		NAB		NCP		WMC	
	$\Delta S_t$	$\Delta O_t$	$\Delta S_t$	$\Delta O_t$	$\Delta S_t$	$\Delta O_t$	$\Delta S_t$	$\Delta O_t$
$\alpha_1 / \alpha_2$	-0.000 (-0.57)	-0.000 (-0.11)	0.000 (0.98)	-0.006 (-2.68)	0.000 (1.27)	0.001 (1.11)	0.000 (0.01)	0.000 (0.01)
$\beta_1 / \theta_1$	-0.002 (-0.13)	0.244 (4.23)**	0.002 (0.15)	0.430 (5.52)**	-0.001 (-0.07)	0.355 (5.93)**	-0.004 (-0.28)	0.425 (6.07)**
$\beta_2 / \theta_2$	0.003 (0.21)	0.136 (2.34)*	0.000 (0.05)	0.482 (6.13)**	-0.014 (-0.91)	0.263 (4.34)**	-0.012 (-0.77)	0.488 (6.94)**
$\beta_3 / \theta_3$	-0.003 (-0.22)	0.154 (2.65)**	0.014 (0.89)	0.261 (3.31)**	0.013 (0.87)	0.213 (3.51)**	0.021 (1.38)	0.559 (7.91)**
$\beta_4 / \theta_4$	-0.012 (-0.82)	0.185 (3.19)	-0.001 (-0.11)	0.173 (2.20)*	0.013 (0.84)	0.188 (3.11)**	-0.001 (-0.10)	0.469 (6.58)**
$\beta_5 / \theta_5$	-0.008 (-0.57)	0.234 (4.05)**	0.015 (1.00)	0.182 (2.32)*	0.018 (1.19)	0.294 (4.86)**	-0.004 (-0.29)	0.472 (6.61)**
$\beta_6 / \theta_6$	-0.006 (-1.46)	0.122 (7.94)**	-0.000 (-0.17)	0.055 (2.44)*	-0.004 (-0.80)	0.106 (5.25)**	-0.013 (-0.82)	0.345 (4.82)**
$\phi_1 / \varphi_1$	0.006 (1.42)	-0.275 (-17.73)**	0.002 (0.66)	-0.569 (-36.69)**	0.006 (1.57)	-0.409 (-26.35)**	0.009 (0.71)	-0.055 (-3.57)**
$\phi_2 / \varphi_2$	-0.001 (-0.39)	-0.120 (-7.57)**	-0.002 (-0.56)	-0.435 (-24.66)**	-0.002 (-0.51)	0.013 (0.83)	0.005 (0.65)	-0.041 (-2.69)**
$\phi_3 / \varphi_3$	0.004 (0.97)	-0.141 (-8.90)**	0.001 (0.50)	-0.322 (-17.47)**	-0.003 (-0.77)	-0.005 (-0.34)	0.001 (0.33)	-0.020 (-1.33)
$\phi_4 / \varphi_4$	0.000 (0.12)	-0.137 (-8.67)**	0.002 (0.72)	-0.236 (-12.89)**	-0.000 (-0.01)	-0.090 (-5.60)**	0.000 (0.20)	-0.048 (-3.18)**
$\phi_5 / \varphi_5$	0.001 (0.35)	-0.155 (-9.79)**	-0.001 (-0.29)	-0.176 (-10.13)**	0.000 (0.14)	-0.129 (-8.26)**	-0.000 (-0.14)	-0.025 (-1.67)
$\phi_6 / \varphi_6$	0.006 (1.48)	-0.118 (-7.74)**	0.000 (0.17)	-0.114 (-7.52)**	0.002 (0.71)	-0.062 (-4.23)**	0.002 (0.86)	-0.003 (-0.24)

F-Test:				
$\Delta O_t$ Does Not Cause $\Delta S_t$	3.59 (Cannot reject)	0.03 (Cannot reject)	1.24 (Cannot reject)	1.64 (Cannot reject)
F-Test:				
$\Delta S_t$ Does Not Cause $\Delta O_t$	106.52** (Reject)	15.86** (Reject)	33.09** (Reject)	38.85** (Reject)

*Direction of Causality*      *Stock to Option*      *Stock to Option*      *Stock to Option*      *Stock to Option*

\*significant at the 5% level. \*\*significant at the 1% level.

$$\ddagger F = \frac{T(RSS_o - RSS_1)}{RSS_1} \sim \chi^2(p)$$

Construction of the F-statistic entails estimation of an unrestricted regression against a restricted regression with all exogenous series. In this, T = sample size, RSS = residual sum of squares with subscripts denoting restricted (1) and unrestricted (0) and P = number of restricted coefficients.

Table 6. Summary Causality Testing

Panel A: Spot and options trading activity (net trade volume<sup>#</sup>) causality testing

Company	Null Hypothesis	F-Statistic	Lead (min)	Direction of Causality
ANZ	<i>Option Activity does not Granger Cause Stock Activity</i>	2.96*	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	1.76		
BHP	<i>Option Activity does not Granger Cause Stock Activity</i>	24.89**	30	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	2.17		
CRA	<i>Option Activity does not Granger Cause Stock Activity</i>	26.19**	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	1.87		
MIM	<i>Option Activity does not Granger Cause Stock Activity</i>	14.82**	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	2.32		
NAB	<i>Option Activity does not Granger Cause Stock Activity</i>	5.93**	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	1.76		
NCP	<i>Option Activity does not Granger Cause Stock Activity</i>	5.04**	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	0.96		
WMC	<i>Option Activity does not Granger Cause Stock Activity</i>	7.63**	15	Options to Stock
	<i>Stock Activity does not Granger Cause Option Activity</i>	1.04		

\*significant at the 5% level. \*\*significant at the 1% level.

<sup>#</sup> Net trading volume is net number of shares traded (buy less sell)

$$\ddagger F = \frac{T(RSS_0 - RSS_1)}{RSS_1} \sim \chi^2(p)$$

Construction of the F-statistic entails estimation of an unrestricted regression against a restricted regression with all exogenous series. In this, T = sample size, RSS = residual sum of squares with subscripts denoting restricted (1) and unrestricted (0) and P = number of restricted coefficients.

Panel B: Stock price innovations vs options trading activity (net trade volume<sup>#</sup>) causality testing

Company	Null Hypothesis	F-Statistic	Lead (min)	Direction of Causality
ANZ	<i>Option Activity does not Granger Cause Stock Prices</i>	8.26**	-	Feedback
	<i>Stock Prices do not Granger Cause Option Activity</i>	3.13**		
BHP	<i>Option Activity does not Granger Cause Stock Prices</i>	4.81**		Options to Stock
	<i>Stock Prices do not Granger Cause Option Activity</i>	0.39	15	
CRA	<i>Option Activity does not Granger Cause Stock Prices</i>	5.04**		Options to Stock
	<i>Stock Prices do not Granger Cause Option Activity</i>	1.23	45	
MIM	<i>Option Activity does not Granger Cause Stock Prices</i>	75.6**		Options to Stock
	<i>Stock Prices do not Granger Cause Option Activity</i>	0.98	30	
NAB	<i>Option Activity does not Granger Cause Stock Prices</i>	0.58		No causality
	<i>Stock Prices do not Granger Cause Option Activity</i>	0.21	-	
NCP	<i>Option Activity does not Granger Cause Stock Prices</i>	0.42		No causality
	<i>Stock Prices do not Granger Cause Option Activity</i>	0.37	-	
WMC	<i>Option Activity does not Granger Cause Stock Prices</i>	16.77**		Options to Stock
	<i>Stock Prices do not Granger Cause Option Activity</i>	1.91	30	

\*significant at the 5% level. \*\*significant at the 1% level.

<sup>#</sup> Net trading volume is net number of shares traded (buy less sell)

Panel C: Stock trading activity (net trade volume<sup>#</sup>) vs options price innovations causality testing

Company	Null Hypothesis	F-Statistic	Lead (min)	Direction of Causality
ANZ	<i>Stock Activity does not Granger Cause Option Prices</i>	6.13**	30	Stock to Options
	<i>Option Prices do not Granger Cause Stock Activity</i>	0.51		
BHP	<i>Stock Activity does not Granger Cause Option Prices</i>	6.94**	45	Stock to Options
	<i>Option Prices do not Granger Cause Stock Activity</i>	0.98		
CRA	<i>Stock Activity does not Granger Cause Option Prices</i>	6.14**	-	Feedback
	<i>Option Prices do not Granger Cause Stock Activity</i>	3.71**		
MIM	<i>Stock Activity does not Granger Cause Option Prices</i>	3.11**	30	Stock to Options
	<i>Option Prices do not Granger Cause Stock Activity</i>	1.69		
NAB	<i>Stock Activity does not Granger Cause Option Prices</i>	3.65**	15	Stock to Options
	<i>Option Prices do not Granger Cause Stock Activity</i>	0.75		
NCP	<i>Stock Activity does not Granger Cause Option Prices</i>	0.34	-	No causality
	<i>Option Prices do not Granger Cause Stock Activity</i>	0.53		
WMC	<i>Stock Activity does not Granger Cause Option Prices</i>	9.62**	15	Stock to Options
	<i>Option Prices do not Granger Cause Stock Activity</i>	0.25		

\*significant at the 5% level. \*\*significant at the 1% level.

<sup>#</sup> Net trading volume is net number of shares traded (buy less sell)