The Implied Volatility of Australian Index Options

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ABSTRACT

We construct a new measure of Australian stock market volatility based on the implied volatility of S&P/ASX Index options. Dubbed the Australian Market Volatility Index (AVIX), it is constructed in a manner similar to the popular CBOE Market Volatility Index (VIX) in the United States. We examine the statistical properties of AVIX and the temporal relationship between AVIX changes and S&P/ASX 200 Index returns, and also investigate the presence of any seasonalities in AVIX before assessing AVIX as a predictor of future volatility. Consistent with VIX, we find that AVIX exhibits large negative first-order autocorrelation, and is also negatively correlated with lagged and contemporaneous S&P/ASX 200 Index returns. However, AVIX exhibits no asymmetry in its response to positive and negative return shocks. As a predictor of future volatility, AVIX performs poorly compared to historical volatility. Interestingly, when nonsynchronous trading is controlled for, we find that AVIX exhibits a much stronger relationship with future volatility.

1 Introduction

Stock market volatility is an important variable for financial decision-making. As a measure of risk, volatility is significant when deciding how and where to invest. Measuring market volatility is also important in the pricing of derivatives. Portfolio insurance and covered-call writing both rely on accurate forecasts of market volatility.

Techniques employed to measure market volatility have been diverse, but they can be broadly separated into two categories. The first is based on using past volatility. The second technique involves using the implied volatility of options contracts. Pioneered by Latane and Rendleman (1976) this involves solving an option pricing formula backwards for the volatility implied by the prevailing option price. Implied volatility has been assessed by many to be a superior predictor of future volatility because it represents the opinion of the market and incorporates a number of factors that historical volatility cannot -- such as upcoming elections or the prospect of war. To employ this technique, stock index options are generally used to derive a measure of market-wide volatility. In the United States of America, an index of market volatility was developed by the Chicago Board Options Exchange (CBOE). Called the Market Volatility Index (VIX), it is constructed using a portfolio of call and put options on the Standard and Poor's (S&P) 100 Index options. VIX has become popular as a measure of market-wide volatility and the CBOE has used the same volatility measurement technique to create the VXN -- which is the equivalent market volatility index on NASDAQ.

By stark contrast, the volatility of the Australian Stock Exchange has not received great attention. In particular, research into the implied volatility characteristics of the Australian market is non-existent. This study seeks to rectify that by making a first attempt at constructing an index of Australian market volatility, in a manner similar to that used by the CBOE. The focus is exploratory and for the most part our results are not conclusive. Rather, we seek to motivate future research into Australian market volatility. The construction of the Australian Market Volatility Index (AVIX) can be refined, and the predictive tests be made more thorough by using more sophisticated modelling. The commonality of volatility between the United States and Australia is also explored here.

This study was inspired by Fleming, Ostdiek and Whaley (1995), who examined the characteristics of VIX, including univariate properties, co-movements with stock returns and its performance as a predictor of future volatility. The results obtained for AVIX are not totally consistent with VIX, and a number of reasons are postulated for this.

This paper is organised as follows. The next section reviews the literature covering stock market volatility and supplies a number of testable hypotheses. Section 3 discusses the relevant features of the S&P/ASX 200 Index options market in Australia. Section 4 outlines the data used and the procedure employed to calculate AVIX, and also discusses the analysis employed to test our hypotheses. Section 5 reports the results of the study. Section 6 offers some conclusions and provides a short summary.

2.1 Calculation of Implied Volatility

The publication of the option pricing model of Black and Scholes (1973) and its extensions by Merton (1973) has to date generated significant interest amongst market participants and finance academics. If the Black-Scholes/Merton option pricing formula is assumed to be correct, then given a prevailing option price we can calculate the volatility that is consistent with this option price. This is known as the *implied* volatility. Unfortunately the complex nature of the Black-Scholes/Merton model means that a closed-form solution for calculating implied volatility does not exist. A common procedure employed is the Newton-Raphson algorithm. This is an iterative search technique whereby different values of volatility are input in the Black-Scholes/Merton formula. The iterative process can be described by the formula

$$\sigma_{i+1} = \sigma_i - \frac{c(\sigma_i) - c_m}{\partial c / \partial \sigma_i}$$

where σ_i = estimate of implied volatility at step i

$c(\sigma_i)$ = call option price supplied by Black - Scholes when σ_i is used as the input for volatility

c_m = known market price of the call option

$\partial c / \partial \sigma_i$ = option vega evaluated using σ_i

This procedure continues until the difference between the option price calculated using the estimated implied volatility and the actual market option price is smaller than some predefined level of accuracy ε ie until

$$\left| c_m - c(\sigma_{i+1}) \right| \leq \varepsilon$$

For the Newton-Raphson technique to be employed an initial estimate of the implied volatility is needed, which we will denote by σ_1. Manaster and Koehler (1982) calculate a starting value that will speed up the rate of convergence of the Newton-Raphson technique

$$\sigma_1 = \left[\left| \ln(S/X) + rT \right| \frac{2}{T} \right]^{\frac{1}{2}}$$

Brenner and Subrahmanyam (1988) suggest a starting value that they believe is superior in terms of computational speed, to the Manaster and Koehler (1982) formula[3]

$$\sigma_1 = (c_m / S) \times \frac{1}{\left(1/\sqrt{2\pi}\right)\sqrt{t}}$$

2.2 Measuring Market Volatility

Latane and Rendleman (1976) were the first researchers to derive and use implied volatilities. This was conducted on 24 individual companies with stock options that traded on the CBOE. A number of related papers also used implied volatility to draw inferences on market volatility. Gastineau (1977) utilised option premiums to create a crude measure of market-wide volatility. He created an index of market volatility by averaging the at-the-money call options of 14 stocks. This was later refined by Cox and Rubenstein (1985) by including multiple call options on each stock. The volatilities of these options were weighted in order to make the index at-the-money and give it a constant time to expiry. Poterba and Summers (1986) used the CBOE Call Option Index to analyse implied volatility. This index was the

[3] This formula is capable of directly finding the implied volatility of an option if the current stock price equals the discounted exercise price.

average percentage option premium relative to the underlying stock price for each stock for a hypothetical six-month at-the-money option.

Whilst providing a broad average of stock option implied volatilities, these indexes were still subject to idiosyncratic risk associated with each of the stocks and options within the index. They did not truly represent a market-wide measure of volatility. Furthermore, Fleming, Ostdiek and Whaley (1995) argued that by only using call options these measures were subject to bias in rapidly rising and falling markets. On March 11, 1983 the CBOE introduced the S&P 100 Index options. Because the S&P 100 represents a well diversified portfolio of stocks, market observers could interpret the implied volatility of these index options as market-wide volatility.

A number of shortcomings have been identified in using index options. Earlier research by Brenner and Galai (1984) warned that using daily closing option prices were significantly different to the daily average option price. They suggested that using daily average option prices would be more appropriate. Harvey and Whaley (1991) examined the characteristics of S&P 100 Index options and found that a number of simplifying characteristics could have a detrimental effect on implied volatility calculation. The index options market closes at 3:15pm each day whereas the underlying stock market closes at 3:00pm. Thus index option closing prices and the S&P 100 closing values are asynchronous. As information arrives after 3pm, the option prices change to reflect the news, but implied volatilities are calculated using the 3pm index level. This causes the implied volatility estimate to change since it is the only variable that can freely change. The following day, the index level changes to reflect the information from the previous day and the implied volatility reverses. This means that negative serial correlation is induced in the implied volatility series. Scholes and Williams (1977) demonstrated that using nonsynchronous return data can lead to a serious errors in variables problem whereby the closing return over a measurement interval is used to measure the true return. This closing return is invariably measured with error because the final trade or quote in the time interval will occur prior to the end of the interval. The result of this is that return variances are overstated and first order negative serial correlation is induced for single securities.[4] Miller, Muthuswamy and Whaley (1994) examine the implications of nonsynchronous trading on the S&P 500 Index basis.[5] Positive serial correlation is induced in the S&P 500 index because as information arrives, frequently traded stocks move immediately, but the more infrequently traded stocks adjust over a number of time intervals. Harvey and Whaley (1991) found that the different closing prices had a pronounced effect on the serial correlation of implied volatility. However, even when 3:00pm option prices were used, the spurious negative autocorrelation remained.

The problems highlighted above presented caveats to analysing the implied volatility of the market. In particular, the choice of index option contracts to use in measuring market volatility was entirely subjective. The CBOE responded by introducing the Market Volatility Index (VIX) in 1993. This index was based on the implied volatilities of eight S&P 100 Index options. These options were weighted such that the index was always at-the-money and had a constant 30 calendar-days to expiry. It includes both put and call options.[6] Whaley (1993) demonstrated that volatility derivatives based on an index such as VIX could hedge

[4] Also see Lo and MacKinlay (1990) who present a model of nonsynchronous trading and demonstrate the consequences of the infrequent trading problem.

[5] The basis is defined as the futures price minus the underlying spot price.

[6] For a detailed explanation of VIX calculation see Whaley (1993) or Fleming, Ostdiek and Whaley (1995).

against volatility risk much more efficiently than using index options. The CBOE has since introduced the NASDAQ-100 Volatility Index (VXN) as an alternative measure of market volatility over the technology-heavy NASDAQ exchange.

2.3 The Relationship between Market Volatility and Returns

Research into stock market returns and volatility has produced some interesting results and a variety of explanations for them. Black (1976) documented a strong negative contemporaneous correlation between returns and volatility. He reasoned that this negative correlation was caused by a "leverage effect". When the value of the firm falls, this causes the stock price to decline which results in a higher leverage of the firm. This higher leverage increases the risk of the stock and subsequently volatility increases. Christie (1982) made similar conclusions using a more formal test of the significance of financial leverage on return volatility. Black (1976) points out that this relationship is not one of direct causation, but rather exogenous factors contribute to returns and volatility being negatively correlated.

An alternative explanation to the leverage effect is the "time-varying risk premium effect". Under this hypothesis the order of causation is reversed, namely shocks to volatility result in a change in the risk premium for a stock and thus causes its price to change. This hypothesis relies on volatility being persistent, such that future volatility and hence future risk premia are affected substantially. This was noted by Poterba and Summers (1986) who modelled the time-varying risk premium hypothesis under the assumption that firms had no leverage. This isolated the effect of volatility shocks on future risk premia. They found that the impact of volatility shocks was very small, and other factors were at work in explaining the negative correlation between stock market returns and volatility. Some support was given to the time-varying risk premium hypothesis by French, Schwert and Strambaugh (1987) who found that a positive relationship exists between volatility and expected returns which implies a negative relationship exists between stock prices and current volatility. They also find unexpected returns are negatively correlated with unexpected changes in volatility. Fleming, Ostdiek and Whaley (1995) also found a negative contemporaneous correlation between VIX changes and S&P 100 Index returns. However, they found a positive relationship between VIX changes and lead and lag index returns, also consistent with French, Schwert and Strambaugh (1987).

Empirically, not only is the relationship between stock market returns and volatility observed to be negative, but also asymmetric (Schwert (1989, 1990)). That is, negative price shocks have a large positive impact on volatility whereas positive price shocks have a smaller impact on volatility. Fleming, Ostdiek and Whaley (1995) found supporting evidence of this using VIX and S&P 100 Index returns. The impact of a negative price shock on volatility was found to be more than twice as large in magnitude to that of a positive price shock. This result was also supported by Davidson et al. (2001) who examined whether asymmetry existed in alternative markets such as interest rates and commodities. A popular explanation for this is "volatility feedback", where a current price shock causes changes to expected volatility as well as current volatility. When bad news is released, the stock price will fall in response, thus increasing volatility. If volatility is assumed to be persistent then this causes expected volatility to rise, thus leading to a further fall in stock price. If the news is good, then the stock price rises, thus increasing current and expected volatility, which causes a fall in stock price that, to some degree, counteracts the initial price movement.

The above theoretical and empirical developments lead to a number of testable hypotheses regarding the relationship between volatility and returns. There are no reasons why the leverage effect or the time-varying risk premium effect should not hold for Australia. This leads to Hypothesis 1:

Hypothesis 1: A negative contemporaneous correlation exists between AVIX and S&P/ASX 200 Index returns.

Furthermore, the volatility feedback effect suggests a second hypothesis:

Hypothesis 2: Changes in AVIX are much larger for negative shocks to S&P/ASX 200 Index returns than positive shocks.

2.4 Implied Volatility as a Predictor of Realised Volatility

The Black-Scholes/Merton model interprets the (known and constant) volatility as the instantaneous volatility of the underlying security. How then do we interpret what implied volatility means? We could deduce that it is the market's measure of volatility at a particular instant in time. Feinstein (1989) however demonstrated that implied volatility can approximate the market expectation of the average volatility over the remaining life of the option. Given this, implied volatility is a forecast of future realised volatility. Thus we can assess how well implied volatility actually forecasts future volatility.

Most research has found that implied volatility is useful in predicting future realised volatility. Latane and Rendleman (1976) found that their weighted implied standard deviations on individual stocks were superior predictors to forecasts using historical volatility. Chiras and Manaster (1977) and Schmalensee and Trippi (1978) produce similar results comparing implied volatility to historical volatility predictions. Chiras and Manaster (1977) found that this predictability resulted in a profitable trading strategy, suggesting that the option markets were not efficient. Unfortunately, only Chiras and Manaster (1977) considered dividends in any form, and they use continuous dividends in the Black-Scholes/Merton (1973) model for European options. Harvey and Whaley (1992) found that the implied volatility of S&P 100 Index options also enabled some predictability of future realised volatility; however, once trading costs were taken into account, a profitable trading strategy did not exist.

A different angle was taken by Day and Lewis (1992) regarding implied volatility as a predictor of future volatility. They added implied volatility as incremental information for forecasting under GARCH and EGARCH volatility specifications. They found that implied volatility added incremental information to the forecasts give by the GARCH and EGARCH models. Furthermore, these conditional heteroskedastic models were found to enhance the forecasts made using implied volatility, suggesting that the best method of forecasting future volatility may be a combination of historical volatility and implied volatility. This was supported by Hol and Koopman (2000) who added implied volatility to a stochastic volatility model. Implied volatility was found to add significant incremental information to forecasts of future volatility, but forecasts based on implied volatility alone were found to be poor, exhibiting an upward bias.

A number of more recent articles have noted that implied volatility is significantly biased in it forecast of future volatility.[7] Furthermore, some articles have found that implied volatility is a poor predictor of future volatility. Gastineau (1977) found this using his crude measure of market volatility, but the central paper arguing against implied volatility forecasts is Canina and Figlewski (1993) who find that implied volatility forecasts are so poor, they are subsumed by historical volatility. These results seem to suggest that option markets are inefficient, and a number of studies have sought to explain them. Perhaps the most comprehensive examination of problems associated with implied volatility comes from Figlewski (1997).[8] A number of reasons are postulated as to why implied volatilities may not be expected to give good forecasts of future volatility. First and foremost, returns do not conform to the log-normal diffusion process as assumed by Black-Scholes/Merton. Typically, returns exhibit "fat tails" whereby there is a greater proportion of large price movements than predicted by the log-normal diffusion process. Second, the costs associated with constructing a riskless hedge to profit from pricing disparity may be prohibitively large. Nowhere is this more true than index options. In order to profit from a pricing disparity in index options, a trader would need to invest in each stock in the index.[9] Third, option traders may behave differently to the way academics predict. Market makers may only have a holding period of a few hours, and Figlewski (1997) argued that they are more interested in what will happen to implied volatility over the course of their holding period rather than over the life of the option. Even if there is an apparent pricing disparity, the market maker may find it more profitable to generate high trading volumes at the current prices and receive the bid-ask spread than set up a hedge (as predicted by Black and Scholes (1973)) in order to profit from the disparity. Figlewski (1997) also raised a number of concerns over options that are deep in- or out-of-the-money with little time to expiry. These centre around the impact of the bid-ask spread and investor behaviour, but since in this study we are dealing with at-the-money options this concern is not highly relevant.

Implied volatilities are a forward-looking measure of market volatility, whereas historical volatility models are backward-looking. On the strength of this argument, and the findings of previous studies, we develop a third hypothesis:

Hypothesis 3: AVIX is a superior predictor of future volatility than historical volatility.

Based on the arguments above, we do not expect implied volatility to present an unbiased forecast of future volatility.

3 Volatility in Australia.

To date research on stock market volatility in general in Australia is under-represented. A historic review of volatility in Australia was conducted by Kearns and Pagan (1993). They

[7] Such as Lamoureax and Lastrapes (1993) on individual stock options, Jorion (1995) with currency options and Fleming (1998) with S&P 100 Index options. Fleming, Ostdiek and Whaley (1995) also find bias in the forecasts supplied by VIX.

[8] See also Mayhew (1995) and Poon and Granger (2001) for discussions on the problems associated with forecasting volatility with implied volatilities.

[9] Furthermore, the overall dollar position of index options is 25 times the index value in the case of the S&P 100 Index options and 10 times the index value in the case of S&P/ASX 200 Index options. In order to hedge this investment, it is likely that odd lots of stock would need to be traded due to the small portion of the index occupied by each stock.

find that volatility in Australia does not behave in a similar fashion to volatility in the United States. The apparent asymmetry in volatility to good and bad news is much more subdued in Australia. This result casts doubt on the accuracy of Hypothesis 2. In addition, Australian volatility in the last twenty years has been disproportionately high compared to its historical average, unlike the United States. A number of other papers have sought to model historical stock market volatility in Australia. Brailsford and Faff (1996) undertook a comprehensive study seeking to fit a number of different models[10] and assessed their predictive performance against different measures of prediction error.[11] No one model was consistently the best, but the GJR-GARCH model did perform relatively well.[12] Of interest is an article by Walsh and Tsou (1998) who evaluate the trade-off between diversification and non-trading. When market volatility is being measured over a narrow index such as the top 20 stocks, non-trading is not a major issue in forecasting volatility, however the lack of diversification leaves models open to errors caused by idiosyncratic risk. If the index used is widened, then diversification removes much of this idiosyncratic risk but the additional stocks added are likely to suffer from non-trading effects. At the hourly level, the non-trading effects were found to be substantial, but they were not as influential for daily and weekly data frequencies.

A common theme throughout is the emphasis on analysing ex-post historical volatility. I was unable to locate any definitive study of implied volatility characteristics or performance for the Australian Stock Exchange, either for individual stock option contracts or indexes. This clearly represents an area with great research potential and is discussed more completely towards the end of this dissertation. Features of S&P/ASX 200 Index Options

3.1 Institutional Details

Options are traded on the Australian Stock Exchange Derivatives (ASXD) market, which is a subsidiary of the Australian Stock Exchange (ASX). Options are traded on the Derivatives Trading Facility (DTF), also known as CLICK because it is based on the popular market trading system of the same name. This system was introduced on October 31, 1997. Prior to this, options were traded on an open outcry system.

Brokers and market makers trade on the DTF by entering orders into a computer terminal situated at their place of business. These orders are transmitted to the host computers of the ASXD, which then transmits information about these orders to other brokers' terminals. Trades are executed by the DTF on a price and time priority basis.

The market for stock options opens from 10:00am in a staggered fashion consistent with the opening procedure on SEATS[13]. The market closes from 12:30pm until 2:00pm and then trades until 4:00pm. Extended trading is allowed but market makers have no obligations during these market phases. Index options trade from 9:50am until 4:30pm with no market closure in the middle of the day. The underlying stock market closes at 4:05pm so this creates

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[10] The models used included the random walk, historical mean, moving average, exponential smoothing, exponentially weighted moving average, simple regression, GARCH and GJR-GARCH.

[11] The prediction errors used were the mean error, mean absolute error, root mean squared error and mean absolute percentage error.

[12] Also see Brailsford and Faff (1993) who model Australian volatility in the ARCH and GARCH frameworks.

[13] Stock Exchange Automated Trading System. This is the automated trading facility for the underlying equities traded on the ASX.

a problem of non-synchronous closing prices in the options and equities markets, similar to that discussed by Harvey and Whaley (1991) for the United States.

The S&P/ASX 200 Index Option contract is designated by the security code XJO on the ASXD. The underlying security is the S&P/ASX 200 Index, and the total underlying value is the index value multiplied by $10. The options are European style and trade on a quarterly expiration cycle. Exercise prices are set 25 index points apart, and both call and put options can be traded. The contracts expire at 4:15pm on the last business day of the expiry month.[14] The options are cash settled.

4 Data and Methodology

Option data for S&P/ASX200 Index options was obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA) for the period from November 8, 1999 to September 27, 2002. It was discovered however that satisfactory data for the creation of a continuous time series of volatility only existed from July 11, 2001. Thus the data set was truncated to start at this time. The data set spans the terrorist attacks on the United States on September 11, 2001 and the uncertainty and rhetoric of a war on Iraq. Since the data does not cover a long time frame, we are overestimating the chances of these somewhat rare events occurring. Therefore, results are reported both including and excluding the two weeks following September 11, 2001.

The data includes the closing ASX/S&P 200 Index level, and bid-ask midpoints, exercise prices and time to expiry for each of the eight required options. Daily Treasury bill rates were used for the risk free rate were obtained from the Reserve Bank of Australia website[15]. The continuous dividend yield on the ASX/S&P 200 Index was also obtained at a daily frequency from SIRCA.

Even though the time period was chosen to maximise the quality of the data, there were a number of days where prices were not available for all eight required option contracts in order to calculate AVIX. This was a result of non-trading in the required option for that day. Measures were employed to estimate these missing prices. If an option price on a given day was missing, the implied volatility of the same class of option contract from the previous day was used as a substitute.[16] This implicitly assumes that volatility follows a random-walk and the best forecast of future volatility is the current volatility. This method was employed in order to reduce the possible impact of interpolation on the time series properties of AVIX. This is also the practice used to calculate a stock index when non-trading occurs in one of the component stocks. As discussed earlier when we use stale prices in order to compute any index we introduce measurement error into our implied volatility data.

4.1 Calculation of AVIX

AVIX will be constructed using eight different S&P/ASX200 Index options' implied volatilities. In order to compute these implied volatilities we need an option price, an option pricing framework, and all the inputs into the option pricing formula (excluding volatility).

[14] From the September 2002 contract this will change to the third Friday of the expiry month.

[15] http://www.rba.gov.au

[16] For example, if the nearest below call option (see Section 4.2 for definitions of nearest and below) was not available, the previous day's nearest below call option was used, regardless of whether it was the same physical contract or not.

The option pricing model used is the standard Black-Scholes/Merton (1973) stock option

$$c = Se^{-qT}N(d_1) - Xe^{-rT}N(d_2)$$

$$p = Xe^{-rT}N(-d_2) - Se^{-qT}N(-d_1)$$

$$d_1 = \frac{\ln\left(\frac{S}{X}\right) + \left(r - q + \frac{\sigma^2}{2}\right)T}{\sigma\sqrt{T}}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

where S = Stock index level

X = Exercise price of the option

r = risk - free interest rate

T = time to expiry of the option in years

σ = volatility of the return on the underlying stock

q = continuous dividend yield

model $N(x)$ = cumulative Normal distribution function

The closing S&P/ASX 200 index level is used as our current index level. The risk-free interest rate was sourced from Treasury bills. Data for 30-day, 60-day and 90-day bills was obtained, and the yield on the bill that has expiry closest to that of the option is used as our risk free rate. The continuous dividend yield on the S&P/ASX 200 was also used.

The option price is found by taking the midpoint of the bid and ask quotes for the option under consideration. This has two advantages over using the actual option price. First, using midpoint prices removes spurious negative autocorrelation described in Roll (1984) resulting from the random "bouncing" of prices between bid and ask prices. Second, midpoints are based on quotes which are more frequently refreshed than trade prices. Not every quote becomes a trade, but every trade is based on two quotes. Thus the risk of using stale prices is reduced. Some of the consequences of using stale prices are discussed in the literature on infrequent trading and non-synchronous trading.[17] It is important that the most recent possible information between the stock index and index option prices is used in order to minimise the impact of nonsynchronicity on our analysis. Implied volatilities were calculated using the Newton-Raphson method with the Manaster and Koehler (1982) starting value.

[17] Miller, Muthuswamy and Whaley (1994) showed that stale prices can cause spurious autocorrelations in the S&P 500 Index basis. Scholes and Williams (1977) and Lo and Mackinlay (1990) also examine the nonsynchronous trading problem in detail.

4.2 Trading-Day Adjustment of Volatility

In computing VIX, the number of trading days to expiry is considered rather than calendar days. This means volatility is expressed as a rate per trading day. French and Roll (1986) found that the return variance of stock returns over the weekend was only 10.7% higher than the trading day variance for all NYSE and AMEX stocks. For the largest quintile, this was only 8.2% higher. Thus it is more appropriate to express volatility on a per-trading-day basis. No comparable Australian study exists so AVIX will be calculated in a similar fashion to preserve consistency.

The component implied volatilities used in the construction of AVIX were also adjusted appropriately. The number of working days until expiry was calculated (ignoring public holidays). Note that this was done simply by aggregating the number of Monday to Friday days left. This is different to the method described in Fleming, Ostdiek and Whaley (1995) because OEX options in the United States always expire on a Friday, whereas up until the June 2002 contract, the S&P/ASX 200 Index options expire on the last business day of the month.

The trading day adjustment is carried out on the implied volatilities as follows,

$$\sigma_t = \sigma_c \left(\sqrt{\frac{N_c}{N_t}} \right)$$

where σ_t = trading day volatlity

σ_c = calendar day volatility

N_t = number of trading days until option expiry

N_c = number of calendar days until option expiry

Fleming, Ostdiek and Whaley (1995) make an important observation regarding this trading-day adjustment. This adjustment is different to simply using the number of trading days to expiry as our input into the Black-Scholes/Merton model. In the model, the time to expiry is important because it describes the expected movement in the index up to expiry as well as the discount that must be applied to our payoffs. These are better described using calendar days until expiry in our option valuation.

4.3 Weighting of Implied Volatilities

The use of index options allows us to derive implied volatilities that are free from idiosyncratic risk. At this stage we will define the "nearest" option series as the option series that is closest to expiry, but with at least eight days to expiry. This is consistent with the CBOE's calculation of VIX. The "second nearest" option series is the one after the nearest option series with regards to time to expiry. The option contract that is "closest above" is the option within a given series that has exercise price closest to, but just above, the current index level. The "closest below" option is defined similarly for the option with exercise price just below the current index level.

We use the following notation:

$X_b(X_a)$ = exercise price of the option just below (above) the current index level

$\sigma_{c,1}^{X_b}$ = implied volatility of the call option (c) just below the current index level (X_b) for the nearest option series (1).

$N_{t_1}(N_{t_2})$ = number of trading days until expiry of the nearest (second nearest) option series

Now we calculate an average implied volatility, using Black and Scholes (1973)/Merton (1973b) option pricing, just below and above the current index level for the closest and second closest index series by:

$$\sigma_1^{X_b} = \frac{\sigma_{c,1}^{X_b} + \sigma_{p,1}^{X_b}}{2}$$

And similarly for $\sigma_1^{X_a}$, $\sigma_2^{X_b}$ and $\sigma_2^{X_a}$.

Having done this, we will assume that the volatility smile is well approximated by a straight line for options close to at-the-money. Thus we create an "at-the-money" implied volatility by linear interpolation between the volatilities either side of the current index level:

$$\sigma_1 = \sigma_1^{X_b}\left(\frac{X_a - S}{X_a - X_b}\right) + \sigma_1^{X_a}\left(\frac{S - X_b}{X_a - X_b}\right)$$

And similarly for σ_2.

The final step is to give the volatility a constant time to expiry. This is done by linear interpolation between the volatilities of the nearest and the second nearest option series. To be consistent with VIX, we will use 22 trading days (30 calendar days) as our constant time to maturity:

$$AVIX = \sigma_1\left(\frac{N_{t_2} - 22}{N_{t_2} - N_{t_1}}\right) + \sigma_2\left(\frac{22 - N_{t_1}}{N_{t_2} - N_{t_1}}\right)$$

An important and possibly problematic distinction must be made between VIX and AVIX construction at this point. The OEX options used to construct VIX have expiry dates every month. Most of the time the nearest option series has less than 22 trading-days until expiry. When the options contracts roll over in calculating VIX, there will be a period of time (approximately 8 trading days) where both options series have more than 22 trading-days to expiry. This means that extrapolation is used rather than interpolation in calculating VIX. The S&P/ASX 200 Index options only trade on a quarterly expiration cycle, so when the options used roll over, the nearest option series is some 65 trading days from expiry, and the second nearest series is around 130 trading-days from expiry. As a result, the creation of a series with constant 22 trading-days to expiry means that rather extreme extrapolation is used. In order to investigate the impact this may have on AVIX, a 66 trading-day AVIX was also constructed and used in our analysis

$$AVIX_{66} = \sigma_1\left(\frac{N_{t_2} - 66}{N_{t_2} - N_{t_1}}\right) + \sigma_2\left(\frac{66 - N_{t_1}}{N_{t_2} - N_{t_1}}\right)$$

There are a number of advantages to using the above approach to calculate market-wide volatility. First, it is relatively simple to calculate if we have all the inputs for the Black-Scholes/Merton option pricing formula. Second, it mitigates bias in rising and falling markets. Fleming, Ostdiek and Whaley (1995) argued that in rising markets, the index level will be stale due to the less frequently traded stocks lagging their true value. This in turn will bias call option implied volatility upwards, but bias put option volatility downwards. Since the bias will be approximately equal and opposite for each, the averaging process will mitigate the inaccuracy. Third, it has the potential to be reportable on a real-time basis in markets. If market data is constantly revised during the day then AVIX could be reported intraday. This will become more viable once the market for S&P/ASX 200 index options develops. There are, of course, disadvantages in using this approach to report market-wide volatility. From a technical viewpoint, it assumes that we have a linear term structure of implied volatility. As described earlier, this is probably more of a problem in the Australian market than in the United States due to the extent of interpolation and extrapolation that is required.

4.4 Statistical Properties of AVIX

As previously discussed, market makers and participants are often more interested in the innovations to volatility rather than the levels of volatility. Thus, with the exception of some descriptive statistics, the changes in AVIX will be examined relative to S&P/ASX 200 Index returns. Our variables of interest will be:

$$\Delta AVIX_t = AVIX_t - AVIX_{t-1}$$

$$r_t = \ln\left(\frac{ASX200_t}{ASX200_{t-1}}\right)$$

$$AVIX_t = \text{the level of AVIX at time t}$$

$$ASX200_t = \text{the level of the S \& P/ASX 200 at time t}$$

Taking the first difference also has the advantage of alleviating the potential nonstationarity of AVIX and the S&P/ASX 200 Index. Such data problems can lead to spurious relationships being found in regression analysis.[18] All variables used in our analysis were verified to be stationary series prior to use.

For both of the above variables we will calculate the mean and standard deviation of the series as well as the first three autocorrelation coefficients. Note that this will also serve as a test for nonsynchronous trading – the presence of positive autocorrelation in the return series would be evidence of possible nonsynchronous trading, consistent with the findings of Scholes and Williams (1977) and Miller, Muthuswamy and Whaley (1994). This should not directly have a large influence on the autocorrelation of AVIX. As discusses above, by using both put and call options in the index construction, any upward (downward) bias in the call option pricing (and hence volatility estimates) will be approximately offset by a downward (upward) bias in the put option pricing. Thus any mispricing as a result of positive serial correlation in the returns should not have a distinct effect on AVIX. The corollary is that any serial correlation found in the AVIX changes could be a result of its own nonsynchronous trading activity. In order to investigate the impact of nonsynchronicity on our parameter estimates, all univariate regressions conducted had their coefficients recalculated using the procedure outlined by Scholes and Williams (1977).

[18] For instance, Granger and Newbold (1974) found that regressing two independent nonstationary series (random walks) against each other resulted in a significant relationship being found in over 75% of cases.

4.4.1 Co-Movement of AVIX and S&P 200 Index Returns

We use a regression to test whether any intertemporal or contemporaneous relationship between changes in AVIX and stock returns are significant. The regression is of the form

$$\Delta AVIX_t = \alpha + \sum_{i=-2}^{2} \beta_{S,i} R_{S,t+i} + \beta_{|S|} \left| R_{S,t} \right| + \varepsilon_t$$

where $R_{S,t+i}$ represents the S&P/ASX 200 lead, lag or contemporaneous return. The $|R_{S,t}|$ term gives the absolute value of the contemporaneous return. This term is designed to detect any asymmetry in the relationship between stock returns and changes in volatility. The net impact of a positive stock return on volatility would be $\beta^+ = \beta_{S,0} + \beta_{|S|}$ and for a negative stock return it would be $\beta^- = \beta_{S,0} - \beta_{|S|}$. Our hypothesis is that volatility changes and contemporaneous stock returns are negatively correlated, thus we expect the sign of $\beta_{S,0}$ to be negative. If volatility feedback drives the asymmetry of the relationship, we expect negative stock returns to have a greater impact that positive returns, thus $\beta^- < \beta^+$. Therefore we expect that $\beta_{|S|}$ will have a positive sign.

4.4.2 AVIX as a Predictor of Future Market Volatility

In order to assess the relationship between a volatility forecast (V^f) and future volatility (V^*), we need to form a rationality regression

$$V_t^* = \alpha + \beta V_t^f + \varepsilon_t$$

However, the time series used in this regression are likely to suffer from nonstationarity. An Augmented Dickey-Fuller test could not reject nonstationarity for AVIX or historical volatility (our forecasters). Thus both variables in the regression have the first lag of the explanatory variable subtracted in order to form stationary series and retain parameter estimates that can be easily interpreted

$$V_t^* - V_{t-1}^f = \alpha + \beta\left(V_t^f - V_{t-1}^f\right) + \varepsilon_t$$

The Augmented Dickey-Fuller test rejects nonstationarity for these differenced series.

The measure of future volatility used was the ex-post actual volatility over the following 28 calendar days (20 trading days) calculated by

$$V_t^* = \left[\left(\frac{n-1}{2}\right)^{\frac{1}{2}} \frac{\Gamma\left(\frac{n-1}{2}\right)}{\Gamma\left(\frac{n}{2}\right)} \right] \left(\hat{V}_t^{*2}\right)^{\frac{1}{2}}$$

where $$\hat{V}_t^{*2} = \frac{1}{n-1} \sum_{i=1}^{n} \left[\ln\left(\frac{S_{t+i}}{S_{t+i-1}}\right) - \overline{R}_t \right]^2$$

$n =$ forecast length in trading days

$S_t =$ stock price at time t

$\overline{R}_t =$ mean S & P/ASX 200 return over the forecast interval

This procedure was used by Fleming, Ostdiek and Whaley (1995).[19] Note that $\hat{V}_t^{*2}$ is simply the variance of the stock return. This is corrected for bias caused by using the square root of the sample variance as an estimator of standard deviation.[20] A period of 28 calendar days (approximately 20 trading days) was selected as the forecast length because it most closely resembled the forecast length of AVIX, whilst not allowing any potential day-of-the-week effects, because equal numbers of each day of the week are included in estimation. When the forecast performance of the 66-day AVIX is considered, a 91 calendar day period (66 trading days) is used, corresponding to 13 weeks.

Two forecast variables are considered. The first is AVIX. We look at both the 22-day and 66-day measures. The second is a measure of historical volatility. For the daily series, historical volatility is measured by taking the standard deviation of the previous daily stock returns, and correcting for estimation bias. Choosing the time interval over which historical volatility is measured is by no means a simple issue. Longer forecasts are likely to contain a greater deal of information but suffer from containing older data, perhaps not relevant to the current market conditions. Alternatively, shorter time intervals will be more likely to suffer from possible distortion due to temporary market movements. Because of this dilemma, three time lengths of 30, 60 and 90 days intervals were chosen for historic volatility.

For our weekly analysis, the historical volatility measures were used to fit a first-order autoregressive process. This process was then used to forecast volatility 4 weeks and 13 weeks ahead and this was compared to the forecasts provided by 22-day and 66-day AVIX respectively.

Once the performance of AVIX and historical volatility was assessed, their orthogonality to one another was evaluated by regressing the residuals from the initial regression on the first difference of the other predictor

$$\varepsilon_t = a + b\left(V_t^{f^1} - V_{t-1}^{f^1}\right) + e_t$$

$$\text{where } f^1 = \begin{cases} Historical & \text{if } AVIX \text{ was initially used} \\ AVIX & \text{if } Historical \text{ was initially used} \end{cases}$$

If each predictor is orthogonal, then the prediction errors of the forecast (measured by ε_t) cannot themselves be predicted by an alternative measure of volatility. Thus we are testing whether historic volatility can provide incremental information to forecasts supplied by AVIX and vice-versa.

5 Results

This section discusses the results of the tests carried out in the previous section, and includes a description of movements in AVIX over the history of the sample. The parameter estimates for the predictive performance of AVIX are also reassessed using estimators that are consistent with nonsynchronous trading.

[19] It was also used by Cox and Rubinstein (1985, p.256)

[20] $\Gamma(\alpha) = \int_0^\infty x^{\alpha-1}e^{-x}dx$ is the gamma function

5.1 Historical Account

The daily computed closing AVIX levels for both the 22-day and 66-day horizons is plotted against the absolute value of the daily return on the S&P/ASX 200 Index in Figure 1. These data are calculated for the period from July 11, 2002 to September 27, 2002 inclusive. First, note the major jump in both volatility measures in September 2001 immediately following the terrorist attacks of September 11 on the World Trade Centre and the Pentagon. Having occurred after market close in Australia on September 11, this was not disseminated until September 12, 2001 and is reflected in the jump in 22-day AVIX from 13.79% to 20.02% from September 11 to September 12. The 66-day AVIX recorded a corresponding jump in volatility from 14.62% to 18.11%. Both volatility measures rose even further in the following days, with 22-day AVIX peaking at 38.64% on September 24 and 66-day AVIX peaking at 29.63% on September 19. This volatility was also reflected in the underlying equity market with S&P/ASX 200 Index returns in excess of one percent in magnitude on numerous occasions. On September 12, the market recorded a one-day fall of 4.21%, and fell by another 4.81% on September 17.

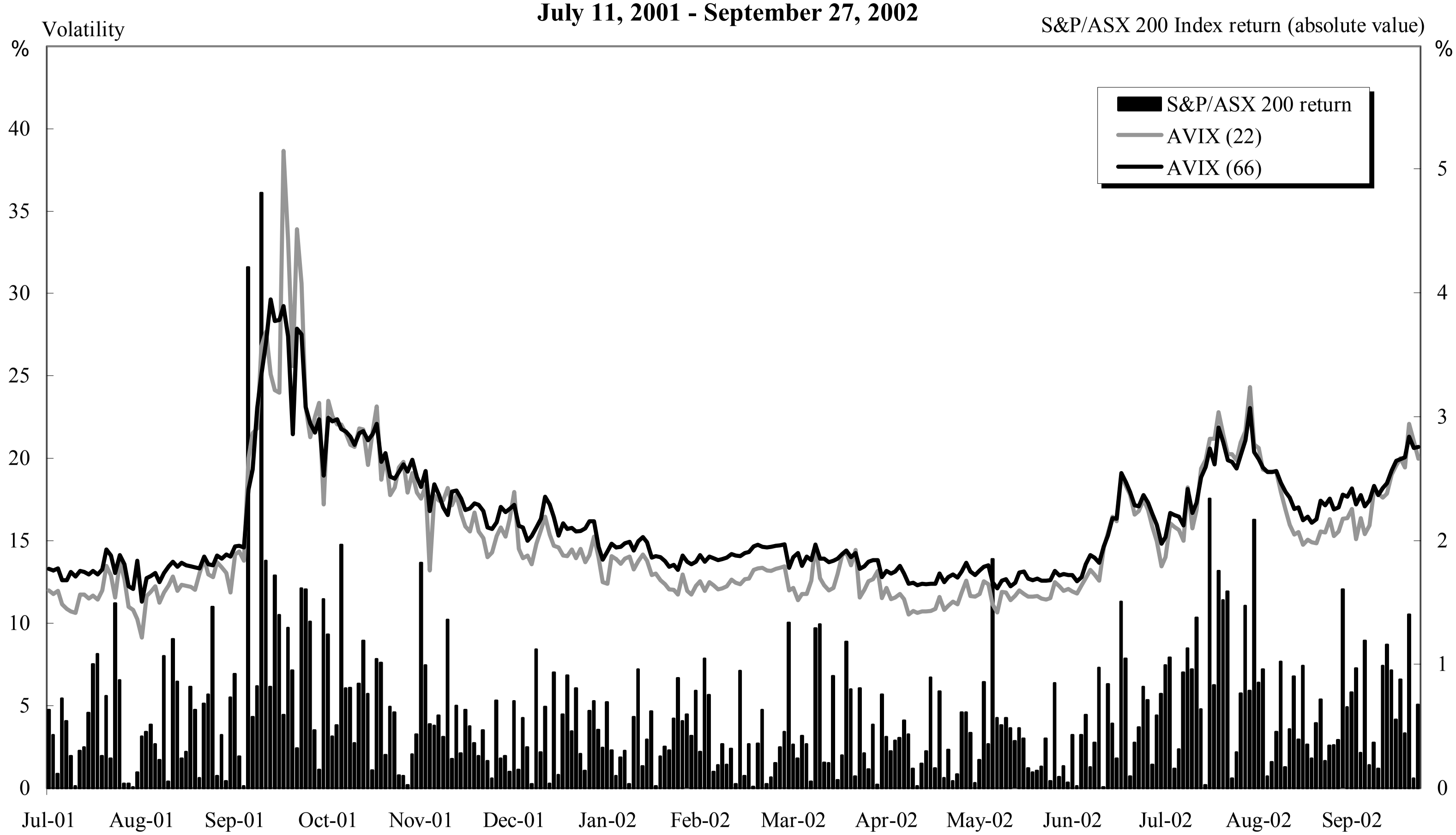
The chart shows that market volatility did not return to pre-September 11 levels until January 2002. From there, it remained remarkably stable, showing a continued downward trend, reaching a post-September 11 low for 22-day AVIX on April 17, 2002 and 66-day AVIX on May 16, 2002 with levels of 10.53% and 12.12% respectively. Returns on the S&P/ASX 200 also remained tightly bound for the most part. In late June, both volatility indexes experienced sharp increases, rising by almost six percentage points. This was matched by increases in the magnitude of S&P/ASX 200 Index returns. This coincided with the deterioration in United States stock prices and increasing pessimism about the strength of economic recovery. Locally, volatility could also have been driven by an announcement by Australia's defence minister, Robert Hill, that Australia would support any pre-emptive strike by the United States on Iraq. As uncertainty prevailed regarding the global economic outlook and the prospects of war, volatility fluctuated substantially during July and early August, peaking on August 6 at 24.33% and 23.05% for 22-day and 66-day AVIX respectively. From there volatility fell dramatically, possibly due to the rising chorus of opposition to war. Domestically, this also coincided with the announcement of a lucrative deal for Australia to supply A$25 billion of natural gas to China – a deal likely to help Australian economic growth in a time of global economic uncertainty. The Reserve Bank of Australia's Statement on Monetary Policy, release on August 8, 2002, was also quite upbeat in its assessment of the Australian economy. However, the continued instability of the United States economy, the hard-line being shown by the United States on Iraq and the first anniversary of September 11 have seen volatility rise rapidly again in September 2002.

The volatility surrounding September 11, 2002 illustrates the susceptibility of the 22-day AVIX to wild swings in value due to the way in which it is calculated. In the two weeks following September 11 the 22-day AVIX fluctuated wildly but in contrast the 66-day AVIX jumped up, and held there albeit with a couple of bounces. For example, the 22-day AVIX increased by 14.65 percentage points from Friday September 21 to Monday September 24, but over the same period the 66-day AVIX only increase by 0.84 percentage points. Therefore we are reminded of the potential misinformation supplied by the 22-day AVIX.

Figure 1

Daily Australian Market Volatility and Returns

July 11, 2001 - September 27, 2002



5.2 Statistical Properties of AVIX

The mean, standard deviation and first three autocorrelation coefficients for changes in 22-day and 66-day AVIX and S&P/ASX 200 Index returns were calculated. Table 1 displays these univariate properties along with the cross-correlations between AVIX changes and lead, lag and contemporaneous S&P/ASX 200 Index returns. The changes in AVIX show statistically significant negative first-order autocorrelation of –0.238 and –0.166 for 22-day and 66-day AVIX respectively. The sample excluding September 11 reports similar correlations of –0.244 and –0.199 respectively. The 22-day AVIX also shows significant negative second-order autocorrelation of –0.249 for the full sample and –0.143 for the sample excluding September 11. For both the 22-day and 66-day AVIX, equal autocorrelation coefficients between the full sample and the sample excluding September 11 effects could be rejected. The hypothesis of equal means between the samples could not be rejected. Thus the events of September 11 did have a substantial impact upon the time series properties of AVIX.

These results are similar to Fleming, Ostdiek and Whaley (1995) (hereafter FOW), however the magnitude of the correlations is much larger than those found for VIX. They found first- and second-order autocorrelations of only –0.073 and –0.104 for their non-crash sample. A number of factors drive these differences. First, as discussed earlier the data set used in this study is quite unique and only spans a narrow time interval, whereas FOW had data spanning 1986 to 1992. Second, the potential impact of nonsynchronous trading in Australia is more profound than in the United States and this could cause spurious autocorrelation in a manner consistent with Scholes and Williams (1977) and Miller, Muthuswamy and Whaley (1994).

The S&P/ASX 200 Index returns are largely uncorrelated, except for the third lag. This correlation disappears once the September 11 effects are removed from the sample. This indicates that nonsynchronous trading does not appear to substantially affect the S&P/ASX 200 Index.

Consistent with Hypothesis 1, the cross-correlations show a significant contemporaneous negative correlation of –0.453 and –0.464 for the 22-day and 66-day AVIX changes respectively. This indicates that the leverage effect and time-varying risk premium effect could exist in Australia. These correlations are largely unaffected by removal of the September 11 effects. Negative correlation was also found between AVIX changes and the first and second lags of S&P/ASX 200. Positive correlation was detected between 22-day AVIX changes and lead index returns but this disappeared when September 11 was excluded. In FOW, the negative contemporaneous correlation was higher, being –0.615 but the intertemporal correlations were all positive with smaller magnitude -- indicating that AVIX takes longer to adjust to stock index returns than VIX. Whilst the bulk of changes in AVIX in response to index returns do occur contemporaneously, some of the response occurs with a lag.

The weekly time series properties for AVIX and S&P/ASX 200 Index returns are displayed in Table 2. Most of the results are consistent with the daily results; however the AVIX changes have lower-order autocorrelation in the case of 22-day AVIX and no significant autocorrelation at all for 66-day AVIX. This is consistent with the impact of nonsynchronous trading. With lower frequency data nonsynchronous trading has less of an effect since the relative staleness of price data becomes smaller.[21] The first-lag cross-correlations also

[21] See Scholes and Williams (1977), Lo and MacKinlay (1990) and Miller, Muthuswamy and Whaley (1994) for a more comprehensive discussion on trading frequency and nonsynchronous trading.

Table 1

Statistical Properties of Daily Closing AVIX Changes[a]

Panel A: 22-Day AVIX

		Volatility Index Changes					*S&P/ASX200 Index Returns*					*Cross Correlations[b]*				
Sample	***N***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***-2***	***-1***	***0***	***+1***	***+2***
All	309	0.00026	0.01733	-0.238[d]	-0.249[d]	0.234[d]	-0.00035	0.00802	-0.002	0.014	0.132[d]	-0.068	-0.117[d]	-0.453[d]	0.119[d]	-0.015
Ex Sept 11[c]	298	-0.00013	0.01361	-0.244[d]	-0.143[d]	0.060	-0.00010	0.00699	0.025	0.087	-0.020	-0.123[d]	-0.040	-0.437[d]	0.072	-0.004

Panel B: 66-Day AVIX

		Volatility Index Changes					*S&P/ASX200 Index Returns*					*Cross Correlations[b]*				
Sample	***N***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***-2***	***-1***	***0***	***+1***	***+2***
All	309	0.00024	0.00999	-0.166[d]	-0.033	0.133[d]	0.00035	0.00802	-0.002	0.014	0.132[d]	-0.179[d]	-0.078	-0.464[d]	0.005	-0.051
Ex Sept 11[c]	298	0.00002	0.0087	-0.199[d]	-0.088	-0.042	-0.00010	0.00699	0.025	0.087	-0.020	-0.141[d]	-0.041	-0.485[d]	0.097	0.015

a The mean, standard deviation (Std Dev) and first three autocorrelations are shown for AVIX changes and S&P/ASX 200 Index returns. Cross correlations are also shown for AVIX changes and lead and lag S&P/ASX 200 Index returns.

b Negative numbers (-2, -1) indicate correlations between AVIX changes and lagged S&P/ASX 200 Index returns. Positive numbers (+1, +2) give correlations with lead values of S&P/ASX 200 Index returns. At zero (0), the contemporaneous correlation is reported.

c The "Ex Sept 11" sample excludes observations between 12/09/2001 and 26/09/2002.

d Signifies statistical significance at the 5% level.

Table 2

Statistical Properties of Weekly Closing AVIX Level Changes[a]

Panel A: 22-Day AVIX

		Volatility Index Changes					*S&P/ASX200 Index Returns*					*Cross Correlations [b]*				
Sample	***N***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***-2***	***-1***	***0***	***+1***	***+2***
All	63	0.001273	0.026401	-0.293[d]	0.205	-0.245	-0.00071	0.006817	0.136	-0.061	-0.207	0.019	-0.350[d]	-0.394[d]	-0.109	0.283[d]
Ex Sept 11[c]	61	-0.0003	0.024854	-0.425[d]	0.127	-0.070	-0.00038	0.00664	0.113	-0.160	-0.186	0.041	-0.282[d]	-0.358[d]	-0.025	0.210

Panel B: 66-Day AVIX

		Volatility Index Changes					*S&P/ASX200 Index Returns*					*Cross Correlations [b]*				
Sample	***N***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***Mean***	***Std Dev***	***ρ(1)***	***ρ(2)***	***ρ(3)***	***-2***	***-1***	***0***	***+1***	***+2***
All	63	0.00117	0.020105	0.097	-0.175	-0.186	-0.00071	0.006817	0.136	-0.061	-0.207	-0.049	-0.295[d]	-0.532[d]	-0.167	0.319[d]
Ex Sept 11[c]	61	-0.00104	0.015993	-0.166	-0.055	0.083	-0.00038	0.00664	0.113	-0.160	-0.186	0.134	-0.227	-0.501[d]	-0.143	0.135

a The mean, standard deviation (Std Dev) and first three autocorrelations are shown for AVIX changes and S&P/ASX 200 Index returns. Cross correlations are also shown for AVIX changes and lead and lag S&P/ASX 200 Index returns.

b Negative numbers (-2, -1) indicated correlations between AVIX changes and lagged S&P/ASX 200 Index returns. Positive numbers (+1, +2) give correlations with lead values of S&P/ASX 200 Index returns. At zero (0), the contemporaneous correlation is reported.

c The "Ex Sept 11" sample excludes observations between 12/09/2001 and 26/09/2002.

d Signifies statistical significance at the 5% level.

become larger in magnitude, indicating that AVIX responds with no more than a one-week delay to S&P/ASX 200 Index returns. A significant positive second lead cross correlation is present in both AVIX measures, but this becomes statistically insignificant once September 11 is removed.

5.3 Co-Movement of AVIX and S&P 200 Index Returns

The intertemporal relationship between daily changes in AVIX and S&P/ASX 200 Index returns is displayed in Table 3. This shows the parameter estimates from regressing AVIX changes on the lead, lag and contemporaneous index returns. An additional variable, for absolute contemporaneous index returns captures any asymmetry in the relationship. This variable was found to be uncorrelated with the contemporaneous index return variable thus averting significant multicollinearity. The Student's t-statistics were calculated using White's (1980) heteroskedasticity consistent covariance matrix.

Panel A shows the results for the 22-day AVIX changes. As expected, the coefficient on contemporaneous index returns is negative and significant, with a parameter estimate of –1.0094. This supports Hypothesis 1. The only other significant parameter estimate is on the first lead index return, and this is not robust to the exclusion of September 11. Contrary to Hypothesis 2, the relationship between AVIX changes and index returns is not asymmetric. The coefficient on the absolute index return is insignificant and has the wrong sign. These results are inconsistent with FOW who found significant parameters on the lead and lagged index returns, and substantial asymmetry in the relationship.

Results for the 66-day AVIX are presented in Panel B. Whilst the negative contemporaneous relationship is still significant, the magnitude of the parameters has fallen. Part of the reason for this can be explained by the significance of the second lagged index return coefficient. As

Table 3
Intertemporal Relationship Between Daily AVIX Changes and S&P/ASX200 Index Returns[a]

Panel A: 22-Day AVIX

		Parameter Estimates							
Sample	***N***	α	$\beta_{s,-2}$	$\beta_{s,-1}$	$\beta_{s,0}$	$\beta_{s,+1}$	$\beta_{s,+2}$	$\beta_{\lvert s\rvert}$	$\bar{R}^2$
All	306	0.0013	-0.1886	-0.2832	-1.0094	0.3166	0.0215	-0.2310	0.2309
		(0.91)	(-1.13)	(-1.77)	(-7.21)	(1.99)	(0.15)	(-1.14)	
Ex Sept 11[b]	295	0.0015	-0.1835	-0.0791	-0.8314	0.1919	0.0564	-0.2927	0.2000
		(1.25)	(-1.69)	(-0.64)	(-6.35)	(1.35)	(0.43)	(-1.40)	

Panel B: 66-Day AVIX

		Parameter Estimates							
Sample	***N***	α	$\beta_{s,-2}$	$\beta_{s,-1}$	$\beta_{s,0}$	$\beta_{s,+1}$	$\beta_{s,+2}$	$\beta_{\lvert s\rvert}$	$\bar{R}^2$
All	306	0.0005	-0.2262	-0.1041	-0.5896	0.0499	-0.0456	-0.0910	0.2435
		(0.60)	(-2.35)	(-1.11)	(-7.10)	(0.50)	(-0.50)	(-0.77)	
Ex Sept 11[b]	295	0.0008	-0.1219	-0.0525	-0.5975	0.1519	0.0627	-0.1480	0.2522
		(1.04)	(-2.06)	(-0.74)	(-7.94)	(1.56)	(0.70)	(-1.20)	

a Parameter estimates are presented for the regression of AVIX changes on lead, lag and contemporaneous S&P/ASX 200 Index returns as well as the absolute index return. Figures in parentheses are White (1980) heteroskedasticity consistent Student's t-statistics. The coefficient of determination has been adjusted for 7 degrees of freedom.

b The "Ex Sept 11" sample excludes observations between 12/09/2001 and 26/09/2002.

described above, this indicates that AVIX takes some time to adjust to S&P/ASX 200 Index returns. Even so, the cumulative effect of the lagged return and contemporaneous return parameters is still lower for the 66-day AVIX than the contemporaneous relationship in the 22-day AVIX. As in the 22-day case, the 66-day AVIX exhibits no significant asymmetry in the relationship, and the sign on the absolute index return is incorrect.

The results for weekly changes in AVIX are presented in Table 4. For the 22-day AVIX there appears to be no significant relationship between AVIX changes and index returns. This is somewhat surprising, but may be driven by the large standard errors resulting from the use of a small data set. An alternative explanation is high collinearity in the explanatory variables. However, upon on inspection of the correlation matrix, this was not found to be evident. The results for weekly 66-day AVIX are not remarkably different from those of the daily 66-day AVIX changes. The negative contemporaneous relationship between AVIX changes and index returns remains, and no asymmetric relationship was found. Therefore, we accept results for weekly 66-day AVIX are not remarkably different from those of the daily 66-day AVIX changes. The negative contemporaneous relationship between AVIX changes and index returns remains, and no asymmetric relationship was found. Therefore, we accept Hypothesis 1 and reject Hypothesis 2.

Table 4

Intertemporal Relationship Between Weekly AVIX Changes and S&P/ASX200 Index Returns[a]

Panel A: 22-Day AVIX

		Parameter Estimates							
Sample	***N***	α	$\beta_{s,-2}$	$\beta_{s,-1}$	$\beta_{s,0}$	$\beta_{s,+1}$	$\beta_{s,+2}$	$\beta_{\|s\|}$	$\bar{R}^2$
All	60	0.0008	0.1181	-1.0371	-1.2892	-0.4187	0.8808	-0.1989	0.2194
		(0.14)	(0.19)	(-1.33)	(-1.68)	(-0.80)	(1.83)	(-0.15)	
Ex Sept 11[b]	58	-0.0002	-0.0129	-0.8405	-1.1611	-0.1708	0.4975	-0.1941	0.1067
		(-0.04)	(-0.02)	(-1.05)	(-1.47)	(-0.31)	(1.05)	(-0.13)	

Panel B: 66-Day AVIX

		Parameter Estimates							
Sample	***N***	α	$\beta_{s,-2}$	$\beta_{s,-1}$	$\beta_{s,0}$	$\beta_{s,+1}$	$\beta_{s,+2}$	$\beta_{\|s\|}$	$\bar{R}^2$
All	60	0.0024	-0.2210	-0.5072	-1.4752	-0.4946	0.8630	-0.5318	0.3751
		(0.74)	(-0.50)	(-1.14)	(-3.90)	(-1.19)	(2.07)	(-0.82)	
Ex Sept 11[b]	58	0.0013	0.1485	-0.4409	-1.1281	-0.3062	0.1973	-0.6559	0.2571
		(0.40)	(0.44)	(-0.97)	(-2.91)	(-1.09)	(0.72)	(-0.87)	

a Parameter estimates are presented for the regression of AVIX changes on lead, lag and contemporaneous S&P/ASX 200 Index returns as well as the absolute index return. Figures in parentheses are White (1980) heteroskedasticity consistent Student's t-statistics. The coefficient of determination has been adjusted for 7 degrees of freedom.

b The "Ex Sept 11" sample excludes observations between 12/09/2001 and 26/09/2002.

5.4 AVIX as a Predictor of Future Market Volatility

The parameter estimates from regressing daily AVIX and historical volatility changes on ex-post future volatility are presented in Table 5. The measures of historical volatility employed were the volatilities on the immediately preceding 30, 60 and 90 calendar days. The 22-day AVIX was used for the 28-day forecasts of volatility, and the 66-day AVIX was used for the 91-day forecasts. Having run the initial regression, the prediction errors of these forecasts were obtained. These errors were then regressed on the forecaster of future volatility not used in the initial regression. This is the "auxiliary regression" and the results for these are presented on the right side of the tables. Since we are testing forecast quality in the initial regression, we are interested in whether the forecast is unbiased. If so, then the intercept (α) should equal zero and the slope coefficient (β) should equal unity. Thus, the t-Statistics reported reflect these null hypotheses, not the hypothesis that each coefficient equals zero. For the auxiliary regressions we are interested in whether any additional information regarding forecasts can be obtained from the alternative forecaster of volatility. This is described by the slope coefficients being non-zero, so the t-Statistics reflect the null hypothesis that the parameter estimates equals zero.

The results shown in Table 5 overwhelmingly reject the notion that AVIX is a superior forecaster of future volatility. This is evidence against Hypothesis 3. The results for the 28-day forecasts in Panel A reject the hypotheses that AVIX is an unbiased forecast. Furthermore, the slope coefficient has the incorrect sign and is not significantly different from zero. However, an examination of the results from the auxiliary regressions, shown in the top half of Panel A, reveals that historical volatility does not add information to the forecast errors provided by AVIX. In the second half of Panel A the initial regression uses historic volatility as the explanatory variable. The null hypothesis that the slope is different from unity cannot be rejected for 30- and 60-day historic volatility. However, before we conclude the superiority of historic volatility, we note that due to the large standard errors on the parameters we cannot reject their being different from zero either. For the 90-day historic volatility, the parameter estimate is so large we can reject it being equal to unity. This suggests that 90-day historic volatility changes understate the changes in future volatility. The right side of Panel A shows that AVIX supplies no additional information to the forecasts provided by historic volatility. The results in Panel B use the same regressions but remove the two weeks following September 11. The inferences obtained from Panel B are consistent with those from the regressions in Panel A.

Panel C shows the results from the 91 calendar-day forecasts for the daily frequency 66-day AVIX and historic volatility. The results are not dissimilar to those for the 28-day forecasts, with AVIX proving to be a poor predictor of future volatility. The regression including 66-day AVIX has an intercept of –0.0349 and a slope of –0.1142. We can reject the hypotheses that the intercept is zero and the slope is unity.

In the auxiliary regression, historic volatility appears to have provided no significant additional information to the forecasts provided by AVIX. The negative adjusted R-squared on each regression is testimony to the poorness of the forecast performance. All historic volatility forecasts in the lower half of Panel C appear to be unbiased, but once again we cannot reject the hypothesis that the slope is zero. The negative adjusted coefficients of determination suggest that these are still poor forecasts. As in the 28-day a forecast, AVIX provides no additional forecast information above that from the initial regression using historic volatility.

Table 5

Volatility Forecast Performance of AVIX and Historical Volatility[a]

Panel A: 28-day forecasts with all observations

	Parameter Estimates							*Parameter Estimates (Auxiliary Regressions)* [b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
298	-0.0299	-0.2449					0.0022	0.0000		0.3211			-0.0009
	(-9.01)	(-3.64)						(0.01)		(0.79)			
	-0.0299	-0.2449					0.0022	0.0000			0.0857		-0.0033
	(-9.01)	(-3.64)						(0.00)			(0.12)		
	-0.0299	-0.2449					0.0022	-0.0001				0.6612	-0.0015
	(-9.01)	(-3.64)						(-0.03)				(0.83)	
298	-0.0002		0.3723				-0.0007	0.0000	0.2960				0.0032
	(-0.05)		(-1.42)					(-0.01)	(0.88)				
	-0.0006			1.0871			0.0048	0.0000	0.2896				0.0032
	(-0.15)			(0.14)				(-0.01)	(1.20)				
	0.0003				2.4373[d]		0.0171	0.0000	0.2522				0.0016
	(0.07)				(2.17)			(-0.01)	(1.34)				

Panel B: 28-day forecasts excluding September 11 [e]

	Parameter Estimates							*Parameter Estimates (Auxiliary Regressions)* [b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
287	-0.0286	-0.2204					-0.0006	0.0002		0.2963			-0.0020
	(-8.70)	(-3.89)						(0.05)		(0.64)			
	-0.0286	-0.2204					-0.0006	0.0000			-0.0582		-0.0035
	(-8.70)	(-3.89)						(0.00)			(-0.07)		
	-0.0286	-0.2204					-0.0006	0.0001				0.8207	-0.0016
	(-8.70)	(-3.89)						(0.03)				(1.27)	
287	0.0012		0.4555				-0.0008	0.0001	0.4475				0.0059
	(0.32)		(-0.97)					(0.03)	(1.07)				
	-0.0009			0.8980			-0.0001	0.0001	0.4059				0.0043
	(-0.24)			(-0.12)				(0.03)	(1.22)				
	-0.0004				2.5131[d]		0.0103	0.0001	0.3637				0.0028
	(-0.09)				(1.98)			(0.03)	(1.32)				

a Parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. The figures in parentheses are White (1980) heteroskedastic consistent Student's t-statisitcs. For the intercept term, the null hypothesis is $\alpha = 0$. For the slope coefficients the null is $\beta = 1$.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c All Student's t-statisitcs for auxiliary regressions are reported for the null hypotheses a = 0 and b = 0.

d Indicates the slope is significantly different from zero.

e Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

Table 5 (continued)

Volatility Forecast Performance of AVIX and Historical Volatility[a]

Panel C: 91 calendar-day forecasts with all observations

	Parameter Estimates							*Parameter Estimates (Auxiliary Regressions)* [b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***F***	$\bar{R}^2$	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
253	-0.0349	-0.1142					-0.0036	0.0000		0.1203			-0.0036
	(-9.72)	(-2.36)						(0.00)		(0.28)			
	-0.0349	-0.1142					-0.0036	0.0000			-0.0038		-0.0040
	(-9.72)	(-2.36)						(0.00)			(-0.01)		
	-0.0349	-0.1142					-0.0036	0.0000				0.0522	-0.0040
	(-9.72)	(-2.36)						(0.00)				(0.06)	
253	0.0049		-0.1129				-0.0007	-0.0001	0.4703				0.0016
	(1.21)		(-1.93)					(-0.02)	(0.67)				
	0.0023			0.4167			-0.0027	-0.0001	0.5343				0.0036
	(0.57)			(-0.88)				(-0.02)	(1.09)				
	0.0012				0.8257		-0.0014	-0.0001	0.5015				0.0026
	(0.29)				(1.17)			(-0.02)	(1.22)				

Panel D: 91 calendar-day forecasts excluding September 11 [e]

	Parameter Estimates							*Parameter Estimates (Auxiliary Regressions)* [b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***F***	$\bar{R}^2$	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
242	-0.0314	-0.1023					-0.0039	0.0005		0.6525			0.0032
	(-8.92)	(-1.82)						(0.13)		(1.35)			
	-0.0314	-0.1023					-0.0039	0.0004			1.0656		0.0022
	(-8.92)	(-1.82)						(0.13)			(1.83)		
	-0.0314	-0.1023					-0.0039	0.0005				1.5127	0.0027
	(-8.92)	(-1.82)						(0.14)				(2.36)	
242	0.0096		0.5985				0.0008	0.0001	0.5166				0.0012
	(2.41)		(-0.57)					(0.02)	(0.55)				
	0.0048			1.3586			0.0037	0.0001	0.5750				0.0022
	(1.18)			(0.45)				(0.02)	(0.83)				
	0.0030				1.8565		0.0034	0.0001	0.5502				0.0015
	(0.73)				(1.00)[d]			(0.02)	(0.94)				

a Parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. The figures in parentheses are White (1980) heteroskedastic consistent Student's t-statisitcs. For the intercept term, the null hypothesis is $\alpha = 0$. For the slope coefficients the null is $\beta = 1$.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c All Student's t-statisitcs for auxiliary regressions are reported for the null hypotheses a = 0 and b = 0.

d Indicates the slope is significantly different from zero.

e Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

When the days following September 11, 2001 are excluded the performance of historic volatility does improve. The upper right quadrant of Panel D in Table 5 shows that there is weak support for 60-day historic volatility being able to predict a component of the prediction errors from AVIX, with a t-Statistic of 1.83. There is strong support for 90-day historic volatility being able to enhance the forecasts provided by AVIX, this time with a t-Statistic of 2.36. The data in the lower half of Panel D also indicate that the slope coefficients increase for historic volatility forecasts. This brings the coefficients on 30-day and 60-day historic volatility closer to unity relative to Panel C. The coefficient on 90-day historic volatility is significantly different from zero. This is consistent with the results for the 28 calendar-day forecasts reported in Panel B.

The above regressions were re-run for weekly frequency AVIX changes and S&P/ASX 200 Index returns, with the results reported in Table 6. Instead of using historic volatility directly as our forecast of future volatility, a first-order autoregressive model was fit to the data, and this model used in-sample to generate volatility forecasts. This is more appropriate for weekly data since we are forecasting four and thirteen time periods away rather than 20 days and 66 days. Across Table 6 we can see that the forecasts supplied by AVIX have not improved by taking weekly data. This is somewhat surprising. With a lower frequency, noise and nonsynchronous trading become less pronounced. We would expect this to lead to less error in forecasting future volatility. This can be explained by market practitioners only being interested in short-term implied volatility rather than the volatility over the life of the option.[22] In contrast, the forecast performance of the autoregressive model is a substantial improvement on the standard historic forecasts used for the daily frequency. In all cases the AR(1) models for 60-day and 90-day historic volatility are unbiased and have slope coefficients significantly different from zero. The adjusted coefficients of determination are all much higher than those for AVIX. The 60-day and 90-day historic AR(1) processes have an adjusted R-Squared of 0.2086 and 0.2466 respectively for the 28-day forecast when data following September 11, 2001 are excluded (Panel B). These drop to 0.0936 and 0.1334 respectively for the 91-day forecasts but are still substantially higher than the 66-day AVIX estimate.

Note also in Panel B and Panel D that predictions based on 60-day and 90-day historic volatility AR(1) models add substantially to the AVIX forecasts. These AR(1) forecasts can successfully predict a portion of the forecast errors from AVIX, thus they add incremental information over and above that supplied by AVIX. In contrast, AVIX supplied no additional information above that captured by the AR(1) models. This can be seen in the lower right quadrant of each Panel in Table 6.

These results are generally in contrast to those of FOW. They found that VIX was largely orthogonal to historic volatility but was biased. The predictions supplied by VIX were found to be superior to historic volatility. Our results are for the most part consistent with Canina and Figlewski (1993) who found that implied volatilities were dominated by historic volatility as a forecaster of future market volatility. On the basis of ordinary least squares estimation, we reject Hypothesis 3.

In light of this, we must ask how the market could apparently be so wrong in forecasting future volatility. A number of reasons are evident and some have already been mentioned. First, the data set employed is short and unique in terms of the events it encompasses. Second, the market for index options in Australia is still evolving and as such may not truly represent the market's true forecast of future volatility, as thinness of the market is likely to

[22] See Figlewski (1997) for a more detailed discussion of the market perception of implied volatility.

Table 6

Volatility Forecast Performance of Weekly AVIX and Historical Volatility Measures[a]

Panel A: 28-day forecasts with all observations

	Parameter Estimates							Parameter Estimates (Auxiliary Regressions)[b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
63	-0.0380	-0.0909					-0.0150	-0.0017		0.1623			-0.0162
	(6.20)	(-0.35)						(-0.20)		(0.29)			
	-0.0380	-0.0909					-0.0150	-0.0028			0.2357		-0.0072
	(6.20)	(-0.35)						(-0.33)			(1.26)		
	-0.0380	-0.0909					-0.0150	-0.0022				0.1051	-0.0147
	(6.20)	(-0.35)						(-0.26)				(0.69)	
59	-0.0071		0.0190				-0.0175	-0.0007	0.4707				0.0173
	(-0.78)		(-1.56)					(-0.08)	(1.21)				
	-0.0067			0.7760			0.0697	-0.0006	0.4436				0.0120
	(-0.73)			(-0.79)[d]				(-0.07)	(1.10)				
	-0.0067				0.7978		0.1078	-0.0007	0.4847				0.0181
	(-0.76)				(-0.91)[d]			(-0.08)	(1.23)				

Panel B: 28-day forecasts excluding September 11[e]

	Parameter Estimates							Parameter Estimates (Auxiliary Regressions)[b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
61	-0.0390	-0.2596					-0.0065	0.0016		1.0758			0.0027
	(-4.79)	(-5.00)						(0.19)		(1.33)			
	-0.0390	-0.2596					-0.0065	-0.0014			0.6638		0.0387
	(-4.79)	(-5.00)						(-0.16)			(3.33)		
	-0.0390	-0.2596					-0.0065	-0.0006				0.4032	0.0131
	(-4.79)	(-5.00)						(-0.07)				(2.49)	
54	-0.0062		0.8044				-0.0055	0.0000	0.1226				-0.0167
	(-0.75)		(-0.26)					(0.01)	(0.49)				
	-0.0074			1.3978			0.2086	0.0000	0.0881				-0.0179
	(-0.88)			(2.02)[d]				(0.00)	(0.35)				
	-0.0071				1.2680		0.2466	0.0000	0.1166				-0.0169
	(-0.85)				(1.59)[d]			(0.01)	(0.49)				

a Parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and an AR(1) prediction based on historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. The figures in parentheses are White (1980) heteroskedastic consistent Student's t-statisitcs. For the intercept term, the null hypothesis is $\alpha = 0$. For the slope coefficients the null is $\beta = 1$.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c All Student's t-statisitcs for auxiliary regressions are reported for the null hypotheses $a = 0$ and $b = 0$.

d Indicates the slope is significantly different from zero.

e Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

Table 6 (continued)

Volatility Forecast Performance of Weekly AVIX and Historical Volatility Measures[a]

Panel C: 91-day forecasts with all observations

	Parameter Estimates							Parameter Estimates (Auxiliary Regressions)[b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
63	-0.0659	-0.2809					-0.0150	-0.0084		-1.6162			-0.0046
	(-6.79)	(-3.22)						(-0.90)		(-0.91)			
	-0.0659	-0.2809					-0.0150	-0.0122			0.4144		-0.0053
	(-6.79)	(-3.22)						(-1.45)			(1.50)		
	-0.0659	-0.2809					-0.0150	-0.0095				0.1338	-0.0153
	(-6.79)	(-3.22)						(-1.17)				(0.59)	
59	-0.0342		-1.0703				-0.0084	-0.0005	0.3509				-0.0009
	(-4.62)		(-1.56)					(-0.07)	(1.03)				
	-0.0353			1.0795			0.0946	-0.0004	0.2680				-0.0085
	(-5.03)			(0.33)[d]				(-0.05)	(0.72)				
	-0.0348				1.0235		0.1519	-0.0004	0.3102				-0.0054
	(-5.18)				(0.13)[d]			(-0.06)	(0.87)				

Panel D: 91-day forecasts excluding September 11[e]

	Parameter Estimates							Parameter Estimates (Auxiliary Regressions)[b,c]					
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	F	$\bar{R}^2$	a	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}	$\bar{R}^2$
61	-0.0649	-0.1530					-0.0159	-0.0085		-4.6439			-0.0072
	(-6.39)	(-1.97)						(-0.84)		(-0.86)			
	-0.0649	-0.1530					-0.0159	-0.0177			1.1319		0.0212
	(-6.39)	(-1.97)						(-1.85)			(2.36)		
	-0.0649	-0.1530					-0.0159	-0.0134				0.5192	0.0006
	(-6.39)	(-1.97)						(-1.53)				(1.58)	
54	-0.0334		-2.4601				-0.0132	0.0000	-0.0421				-0.0191
	(-4.38)		(-0.96)					(-0.01)	(-0.11)				
	-0.0385			1.5123			0.0936	-0.0002	-0.1649				-0.0169
	(-5.35)			(1.53)[d]				(-0.02)	(-0.41)				
	-0.0355				1.1896		0.1334	-0.0001	-0.1036				-0.0183
	(-5.26)				(0.82)[d]			(-0.01)	(-0.25)				

a Parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and an AR(1) prediction based on historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. The figures in parentheses are White (1980) heteroskedastic consistent Student's t-statisitcs. For the intercept term, the null hypothesis is $\alpha = 0$. For the slope coefficients the null is $\beta = 1$.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c All Student's t-statisitcs for auxiliary regressions are reported for the null hypotheses a = 0 and b = 0.

d Indicates the slope is significantly different from zero.

e Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

impede price discovery. Third, the nonsynchronous trading of index options used to construct AVIX will result in an error in variables problem. In order to test this, Scholes and Williams estimates of the regression parameters were calculated and the results are discussed below. Fourth, clientele effects might see options trade at prices inconsistent with the market's forecast of future volatility. For example, an index fund may need to hedge itself against movements in the index and is not interested in whether options prices are consistent with the market's view on future volatility. Thus the price of these options may trade at a premium to their theoretical value. In the case of index options this is exacerbated by the fact that arbitrage based on option mispricing is prohibitively difficult. To arbitrage, an investor would need to trade every stock in the index in odd lots in order to match the position of the option.

5.5 Scholes and Williams Estimates

In order to control for the presence of nonsynchronous trading of index options and its impact on our parameter estimates, the parameters were re-estimated using the Scholes and Williams (1977) consistent estimators

$$\hat{\alpha} = \frac{1}{T-2}\sum_{t=1}^{T-1} y_t - \hat{\beta}\frac{1}{T-2}\sum_{t=1}^{T-1} x_t$$

$$\hat{\beta} = \frac{b^- + b + b^+}{1 + 2\hat{\rho}}$$

where
$$\hat{\rho} = \frac{\operatorname{cov}(x_t, x_{t-1})}{\sqrt{\operatorname{var}(x_t)\operatorname{var}(x_{t-1})}}$$

$$b^- = \frac{\operatorname{cov}(y_t, x_{t-1})}{\operatorname{var}(x_{t-1})}$$

$$b = \frac{\operatorname{cov}(y_t, x_t)}{\operatorname{var}(x_t)}$$

$$b^+ = \frac{\operatorname{cov}(y_t, x_{t+1})}{\operatorname{var}(x_{t+1})}$$

The results of these estimates for daily data are presented in Table 7. The calculation of standard errors and coefficients of determination for Scholes and Williams's consistent estimators is beyond the scope of this paper, so we can only make casual inferences based on the parameter values. The results suggest that nonsynchronous trading has a major influence. The parameter estimates have changed dramatically, and many have even reversed in sign. Panel A shows the performance of 22-day AVIX as a forecaster of 28 calendar-day future volatility. Whilst our intercept term has not changed substantially, the slope coefficient has changed markedly. In our standard analysis, the slope was -0.2449 and was significantly different from unity. Using Scholes and Williams, the slope is 1.1130 and whilst we cannot infer its significance, it is much closer to unity and as such suggests that AVIX may not be as poor a forecast as first thought.

The coefficients for historical volatility have also increased dramatically, suggesting that it too can be used to forecast future volatility. The slope coefficient on the 28-day forecasts provided by 90-day historic volatility has increased from 2.4373 to a staggering 8.0673. Given coefficients of this magnitude it is highly unlikely that they are consistent

Table 7

Scholes-Williams Volatility Forecast Performance of Daily AVIX and Historical Volatility[a]

Panel A: 28-day forecasts with all observations

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
298	-0.0301	1.1130				0.0000		1.3407		
	-0.0301	1.1130				-0.0001			1.0313	
	-0.0301	1.1130				-0.0001				2.9995
298	-0.0001		2.1350			0.0001	2.0925			
	-0.0004			3.9114		0.0000	2.0911			
	0.0006				8.0673	0.0000	1.8758			

Panel B: 28-day forecasts excluding September 11 [c]

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
287	-0.0289	1.9945				0.0000		0.9308		
	-0.0289	1.9945				0.0000			0.0350	
	-0.0289	1.9945				0.0000				2.6396
287	0.0011		2.1558			0.0000	3.5893			
	-0.0010			2.9015		-0.0001	3.1726			
	-0.0006				7.5837	-0.0001	2.7458			

Panel C: 91-day forecasts with all observations

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
298	-0.0356	1.1168				-0.0004		0.5170		
	-0.0356	1.1168				-0.0004			0.3314	
	-0.0356	1.1168				-0.0004				0.6656
298	0.0048		0.6664			-0.0002	1.9952			
	0.0020			1.9762		-0.0003	2.2948			
	0.0008				3.4077	-0.0003	2.1473			

Panel D: 91-day forecasts excluding September 11 [c]

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
287	-0.0320	2.1192				-0.0003		1.7684		
	-0.0320	2.1192				-0.0003			2.5117	
	-0.0320	2.1192				-0.0003				4.2240
287	0.0091		2.4760			-0.0002	3.5925			
	0.0040			3.9098		-0.0004	3.5618			
	0.0021				5.9327	-0.0004	3.3323			

a Scholes amd Williams (1977) parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. Calculating Scholes and Williams standard errors is beyond the scope of this paper.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

with the null hypothesis that they are equal to one, thus they are probably biased forecasts. The slope coefficients on the auxiliary regressions have also increased substantially, with all of them exceeding one and a number of them greater than two. This suggests that the forecasts provided by AVIX can be improved upon by using historic volatility, and forecasts using historic volatility can be improved upon by using AVIX. In other words, the two forecasts are probably not orthogonal. Even though we cannot conclude with certainty whether these coefficients are significant, their magnitudes suggest that both AVIX and historic volatility can be used together to generate useful forecasts of future volatility.

Because the slope coefficients are frequently distant from unity it is unlikely that the forecasts provided are unbiased. A final observation is that the exclusion of days following September 11, 2001 has a significant impact on our coefficient estimates. The changes caused by this filtering are not all consistently in one direction, rather some coefficients increase in magnitude whilst other decrease. There is evidence that the events of September 11 do indeed have a large impact on our parameter estimates.

The corresponding results using Scholes and Williams for weekly data are displayed in Table 8. Panel A and Panel B present the results for predictions of future volatility 28 days ahead both with and without the two weeks after September 11 respectively. As in the case of the daily data, the parameter estimates have been dramatically changed for the regressions involving AVIX, including the auxiliary regressions. Panel A shows that the slope coefficient on the initial regression involving AVIX has changes from -0.2809 to 2.2806. This indicates that even at a weekly frequency nonsynchronous trading can substantially distort our parameter estimates. The auxiliary regression slopes have increased by a factor of ten. Thus, Scholes and Williams estimates suggest that AVIX may also be important as a forecast of future volatility at a weekly frequency. The differences in parameters for historical volatility are not as substantial for Panel A and Panel B. These seem to suggest that nonsynchronous trading has the effect of understating the parameters for AVIX predictions more than historical volatility predictions.

The results in Panel C and Panel D for 91-day forecasts are not as one sided. In Panel C, the slope coefficient on the AVIX forecast has become positive, but at only 0.2489 it is still relatively close to zero. The coefficients on 60-day and 90-day historic volatility are largely unchanged in both Panel C and Panel D. The slope coefficients on the 30-day historic volatility predictions have all increased in magnitude, and in Panel C they have also changed sign. In Panel D, the additional information provided by AVIX over and above historic volatility is still negligible. This can be seen by the small slope coefficients in the bottom-right quadrant. However, AVIX alone does provide reasonable forecasts of future volatility based on the slope coefficient of 1.3151 in the top-left quadrant of Panel D.

We have shown that future research into Australian index options needs to account for the nonsynchronous nature of trading because it can have a substantial impact upon the parameter estimates obtained from ordinary least squares regressions. Even at a weekly frequency this effect remains noticeable. Our previous rejection of Hypothesis 3 is now doubtful based on the parameter estimates obtained using the approach of Scholes and Williams. In fact, the magnitudes of the slope coefficients on AVIX are typically closer to unity than for historic volatility, suggesting that AVIX may be less biased as a forecaster of future volatility than historic volatility. As mentioned earlier, solid conclusions based on Scholes Williams cannot be obtained due to the absence of standard errors on the parameter estimates. This is left for future research.

Table 8

Volatility Forecast Performance of Weekly AVIX and Historical Volatility Measures[a]

Panel A: 28-day forecasts with all observations

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
63	-0.0368	2.2806				-0.0009		-0.1935		
	-0.0368	2.2806				-0.0048			0.1785	
	-0.0368	2.2806				-0.0043				0.0981
59	-0.0065		-0.0755			0.0025	3.4757			
	-0.0062			0.8138		0.0025	3.5886			
	-0.0062				0.8440	0.0025	3.6486			

Panel B: 28-day forecasts excluding September 11 [c]

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
61	-0.0382	6.4120				-0.0007		1.1646		
	-0.0382	6.4120				-0.0032			0.5884	
	-0.0382	6.4120				-0.0024				0.3848
54	-0.0076		1.2249			0.0016	5.2438			
	-0.0069			1.4067		0.0017	4.7781			
	-0.0068				1.2860	0.0020	4.9871			

Panel C: 91-day forecasts with all observations

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
63	-0.0683	0.2489				-0.0089		-3.9479		
	-0.0683	0.2489				-0.0175			0.2902	
	-0.0683	0.2489				-0.0168				0.0788
59	-0.0357		2.4558			0.0018	0.9090			
	-0.0354			1.0276		0.0015	0.9342			
	-0.0357				0.9972	0.0016	0.9592			

Panel D: 91-day forecasts excluding September 11 [c]

	Parameter Estimates					Parameter Estimates (Auxiliary Regressions) [b]				
N	α	β_{AVIX}	β_{30DAY}	β_{60DAY}	β_{90DAY}	***a***	b_{AVIX}	b_{30DAY}	b_{60DAY}	b_{90DAY}
61	-0.0669	1.3151				-0.0091		-10.7480		
	-0.0669	1.3151				-0.0163			1.0089	
	-0.0669	1.3151				-0.0171				0.4771
54	-0.0350		-6.5755			0.0016	-0.1374			
	-0.0351			1.3955		0.0012	-0.2264			
	-0.0350				1.1657	0.0014	-0.0637			

a Scholes amd Williams (1977) parameter estimates for regression of ex-post future volatility on volatility forecasts provided by AVIX and historic volatility. For the 28-day forecasts, the 22-day AVIX was used, and for the 91-day forecast the 66-day AVIX was used. Calculating Scholes and Williams standard errors is beyond the scope of this paper.

b Auxiliary regression coefficents were obtained from regressing the prediction errors from the initial regression on the predictor of volatility not used as an intial explanatory variable.

c Sample excluding September 11 omits observations between 12/09/2001 and 26/09/2001.

6. Summary and Conclusions

This study is the first to consider a broad index of market volatility on the Australian Stock Exchange. The Australian Market Volatility Index (AVIX) was computed in a manner consistent with the CBOE Market Volatility Index (VIX). However, the quarterly expiration cycle of S&P/ASX 200 Index options lead to potential problems in calculating AVIX since large extrapolation of the implied volatility data was needed to create a 22 trading-day expiry. To correct for this, AVIX was also calculated with a 66 trading-day horizon.

The data set used in this study was both short and unique, covering the terrorist attacks of September 11, 2001 and the following rhetoric of war with Iraq. As such, the external validity of our results is doubtful. Ideally, a wider data set would be used in subsequent research. The S&P/ASX 200 Index options are also much more thinly traded than the S&P 100 Index options that underlie VIX in the United States. Thus nonsynchronous trading is a large problem in the Australian market and standard parametric analysis will suffer from an error in variables problem. The thin trading problem suggests that the results of this study must be interpreted with caution.

We found that AVIX increased substantially in response to the terrorist attacks of September 11, 2001. It also rose more recently in June 2002 in response to the higher likelihood of a war between the United States and Iraq involving Australia. AVIX was also found to be negatively correlated with stock returns. This is consistent with the results of Fleming, Ostdiek and Whaley (1995). However, unlike VIX, AVIX exhibited no asymmetry in its response to positive and negative stock returns.

The results for AVIX as a predictor of future volatility were inconclusive. Using ordinary least squares, AVIX is for the most part ineffective at forecasting future volatility. At a daily frequency, historic volatility was only marginally better. A first-order autoregressive model of historic volatility was a superior forecaster to AVIX at a weekly frequency. However, when Scholes and Williams (1977) consistent estimates were calculated, the performance of AVIX as a predictor of future volatility was much improved. In some instances, the parameter estimates strongly suggested that the forecasts were also unbiased. Historical volatility parameter estimates based on Scholes and Williams were also different from those obtained under ordinary least squares, but the change was not as dramatic. However, without standard errors for these estimates, solid conclusion cannot be drawn.

Accurate forecasts of future volatility are important to asset allocation decisions as well as option pricing. Thus users of volatility forecasts will include option market makers, hedge funds, arbitrageurs and speculators. Assessing the information content of implied volatility has implications for option pricing theory, investor behaviour and market efficiency. If option markets do not efficiently price options in a manner consistent with market forecasts, what is preventing arbitrageurs from making abnormal profits? There are clearly implications for option market microstructure. AVIX, and other measures of implied volatility in Australia can be added to the toolkit of the financial economist. These measures can be used in event studies in a manner similar to studies conducted in the United States, such as Day and Lewis (1988) and Schwert (1997). However, before Australian implied volatility can be used in such ways, we must understand its characteristics first. The motivation for this study was the apparent lack of research into understanding Australian stock market volatility. The aim is to encourage future research into the volatility of the Australian stock market such that it may be better represented in the finance literature.

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