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The information content of implied volatility in the Hong Kong and Singapore covered warrants markets

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Abstract

This paper examines the informational content and predictive power of implied volatility over different forecasting horizons in a sample of European covered warrants traded in the Hong Kong and Singapore markets. The empirical results show that time-series-based volatility forecasts outperform implied volatility forecast as a predictor of future volatility. The finding also suggests that implied volatility is biased and informationally inefficient. The results are due to the fact in Hong Kong and Singapore the covered warrants markets are dominated by retail investors, who tend to use covered warrants' leverage to speculate on the price movements of the underlying rather than to express their view on volatility.

1. Introduction

Conventional wisdom suggests that the volatility implied by the option premium reflects the market expectation and hence should be a reliable predictor of future volatility. However, empirical evidence is mixed. Feinstein (1989) and Chu and Freund (1996) support such contention and report that implied volatility is a more efficient forecast of volatility than historical volatility. Flemming (1998) shows that although implied volatility is a biased predictor, it outperforms historical volatility. On the other hand, Canina and Figlewski (1993), Gwilym (2001) and Li (2002) did not find any empirical evidence that supports the superior performance of implied volatility and conclude that implied volatility is informationally inefficient.

In this paper, we examine the predictive power and the information content of implied volatility in the Hong Kong and Singapore covered warrants markets. In particular, we focus on European call covered warrants traded on the Hong Kong Exchanges and Clearing (HKEx) and the Singapore Exchange (SGX). We compare the predictive performance of volatility of time-series models, namely, historical volatility, GARCH-based volatility and EGARCH-based volatility, with implied volatility derived from the Black-Scholes model. Furthermore, we test the forecasting power of implied volatility over different time horizons, i.e., 1-month, 2-month, 3-month, 6-month, 9-month, and 12-month horizons.[1]

While numerous studies have investigated the informational content of implied volatility for index and stock options (Feinstein 1989, Day and Lewis 1992 and Canina and Figlewski 1993), currency options (Scott 1992, Jorion 1995, Guo 1998 and Covrig and Low 2003) and futures (Day and Lewis 1993 and Neely 2003), little research has been done on the covered warrants markets. Huang and Chen (2002) compared stochastic volatility obtained from the Hull and White (1987) with implied volatility and a range of time series based measures of volatility using the 10 most actively traded warrants in Taiwan. To our knowledge, no study has investigated the quality of implied volatility in the covered warrants market as a predictor of future volatility.[2]

The study of covered warrants is of particular interest for three reasons. Firstly, unlike options trading which is dominated by institutional investors, the covered warrants market in both Hong Kong and Singapore is characterized by a strong presence of retail investors. In Singapore, for example, approximately 75% of warrants traders are retail investors.[3] As retail investors are likely to be less informed than institutional investors, the prominence of retail investors in the warrants market is expected to have a bearing on the quality of information conveyed by implied volatility. While institutional option traders typically dynamically hedge their delta (directional) risk and use options to express their view on volatility, retail investors care less about volatility in covered warrants. Most retail investors, with limited funding, are attracted to the product by the leverage of covered warrants and buy or sell them according to the subjective views on the directional change in the price of the underlying assets rather than volatility (Cheng, 2002). In other words, they view covered warrants as a pure substitute of the underlying stocks. Recent surveys undertaken by the Securities and Futures Commission (SFC) of Hong Kong indicate that a significant number of warrants investors do not fully understand the product. According to the survey, 10.8% of the surveyed investors admitted they knew nothing about covered warrants

[1] Even though the data set includes the 12-month maturity warrants in Hong Kong, the regression results do not include the 12-month horizon due to having an insufficient amount of series to be analyzed.

[2] Covered or structured warrants differ from corporate warrants in a few ways. Firstly, covered warrants are issued by third parties whereas corporate warrants are issued by companies. Covered warrants are hence straightforward options which can be priced with Black-Scholes model whereas corporate warrants involve issuing new shares and adjustment for the dilution effects should be made when it comes to pricing. Secondly, covered warrants can be plain-vanilla calls and puts as well as exotic options, corporate warrants are typically call options only. Thirdly, the covered warrant market is relatively new and fast growing whereas the corporate warrant market is established and static. Finally, the covered warrant market has better liquidity as issuers/writers double as market-makers.

[3] See Lin (2005), “Warrants trading promotes punting: analysts”, Channel New Asia for details.

while more than half of the respondents (52.4%) did not understand that a higher implied volatility corresponds with a higher warrants price. Our study is expected to provide useful insights into the quality of implied volatility of the fast-growing covered warrant market given the limited understanding of these structured products by investors.

Secondly, compared to the corporate warrants market and other equity options traded on the exchange, cover warrants are characterized by high liquidity. In addition, liquidity providers in Hong Kong and designated market-makers in Singapore are appointed by the covered warrant issuers to enhance transparency and liquidity to the market.[4] As a result, our study does not suffer from many estimation issues brought about by thin trading.

Thirdly, compared to the study on over-the-counter (OTC) currency options market where data are indicative quotes from market-makers (Covrig and Low, 2003), the data used in this study are transacted prices in the market.

The HKEx and Singapore Exchange provide an ideal setting to investigate the informational content of implied volatility. Hong Kong is consistently ranked as the world's 2nd largest covered warrants market by turnover in 2004 after Germany. The Singapore covered warrants market, on the other hand, is currently ranked 5th in the world according to statistics compiled by the World Federation of Exchanges. Like other Asian markets, both of Hong Kong and Singapore exchanges have experienced significant growth in the last few years, though Hong Kong is well ahead of Singapore (see Table 1).[5]

[INSERT TABLE 1 HERE]

Our results show that implied volatility is a biased and inefficient predictor of future volatility compared to time-series-based volatilities (historical volatility, GARCH-based volatility and EGARCH-based volatility). The explanation for the results is that the covered warrants markets in both Hong Kong and Singapore are dominated by retail investors who lack knowledge and skills in option trading. As a result, covered warrants markets are less efficient than other option

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[4] The Singapore Exchange covered warrants market did not take off until 2004 when they require issuers to also act as market-makers, providing two-way quotes for buyers and sellers all the time, thus ensuring liquidity. Two previous launches in 1995 and 1999 failed.

[5] The average daily turnover of Hong Kong covered warrants rose six times during 2002-2005 and during the first quarter of 2006, the average daily turnover was HK$6.1 billion which is 75% higher than 2005's turnover. Similarly, the SGX experienced a rapid growth in covered warrants turnover with a trading value of S$3.4 billion in the first quarter of 2005 compared to S$0.2 billion in 2004.

markets in predicting future volatility. Our findings are similar to those of Chen (1999) and Gwilym (2001) who conclude that GARCH-based volatility forecast outperforms implied volatility. Additionally, in sharp contrast to most previous studies, our results show that the predicting power of implied volatility does not diminish as forecasting horizon changes. Our results are robust to different data frequency and measurement error tests.

The remainder of the paper is organized as follows. Section 2 provides a brief literature review. Section 3 outlines the data and research methodology. In Section 4, we discuss the empirical results and in Section 5 we conduct robustness tests and checks. Section 6 concludes the study.

2. Literature Review

A number of studies have investigated the informational content of implied volatility in various markets and the empirical evidence is mixed. Feinstein (1989) examines options on the S&P 500 index futures during the 1983 to 1988 period and concludes that implied volatility derived from the Black–Scholes model is more efficient than historical volatility. Chu and Freund (1996) study options on the S&P 100 and S&P 500 index futures issued from 1981 to 1986 and report that implied volatility outperforms both GARCH-based volatility and historical volatility. However, Lamoureux and Lastrapes (1993) suggest that combining historical prices in forecasting models provides more accurate forecasting than implied volatility alone. They also find that even though the implied volatility contains useful information about future volatility, time-series models contain information incremental to the implied volatility. Similarly, Day and Lewis (1992) analyse a sample of S&P 100 index options and find that the implied volatility and the conditional volatility from GARCH and EGARCH models cannot characterize in-sample conditional stock market volatility completely. However, there is limited evidence from out-of-sample testing which shows that the predictive power of GARCH models outperforms EGARCH models. Furthermore, Pagan and Schwert (1990) show that parametric models are better than nonparametric models. Specifically, EGARCH is shown to be the best predictor of future volatility because of its ability to capture volatility asymmetry. Fleming (1998) finds that the implied volatility outperforms historical volatility and although it is a biased forecast, implied volatility provides useful information about future volatility.

In the currency market, implied volatility is found to be useful information in forecasting future volatility with a very small bias (see Scott 1992, Jorion 1995, Bates 1996 and Guo 1998). More recently, Covrig and Low (2003) use daily quoted implied volatility of currency in the OTC currency market from 1996 to 2000 and find that quoted implied volatility has more predictive power of future volatility than historical volatility, EWMA, and GARCH-based volatility forecasts.

In the oil market, Day and Lewis (1993) report that the implied volatility can predict future volatility for horizons up to two months. Although there are some evidences that GARCH-based and EGARCH-based volatility measures have incremental information, the results of out-of-sample tests and forecasting accuracy tests indicate that adding GARCH forecasts and historical volatility to the forecasting models does not significantly increase the explanatory power of implied volatility based forecast.

In the corporate warrant market, Hung and Chen (2002) compare stochastic volatility obtained from the Hull and White (1987), implied volatility, historical volatility, GARCH-based volatility, and EGARCH-based volatility by using the ten most actively traded issues in the TSE during the period from 1999 to 2001. They find that the best pricing model is the combination of the stochastic volatility and the implied volatility in forecasting warrants prices. After considering price biases related to the warrant strike price, time to maturity, interest rate and volatility, the implied volatility performs better than historical volatility even though the model tends to underprice in-the-money and overprice out-of-the-money warrants.

3. Data and Methodology

3.1. Data and Descriptive Statistics

The daily closing prices for European call covered warrants and daily closing prices of the underlying stocks were downloaded from Datastream.[6] Details on the covered warrants, such as expiry date, strike price and gearing ratio are manually collected from the official publications of the HKEx and SGX. Our final data set consists of 76 European call covered warrants traded on the HKEx from January 28, 2002 to October 18, 2005 and 55 European call covered warrants traded on the SGX from March 1, 2002 to October 17, 2005. In total, there are 131 covered

[6] We employ daily data in our study. This is consistent with Andersen, Bollerslev, & Lange (1999) who suggest that generally when data sampling frequency increases relative to forecasting horizon, volatility forecast accuracy improves.

warrants in our sample and only expired covered warrants on individual stocks are included in the sample to facilitate the calculation of the actual realised as well as implied volatility.

Interbank rates are used as a proxy of risk-free rates. There are two reasons for this: firstly, there is no liquid government securities market in Hong Kong or Singapore. Secondly, option traders tend to borrow from and lend to the interbank market rather than use government securities in their transactions (Hull 2005). The daily Hong Kong Interbank Offered Rates (HIBOR) of various maturity ranging from 1 to 9 months for Hong Kong and daily Singapore Interbank Offered Rates (SIBOR) in 1, 2, 3, 6 and 12 months maturity for Singapore are downloaded from Datastream.

3.2 Methodology

We first estimate three different types of volatility: realized volatility, implied volatility and volatility estimated based on econometric models. Regression analysis is then used to compare the predictive power of implied volatility versus other types of volatility estimates.

Realized volatility is obtained by calculating the annualized daily standard deviation of daily returns over the life of the covered warrants. 1-month volatility is calculated over 21 days which is the number of trading days in a month. Similarly, the 2-month volatility is calculated over 42 working days, 3-month over 63 working days, 6-month over 126 working days, 9-month over 189 working days and 12 months over 252 working days. For comparison purposes, the standard deviation is then annualized using a multiplier being the square root of the number of trading days (252) per year.

Using the stock prices, the covered warrants and interest rates, we calculate the implied volatility for each covered warrant on a daily basis using the Black-Scholes model. From the time series of implied volatility of all the covered warrants, we then obtain the cross-sectional data of implied volatility for one month, two months, three months, six months and nine months. In the case of Singapore, the one-year volatility is also obtained.

For the volatility based on econometric models, we use three different time-series models: historical volatility (or standard deviation), GARCH (1,1) and EGARCH (1,1).[7] Cross-sectional volatilities for the one to 12 months maturities are estimated for each stock.

Implied volatility is widely believed to be the best predicting tool of future volatility. Therefore, our hypothesis is that the forecasting power of implied volatility derived from the Black–Scholes model outperforms the historical volatility, GARCH-based and EGARCH-based volatility of future volatility.

Following Jorion (1995) and Covrig & Low (2003), we use the following model to test for the predictive power of implied volatility:

$$\sigma_{RV,t,T} = \alpha_0 + \alpha_1 \sigma_{IV,t,T} + \alpha_2 \sigma_{TV,t,T} + \varepsilon_t \tag{1}$$

where $\sigma_{RV,t,T}$ is the realized volatility over the period t to t + T and $\sigma_{IV,t,T}$ is the volatility forecast derived from the Black–Scholes model that is measured on day t for a warrant that expires on t + T, taken as implied volatility. $\sigma_{TV,t,T}$ is a time-series-based volatility measure (historical standard deviation, GARCH-based volatility, and EGARCH-based volatility).

For each time horizon and for each market, seven regression models are estimated. Models 1 to 4 are simple regression models. We regress the realized volatility against the implied volatility, historical volatility GARCH (1,1) and EGARCH (1,1) volatility, respectively. On the other hand, Models 5 to 7 are multiple regression models. In Models 5, 6 and 7, we regress realised volatility against implied volatility jointly with historical volatility, GARCH (1,1) and EGARCH (1,1) volatility, respectively.

Only the volatilities in the same forecasting horizon are regressed together because any comparison of implied volatility with time-series-based volatilities from different forecasting horizons is inappropriate (Burghardt and Lane, 1990). Our data set contains different forecasting horizons, 1, 2, 3, 6, and 9 months for Hong Kong and 1, 2, 3, 6, 9, and 12 months for Singapore which can be used to test the relationship between the significance of implied volatility and the forecasting horizons.

Regressing the implied volatility jointly with a time-series-based volatility allows us to test

[7] The GARCH (1,1) and EGARCH (1,1) are standard test now. We do not specify and discuss them here. In our study, Eviews is used to obtain the volatility estimates.

whether implied volatility is the optimal forecast of future volatility. We can then compare the predictive power of implied volatility with time-series-based volatilities.

If implied volatility is unbiased, the intercept, $\alpha_{0,}$ should be zero and α_1 should be unity.[8] Wald Test 1 is used to test if the volatility is unbiased. If implied volatility contains substantial information about future volatility, α_1 should be statistically significantly different from zero. If implied volatility is informationally efficient, α_2 should be zero and the second Wald test is employed to test the hypothesis (α_0 = 0, α_1 = 1, and α_2 = 0).

According to Jorion (2005), the predicative power of implied volatility is best in the short-term (two weeks to three months). Therefore, if implied volatility is negatively related to the forecasting horizons, the slope coefficient, $\alpha_{1,}$ should decrease in economic and statistical significance with the forecasting horizons.

4. Empirical Results

Table 2 presents descriptive statistics for the two volatility series: the actual realized volatility (RV) of the stock returns and the implied volatility (IV) based on the covered warrants in both Hong Kong (Panel A) and Singapore (Panel B).

[INSERT TABLE 2 HERE]

Table 2 shows that the realized volatility is significantly different from implied volatility and that implied volatility tends to overstate realized volatility. The magnitude of the discrepancy between implied volatility and realized volatility does not seem to increase with time horizon. Further, while implied volatility is generally negatively related to time, the mean value of realized volatility seems quite random and does not change significantly over different time horizons.

It is also of interest to note that in both markets implied volatility has a much higher standard deviation than realized volatility. Consistent with Covrig and Low (2003) and Campa and Cheng

[8] Figlewski (1997) uses this hypothesis to test both the unbiasedness and information efficiency of implied volatility. We, however, only use this hypothesis to test unbiasedness. The Wald test 2 is used to test if the implied volatility is informationally efficient which follows the work of Jorion (1995) and Covrig and Low (2003).

(1995), the standard deviation of both implied volatility and realized volatility appears to decrease with longer warrants maturity except for the case of the 9-month warrants in Hong Kong and 9 and 12 months warrants in Singapore.

Estimation results of Equation (1) are reported in Table 3. As can be seen in Panel A, in the Hong Kong market, when realized volatility is regressed solely on implied volatility, the coefficients of implied volatility (α_1) are significantly different from zero at the 1% level regardless of the forecasting horizon. Further, as shown in Panel B, this finding also holds in the case of Singapore except for the 9-month horizon.

[INSERT TABLE 3 HERE]

The result indicates that implied volatility contains significant information about future volatility across the markets, but it does not necessarily suggest that implied volatility is a more accurate forecast of future volatility. As a matter of fact, the results of Wald Test 1 suggest that implied volatility is a biased predictor of actual volatility for all forecasting horizons in both markets except for Singapore in the 12-month maturity. In terms of economic significance, it also appears that implied volatility contains more information about realized volatility as time horizon lengthens. The coefficient on implied volatility increases up to 0.81 for the 6-month horizon in Hong Kong and 1.08 for the 12-month horizon in Singapore. The coefficients for time-series-based volatility measures are statistically significantly different across forecasting horizons. The *R*-squared further shows that these time-series measures explain a larger degree of fluctuation in realized volatility. In terms of *R*-squared, GARCH measure outperforms other models followed by EGARCH measure while historical volatility performs better in the case of the 6-month warrants in Hong Kong and the 12-month warrants in Singapore.

When implied volatility and the time-series-based volatility are regressed jointly, the time-series-based volatility coefficients are significant at the 1% level across the different forecasting horizons in both Hong Kong and Singapore markets except for the 12-month maturity in Singapore. The coefficient, α_2, ranges from 0.42 to 1.11 in Hong Kong and 0.35 to 1.57 in Singapore. In contrast, for both markets, the slope coefficients of implied volatility become smaller and statistically insignificant. For example, α_1 ranges from 0 to 0.47 in Hong Kong and –0.30 to 0.55 in Singapore. In Singapore, none of the coefficients of implied volatility are statistically different from zero except for the case of the 12-month warrants.

In terms of biasness test, the statistical results of the first Wald test show that implied volatility is biased for most of forecasting horizons in both markets when implied volatility and a time-series-based volatility are regressed jointly. However, implied volatility appears to be an unbiased predictor of future volatility in the following situations. First, when implied volatility is regressed with GARCH (1,1) in the 6-month maturity in Hong Kong. Second, when implied volatility is regressed with GARCH (1,1) and EGARCH (1,1) in the 12-month maturity in Singapore. Finally, implied volatility is found to be an unbiased predictor in the case of 9-month warrants in Singapore in all regression results. The second Wald test, aiming at testing the informational efficiency of implied volatility, shows that implied volatility is not informationally efficient except for the 12-month maturity in Singapore. In general, implied volatility contains less information about future volatility than historical volatility, GARCH-based, and EGARCH-based volatility.

Consistent with many previous studies, our results show that implied volatility contains a certain degree of information about future volatility. However, in comparison with time-series-based volatilities, implied volatility appears to be informationally inefficient and biased. In terms of the predictive power, implied volatility forecast generally underperforms time-series-based volatility forecasts. Our result also supports the use of GARCH-based volatility as the most reliable predictor of future volatility in the case of covered warrants market. However, unlike most previous studies, we find the significance of implied volatility is not negatively related to forecasting horizons.

The explanation for our results is that, unlike other option markets, the covered warrant markets are predominantly dominated by retail investors who are attracted by the high leverage offered by the covered warrants. Without sufficient knowledge and expertise of option trading, they tend to use covered warrants to speculate on the direction of stock prices rather than volatility. As a result, covered warrant markets are more likely to be less efficient than other option markets.

5. Robustness Testing

In this section we test the robustness of our results by running Equation (1) using monthly data and by measuring forecasting errors. The details of these two tests are elaborated below.

5.1 Alternative Data Frequency

Monthly sampling is employed to overcome the biased standard errors which may occur when regressed by OLS with overlapping data. It may be biased because in the OLS estimation the assumption is made that each day has an independent observation. Nevertheless, in daily sampling, the volatility of the previous day is only different from the current day by one daily return observation. As a result, daily volatility observations may not be independent. The new time series is formed by re-sampling daily data to the closing price of the underlying stock and warrant in the last trading day at each month up to the 9-month horizons in Hong Kong and Singapore. This new setup will allow us to determine how sensitive the results are to sampling frequency.

Table 4 reports results relating to monthly sampling. These results are directly comparable with previous results presented in Table 3 and they consistently show that although being biased implied volatility contains significant information about future volatility in both markets. The coefficients of implied volatility (α_1) in Hong Kong are significantly different from zero at the 1% level except in the 9-month maturity. Similarly, in Singapore, α_1 is also significantly different from zero at the 1% level except in the 1-month and the 9-month maturity. Furthermore, the results of the Wald test 1 indicate that implied volatility is biased for all forecasting horizons except for the 9-month maturity in Singapore.

[INSERT TABLE 4 HERE]

The relationship between the significance of implied volatility and forecasting horizons again differs slightly between Hong Kong and Singapore. There is a positive relationship between the two variables suggesting that the significance of implied volatility increases as forecasting horizon increases. In Hong Kong, the pattern is not so straight forward, In particular, implied volatility decrease from the 1-month to 2-month forecasting horizons and increases steadily throughout the remaining forecasting horizon. In Singapore, implied volatility increases between the 1 month and 2 month horizons, then drops in the third month, and increases steadily for the remainder of the horizon.

However, the results show a small increase in the coefficients that correspond to implied volatility and a decrease in those that correspond to time-series-based volatilities. Additionally, in Hong Kong, the 1-month and the 3-month maturity warrants have the highest *R* squared in EGARCH model while the GARCH model best explains realized volatility in the 2-month maturity. Implied volatility performs well in the 6-month maturity while historical standard deviation in the 9-month maturity has the highest *R* squared. Furthermore, although the predictive power of historical standard deviation increases with time horizons GARCH-based volatility forecast tend to outperform implied volatility, historical volatility and EGARCH volatility in most maturities.

In joint regressions, the coefficients on implied volatility appear to increase in economic significance while the incidence of statistical significant remains largely unchanged. The coefficients on the three time series based measures, on the other hand, show a general decrease in economic significance but statistically they remain strongly significant. As far as biasness is concerned, the previous results hold. Implied volatility is found to be largely biased and informationally inefficient.

In general, the results in Table 4 indicate that the substance of our findings reported in Table 3 remains robust to alternative data sampling frequency. It is also of interest to note that realized volatility is explained better in regressions using daily data than monthly data. This finding is largely consistent with Covrig & Low (2003) and Bollerslev, & Lange (1999) who suggest that volatility forecast accuracy improves when data sampling frequency increases relative to forecasting horizon.

5.2 Measuring Forecasting Errors

In this section, we employ the root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) to evaluate the forecasting accuracy of the four volatility forecast models from different estimated procedures. The first two forecast error statistics depend on the scale of the dependent variable and the last one is scale invariant. Therefore, RMSE and MAE measures need to be used as relative measures to compare forecasts for the same series across different models.

The statistical measures of forecast error statistics are computed as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum(\sigma_{RV,t} - \sigma_{TV,t})^2}$$

$$MAE = \frac{1}{n}\left|\sigma_{RV,t} - \sigma_{TV,t}\right|$$

$$MAPE = \frac{1}{n}\sum\left|\frac{\sigma_{RV,t} - \sigma_{TV,t}}{\sigma_{RV,t}}\right| \qquad (2)$$

where n is the number of forecast data, $\sigma_{RV,t}$ is realized volatility of warrants, $\sigma_{TV,t}$ is the volatility forecast measured on daily or monthly t, taken as implied volatility inverted from the Black-Scholes model, historical standard deviation, GARCH-based, and EGARCH-based volatility.

The results of these measures are shown in Table 5. The statistics results that correspond to the daily sampling are presented in Panel A, and those correspond to the monthly sampling are presented in Panel B. If a volatility forecast is a better predictor of future volatility, it should have a smaller RMSE, MAE, and MAPE.

[INSERT TABLE 5 HERE]

In general, regardless of the sample frequencies, the results show that GARCH (1,1) forecasting is a better predictor of future volatility than implied volatility, historical volatility, and EGARCH volatility in 1-month, 2-month and 3-month horizons across markets. However, the results are slightly sensitive to the data frequency in longer forecasting horizons. For example, in the Hong Kong market, GARCH-based volatility seems to be a better predictor of future volatility at the 9-month forecasting horizon using daily sampling, but in monthly sampling, historical volatility is the best predictor. In Singapore, EGARCH and GARCH volatility forecasts outperform implied volatility and historical volatility at the 9-month time horizon in daily sampling, but historical volatility outperforms other volatility forecasts in monthly sampling. There is also some evidence that implied volatility is a better predictor of future volatility in Hong Kong’s 6-month warrants and Singapore’s 2-month warrants but overall there is strong evidence that time series based volatility forecasts outperform implied volatility as a predictor of future volatility. Additionally, GARCH (1,1) volatility measure appears to be the best time series based forecast.

6. Conclusions

In this study we investigated various volatility measures including Black-Scholes implied volatility, historical standard deviation, GARCH-based and EGARCH-based volatility to examine the information content and the predictive power of implied volatility with different forecasting horizons in covered warrants traded on the HKEx and the SGX.

Our results show that implied volatility contains information about future volatility, but when compared to the time-series models, the degree of information is relatively marginal. Additionally, implied volatility appears to be informationally inefficient and biased across markets. Implied volatility also underperforms time series based volatility measures as a predictor of future volatility although there is some evidence that the significance of implied volatility improves with time horizon. Finally, despite the discrepancy in market size between Hong Kong and Singapore, we fail to find any substantial difference in the informational content and predictive power of implied volatility in these two markets. This finding suggests that turnover does not have an impact on the information content of implied volatility; rather it is the degree of investors' sophistication that is likely to improve the information value conveyed by implied volatility. Retail investors, with limited funding opportunities, use covered warrants as a speculative tool to bet on the price direction of stocks. Our results there highlight the need of investors' education so that they have a better understanding of covered warrants which are highly leveraged and whose value depends on, among other things, both price of the underlying assets and their volatility.

References

Andersen, T.G., Bollerslev, T., & Lange, S. (1999). Forecasting financial market volatility: Sample frequency vis-à-vis forecasting horizon. *Journal of Empirical Finance, 6,* 457-477.

Akgiray, V. (1989). Conditional heteroscedasticity in time series of stock return evidence and forecasts. *Journal of Business*, *62*, 55-59.

Bates, D. (1996). Jumps and stochastic volatility: Exchange rate processes implicit in Deutsche mark options. *Review of Financial Studies, 9*, 69-107.

Black, F., & Scholes, M.S. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*, 637–659.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of Econometrics*, *31*, 307-327.

Burghardt, G., & Lane, M. (1990). How to tell if options are cheap. *Journal of Portfolio Management, 16,* 72-78.

Campa, J. & Chang, K. (1995). Testing the expectations hypothesis on the term structure of volatilities in foreign exchange options. *Journal of Finance,* 50, 529-547.

Canina, L., & Figlewski, S. (1993). The information content of implied volatility. *Review of Financial Studies, 6*, 659–681.

Chen, W.P. (1998). *A comparison of the forecasting performance between GARCH and implied volatility models*. Unpublished master's thesis, TamKang University, Taiwan.

Cheng, W.Y. (2002). *A simple method to rank warrants.* Retrieved June 10, 2006, from http://hkumath.hku.hk/~org/seminars/ORGMay16.pdf

Christensen, B.J., & Hansen, C.S. (2002). New evidence on the implied-realized volatility relation. *The European Journal of Finance, 8,* 187-205.

Chu, S.H., & Freund, S. (1996). Volatility estimation for stock index options: a GARCH approach. *The Quarterly Review of Economics and Finance*, *36,* 431-450.

Covrig, V., & Low, B.S. (2003). The quality of volatility traded on the over-the-counter currency market: A multiple horizons study. *The Journal of Futures Markets*, *23*, 261-285.

Day, T.E., & Lewis, C.M. (1992). Stock market volatility and the information content of stock index options. *Journal of Econometrics*, *52*, 267–287.

Day, T.E., & Lewis, C.M. (1993). Forecasting futures market volatility. *Journal of Derivatives, 1*, 33-50.

Engle, R. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of UK inflation. *Econometrica*, *50,* 987-1108.

Fair, R., & Schiller, R. (1990). Comparing information in forecasts from econometric models. *American Economic Review, 80*, 375-389.

Feinstein, S. (1989). Forecasting stock market volatility using options on index futures. *Economic Review- Federal Reserve Bank of Atlanta, 74*, 12-30.

Figlewski, S. (1997). Forecasting volatility. *Financial Markets, Institutions, Instruments, 6*, 1-88.

Fleming, J. (1998). The quality of market volatility forecasts implied by S&P 100 index option prices, *Journal of Empirical Finance, 5*, 317-345.

Guo, D. (1998). The risk premium of volatility implicit in currency options. *Journal of Business and Economic Statistics*, *16*, 698-507.

Gwilym, O.A. (2001). Forecasting volatility for options pricing for the U.K stock market. *Journal of Financial Management and Analysis, 14*, 55-62.

Heston, S. (1993). A close form solution for options with stochastic volatility. *Review of Financial Studies, 6*, 327-343.

Hodges, S., & Tompkins, R. (2002). Volatility Cones and Their Sampling Properties. *Journal of Derivatives, 10*, 27-43.

Hull, J. (2005), Options, futures and other derivatives, 6th edition, Prentice Hall.

Hull, J., & White, A. (1987). The pricing of options on assets with stochastic volatilities. *Journal of Finance, 42*, 281–300

Huang Y.C., & Chen, S.C. (2002). Warrants pricing: Stochastic volatility vs. Black-Scholes. *Pacific-Basin Finance Journal*, *10*, 393-409.

Jorion, P. (1995). Predicting volatility in the foreign exchange market. *Journal of Finance, 50*, 507–528

Jorion, P. (2005). *Financial Risk Manger Handbook* (3rd ed.). Hoboken: Wiley.

KBC Financial Products. (2004). *A Survey on Hong Kong Investors' Understandings in Covered Warrants Market.* Retrieved May 2, 2005, from http://www.kbcwarrants.com.hk/content/pdf/Warrants%20Commentary310504

Lamoureux, C.G., & Lastrapes, W.D. (1993). Forecasting stock return variance: toward an understanding of stochastic implied volatilities. *The Review of Financial Studies, 6*, 293–326

Li, K. (2002). Long-memory versus option-implied volatility prediction. *Journal of Derivatives, 9*, 9-25.

Lim, F. (2005). *Warrants trading promotes punting: analysts.* Retrieved July 6, 2005, from http://www.channelnewsasia.com/stories/singaporebusinessnews/view/1

McMillan, D., Speight, A., & Gwilym, O.A. (2000). Forecasting UK stock market volatility. *Applied Financial Economics, 10,* 435-448.

Neely, C. (2003). *Forecasting foreign exchange volatility: Is implied volatility the best we can do?* [Working Paper, Federal Reserve Bank of St. Louis.] Retrieved May 30, 2006, from http://venus.icre.go.kr/metadata/25805_2002-017.pdf

Nelson, D. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica, 59,* 347-370.

Newey, W.K., & West, K.D. (1987). A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55,* 702-708.

Pagan, A.R., & Schwert, G.W. (1990). Alternative models for conditional stock volatility. *Journal of Econometrics, 45,* 267-290.

Scott, L.O. (1992). The information content of prices in derivative security market. *IMF Staff Paper, 39,* 592-625.

Taylor, S., & Xu, X. (1997). The incremental volatility information in one million foreign exchange quotations. *Journal of Empirical Finance, 4,* 317-249.

The Hong Kong Exchanges and Clearing. (2005). *HKEx discusses derivative warrants and invites feedback.* Retrieved October 10, 2005, from http://www.hkex.com.hk/news/hkexnews/051010news.htm

The Hong Kong Exchanges and Clearing. (2006). *Cash market transaction survey 2004/05.* Retrieved May 15, 2006, from http://www.hkex.com.hk/research/cmtrsur/CMTS05.pdf

The Securities and Futures Commission. (2004). *Derivative warrants are not for everyone.* Retrieved June 5, 2006, from http://www.invested.hk/invested/doc/EN/features/222_dr_wise_july04_eng.pd

The Securities and Futures Commission. (2005). *Warrants: if in doubt, stay out.* Retrieved June 5, 2006, from http://www.invested.hk/invested/doc/EN/features/drwise_sept05_eng.pdf

The Securities and Futures Commission. (2006a). *Investors Consider Warrants Highly Risky.* Retrieved June 5, 2006, from http://eapp01.sfc.hk/apps/cc/PressRelease.nsf/eng/lkupNewsCodeEng/06PR43

The Securities and Futures Commission. (2006b). *Hong Kong's derivative warrants market – moving with times amid rapid developments in other warrants markets in Asia.* Retrieved June 5, 2006, from http://www.sfc.hk/sfc/doc/EN/research/research/RS%20paper%2028.pdf

The Singapore Exchange. (2005). *SGX achieved a record quarter performance for1Q FY2006.* Retrieved May 30, 2006, from http://info.sgx.com/webnewscentre.nsf/b9c790d0d5ba5d2548256dcf0049ce28/4825683800 2f07b1482570ba000b4a8a?OpenDocument

The Singapore Exchange. (2006). *SGX records highest profit to 3Q FY 2006 since going public.* Retrieved April 20, 2006 from http://info.sgx.com/webnewscentre.nsf/b9c790d0d5ba5d2548256dcf0049ce28/4825683800 2f07b14825714d0033e05e?OpenDocument

The World Federation of Exchanges. (2006). *World Federation of Exchanges markets highlights.* Retrieved March 20, 2006 from http://www.world-exchanges.org/publications/WFE%20Markets%20highlights%202005.pd f

Xu, X., & Taylor, S. (1994). The term structure of volatility implied by foreign exchange options. *Journal of Financial and Quantitative Analysis, 29,* 57–74.

Xu, X., & Taylor, S. (1995). Conditional volatility and the informational efficiency of the PHLX currency options market. *Journal of Banking and Finance*, 19, 803–821.

Table 1: Covered warrants in Asia

	Number of covered warrants listed (at year end)		Trading value (USD millions)		Number of trades (in thousands)	
	2005	2004	2005	2004	2005	2004
Hong Kong	1,304	863	110,168	67,337	11,438	8,704
Korea	72	3	41	6	228	-
Malaysia	12	10	277	630	NA	NA
China	4	-	21,548		12,686	
Singapore	455	146	6,521	931	NA	NA
Taiwan	540	191	4,424	6,252	8,010	7,757
Thailand	-	1	-	3,060	-	886

Source: Annual Report, World Federation of Exchanges, 2005.

Table 2: Descriptive Statistics for Realized Volatility and Implied Volatility

This table summarises the mean, median, standard deviation, skewness, kurtosis, maximum, and the number of observations (in days) of realized volatility (RV) and implied volatility (IV) for warrants that have 1 month (1M), 2 months (2M), 3 months (3M), 6 months (6M), 9months (9M), and 12 months (12M) maturity. The statistics are computed from January 28th 2002 to October 18th 2005 in Hong Kong and from March 1st 2002 to 17th October 2005 in Singapore.

	Variable	Mean	Median	Std. D.	Skewness	Kurtosis	Max.	Observations
Panel A: Hong Kong								
1M	RV	0.202	0.183	0.111	1.195	4.924	0.896	1596
	IV	0.441	0.247	0.570	2.740	14.275	5.437	1596
2M	RV	0.204	0.192	0.103	1.047	4.449	0.896	3192
	IV	0.342	0.225	0.434	3.651	24.299	5.437	3192
3M	RV	0.204	0.196	0.097	0.939	4.194	0.896	4790
	IV	0.302	0.216	0.368	4.282	33.285	5.437	4790
6M	RV	0.203	0.196	0.089	0.797	3.831	0.896	9438
	IV	0.267	0.217	0.276	5.476	56.252	5.437	9438
9M	RV	0.240	0.259	0.087	0.102	3.916	0.896	3210
	IV	0.285	0.240	0.283	4.000	32.730	3.477	3210
12M	RV	0.238	0.240	0.058	-0.259	3.384	0.424	1005
	IV	0.328	0.268	0.212	1.471	14.400	2.494	1005
Panel B: Singapore								
1M	RV	0.225	0.221	0.096	0.447	3.550	0.637	1154
	IV	0.604	0.295	1.023	3.882	25.252	10.419	1154
2M	RV	0.239	0.234	0.091	0.540	4.318	0.640	2310
	IV	0.448	0.281	0.768	5.121	43.612	10.419	2310
3M	RV	0.243	0.245	0.086	0.417	4.124	0.640	3466
	IV	0.384	0.279	0.646	6.013	60.557	10.419	3466
6M	RV	0.249	0.254	0.082	0.251	3.604	0.640	6162
	IV	0.312	0.267	0.493	7.916	104.662	10.419	6162
9M	RV	0.235	0.213	0.086	0.647	3.045	0.637	2450
	IV	0.308	0.272	0.442	9.687	161.706	10.380	2450
12M	RV	0.245	0.220	0.093	0.855	3.054	0.637	1508
	IV	0.337	0.296	0.352	5.308	51.022	5.095	1508

Table 3: Regressions Results – Daily Sampling

This table reports the regression results of the following equation:

$$\sigma_{RV,t,T} = \alpha_0 + \alpha_1 \sigma_{IV,t,T} + \alpha_2 \sigma_{TV,t,T} + \varepsilon_t \qquad (5)$$

Where $\sigma_{RV,t,T}$ is the realized volatility over the period t to t + T and $\sigma_{IV,t,T}$ is the volatility forecast derived from the Black–Scholes model that is measured on day t for a warrant that expires on t + T, taken as implied volatility. $\sigma_{TV,t,T}$ contains three different types of time-series-based volatilities, namely historical standard deviation, GARCH-based volatility, and EGARCH-based volatility. These volatilities are forecasted over the period t to t + T. Historical standard deviation is calculated using daily underlying stock price over 21 days before the forecast day for the 1-month warrant, 42 days for the 2-month warrant, 63 days for the 3-month warrant, 126 days for the 6-month warrant, 189 days for the 9-month warrant, and 252 days for the 12-month warrant. GARCH forecasts are obtained by GARCH (1,1) model and EGARCH (1,1) forecasts are based on the Nelson's (1991) model. The Wald test 1 is used to test if implied volatility is unbiased, the hypothesis being $\alpha_0 = 0$, $\alpha_1 = 1$. The Wald test 2 tests if implied volatility is informative when regressed jointly with a time-series-based volatility, the hypothesis being $\alpha_0 = 0$, $\alpha_1 = 1$, and $\alpha_2 = 0$.

Panel A :Hong Kong								
Horizon / Model	α_0	IV (α_1)	HV (α_2)	GARCH(α_2)	EGARCH (α_2)	R^2	Wald test 1	Wald test 2
1 month / Model 1	-0.97**	0.59**				0.59	33.95**	
Model 2	-0.32**		0.82**			0.68		
Model 3	-0.04			0.98**		0.73		
Model 4	-0.12				0.97**	0.69		
Model 5	-0.41	0.24	0.59**			0.73	18.39**	59.31**
Model 6	-0.11	0.13		0.85**		0.76	33.70**	67.08**
Model 7	-0.22	0.17*			0.80**	0.74	41.73**	89.89**
2 months / Model 1	-0.63**	0.72**				0.54	12.37**	
Model 2	-0.09		0.93**			0.70		
Model 3	0.07			1.02**		0.84		
Model 4	0.03				1.04**	0.76		
Model 5	-0.04	0.18*	0.82**			0.76	19.52**	23.13**
Model 6	0.10	0.00		1.04**		0.86	45.62**	47.00**
Model 7	0.00	0.15			0.90**	0.77	16.67**	27.98**
3 months / Model 1	-0.61**	0.71**				0.54	6.29**	
Model 2	-0.07		0.94**			0.58		
Model 3	0.05			1.01**		0.82		
Model 4	0.06				1.06**	0.75		
Model 5	-0.12	0.27	0.68**			0.62	5.52**	6.03**
Model 6	0.05	0.10		0.92**		0.84	58.81**	64.36**
Model 7	0.13	0.00			1.11**	0.81	39.38**	47.47**

6 months / Model 1	-0.52**	0.81**				0.58	20.52**	
Model 2	-0.03		1.07**			0.78		
Model 3	-0.48**			0.69**		0.60		
Model 4	-0.25				0.80**	0.66		
Model 5	-0.05	0.11	0.96**			0.79	14.13**	63.25**
Model 6	-0.28	0.47		0.42**		0.70	2.86	36.54**
Model 7	-0.15	0.41*			0.53**	0.72	4.25*	31.82**
9 months / Model 1	-0.74**	0.54**				0.46	20.64**	
Model 2	-0.64**		0.72**			0.66		
Model 3	-0.04			0.96**		0.86		
Model 4	-0.15				0.86**	0.75		
Model 5	-0.33	0.34**	0.57**			0.83	40.73**	27.21**
Model 6	-0.04	0.01		0.95**		0.86	62.07**	53.23**
Model 7	-0.15	0.11			0.76**	0.76	64.95**	43.31**
Panel B: Singapore								
Horizon / Model	α_0	IV (α_1)	HV (α_2)	GARCH(α_2)	EGARCH (α_2)	R^2	Wald test 1	Wald test 2
1 month / Model 1	-1.30**	0.22**				0.10	171.20**	
Model 2	-0.67**		0.55**			0.36		
Model 3	-0.38**			0.77**		0.58		
Model 4	-0.42**				0.75**	0.59		
Model 5	-0.57*	0.02	0.60**			0.43	32.63**	83.41**
Model 6	-0.29	-0.05		0.86**		0.67	68.79**	128.11**
Model 7	-0.36	-0.03			0.82**	0.71	80.93**	386.67**
2 months / Model 1	-1.14**	0.30*				0.16	33.26**	
Model 2	-0.37**		0.74**			0.56		
Model 3	-0.24**			0.82**		0.85		
Model 4	-0.24**				0.84**	0.73		
Model 5	-0.47	0.07	0.62**			0.50	17.36**	132.05**
Model 6	-0.28	0.03		0.77**		0.83	61.73**	264.75**
Model 7	0.34	0.01			0.77**	0.71	38.54**	293.89**
3 months / Model 1	-1.03**	0.34*				0.21	12.39**	
Model 2	-0.29**		0.79**			0.75		
Model 3	-0.38**			0.72**		0.76		
Model 4	-0.36**				0.75**	0.74		
Model 5	-0.28	-0.01	0.81**			0.73	49.58**	172.82**
Model 6	-0.42	0.07		0.64**		0.75	69.83**	259.08**
Model 7	-0.34	0.06			0.71**	0.74	50.05**	140.37**
6 months / Model 1	-0.70**	0.61**				0.25	16.04**	
Model 2	0.02		1.03**			0.58		

Model 3	-0.43**			0.65**		0.83		
Model 4	0.01				0.99**	0.88		
Model 5	0.01	-0.18	1.19**			0.59	16.26**	49.44**
Model 6	-0.27	0.20		0.60**		0.86	38.98**	86.05**
Model 7	-0.04	-0.05			1.00**	0.88	92.61**	117.37**
9 months / Model 1	-0.31	1.00				0.34	8.09**	
Model 2	0.43		1.47**			0.71		
Model 3	-0.58**			0.63**		0.65		
Model 4	-0.57**				0.63**	0.82		
Model 5	0.24	-0.31	1.57**			0.72	3.49	106.41**
Model 6	-0.52	0.10		0.56**		0.73	0.84	34.22**
Model 7	-0.61	0.00			0.59**	0.79	1.29	34.92**
12 months / Model 1	-0.15	1.08**				0.46	3.13	
Model 2	1.24**		2.07**			0.87		
Model 3	-0.72			0.54*		0.50		
Model 4	-0.41				0.78**	0.70		
Model 5	1.48**	0.54**	1.75**			0.96	81.57**	55.37**
Model 6	-0.30	0.55		0.35		0.56	0.34	14.13*
Model 7	-0.57	-0.30			0.93	0.71	3.46	7.44

Table 4: Regressions Results – Monthly Sampling

This table reports the regression results of the following equation:

$$\sigma_{RV,t,T} = \alpha_0 + \alpha_1 \sigma_{IV,t,T} + \alpha_2 \sigma_{TV,t,T} + \varepsilon_t \qquad (5)$$

Where $\sigma_{RV,t,T}$ is the realized volatility over the period t to t + T and $\sigma_{IV,t,T}$ is the volatility forecast derived from the Black–Scholes model that is measured on day t for a warrant that expires on t + T, taken as implied volatility. $\sigma_{TV,t,T}$ contains three different types of time-series-based volatilities, namely the historical standard deviation, GARCH-based volatility, and EGARCH-based volatility. These volatilities are forecasted over the period t to t + T. Historical standard deviation is calculated using daily underlying stock price over 21 days before the forecast day for the 1-month warrant, 42 days for the 2-month warrant, 63 days for the 3-month warrant, 126 days for the 6-month warrant, 189 days for the 9-month warrant, and 252 days for the 12-month warrant. GARCH forecasts are obtained by GARCH (1,1) model and EGARCH (1,1) forecasts are based on the Nelson's model. The Wald test 1 is used to test if the implied volatility is unbiased, the hypothesis being $\alpha_0 = 0$, $\alpha_1 = 1$. The Wald test 2 tests if the implied volatility is informative when regressed jointly with a time-series-based volatility, the hypothesis being $\alpha_0 = 0$, $\alpha_1 = 1$, and $\alpha_2 = 0$.

				Panel A: Hong Kong				
Horizon / Model	α_0	IV (α_1)	HV (α_2)	GARCH(α_2)	EGARCH (α_2)	R^2	Wald test 1	Wald test 2
1 month/ Model 1	-1.57**	0.63**				0.14	25.49**	
Model 2	-1.54**		0.34**			0.11		
Model 3	-1.24**			0.45**		0.12		
Model 4	-1.06**				0.51**	0.26		
Model 5	-0.95	0.54	0.34*			0.24	3.57*	19.83**
Model 6	-0.82	0.39		0.45**		0.21	4.38*	20.06**
Model 7	-0.95	0.17			0.47**	0.27	7.45**	23.21**
2 months/Model 1	-1.36**	0.44**				0.10	19.59**	
Model 2	-2.11**		-0.04			0.00		
Model 3	-0.63**			0.60**		0.47		
Model 4	-1.51**				0.19**	0.17		
Model 5	-1.43**	0.45	-0.04			0.10	11.23*	13.02**
Model 6	-0.42	0.22		0.55**		0.45	18.17**	34.08**
Model 7	-1.15**	0.33			0.14**	0.19	9.31**	16.79**
3 months/Model 1	-0.80**	0.71**				0.29	16.63**	
Model 2	-1.42**		0.27**			0.07		
Model 3	-0.71**			0.56**		0.36		
Model 4	-0.84**				0.48**	0.39		
Model 5	-0.67	0.67**	0.12			0.30	3.68*	11.41**
Model 6	-0.15	0.48		0.48**		0.48	9.29**	22.58**
Model 7	-0.54*	0.33			0.38**	0.44	9.25**	19.45**

6 months/Model 1	-0.59*	0.77**				0.55	22.73**	
Model 2	-1.21**		0.30**			0.09		
Model 3	-0.92**			0.38**		0.32		
Model 4	-0.76**				0.43**	0.44		
Model 5	-0.58	0.77**	0.00			0.55	5.76**	14.80**
Model 6	-0.52	0.62		0.15*		0.59	6.30**	17.39**
Model 7	-0.48	0.46			0.27**	0.67	10.07**	24.67**
9 months/Model 1	-1.81**	-0.58				0.19	6.50*	
Model 2	0.61		1.18*			0.45		
Model 3	-0.96			0.03		0.00		
Model 4	-0.16				0.48	0.05		
Model 5	-0.14	-0.47	1.09**			0.57	11.30*	8.23*
Model 6	-1.18	-1.04		0.82		0.34	5.41	4.86
Model 7	-0.89	-0.60			0.53	0.25	4.96	4.06
				Panel B: Singapore				
1 month/Model 1	-2.56**	-0.07				0.00	26.74**	
Model 2	-2.33**		0.00			0.00		
Model 3	-0.78**			0.71**		0.28		
Model 4	-1.97**				0.15	0.02		
Model 5	-2.39	-0.08	0.08			0.00	9.32**	16.65**
Model 6	-1.34	-0.13		0.57**		0.20	9.16**	24.28**
Model 7	-2.42 **	-0.08			0.06	0.01	11.71**	17.45**
2 months/Model 1	-1.07**	0.74**				0.31	47.00**	
Model 2	-1.65**		0.17**			0.06		
Model 3	-0.84**			0.52**		0.38		
Model 4	-2.03**				-0.01	0.00		
Model 5	-0.89	0.67	0.14**			0.36	7.38**	33.85**
Model 6	-0.71	0.55		0.27**		0.43	5.26*	39.68**
Model 7	-1.13	0.79			-0.04*	0.33	27.49**	32.16**
3 months/Model 1	-1.10**	0.55**				0.11	17.10**	
Model 2	-1.02**		0.38**			0.22		
Model 3	-0.65**			0.54**		0.58		
Model 4	-1.24**				0.22**	0.16		
Model 5	-0.73	0.15	0.47**			0.30	5.09*	17.05**
Model 6	-0.24	0.41		0.51**		0.62	8.36**	40.58**
Model 7	-0.82	0.47			0.18*	0.20	2.94	13.66**
6 months/Model 1	-0.77**	0.68**				0.25	14.37**	
Model 2	-0.56**		0.63**			0.31		
Model 3	-0.08			0.89**		0.86		
Model 4	-1.21**				0.18**	0.32		

Model 5	-0.30	0.22	0.61**			0.47	6.93**	18.05**
Model 6	0.08	0.27		0.79**		0.86	68.08**	136.61**
Model 7	-0.37	0.52			0.28**	0.42	3.37	15.42**
9 months/Model 1	0.84	2.36				0.35	5.25	
Model 2	1.24**		2.07**			0.75		
Model 3	-1.10**			0.31**		0.59		
Model 4	-0.64				0.53**	0.68		
Model 5	2.30	1.41	1.69**			0.83	2.76	12.67*
Model 6	-1.19	-0.37		0.48		0.58	0.14	4.65

*Significantly different from zero at 5% level
** Significantly different from zero at 1% level.

Table 5: Predictive Power of Volatility Measured by Forecasting Errors

This table reports the root mean square error (RMSE), the mean absolute error (MAE), and the mean absolute percentage error (MAPE) of implied volatility (IV), historical volatility (HV), GARCH (1,1) volatility, and EGARCH (1,1) volatility for Hong Kong and Singapore covered warrants markets.

		Hong Kong			***Singapore***		
Horizon	Volatility	RMSE	MAE	MAPE	RMSE	MAE	MAPE
			Panel A: Daily sampling				
1 month	IV	0.318	0.266	16.568	0.350	0.274	22.852
	HV	0.268	0.211	14.360	0.276	0.224	18.143
	GARCH	0.247	0.191	12.344	0.224	0.169	14.082
	EGARCH	0.262	0.221	13.865	0.221	0.175	13.310
2 months	IV	0.329	0.262	12.987	0.296	0.238	17.588
	HV	0.250	0.195	12.195	0.219	0.164	12.401
	GARCH	0.184	0.143	9.198	0.128	0.099	7.760
	EGARCH	0.224	0.183	11.961	0.173	0.133	10.649
3 months	IV	0.308	0.263	16.783	0.295	0.241	16.879
	HV	0.287	0.246	16.224	0.159	0.129	9.960
	GARCH	0.188	0.135	8.918	0.157	0.123	9.303
	EGARCH	0.220	0.177	11.253	0.163	0.130	10.399
6 months	IV	0.246	0.201	16.763	0.301	0.218	15.111
	HV	0.177	0.144	9.643	0.218	0.168	12.077
	GARCH	0.239	0.182	11.284	0.138	0.108	7.762
	EGARCH	0.222	0.171	10.811	0.117	0.093	7.097
9 months	IV	0.252	0.190	12.513	0.274	0.206	16.203
	HV	0.200	0.172	11.605	0.195	0.171	12.362
	GARCH	0.128	0.102	7.159	0.213	0.159	12.196
	EGARCH	0.170	0.136	9.471	0.152	0.124	10.302
			Panel B: Monthly sampling				
1 month	IV	1.163	0.917	58.665	1.348	0.917	42.418
	HV	1.095	0.815	58.705	1.323	0.939	55.867
	GARCH	1.089	0.764	47.975	1.111	0.731	37.173
	EGARCH	1.002	0.767	46.377	1.296	0.919	52.845
2 months	IV	0.759	0.573	34.986	0.508	0.412	27.218
	HV	0.777	0.602	37.295	0.722	0.544	36.575
	GARCH	0.565	0.388	22.229	0.586	0.463	27.539
	EGARCH	0.709	0.528	32.201	0.746	0.565	38.773
3 months	IV	0.530	0.433	27.285	0.615	0.528	40.046
	HV	0.579	0.422	26.957	0.529	0.429	30.779
	GARCH	0.482	0.337	21.424	0.390	0.300	19.815
	EGARCH	0.470	0.365	23.338	0.548	0.456	32.691

6 months	IV	0.275	0.225	13.921	0.424	0.351	26.278
	HV	0.427	0.323	27.222	0.417	0.302	22.052
	GARCH	0.370	0.280	24.002	0.185	0.143	9.390
	EGARCH	0.336	0.253	23.320	0.414	0.307	23.359
9 months	IV	0.501	0.392	86.993	0.447	0.400	31.133
	HV	0.412	0.366	69.722	0.282	0.252	13.500
	GARCH	0.556	0.447	112.004	0.362	0.287	22.054
	EGARCH	0.541	0.441	107.115	0.320	0.266	17.076