An Empirical Analysis of the Price Behavior of Taiwanese Stock Warrants

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Abstract

Taiwanese stock warrants have been traded well above their theoretical prices since their inception in 1997. Instead of trying to provide explanations for the overpricing phenomenon, we investigate the behavior of the magnitude of overpricing over time. Through AR model, we first find significantly negative relationship between the magnitude of market overpricing and the returns of the underlying shares. However, the negative relationship vanishes when all end-of-month data are discarded and the usual factors such as the time-to-expiration, moneyness and liquidity are controlled. Month-end buying activities may have been created mostly by the warrant-issuing securities firms for the fear of reporting too much unrealized loss on their warrant positions, especially in the market downturns. Alternatively, if naïve warrant investors prefer to hold their positions due to the lack of liquidity in the unfavorable market situations, the overpricing of warrants would also get more serious.

When the unexpected shocks are fitted into the AR-GARCH model, the-first-order autocorrelation of daily mispricing is clearly verified. Both GARCH and ARCH effects are detected in the variance equation in most cases. For asymmetric analysis, we find that the impacts of bad news on future volatility is greater than those of good news of the same magnitude, consistent with the previous literature. The leverage effect and volatility feedback effect, however, fail to capture the essence of warrant overpricing.

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I. Introduction

Taiwan Stock Exchange started to trade call warrants on stocks on September 4, 1997. Most empirical studies on warrant pricing accuracy have pointed to positive bias on the market side, no matter what types of theoretical pricing models were employed. Possible explanations cited include market inefficiency, inaccurate estimation of vital parameters, and errant dividend adjustment in addition to the usual liquidity, moneyness and time-to-expiration effects. Lee and Yang (2000) offered yet another hypothesis that the ownership structure of the outstanding warrants may deviate from perfect competition, which in turn induces positive pricing error when monopolistic power is exercised to a certain degree. Since short selling is not allowed in the warrant market, their argument was supported when Herfindahl index was used as a proxy for the monopolistic power.

It is also interesting to further investigate the behavior of the magnitude of the positive pricing error when stock price changes. Black (1976) first argued that volatility typically gets higher after the underlying stock price falls, i.e., future volatility is negatively correlated with stock return. If this is the case, and the estimated volatility fails to reflect this phenomenon, then we would observe large positive pricing error of the warrants in the down market. We call it the volatility feedback effect. Brown, Harlow and Tinic (1988), French, Schwert and Stambaugh (1987), Haugen, Talmor and Torous (1991) and Yeh and Lee (2000) have demonstrated the existence of volatility feedback effect. Leverage effect represent yet another explanation why volatility tends to become higher facing stock downturns. When stock price falls, leverage in terms of market value becomes higher, which causes higher financial risk and hence the volatility of the stock. Leverage effect leads to the well-known Constant Elasticity of Variance (CEV) model of Cox and Ross (1976).

On the other hand, Rubinstein (1985) argued that even though volatility is unstable and varies along the movement of stock price, the direction of volatility changes can go either way depending on the risk characteristics of the assets of the stock-issuing company. If the volatility varies positively with the stock price, then when stock price falls, Black and Scholes (BS) model tends to overprice calls. In this case, the overpricing of the Taiwan warrants will be smaller.

From a market microstructure point of view, if naïve warrant holders are reluctant to realize the loss facing market downturns, and if short selling is restricted, then the positive price errors will be enlarged in the bear market and vice versa. Thus the magnitude of positive warrant mispricing will be negatively correlated with stock price.

Accounting treatment may also contribute to the magnitude of warrant overpricing. Warrants traded in Taiwan are issued by securities firms (so-called sponsored warrants or third-party warrants). The issuing securities firms usually play the role of market makers. They reserve a portion of the warrants for market making purposes. This reserved warrant position will carry unrealized losses when premium falls. However, current accounting treatment requires that unrealized loss be reported at the month-end unaudited financial statements. In order to minimize the loss, the market makers tend to trade up the warrant price, especially toward the month-end. This type of trading behavior may cause higher warrant overpricing in the down market.

To sum up, the overpricing of Taiwan warrants may not be stable. The magnitude of overpricing may be positively or negatively related to the price of the underlying stocks. If the hypothesis of volatility feedback effect is true, and the warrant pricing models fail to use correct volatility estimates (which are higher in the down market), then the overpricing will be negatively correlated with the stock price. If the naïve investors hold their warrant positions or if the market makers try to minimize accounting losses facing market downturns, then again we will see warrant overpricing to be negatively correlated with the price of the underlying stock. Rubinstein's (1985) arguments cannot predict the relationship between warrant mispricing and the returns of the underlying shares, unless we know the risk characteristics of the stock-issuing company.

Our empirical efforts are therefore three folds. First of all, we'd like to empirically test whether the warrant overpricing display autocorrelation. Secondly, we will try to investigate the existence of GARCH phenomenon in the conditional volatility. Finally, asymmetric impacts of stock returns on warrant mispricing will be tested. Section II discusses the factors that might affect option or warrant mispricing along with the asymmetric impacts that the volatility of the underlying shares might have on the warrant price. Section III describes our empirical data and their characteristics. Section IV sets up the empirical models followed by the empirical findings in Section V. Finally, we summarize the results in Section VI.

II. Factors affecting option mispricing and the related asymmetric impacts

Ever since the seminal model proposed by Black and Scholes (1973), there have been numerous empirical studies regarding the model's pricing accuracy. For example, Black (1975) and Lauterbach and Schultz (1990) concluded that the Black-Scholes Model tends to overprice in-the-money calls and underprice out-of-the-money ones, even though MacBeth and Merville (1979) had opposite argument. Other studies, such as Rubinstein (1985), Merton (1976) and Hull and White (1987) have also detected so-called systematic pricing errors in Black-Scholes Model.

In contrast to the fixed variance assumption in Black-Scholes Model, several researchers have observed the negative relation between the volatility of stock return and the equity price. Therefore, scholars including McBeth and Mervill (1979), Beckers (1980), Swidler and Diltz (1992), Lauterbach and Schuktz (1990), Hauser and Lauterbach (1997) suggested that the CEV Model outperform Black-Scholes Model while Ferri, Kremer and Oberhelman (1986) obtained the opposite findings.

As to the estimation of specific parameters, Lauterbach and Schultz (1990) challenged the appropriateness of risk measure for warrants due to their longer time to expire. Moreover, Latane and Rendleman (1976), Chiras and Manaster (1978) claimed that the implied volatility possesses a better prediction power for true variance, however, Choi and Shastri (1989) argued that the existence of bid-ask spread may overvalue market price, therefore the implied volatility, and hence the magnitude of mispricing.

Dividend payments are one of the factors that contribute to the option mispricing. For European options with dividend-paying underlying securities, adjusting methods suggested by Geske (1979), Whaley (1981) and Merton (1973) provided some useful solutions. But, on the contrary, dividend payment may trigger early exercise for American options and then affect pricing accuracy. Whaley (1982) and Sterk (1986) found that the mispricing of options could be minimized when the underlying security pays only one-time dividend. Geske, Roll and Shastri (1982) also pointed out that errant dividend-adjusting approach might contribute to mispricing. And for the same reason, dilution-adjusting approach such as those proposed by Galai and Schneller (1978), Lauterbach and Schultz (1990) also provided some partial explanations for mispricing.

Tauchen and Pitts (1983), and Choi and Shastri (1989) focused on the role of trading volume in the option mispricing. Using regression models, Long and officer (1997) indicated that heavily traded call options are priced more efficiently and have lower mispricing errors than thinly traded options. However, largely increased volume might reflect the arrival of new and changing market information, which leads to inefficient pricing.

For domestic studies, both Yang (1990) and Hung (1997) adopted multi-regression method that was suggested by Hauser and Lauterbach (1997), and found that out-of-the-money and short time to expiration are the major reasons for mispricing. Hung (1997) also suggested that the lack of liquidity makes warrant holders unwilling to suffer inevitable loss when selling, and hence the result of biased market price. Moreover, the prohibition of short selling in the warrant market may enhance the prevailing situation. Furthermore, Lee and Yang (2000) found that the higher the Herfindahl index is, the higher degree warrant mispricing will be. This suggests that in an imperfect market, the concentration of the warrant ownership and thus the monopoly power, can causes the market price of warrants to be higher than the theoretical price.

It was first discussed by Black (1976) that volatility is typically higher after the stock market falls than rises, i.e., stock returns are negatively correlated with future volatility. Subsequently, numerous researches have focused on the return volatility of financial assets, especially the asymmetric impact of good and bad news. Brown, Harlow and Tinic (1988) demonstrated that the stock price reactions to unfavorable news tend to be larger than the reactions to favorable events, and they attributed this finding to volatility feedback. In contrast, Poterba and Summers (1986) argued that volatility feedback might be too short-lived to have a major effect on stock prices. French, Schwert and Stambaugh (1987) regressed stock returns on innovations in volatility and found negative correlations attributing to the volatility feedback. Similar result was demonstrated by Haugen, Talmor and Torous (1991).

Bollerslev, Chou and Kroner (1992), Bollerslev, Engle and Nelson (1995) and Hentschel (1995) concluded that negative shocks introduced more volatility than positive ones, and this effect shows particularly apparent influence for the largest shocks. Campell and Hentschel (1992) suggested that such phenomenon might result from the "leverage effect" and "volatility feedback effect".

For the leverage effect, the debt-equity ratio (measured in market value terms) rises as a consequence of the drop of stock price caused by negative shocks. Hence, the increased financial risk results in higher volatility in stock returns. For the volatility feedback effect, it seems plausible that changes in volatility may have important effect on the required stock returns and thus the level of stock price. However, large pieces of good news tend to be followed by other large positive shocks which increases future expected volatility, thus in turn increases the required rate of return on the stock, dampening the positive impact. On the other hand, the increased expected volatility caused by bad news will also increase the required rate of return and lower the stock price, which amplifies the impact of negative shocks.

In order to capture the asymmetric impacts that stock returns might have on warrant mispricing, the empirical model must first correct all possible pricing errors that liquidity, moneyness and time-to-expiration may induce. Section IV will deal with this problem when we model our empirical methodology.

III. The data

In order to analyze the behavior of warrant mispricing, we collected daily data of 113 individual warrants and their underlying securities from the Taiwan Economic Journal and the websites of Taiwan Stock Exchange and Yuanta Securities, Co.. Among these warrant samples, 86 out of 113 had expired by February 15, 2001. The sample period of the other 27 warrants started from their respective first trading date and ended at February 15, 2001.

We first adopted both BS Pricing Model and CEV Pricing Model to obtain daily theoretical prices for all warrants, using historical volatility as the estimates for the true variance. For warrant i ($i = 1, 2, ..., 113$), the daily percentage deviation is then calculated and denoted as $PD_{i,t}$ ($PD_{i,t} = \frac{W_{m,i,t} - W_{T,i,t}}{W_{m,i,t}}$, where $W_{m,i,t}$ and $W_{T,i,t}$ are defined as the market price and theoretical price respectively). The sample size, mean, standard deviation, skewness, kurtosis, Lagrangian multiplier test statistic with 12-period lag [LM (12)] and Ljung-Box Q test statistic with 12-period lag [LBQ (12)] for PD_{BS} and PD_{CEV} are presented in Appendix A. Besides, the percentage of positive mispricing among all the trading days was calculated for each warrant.

All warrants experienced positive mean of percentage deviation during the sample period, and this figure is nearly 50% for BS model and 46% for CEV model, enhancing the popular existence of mispricing. The average standard deviation of mispricing under CEV model is about 22%, slightly higher than the average of 19% for BS model. On average, warrant mispricing had a positive skewness under both models (0.2121 for BS model and 0.1371 for CEV model), indicating that large positive mispricings are more common than large negative ones. When daily mispricing data was classified according to the sign, quite a few warrants were found with all positive mispricing throughout the sampling period. Generally speaking, warrant price closed higher than their theoretical counterparts more than 90% of the time.

LM (q) test statistics proposed by Engle (1982) is aimed to detect the characteristic of autoregressive conditional heteroskedasticity (ARCH). In order to test the null hypothesis of no ARCH up to order q in the residuals, the sugared residuals are regressed against a constant and lagged squared residuals up to order q,

$$e_t^2 = b_0 + b_1 e_{t-1}^2 + b_2 e_{t-2}^2 + ... + b_q e_{t-q}^2 + v_t \quad (1)$$

where e is the residual term of the mean equation. Similar to Yeh and Lee (2000), 12-day lag is also chosen here. In fact, with the exception of nine warrant series, LM (q) for all $q = 1, 2, ..., 12$ are significant at 1% level for most warrants, indicating the existence of ARCH phenomenon.

The Ljung-Box Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k and is computed as

$$Q_{LB} = T(T+2)\sum_{j=1}^{k}\frac{g_j^2}{T-j} \tag{2}$$

where g_j is the j-th autocorrelation and T is the number of observations. Similarly, a lag of 12-order is chosen to provide autocorrelation check for white noise. The results of most warrants are significant at 1% level, except for three warrants under both models. Combination of the statistics of kurtosis, Ljung-Box Q and Lagrange Multiplier test for ARCH effect reveals that most warrnats are serially correlated, heteroskedastic and leptokurtic, which indicates the appropriateness of employing AR-GARCH model to explain the data. Warrants which are insignificant in LM (12) test and LBQ (12) test are excluded in this study.

IV. The empirical model

IV.1 The mean equation

We first examine the significance of percentage deviation between warrant market price and model price. The null hypothesis of no mispricing is rejected significantly at 1% level for all samples. Given the significant existence of mispricing, whether or not the percentage deviation of warrants is affected by underlying securities' return is one of our major focuses. We then estimate equation (3) with an extra term $b_{13}R_{i,t}^{+}R_{i,t}$ to detect the asymmetric effect of spot return,

$$PD_{i,t} = b_{10} + b_{11}PD_{i,t-1} + b_{12}R_{i,t} + b_{13}R_{i,t}^{+}R_{i,t} + e_{1i,t} \tag{3}$$

where $R_{i,t}$ is the return of the underlying stock of warrant i at time t and $R_{i,t}^{+}$ is a dummy variable which takes the value of one if $R_{i,t} > 0$, and zero otherwise.

In equation (3), if the underlying stocks experience positive return at time t, then the warrant mispricing responds by a magnitude of $(b_{12} + b_{13})$. If negative return occurs for the underlying, however, the reaction of mispricing is only b_{12}.

When trading data is observed daily, it can be found that the performance of warrants tend to behave somewhat abnormally when it approaches the end of month, although this may not be absolutely true to all warrants. Usually, the percentage deviation of warrant price seems to maintain its previous level or even enlarges toward the month-end. It has been suspected that the abnormity comes as a result of warrant issuers' strategy. Since the issuers have to recognize losses if the warrant they hold experience considerable drop in prices, making their month-end financial reports less attractive. Issuers then have the incentive to prevent the market prices from further declines. Based on this hypothesis, equation (4) is then estimated to exclude the possible end-of-month effect and re-examine the relationship between stock price and the warrant price.

For each warrant, data for the last two trading days of each month are omitted and only the remaining data is used to fit equation (4),

$$mPD_{i,t} = b_{20} + b_{21} mPD_{i,t-1} + b_{22} R_{i,t} + b_{23} R^{+}_{i,t} R_{i,t} + e_{2i,t} \quad (4)$$

where $R_{i,t}$ and $R^{+}_{i,t}$ are defined as in equation (3) and $mPD_{i,t}$ stands for the daily data of $PD_{i,t}$ excluding the last two trading days of every month.

It is also interesting to know the influence upon warrant mispricing of unexpected return shocks from the underlying stock. For all warrants, we first regressed the return of underlying security ($R_{i,t}$) on a constant and $R_{i,t-1},\ldots, R_{i,t-p}$ to obtain a proxy of unexpected shocks ($e_{i,t}$). As to the determination of optimal lag period (p) in equation (5), Akaike Information Criterion (AIC) and Schwarz Criterion (SC) are employed. The result in Appendix B shows that a lag of one period is enough in most cases, with four exceptions where a 2- period lag is suitable and one case where a 3- period lag is suitable.

$$R_{i,t} = a_0 + a_1 R_{i,t-1} + a_2 R_{i,t-2} + \ldots + a_p R_{i,t-p} + e_{i,t} \quad (5)$$

We then tried to fit the relations between $PD_{i,t}$ and $e_{i,t-1}$. If there is an unexpected return shock in warrant i's underlying security at time $t-1$, would it affect the magnitude of mispricing of warrant i at time t? If the answer is " yes ", which direction would the process take place? Moreover, is there any asymmetric effect of shocks from the stock market on the magnitude of warrant mispricing? To answer all these questions, we construct equation (6a) and introduced a dummy variable S^{-} to distinguish stock return shocks from different directions. In equation (6a), a positive $e_{i,t-1}$ implies that the underlying security has a positive unexpected shock in period $t-1$, defined as good news. c_2 represents the impact coefficient of good news upon mispricing ($PD_{i,t}$). In contrast, negative $e_{i,t-1}$ implies a negative unexpected return shock in period $t-1$, defined as bad news, and the impact coefficient of bad news upon $PD_{i,t}$ is $c_2 + c_3$.

$$PD_{i,t} = c_0 + c_1 PD_{i,t-1} + c_2 e_{i,t-1} + c_3 S^{-}_{i,t-1} e_{i,t-1} + v_{i,t} \quad (6a)$$

where $S^{-}_{i,t}$ is a dummy variable that takes the value of one if $e_{i,t} < 0$, and zero otherwise.

Coefficient c_1 in equation (6a) serves to detect the existence of first-order autocorrelation of PD_i. A positive c_2 implies positive relationship between $e_{i,t-1}$ and $PD_{i,t}$. In other words, higher degree of mispricing is expected if positive unexpected shock in stock market is larger, and vice versa. Finally, positive c_3 indicates the asymmetric situation that bad news from the underlying introduces more influence upon mispricing than good ones.

As mentioned in Section I and II, various factors have been pointed out to explain mispricing. Among which three variables including time to expiration (T), moneyness ($M = \frac{S - X}{X}$) and liquidity ($L = \frac{\text{daily trading volume}}{\text{outstanding volume}}$) are considered as the most influential. Therefore, we tried to regress PD on a constant, T, M and L in equation (7) to get the residual term $W_{i,t}$. Since possible effects from these three factors have been removed, $W_{i,t}$ is then called " modified mispricing " (modified PD) of warrant i at time t.

$$PD_{i,t} = b_0 + b_1 T_{i,t} + b_2 M_{i,t} + b_3 L_{i,t} + W_{i,t} \qquad (7)$$

Similar to the logic of equation (6a), we then model $W_{i,t}$ (the modified PD) as the dependent variable in equation (6b) and all the regressive coefficients carry stars (*) for distinguishing purposes.

$$W_{i,t} = c_0^* + c_1^* W_{i,t-1} + c_2^* e_{i,t-1} + c_3^* S_{i,t-1}^- e_{i,t-1} + v_{i,t}^* \qquad (6b)$$

IV.2 Variance Equation

Engle and Ng (1993) developed a new diagnostic test that emphasized the asymmetry of volatility response to news. By testing the empirical data of the Japan stock market with several related GARCH models including GARCH model (Bollerslev, 1986), exponential GARCH (EGARCH, Nelson, 1990), asymmetric GARCH (AGARCH, Engle, 1990), nonlinear asymmetric GARCH model (NGARCH, Engle and Ng, 1993) and GJR (Glosten, Jagannathan and Runkle) GARCH model, Engle and Ng (1993) suggested that the GJR GARCH model is the best parametric model. Further, Yeh and Tsai (1996) applied the new diagnostic test to the Taiwan Stock Market with the GARCH, GJR GARCH, and EGARCH models. Their results were consistent with those of Engle and Ng (1993) and supported that the GJR GARCH model is most capable of capturing the asymmetric impact of new information on return volatility.

As suggested by Engle and Ng (1993), the GJR GARCH (1,1) model is the best ARCH family model to capture the asymmetric impacts of new information. We then extend the procedure proposed by Pagan and Schwert (1990), Engle and Ng (1993) and make some reasonable adjustments to examine the influence of unexpected shock upon volatility (the conditional variance) in the warrant market. Our conditional variance equation (8a) follows the GJR GARCH model with an extra term of $W_{i,t-1}^- v_{i,t-1}^2$,

$$h_{i,t} = d_0 + d_1 v_{i,t-1}^2 + d_2 W_{i,t-1}^- v_{i,t-1}^2 + d_3 h_{i,t-1} \qquad (8a)$$

where $h_{i,t}$ stands for the conditional variance of $v_{i,t}$ given information set available at time $t-1$ $[h_{i,t} = Var(v_{i,t} | I_{i,t-1})]$ and $W_{i,t}^-$ is a dummy variable which takes the value of one if $v_{i,t} < 0$, and zero otherwise.

In equation (8a), $v_{i,t-1} > 0$ implies positive unexpected shocks of warrant i at period $t-1$. The impact coefficient of good news upon the conditional volatility of warrant i ($h_{i,t}$) is

d_1. Negative shocks, however, affect warrants' volatility through the coefficient $d_1 + d_2$. Positive d_3 indicates the nature of time-varying volatility and volatility clustering. If $h_{i,t}$ is higher due to larger $v_{i,t-1}$ in absolute terms, d_1 would be positive. Positive d_2, on the other hand, implies that bad news introduces more volatility in the warrant market than good ones.

Since $h_{i,t}$ is defined as the conditional variance of $v_{i,t}$ derived from equation (6a), equation (8a) can be viewed as an extension of equation (6a). Similar logic can then be augmented to model equation (8b),

$$h^*_{i,t} = d^*_0 + d^*_1 (v^*_{i,t-1})^2 + d^*_2 W^{-*}_{i,t-1} (v^*_{i,t-1})^2 + e^*_3 h^*_{i,t-1} \tag{8b}$$

where $h^*_{i,t}$ stands for the conditional variance of $v^*_{i,t}$ given information set available at time $t-1$ [$h^*_{i,t} = Var(v^*_{i,t} | I_{i,t-1})$] and $W^{-*}_{i,t}$ takes the value of one if $v^*_{i,t} < 0$, and zero otherwise.

Since equation (3) through (8b) have to be fitted for each individual warrant and diversities among the samples are expected, the average coefficient and test statistics proposed by Fama and MacBeth (1973) will be adopted to make inferences about the overall warrant market.

V. Model estimation and results analysis

V.1 Relations between stock return and warrant mispricing

We estimate equation (3) and (4) under AR (1) and the results are tabulated in Table 1. The results indicate that the coefficient b_{11} for all warrants is significantly positive at 1% level under both BS and CEV model. This fact is also found when b_{21} is observed. In contrast, the estimate for b_{12} and b_{22} is significantly negative at 1% level in most cases. Coefficients b_{13} and b_{23}, however, tell quite different stories. For b_{13}, only 15 and 16 samples carry significant results at 5% level under BS and CEV model respectively. b_{13} is positive in most of the significant cases (13 out of 15 and 13 out of 16 respectively). Compared to b_{13}, 26 (with 18 positive ones) and 29 (with 20 positive ones) samples are found with significant b_{23} at 5% level under BS and CEV model respectively. In spite of the insignificance, both the average of b_{13} and b_{23} for all samples are positive, which indicates that the mispricing tends to react more to negative stock returns than positive ones.

Both b_{11} and b_{21} are significantly positive for most samples, which reveals that the magnitude of warrant mispricing can partially be explained by one-period-lagged mispricing. This highlights that the phenomenon of first-order autocorrelation does exist in daily mispricing in the Taiwan warrant market. The average level of b_{12} for all samples is -0.8376 and -0.8705 under BS and CEV model respectively. Despite the overwhelming significance at 1% level, none of them is positive, indicating that the return of underlying security ($R_{i,t}$) has negative influence upon warrant mispricing. In other words, positive mispricing gets more serious in down market situation.

Given the basic statistics presented in Appendix A, it is undoubted that positive mispricing is expected as the " normal " situation in the Taiwan warrant market till now. The combination of positive mispricing and negative b_{12} points to an interesting story. On average, the magnitude of mispricing evaluated under BS model will be driven down 0.8376% when the underlying stock market experience 1% positive return. Thus positive returns in the underlying stock market help to narrow the mispricing in the warrant market and bring the market price closer to the theoretical price. Under down market condition, however, the percentage deviation of warrant price increases by 0.8376% for every percentage of negative return in the stock market.

In order to provide a better explanation, we try to examine the stock market performance during the sample period. The TAIEX Index on September 4, 1997 is 9147.85 and went down to 6104.24 on February 15, 2001. Despite of the rise from early 1999 to early 2000, the downward trend is quite obvious if we plot the daily index from 1997 to 2001. As a result, the warrant price performed " relatively well " than the underlying stock price. In other words, the warrant price appeared to show downward rigidity even when its underlying security performed badly.

Table 1

AR analysis of the effect of underlying returns upon mispricing in the warrant market

Compute the percentage deviation ($PD_{i,t}$) under both Black-Scholes Model and CEV Model. Next, estimate equations (3) and (4) under AR (1) with an extra term $R^{+}_{i,t}R_{i,t}$ aimed to detect the asymmetric impact. Then, substitute $mW_{i,t}$ for $mPD_{i,t}$ to exclude both the end-of-month effect resulted from issuers' support and major influencing factors (T, M, L) and estimate equation (9).

$$PD_{i,t} = b_{10} + b_{11}PD_{i,t-1} + b_{12}R_{i,t} + b_{13}R^{+}_{i,t}R_{i,t} + e_{i,t} \quad (3)$$

$$mPD_{i,t} = b_{20} + b_{21}mPD_{i,t-1} + b_{22}R_{i,t} + b_{23}R^{+}_{i,t}R_{i,t} + e_{i,t} \quad (4)$$

$$mW_{i,t} = b_{30} + b_{31}mW_{i,t-1} + b_{32}R_{i,t} + b_{33}R^{+}_{i,t}R_{i,t} + e_{i,t} \quad (9)$$

$$R^{+}_{i,t} = 1 \ if \ R_{i,t} > 0, \ R^{+}_{i,t} = 0 \ if \ else$$

$mPD_{i,t} : PD_{i,t}$ after the last two trading days of each month have been excluded

		Equation (3)				Equation (4)				Equation (9)			
		b_{10}	b_{11}	b_{12}	b_{13}	b_{20}	b_{21}	b_{22}	b_{23}	b_{30}	b_{31}	b_{32}	b_{33}
BS	10%	31 (31)*	104 (104)	103 (0)	27 (23)	32 (32)	104 (104)	91 (1)	25 (22)	18 (8)	104 (104)	47 (16)	32 (19)
	5%	25 (25)	104 (104)	102 (0)	15 (13)	26 (26)	104 (104)	89 (0)	14 (14)	12 (4)	104 (104)	38 (13)	23 (15)
	1%	15 (15)	104 (104)	100 (0)	4 (4)	14 (14)	104 (104)	86 (0)	0 (0)	4 (1)	104 (104)	29 (10)	10 (8)
	Coef.	0.0084	0.9735	-0.8376	0.1085	0.0089	0.9719	-0.7294	0.0994	-0.0003	0.8809	-0.0882	0.0309
	t	1.4361 [c]	79.5502 [a]	-6.9695 [a]	0.5378	1.4168 [c]	74.1420 [a]	-5.6365 [a]	0.4572	-0.0915	27.9244 [a]	-0.6839	0.1438

	10%	36 (36)	104 (103)	102 (0)	23 (19)	35 (35)	104 (104)	90 (1)	24 (19)	20 (8)	104 (104)	47 (14)	32 (20)
	5%	32 (32)	104 (103)	100 (0)	16 (13)	25 (25)	104 (104)	88 (0)	11 (10)	11 (3)	104 (104)	40 (12)	22 (14)
CEV	1%	17 (17)	104 (103)	98 (0)	2 (2)	13 (13)	104 (104)	86 (0)	2 (2)	3 (1)	104 (104)	29 (10)	10 (7)
	Coef.	0.0177	0.9575	-0.8705	0.0953	0.0084	0.9714	-0.7640	0.0896	-0.0006	0.8798	-0.0964	0.0494
	t	3.1303 [a]	73.6165 [a]	-6.3544 [a]	0.4173	1.3898 [c]	74.2809 [a]	-5.2641 [a]	0.3679	-0.1501	27.4461 [a]	-0.6588	0.2025

* Numbers in parentheses are the samples with significantly positive coefficient

a : significance at 1% level

b : significance at 5% level

c : significance at 10% level

Table 1 also offers the estimates for equation (4). After excluding the data of the last two trading days, the overall regression results are quite similar to those of equation (3). The most exciting finding is that b_{22}, though still negatively significant at 1% for almost every sample, becomes smaller (in absolute term) with an average of -0.7294 and -0.7640 under BS and CEV model respectively. After the adjustment of end-of-month effect, only 0.7294% decline in mispricing (evaluated by BS model) is expected when the underlying stock experiences 1% positive return. Compared with equation (3), positive stock return also pulls down the market price of warrants to their theoretical price, but in a lower speed. In bad condition, the percentage deviation in the warrant market widens only 0.7294% following a 1% negative return in the stock market, indicating that the warrant price seems to be less rigid.

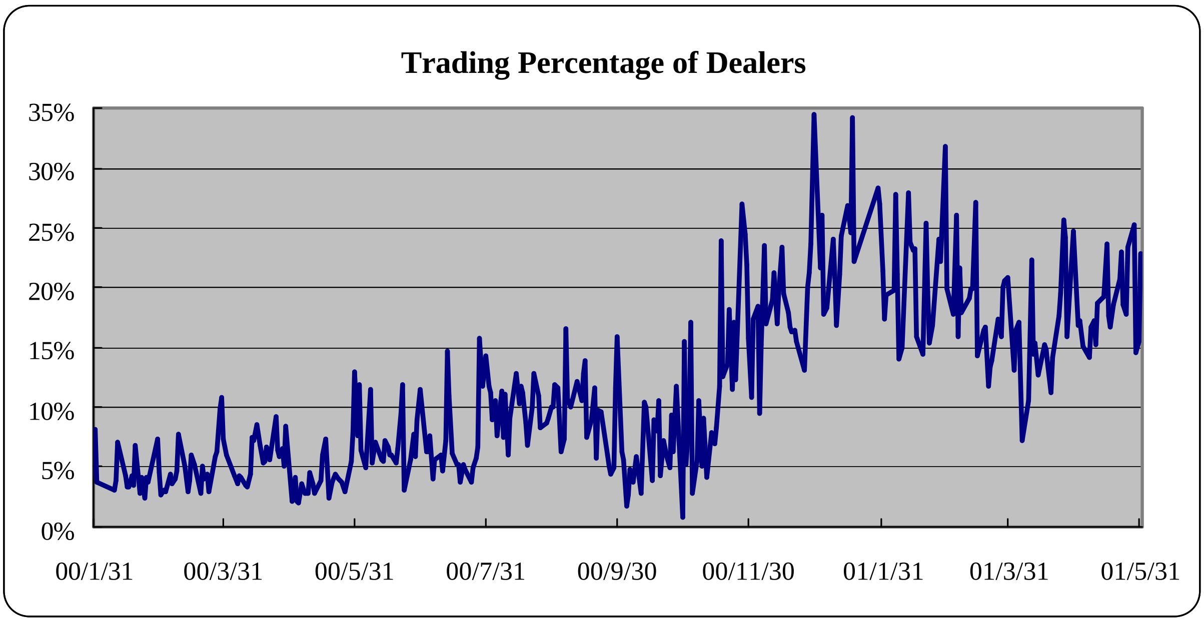
The comparison of the estimates of equation (3) and (4) can be used to interpret the effect resulted from warrant issuers' strategy. When the stock market is going up, the price of warrants approach down to the theoretical price. Warrant issuers' action, if exists, helps to speed up this process and narrow down the overpricing more quickly. In the case of negative stock returns, overpricing tends to widen. Warrant issuers' supporting action for the fear of accounting losses helps to strengthen (or even enhance) the price rigidity of warrants and enlarge the overpricing.

To further support our conjecture about warrant issuers' market making activities at the month-end, we collect the data of the issuers' trading volume for each day from January 2000 to May 2001. The issuers' market share (defined as their trading volume divided by the total trading volume of the warrant market) for the last two trading days of each month are calculated and denoted as Ratio 2. In contrast, Ratio 1 denotes the trading share of the warrant issuers for trading days other than the last two. It's quite clear from Table 2 that Ratio 2 is higher than Ratio 1 throughout the whole period. The U-statistic of Mann-Whitney-Wilcoxon significantly reject the null hypothesis that Ratio 2 is equal to or smaller than Ratio 1 at 5% level, indicating that the participation of dealers grows much higher at the month-end, consistent with the hypothesis of price support strategy. The cyclic trend can also be captured in Figure 1. If we further define ΔRatio = Ratio 2 $-$ Ratio 1, the correlation coefficient r between ΔRatio and Index Return is -0.27527.

Table 2 Ratio 1, Ratio 2, and Index Return

Year / Month	Ratio 1	Ratio 2	△Ratio	Index Return
00/1	4.57%	5.60%	1.03%	10.69%
00/2	4.07%	5.49%	1.42%	0.68%
00/3	4.63%	9.10%	4.47%	2.75%
00/4	5.75%	6.72%	0.97%	-13.54%
00/5	3.77%	10.46%	6.69%	5.92%
00/6	7.04%	10.20%	3.16%	-7.21%
00/7	6.71%	12.96%	6.25%	0.77%
00/8	9.82%	9.98%	0.16%	-2.95%
00/9	9.41%	13.77%	4.36%	-22.01%
00/10	6.41%	8.14%	1.73%	-10.26%
00/11	11.99%	18.84%	6.85%	-9.76%
00/12	17.58%	29.04%	11.46%	-10.76%
01/1	23.37%	24.23%	0.86%	21.01%
01/2	20.02%	23.09%	3.07%	-0.09%
01/3	18.83%	20.70%	1.87%	5.28%
01/4	15.85%	20.29%	4.44%	-8.07%
01/5	18.53%	19.19%	0.66%	-4.93%
Average	11.08%	14.58%	3.50%	-2.50%
U-statistic	$U = 94 < U(n_1 = 17, n_2 = 17, a = 0.05) = 96$		$r = -0.27527$	

Figure 1 Daily Trading Percentage of Dealers



In addition to the end-of-month effect resulting from issuing entities' support, it is possible that general investors' attitude toward the warrant market also contributes to the warrant price rigidity. It has been observed that warrant investors become more reluctant to sell when the spot market gets bearish. Since considerable loss due to lack of liquidity is inevitable, they prefer to hold and wait. Consequently, the warrant price may be too weak to reflect the true value and the positive bias is then expected, especially when short selling warrants is prohibited.

Based on this hypothesis, we construct equation (9) and modeled $mW_{i,t}$ as the dependent variable, where $mW_{i,t}$ is the residual of equation (7) after excluding the data of the two month-end trading days, and adjusting for the biases caused by $T,\ M\ and\ L$. The results are tabulated in the third panel of Table 1.

$$mW_{i,t} = b_{30} + b_{31} mW_{i,t-1} + b_{32} R_{i,t} + b_{33} R^{+}_{i,t} R_{i,t} + e_{3i,t} \qquad (9)$$

After the substitution of the dependent variable $mW_{i,t}$, only b_{31} remains significant verifying the characteristic of first-order autocorrelation. The average of b_{32} turns to -0.0882 and -0.0964 under BS and CEV model respectively, much smaller (in absolute term) than b_{22} and b_{12}. Moreover, only approximately 40% of the total samples carry significant b_{32} and the average test statistics for both models are insignificant (t-statistics = -0.6839 and -0.6588 respectively).

All the estimates of equation (3), (4) and (9) illustrate consistent and interesting results. Using BS model as the example: while the original percentage deviation ($PD_{i,t}$) is significantly affected by the spot return ($R_{i,t}$) through the impact coefficient of -0.8376, this negative relation also exists after the adjustments of end-of-month effect. The impact coefficient, however, changes to -0.7294, indicating the effect of warrant issuers' support which helps to drive down warrant price to its theoretical level when the stock market experiences positive return but strengthen the price rigidity of warrants (preventing warrant price from further declines) and enlarge the warrant overpricing in the case of negative stock return. The negative relations between mispricing and stock return finally disappear when three factors ($T,\ M,\ L$) are adjusted. Investors' unwillingness to sell and to recognize losses due to lack of liquidity does result in biased market price and hence widen the overpricing when the spot market becomes unfavorable.

V.2 The impact of unexpected shocks on return and volatility

Equation (6a), (8a), (6b) and (8b) are estimated under AR (1) and GARCH (1,1) specifications using the algorithm developed by Berndt, Hall, Hall and Hausman (1974) and the results are tabulated in Table 3 and Table 4. For mean equation (3a) and (3b), the coefficients c_1 and c_1^* for all warrants are significantly positive at 1% level under both BS model and CEV model, verifying the characteristic of autocorrelation in the Taiwan warrant market again. The signs of the estimates for c_2 and c_3 (c_2^* and c_3^*), however, appear to be quite mixed. For c_2, only 32 and 40 samples show statistical significance at 5% level under BS and CEV model respectively. Among the samples with significant c_2, only 28% (9out of 32) are positive for BS model and 40% (16 out of 40) are positive for CEV model. The situation of c_2^* is even less appealing for only 14 (with 5 positive ones) and 14 (with 4 positive ones) significant samples at 5% level under BS and CEV model respectively. The results also demonstrate the lack of evidence to support the asymmetric influence of unexpected shocks from spot market since only 18 (with 9 positive ones) and 32 (with 25 positive ones) samples with significant c_3 and 14 and 16 samples with significant c_3^* are observed.

Table 3

AR-GARCH analysis of conditional means and variances

Regress the return of underlying security ($R_{i,t}$) on a constant and suitable lagged $R_{i,t-p}$ according to AIC and SC) to form the proxy of unexpected return shocks ($e_{i,t}$). Then, estimate equations (6a) and (8a) under AR (1) and GARCH (1,1) specifications using the algorithm developed by Berndt, Hall, Hall and Hausman (1974).

$$R_{i,t} = a_0 + a_1 R_{i,t-1} + a_2 R_{i,t-2} + ... + a_p R_{i,t-p} + e_{i,t} \quad (5)$$

Means : $$PD_{i,t} = c_0 + c_1 PD_{i,t-1} + c_2 e_{i,t-1} + c_3 S^-_{i,t-1} e_{i,t-1} + v_{i,t} \quad (6a)$$

Variance : $$h_{i,t} = d_0 + d_1 v^2_{i,t-1} + d_2 W^-_{i,t-1} v^2_{i,t-1} + d_3 h_{i,t-1} \quad (8a)$$

$$h_{i,t} = Var(v_{i,t} | I_{i,t-1})$$

$$S^-_{i,t} = 1 \ \ if \ \ e_{i,t} < 0 , \ \ S^-_{i,t} = 0 \ \ if \ \ else$$

$$W^-_{i,t} = 1 \ \ if \ \ v_{i,t} < 0 , \ \ W^-_{i,t} = 0 \ \ if \ \ else$$

		Equation (6a)				Equation (8a)			
		c_0	c_1	c_2	c_3	d_0	d_1	d_2	d_3
BS	10%	69 (68)	104 (104)	38 (12)	25 (11)	32 (32)	77 (77)	51 (32)	100 (100)
	5%	59 (58)	104 (104)	32 (9)	18 (9)	25 (25)	67 (67)	46 (30)	100 (100)
	1%	43 (42)	104 (104)	22 (6)	13 (7)	15 (15)	49 (49)	31 (19)	99 (99)
	Coef.	0.0136	0.9638	-0.0454	0.0318	0.0001	0.1826	0.0548	0.7564
	t	2.5093 [a]	76.4225 [a]	-0.5095	0.1968	2.2209 [b]	2.3966 [a]	0.4956	14.0705 [a]
CEV	10%	70 (68)	104 (104)	45 (18)	36 (17)	34 (34)	83 (83)	44 (24)	100 (100)
	5%	63 (62)	104 (104)	40 (16)	32 (15)	26 (26)	74 (74)	37 (21)	100 (100)
	1%	45 (44)	104 (104)	30 (11)	27 (13)	11 (11)	55 (55)	25 (14)	98 (98)
	Coef.	0.0125	0.9625	-0.0501	0.0360	0.0002	0.2439	0.0094	0.7340
	t	2.7320 [a]	80.7804 [a]	-0.5385	0.2120	1.6839 [b]	2.6684 [a]	0.0753	13.0148 [a]

* Numbers in parentheses are the samples with significantly positive coefficient
a : significance at 1% level
b : significance at 5% level
c : significance at 10% level

Table 4

AR-GARCH analysis of conditional means and variances

Substitute $W_{i,t}$ for $PD_{i,t}$ and estimate equations (6b) and (8b) under AR (1) and GARCH (1,1) specifications using the algorithm developed by Berndt, Hall, Hall and Hausman (1974).

$$\text{Means}: \quad W_{i,t} = c_0^* + c_1^* W_{i,t-1} + c_2^* e_{i,t-1} + c_3^* S_{i,t-1}^- e_{i,t-1} + v_{i,t}^* \qquad (6b)$$

$$\text{Variance}: \quad h_{i,t}^* = d_0^* + d_1^* (v_{i,t-1}^*)^2 + d_2^* W_{i,t-1}^{-*} (v_{i,t-1}^*)^2 + e_3^* h_{i,t-1}^* \qquad (8b)$$

$$h_{i,t}^* = Var(v_{i,t}^* | I_{i,t-1})$$

$$S_{i,t}^- = 1 \ if \ e_{i,t} < 0, \ S_{i,t}^- = 0 \ if \ else$$

$$W_{i,t}^{-*} = 1 \ if \ v_{i,t}^* < 0, \ W_{i,t}^{-*} = 0 \ if \ else$$

		Equation (6b)				Equation (8b)			
		c_0^*	c_1^*	c_2^*	c_3^*	d_0^*	d_1^*	d_2^*	d_3^*
BS	10%	15 (10)	104 (104)	19 (6)	20 (16)	72 (72)	66 (66)	63 (52)	93 (93)
	5%	8 (6)	104 (104)	14 (5)	14 (10)	61 (61)	55 (55)	47 (39)	91 (91)
	1%	7 (5)	104 (104)	8 (4)	4 (3)	40 (40)	33 (33)	25 (20)	91 (91)
	Coef.	0.0004	0.9057	-0.0259	0.0646	0.0002	0.1739	0.1519	0.6383
	t	0.1607	33.3548 [a]	-0.2750	0.3924	3.3318 [a]	2.1861 [b]	1.1314	8.3519 [a]
CEV	10%	16 (13)	104 (104)	22 (6)	21(18)	69 (69)	68 (68)	52 (39)	93 (93)
	5%	12 (10)	104 (104)	14 (4)	16 (14)	54 (54)	57 (57)	43 (32)	91 (91)
	1%	4 (4)	104 (104)	7 (1)	6 (6)	39 (39)	35 (35)	25 (18)	91 (91)
	Coef.	0.0006	0.9027	-0.0380	0.0864	0.0002	0.1928	0.1287	0.6448
	t	0.2240	33.3190 [a]	-0.3618	0.4672	2.6125 [a]	2.3245 [a]	0.9286	7.6750 [a]

* Numbers in parentheses are the samples with significantly positive coefficient
a : significance at 1% level
b : significance at 5% level
c : significance at 10% level

Positive c_1 and c_1^* support the existence of autocorrelation for the daily mispricing in the Taiwan warrant market. For warrants with significantly negative c_2, mispricing widens in response to bad news from the stock market and narrows down when good news hits the market. This process, however, may not be interpreted as the common phenomenon due to the insignificant average test statistic. Even fewer samples with significant c_2^* indicates that the modified mispricing ($W_{i,t}$) is less sensitive to shocks from the stock market. This interpretation is somewhat instinctively reasonable since the factor of moneyness ($M = \frac{S - X}{X}$) has been removed from $W_{i,t}$ so that information effect of the stock price movement has been reflected.

Furthermore, the suspicion of asymmetric influence upon mispricing of stock market shocks cannot be concluded thoroughly due to the diverse regression results for both c_3 and c_3^*. Taking c_3 of CEV model as an example, the figures in Table 3 show that 15 (17) warrants' mispricing react more to bad (good) news of their underlying than good (bad) ones while the other 72 samples do not show any asymmetry significantly. However, since the average test statistic is not significant and so minor are the significant cases that we may have difficulty to generalize the results to the whole warrant market.

Variance equation (8a) and (8b) are designed to analyze the potential influence of unexpected shocks upon conditional volatility. Notice that the coefficient d_3, aimed to detect GARCH effect, is significantly positive at 1% level in most cases under both BS and CEV model (99 and 98 samples respectively). These overwhelming results suggest the time-varying volatility and volatility clustering. For ARCH effect, 67 and 74 warrants are found to carry significantly positive d_1 respectively. The relevant figures for significant d_1^* in equation (8b) are 55 and 57 cases. Finally, the number of samples with significant d_2 is 46 for BS model and 37 for CEV model while 47 and 43 cases are found with significant d_2^* under two pricing models.

Positive d_1 implies that $h_{i,t}$ will be higher if original mispricing ($PD_{i,t}$) has large $v_{i,t-1}$ in absolute terms. For similar interpretation, positive d_1^* also shows the positive relations between $h_{i,t}^*$ and $v_{i,t-1}^*$ in absolute terms. Despite some of insignificant cases, both the average test statistics are significant at 5% level, suggesting the warrant market is ARCH-related.

The d_2 phenomenon is positive for about 60% of the significant warrants (30 out of 46 and 21 out of 37), which may infer the existence of leverage effect and volatility feedback effect. For leverage effect, higher volatility is expected when financial risk increases as a consequence of the decline of mispricing caused by negative shocks. For volatility feedback effect, expectation of higher volatility caused by bad news would increase the required rate of return and lower the price, which amplifies the impact of negative shocks. Significantly negative cases, on the other hand, convey that when there exist good news from the warrant market itself ($v_{i,t-1} > 0$), warrant mispricing reacts favorably, causing volatility to rise. And it will increase consistently if investors chase after good news, which contributes to a further increase in volatility. Whether positive or negative, however, cases of significant d_2 represent only a small portion of the total samples and the average test statistics also deny the overall asymmetry in the warrant market. Since this is also true for d_2^*, it is difficult to achieve the overall conclusion of asymmetric influence of unexpected shocks upon conditional variance.

V.3 Diagnostic test

In order to ensure that the specification of AR-GARCH model are correct, two more tests for the residual term (unexpected return shocks) of equation (6a) and (6b) are carried out. First of all, Ljung-Box Q test on autocorrelations and partial autocorrelations of the standardized residuals is used to test for remaining serial correlation in mean equation. If the mean equation is correctly specified, all Q-statistics should not be significant. Besides, Correlogram Squared Residuals that emphasize the squared standardized residuals are applied to check the specification of variance equation, particularly the remaining ARCH effect. For a correctly specified variance equation, there should be no ARCH left.

Most of the Ljung-Box (24) for residuals is insignificant, which supports the white noise nature of the residuals. Ljung- Box (18) is further computed for those exceptions and the result turns insignificant, indicating that the residuals are only autoregressive in the higher order. Correlogram Squared Residuals test statistics also suggest that there remains no ARCH effect in the squared standardized residuals for most samples. In general, both the mean equations and variance equations are quite correctly specified. In addition, the τ statistics of Dicky-Fuller test are all significantly different from zero, rejecting the null hypothesis that the time series data has unit roots.

Furthermore, diagnostic tests on the GJR GARCH model are utilized to test the capability of capturing the asymmetric impact of good and bad news upon conditional variance. For instance, equation (10) is constructed for equation (6a) and (8a),

$$(\frac{v_{i,t}}{\sqrt{h_{i,t}}})^2 = k_0 + k_1 W_{i,t-1}^{-} + k_2 W_{i,t-1}^{-} v_{i,t-1} + k_3 W_{i,t-1}^{+} v_{i,t-1} + q_{i,t} \qquad (10)$$

The purpose of the test for coefficient k_1 (sign bias test) is to clarify whether positive and negative innovations affect future volatility of warrants differently from the model prediction. The coefficient k_2 (k_3) is used to test whether larger negative (positive) innovations are correlated with larger biases in predicted volatility, which is called a negative (positive) size bias test. In most cases, all the sign and size bias tests together with a joint test suggest that the squared standardized residual $(\frac{v_{i,t}}{\sqrt{h_{i,t}}})^2$ is i.i.d., as none of the coefficients are significantly different from zero, and hence, GJR GARCH model is considered acceptable in this research.

VI. Conclusions

The warrant market of Taiwan has experienced a great positive mispricing since its inception when Black-Scholes model and CEV model are used as the benchmark. The average positive mispricing may be as high as 50%. In this study, we observed significantly negative relations between warrant mispricing and returns of the underlying securities, which implies that positive stock returns help to reduce the discrepancies between market price and theoretical price while negative returns in the stock market tend to result in more serious mispricing. The average coefficient is -0.8376 for BS model and -0.8705 for CEV model.

After the exclusion of end-of-month effect and major influencing variables (T, M, L), the impact coefficient adjusts down to only -0.0882 and -0.0964 respectively and becomes insignificant. This result reveals that warrant issuers' supporting strategy, if exists, helps to narrow mispricing in good market but solidify the price rigidity of warrants (prevent market price from further declines) and enlarge the overpricing in bad market. Besides, warrant investors become more reluctant to sell and prefer to hold when the spot market gets less attractive since considerable loss due to lack of liquidity is inevitable.

When the unexpected shocks ($v_{i,t}$) are modeled to explain daily mispricing in the warrant market, the overall influence cannot be clearly identified due to the diverse results and the insignificant average test statistic. Only the existence of first-order autocorrelation of daily mispricing can be verified through the empirical results.

For the analysis of the influence upon conditional variance of unexpected shocks, both the GARCH and ARCH effect are proven significant in most cases. The estimates for asymmetry toward unexpected shocks from the stock market, however, tell quite different stories. Some evidences are found that conditional volatility of mispricing reacts more to bad news than to good ones under the GJR GARCH model. The leverage and volatility feedback effects supported by some significant samples, however, fail to capture the essence of the overall warrant market. Therefore, it is difficult to conclude volatility asymmetry as the common phenomenon in the warrant market. Finally, all the impact coefficients of unexpected stock returns seem to confirm the efficiency of the warrant market for no more volatility is introduced by unexpected return shocks from the underlying securities.

As a final note, if the accounting requirements induce abnormal trading behavior of the warrant issuers and the restriction on warrant short selling further enhance the pricing bias, especially in bearish market, then the market can never learn to function itself through market mechanism. Taiwan Futures Exchange is scheduled to launch stock index options toward the end of the year 2001. We hope all related tax and accounting treatments are well designed so that market efficiency can be achieved.

Appendix A

Basic Statistic

	BS Model								CEV Model						
Code	obs	Mean	S. D.	Skewness	Kurtosis	%[(1)]	LM (12)[(2)]	LB (12)[(3)]	Mean	S. D.	Skewness	Kurtosis	%[(1)]	LM (12)[(2)]	LB (12)[(3)]
0501	271	0.738	0.192	-0.225	2.309	100	215.88[a]	2278.90[a]	0.725	0.224	-0.538	2.513	100	210.43[a]	1814.70[a]
0502	271	0.672	0.201	0.559	1.706	100	187.53[a]	1683.20[a]	0.648	0.225	0.513	1.621	100	190.93[a]	1708.80[a]
0503	270	0.336	0.242	0.944	3.233	98.15	193.53[a]	1608.30[a]	0.222	0.307	0.846	2.787	71.85	170.46[a]	1386.60[a]
0504	269	0.601	0.287	0.209	1.295	100	211.05[a]	1562.90[a]	0.588	0.309	0.188	1.271	100	210.23[a]	1496.20[a]
0505	268	0.318	0.332	0.528	1.990	81.72	44.98[a]	1635.30[a]	0.222	0.416	0.447	1.761	59.33	43.24[a]	1600.40[a]
0506	267	0.239	0.148	-0.218	2.397	95.51	109.85[a]	809.86[a]	0.148	0.216	-0.362	2.131	63.67	130.25[a]	940.70[a]
0507	274	0.690	0.195	-0.280	2.145	100	110.62[a]	1204.00[a]	0.681	0.220	-0.417	2.150	100	132.95[a]	99.43[a]
0508	274	0.630	0.212	-0.248	2.272	100	211.70[a]	1339.30[a]	0.622	0.240	-0.351	2.212	100	193.19[a]	1268.40[a]
0509	267	0.353	0.167	0.135	3.049	100	112.57[a]	921.43[a]	0.263	0.240	-0.204	2.362	76.03	124.99[a]	1126.40[a]
0510	267	0.762	0.178	-0.909	3.799	100	177.65[a]	1368.30[a]	0.714	0.222	-0.792	3.419	100	181.24[a]	1421.00[a]
0511	267	0.647	0.223	0.157	1.848	100	144.56[a]	1198.70[a]	0.628	0.256	-0.061	1.764	100	147.30[a]	1031.60[a]
0512	267	0.697	0.237	-0.399	2.033	100	140.20[a]	1327.30[a]	0.691	0.257	-0.519	2.104	100	146.99[a]	1583.30[a]
0513	267	0.728	0.281	-0.797	2.200	100	126.76[a]	1160.00[a]	0.677	0.388	-0.958	2.456	90.26	100.84[a]	1145.10[a]
0514	267	0.748	0.184	0.135	1.710	100	203.23[a]	1065.00[a]	0.744	0.199	-0.039	1.793	100	189.78[a]	982.92[a]
0515	266	0.558	0.185	0.192	2.630	100	159.46[a]	1312.80[a]	0.544	0.207	0.238	2.315	100	159.66[a]	1298.70[a]
0516	266	0.232	0.109	-0.039	2.871	97.74	122.09[a]	1094.60[a]	0.162	0.121	0.454	2.646	95.49	110.12[a]	1144.70[a]
0517	264	0.161	0.131	0.105	1.385	90.91	171.77[a]	919.64[a]	0.120	0.160	0.179	1.425	71.21	138.83[a]	743.35[a]
0518	264	0.270	0.221	0.992	2.716	99.24	162.30[a]	1326.70[a]	0.208	0.248	0.892	2.559	83.33	172.56[a]	1332.20[a]
0519	264	0.145	0.076	0.658	3.419	98.48	162.50[a]	1189.20[a]	0.108	0.071	-0.270	5.391	94.70	167.92[a]	1168.60[a]
0520	402	0.298	0.074	0.035	1.602	100	201.47[a]	1853.90[a]	0.281	0.071	0.371	1.851	100	192.27[a]	1663.40[a]
0521	264	0.096	0.098	0.711	2.403	84.85	147.00[a]	932.58[a]	0.043	0.064	1.040	4.472	77.65	152.21[a]	737.02[a]
0522	265	0.271	0.080	-2.583	8.521	97.74	148.33[a]	464.08[a]	0.259	0.096	-2.538	8.148	94.34	126.96[a]	446.46[a]
0523	263	0.154	0.048	1.649	5.362	100	183.33[a]	724.43[a]	0.127	0.057	1.072	5.323	98.48	176.65[a]	543.49[a]
0524	265	0.156	0.041	-0.434	4.630	100	15.41	201.05[a]	0.121	0.067	-0.869	3.156	92.83	33.15[a]	563.96[a]
0525	265	0.208	0.094	0.793	2.533	100	67.56[a]	368.35[a]	0.161	0.085	0.544	2.958	97.74	68.05[a]	374.03[a]
0526	265	0.063	0.090	1.166	4.673	72.83	207.59[a]	956.37[a]	0.016	0.076	-0.544	5.853	57.74	214.05[a]	839.70[a]
0527	265	0.251	0.098	0.511	3.063	100	145.54[a]	697.07[a]	0.193	0.116	0.508	3.262	95.09	139.72[a]	669.20[a]
0528	265	0.243	0.067	0.340	2.737	100	152.16[a]	560.92[a]	0.200	0.064	0.153	2.839	100	131.41[a]	523.94[a]
0529	265	0.451	0.111	1.633	7.801	100	148.86[a]	571.69[a]	0.418	0.126	1.422	6.762	100	146.88[a]	595.53[a]
0530	265	0.112	0.104	1.157	5.445	89.43	157.26[a]	924.16[a]	0.076	0.102	1.225	4.102	78.49	144.55[a]	790.29[a]
0531	373	0.414	0.222	0.744	2.697	100	169.18[a]	924.64[a]	0.388	0.237	0.874	2.803	100	173.75[a]	933.50[a]
0532	267	0.553	0.226	0.774	2.491	100	125.81[a]	1040.00[a]	0.531	0.242	0.762	2.402	100	135.49[a]	1057.30[a]
0533	267	0.163	0.179	1.310	3.931	97.00	195.90[a]	512.14[a]	0.120	0.167	1.636	5.862	82.40	193.83[a]	528.27[a]
0534	266	0.119	0.161	1.373	4.317	83.08	172.73[a]	758.67[a]	0.074	0.150	1.857	7.048	56.02	172.72[a]	748.75[a]

		BS Model							CEV Model						
Code	obs	Mean	S. D.	Skewness	Kurtosis	%[(1)]	LM (12)[(2)]	LB (12)[(3)]	Mean	S. D.	Skewness	Kurtosis	%[(1)]	LM (12)[(2)]	LB (12)[(3)]
0535	266	0.430	0.289	0.779	2.260	100	171.50[a]	1232.70[a]	0.376	0.327	0.735	2.141	95.86	178.51[a]	1294.50[a]
0536	267	0.249	0.204	2.509	8.717	100	149.61[a]	1410.30[a]	0.216	0.218	2.490	8.509	99.25	147.45[a]	1435.20[a]
0537	267	0.091	0.140	1.408	5.526	80.52	197.17[a]	198.87[a]	0.047	0.129	1.943	8.888	50.94	193.84[a]	208.38[a]
0538	266	0.271	0.184	2.630	9.954	100	191.25[a]	1478.10[a]	0.230	0.199	2.566	9.561	99.25	191.26[a]	1483.90[a]
0539	266	0.208	0.228	2.491	8.545	96.99	167.79[a]	1275.30[a]	0.165	0.239	2.634	9.035	91.35	167.93[a]	1297.20[a]
0540	266	0.120	0.095	0.468	2.420	90.60	175.07[a]	1402.80[a]	0.088	0.079	0.397	3.793	82.71	158.14[a]	1087.20[a]
0541	266	0.657	0.302	-0.238	1.454	100	135.06[a]	1110.60[a]	0.612	0.360	-0.312	1.493	98.12	131.56[a]	1182.70[a]
0542	266	0.090	0.159	1.358	4.757	66.54	214.84[a]	385.14[a]	0.044	0.156	1.743	6.507	40.60	211.49[a]	390.05[a]
0543	267	0.430	0.280	1.106	2.708	100	168.43[a]	1853.90[a]	0.397	0.306	1.077	2.598	100	163.32[a]	1861.60[a]
0544	267	0.062	0.123	3.554	22.582	71.16	238.37[a]	190.12[a]	0.027	0.120	4.250	29.368	37.45	238.20[a]	184.88[a]
0545	267	0.426	0.311	0.978	2.409	100	150.71[a]	1515.70[a]	0.379	0.341	0.994	2.355	98.88	167.54[a]	1575.10[a]
0546	267	0.104	0.177	2.493	10.912	75.28	226.52[a]	720.96[a]	0.061	0.184	2.692	11.741	46.07	225.84[a]	713.13[a]
0547	267	0.286	0.306	1.050	3.269	84.27	65.64[a]	863.65[a]	0.234	0.340	0.985	3.067	73.78	73.42[a]	863.54[a]
0548	267	0.271	0.288	0.939	3.291	79.78	130.16[a]	548.27[a]	0.236	0.314	0.909	3.100	68.16	125.28[a]	541.17[a]
0549	267	0.386	0.259	1.453	3.943	100	147.83[a]	1299.40[a]	0.343	0.285	1.413	3.776	98.50	139.67[a]	1208.70[a]
0550	267	0.514	0.345	0.081	1.564	100	168.52[a]	1557.50[a]	0.470	0.392	0.040	1.544	87.64	175.89[a]	1565.20[a]
0551	267	0.420	0.276	1.125	2.839	100	132.70[a]	1018.40[a]	0.390	0.303	1.103	2.698	100	117.55[a]	1010.30[a]
0552	267	0.794	0.193	-0.415	1.858	100	205.16[a]	1461.50[a]	0.778	0.223	-0.592	2.026	100	198.87[a]	1367.50[a]
0553	75	0.074	0.093	0.748	3.765	82.67	4.85	19.16[c]	0.012	0.129	0.327	2.788	54.67	13.75	22.81[b]
0554	267	0.714	0.240	-0.282	1.945	100	152.10[a]	1003.30[a]	0.695	0.271	-0.354	1.913	100	156.54[a]	1119.20[a]
0555	267	0.799	0.211	-0.761	2.337	100	132.96[a]	954.62[a]	0.784	0.239	-0.828	2.439	100	132.11[a]	1010.10[a]
0556	267	0.417	0.351	0.667	1.978	97.38	195.58[a]	917.78[a]	0.356	0.386	0.751	1.998	82.40	197.07[a]	945.11[a]
0557	266	0.394	0.312	0.921	2.314	100	156.02[a]	1245.40[a]	0.365	0.349	0.846	2.108	97.37	155.56[a]	1176.70[a]
0558	270	0.297	0.159	1.594	6.633	98.89	163.99[a]	397.99[a]	0.240	0.182	1.741	6.264	98.52	162.98[a]	445.89[a]
0559	24	0.439	0.146	-1.507	4.938	95.83		7.94	0.381	0.139	-1.188	4.199	95.83		6.88
0560	270	0.674	0.199	0.189	2.190	100	157.43[a]	929.89[a]	0.646	0.231	0.039	2.317	100	134.64[a]	820.48[a]
0561	269	0.616	0.256	0.505	1.686	100	130.44[a]	1140.10[a]	0.590	0.289	0.378	1.594	100	164.25[a]	1329.20[a]
0562	269	0.624	0.195	0.163	2.551	100	213.28[a]	1802.40[a]	0.601	0.228	-0.039	2.636	100	202.78[a]	1728.80[a]
0563	269	0.967	0.039	-1.039	3.031	100	174.77[a]	1068.40[a]	0.978	0.031	-1.552	4.365	100	199.12[a]	1065.20[a]
0564	269	0.836	0.202	-0.987	2.629	100	197.57[a]	2094.60[a]	0.817	0.243	-1.118	2.869	100	190.17[a]	1918.90[a]
0565	269	0.453	0.298	0.718	2.097	100	140.89[a]	1523.50[a]	0.404	0.353	0.637	1.852	95.91	115.59[a]	1247.50[a]
0566	268	0.543	0.354	0.125	1.527	100	212.16[a]	1461.20[a]	0.469	0.414	0.170	1.486	83.21	227.56[a]	1650.80[a]
0567	268	0.716	0.229	-0.387	2.292	100	181.91[a]	1378.60[a]	0.696	0.262	-0.335	2.034	100	156.05[a]	1217.70[a]
0568	267	0.657	0.261	0.060	1.741	100	93.55[a]	753.26[a]	0.605	0.310	0.045	1.674	100	105.98[a]	803.45[a]
0569	267	0.771	0.232	-0.521	1.967	100	161.60[a]	1855.00[a]	0.755	0.274	-0.699	2.183	100	166.38[a]	1801.70[a]
0570	267	0.886	0.123	-1.141	3.629	100	164.76[a]	1540.50[a]	0.887	0.136	-1.361	4.157	100	161.00[a]	1554.30[a]
0571	266	0.777	0.184	-0.156	1.732	100	185.69[a]	1094.50[a]	0.764	0.208	-0.229	1.663	100	188.34[a]	1270.50[a]

	BS Model								CEV Model						
Code	obs	Mean	S. D.	Skewness	Kurtosis	%[1]	LM (12)[2]	LB (12)[3]	Mean	S. D.	Skewness	Kurtosis	%[1]	LM (12)[2]	LB (12)[3]
0572	265	0.769	0.180	0.121	1.489	100	165.76 [a]	1465.50 [a]	0.765	0.202	-0.123	1.582	100	190.71 [a]	1591.30 [a]
0573	265	0.473	0.303	0.642	1.930	100	150.31 [a]	1251.70 [a]	0.423	0.362	0.540	1.694	95.85	123.95 [a]	865.87 [a]
0574	265	0.674	0.203	-0.072	2.118	100	191.58 [a]	651.97 [a]	0.643	0.237	-0.121	2.177	100	192.12 [a]	595.15 [a]
0575	265	0.903	0.121	-1.337	3.956	100	97.80 [a]	1078.60 [a]	0.899	0.143	-1.573	4.611	100	112.87 [a]	1185.40 [a]
0576	264	0.761	0.191	-0.011	1.614	100	187.02 [a]	1538.30 [a]	0.741	0.222	-0.172	1.653	100	193.75 [a]	1595.20 [a]
0577	262	0.316	0.287	0.716	2.077	95.42	89.89 [a]	478.85 [a]	0.232	0.354	0.672	1.936	59.16	78.68 [a]	467.13 [a]
0578	262	0.435	0.313	0.687	2.038	99.24	118.31 [a]	1470.10 [a]	0.384	0.372	0.593	1.796	91.22	99.02 [a]	1068.10 [a]
0579	267	0.456	0.231	0.727	3.241	98.13	160.34 [a]	834.37 [a]	0.441	0.259	0.595	2.711	97.75	140.27 [a]	780.09 [a]
0580	267	0.912	0.085	-0.351	1.759	100	162.79 [a]	1175.80 [a]	0.924	0.081	-0.732	2.404	100	94.24 [a]	854.71 [a]
0581	267	0.924	0.119	-1.580	4.275	100	132.68 [a]	1431.20 [a]	0.922	0.138	-1.817	5.144	100	116.12 [a]	1223.00 [a]
0582	267	0.835	0.154	-0.377	1.811	100	197.22 [a]	1539.60 [a]	0.824	0.178	-0.553	1.961	100	187.45 [a]	1459.40 [a]
0583	267	0.773	0.227	-0.430	1.714	100	195.58 [a]	1769.00 [a]	0.756	0.271	-0.611	1.893	100	191.51 [a]	1750.00 [a]
0584	267	0.638	0.276	0.005	1.509	100	195.64 [a]	1238.90 [a]	0.573	0.357	0.006				