Interaction and Pricing between the Taiex Call Options and Spot Market among Different Levels of Moneyness: Application of Bi-Egarch Model and Neuron Algorithm

Tien-Shih Hsieha,*, Chen-Ling Fangb, Yeon-Jia Gooc

aDepartment of Accountancy, Bentley University, Massachusetts, USA.
bDepartment of Cooperatives Economics, National Taipei University, Taiwan
cDepartment of Business Administration, National Taipei University, Taiwan

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Abstract

This investigation attempts to achieve two objectives. The first aim is to study the relationship between the TAIEX call options market and the spot market among different levels of Moneyness, namely, deep-in-the-money, in-the-money, at-the-money, deep-out-of-the-money, as well as out-of-the-money. The other one is to build a pricing model of TAIEX call options. The experimental data presented in this study come from the daily closing transaction price of TAIEX call options and the associated spot market from September 24, 2001 to August 31, 2003. This investigation applied the Bi_EGARCH model to study the interactive relationship of returns and volatility between TAIEX call options and the spot market, and used the Neuron Algorithm to establish a model for pricing TAIEX call options. This study reaches two main findings. First, the interactive relationship between TAIEX call options and the spot market differs among different Moneyness, and investors take larger risks under out-of-the-money and deep-out-of-money situations. Second, the prediction ability of the neural network pricing model is better than that of the regression model given different levels of Moneyness in most circumstances.

Keywords: Options, pricing, GARCH, artificial neural network

1. Introduction

1.1 Research background

According to a report by the International Options Market Association (IOMA) which analysed the structures and trends of global derivatives markets in 2002, annual transaction volume in 2002 exceeded 5 billion contracts for the first time. Among these contracts, options contracts comprised 41%, and exhibited 34% growth year on year. Additionally, regarding asset categories, index options contracts ranked 1st in terms of transaction volume (IOMA, 2003). In Taiwan, beginning from 24 December 2001, the government followed this global trend and approved the launch of transactions for stock market index options (TAIEX Index Options) and, subsequently, equity options were also rolled out for the Taiwan Futures Exchange (TAIFEX) over years ago. During this period, the total number of options contracts, both mature and immature, has grown incrementally (as illustrated in Fig. 1). Generally, both domestic and international options markets have experienced considerable growth and sustained momentum that promises to overtake other derivatives like futures and bonds in

* Corresponding author. E-mail: ralph23.tw@yahoo.com.tw
terms of transaction volume. Furthermore, the wide variety of options portfolios available, as well as the support from other derivatives such as futures and bonds, has improved the diversity and comprehensiveness of channels for investing and hedging risk in the stock market.

Figure 1. A growing trend in transaction volumes of completed and outstanding TAIEX index options contracts.

Since its inception, the Taiwanese options market has matured and seen increasing transaction volumes. Options products have long existed in other national markets, and have been a subject of discussions and studies on interactions between options and spot markets by numerous scholars, including Manaster and Rendleman (1982) and Bhattacharya (1987). In Taiwan options products remain relatively new. Even though Lee and Chen (2005), and Wang (2006) have discussed the relationship and pricing problem of Taiwan's options market and it's underlying market, but studies on the correlation between options and spot markets have been rather insufficient. Additionally, to date most studies conducted in different countries have focused on the product and underlying options instruments, however the design of options contracts, transaction systems and regulatory environments varies between countries, and such variations are further complicated by differences in data collection and research methodology, which in turn produce a lack of consensus in the research writings of scholars like Easley et al. (1998) and Anthony (1988). Consequently, one motivation of this investigation is to conduct an in-depth investigation of the correlations between TAIEX options and its underlying instruments in the Taiwan stock market, in the hope of providing helpful information for investors purchasing options. Another motivation for this work analyzing the correlations between options and spot markets is the fact that most studies in other countries have focused only on at-the-money options and have paid less attention to in-the-money or out-of-the-money options.

Individual investors have long played a key part in the investment structure of Taiwanese Stock market and this structure has resulted in a high percentage of transaction volumes involving individual investors, with the 2003 turnover rate of the centralized securities market in Taiwan reaching up to 192.08%, and, despite a gradual decline over the recent years, remaining several times the level of all other major markets other than South Korea (as shown in Table 1). Such extremely high turnover rates in securities markets imply high turnover frequencies of stock holdings, thriving market transactions, and frequent short-term trading, all of which tend to cause increased short-term price volatility and consequently increased transaction risk. The constant uncertainty in Taiwanese stock markets, probably best exemplified by external factors such as local political elections, has caused capricious directions or sharp fluctuations in the market, both of which have in turn increased non-systemic risks for investors. Accordingly, options products have logically become the optimum choice for investors for hedging risks. This fact further underlines the importance of obtaining an adequate valuation model for options products, and consequently a key aim of this study is to develop a good valuation model for TAIEX Index options.
### Table 1. Comparison of centralized market turnovers between major countries (Unit: %).

<table>
<thead>
<tr>
<th>Year</th>
<th>Taiwan</th>
<th>New York</th>
<th>Tokyo</th>
<th>London</th>
<th>Hong Kong</th>
<th>South Korea</th>
<th>Singapore</th>
</tr>
</thead>
<tbody>
<tr>
<td>1989</td>
<td>590.14</td>
<td>52.00</td>
<td>73.10</td>
<td>51.30</td>
<td>49.00</td>
<td>111.85</td>
<td>31.00</td>
</tr>
<tr>
<td>1990</td>
<td>506.04</td>
<td>43.00</td>
<td>38.41</td>
<td>45.60</td>
<td>44.00</td>
<td>68.57</td>
<td>61.60</td>
</tr>
<tr>
<td>1991</td>
<td>321.90</td>
<td>47.00</td>
<td>28.38</td>
<td>43.70</td>
<td>35.00</td>
<td>82.38</td>
<td>12.00</td>
</tr>
<tr>
<td>1992</td>
<td>161.33</td>
<td>44.00</td>
<td>19.91</td>
<td>42.60</td>
<td>53.00</td>
<td>133.42</td>
<td>12.80</td>
</tr>
<tr>
<td>1993</td>
<td>252.42</td>
<td>53.00</td>
<td>25.86</td>
<td>80.50</td>
<td>61.00</td>
<td>186.55</td>
<td>26.20</td>
</tr>
<tr>
<td>1994</td>
<td>366.11</td>
<td>53.00</td>
<td>24.93</td>
<td>77.10</td>
<td>55.00</td>
<td>174.08</td>
<td>26.70</td>
</tr>
<tr>
<td>1995</td>
<td>227.84</td>
<td>59.00</td>
<td>26.77</td>
<td>77.60</td>
<td>38.00</td>
<td>105.11</td>
<td>17.80</td>
</tr>
<tr>
<td>1996</td>
<td>243.43</td>
<td>62.00</td>
<td>28.94</td>
<td>78.60</td>
<td>41.00</td>
<td>102.98</td>
<td>13.60</td>
</tr>
<tr>
<td>1997</td>
<td>407.32</td>
<td>65.71</td>
<td>32.93</td>
<td>44.03</td>
<td>90.92</td>
<td>145.56</td>
<td>56.28</td>
</tr>
<tr>
<td>1998</td>
<td>314.06</td>
<td>69.88</td>
<td>34.13</td>
<td>47.10</td>
<td>61.94</td>
<td>207.00</td>
<td>63.95</td>
</tr>
<tr>
<td>1999</td>
<td>288.62</td>
<td>74.62</td>
<td>49.37</td>
<td>56.71</td>
<td>50.60</td>
<td>344.98</td>
<td>75.16</td>
</tr>
<tr>
<td>2000</td>
<td>259.16</td>
<td>82.40</td>
<td>58.86</td>
<td>63.81</td>
<td>62.99</td>
<td>301.56</td>
<td>64.97</td>
</tr>
<tr>
<td>2001</td>
<td>206.95</td>
<td>87.62</td>
<td>56.52</td>
<td>76.10</td>
<td>46.55</td>
<td>218.24</td>
<td>56.07</td>
</tr>
<tr>
<td>2002</td>
<td>217.41</td>
<td>88.98</td>
<td>65.21</td>
<td>89.17</td>
<td>42.78</td>
<td>254.53</td>
<td>59.81</td>
</tr>
<tr>
<td>2003</td>
<td>190.82</td>
<td>86.33</td>
<td>66.23</td>
<td>95.76</td>
<td>38.03</td>
<td>194.11</td>
<td>51.84</td>
</tr>
</tbody>
</table>


To summarize, several years have passed since the establishment of the Taiwanese options market, and transaction volume has been gradually expanding. However, owing to the nature of options as a relatively new product type in this market, the literature on the correlations between options and spot markets has still not clearly answered the following question: Which of the two markets is leading the other, or do they exert a mutual influence on one another? These questions merit further in-depth investigation. Facing gradual globalization and liberalization of domestic financial markets, investors undoubtedly need more diverse tools for investing and risk-hedging, and options portfolios is one such tool. Therefore, another topic that should be discussed is to identify the specific features of an adequate model for valuing options products.

### 1.2 Research objectives

This investigation focuses on in-depth analyses of TAIEX Index options and their underlying instruments, the TAIEX Index, area neglected by the previous literature, and uses more abundant data in Taiwan’s stock market than before to be our in here. This study has two objectives:

(a) To study the correlations between the TAIEX Index options and spot markets by classifying products among deep-in-the-money, in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money.

(b) To construct, using artificial neural computing algorithms, an adequate forecasting model based on the correlations between TAIEX Index options and their underlying instruments, obtained from our first objective which tells us relationships among deep-in-the-money,
in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money conditions and using these as network input variables.

1.3 Research framework

This investigation comprises five sections. Section I: Introduction provides an overview of financial markets and background of the study and describes research purposes and research framework. Subsequently, Section II: Literature Review comprises two parts, namely studies on the correlations between options and spot markets in different countries, and a literature review focused on the application of computational intelligence to forecasting options prices. Section III: Research Methodology then introduces the analysis of inter-market correlations with the bi-asymmetric GARCH model, and then explains the valuation of options with an artificial neural network in computational intelligence. Next, Section IV describes the analyses of empirical data, and begins by analyzing the correlations between the two markets, then predicts options values based on relevant data derived from estimation based on such a correlation of TAIEX options market and its spot market among different levels of Moneyness and other variables. Finally, Section V provides conclusions based on the outcomes of the empirical study.

2. Literature review

2.1. Market correlation

A review of the literature has demonstrated that scholars generally agree that the markets for options and their underlying instruments respond at different speeds to the impact of new information, a lag which leads to imperfect market conditions.

This study reviews on correlation and price prediction, for example those written by Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988), Stephan and Whaley (1990), Chan et al. (1993), Diltz and Kim (1996), Easley et al. (1998), are reviewed in this investigation, and then summarizes the contributors to the causal relationship between options and spot markets into the following types:

(a) Non-synchronized transactions: Because a stock market index comprises multiple individual stocks, transactions do not necessarily exist at each time that stock market index estimations are performed. Thus stocks without any transactions are estimated using the data of their last transaction instead of their next transaction prices. Consequently, data for the stocks that comprise the stock market index derives partly from the previous period, and index options lead their spot counterparts in responding to impact of new market information.

(b) Market fluidity: Since stocks included in the stock market index do not necessarily have the same level of fluidity, transaction volumes of stocks with higher fluidity can sometimes be dozens or even hundreds of times higher than their counterparts. Consequently, stock indexes tend to respond to new information slower than do derivatives, leading to discrepancies between markets.

(c) Leverage effect: This describes the condition under which the leverage ratio of options transactions exceeds that of spot transactions given the same investment volume. Consequently, all other things being equal, investors with insider information will choose options market transactions with a higher leverage ratio, again leading to discrepancies between the two markets.

(d) Transaction costs: Transaction costs include transaction fees, brokerage, and bid/ask spread. In reality, the existence of transaction costs in a market may create arbitrage opportunities. Particularly, when profits from arbitrage are too low to offset transaction costs, significant discrepancies may occur between markets. Under such a condition,
transaction costs for buying spot shares frequently exceed those for derivatives, leading to
the derivatives market leading the spot market in terms of response capacity to impact of
new information.

c) Government interference: Most governments regulate derivatives markets less tightly
than the markets for their underlying securities. If investors cannot go short in a spot
market when they expect to be able to, derivatives markets offer their only alternative to
short the stock which they want to short, contributing to a discrepancy between markets.

2.2 Options valuation models

The primitive Black-Scholes pricing model makes several unreasonable assumptions that
have resulted in large discrepancies between theoretical and actual prices when estimating
options prices, as indicated by the famous smile curve. Studies by Hutchinson et al. (1994),
Garcia and Geççay (2000), Meissner and Kawano (2001), Winne et al. (2001), and Barria and
Hall (2002) have found that artificial neural networks possess highly adaptive learning
capability and high flexibility in the model uses, and also provide more accurate predictions
of options prices compared to primitive Black-Scholes models most of the time. This
investigation thus focuses on artificial neural networks as a theoretical model for forecasting
options prices, and considers the issue of correlation between options and their underlying
spot markets (such as, TAIEX Index options and its spot market), which has been neglected
by the previous literature on estimating the volatility of underlying instruments. Consequently,
the price volatility of options and their underlying instruments, together with consideration of
the correlations between options markets and their underlying instruments together with
consideration of the correlations, is used as a variable for estimating options prices.
Prediction performance is also compared between artificial neural network pricing model and
the traditional regression model is also conducted in the manner adopted by Lajbcyaier (1996)
to study whether artificial neural networks provide a basis for improved pricing capability.

Furthermore, since the literature has focused primarily on at-the-money data based
analyses, and since few studies have examined specific conditions such as deep-in-the-money,
in-the-money, out-of-the-money, and deep-out-of-the-money, this investigation divides the
study samples of Taiwanese stock and options markets into these five categories for empirical
analyses. The objective is to identify whether correlations between the two markets vary
according to those conditions, such as deep-in-the-money, in-the-money, at-the-money, out-
of-the-money, and deep-out-of-the-money and whether the performance of predicting options
prices using an artificial neural network model varies according to those conditions of
Moneyness.

3. Research methodology

This investigation conducts an empirical investigation in two parts. First, the correlation
between TAIEX Index options and their underlying instrument, TAIEX Index, is studied to
determine whether any lead/lag effects exist between the two markets because of the
difference in their respective speed in responding to the impact of new information owing to
information disparities between the two markets. Second, after examining the correlation
between the two markets, estimated volatilities of variables for the two markets are used,
along with other relevant variables, as one of the variables of the artificial neural network
model to predict option values. Relevant statistical tests are then used to evaluate the
performance of the prediction results. The main models used in this investigation comprise
two groups, described below.
3.1 VAR (p)-Bi-EGARCH empirical model

The ARCH and GARCH models, proposed by Mandelbort (1963) and Bollerslev (1986), respectively, have reduced the unreasonable assumptions associated with Homoscedasticity in a traditional regression model and effectively express phenomena like heterogeneous volatility and volatility cluster. However, these models still suffer certain flaws: (a) they cannot be used to analyze the problem of volatility asymmetry; (b) the fact that model parameters must be always positive prevents the models from describing the oscillation of conditional Heteroscedasticity; (c) the GARCH model fails to offer a good explanation for the time span of affect on conditional Heteroscedasticity for the current period, which resulted from the impact from the previous period.

To address the above flaws, Nelson (1991) proposed the EGRCH model, also used in this investigation. This study focuses on how information is transmitted between the TAIEX Index options market and the spot market and attempts to identify the volatility asymmetry in the dynamic transmission of information between variables.

Furthermore, empirical studies by Bollerslev (1990), Kearney and Patton (2000), and Wang and Wang (2001) have all demonstrated that the GARCH (1, 1) model has good adaptability for time series data. Consequently, this investigation employs the VAR(P)-Bi-EGARCH(1,1) model (where P refers to Vector Autoregressive, or VAR in short, and the optimal number of lagged periods for the model is determined according to minimum AIC) to effectively estimate the correlation between TAIEX Index options and their spot market and to identify any volatility asymmetry. Specific settings of the VAR (P)-Bi-EGARCH (1, 1) model are as follows:

\[
R_{C,t} = \beta_{C,0} + \sum_{j=1}^{k} \beta_{C,j} R_{C,t-j} + \sum_{j=1}^{k} \beta_{S,j} R_{S,t-j} + \epsilon_{C,t} 
\]

\[
R_{S,t} = \alpha_{S,0} + \sum_{j=1}^{k} \alpha_{S,j} R_{S,t-j} + \sum_{j=1}^{k} \alpha_{C,j} R_{C,t-j} + \epsilon_{S,t} 
\]

\[
\ln(h_{C,t}) = VC_C + VA_C \ln(h_{C,t-1}) + VB_C \left( \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} - \sqrt{\frac{2}{\pi}} \right) + VC - \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} 
\]

\[
+ VC \left( \frac{\epsilon_{S,t-1}}{\sqrt{h_{S,t-1}}} - \sqrt{\frac{2}{\pi}} \right) + VC_C \left( \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} - \sqrt{\frac{2}{\pi}} \right) 
\]

\[
\ln(h_{S,t}) = VC_S + VA_S \ln(h_{S,t-1}) + VB_S \left( \frac{\epsilon_{S,t-1}}{\sqrt{h_{S,t-1}}} - \sqrt{\frac{2}{\pi}} \right) + VC - \frac{\epsilon_{S,t-1}}{\sqrt{h_{S,t-1}}} 
\]

\[
+ VC_S \left( \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} - \sqrt{\frac{2}{\pi}} \right) + VC_S \left( \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} - \sqrt{\frac{2}{\pi}} \right) 
\]

\[
\ln(h_{SC,t}) = VC_{CS} + VA_{CS} h_{CS,t-1} + VB_{CS} \left( \frac{\epsilon_{S,t-1}}{\sqrt{h_{S,t-1}}} - \frac{\epsilon_{C,t-1}}{\sqrt{h_{C,t-1}}} \right)
\]

Equations (1) and (2) refer to the conditional mean equation of return rate for TAIEX Index options market and their spot market respectively; Equations (3) and (4) refer to the conditional Heteroscedasticity equation of return rate for TAIEX Index options market and their spot market respectively; and, finally, Equation (5) refers to the conditional covariance
function of return rates of the two markets. Definitions of respective parameters are as follows: \( \beta_{C,0} \) and \( \alpha_{S,0} \) are the intercept in conditional mean equation of TAIEX Index options and their spot market respectively in empirical modeling analysis; \( \beta_{C,i} \) and \( \beta_{S,i} \) refer to the degree to which return rate of the options market for the current period is influenced by the options and spot markets for lagged period \( i \); \( \alpha_{S,i} \) and \( \alpha_{C,i} \) refer to the degree to which return rate of spot market for the current period is influenced by the options and spot markets for lagged period \( i \); \( \varepsilon_{C,i} \) and \( \varepsilon_{S,i} \) refer to random error of their respective markets in the model. \( v_{CC} \) and \( v_{CS} \) refer to long term information in the conditional Heteroscedasticity equations in empirical modeling analysis; \( v_{AC} \) and \( v_{AS} \) are used to estimate volatility persistence in options and spot markets respectively; \( v_B \), \( v_{BE} \), \( v_{EC} \) and \( v_{ES} \) are used to identify weather there is any ARCH effect in options and spot markets or not and also to measure the degree of such an effect and its impact on a market and its counterpart; \( v_{DC} \), \( v_{DS} \), \( v_{FC} \) and \( v_F \) are used to measure any discrepancy in volatility between the two markets that has been caused by good news or bad news. \( \frac{\varepsilon_{C,i}}{v_{Cc,i}} \) and \( \frac{\varepsilon_{S,i}}{v_{CS,i}} \) standardized residual in the asymmetrically general conditional Heteroscedasticity equation for respective markets. Solution is derived using BHNN algorithm proposed by Berndt et al. (1974).

3.2 Back-propagation artificial neural networks

Back-Propagation artificial neural networks include a supervisory mode of training and a learning mode based on least square variance and use a search technique that features the Gradient Steepest Descent Method to identify the minimum error equation. This method of network learning comprises two main parts: Forward Pass and Backward Pass. Appendix A contains detailed explanation of Back-Propagation.

4. Empirical analyses

4.1. Operational definitions of variables

Regarding market correlation between the options and spot markets, this investigation selected the return rates of the TAIEX Index options and the TAIEX spot market as the variables representing the correlation between the two markets. This study estimates return rate as follows:

\[
R_{i,t} = \left( \ln P_{i,t} - \ln P_{i,t-1} \right) * 100
\]

where \( i = C \) (return rate of options market), \( S \) (return rate of spot market); \( R_{i,t} \): daily return rate of market \( i \) for period \( t \); \( P_{i,t} \): closing price of market \( i \) for period \( t \); \( P_{i,t-1} \): closing price of market \( i \) for period \( t-1 \).

In selecting input variables of an artificial neural network, Huchinson (1994) first adopted artificial neural network to predict options prices. Numerous other scholars, including Meissner and Kawano (2000) and Garcia and Gencay (2000), have adopted similar settings which use variables related to options prices in the primitive Black-Scholes equation. Thus, this investigation follows the same tradition of using this equation as a basis for choosing variables for an artificial neural network. Furthermore, data regarding the TAIEX options and spot markets have demonstrated that the relationships between the two variables of \( \frac{C}{S} \) (known as call rights value in this work) and \( \frac{S}{P} \) (referred to as Moneyness in this study) move from a linear pattern towards an exponential pattern as the market changes from deep-in-the-money...
to at-the-money, out-of-the-money, and deep-out-of-the-money, as shown in Figs. 2 to 6, indicating that the nature of the relationship between the two markets varies with Moneyness. Additionally, since options exercise price is an important contributor to Moneyness, this investigation divides options markets according to Moneyness into five types, including deep-in-the-money, in-the-money, at-the-money, out-of-the-money, and deep-out-of-the-money, according to various exercise prices, to study the leading/lagging relationship between the rates of return of the two markets. Moreover, this investigation uses the classification standard in Rubinstein (1985) to categorize the raw data of TAIEX into five groups. The classification rules as follows:

- \( \text{Moneyness} \geq 1.15 \) Deep-in-Money
- \( 1.15 > \text{Moneyness} \geq 1.05 \) In-the-Money
- \( 1.05 > \text{Moneyness} \geq 0.95 \) at-the-Money
- \( 0.95 > \text{Moneyness} \geq 0.85 \) Out-of-the-Money
- \( 0.85 < \text{Moneyness} \) Deep-Out-of-Money

Phenomena such as volatility cluster and the asymmetry effect are considered in estimating volatility as an input variable for the proposed artificial neural network model. Finally, the factor of interest rate is included, as suggested in a subsequent study by Garcia and Gencay (2000), to further expand the function as follows:

\[
\frac{C_t}{K} = f \left( \frac{S_t}{K}, \tau, R, V_c, V_s \right)
\] (7)

where \( C_t \) is the options price for period \( t \); \( S_t \) is the price of underlying instrument for the period \( t \); \( K \) is the exercise price of options; \( \tau \) is the maturity days of options; \( R \) is the risk-free interest rate, which is substituted by interest rate of 30-day commercial paper in this study; \( V_c \) is return rate volatility of options market estimated by volatility estimation model; and \( V_s \) is return rate volatility of spot market estimated by volatility estimation model.

Finally, variables in (7) are used as a basis for selecting input variables when predicting options value using an artificial neural network. Besides, in the artificial neural network, we designed a program by using SAS to randomly decide the parameters in our artificial neural network, such as hidden layer and learning rate, and then select the values of parameters which optimize the result of our model. Hence, we can have the best prediction result of our data.

![Figure 2. C/K and S/K distribution: Deep-in-the-money.](image)
Figure 3. C/K and S/K distribution: In-the-money.

Figure 4. C/K and S/K distribution: At-the-money.

Figure 5. C/K and S/K distribution: Out-of-the-money.
4.2 Sources and processing of data

In the beginning of launching TAIEX index options, the transactions volume in options contracts with maturity due in one month is more sufficient than options contracts with maturity due in more than one month. Thus, we only chose the options contract which has the most sufficient transaction volume in this investigation in order to classify the data of TAIEX in to five groups. Hence, data samples used in this work include daily data of the TAIEX Weighted Stock Index from 24 December 2001 to 31 August 2003, comprising 417 records of 417 trading days over a period of 18 months, and daily data of TAIEX Index call options contracts with maturity due in one month. From this daily data, call options contracts are chosen and divided based on exercise price into five categories of deep-in-the-money, in-the-money, at-the-money, out-of-the-money, and deep-out-of-the-money for empirical investigation.

This study also analyzes the correlation between options and spot markets in these five categorizations. Regarding input variables for artificial neural network, return rate volatility and Moneyness of the two markets, interest rate of 30-day commercial papers, and maturity date of options contract are selected as input variables, while options value serves as the network output variable.

4.3. Empirical modeling analyses of market correlation

To study whether information asymmetry produces leading/lagging relationships in terms of correlation between the TAIEX Index options market and the TAIEX Index, and whether such correlations vary according to the five conditions of deep-in-the-money, in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money, this investigation adopted an EGARCH model proposed by Nelson (1991) for empirical analyses of the correlation between the two markets under five different conditions following passing stationary, serial correlation, and ARCH effect tests. The outcomes of the empirical analyses are listed in Table 2 and explained as follows:

(a) Deep-in-the-money: The spot return rate for the current period is influenced by the return rate for the lagged period 1, and volatility persistence is significant only in the options market, and has a half-life of 0.319891 days and 0.425188 days for the current and lagged periods, respectively. Volatility cluster is significant only in the options market, and in the deep-in-the-money condition, the options market leads the spot market in terms of volatility. Volatility asymmetry and volatility spillover are only significant in the options market.
market in the deep-in-the-money condition.

(b) In-the-money: No significant volatility exists in either of the two markets, which have half-lives of 0.217839 day and 0.216404 day, respectively. Volatility cluster is significant in both markets in the in-the-money condition, and the options market leads the spot market in terms of return rate in the in-the-money condition.

(c) At-the-money: The return rate of call options for the current period is influenced by that of the options market for the lagged period 1. No significant volatility exists in either of the two markets, which have half-lives of 0.250466 day and 0.182719 day, respectively. The volatility cluster is significant in both markets, with mutual feedback in volatility between the two markets. Moreover, volatility asymmetry and volatility spillover are significant for both markets.

(d) Out-of-the-money: Volatility persistence is significant in both markets, with half-lives of 0.323447 day and 0.223267 day respectively. Volatility cluster is significant only in the options market, and the spot market significantly leads the options market in return rate.

(e) Deep-out-of-the-money: Volatility persistence is significant only in the options market, with a half-life of 1.103111 days. The volatility cluster is significant only in the options market. Mutual feedback in volatility exists between the two markets in the deep-out-of-the-money.

Table 2. Outcomes of VAR(1) Bi-EGARCH(1,1).

<table>
<thead>
<tr>
<th>Parameter</th>
<th>T-Stat</th>
<th>Signif</th>
<th>Parameter</th>
<th>T-Stat</th>
<th>Signif</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deep-in-the-money</td>
<td></td>
<td></td>
<td>At-the-money</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(\alpha_{S,1})</td>
<td>2.3693</td>
<td>0.0178</td>
<td>(\beta_{C,1})</td>
<td>-7.5576</td>
<td>0.0000</td>
</tr>
<tr>
<td>VAc</td>
<td>2.1754</td>
<td>0.0296</td>
<td>VBc</td>
<td>5.3633</td>
<td>0.0000</td>
</tr>
<tr>
<td>VBc</td>
<td>5.4600</td>
<td>0.0000</td>
<td>VDC</td>
<td>6.5738</td>
<td>0.0000</td>
</tr>
<tr>
<td>VDC</td>
<td>-25.0317</td>
<td>0.0000</td>
<td>VEC</td>
<td>3.3422</td>
<td>0.0008</td>
</tr>
<tr>
<td>VEC</td>
<td>8.8974</td>
<td>0.0000</td>
<td>VFc</td>
<td>7.5478</td>
<td>0.0000</td>
</tr>
<tr>
<td>VFc</td>
<td>7.4606</td>
<td>0.0000</td>
<td>VBS</td>
<td>-2.1572</td>
<td>0.0310</td>
</tr>
<tr>
<td>At-the-money</td>
<td></td>
<td></td>
<td>In-the-money</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VBc</td>
<td>-2.2805</td>
<td>0.0226</td>
<td>VDc</td>
<td>1.8527</td>
<td>0.0639</td>
</tr>
<tr>
<td>VEc</td>
<td>9.7289</td>
<td>0.0000</td>
<td>VEs</td>
<td>-2.3971</td>
<td>0.0165</td>
</tr>
<tr>
<td>VBS</td>
<td>-2.6771</td>
<td>0.0074</td>
<td>VFs</td>
<td>3.0849</td>
<td>0.0020</td>
</tr>
<tr>
<td>Out-of-the-money</td>
<td></td>
<td></td>
<td>Deep-out-of-the-money</td>
<td></td>
<td></td>
</tr>
<tr>
<td>VAc</td>
<td>2.7036</td>
<td>0.0069</td>
<td>VAc</td>
<td>7.8586</td>
<td>0.0000</td>
</tr>
<tr>
<td>VBc</td>
<td>5.2727</td>
<td>0.0000</td>
<td>VBC</td>
<td>3.7978</td>
<td>0.0001</td>
</tr>
<tr>
<td>VEs</td>
<td>-2.2886</td>
<td>0.0221</td>
<td>VEC</td>
<td>2.2428</td>
<td>0.0249</td>
</tr>
<tr>
<td>VEs</td>
<td>-1.8047</td>
<td>0.0711</td>
<td>VES</td>
<td>-2.1572</td>
<td>0.0310</td>
</tr>
</tbody>
</table>

4.4. Market correlation

The correlation between the rates of return of options and spot markets under the five conditions of deep-in-the-money, in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money are listed in Tables 3 and 4, and provide a reference for the discussions regarding whether correlation varies according to specific conditions. G1, G2, G3, G4, and G5 represents the five conditions of deep-in-the-money, in-the-money, at-the-money, out-of-the-money, and deep-out-of-the-money respectively; (+) stands for a positive correlation, and (-) for a negative correlation.
Table 3. Relationship between return of options and spot markets.

<table>
<thead>
<tr>
<th></th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return rate of spot price for the previous period vs. Return rate of options price for the current period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Return rate of options price for the previous period vs. Return rate of options price for the current period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(−)</td>
</tr>
<tr>
<td>Return rate of options price for the previous period vs. Return rate of spot price for the current period</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(+)</td>
</tr>
<tr>
<td>Return rate of spot price for the previous period vs. Return rate of spot price for the current period</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4. Relationship between return rate volatility of options and spot markets.

<table>
<thead>
<tr>
<th>Volatility in return rate of call options price</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
<th>Volatility in return rate of spot price</th>
<th>G1</th>
<th>G2</th>
<th>G3</th>
<th>G4</th>
<th>G5</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volatility persistence</td>
<td>(+)</td>
<td></td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>Volatility persistence</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volatility cluster</td>
<td>(−)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>Volatility persistence</td>
<td>(−)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
</tr>
<tr>
<td>Volatility leading effect</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>Volatility leading effect</td>
<td>(−)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
</tr>
<tr>
<td>Volatility asymmetry effect</td>
<td>(−)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>Volatility asymmetry effect</td>
<td>(−)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
<td>(+)</td>
</tr>
<tr>
<td>Volatility spillover effect</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Volatility spillover effect</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
<td>(−)</td>
</tr>
</tbody>
</table>

Table 3 shows that, among the five different conditions, the return rate of options market price is influenced by that during the previous period only in the at-the-money condition; the return rate of the spot price for the current period is affected by that of the previous period only in the deep-in-the-money condition; and no significant leading/lagging relationship exists in the return rates of the two markets under other conditions.

Table 4 shows a correlation in the volatility of the two markets under the five different conditions, as follows: Volatility persistence is not significant when the options market is in-the-money or at-the-money but is significant under other conditions, whereas in the spot market volatility persistence exists only when the market is deep-in-the-money. Investors thus may be exposed to investment risks exceeding those in the spot market when the options market is out-of-the-money or deep-out-of-the-money. In terms of volatility cluster, it is significant under all conditions except when the spot market is deep-in-the-money, out-of-the-money, or deep-out-of-the-money. Regarding volatility leading effect between the two markets, outcomes of empirical investigation demonstrate that the options market leads the spot market in terms of return rate when the options market is deep-in-the-money or in-the-money, and demonstrates the existence of mutual feedback between the two markets in terms of volatility when the options market is at-the-money or deep-out-of-the-money, and moreover that the spot market leads the options market in return rate volatility when the options market is out-of-the-money. Volatility asymmetry exists only when the options market is deep-in-the-money or at-the-money, or when the spot market is at-the-money. Finally, volatility spillover occurs only when the options market is deep-in-the-money or when the spot market is at-the-money or deep-out-of-the-money.

4.5 Artificial neural network modeling analyses

Parameters such as number of hidden layers, number of units in per hidden layer and
learning speed are important contributors to the outcomes of artificial neural network predictions. The existing literature contains no consensus about the setting of these parameters, and thus most studies still set parameters within a specific range via trail-and-error and then assign a rate of decrease to seek an optimal mode. This work adopts a similar approach.

Hyperbolic transfer function is used to transfer output data for each processing unit. Moreover, random search is employed to identify an optimal hidden layer in layers 1-20. In terms of learning speed, an initial value is assigned at the beginning of a random search to avoid partial optimization. The cycle number is set to 8,000 times, and an optimal model is chosen based on the criterion of minimum MAPE. Finally, network prediction performance is measured using the three indicators of MAPE, Coefficient of Determination, and hit ratio, and then compared with the performance of a traditional regression model, as done by Lajbcyaier (1996), to determine whether artificial neural network has superior pricing capability. Empirical data under various Moneyness conditions are used to compare model performance.

Table 5 presents the prediction performances of the Back-Propagation network model and the multi-regression model under various Moneyness conditions, as well the optimal number of hidden layers for an artificial neural network. The results show that Back-Propagation network performances are not considerably better than those of a traditional multi-regression model only when the market is in-the-money, and all of their error values are less than those of a traditional regression model under the remaining four conditions.

Table 5. Comparison of prediction performance between models.

<table>
<thead>
<tr>
<th>Condition</th>
<th>MAPE</th>
<th>Rsq</th>
<th>Hit ration</th>
<th>Number of hidden layers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Multi-regression model</td>
<td>9.9713</td>
<td>92.34</td>
<td>91.81</td>
</tr>
<tr>
<td>In-the-money</td>
<td>Back-propagation network model</td>
<td>10.0878</td>
<td>95.02</td>
<td>91.11</td>
</tr>
<tr>
<td></td>
<td>Multi-regression model</td>
<td>9.9067</td>
<td>92.34</td>
<td>91.81</td>
</tr>
<tr>
<td>At-the-money</td>
<td>Back-propagation network model</td>
<td>22.4269</td>
<td>78.98</td>
<td>80.77</td>
</tr>
<tr>
<td></td>
<td>Multi-regression model</td>
<td>26.1023</td>
<td>53.31</td>
<td>78.61</td>
</tr>
<tr>
<td>Out-of-the-money</td>
<td>Back-propagation network model</td>
<td>7.2883</td>
<td>87.71</td>
<td>92.07</td>
</tr>
<tr>
<td></td>
<td>Multi-regression model</td>
<td>17.8296</td>
<td>59.61</td>
<td>82.69</td>
</tr>
<tr>
<td>Deep-out-of-the-money</td>
<td>Back-propagation network model</td>
<td>7.0550</td>
<td>85.94</td>
<td>91.35</td>
</tr>
<tr>
<td></td>
<td>Multi-regression model</td>
<td>16.0905</td>
<td>56.31</td>
<td>81.41</td>
</tr>
</tbody>
</table>

Performance indicators alone may be insufficient to confirm the comparative advantage of one model versus another. To further examine whether artificial neural networks provide better pricing capability, and since artificial neural networks can be considered a
non-parametric method, this study adopts the Wilcoxon Scores Rank Sums Test, the approach used by Chu and Freund (1986), to study the null hypotheses. Table 6 lists the outcomes.

Table 6. Wilcoxon Scores rank sums test.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Z value</td>
<td>-1.9159</td>
<td>0.3856</td>
<td>-2.3007</td>
<td>-14.122</td>
<td>-13.9472</td>
</tr>
<tr>
<td>p_value</td>
<td>0.0277</td>
<td>0.3499</td>
<td>0.0107</td>
<td>&lt;.0001</td>
<td>&lt;.0001</td>
</tr>
</tbody>
</table>

Table 6 shows that, owing to testing under various conditions, the performance of a Back-propagation network is not necessarily better than that of a traditional multi-regression model only when the market is in-the-money, but the performance of a Back-Propagation network is better than a traditional multi-regression model in deep-in-the-money, at-the-money, out-of-the-money and deep-out-of-the-money conditions, and their error values are all lower than those of traditional regression models under the other four conditions. This finding is consistent with the outcomes of performance indicator based comparisons.

5. Conclusions and suggestions

This investigation was the first to employ the VAR (p)-Bi-EGACH model to investigate the correlation between the TAIEX Index options market and its underlying instrument market, and then determined the volatility of the two markets and included this in the price prediction model to develop an improved pricing model. Thus, the conclusions of this work comprise two parts:

(a) Market correlation:

According to the results of this investigation, the correlation between return rates of the two markets varies with different conditions. Volatility of options market return rate leads spot market return rate volatility in the deep-in-the-money and in-the-money conditions; mutual feedback of return rate volatility between the two markets exists under at-the-money and deep-out-of-the-money conditions; and spot market return rate volatility leads options market return rate volatility in the out-of-the-money condition. Furthermore, volatility persistence is more significant in the options market than the spot market when the options market is out-of-the-money or deep-out-of-the-money, showing that, from the perspective of investors, the investment risk increases with how out-of-the-money the options are. The phenomenon about investment risk increasing with how out of the options are could be one of important reasons why correlation between the two markets varies with Moneyness. Another reason could be that, despite its strong growth since its launch over two years ago, the TAIEX Index options market remains less mature than markets in other countries in terms of both transaction volume and investor acceptance, making it difficult for options products to fully utilize their price discovery capability, and thus resulting in the existence of leading or lagging phenomenon between the two markets.

(b) Options price prediction model:

Empirical outcomes from prediction performance or determined by non-parametric test have shown that artificial neural networks provide more accurate prediction under most conditions. Consequently, the superior prediction capability of Back-Propagation networks in options price prediction makes it an important basis for reasonable pricing of options products when investors are trading in options markets.
References


