行政院國家科學委員會補助專題研究計畫 □ 成 果 報 告 ■期中進度報告

違約風險的經濟因素與 Levy 過程下之動態違約評價模型及預警系統

(第 1 年)

計畫類別：■個別型計畫　　□ 整合型計畫

計畫編號：NSC 98-2410-H-004-064-MY2

執行期間：　2009 年 08 月 01 日至 2010 年 07 月 31 日

計畫主持人：廖四郎

計畫參與人員：李嘉晃

成果報告類型(依經費核定清單規定繳交)：■精簡報告　□完整報告

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執行單位：政治大學金融學系

中　華　民　國　2010 年 05　月 24 日

壹、中、英文摘要及關鍵詞。

摘要

本文透過經濟因子建構信用衍生性商品評價模型以評價信用違約交換指數並量化信用市場與經濟環境的關係。本文並非僅挑選特定經濟變數，乃是藉由整合許多經濟與財務變數，將龐雜的經濟資訊彙整為少量的經濟因子，再透過無套利條件，決定經濟因子對違約強度過程的影響。實證結果顯示，經濟因子在信用風暴發生前已顯示出信用問題，而且經濟狀況對於信用市場影響甚鉅。樣本外評價結果顯示，動態經濟因子能定義信用環境的改變。因此，藉由量化經濟環境與信用市場關係所建構之經濟因子評價模型，不僅有助於衡量違約機率並能更有效的控管違約風險。

關鍵字：信用價差、經濟因子、違約強度、次級房貸風暴、信用違約交換指數。

Abstract

This paper constructs a credit derivative pricing model using economic fundamentals to evaluate CDX indices and quantify the relationship between credit conditions and the economic environment. Instead of selecting specific economic variables, numerous economic and financial variables have been condensed into a few explanatory factors to summarize the noisy economic system. The impacts on default intensity processes are then examined based on no-arbitrage pricing constraints. The approximated results show that economic factors indicated credit problems even before the recent subprime mortgage crisis, and economic fundamentals strongly influenced credit conditions. Testing of out-of-sample data shows that credit evolution can be identified by dynamic explanatory factors. Consequently, the factor based pricing model can either facilitate the evaluation of default probabilities or manage default risks more effectively by quantifying the relationship between economic environment and credit conditions.

Key Words: Credit spread, Economic determinant, Default intensity, Subprime mortgage crisis, CDX.

貳、報告內容

1. Introduction

This paper modifies the reduced-form model to evaluate credit derivatives with economic fundamentals. To identify actual credit evolution, the influences of economic conditions on default risks are quantified through no-arbitrage pricing constraints. In a changing economic environment, the proposed credit derivative pricing model facilitates the evaluation of credit risks and raises awareness of aggravated credit conditions for effective risk management.

This paper has three objectives: identifying relevant explanatory factors for default risks, quantifying the influences of these economic factors on default risks and pricing credit derivatives based on economic conditions. First, a dynamic model is constructed to summarize information from relevant economic and financial data to assess changes in the economic environment. Instead of using specific macroeconomic variables, we choose dynamic explanatory factors from a large number of variables to represent the complex economic system. Because firms are exposed to the same macroeconomic conditions, systematic factors, and financial markets, contagious default intensities lead to temporal clustering of defaults. Macroeconomic indicators were incorporated into real activity and inflationary groups as in previous studies (Ang and Piazzesi, 2003, Ang *et al*., 2004 and Wu and Zhang, 2008). Moreover, mortgage related derivatives have a dominant market share,[1] which contributed to the subprime mortgage bubble in the US that led to a general economic recession. Housing market financial data are used to obtain a housing factor, as the US housing market was the first to be affected by the current credit crunch, and losses in that market have caused ripple effects throughout the world economy. To obtain useful information from the US housing market regarding rising delinquency and foreclosure risk, relevant indicators from default risks are included as the third explanatory factor. In sum, this paper combines various economic and financial variables into three explanatory factors: the real economy, inflation and housing.

Second, survival probabilities are modeled using these explanatory factors to quantify how they influence default conditions. By imposing no-arbitrage pricing constraints and constructing default intensity processes as an affine model of fundamental economic factors, unobservable default intensities are taken from credit derivative spreads. This approach makes it possible to derive survival probabilities from default intensities and quantify the influence of various economic and financial factors on default risks.

[1] U.S. credit markets include corporate bonds, municipal bonds, commercial paper, asset backed securities, CDOs, and mortgage related securities. From the statistics provided by the Securities Industry and Financial Markets Association (SIFMA), at the end of 2005, mortgage related credit derivatives reached a 63% market share in U.S. credit markets, with the issuances of $3.546 trillion notional.

Third, if explanatory factors influence default probabilities in a credit derivative pricing model, analyzing the changes of these fundamental economic factors can provide useful indicators of credit evolution. After deriving the impacts of various economic variables on survival probabilities through the no-arbitrage dynamic model, they are applied to price CDX index spreads. The resulting spreads reveal clear changes in credit conditions before 2007.

2. Literature Review

Changes in the economic environment have some impact on total credit risk. Bhansali *et al.* (2008) separated credit risk into idiosyncratic, sector wide and economy wide defaults. Longstaff and Rajan (2008) demonstrated that economy wide credit risk had been rising markedly since 2007 and was the main cause of increased credit spreads during 2007. This is consistent with the recognition of many studies that defaults clustered and were contagious (Davis and Lo, 2001, Das *et al.*, 2006, Giesecke and Weber, 2004, 2006, Haworth *et al.*, 2008, Lonstaff and Rajan, 2008, Jorion and Zhang, 2007, Jarrow and Yu, 2001 and Rösch and Winterfeldt, 2008). Numerous studies have also proposed that corporate defaults and bankruptcies can be better understood using systematic components and macroeconomic indicators, such as gross domestic product (GDP) and personal income growth (Das *et al.*, 2007, Lo, 1986, Lennox, 1999, McDonald and Van de Gucht, 1999, Collin-Dufresne *et al.*, 2001, Couderc and Renault, 2004, Altman *et al.*, 2005 and Duffie *et al.*, 2007). Some researchers have focused on the relationship between theoretical determinants of CDS spreads and default risks (Amato, 2005, and Ericsson *et al.*, 2009). This paper examines the relationship between economic variables and credit evolution with the combination of several economic indicators to provide more insight into movements of default probabilities driven by economic determinants.

Unlike previous research (Amato and Luisi, 2006, and Wu and Zhang, 2008), this paper analyzes and models the influences of economic indicators on the credit spreads of CDX indices, which comprise various entities and are well diversified. As the current credit crunch was triggered by the subprime mortgage crisis, it spilt over through credit derivative instruments eventually resulting in clustered defaults of financial institutions. Estimated results indicate that all parameters are statistically significant and factor dynamics coincide with actual economic phenomenon. Both inflation and housing factors strongly and positively affected default intensities. In contrast, the real economic factor exerts a significant negative influence. After pricing with default intensity processes, the credit spreads show that economic indicators revealed the extent of the credit disarray before 2007. Examining the economic and financial data and quantifying the linkage between the explanatory factors and default risks can improve understanding of the credit crunch and manage credit risks more effectively in the future.

3. Methodology

Credit default swaps are the most popular instruments in the credit derivative market. To facilitate trading, standard credit default swap indices (CDX) are used as benchmarks for credit risks. In the literature, both structural and reduced-form models have been used to price credit derivatives. Owing to the difficulties of calibrating the specific dynamic model to individual credit entities in structural models and the disadvantage of determining the default environment based on a single factor model, a reduced-form model examining fundamental factors is proposed.

The economic environment changes stochastically with the release of new information. To simplify a noisy economic system, explanatory factors are combined from numerous variables using the Kalman filter. These factors are used rather than specific variables, and each factor is updated once new observations become available.

3.1 Compressing economic and financial variables into three explanatory factors

Instead of examining the potential role of economic variables in default intensities and using regression method with specific choice of some explanatory variables, we divide variables into three dynamic factors. The dynamic factor model can extract information from economic and financial data and suppress noise. Real activities and inflation variables are classified to identify specific effects on default intensities. Housing market variables are employed to determine the relationship between the housing bubble and the credit crunch. At the end of 2005, mortgage related credit derivatives reached a 63% market share, with 3.546 trillion issuances. Since mortgage related derivatives dominated the markets, it is necessary to properly consider the systematic risk from credit markets. Moreover, the 2008 credit crunch was caused by the subprime mortgage crisis which in turn was triggered by the housing market downturn, excessively loose lending standards and overly complex structured credit derivatives. When managing risk it is important to quantify the magnitude of housing market performance.

The dynamics of explanatory factors in physical measure $\mathbb{P}$ are represented as

$$dN_t = -\varphi N_t dt + dB_t^P, \tag{1}$$

where φ denotes an $n \times n$ transition matrix, and B_t^P represents a vector of standard Brownian motions under the physical measurement $\mathbb{P}$. The matrix φ is restricted to a diagonal matrix yielding independent explanatory factors. By Euler approximation, we obtain the discrete-time version of the factor dynamics in Equation (1) as

$$N_t = \Phi N_{t-\Delta t} + \varepsilon_t . \tag{2}$$

where vector N_t denotes the explanatory factors with dimension $n\times 1$, $N_t \in \mathbb{R}^n$. The autoregressive coefficient matrix Φ is an $n\times n$ matrix, Δt is the time interval, and $\varepsilon_t \sim N(0,Q)$ is an $n\times 1$ normal innovation vector where Q is a diagonal covariance matrix. Since this paper groups economic and financial variables into three explanatory factors, $n=3$. Observable economic and financial data series are set as affine functions of explanatory factors N_t through the following measurement equation:

$$M_t = CN_t + \varepsilon_t^M, \tag{3}$$

where M_t denotes the observable economic and financial variables with dimension $m\times 1$, $M_t \in \mathbb{R}^m$. C represents the coefficient matrix with dimension $m\times n$, and the disturbance $\varepsilon_t^M \sim N(0, R^M)$ is an m-vector with zero mean and measurement error covariance matrix R^M. This disturbance can be seen as the residual effects not measured by explanatory factors. Finally, ε_t and ε_t^M are assumed to be independent.

Between observations, the *priori* estimation of explanatory factors and their covariance before time t are denoted as $\hat{N}_{t^-}$ and $\hat{P}_{t^-}$, respectively:

$$\hat{N}_{t^-} = \Phi \hat{N}_{t-\Delta t},$$

$$\hat{P}_{t^-} = \Phi \hat{P}_{t-\Delta t}\Phi^T + Q,$$

where Φ^T denotes the transposition of Φ. The one-step ahead prediction of measurement variable $\hat{M}_{t^-}$, and its covariance $\hat{\Sigma}_{t^-}$ are

$$\hat{M}_{t^-} = C\hat{N}_{t^-},$$

$$\hat{\Sigma}_{t^-} = C\hat{P}_{t^-}C^T + R^M.$$

After new observations become available, the Kalman filter procedure is used to refine the *priori* predictions of explanatory factors and their covariance to derive *posteriori* predictions and their covariance:

$$\hat{N}_t = \hat{N}_{t^-} + K_t\left(M_t - C\hat{N}_{t^-}\right),$$

$$\hat{P}_t = \hat{P}_{t^-} - K_t C\hat{P}_{t^-},$$

where

$$K_t = \hat{P}_{t^-}C^T\left(C\hat{P}_{t^-}C^T + R^M\right)^{-1}$$

denotes the Kalman gain. Consequently, all estimates were improved with the availability of additional observations. As we assume that prediction errors follow a normal distribution, the log likelihood function can be defined as

$$L_t\left(\varphi, C, R^M\right) = -\frac{1}{2}\log\left|\hat{\Sigma}_{t^-}\right| - \frac{1}{2}\left[\left(M_t - \hat{M}_{t^-}\right)^T\left(\hat{\Sigma}_{t^-}\right)^{-1}\left(M_t - \hat{M}_{t^-}\right)\right]. \tag{4}$$

Then we obtain the parameter estimates by maximizing the sum of the log likelihood values of prediction errors from all sample periods.

3.2 Influence of economic environment on default intensity

To investigate the effect of the economic environment on default intensity, and evolution of the credit environment with changing economic and financial conditions, it was assumed that default intensity is an affine function of the three dynamic explanatory factors extracted from economic and financial data, where:

$$\lambda(N_t) = \alpha + \beta^T N_t, \tag{5}$$

The coefficient vectors, α and β, represent the simultaneous effects on default intensity from changes in explanatory factors, thus linking the dynamics of default intensity to shocks on economic variables. The measurement equation in the Kalman filter procedure is then defined as:

$$\lambda_t = \alpha + \beta^T N_t + \varepsilon_t^{\lambda}, \tag{6}$$

Measurement error ε_t^{λ} is identified as disturbances that are not measured by explanatory factors and are independent of each explanatory factor N_t.

3.3 Dynamic pricing model for credit derivatives and default intensity processes with no-arbitrage constraints

As this paper utilizes data from the Dow Jones CDX North America Investment Grade (DJ CDX NA IG) index to find the relationship between default intensities and economic conditions, it is necessary to calibrate CDX market quotes to obtain parameter estimates of default intensities. The DJ CDX NA IG index is a standard credit default index designed to facilitate trading and improve the liquidity of credit default swaps (CDSs). Valuation for CDX index contracts differs slightly from single-name CDSs. For single-name CDS contracts the payment for swap premium ceases following default events. In contrast, on the CDX, default entities are removed from the index and swap premium payments continue at a decreased notional amount until maturity.

Under risk neutral measure $\mathbb{Q}$, investors will receive payments at times t_1 to t_T with the present value of these regular payments being denoted as the first part of the premium leg:

$$PL_1 = s\sum_{c=1}^{T}(t_c - t_{c-1})E^{\mathbb{Q}}(t_c)D(t_c),$$

where s denotes CDX spread, t_c represents payment dates, $E^{Q}(t_c)$ is the expected principal at time t_c, and $D(t_c)$ denotes the discount factor. Assuming defaults on average occur during the middle of payment dates, the present value of accrual payments in default comprises the other part of the premium leg:

$$PL_2 = s\left[0.5\sum_{c=1}^{T}(t_c - t_{c-1})\left(E^{\mathbb{Q}}(t_{c-1}) - E^{\mathbb{Q}}(t_c)\right)D\left(t_c^d\right)\right],$$

where $t_c^d = 0.5(t_{c-1} + t_c)$.[2]

The present value of the premium leg is represented as

$$PL = PL_1 + PL_2.$$

The present value of the default leg is

$$DL = \sum_{c=1}^{T}\left(E^{\mathbb{Q}}(t_{c-1}) - E^{\mathbb{Q}}(t_c)\right)D\left(t_c^d\right).$$

Since the CDX index is defined as the breakeven spread, the credit spread is obtained while the present value of the default leg equals the premium leg and leaves no arbitrage opportunities:

$$s = \frac{\sum_{c=1}^{T}\left(E^{\mathbb{Q}}(t_{c-1}) - E^{\mathbb{Q}}(t_c)\right)D\left(t_c^d\right)}{\sum_{c=1}^{T}(t_c - t_{c-1})E^{\mathbb{Q}}(t_c)D(t_c) + 0.5\sum_{c=1}^{T}(t_c - t_{c-1})\left(E^{\mathbb{Q}}(t_{c-1}) - E^{\mathbb{Q}}(t_c)\right)D\left(t_c^d\right)}. \tag{7}$$

Without loss of generality, we assume the principal $V = 1$. The expected value at each payment time is

$$E^{\mathbb{Q}}(t_c) = V \cdot E^{\mathbb{Q}}\left[S(t_c)\middle|\mathbb{F}_t\right] = E^{\mathbb{Q}}\left[S(t_c)\middle|\mathbb{F}_t\right], \tag{8}$$

where $E^{\mathbb{Q}}\left[S(t_c)\middle|\mathbb{F}_t\right]$ denotes the expected cumulative survival probability at time t_c, $t_c > t$, conditional on time-t information $\mathbb{F}_t$ under measure $\mathbb{Q}$. For simplicity, the expected cumulative survival probabilities at time τ, $\tau \geq t$, are denoted as

$$S_t(\tau) \equiv E^{\mathbb{Q}}\left(S(\tau)\middle|\mathbb{F}_t\right).$$

According to the default intensity model, the cumulative survival probability is defined as a conditional function on the path of default intensity λ_t. It can be represented as

$$\mathrm{S}_t(\tau) = E^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\tau}\lambda_s ds\right)\middle|\mathbb{F}_t\right].$$

[2] Consistent with Hull and White (2008).

Since the physical survival probabilities of explanatory factors are not relevant for the pricing of financial derivatives, by using Girsanov's theorem, we obtain the Radon-Nikodým derivative of $\mathbb{Q}$ with respect to $\mathbb{P}$:

$$\frac{d\mathbb{Q}}{d\mathbb{P}} = \exp\left(-\int_t^{t+\tau} \eta_s \, dB_s + \frac{1}{2}\int_t^{t+\tau} \eta_s^2 ds\right),$$

where η_t is defined as the difference between actual and risk-neutral default probability reflecting the market price of the default risk premium. Then, from Equation (6):

$$\begin{aligned} \mathrm{S}_t(\tau) &= E^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\tau}\left(\alpha + \beta^T N_s + \varepsilon_s^{\lambda}\right) ds\right) \middle| \mathbb{F}_t\right] \\ &= E^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\tau}\left(\alpha + \beta^T N_s\right) ds\right) \middle| \mathbb{F}_t\right] \cdot E^{\mathbb{Q}}\left[\exp\left(-\int_t^{t+\tau} \varepsilon_s^{\lambda} ds\right) \middle| \mathbb{F}_t\right], \quad (9) \end{aligned}$$

where ε_s^{λ} is the disturbance of the cumulative survival probability, not attributed to explanatory factors. This paper only discusses the portion which can be determined by explanatory factors. Under some technical conditions described in Duffie *et al*. (2000), $\mathrm{S}_t(\tau)$ in Equation (9) can be derived as

$$\mathrm{S}_t(\tau) = \exp\left[\alpha_\lambda(\tau) + \beta_\lambda^T(\tau) N_t^{\mathbb{Q}}\right], \quad (10)$$

where $N_t^{\mathbb{Q}}$ denotes the explanatory factors under $\mathbb{Q}$ measure. To obtain the expected survival probabilities under risk-neutral measure $\mathbb{Q}$ for credit derivative pricing, it is necessary to change the dynamics of the three explanatory factors from $\mathbb{P}$ to $\mathbb{Q}$. Since η_t denotes the market price of default risk, without loss of generality, it can be specified as an affine model of explanatory factors:

$$\eta_t = \alpha_\eta + \beta_\eta N_t .$$

The dynamics of explanatory factors under the risk neutral measure can then be expressed as:

$$\begin{aligned} dN_t^{\mathbb{Q}} &= \left[-\alpha_\eta - \left(\varphi + \beta_\eta\right) N_t\right] dt + dB_t^{\mathbb{Q}} \\ &= \left(\varphi + \beta_\eta\right)\left[-\alpha_\eta \left(\varphi + \beta_\eta\right)^{-1} - N_t\right] dt + dB_t^{\mathbb{Q}}. \quad (11) \end{aligned}$$

From Equations (10) and (11), $\alpha_\lambda(\tau)$ and $\beta_\lambda(\tau)$ are given as solutions to the following Riccati ordinary differential equations:

$$\frac{d\alpha_\lambda(\tau)}{dt} = \alpha - \beta_\lambda^T(\tau) \cdot \alpha_\eta - \frac{1}{2}\beta_\lambda^T(\tau)\beta_\lambda(\tau),$$

$$\frac{d\beta_\lambda(\tau)}{dt} = \beta - \left(\varphi + \beta_\eta\right)^T \beta_\lambda(\tau),$$

with boundary conditions $\alpha_{\lambda}(0)=0$ and $\beta_{\lambda}(0)=0$. The coefficients α and β in Equation (6) are obtained by solving these differential equations through numerical procedure.

3.4 Estimating correlations between default intensities and explanatory factors

As discussed in section 3.1, this paper derives three explanatory factors from a set of economic and financial variables from measurement equation (3) using Kalman filter approach. Another measurement equation derives the linkage between default intensities and these explanatory factors:

$$X_t = \mathrm{X}_{Model}\left(N_t, j\right) + \varepsilon_t^X,$$

where X_t denotes the observable market CDX index spread at time t, $\mathrm{X}_{Model}\left(N_t, j\right)$ represents the model spread determined by functions of survival probabilities and explanatory factors as mentioned in section 3.3, j is the maturity of CDX, and $\varepsilon_t^X \sim N\left(0, R^X\right)$ denotes measurement errors and is assumed to be normally distributed with zero mean and covariance matrix R^X. Because the CDX index spread is not linearly related to these explanatory factors N_t, we apply the extended Kalman filter approach to approximate the following linear measurement equation for estimating the parameters by maximizing the sum of the log likelihood values:

$$X_t \approx x_t \cdot N_t + \varepsilon_t^X,$$

where $x_t = \dfrac{\partial \mathrm{X}_{Model}\left(N_t, j\right)}{\partial N_t}\Big|_{N_t=\hat{N}_t}$.

The log likelihood function is defined as

$$L_t\left(\alpha_\eta, \varphi+\beta_\eta, \alpha_\lambda, \beta_\lambda, R^X\right) = -\frac{1}{2}\log\left|\hat{\Sigma}_{t^-}^X\right| - \frac{1}{2}\left[\left(X_t - \hat{X}_{t^-}\right)^T \left(\hat{\Sigma}_{t^-}^X\right)^{-1}\left(X_t - \hat{X}_{t^-}\right)\right], \quad (12)$$

where $\hat{X}_{t^-}$ and $\hat{\Sigma}_{t^-}^X$ denote the *priori* estimated state and the variance of this estimation error, respectively, which are defined as

$$\hat{X}_{t^-} = \mathrm{X}_{Model}\left(\hat{N}_{t^-}, j\right),$$

$$\hat{\Sigma}_{t^-}^X = x_t \hat{P}_{t^-} x_t^T + R^X.$$

The Kalman filter procedure improves all model spreads as additional market CDX spreads become available, thus the default intensities are derived using the no-arbitrage CDX pricing model mentioned in section 3.3.

4. Conclusion

This paper provides more complete insight into the movements of default probabilities driven by economic determinants through the no-arbitrage dynamic factor model, and prices credit derivatives by applying these explanatory factors to the reduced-form pricing model. Since the paper defines the default intensities as affine functions of explanatory factors, the default risks vary with economic conditions. The estimated results and out-of-sample valuations show that the link between economic conditions and default risks can depict credit evolution and more effectively manage default risks.

This study summarizes relevant information through continuously updated observations from many economic and financial variables, and then sorts these variables into three components. The extracted factors include the real economy, inflation and housing. Because mortgage related derivatives are the main components in credit markets, it is necessary to carefully quantify mortgage related shocks to credit derivative pricing. Housing is another indicator, in addition to real economy and inflation factors. Subsequently, this investigation condenses various economic and financial indicators into three dynamic explanatory factors, and updates each factor as new observations arrive.

By imposing no-arbitrage restrictions, the credit environment is linked with economic conditions by setting default intensity process as an affine function of explanatory factors. The results indicate explanatory factors significantly affect default intensities. Corresponding to actual economic conditions, the inflation and housing factors both strongly and positively affect default risks, while the real economic factor exerts a significant and negative influence. The estimated results are then used to derive the responses of survival probabilities to the shocks of individual economic and financial series, and applied to value out-of-sample CDX spreads.

Extending traditional credit derivative pricing formulas, estimated parameters of economic fundamentals are used to value CDX spreads across maturities by adopting a reduced-form model. Our pricing results support that economic conditions have a considerable impact on credit risks. Although the market spreads markedly increased during mid-2007, the out-of-sample valuations of credit spreads reveal the economic environment had already displayed aggravated credit conditions at the end of 2006. Therefore, identifying the economic environment from different economic and financial series and quantifying their relationship with default risks can raise awareness of credit evolution and contribute to managing credit risks more effectively.

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附件

出差與研習心得

本人於 2010 年 4 月 16 日由台灣搭機赴中國大陸山西太原，參加「2010 年中國金融工程學年會暨金融工程與風險管理論壇」。於 4 月 16 日下午四點左右抵位於山西太原的主辦單位山西財經大學。晚上住宿於該大學的實習旅館，並與來自全中國的金融工程學教授與業者共敘晚宴。台灣方面的參加者除本人外，另有武漢大學金融學博士劉榮輝先生與金融研訓院院長許振明教授。

4 月 17 日參加整天的研討會，本人擔任一場學術研討會的論文評論人及另一場學術會議的論文發表人，發表論文「信用風險與信用衍生性商品評價」，由中國人民大學教授林清泉先生擔任評論人。

此次參加該會，除增進兩岸學術交流的目的外，亦深覺大陸地區之學者正在拚力追趕西方的研究，並擁有其自有的哲學判斷標準，不盡與台、美、日之學術觀點完全相同。本人除與學術界人士接觸交流外，亦與大陸地區之證監會與業界人士進行意見交流，對本人及大陸人士在兩岸互相瞭解的方面均有頗大之助益。