ESSAYS OF CAPITAL STRUCTURE, RISK MANAGEMENT, AND OPTIONS ON INDEX FUTURES

by

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ABSTRACT OF THE DISSERTATION

Essays of Capital Structure, Risk Management, and Options on Index Futures

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This dissertation includes the following three essays involved in the joint determination of capital structure and stock rate of return, fair deposit insurance premium estimation, and the prediction of implied volatility of options on index futures.

The first essay identifies the joint determinants of capital structure and stock returns by using three alternative approaches to deal with the measurement error-in-variable problem. The main contribution of this essay is the comprehensive confirmation on theories in corporate finance. The empirical results from the structural equation modeling (SEM) with confirmatory factor analysis (CFA) show that stock returns, asset structure, growth, industry classification, uniqueness, volatility and financial rating, profitability, government financial policy, and managerial entrenchment are main factors of capital structure in either market- or book- value basis. Finally, the results in robustness test by using the Multiple Indicators and Multiple Causes (MIMIC) model and the two-stage, least square (2SLS) method show the necessity and importance of latent attributes to

describe the trade-off between the financial distress and agency costs in capital structure choice.

In the second essay, we use the structural model in terms of the Stair Tree model and barrier option to evaluate the fair deposit insurance premium in accordance with the constraints of the deposit insurance contracts and the consideration of bankruptcy costs. The simulation results suggest that insurers should adopt a forbearance policy instead of a strict policy for closure regulation to avoid losses from bankruptcy costs. An appropriate deposit insurance premium can alleviate potential moral hazard problems caused by a forbearance policy.

In the third essay, we use two alternative approaches, time-series and cross-sectional analysis and constant elasticity of variance (CEV) model, to give different perspective of forecasting implied volatility. We use call options on the S&P 500 index futures expired within 2010 to 2013 to do the empirical work. The abnormal returns in our trading strategy indicate the market of options on index futures may be inefficient. The CEV model performs better than Black model because it can generalize implied volatility surface as a function of asset price.

DEDICATION

This dissertation is dedicated to my family, Chun-Ping Hilton Tai, Li-Chin Susan Peng, Jui-Hung Ray Tai, and Jui-Chuan Lewis Tai.

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CHAPTER 1

Introduction

This thesis investigates three important issues in finance: capital structure, deposit insurance, and options on index future. The first essay investigates the joint determination of capital structure and stock rate of return by using LISREL model to reduce measurement error-in-variable problem. The second essay examines fair deposit insurance premium in accordance with the restrictions of insurance contracts by the structural model approach in terms of the Stair Tree model and the barrier option model. In the third essay, we forecast the implied volatility of options on index futures by using either time-series and cross-sectional analysis or constant elasticity of variance (CEV) model.

Most previous studies in capital structure investigate unobservable theoretical variables which affect the capital structure of a firm. However, the use of observed accounting variables as theoretical explanatory latent variables will cause measurement error-in-variable problems during the analysis of the factors of capital structure. Therefore, in the first essay, we employ LISREL approach to solve the measurement errors problems in the analysis of the determinants of capital structure. This is the comprehensive study to confirm the trade-off theory between the financial distress and agency costs, pecking order theory, and signaling theory with asymmetric information in corporate finance literature. The purpose of this essay is to investigate whether the factors of capital structure that are related to the firm, manager, and macroeconomic characteristics are consistent with theories in previous literature. This essay also aims at the interrelation between capital structure and stock rate of returns. First, we employ structural equation modeling (SEM) with confirmatory factor analysis (CFA) approach to classify the observed variables into several groups (attributes) to verify these theories. Then, we can test endogenous supply relationship between short-term public debt and private debt through macroeconomic factor analysis. Finally, Dittmar's and Thakor's (2007) "managerial investment autonomy" also can be verified via simultaneous equations of capital structure and stock returns. Our empirical results show that there are two significant theoretical attributes on the decision of capital structure. However, all attributes become significant determinants of capital structure and stock returns. The evidence shows that the interaction of a firm's leverage and its stock price should be necessarily considered in capital structure research. In addition, the results in robustness test by using the Multiple Indicators and Multiple Causes (MIMIC) model and the two-stage, least square (2SLS) method show the necessity and importance of latent attributes to describe the trade-off between the financial distress and agency costs in capital structure choice. Therefore, we claim that SEM with CFA approach is preceded by adding latent attributes of capital structure and solving measurement error-in-variable problem.

Since subprime mortgage crises broke out in August, 2007, pricing fair deposit insurance premium became an important issue again because the panic of depositors arose from many financial institutions with financial and liquidity distress. The Federal Deposit Insurance Corporation (FDIC) should adjust the proper deposit insurance premium as the trade-off that offsets the costs of bailout plans and the costs of taking over the deposit account business and partial debt once the financial institutions are announced bankruptcies. Based on the critical role that insurance deposit risk plays in financial institutions, the purpose of the second essay is to investigate the pricing fair value of deposit insurance. The most studies estimate fair-market FDIC insurance premium by a structural approach, which typically bases the firm’s asset and the volatility of its asset on its equity price. However, the structural models used in previous studies neglects the restrictions of the deposit insurance contacts. In hence, the second essay proposes the structural model approach in terms of the barrier option model and the Stair Tree model to deal with bankruptcy costs, the limited indemnification for depositors, discretely monitoring banks' situations and the adjustment of the insurance premium in different financial institution based on a risk-based assessment system. We are then able to build a fair insurance premium system and calculate the reasonable implied barrier critical points to determine whether FDIC's supervisory policy is strict or forbearing. The simulation results suggest that insurers should adopt a forbearance policy instead of a strict policy for closure regulation to avoid losses from bankruptcy costs. In addition, an appropriate deposit insurance premium can alleviate potential moral hazard problems caused by a forbearance policy.

Forecasting volatility is crucial to risk management and financial decision for future uncertainty. The third essay aims to improve the ability to forecast the implied volatility (IV) for options on index futures. We use option prices instead of relying on the past behavior of asset prices to infer volatility expectations of underlying assets. The two alternative approaches used in this paper give different perspective of estimating IV. The cross-sectional time series analysis focuses on the dynamic behavior of volatility in each option contracts. The predicted IV obtained from the time series model is the estimated conditional volatility based on the information of IV extracted from Black model. Although the estimated IVs in a time series model vary across option contracts, this kind of model can seize the specification of time-vary characteristic that links ex post volatility to ex ante volatility for each option contract. In addition, cross-sectional analysis can capture other trading behaviors such as week effect and in- /out- of the money effect. On the other hand, CEV model generalizes implied volatility surface as a function of asset price. It can reduce more computational and implementation costs rather than the complex models such as jump-diffusion stochastic volatility models because there is only one more variable compared with Black model. Although the constant estimated IV for each trading day may cause low forecast power of whole option contacts, it is more reasonable that the IVs of underlying assets are independent of different strike prices and times to expiration. The empirical results show that volatility changes are predictable by using cross-sectional time series analysis and CEV model. The prediction power of these two methods can draw specific implications as to how Black model might be misspecified. In addition, the abnormal returns based on our trading strategy with the consideration of transaction costs imply the inefficiency of options on index future market.

The structure of this thesis is as follows. Chapter 2 is the first essay entitled "The Joint Determinants of Capital Structure and Stock Rate of Return: A LISREL Model Approach". The second essay entitled "Pricing Fair Deposit Insurance: Structural Model Approach" is described in Chapter 3. Chapter 4 is the third essay entitled "Forecasting

Implied Volatilities for Options on Index Futures: Time Series and Cross-Sectional Analysis versus Constant Elasticity of Variance (CEV) Model". Finally, Chapter 5 represents the conclusions and future study of these three essays.

CHAPTER 2

The Joint Determinants of Capital Structure and Stock Rate of Return: A LISREL Model Approach

2.1 Introduction

The abundant studies in capital structure indicate that the optimal capital structure is determined by a trade-off related to the marginal costs from financial distress and agency problem, the benefits from tax shields, and reduction of free cash flow problems (Grossman and Hart, 1982; Stulz and Johnson, 1985; Rajan and Zingales, 1995; Parrino and Weisbach, 1999; Frank and Goyal, 2009). Fischer, Heinkel, and Zechner (1989) develop a dynamic capital structural model without the setting of static leverage measures. The empirical results in Fisher et al. (1989) support their theoretical framework that the debt-to-equity ratio changed over time and therefore the firm’s financing decisions should be analyzed under a dynamic setting framework. However, Leary and Roberts (2005) claim that the adjustment costs of rebalancing capital structure are of importance in the determinants of capital structure. Although the debt-to-equity ratio should follow a dynamic capital structural framework, firms may not change their leverage ratios frequently because of the adjustment costs. Therefore, a firm’s capital structure is not changed over time if its leverage ratio stays within an optimal range. To capture the determinants of capital structure within an optimal range of leverage ratio, the traditional linear regression analysis may be not a suitable methodology to investigate capital structure because the estimates of independent variables (determinants of capital structure) directly affect the dependent variables (leverage ratio) in regression. In addition, regression analysis has difficulty in usage of dummy variables to control the size of the effects of independent factor variables on leverage ratio within optimal range since the optimal leverage ranges of firms are various and have difficulty in designing the critical value of dummy variables.

Moreover, in previous research in capital structure, many models are derived based on theoretical variables; however, these variables are often unobservable in the real world. Therefore, many studies use the accounting items from the financial statements as proxies to substitute for the theoretically derived variables. In the regression analysis, the estimated parameters from accounting items as proxies for unobservable theoretical attributes would cause some problems. First, there are measurement errors between the observable proxies and latent variables[1]. According to the previous theoretical literature

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[1] In statistics, latent variables (as opposed to observable variables), are variables that are not directly observed but are rather inferred (through a mathematical model) from other variables that are observed (directly measured).

in corporate finance, a theoretical variable can be formed with either one or several observed variables as a proxy. But there is no clear rule to allocate the unique weights of observable variables as the perfect proxy of a latent variable. Second, because of unobservable attributes to capital structure choice, researchers can choose different accounting items to measure the same attribute in accordance with the various capital structure theory and the their bias economic interpretation. The use of these observed variables as theoretical explanatory latent variables in both cases will cause error-in-variable problems. Joreskog (1977), Joreskog and Sorbom (1981, 1989) and Jorekog and Goldberger (1975) first develop the structure equation modeling (hereafter called SEM) to analyze the relationship between the observed variables as the indicators and the latent variables as the attributes of the capital structure choice.

Since Titman and Wessels (1988) (hereafter called TW) first utilize LISREL system to analyze the determinants of capital structure choice based on a structural equation modeling (SEM) framework, Chang, Lee and Lee (2009) and Yang, Lee, Gu and Lee (2010) extend the empirical work on capital structure choice and obtain more convincing results. These papers employ structural equation modeling (SEM) in LISREL system to solve the measurement errors problems in the analysis of the determinants of capital structure and to find the important factors consistent with capital structure theories.

Although TW initially apply SEM to analyze the factors of capital structure choice, their results are insignificant and poor to explain capital structure theories. Maddala and Nimalendran (1996) point out the problematic model specification as the reason for TW's poor finding and propose a Multiple Indicators and Multiple Causes (hereafter called MIMIC) model to improve the results. Chang et al. (2009) reproduce TW's research on determinants of capital structure choice but use MIMIC model to compare the results with TW's. They state that the results show the significant effects on capital structure in a simultaneous cause-effect framework rather than in SEM framework. Later, Yang et al. (2010) incorporate the stock returns with the research on capital structure choice and utilize structural equation modeling (SEM) with confirmatory factor analysis (CFA) approach to solve the simultaneous equations with latent determinants of capital structure. They assert that a firm's capital structure and its stock return are correlated and should be decided simultaneously. Their results are mainly same as TW's finding; moreover, they also find that the stock returns as a main factors of capital structure choice.

The purpose of this paper is to investigate whether the factors of capital structure that are related to the firm, manager, and macroeconomic characteristics are consistent with theories in previous literature. This essay also aims at the interrelation between capital structure and stock rate of returns. This is the comprehensive study to confirm the trade-off theory between the financial distress and agency costs, pecking order theory, and signaling theory with asymmetric information in corporate finance literature. We employ SEM with CFA approach to classify the observed variables into several groups (attributes) to verify these theories. Then, we can test McDonald's (1983) endogenous supply relationship between short-term public debt and private debt through macroeconomic factors. Finally, Dittmar's and Thakor's (2007) "managerial investment autonomy" also can be verified via simultaneous equations of capital structure and stock returns. The MIMIC model and 2SLS method are used in this paper for robust test. The results of robust test show the necessity and importance of the classifications of variables. Therefore, we claim that SEM with CFA approach is preceded by adding latent attributes of capital structure and solving measurement error-in-variable problem.

This paper is organized as follows. In section 2.2, we discuss the accounting items, macroeconomic factors, and manager characteristics used as proxies of the factors of capital structure. The additional factors of stock prices are also considered in the investigation of joint determinants of capital structure and stock rate of return. Then, the description of sample period and data sources is included in this section. Section 2.3 introduces three alternative methods: SEM approach, MIMIC model, and SEM with CFA and illustrate how these models investigate the joint determinants of capital structure and stock rate of returns in LISREL system. Section 2.4 shows the empirical results, the comparison with previous literature, and analysis of robust test. Finally, section 2.5 represents the conclusions of this essay.

2.2 Determinants of Capital Structure and Data

Before we use SEM approach to analyze the determinants of capital structure and joint determinants of capital structure and stock rate of return, the observable indicators are first briefly described in this section, and then the data used in this paper is subsequently introduced.

2.2.1 Determinants of Capital Structure

There are several factors discussed in previous literature and categorized into three groups in this essay: firm characteristics, macroeconomic factors, and manager characteristics.

2.2.1.1 Firm characteristics

TW provide eight characteristics to determine the capital structure: asset structure, non-debt tax shields, growth, uniqueness, industry classification, size, volatility, and profitability. These attributes are unobservable; therefore, some useful and observable accounting items are classified into these eight characteristics in accordance with the previous literature on capital structure. The attributes as latent variables, their indicators as independent variables, and the indicators of capital structure as dependent variables are shown in Table 2.1. The parentheses in indicators are the notations used in LISREL system. Moreover, TW adopt the long-term debt, the short-term debt, and the convertible debt over either market value of equity or book value of equity as the indicators of capital structure as shown in the bottom of Table 2.1.

Table 2.1 TW Attributes and Indicators

Attributes	**Indicators**
Asset structure	Intangible asset/total assets(INT_TA) Inventory plus gross plant and equipment /total assets(IGP_TA)
Non-debt tax shield	Investment tax credits/total asset (ITC_TA) Depreciation/total asset(D_TA) Non-debt tax shields/total asset(NDT_TA)
Growth	Capital expenditures/total asset (CE_TA) The growth of total asset (GTA) Research and development/Sales (RD_S)
Uniqueness	Research and development/Sales (RD_S) Selling expense/sales (SE_S) Quit Rates (QR)
Industry Classification	SIC code (IDUM)
Size	Natural logarithm of sales (LnS)
Volatility	The standard deviation of the percentage change in operating income (SIGOI)
Profitability	Operating income/sales (OI_S) Operating income/total assets (OI_TA)
Capital Structure (dependent variables)	Long-term debt/market value of equity (LT_MVE) Short-term debt/market value of equity (ST_MVE)

	Convertible debt/market value of equity (C_MVE) Long-term debt/book value of equity (LT_BVE) Short-term debt/ book value of equity (ST_BVE) Convertible debt/ book value of equity (C_BVE)

Since we will use confirmatory factor analysis (CFA) approach to test whether observed variables are good proxies to measure attributes effectively, we add additional indicators and a financial rating attribute as shown in Table 2.2. These indicators can be alternative suitable proxies of attributes to replace TW indicators.

Table 2.2 Additional Attributes and Indicators

Attributes	**Indicators**
Growth	Research and development/ total assets (RD_TA)
Industry Classification	Quit Rates (QR)
Volatility[2]	Coefficient of Variation of ROA (CV_ROA) Coefficient of Variation of ROE (CV_ROE) Coefficient of Variation of Operating Income (CV_OI)
Financial Rating	Altman's Z-score (Z_Score) S&P Domestic Long Term Issuer Credit Rating (SP_Rate) S&P Investment Credit Rating (SP_INV)
Capital Structure (dependent variables)	Long-term debt/market value of total assets (LT_MVA) Short-term debt/market value of total assets (ST_MVA) Convertible debt/market value of total assets (C_MVA) Long-term debt/book value of total assets (LT_BVA) Short-term debt/ book value of total assets (ST_BVA) Convertible debt/ book value of total assets (C_BVA)

[2] The additional indicators of volatility are referred to Chang et al. (2008).

Asset structure

Based on the trade-off theory and agency theory, firms with larger tangible and collateral assets may have less bankruptcy, asymmetry information and agency costs. Myers and Majluf (1984) indicate that companies with larger collateral assets attempt to issue more secured debt to reduce the cost arising from information asymmetry between managers and outside investors. Moreover, Jensen and Meckling (1976) and Myers (1977) state that there are agency costs related to underinvestment problem in the leveraged firm. High leveraged firm prefer to invest suboptimal investment which only benefits shareholders and expropriates profits from bondholders. Therefore, the collateral assets are positive correlated to debt ratios. Rampini and Viswanathan (2013) build a dynamic agency-based model and claim the importance of collateral asset as a determinant of the capital structure of a firm.

According to TW paper, the ratio of intangible assets to total assets (INT_TA) and the ratio of inventory plus gross plant and equipment to total assets (IGP_TA) are viewed as the indicators to evaluate the asset structure attribute.

Non-debt tax shield

DeAngelo and Masulis (1980) extend Miller’s (1977) model to analyze the effect of non-debt tax shields increasing the costs of debt for firms. Bowen, Daley, and Huber

(1982) find their empirical work on the influence of non-debt tax shields on capital structure consistent with DeAngelo and Masulis's (1980) optimal debt model. Graham (2000) tests how large the effect of tax shield benefits by issuing debts on firms would be and finds the significant magnitude of tax-reducing value of the interest payments. However, the firms with large size, more profitability, and high liquidity use less debt as financing sources even though the reducible tax from interests of debt can profit the earnings of firms with less bankruptcy possibility. Lin and Flannery (2013) investigate whether personal taxes affect the cost of debt and equity financing and find that personal tax is an important determinant of capital structure. Their empirical study shows that tax cut policy in 2003 has negative influence on firms' leverage ratio.

Following Fama and French (2000) and TW paper, the indicators of non-debt tax shields are investment tax credits over total asset (ITC_TA), depreciation over total asset (D_TA), and non-debt tax shields over total asset (NDT_TA) which NDT is defined as in TW paper with the corporate tax rate 34%. Since the tax cut policy is a special event, it is hard to find the indicator of personal tax for all shareholders every year. Therefore, we left the influence of personal taxes on capital structure for future research.

Growth

According to TW paper, we use capital expenditures over total asset (CE_TA), the growth of total asset (GTA), and research and development over sales (RD_S) as the indicators of growth attribute. The research and development over total asset (RD_TA) are added in this attributes to test construct reliability in confirmatory factor analysis[3]. TW argue the negative relationship between growth opportunities and debt because growth opportunities only add firm's value but cannot collateralize or generate taxable income.

Uniqueness and Industry Classification

Furthermore, the indicators of uniqueness include development over sales (RD_S) and selling expense over sales (SE_S). Titman (1984) indicate that uniqueness negatively correlate to debt because the firms with high level uniqueness will cause customers, suppliers, and workers to suffer relatively high costs of finding alternative products, buyers, and jobs when firms liquidate.

SIC code (IDUM) as proxy of industry classification attribute is followed Titman's (1984) and TW's suggestions that firms manufacturing machines and equipment have high liquidation cost and thus more likely to issue less debt. Graham (2000) uses sales- and assets- Herfindahl indices to measure industry concentration (Phillips, 1995;

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[3] Since the denominator of CE_TA and GTA are total asset, RD_TA may reduce the scale problem in SEM. Therefore, we add RD_TA in growth to test whether the convergent validity of RD_TA is better than RD_S.

Chevalier, 1995) and utilize the dummy of SIC codes to measure product uniqueness. Graham concluded that more unique of product of a firm, less debt would be used. Here we assign one to firms in manufacturing industry (SIC codes 3400 to 4000) and zero to other firms.

Quit Rates (QR) are used in both uniqueness and industry classification to represent the cost of human capital. Low quit rates implicitly symbolize high level of job-specific costs that workers encounter costly find alternative jobs in same industry. Therefore, we expect quit rates negatively related to debt ratio.

Size

The indicator of size attribute is measured by natural logarithm of sales (LnS). The financing cost of firms may relate to firm size since small firms have higher cost of non-bank debt financing (see Bevan and Danbolt (2002)). Therefore size is supposed to be positive associated with debt level.

Volatility and Financial Rating

The previous literature on dynamic capital structural model focused on the trade-off between the benefits of debt tax shields and the costs of financial distress (Fisher, Heinkel, and Zechner (1989), Leland and Toft (1996), Leland (1994)).

The tax benefits by issuing debts can be offset by the costs of financial distress. Therefore, Graham (2000) uses Altman's (1968) Z-score as modified by MacKie-Mason (1990) to measure bankruptcy and shows that the policy of debt conservatism is positively related to Z-score. It implies that firms using less of debt can avoid financial distress. Here we use Altman's (1986) Z-score[4] (Z_Score) as an indicator of financial rating.

Besides, volatility attribute is estimated by the standard deviation of the percentage change in operating income (SIGOI), Coefficient of Variation of ROA (CV_ROA), Coefficient of Variation of ROE (CV_ROE), and Coefficient of Variation of Operating Income (CV_OI). The large variance in earnings means higher possibility of financial distress; therefore, to avoid bankruptcy happen, firms with larger volatility of earnings will have less debt.

In addition, we also consider the cost of issuing debt measured by Standard & Poor's (S&P) Long Term Credit Rating (SP_Rate) and S&P Investment Credit Rating (SP_INV)[5]. High level of financial ratings can decrease the cost of issuing debt.

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[4] Altman (1968) Z-score formula is:

$$\text{Z-score} = 3.3 \times \frac{\text{EBIT}}{\text{Total Asset}} + 0.99 \times \frac{\text{SALE}}{\text{Total Asset}} + 0.6 \times \frac{\text{Market value of Equity}}{\text{Total Debt}} + 1.2 \times \frac{\text{Working Capital}}{\text{Total Asset}} + 1.4 \times \frac{\text{Retained Earnings}}{\text{Total Asset}}$$

[5] Standard & Poor's (S&P) Long Term Credit Ratings can be classified into 22 categories on the scale from AAA to D. Here we give value of these ratings from 1(AAA rating) to 22 (D rating) in order to measure the attribute of financial ratings. For S&P Investment Credit Rating (SP_INV), we give weights 1 to long-term investment rating class (AAA to BBB), 2 to non-investment rating class (BB to C), and 3 to default rating class (SD and D). Thus, firms with higher value (lower level) of S&P long term credit rating will use lower

Therefore, according to pecking order theory, the level of financial ratings should be positively related to the leverage ratio.

Profitability

Finally, the pecking order theory developed in Myers (1977) paper indicates that firms prefer to use internal finance rather than external finance when raising capital. The profitable firms are likely to have less debt and profitability in hence is negatively related to debt level. The pervious empirical studies find the negative relation between debt usage and profitability which is consistent with the statement of free cash flow problem by Jensen (1986). However, Stulz (1990) states that a firm would not lose on free cash flow problem if it has profitable investment opportunities. Graham (2000) uses ROA (cash flow from operations divided by total assets) as the measure of profitability. Following TW paper, the indicators of profitability are operating income over sales (OI_S) and operating income over total assets (OI_TA).

2.2.1.2 Macroeconomic factors

McDonald (1983) extends Miller (1977) theory and investigates the impact of government financial decisions on capital structure. The equilibrium of McDonald's (1983) model shows that the corporate debt-to-wealth ratio is negatively related to the

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leverage ratio.

government debt-to-wealth ratio. It implies that the decrease in federal borrowing would lead to the increase in firm's debt-equity ratio.

The previous studies (Greenwood, Hanson, and Stein, 2010; Bansal, Coleman, and Lundblad, 2011; Krishnamurthy and Vissing-Jorgensen, 2012; Graham, Leary, and Roberts, 2012; Greenwood and Vayanos, 2008, 2010) have shown the negative relationship between government leverage and private sector debt. Bansal, Coleman, and Lundblad (2011) provide an equilibrium model to illustrate the endogenous supply relationship between short-term public debt and private debt. They employ Vector Auto-regression (VAR) to do empirical work and confirm the prediction of their model that an increase in government leverage leads to the decrease in private debt. Krishnamurthy and Vissing-Jorgensen (2012) show the negative correlation between the government leverage and the corporate bond spread which is the difference of yields on Aaa corporate bonds and long maturity Treasury bonds. When the supply of public debt decreases, the wide corporate bond spread implies the increase in supply of corporate debt. This evidence consists with the finding in Greenwood, Hanson, and Stein (2010) that the issues of private debts seem shifts in supply of government debt. Graham, Leary, and Roberts (2012) use both macroeconomic factors and firm characteristics to investigate the determinants of capital structure and find government leverage (debt-to-GDP ratio), which is defined as the ratio of federal debt held by public to GDP, is an important determinant of variation in aggregate leverage which is defined as the ratio of aggregate total debt to aggregate book value.

Based on previous literature, we use debt-to-GDP ratio (D_GDP), corporate bond spread (Spread), and total public debt (TPD) as indicators of macroeconomic attribute to capital structure. We expect that D_GDP and TPD are negatively related to leverage ratio and the correlation between leverage ratio and Spread is negative.

2.2.1.3 Manager character

Berger et al. (1997) build a measure of managerial entrenchment to investigate the agency problem between managers and shareholders, that is, managers would prefer to issue less debt to benefit their own private profits rather than pursue the optimal capital structure to benefit shareholders. Berger et al. (1997) find that the usage of debt decrease with the options and stocks held by CEO, log of number of directors and percentage of outside directors, but increase with the length of tenure of CEO. Graham (2000) utilize the same variables from Berger et al. (1997) to measure the managerial entrenchment and the results are similar to Berger et al. (1997) finding that strong managerial entrenchment would lead to decrease the debt usage of a firm. The variables used to measure the managerial entrenchment are the stocks and options held by CEO, the length of working years and tenure of CEO, log of number of directors, percentage of outside directors.

Bhagat, Bolton, and Subramanian (2011) develop a dynamic capital structural model incorporated with taxes effect, bankruptcy costs and manager characteristics and investigate the effects of manager characteristics on the firm's capital structure. Their model, which incorporates with the concept of agency problems between manager and shareholders, can be viewed as the application of trade-off theory and agency conflict problem which utilizes tax effects and bankruptcy costs as external factors and manager characteristics as internal factors to analysis financing decisions of a firm. Their model can be viewed as the application of trade-off theory and agency conflict problem which utilizes tax effects and bankruptcy costs as external factors and manager characteristics as internal factors to analysis financing decisions of a firm. They find manager characteristics are important determinants of capital structure decisions and the manager's ability is negative correlated to total debt ratio (total debt / total asset) and the results of their empirical work are consistent with the inference of their model. The variables, CEO cash compensation, CEO cash compensation to asset ratio, CEO tenure, CEO tenure divided by CEO age and CEO ownership (numbers of shares of common stock plus the number of options held by CEO), will be used as the proxies of CEO ability to test the influence of manager-shareholder agency conflicts on a firm's financing decisions.

Here we use CEO Tenure over CEO age (Tenu_age), log of CEO tenure (log_Tenu), log of CEO total compensation (log_TC), CEO bonus (in millions) (Bonus), log of number of directors (log_Dir) and percentage of outside directors (Out_Dir) as indicators of manager character. Since both manager's ability and strong managerial entrenchment would lead to the decrease of debt usage, the manager character of a firm is expected to be negatively related to this firm's leverage.

2.2.2 Joint Determinants of Capital Structure and Stock Rate of Return

Marsh (1982) analyze the empirical study in financing decisions of UK companies and find their capital structures are heavily influenced by their stock prices. Baker and Wurgler (2002) provide the empirical evidence that the capital structure of a firm is significantly related to its historical stock price. The firms prefer to issue equity when their stock prices are relative high (market-to-book ratio high) and repurchase equity when the stock prices are relative low. However, the regression equations used in Baker and Wurgler (2002) seem not very suitable for description of relationship between capital structure and stock price. The stock price and capital structure change simultaneously since the stock price will response the investors' perspective on financing and investment decisions and managers would take account of both reaction of stock prices and the firm's long-term equity value when making financing decisions, vice versa. Therefore, we can use simultaneous structural equation to investigate the relationship between capital structure and stock price.

Welch (2004) investigates whether companies change their capital structure in accordance with the changes in stock prices or not. Welch (2004) finds that the stock price is primary factor of dynamic capital structure. However, the firms don't readjust their capital structure to response the changes in stock prices. Jenter (2005) and Jenter et al. (2011) provide the different aspect of a firm's financing activity affected by its stock price. Jenter et al. (2011) state that managers attempt to take advantage of the mispricing their firms' equity through corporate financing activities. This behavior is called "time to market" under the agency problem between the manager and outside investors. The different beliefs between the manager and investors will cause market timing behavior (Jung and Subramanian, 2010). Yang (2013) estimate the influence of the difference in beliefs on firms' leverage ratio and claim that market timing behavior has the significant effect on capital structure. The strong investor beliefs (higher stock price) lead to decreases in firms' leverage.

Dittmar and Thakor (2007) state a new theory called "managerial investment autonomy" to explain that a firm's stock price and its capital structure are simultaneously decided. The "autonomy" means that the firm's stock price is higher when the likelihood of investors' disagreement with investment and financing decisions made from managers is lower, and vice versa. Since managers consider about the response of shareholders to the investment decisions and capital financing decisions, managers can use stock prices as signal whether investors agree or disagree the capital budgeting decisions. Their empirical findings support the argument that a firm will issue equity rather than debt as external financing sources when its stock price is high.

For the stock rate of return, we use the annual close prices of a firm in accordance with its annual reports released date to calculate annual stock returns. Here we add two attributes, liquidity and value as attributes of stock returns. The indicators of liquidity are referred from Pastor and Stambaugh's (2003) innovations in aggregate liquidity (PS_Innov), level of aggregate liquidity (PS_Level), and traded liquidity factors (PS_Vwf). The indicators of value are referred to Fama-French five factors[6] model: small minus big (smb), high minus low (hml), excess return on the market (mktrf), risk-free interest rate used by 1-month T-bill rate (rf), and momentum (umd). In addition, the attributes of firm characteristics, growth and profitability, are expected to affect stock

[6] Fama and French (1992) found three factors related to firm size, excess return on the market, and book-to-market equity ratio have strong explanation of stock returns.

price directly. Therefore, we will set these two attributes as joint determinants of stock return and capital structure. The list of all indicators and attributes can be found in Table 2.3.

Table 2.3 All Attributes and Indicators

Attributes	**Indicators**
Asset structure (AtStruct)*	Intangible asset/total assets(INT_TA) Inventory plus gross plant and equipment /total assets(IGP_TA)
Non-debt tax shield (Nd_tax)	Investment tax credits/total asset (ITC_TA) Depreciation/total asset(D_TA) Non-debt tax shields/total asset(NDT_TA)
Growth (Growth)	Capital expenditures/total asset (CE_TA) The growth of total asset (GTA) Research and development/Sales (RD_S) Research and development/ total assets (RD_TA)
Uniqueness (Unique)	Research and development/Sales (RD_S) Selling expense/sales (SE_S) Quit Rates (QR)
Industry classification (Industry)	SIC code (IDUM) Quit Rates (QR)
Size (Size)	Natural logarithm of sales (LnS)
Volatility (Vol)	The standard deviation of the percentage change in operating income (SIGOI) Coefficient of Variation of ROA (CV_ROA) Coefficient of Variation of ROE (CV_ROE) Coefficient of Variation of Operating Income (CV_OI)
Profitability (Profit)	Operating income/sales (OI_S) Operating income/total assets (OI_TA)
Financial rating (Rate)	Altman’s Z-score (Z_Score) S&P Domestic Long Term Issuer Credit Rating (SP_Rate)

	S&P Investment Credit Rating (SP_INV)
Macroeconomic factors (Macroeco)	Debt-to-GDP ratio (D_GDP) Corporate bond spread (Spread) Total public debt (TPD)
Manager character (Manager)	CEO Tenure over CEO age (Tenu_age) log of CEO tenure (log_Tenu) log of CEO total compensation (log_TC) CEO bonus in millions (Bonus) log of number of directors (log_Dir) Percentage of outside directors (Out_Dir)
Liquidity (Liquid)	Innovations in aggregate liquidity (PS_Innov) Level of aggregate liquidity (PS_Level) Traded liquidity factors (PS_Vwf)
Value (Value)	Small minus big (smb) High minus low (hml) Excess return on the market (mktrf) Risk-free interest rate (rf) Momentum (umd)
Capital structure (CapStruc)	Long-term debt/market value of equity (LT_MVE) Short-term debt/market value of equity (ST_MVE) Convertible debt/market value of equity (C_MVE) Long-term debt/book value of equity (LT_BVE) Short-term debt/ book value of equity (ST_BVE) Convertible debt/ book value of equity (C_BVE) Long-term debt/market value of total assets (LT_MVA) Short-term debt/market value of total assets (ST_MVA) Convertible debt/market value of total assets (C_MVA) Long-term debt/book value of total assets (LT_BVA) Short-term debt/ book value of total assets (ST_BVA) Convertible debt/ book value of total assets (C_BVA)
Stock rate of return (StReturn)	Annual stock return (SR)

* The name in parentheses is used in LISREL program since the labels of variables in LISREL are limited in 8 characters.

2.2.3 Data

Since the data for indicators of firm characteristics, macroeconomic factors, manager character, and the determinants of stock returns are collected from different datasets, the sample period is constrained by the common period of these datasets. The sample period is 2001 to 2012. The annual stock price and data of firm characteristics except quit rates are collected from Compustat. S&P Credit Rating information can be obtained in rating category of Compustat. The time length to measure the indicators of volatility attribute is 5 years (past four years to current year).The codes of the accounting items used to calculate the observed variables in Compustat are shown in Table 2.4.

The data used for manager character, macroeconomic factors, and quit rates are collected from Corporate Library, Board of Governors of the Federal Reserve System and Bureau of Labor Statistics of United States Department of Labor, respectively. The Pastor and Stambaugh's (2003) three liquidity[7] factors and Fama-French five factors are collected from Fama-French Portfolios and Factors dataset in WRDS. Since the data from Fama-French Portfolios and Factors dataset is monthly data, we combine them with other data by calendar date. Because these factors are used to forecast stock returns, the measuring year of these factors is one month before annual report released date.

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[7] The details of liquidity factors are described in Pastor and Stambaugh (2003).

Table 2.4 The Compustat Code of Observable Data

Accounting	**Code**	**Accounting**	**Code**
Total Asset	AT	R&D expense	RDIP
Intangible Asset	INTAN	Sales	SALE
Invenstory	INVT	Selling expense	XSGA
Gorss plant & equipment	PPEGT	SIC code	SIC
Investment tax credits	ITCB	Short-term debt	DLC
Depreciation	DPACT	Long-term debt	DLTT
Income tax	TXT	Convertible debt	DCVT
Operating income	EBIT	Book value of equity	SEQ
Interest payment	XINT	Outstanding shares	CSHO
Capital expenditures	CAPX	Book value per share	BKVLPS
Net income	NI	Market Value of Equity	MKVALT
Working Capital	WCAP	Price Close-Fiscal Annual	PRCC_F
Retained Earnings	RE	NAICS code*	NAICS

*NAICS code is used to combine data with quit rates obtained from Bureau of Labor Statistics of United States Department of Labor.

The firms with incomplete record on variables and with negative values of total asset are deleted from the samples. After combining all data from Compustat, Corporate Library, Board of Governors of the Federal Reserve System and Bureau of Labor

Statistics of United States Department of Labor, total sample size during 2001 to 2012 is 3118.

2.3 Methodologies and LISREL System

In this section, we first introduce the SEM approach and present an example of path diagram to show the structure of structural model and measurement model in SEM framework. Subsequently, Multiple Indicators Multiple Causes (MIMIC) model and its path diagram show alternative way to investigate the determinants of capital structure. Finally, Confirmatory Factor Analysis (CFA) is provided to improve the explanation of relations between indicators and latent variables in measurement model of SEM framework.

2.3.1 SEM Approach

The SEM incorporates three equations as follows:

$$Structural\ model: \eta = \beta\eta + \Phi\xi + \varsigma \tag{2.1}$$

$$Measurement\ model\ for\ y: y = \Lambda_{\mathrm{y}}\eta + \upsilon \tag{2.2}$$

$$Measurement\ model\ for\ x: x = \Lambda\xi + \delta \tag{2.3}$$

x is the matrix of observed independent variables as the indicators of attributes, y is the matrix of observed dependent variables as the indicators of capital structure, ξ is the matrix of latent variables as attributes, η is the latent variables that link determinants of capital structure (a linear function of attributes) to capital structure(y).

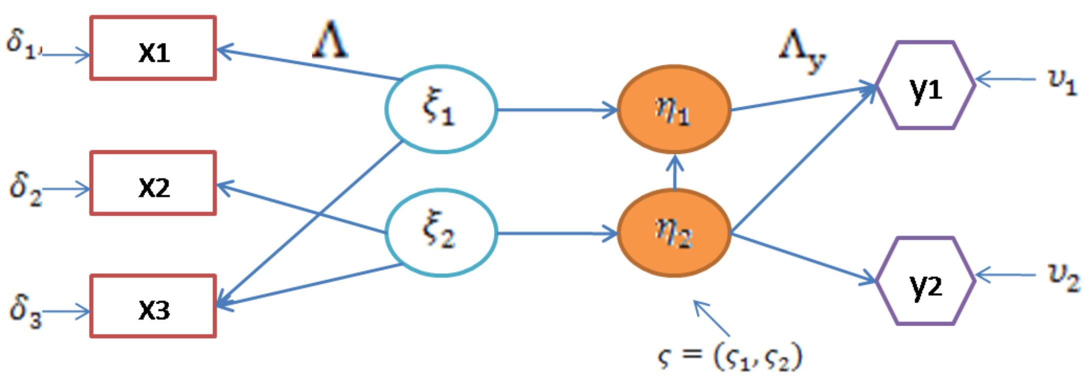
Figure 2.1 shows an example of the path diagram of SEM approach where the observed independent variables x= $(x_1, x_2, x_3)'$ are located in rectangular, the observed dependent variables y= $(y_1, y_2)'$ are set in hexagons, variables$\eta = (\eta_1, \eta_2)'$, $\xi = (\xi_1, \xi_2)'$ in ovals denote the latent variables and the corresponding sets of disturbance are $\varsigma = (\varsigma_1, \varsigma_2)'$, $\upsilon = (\upsilon_1, \upsilon_2)'$, and $\delta = (\delta_1, \delta_2, \delta_3)'$.

Figure 2.1 Path Diagram of SEM Approach

In this path diagram, the SEM formulas (2.1), (2.2) and (2.3) are specified as follows:

$$\beta = \begin{bmatrix} 0 & \beta_1 \\ 0 & 0 \end{bmatrix}, \Phi = \begin{bmatrix} \Phi_1 & 0 \\ 0 & \Phi_2 \end{bmatrix}, \Lambda_y = \begin{bmatrix} \Lambda_{y_1} & \Lambda_{y_2} \\ 0 & \Lambda_{y_3} \end{bmatrix}, \Lambda = \begin{bmatrix} \Lambda_1 & 0 \\ 0 & \Lambda_2 \\ \Lambda_3 & \Lambda_4 \end{bmatrix}$$

where $\Lambda_{y_1}, \Lambda_{y_2}, \Lambda_{y_3}, \Lambda_1, \Lambda_2, \Lambda_3, and\ \Lambda_4$ denote unknown factor loadings, $\beta_1, \Phi_1, and\ \Phi_2$ denote unknown regression weights, $\upsilon_1, \upsilon_2, \delta_1, \delta_2, and\ \delta_3$ denote measurement errors, and $\varsigma_1, and\ \varsigma_2$ denote error terms.



The structural model can be specified as the system of equations which combines equations (2.1) and (2.2), and then we can obtain the structural model in TW paper as follows:

$$y = \Gamma\xi + \varepsilon \qquad (2.4)$$

In this paper, the accounting items can be viewed as the observable independent variables (x) which are the causes of attributes as the latent variables (ξ) ,and the debt-equity ratios represented the indicators of capital structure are the observable dependent variables (y).

The fitting function for maximum likelihood estimation method for SEM approach is:

$$F = log|\Sigma| + tr\left(S\Sigma^{-1}\right) - log|S| - (p+q) \qquad (2.5)$$

where S is the observed covariance matrix, Σ is the model-implied covariance matrix, p is the number of independent variables (x), and q is the number of dependent variables (y).

2.3.2 Illustration of SEM Approach in LISREL System

In general, SEM consists of two parts, the measurement model and structural model. The measurement model analysis the presumed relations between the latent variables viewed as the attributes and observable variables viewed as the indicators. For example, capital expenditures over total assets (CE_TA) and research and development over sales (RD_S) are the indicators of the growth attributes (Growth). In the measurement model, each indicator is assumed to have measurement error associated with it. On the other hand, the structure model presents the relationship between unobserved variables and outcome. For instance, the relationship between attributes and the capital structure is represented by the structure model. The relationship between the capital structure and its indicators estimated by debt-equity ratios and debt-asset ratios is modeled by the measurement model.

Figure 2.2a Matrices of Observed Variables and Their Attributes

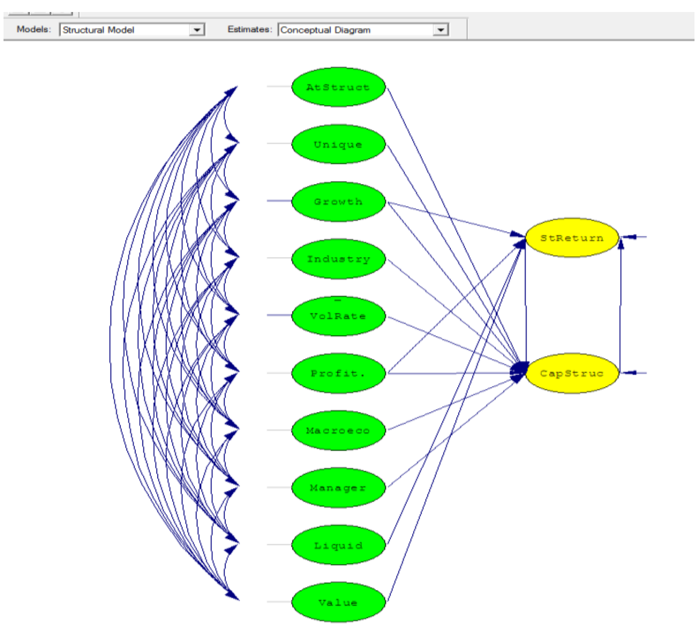
$$x = \begin{bmatrix} INT\_TA \\ IGP\_TA \\ ITC\_TA \\ D\_TA \\ NDT\_TA \\ CE\_TA \\ GTA \\ RD\_S \\ RD\_TA \\ SE\_S \\ QR \\ IDUM \\ LnS \\ SIGOI \\ CV\_ROA \\ CV\_ROE \\ CV\_OI \\ OI\_S \\ OI\_TA \\ Z\_Score \\ SP\_Rate \\ SP\_INV \\ D\_GDP \\ Spread \\ TPD \\ Tenu\_Age \\ \text{log\_Tenu} \\ log\_TC \\ Bonus \\ log\_Dir \\ Out\_Dir \\ PS\_Innov \\ PS\_Level \\ PS\_Vwf \\ smb \\ hml \\ mktrf \\ rf \\ umd \end{bmatrix}, \qquad \xi = \begin{bmatrix} Atstruct \\ Nd\_tax \\ Growth \\ Unique \\ Industry \\ Size \\ Vol \\ Profit \\ Rate \\ Macroeco \\ Manager \\ Liquidity \\ Value \end{bmatrix},$$

Figure 2.2b Matrices of Factor Loadings and Their Measurement Errors

$$
\Lambda = \begin{bmatrix}
\Lambda_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\Lambda_2 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \Lambda_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \Lambda_4 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & \Lambda_5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \Lambda_6 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \Lambda_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \Lambda_8 & \Lambda_{10} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & \Lambda_9 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \Lambda_{11} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & \Lambda_{12} & \Lambda_{13} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & \Lambda_{14} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{15} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{16} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{17} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{18} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{19} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{20} & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{21} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{22} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{23} & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{24} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{25} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{26} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{27} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{28} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{29} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{30} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{31} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{32} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{33} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{34} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{35} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{36} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{37} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{38} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{39} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \Lambda_{40} \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}, \delta = \begin{bmatrix}
\delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ 0 \\ \delta_6 \\ \delta_7 \\ \delta_8 \\ \delta_9 \\ \delta_{10} \\ \delta_{11} \\ \delta_{12} \\ \delta_{13}
\end{bmatrix}
$$

Based on 13 attributes as latent variables for capital structure, 39 indicators for determinants of capital structure choice and stock rate of return, three indicators of capital structure[8], and one indicator of stock rate of return, the SEM measurement model formula (2.3) is specified as Figure 2.2 and the path diagram of structural model formula (2.4) can be found in Figure 2.3 where the variables for x, y and ξ are defined as in Table 2.3.

Figure 2.3 Path Diagram of Structural Model for Joint Determinants of Capital Structure and Stock Returns



[8] The indicators of capital structure are divided into four groups. The denominators of each group are based on market value of equity, book value of equity, market value of asset, book value of asset, respectively.

2.3.3 Multiple Indicators Multiple Causes (MIMIC) Model

MIMIC model is the specified SEM that uses latent variables to investigate the relationship between the indicators and causes of these latent variables. The MIMIC model incorporates two equations as follows:

$$\eta = \gamma x + \varsigma \qquad (2.5)$$

$$y = \lambda\eta + \upsilon \qquad (2.6)$$

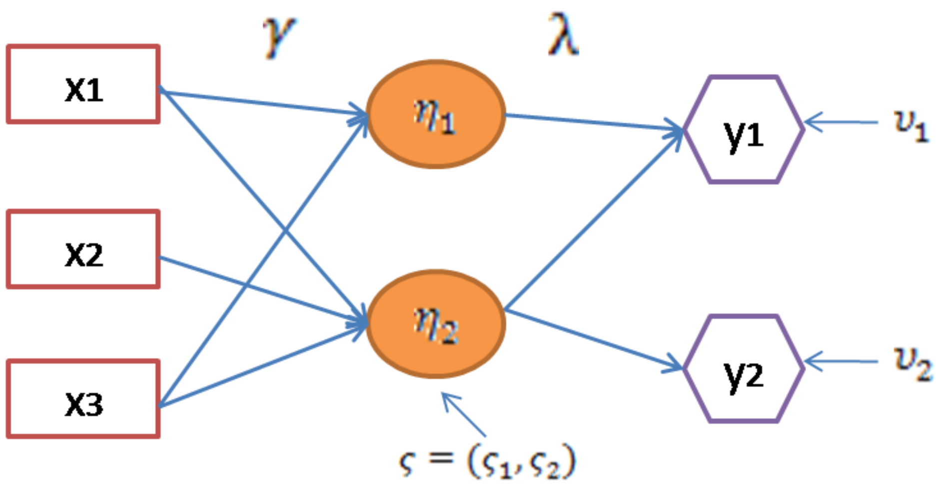
η is the matrix of latent variables that link determinants of capital structure(x) to capital structure(y); x is the matrix of observed independent variables as the causes of η; y is the matrix of observed dependent variables as the indicators of η; ς and υ are error terms. In this essay, there is only one latent variable in η, which is called leverage.

Figure 2.4 shows an example of the path diagram of MIMIC model where the observed independent variables x= $(x_1, x_2, x_3)'$ are located in rectangular, the observed dependent variables y= $(y_1, y_2)'$ are set in hexagons, variables η= $(\eta_1, \eta_2)'$, in ovals denote the latent variables and the corresponding sets of disturbance are $\varsigma = (\varsigma_1, \varsigma_2)'$, and $\upsilon = (\upsilon_1, \upsilon_2)'$.

Figure 2.4 Path Diagram of MIMIC Model

In this path diagram, the MIMIC model formulas (2.5) and (2.6) are specified as follows:

$\gamma = \begin{bmatrix} \gamma_1 & 0 & \gamma_2 \\ \gamma_3 & \gamma_4 & \gamma_5 \end{bmatrix}, \lambda = \begin{bmatrix} \lambda_1 & \lambda_2 \\ 0 & \lambda_3 \end{bmatrix}$ where $\gamma_1, \gamma_2, \gamma_3, \gamma_4, \gamma_5, \lambda_1, \lambda_2$ and λ_3 denote unknown factor loadings, υ_1 and υ_2 denote measurement errors, and ς_1 and ς_2 denote error terms.



In this essay, the MIMIC model formulas (2.5) and (2.6) are specified as Figure 2.5 where the variables of matrixes x and y are defined as in Table 2.3.

Figure 2.5 Matrices for Determinants of Capital Structure and Stock Rate of Return in MIMIC model

$$x = \begin{bmatrix} INT\_TA \\ IGP\_TA \\ ITC\_TA \\ D\_TA \\ NDT\_TA \\ CE\_TA \\ GTA \\ RD\_S \\ RD\_TA \\ SE\_S \\ QR \\ IDUM \\ LnS \\ SIGOI \\ CV\_ROA \\ CV\_ROE \\ CV\_OI \\ OI\_S \\ OI\_TA \\ Z\_Score \\ SP\_Rate \\ SP\_INV \\ D\_GDP \\ Spread \\ TPD \\ Tenu\_Age \\ \text{log\_Tenu} \\ \text{log\_TC} \\ Bonus \\ \text{log\_Dir} \\ Out\_Dir \\ PS\_Innov \\ PS\_Level \\ PS\_Vwf \\ smb \\ hml \\ mktrf \\ rf \\ umd \end{bmatrix}, \eta = \begin{bmatrix} CapStruc \\ StReturn \end{bmatrix}, y = \begin{bmatrix} LT\_MVA \\ ST\_MVA \\ C\_MVA \\ SR \end{bmatrix}, \lambda = \begin{bmatrix} \lambda_1 & 0 \\ \lambda_2 & 0 \\ \lambda_3 & 0 \\ 0 & 1 \end{bmatrix}, \upsilon = \begin{bmatrix} \upsilon_1 & 0 \\ \upsilon_2 & 0 \\ \upsilon_3 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\gamma = \begin{bmatrix} \gamma_1 & \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots & \gamma_{39} \\ 0 \cdots 0 & \gamma_6 \gamma_7 \gamma_8 \gamma_9 \; 0 \cdots 0 \; \gamma_{18} \gamma_{19} \; 0 \cdots \; 0 \; \gamma_{32} \; \gamma_{33} \gamma_{34} \gamma_{35} \; \gamma_{36} \gamma_{37} \gamma_{38} & \gamma_{39} \end{bmatrix}, \varsigma = [\varsigma_1, \varsigma_2]$$

2.3.4 Confirmatory Factor Analysis (CFA)

In SEM framework, the usage of confirmatory factor analysis (CFA) in measurement model is to test whether the data fit a hypothesized measurement model which is based on theories in previous literature. CFA is usually utilized as the first step to assess a designed measurement model in SEM since it is a theory-driven analysis that evaluates the consistency between a priori hypotheses and the parameter estimates in the relations between observed variables and latent variables. If CFA shows the poor confirmation of a measurement model, and then the results of SEM will indicate a poor fit, the model will be rejected, and the parameter estimates will be unexplainable. Therefore, we should first utilize CFA to adjust the relations between observed and latent variables in SEM, and subsequently conclude the results in accordance with assessment of model fit statistics[9].

CFA can evaluate the confirmation of a designed model via the construct validity of a proposed measurement theory. Two major validities, convergent validity and discriminant validity, are the important components of construct validity which is the extent to test whether a set of measured items actually reflects the theoretical latent

[9] With regard to selecting model-fit evaluation, CFI (Comparative-Fit Index), RMSEA (Root Mean Square Error of Approximation), the ratio of Chi-Square value to degree of freedom, and SRMR (Standardized Root Mean Square Residual) are common goodness-of-fit measures.

construct in measurement model. There are three approaches to evaluate convergent validity: factor loadings, average variance extracted (AVE), and composite reliability (CR). In general, the factor loadings (the parameter estimates) larger than the critical value 0.5 imply that the latent variables can appropriately explain the observed variables and the measurement model has good convergent validity. The formulas of average variance extracted (AVE) and composite reliability (CR) for a latent variable are as follows:

$$AVE = \frac{\sum \lambda^2}{\sum \lambda^2 + \sum \theta}$$

$$CR = \frac{(\sum \lambda)^2}{(\sum \lambda)^2 + \sum \theta}$$

Where λ denotes the standardized factor loadings (the standardized parameter estimates) of a latent variable and θ denotes the indicator error variances of observed variables related to this latent variable. In LISREL system, we can obtain Squared Multiple Correlations (SMC) of observed variables. SMC value can be viewed as the coefficient of determination, R^2 in linear regression analysis, and the value θ of an observed variable equals to the value of one minus SMC of that observed variable. If AVE and CR of a latent variable are larger than 0.5, then this latent variable is reasonably set in measurement model and the model has good convergent validity of this latent variable.

In addition, there are three ways to measure discriminant validity of a measurement model. The first method is to compare the original measurement model with the restricted measurement model which fixes the coefficient of correlation between two latent variables equal to 1.00. Secondly, the alternative method of setting the restricted measurement model is to combine two latent variables into one latent variable in the model. If the difference of Chi-Square value of the original and the restricted models is significant[10], then the set of measurement model performs good discriminant validity and the latent variables are of significant difference that can represent different characteristics in SEM. The third method is the comparison of AVE value of a latent variable and the square of the coefficient of correlation between two latent variables; if the square of the coefficient of correlation between two latent variables is larger than both AVE of these latent variables, then these latent variables can perform discriminative characters well.

2.4 Empirical Analysis

In this section, we first do empirical work on determinants of capital structure and then investigate the joint determinants of capital structure and stock rate of return. We use both SEM with CFA and MIMIC model to illustrate the structural equal modeling

[10] The 5% and 1% significant value of the difference of Chi-Square value between original measurement model and the restricted model are 3.841 and 6.64 respectively.

approach and compare their results. Finally, we will compare our results to the empirical results of TW, Chang et al. (2008) and Yang et al. (2010).

2.4.1 Determinants of Capital Structure by SEM with CFA

During CFA test, we delete some indicators to solve singularity problem in covariance matrix and combines some attributes to satisfy discriminant and convergent validity measures[11]. The conceptual diagram of structure model for determinants of capital structure is illustrated in Figure 2.6. Here we combine attributes, uniqueness and industry classification, into one attribute called "Uni_Ind" to solve the collinearity problem since the indicators of these attributes are similar. Another combined attribute is called "Vol_Rate" from volatility and financial rating attributes because both attributes are used to measure financial distress costs.

The estimates of the parameters of measurement model without CFA are presented in Table2.5 and Table 2.7. There are 23 indicators and 9 attributes in SEM with CFA model for determinants of capital structure[12].

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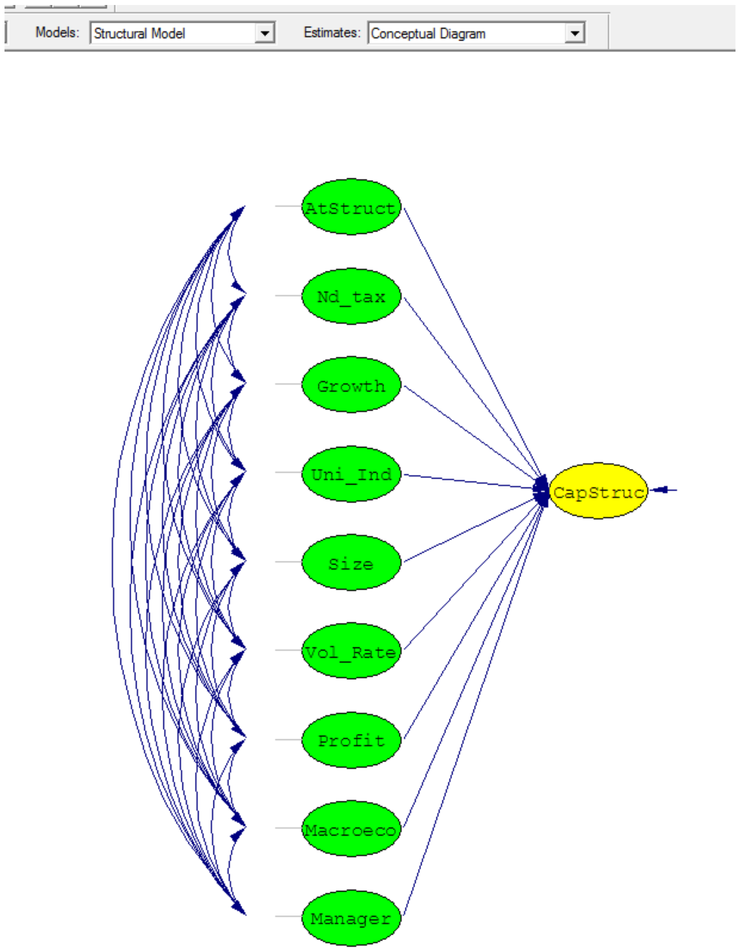
[11] The Chi-Square value = 6905.61, Degree of Freedom = 252, Normed Fit Index (NFI) = 0.79, Comparative Fit Index (CFI) = 0.79, Root Mean Square Error of Approximation (RMSEA) = 0.092, Root Mean Square Residual (RMR) = 0.15, Standardized RMR = 0.076 and Goodness of Fit Index (GFI) = 0.85. Since the sample size is too big, the insignificant value of Chi-Square cannot be good indicator of model fitness. Based on CFA criteria, CFI, GFI, RMSEA and RMR show our model is acceptable.

[12] We have collected 31 indicators to analyze the determinants of capital structure. However, the covariance matrix is not positive definite and results in singularity problem. Therefore, we delete some

Figure 2.6 Conceptual Diagram of Structure Model for Determinants of Capital Structure



Except the indicators of Growth and Size, others are significant as proxies of attributes. According to Table 2.6, asset structure and non-debt tax shield are highly correlated because their indicators are closely related. For example, depreciation indicator

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observed variables which are high correlated to other indicators.

(D_TA) of non-debt tax shield is positively related to gross plant and equipment indicator (IGP_TA) of asset structure. The high correlation of attributes will cause problems in estimating the model. In addition, too many latent variables and the lack of using indicators with unique weights corresponding to their attributes may also cause the week results (Maddala and Nimalendran, 1996). Therefore, we can expect more significant results if we delete either asset structure or non-debt tax shield attribute. We will also remove some insignificant attributes, e.g. growth or size, to test whether the results are more significant under confirmatory factor analysis.

Based on the results in Table 2.7, we find profitability having significant effect on capital structure in either short-term or long-term aspect. The positive relationship between profitability and capital structure is inconsistent with pecking order theory (Myers, 1977) and free cash flow theory (Jensen, 1986). However, we can infer that profitable firms may utilize both internal sources and debts to invest profitable opportunities and to avoid agency costs (Stulz, 1990). Volatility and financial rating only influence on market-based short-term leverage ratio. This evidence implies that even though the credit risk affects the fluctuation of stock price, bankruptcy cost may not change long-term target leverage ratios. It also consists with Welch’s (2004) inference that firms don’t readjust target leverage ratios responding to their fluctuated stock prices.

Table 2.5 Measurement Model: Factor Loadings of Indicators for Independent Variables (x)

The bold numbers are significant at 1% level where the t-statistics are in parentheses. The variables and attributes are referred to Table 2.3.

	Attributes (The Latent Variables)									
Variable(x)	**AtStruct**	**Nd_tax**	**Growth**	**Uni_Ind**	**Size**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	σ_δ^2
INT_TA	**0.11** (32.81)									0.03
IGP_TA	**-0.41** (-82.35)									-0.03
ITC_TA		**0.00** (-4.46)								0.00
D_TA		**-0.17** (-23.73)								0.02
NDT_TA		**0.01** (6.40)								0.00
CE_TA			-0.02 (-1.49)							0.00
GTA			0.01 (1.22)		-0.01 (-0.57)					0.09
RD_TA			0.00 (1.23)							0.00
SE_S				**0.05** (19.30)						0.01
QR				**-0.03** (-18.61)						0.01
IDUM				**0.18** (18.95)						0.16
LnS					-0.31 (-0.63)				0.33 (1.41)	1.72

	Attributes (The Latent Variables)									
Variable(x)	**AtStruct**	**Nd_tax**	**Growth**	**Uni_Ind**	**Size**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	σ_δ^2
OI_S							**0.07** (31.00)			0.01
OI_TA							**0.07** (52.73)			0.00
D_GDP								**0.15** (60.78)		0.00
TPD								**0.35** (71.13)		-0.01
Tenu_Age									**-0.13** (-49.73)	0.00
Log_Tenu									**-0.33** (-41.63)	0.05
Out_Dir									**0.02** (11.15)	0.01
Log_Dir									**0.01** (4.50)	0.01
CV_ROE						**-1.62** (-22.64)				13.93
SP_Rate						**2.18** (40.47)				5.52
Z_Score						**-1.40** (-40.81)				2.23

Table 2.6 The Estimated Covariance Matrix of Attributes

The bold numbers are significant at 1% level where the t-statistics are in parentheses. Because it is standardized covariance matrix, the elements can be viewed as correlation coefficients. The attributes are referred to Table 2.3.

	Attributes (The Latent Variables)								
	AtStruct	**Nd_tax**	**Growth**	**Uni_Ind**	**Size**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**
AtStruct	1.00								
Nd_tax	**0.98** (25.28)	1.00							
Growth	-0.29 (-0.45)	-0.48 (-0.45)	1.00						
Uni_Ind	**0.55** (22.04)	**0.36** (9.54)	-0.03 (-0.45)	1.00					
Size	-0.35 (-0.44)	-0.83 (-0.45)	0.35 (0.31)	0.52 (0.45)	1.00				
Vol_Rate	**-0.14** (-7.18)	**-0.19** (-6.87)	0.32 (0.44)	**-0.18** (-4.97)	0.57 (0.45)	1.00			
Profit	**0.08** (5.42)	**0.12** (5.99)	-0.26 (-0.45)	-0.01 (-0.29)	-0.22 (-0.45)	**-0.68** (-36.57)	1.00		
Macroeco	-0.01 (-1.04)	**-0.05** (-3.05)	-0.23 (-0.45)	**0.18** (8.41)	-0.01 (-0.16)	**0.04** (2.74)	-0.02 (-2.03)	1.00	
Manager	**-0.05** (-3.36)	-0.04 (-1.84)	0.67 (0.45)	-0.06 (-2.26)	-0.35 (-0.33)	**0.11** (5.68)	**-0.05** (-3.48)	**-0.06** (-5.59)	1.00

Table 2.7 Estimates of Structural Coefficients

The bold numbers are significant at 5% level where the t-statistics are in parentheses. The indicators and attributes are referred to Table 2.3. Here we use long-term, short-term, and convertible leverage ratios as indicators of capital structure. CapStru_MV is the latent variable, capital structure, constructed by market-value base leverage ratios (market value of total assets as denominator), and CapStru_BV is constructed by book-value base leverage ratios (book value of total assets as denominator).

Total Effects of Attributes on Capital Structure									
CapStruc	**AtStruct**	**Nd_tax**	**Growth**	**Uni_Ind**	**Size**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**
CapStruc_MV	-3.55	3.10	0.19	0.23	0.13	**1.25**	**0.28**	-0.01	-0.10
	(-0.41)	(0.46)	(0.28)	(0.19)	(0.51)	(2.34)	(2.28)	(-0.09)	(-0.73)
LT_MVA	-0.30	0.26	0.02	0.02	0.01	0.11	**0.02**	0.00	-0.01
	(-0.41)	(0.46)	(0.28)	(0.19)	(0.51)	(0.51)	(2.28)	(-0.09)	(-0.73)
ST_MVA	-0.01	0.01	0.00	0.00	0.00	**0.00**	**0.00**	0.00	0.00
	(-0.41)	(0.46)	(0.28)	(0.19)	(0.51)	(2.13)	(2.09)	(-0.09)	(-0.72)
C_MVA	-0.04	0.03	0.00	0.00	0.00	0.01	**0.00**	0.00	0.00
	(-0.41)	(0.46)	(0.28)	(0.19)	(0.51)	(0.30)	(2.25)	(-0.09)	(-0.73)
CapStruc_BV	-4.18	3.42	-0.16	0.53	0.04	1.27	**0.54**	-0.04	0.05
	(-0.27)	(0.28)	(-0.22)	(0.23)	(0.36)	(1.33)	(2.33)	(-0.19)	(0.29)
LT_BVA	-0.45	0.37	-0.02	0.06	0.00	0.14	**0.06**	0.00	0.01
	(-0.27)	(0.28)	(-0.22)	(0.23)	(0.36)	(1.33)	(2.33)	(-0.19)	(0.29)
ST_BVA	0.02	-0.01	0.00	0.01	0.00	0.02	**0.00**	0.00	0.00
	(0.27)	(-0.28)	(0.22)	(0.23)	(0.36)	(1.31)	(-2.04)	(0.19)	(-0.29)
C_BVA	-0.05	0.04	0.00	0.01	0.00	0.02	**0.01**	0.00	0.00
	(-0.27)	(0.28)	(-0.22)	(0.23)	(0.36)	(1.31)	(2.24)	(-0.19)	(0.29)

2.4.2 Determinants of Capital Structure by MIMIC Model

To enhance the explanation of the factors of capital structure, I use MIMIC model to reduce the latent variable and improve the results shown in Figure 2.7 and Table 2.8. The standardized estimates of determinants of capital structure in market value basis are illustrated by path diagram in Figure 2.7 where there is only one latent variable (attribute), Capital Structure (CapStruc), and all observed variables are the indicators of this attribute. The selection of indicators for determinants of capital structure in MIMIC model is same as it in SEM with CFA to compare the performance between two models. The goodness-of-fit measures show that MIMIC model performed better than SEM with CFA[13] because of the decrease in latent variables.

The parameter estimates of determinants of capital structure in both market value basis and book value basis are shown in Table 2.8. Compared to SEM with CFA method, at least one indicator of attributes, AtStruct, Nd_tax, Growth, Uni_Ind, Vol_Rate and Macroeco, has explanation power of capital structure in both market and book value

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[13] The Chi-Square value = 678.80, Degree of Freedom = 46, Normed Fit Index (NFI) = 0.98, Comparative Fit Index (CFI) = 0.98, Root Mean Square Error of Approximation (RMSEA) = 0.066, Root Mean Square Residual (RMR) = 0.0013, Standardized RMR = 0.029 and Goodness of Fit Index (GFI) = 0.98. Since the sample size is too big, the insignificant value of Chi-Square cannot be good indicator of model fitness. Based on CFA criteria, CFI, GFI, RMSEA and RMR show our model is acceptable. The goodness-of-fit measure, RMR and RMSEA in MIMIC model smaller the values in SEM with CFA shows MIMIC model performed better than SEM with CFA.

bases. Size and Profit attributes only have significant effects on leverage ratios in book value basis. In addition, manager only influences on capital structure in market value basis.

Although there are many significant indicators to determine capital structure, some of them are incompatible with each others. For example, INT_TA and IGP_TA should have inversely influences on capital structure while they both are positively related to capital structure in MIMIC model. All indicators of Nd_tax should be negatively relation to capital structure while NDT_TA has significantly positive relation to it. Therefore, we would claim that SEM with CFA would be more proper to investigate the determinants of capital structure rather than MIMIC model if we can establish SEM with CFA under better goodness-of-fit measures.

According to the results in both SEM with CFA and MIMIC model, the long-term debt ratio in both market and book value bases has heavy factor loading in capital structure. Therefore, we claim that the factors of capital structure focus on long-term rather than short-term leverage ratios.

Figure 2.7 Path Diagram of Results in MIMIC Model

The indicators and attributes are referred to Table 2.3. The numbers on the links between each indicators and CapStru are the standardized estimates of determinants of capital structure.

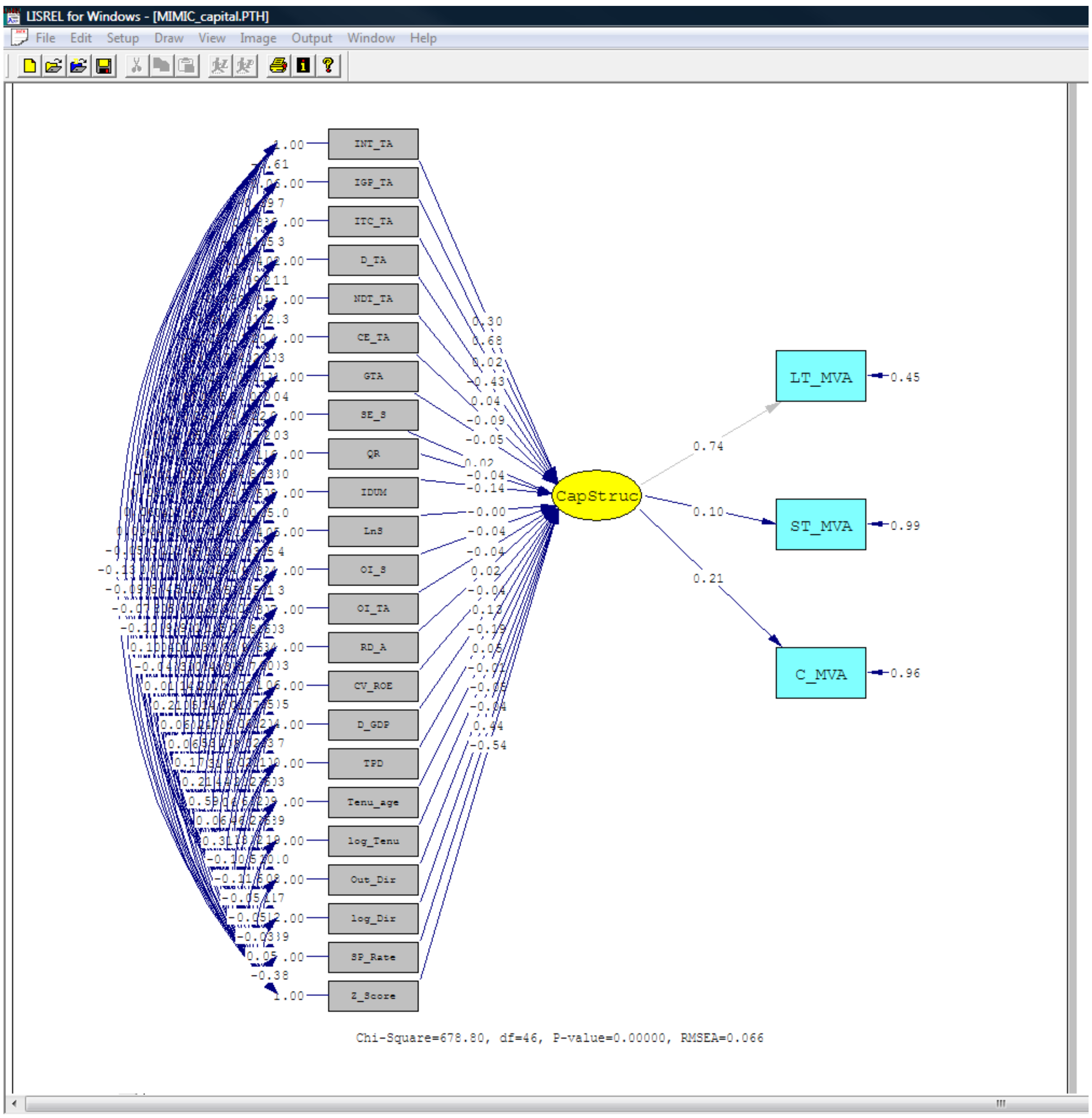

Table 2.8 The Standardized Estimates of Determinants of Capital Structure in MIMIC Model

The bold numbers are significant at 5% level where the t-statistics are in parentheses. The indicators and attributes are referred to Table 2.3.

Standardized Factor Loadings in MIMIC Model			
Attributes	**Indicators**	**Market Value Basis**	**Book Value Basis**
AtStruct	INT_TA	**0.30** (12.99)	**0.24** (15.24)
AtStruct	IGP_TA	**0.68** (14.26)	**0.42** (12.72)
Nd_tax	ITC_TA	0.02 (1.41)	0.01 (0.77)
Nd_tax	D_TA	**-0.43** (-11.51)	**-0.22** (-8.51)
Nd_tax	NDT_TA	**0.04** (2.37)	**0.03** (2.15)
Growth	CE_TA	**-0.09** (-4.00)	**-0.03** (-2.11)
Growth	GTA	**-0.05** (-3.04)	-0.02 (-1.75)
Growth	RD_TA	0.02 (1.09)	0.02 (1.71)
Uni_Ind	SE_S	0.02(1.23)	**0.03** (2.11)
Uni_Ind	QR	-0.04 (-1.80)	0.00 (0.22)
Uni_Ind	IDUM	**-0.14** (-7.45)	**-0.08** (-6.67)
Size	LnS	0.00 (-0.20)	**-0.07** (-4.37)
Profit	OI_S	-0.04 (-1.89)	**-0.04** (-2.78)
Profit	OI_TA	-0.04 (-1.50)	**0.20** (10.49)
Macroeco	D_GDP	0.13 (1.95)	**0.31** (6.72)
Macroeco	TPD	**-0.19** (-2.75)	**-0.36** (-7.73)
Manager	Tenu_Age	0.05 (1.50)	0.00 (-0.01)
Manager	Log_Tenu	-0.01 (-0.40)	0.01 (0.46)
Manager	Out_Di r	**-0.05** (-2.54)	0.01 (0.56)
Manager	Log_Dir	-0.04 (-1.89)	0.00 (0.13)
Vol_Rate	CV_ROE	**-0.04** (-2.02)	-0.02 (-1.28)
Vol_Rate	SP_Rate	**0.44** (17.00)	**0.20** (11.36)
Vol_Rate	Z_Score	**-0.54** (-23.29)	**-0.39** (-24.28)

2.4.3 Joint Determinants of Capital Structure and Stock Returns by SEM with CFA

Since there are too many indicators and attributes in the investigation of joint determinants of capital structure and stock returns, we delete some the attributes and indicators in this section. The conceptual diagram and the estimates of structure model for joint determinants of capital structure and stock returns is illustrated in Figure 2.8. The attributes are removed in accordance with the results of determinants of capital structure. Based on the results in Table 2.6, we delete non-debt tax shield (Nd_tax) attribute because of high correlation between it and asset structure (AtStruct). In addition, we delete size attribute in accordance with insignificant results in Table 2.5 and Table 2.6. The indicator, LnS in hence is removed in our structural equation modeling. However, the size effect still exists in our framework because it is one of elements (Sales/Total Asset) in Altman's Z-score which is the indicator of financial rating attribute (Rate).

The estimates of the parameters in SEM with CFA are presented in Table2.9 and Table 2.11. There are 27 indicators and 10 attributes in SEM with CFA model for joint determinants of capital structure and stock returns[14]. To confirm the theories in corporate finance, we analyze the simultaneous results of Table 2.11 in accordance with capital

[14] We have collected 39 indicators to analyze the joint determinants of capital structure and stock returns. However, the covariance matrix is not positive definite and results in singularity problem. Therefore, we delete some observed variables which are high correlated to other indicators.

structure theories in Table 2.12. First, negative values in asset structure and growth attributes are consistent with trade-off theory and agency cost theory, that is, higher collateral assets, less bankruptcy and agency costs. This evidence is consistent with the finding in Rampini and Viswanathan (2013). Industry attribute shows that firms with high liquidation cost prefer to issue less debt, while positive uniqueness attribute contradicts the statements in Titman and Wessels (1988). Our explanation of quit rates positively related to leverage ratios is based on Burdett's (1978) theory of job quits and quit rates. Burdett claims that workers quit only because a better wage offer is found. In this theory, quit rates can be viewed as wage quit rates. Workers do not accumulate firm-specific human capital because they know a job before starting employment. Therefore, quit rates is negatively related to growth firms with high salary offers. The growth firms usually use less debt. It implies that the lower quit rates, lower debts used in firms. Thus, the relationship between uniqueness and firms' leverage would be positive. The negative value of volatility and financial rating attribute shows that firms with higher financial distress costs prefer to issue less debt.

In contrast to the negative relationship between profitability and capital structure in previous literature, our results show significantly positive influence of profitability on leverage ratios. However, the evidence doesn't violate pecking order theory because profitable firms still prefer debt to equity as external sources of funds. Our explanation for this positive relation is that firms may raise debts to profitable investment opportunities if the retained earnings are not enough to invest. In addition, the profitable firms have lower transaction and issuing costs on debts. Therefore, the profitable firms would utilize more leverage to invest profitable opportunities in accordance with the decrease of agency costs and the inexpensive issuing costs of debts.

Except the attributes from firm characteristics, macroeconomic factors have significant effects on capital structure in either market-value or book-value bases. The negative relationship between macroeconomic attribute and capital structure confirm McDonald's (1983) theory and previous empirical studies. That is, the increase in government leverage would lead the decrease in private debt. Since we use individual instead of aggregate debt ratios in our model, the scale of the relationship between the government financial policy and firms' capital structure is very small. Manager attribute negatively correlated to firms' leverage consists with agency costs in previous literature. The strong managerial entrenchment and a manager's ability would lead the decrease in debt because managers prefer private benefits to the shareholder's profits.

For the simultaneous relationship between capital structure and stock rate of returns, the usage of debt can be viewed as positive signal to shareholder because of asymmetric information. Therefore, increasing leverages increases stock returns (Ross, 1977). However, high stock price would lead the decrease of debt usage in accordance with "managerial investment autonomy" theory in Dittmar and Thakor (2007) and "market timing behavior" phenomenon in Yang (2013). In Table 2.11, the stock returns have negative influence on capital structure in market-value basis, not in book-value basis. So we question about high stock price as an agreement signal that firm would prefer equity to debt as external financing sources. The evidence of negative effect of stock returns on market-value based leverages is more likely to consist with Welch's (2004) statement. That is, firms don't readjust their capital structure to response the changes in stock prices though stock price is significant factor of dynamic capital structure. When the stock price increases, market value of total assets increases and leverage ratios in market-value basis in hence decrease.

Figure 2.8 Conceptual Diagram and Estimates of Structure Model for Joint Determinants of Capital Structure and Stock Returns

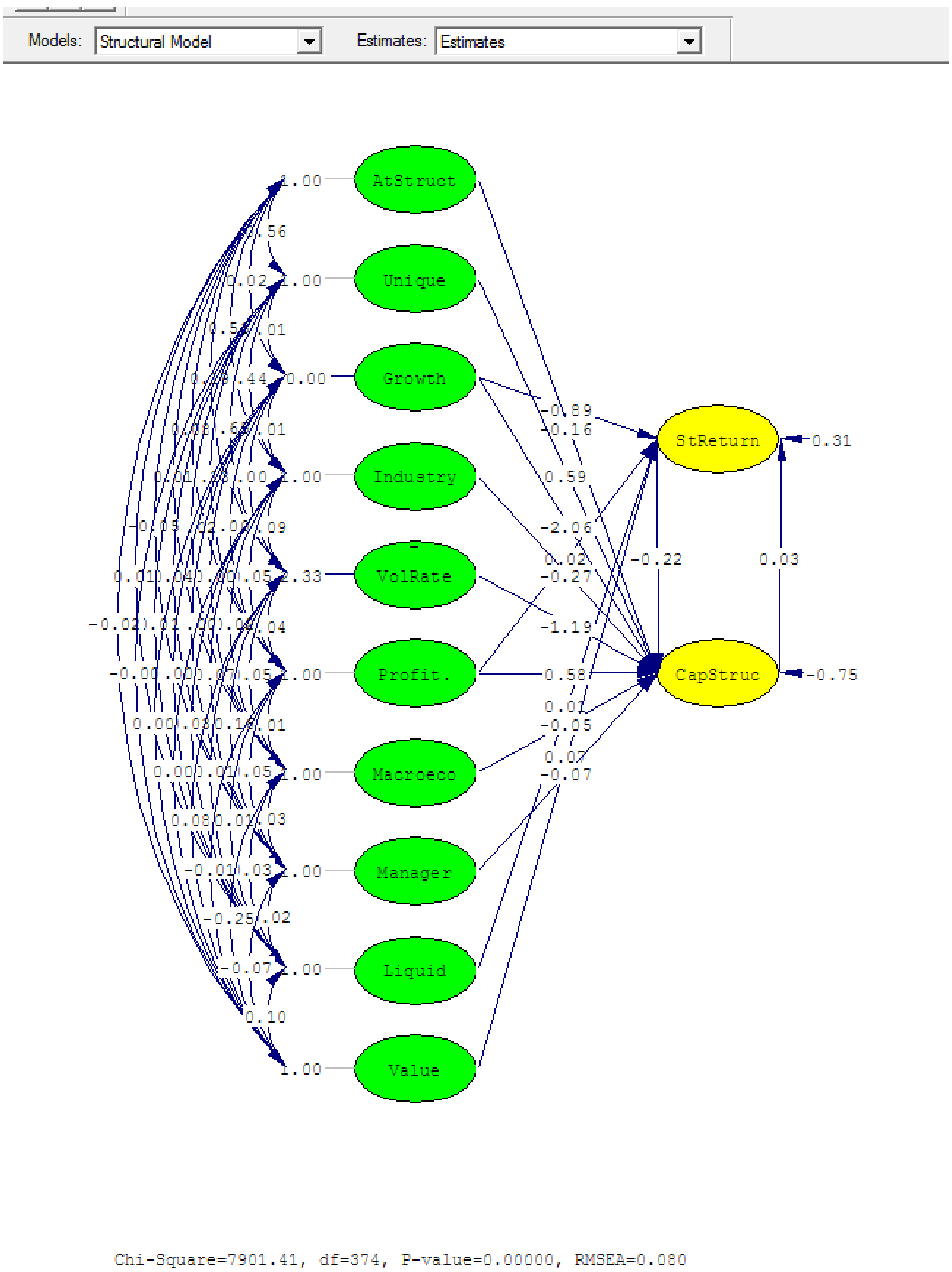

Table 2.9 Measurement Model: Factor Loadings of Indicators for Independent Variables (x)

The bold numbers are significant at 1% level where the t-statistics are in parentheses. The variables and attributes are referred to Table 2.3.

	Attributes (The Latent Variables)										
Variable(x)	**AtStruct**	**Growth**	**Industry**	**Unique**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	**Value**	**Liquid**	σ_δ^2
INT_TA	**0.12** (36.78)										0.02
IGP_TA	**-0.36** (-56.12)										0.01
CE_TA		**-1.64** (-4.39)									0.00
GTA		1.00									0.09
RD_TA		0.01 (1.88)									0.00
SE_S				**0.08** (10.75)							0.01
QR			**-0.05** (-14.20)	**0.02** (5.19)							0.00
IDUM			**0.27** (22.41)								0.12
CV_ROE					**1.08** (22.39)						13.83
SP_Rate					**-1.26** (-33.85)						1.86
Z_Score					1.00						
OI_S						**0.06** (28.48)					0.01
OI_TA						**0.08** (50.24)					0.00
D_GDP							**0.11** (23.10)				0.01
TPD							**0.48** (27.42)				-0.12
Tenu_Age								**0.13** (48.16)			0.00

	Attributes (The Latent Variables)										
Variable(x)	**AtStruct**	**Growth**	**Industry**	**Unique**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	**Value**	**Liquid**	σ_δ^2
Log_Tenu								**0.32** (39.34)			0.05
Bonus								0.00 (-0.02)			2.91
Out_Dir								**-0.02** (-11.37)			0.01
Log_Dir								**-0.01** (-4.57)			0.01
PS_Innov										**0.19** (4.39)	-0.03
PS_Level										**0.02** (4.23)	0.00
PS_Vwf										**0.00** (-3.17)	0.00
Mktrf							**0.00** (8.02)		**0.05** (63.70)		0.00
Smb									**0.01** (31.78)		0.00
Hml									**0.01** (23.08)		0.00
Umd									**-0.03** (-33.68)		6.55

Table 2.10 The Estimated Covariance Matrix of Attributes

The bold numbers are significant at 1% level where the t-statistics are in parentheses. Because it is standardized covariance matrix, the elements can be viewed as correlation coefficients. The attributes are referred to Table 2.3.

	Attributes (The Latent Variables)									
	AtStruct	**Growth**	**Industry**	**Unique**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	**Value**	**Liquid**
AtStruct	1.00									
Growth	**0.02** (4.45)	1.00								
Industry	**0.53** (19.40)	**0.01** (4.30)	1.00							
Unique	**0.56** (10.27)	**0.01** (3.93)	**0.44** (8.19)	1.00						
Vol_Rate	**0.19** (5.30)	**0.00** (2.37)	0.09 (1.71)	**0.65** (8.74)	1.00					
Profit	**0.08** (4.78)	**0.00** (2.58)	-0.05 (-2.25)	**0.13** (4.91)	**0.94** (27.85)	1.00				
Macroeco	0.01 (1.45)	0.00 (-2.19)	-0.02 (-2.26)	-0.02 (-1.68)	**-0.05** (-4.21)	0.01 (2.28)	1.00			
Manager	**-0.05** (-3.25)	**0.00** (-3.78)	**-0.07** (-2.96)	0.01 (1.70)	**-0.16** (-5.22)	**-0.05** (-3.45)	**0.03** (5.21)	1.00		
Value	-0.02 (-1.25)	0.00 (1.89)	0.00 (0.23)	0.00 (-0.14)	**0.08** (3.22)	-0.01 (-0.95)	**-0.25** (-10.36)	**-0.07** (-4.94)	1.00	
Liquid	0.01 (1.21)	0.00 (1.68)	**0.03** (2.85)	-0.01 (-1.04)	-0.01 (-1.01)	-0.01 (-1.64)	**-0.03** (-3.49)	**-0.02** (-2.97)	**0.10** (3.74)	1.00

Table 2.11 Estimates of Structural Coefficients

The bold numbers are significant at 5% level where the t-statistics are in parentheses. The indicators and attributes are referred to Table 2.3. Here we use long-term, short-term, and convertible leverage ratios as indicators of capital structure. (MV) and (BV) are represented market-value basis and book-value basis leverage ratios used in capital structure attribute, respectively.

Total Effects of Attributes on Capital Structure and Stock Returns												
	CapStruc	StReturn	AtStruct	Growth	Industry	Unique	Vol_Rate	Profit	Macroeco	Manager	Value	Liquid
CapStruc (MV)		**-0.22** (-6.60)	-0.16 (-1.55)	**-2.06** (-2.51)	**-0.27** (-4.91)	**0.59** (3.62)	**-1.19** (-12.08)	**0.58** (6.59)	**-0.05** (-5.53)	-0.07 (-1.89)		
StReturn	**0.03** (2.60)			**-0.89** (-3.33)				0.02 (1.70)			**0.07** (8.64)	0.01 (1.81)
LT_MVA		**-0.02** (-6.65)	-0.01 (-1.55)	**-0.16** (-2.28)	**-0.02** (-4.90)	**0.05** (3.62)	**-0.10** (-12.07)	**0.05** (6.55)	**0.00** (-5.53)	-0.01 (-1.89)		
ST_MVA		**0.00** (-4.69)	0.00 (-1.51)	**-0.01** (-2.16)	**0.00** (-3.95)	**0.00** (3.18)	**0.00** (-5.82)	**0.00** (4.66)	**0.00** (-4.25)	0.00 (-1.82)		
C_MVA		**0.00** (-5.95)	0.00 (-1.54)	**-0.02** (-2.25)	**0.00** (-4.61)	**0.01** (3.49)	**-0.01** (-8.97)	**0.01** (5.89)	**0.00** (-5.11)	0.00 (-1.87)		
CapStruc (BV)		-0.04 (-1.02)	**-0.20** (-2.10)	-0.83 (-1.26)	**-0.23** (-4.81)	**0.57** (3.68)	**-0.87** (-9.95)	**0.61** (7.65)	**-0.05** (-5.68)	**-0.07** (-2.19)		
StReturn	**0.03** (2.12)			**-0.92** (-3.55)				0.01 (0.82)			**0.07** (8.41)	0.01 (1.81)
LT_BVA		0.00 (-1.02)	**-0.02** (-2.10)	-0.09 (-1.20)	**-0.03** (-4.81)	**0.07** (3.68)	**-0.10** (-9.96)	**0.07** (7.65)	**-0.01** (-5.68)	**-0.01** (-2.19)		
ST_BVA		0.00 (0.99)	0.00 (1.78)	0.00 (1.13)	**0.00** (2.76)	**0.00** (-2.48)	**0.00** (3.19)	**0.00** (-3.08)	**0.00** (2.90)	0.00 (1.84)		
C_BVA		0.00 (-1.03)	**0.00** (-2.03)	-0.01 (-1.18)	**0.00** (-4.07)	**0.01** (3.32)	**-0.01** (-6.07)	**0.01** (5.41)	**0.00** (-4.58)	**0.00** (-2.11)		

Table 2.12 Relationship between Attributes and Capital Structure Theories

The attributes are referred to Table 2.3.

Total Effects of Attributes on Capital Structure and Stock Returns									
	StReturn	AtStruct	Growth	Industry	Unique	Vol_Rate	Profit	Macroeco	Manager
CapStruc	–	–	–	–	–	–	-	–	–
Theories in Capital Structure									
Managerial investment autonomy	√								
Agency cost		√	√				√		√
Pecking order theory							√		
Government financial policy								√	
Convenience to leverage		√	√				√		
Financial distress cost		√	√	√	√	√			

2.4.4 Robustness for Joint Determinants of Capital Structure and Stock Returns

In this section, we will use the two-stage, least square (2SLS) approach and MIMIC model to confirm the results in SEM with CFA approach. According to the results of joint determinants of capital structure and stock returns in Table 2.11, most determinants only have significantly quantitative influences on long-term debt ratio. Besides, we cannot analyze more than one dependent variable as proxies of capital structure in 2SLS model. Therefore, we focus on the confirmation of joint determinants of firms' long-term debt ratio and stock returns in terms of 2SLS and MIMIC models.

The joint factor loadings on long-term debt ratio and stock returns in terms of SEM with CFA approach are presented in Table 2.13. The significant attributes are similar to the estimated coefficients in Table 2.11. This evidence shows that most factors have significantly influences on long-term leverage ratios rather than short-term leverage ratios. However, the goodness-of-fit measures [15] are better when there are more than one

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[15] The goodness-of-fit measures of Table 2.11 and Table 2.13 are shown in the table below. The smaller value of goodness-of-fit measures in Table 2.11 shows that the usage of more than one leverage ratios as proxies of capital structure performs better than only using long-term debt ratio to represent capital structure.

	NFI	CFI	RMSEA	RMR	Standardized RMR	GF
Table 2.11	0.77	0.78	0.080	0.13	0.074	0.86
Table 2.13	0.78	0.79	0.083	0.14	0.075	0.86

leverage ratios to represent capital structure attribute in SEM framework.

In Table 2.14 and 2.15, we can find that the significant factors in 2SLS and MIMIC models are the same. However, the estimated weights are quite different. We conjecture that the estimated factor loadings are biased in 2SLS method. That is, the coefficients in 2SLS model are under-estimated because of error-in-variable problem. Therefore, the estimated coefficients in MIMIC model are larger than it in 2SLS model while the significant factors in both models are consistent.

The results of robust test show the use of MIMIC model instead of 2SLS model should be preceded by the elimination of measurement error-in-variable problem in MIMIC model. However, MIMIC model cannot well identify the influences of factors on long-term leverage decisions in accordance with capital structure theories. Therefore, I suggest that the setting of latent attributes to capital structure is necessary when we investigate the joint determinants of capital structure and stock returns.

Table 2.13 Coefficients of Attributes on Long-Term Debt Ratio and Stock Returns

The bold numbers are significant at 5% level where the t-statistics are in parentheses. The indicators and attributes are referred to Table 2.3. Here we use long-term, short-term, and convertible leverage ratios as indicators of capital structure. (MV) and (BV) are represented market-value basis and book-value basis leverage ratios used in capital structure attribute, respectively.

Coefficients of Attributes on Long-Term Debt Ratio and Stock Returns											
	LT_MVA	**StReturn**	**AtStruct**	**Growth**	**Industry**	**Unique**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	**Value**	**Liquid**
LT_MVA		**-0.02**	-0.01	**-0.17**	**-0.03**	**0.04**	**-0.10**	**0.05**	**-0.00**	**-0.01**		
		(-5.37)	(-1.46)	(-2.60)	(-5.82)	(3.30)	(-12.69)	(6.92)	(-5.51)	(-2.57)		
StReturn	**0.30**			**-0.90**				0.01			**0.07**	0.01
	(2.20)			(-3.38)				(1.45)			(8.62)	(1.77)
Standardized Solution												
LT_MVA		**-0.11**	-0.09	**-1.40**	**-0.22**	**0.33**	**-1.20**	**0.39**	**-0.03**	**-0.06**		
StReturn	**0.07**			**-1.61**				0.02			**0.13**	0.01
	LT_BVA	**StReturn**	**AtStruct**	**Growth**	**Industry**	**Unique**	**Vol_Rate**	**Profit**	**Macroeco**	**Manager**	**Value**	**Liquid**
LT_BVA		-0.01	0.18	0.01	**-0.22**	**0.04**	**-0.07**	0.00	**-0.01**	**-0.02**		
		(-1.58)	(1.04)	(1.49)	(-5.17)	(2.24)	(-7.69)	(-0.70)	(-3.64)	(-2.14)		
StReturn	**0.28**			**-0.91**				0.01			**0.07**	0.01
	(2.14)			(-3.52)				(0.82)			(8.42)	(1.85)
Standardized Solution												
LT_BVA		-0.04	1.34	0.07	**-1.63**	**0.30**	**-0.83**	0.00	**-0.07**	**-0.14**		
StReturn	**0.07**			**-1.64**				0.01			**0.13**	0.01

Table 2.14 The Standardized Estimates of Joint Determinants of Long-Term Debt Ratio and Stock Returns in MIMIC Model

The indicators and attributes are referred to Table 2.3. The bold numbers are significant at 5% level in Table 2.15.

Standardized Factor Loadings in MIMIC Model					
Attributes	**Indicators**	**Market Value Basis**		**Book Value Basis**	
		LT_MVA	StReturn	LT_BVA	StReturn
CapStruc	LT_MVA/ LT_BVA		**0.16**		**0.12**
StReturn	SR	**-0.17**		**-0.08**	
AtStruct	INT_TA	**0.18**		**0.24**	
AtStruct	IGP_TA	**0.19**		**0.22**	
Growth	CE_TA	**-0.06**	**-0.07**	-0.02	**-0.07**
Growth	GTA	-0.02	**0.05**	-0.01	**0.05**
Growth	RD_TA	0.01	-0.02	0.03	-0.02
Industry	IDUM	**-0.13**		**-0.10**	
Unique&Industry	QR	0.01		0.03	
Unique	SE_S	-0.01		**0.05**	
Vol_Rate	CV_ROE	-0.01		0.01	
Vol_Rate	SP_Rate	**0.36**		**0.32**	
Vol_Rate	Z_Score	**-0.40**		**-0.47**	
Profit	OI_S	0.00	-0.01	-0.01	-0.01
Profit	OI_TA	-0.03	**0.07**	**0.22**	0.02
Macroeco	D_GDP	**0.27**		**0.48**	
Macroeco	TPD	**-0.30**		**-0.57**	
Manager	Tenu_Age	0.00		0.00	
Manager	Log_Tenu	0.02		0.02	
Manager	Bonus	**-0.03**		**-0.05**	
Manager	Out_Di r	**-0.03**		0.01	
Manager	Log_Dir	0.00		-0.02	
Value	Mktrf		**0.14**		**0.14**
Value	Smb		0.00		0.00
Value	Hml		**0.12**		**0.11**
Value	Umd		**0.10**		**0.10**
Liquid	PS_Innov		0.05		0.05
Liquid	PS_Level		**-0.08**		**-0.08**
Liquid	PS_Vwf		0.03		0.02

Table 2.15 Estimates of Joint Determinants of Long-Term Debt Ratio and Stock Returns in MIMIC Model and 2SLS approach

The indicators and attributes are referred to Table 2.3. The bold numbers are significant at 5% level where the t-statistics are in parentheses.

(a) Factor Loadings in MIMIC Model – Market Value Basis

Attributes	**Indicators**	**MIMIC model**		**2SLS approach**	
		LT_MVA	StReturn	LT_MVA	StReturn
CapStruc	LT_MVA		**0.16**(5.12)		**0.56**(3.83)
StReturn	SR	**-0.17**(-8.66)		**-0.12**(-5.05)	
AtStruct	INT_TA	**0.95**(10.63)		**0.11**(8.40)	
AtStruct	IGP_TA	**0.51**(9.72)		**0.07**(8.86)	
Growth	CE_TA	**-1.11**(-3.44)	**-1.31**(-3.93)	**-0.22**(-4.23)	**-0.72**(-3.87)
Growth	GTA	-0.06(-1.37)	**0.17**(2.68)	0.00(0.37)	**0.09**(2.66)
Growth	RD_TA	0.70(0.42)	-2.42(-1.06)	-0.09(-0.35)	-1.46(-1.14)
Industry	IDUM	**-0.29**(-9.14)		**-0.04**(-7.70)	
Unique&Industry	QR	0.18(0.98)		0.02(0.65)	
Unique	SE_S	-0.08(-0.73)		0.01(0.66)	
Vol_Rate	CV_ROE	0.00(-0.38)		0.00(-0.23)	
Vol_Rate	SP_Rate	**0.11**(20.90)		**0.02**(15.84)	
Vol_Rate	Z_Score	**-0.20**(-22.49)		**-0.02**(-18.01)	
Profit	OI_S	0.02(0.11)	-0.08(-0.41)	0.02(0.73)	-0.03(-0.28)
Profit	OI_TA	-0.37(-1.19)	**0.97**(2.40)	-0.04(-0.83)	0.39(1.72)
Macroeco	D_GDP	**1.65**(5.09)		**0.39**(5.47)	
Macroeco	TPD	**-0.90**(-5.77)		**-0.20**(-5.86)	
Manager	Tenu_Age	0.02(0.08)		0.00(-0.05)	
Manager	Log_Tenu	0.04(0.64)		0.00(0.38)	
Manager	Bonus	**-0.02**(-2.42)		0.00(-1.50)	
Manager	Out_Di r	**-0.38**(-2.42)		**-0.04**(-1.98)	
Manager	Log_Dir	-0.05(-0.32)		0.00(0.15)	
Value	Mktrf		**3.32**(4.30)		**1.82**(4.22)
Value	Smb		0.17(0.18)		0.11(0.19)
Value	Hml		**5.48**(5.23)		**2.99**(5.10)
Value	Umd		**1.72**(4.02)		**0.95**(3.97)
Liquid	PS_Innov		0.68(1.86)		0.38(1.87)
Liquid	PS_Level		**-1.34**(-2.95)		**-0.77**(-3.02)
Liquid	PS_Vwf		0.84(1.24)		0.45(1.18)

(b) Factor Loadings in MIMIC Model– Book Value Basis

Attributes	**Indicators**	**MIMIC model**		**2SLS approach**	
		LT_BVA	StReturn	LT_BVA	StReturn
CapStruc	LT_BVA		**0.12**(4.18)		**0.45**(3.58)

StReturn	SR	**-0.08**(-3.65)		**-0.06**(-2.25)	
AtStruct	INT_TA	**1.24**(12.53)		**0.16**(11.70)	
AtStruct	IGP_TA	**0.58**(9.95)		**0.08**(9.62)	
Growth	CE_TA	-0.36(-1.00)	**-1.32**(-4.00)	-0.09(-1.55)	**-0.73**(-3.95)
Growth	GTA	-0.04(-0.76)	**0.16**(2.63)	0.00(-0.06)	**0.09**(2.63)
Growth	RD_TA	3.62(1.96)	-3.09(-1.37)	0.40(1.55)	-1.74(-1.38)
Industry	IDUM	**-0.24**(-6.69)		**-0.03**(-6.41)	
Unique&Industry	QR	0.34(1.65)		0.04(1.51)	
Unique	SE_S	**0.34**(2.94)		**0.05**(3.16)	
Vol_Rate	CV_ROE	0.00(0.31)		0.00(0.34)	
Vol_Rate	SP_Rate	**0.10**(16.75)		**0.01**(13.30)	
Vol_Rate	Z_Score	**-0.23**(-23.96)		**-0.03**(-22.3)	
Profit	OI_S	-0.10(-0.59)	-0.06(-0.32)	-0.01(-0.29)	-0.03(-0.26)
Profit	OI_TA	**3.29**(9.51)	0.32(0.90)	**0.44**(9.21)	0.14(0.73)
Macroeco	D_GDP	**2.97**(8.27)		**0.4**8(6.33)	
Macroeco	TPD	**-1.71**(-9.82)		**-0.27**(-7.36)	
Manager	Tenu_Age	0.01(0.06)		0.00(0.01)	
Manager	Log_Tenu	0.06(0.79)		0.01(0.70)	
Manager	Bonus	**-0.03**(-3.51)		**0.00**(-3.11)	
Manager	Out_Di r	0.06(0.33)		0.01(0.35)	
Manager	Log_Dir	-0.20(-1.24)		-0.02(-1.00)	
Value	Mktrf		**3.15**(4.13)		**1.75**(4.11)
Value	Smb		0.15(0.15)		0.09(0.16)
Value	Hml		**5.14**(4.98)		**2.86**(4.94)
Value	Umd		**1.71**(4.05)		**0.9**5(4.01)
Liquid	PS_Innov		0.67(1.84)		0.37(1.84)
Liquid	PS_Level		**-1.38**(-3.07)		**-0.78**(-3.08)
Liquid	PS_Vwf		0.70(1.05)		0.39(1.04)

2.5 Conclusion

This essay utilizes the structure equation modeling (SEM) with CFA approach estimate the impacts of unobservable attributes on capital structure. First, we use the sample period from 2001 to 2012 to test whether the influences of important factors related to accounting information, macroeconomic and manager characters on capital structure consistent with the literature theories. Then, we investigate the joint determinants of capital structure and stock rates of returns where we add two attributes, value and liquidity, to stock returns.

Our empirical work only shows “Profitability” and “Volatility & Financial Rating” are significant attributes on the decision of capital structure. However, all attributes become significant determinants of capital structure and stock returns in either market- or book- value basis. The evidence shows that the interaction of a firm’s leverage and its stock price should be necessarily considered in capital structure research. Besides the proof of trade-off between financial distress and agency costs in previous theories, our results confirm the endogenous supply relationship between public and private debts. Moreover, the interrelation between leverage ratios and stock returns verifies the signal theory under the assumption of asymmetric information between managers and investors. Only significantly negative influence of stock returns on market-value based leverage ratios supports Welch’s (2004) statement. That is, although stock price is of importance in dynamic capital structure, a firm would not readjust its capital structure to response the changes in stock prices.

Finally, we do robustness check by using MIMIC model and the two-stage, least square (2SLS) estimating method. The results show that the factor loadings are under-estimated in 2SLS approach. Thus, we claim that MIMIC model performs better because it can solve measurement error-in-variable problem. However, MIMIC model cannot well identify the influences of factors on long-term leverage decisions in accordance with capital structure theories. According to comparison of the results in MIMIC and SEM with CFA models, the setting of latent attributes is necessary to clarify and confirm theories in capital structure. Therefore, I would suggest using structural equation modeling (SEM) with confirmatory factor analysis (CFA) to capture the appropriate factors of firms' leverage decisions.

In future research, the personal taxes and the differences in beliefs between the manager and outside investors can be taken account into investigation of joint determinants of capital structure and stock return (Lin and Flannery, 2013; Yang, 2013).

Appendix 2.A: Codes of Structure Equation Modeling (SEM) in LISREL System

(a) Determinants of Capital Structure by SEM with CFA

TI SEM Joint Determinants of Capital Structure and Stock Rate of Return -Only Capital Structure (Book value)
Observed Variables: V1 V2 V3 V4 V5 V6 V7 V8 V8_1 V9 V10 V11_3 V12 V14 V15 V16_1 V17_1 V18_1 V19_1 V20_1 V21_1 V23 V24 V25 V26 V27 V30 V31 V32 V33 V35_2 V36 V37 V48 V49 V50
Raw data from file Only_capital.psf

sample size = 3118
Latent Variables: AtStruct Nd_tax Growth Uni_Ind Unique Industry Size Vol_Rate Profit Macroeco Manager CapStruc
Relationships:
V1 V2 =AtStruct
V3 V4 V5=Nd_tax
V6 V7 V23 =Growth
V9 V10 V11_3 = Uni_Ind
V12 V7 =Size
V50 V25 V48 = Vol_Rate
V15 V14 = Profit
V32 V33 V36 V37 V12 = Manager
V27 V31 =Macroeco
V16_1 V17_1 V18_1 =CapStruc

Paths:

AtStruct Nd_tax Growth Uni_Ind Vol_Rate Profit Macroeco Manager Size-> CapStruc

Path Diagram
LISREL Output:ND=4 SC SE SS ME=ML TV AL EF RS AD=off

End of Problem

(b) Joint Determinants of Capital Structure and Stock Returns by SEM with CFA

```
TI SEM Joint Determinants of Capital Structure and Stock Rate of Return -Capital Structure and Stock return
Observed Variables:   NV1-NV45
Raw data from File new_variable_LISREL.psf
sample size = 3118
Latent Variables: AtStruct Unique   Growth   Industry   Vol&Rate    Profit Macroeco Manager Liquid Value    StReturn CapStruc
! labal variable only can be read the first 8 character
Relationships:

NV2    NV1         = AtStruct
!NV21     =1.0*Unique
NV10 NV9 =Unique
NV11    NV10      = Industry
NV21    NV6    =Growth
NV7      =1.0*Growth
NV37 NV38 NV39 NV40 =Value
NV34 NV35 NV36    =Liquid
NV14 NV13        =Profit
NV28 NV29 NV32 NV33 NV31    =    Manager
NV45    = 1.0*Vol&Rate
NV43 NV23 =Vol&Rate
NV25 NV27 NV37=Macroeco
NV41 = 1.0*StReturn
NV18 - NV20 = CapStruc
set error of NV41 to 0
Paths:

CapStruc     Value    Liquid     Growth Profit -> StReturn
Vol&Rate        StReturn    Growth  Profit  Macroeco    Manager  AtStruct    Industry Unique-> apStruc
Path Diagram
LISREL Output:ND=4 SC SE SS ME=ML TV AL EF RS AD=off
End of Problem
```

Appendix 2.B: Codes of MIMIC Model in LISREL System

(a) Determinants of Capital Structure by MIMIC Model

```
Raw Data from file MIMICOnly_capital.psf
Sample Size = 3118
Latent Variables    CapStruc
Relationships
LT_BVA    = CapStruc
ST_BVA    = CapStruc
C_BVA= CapStruc
CapStruc = INT_TA   SE_S IGP_TA   ITC_TA   D_TA NDT_TA CE_TA GTA QR
IDUM LnS OI_S OI_TA
CapStruc = RD_A CV_ROE D_GDP TPD Tenu_age log_Tenu Out_Dir log_Dir
SP_Rate
CapStruc = Z_Score INT_TA IGP_TA ITC_TA SE_S
Path Diagram
LISREL Output:ND=4 SC SE SS ME=ML TV AL EF RS AD=off
End of Problem
```

(b) Joint Determinants of Capital Structure and Stock Returns by MIMIC Model

```
Raw Data from file new_variable_LISREL.psf
Sample Size = 3118
Latent Variables    CapStruc StReturn
Relationships
NV41 = StReturn
NV15 = CapStruc
CapStruc = StReturn
StReturn = CapStruc
CapStruc = NV1 NV2 NV6 NV7 NV21 NV9 NV10 NV11 NV13
CapStruc = NV14 NV23 NV43 NV45 NV25 NV27 NV28 NV29 NV31
CapStruc = NV32 NV33
StReturn = NV6 NV7 NV21 NV13 NV14 NV34 NV35 NV36 NV37
StReturn = NV38 NV39 NV40
Set Error Variance of NV41 To 0.0
Set Error Variance of NV15 To 0.0
Path Diagram
LISREL Output:ND=4 SC SE SS ME=ML TV AL EF RS AD=off
End of Problem
```

CHAPTER 3

Pricing Fair Deposit Insurance: Structural Model Approach

3.1 Introduction

The primary function of a bank is to grant loans to borrowers and receive deposits from the public. The banks in hence are not only subject to both default and market risks on the funds they lends, but also to withdrawal risk on the funds they borrowers (O'Hara, 1983). Diamond and Dybig (1983) shows that banks as financial intermediations offer the demand deposit contracts to increase liquidity by the transformation of illiquid assets into liquid liabilities. But the deposit contracts may cause real economic damages. During a bank run, depositors panic and withdraw their deposits immediately because they expect the bank to fail. Therefore, even a healthy bank can be bankrupt because of the panics of depositors. In this situation, the bank recalls loans, terminates its investment projects and then cause real economic damages. Due to maintain the confidence of depositors in banks' operations, Diamond and Dybig (1983) indicate that the deposit insurance offered from the government can eliminate the problem of bank runs. Gorton and Pennacchi (1990) also show that the insured deposit contracts attract uninformed investors who suffer from trading losses associated with information asymmetries. However, the deposit insurance may bring moral hazard problems. Laeven(2002) argues that depositors have less incentives to exert and monitor the behavior of banks, and thus banks can tacitly take excessive risks. VanHoose (2007) asserts that the fair pricing of deposit insurance can alleviate the moral hazard problems. LeRoy and Singhania (2013), however, conclude that there is no way to eliminate the moral hazard distortion implied by deposit insurance. Gan and Wang (2013) state that the necessity and significance of deposit insurance varies across countries and find that low income countries provide more insurance protection.

Since subprime mortgage crises broke out in August, 2007, pricing fair deposit insurance premium became an important issue again because the panic of depositors arose from many financial institutions with financial and liquidity distress. The Federal Deposit Insurance Corporation (FDIC) should adjust the proper deposit insurance premium as the trade-off that offsets the costs of bailout plans and the costs of taking over the deposit account business and partial debt once the financial institutions are announced bankruptcies. Based on the critical role that insurance deposit risk plays in financial institutions, the purpose of this project is to investigate the pricing fair value of deposit insurance.

Regard to the deposit insurance, the insurer must be the government or one of its agencies such as the FDIC to make the insured deposits as the risk free assets. Deposit insurance guarantees that the promised return will be paid to all who withdraw deposits, thus it imposes costs on the insurer. Hence an insurer such as the FDIC will receive the deposit insurance premium as the compensation of the loss of deposit insurance. Blocher, Seale and Vilim (2003) discuss that the different level of insurance premium received from banks is based on a risk-based assessment system established by the Federal deposit insurance corporation (the FDIC). Begin Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991, the first risk-related premium system is categorized into nine situations which depend on capital levels and supervisory ratings[1] (FDIC, 2006). Blocher et al. (2003) shows that the assessment rates of deposit insurance fluctuated over time in accordance with economic situations. Due to large amounts of financial institutions' bankruptcies in subprime mortgage crisis, the FDIC lost enormous deposit insurance fund to take over bankrupt banks and protect the wealth of depositors. Therefore, FDIC increased the deposit insurance premium to response the financial tsunami. This evidence shows that pricing deposit insurance is of importance especially in financial crisis and should be adjusted in accordance with risk-based scheme (Horvitz,

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[1] The supervisory ratings are generally based on CAMELS rating. The CAMELS rating is an acronym for component ratings assigned in a bank examination: **C**apital, **A**sset, **M**anagement, **E**arnings, **L**iquidity and **S**ensitivity to market risk. Each component elements has a rating from 1(the best) to 5(the worst), and the overall composite rating, CAMELS rating, based on these component ratings is then assigned to the bank.

1983; Kane 1986). Karas et al. (2013) use Russia banks data to do empirical study and shows deposit insurance in the presence of a financial crisis can mute depositors' panic. Policymaker thereby should be cautioned with respect to the effect of deposit insurance in financial crisis.

Several models for assessing deposit insurance premium can be grouped into three main categories: bank failure prediction approach, reduced-form approach, and a structural approach. The advantage of the bank failure prediction approach is to determine what variables should be used in a risk-based deposit insurance system (Sinkey, 1975; Avery, Hanweck, and Kwast, 1985). Under this framework, the probability of bank failure is estimated by the logit model. Hwang, Lee and Liaw (1997) utilize logistic regressions to identify the financial ratios significantly contributed to bank failures. They find the financial ratios related to equity capital, profitability and liquidity have significantly influences on the probability of bank failure. The fair deposit insurance premium then can be calculated by the probability of failure times the liquidation costs. Thomson (1991) indicates that the ratio of non-deposit liability to cash and investment securities significantly affect the bank failure. However, Thomson (1991) states that the logit estimation is not sensitive to uneven sampling frequencies problem. Thomson (1992) applies two-step logit regressions to modeling the bank regulator's closure decision. The first step is the regression of bank's market value on accounting data, and the second step is logistic regression to predict bank failure based on the estimated market value of bank in first step and the constraints on the FDIC's ability to close insolvent banks.

With regard to reduced-form methodology, Duffie Jarrow, Purnanandam and Yang (2003) proposed the approach based on reduced-form to price deposit insurance and claimed this approach need not treat the exact form of the insurance contract because it does not depend on the liability structure or auditing process of the bank. It is difficult to capture regulations of an insurance contract within the bank's capital structure, especially for banks that are not publicly traded (Falkenheim and Pennacchi, 2003). Duffie et al. (2003) points out that the fair-market deposit insurance rates can be the product of bank's short-term credit spread and the ratio of the insurer's expected loss at failure per dollar of assessed deposit to the bond investors' expected loss at failure per dollar of principal. Although the reduced-form model can solve the influence of the deposit insurance contract on evaluation of the deposit insurance premium, there are too many parameters to be estimated that probably influence the currency of results.

The most studies estimate fair-market FDIC insurance premium by a structural approach, which typically bases the firm's asset and the volatility of its asset on its equity price (Black and Scholes, 1973; Black and Cox, 1976; Merton, 1977, 1978; Leland, 1994;

Anderson and Sundaresan, 2000; Bloecher et al. 2003; Brockman and Turle, 2003; Episcopos, 2008). Merton (1977, 1978) first gives the insight into the relationship between the deposit insurance and put option. If bank assets cannot meet the amount of deposits, the bank is insolvent and receives nothing. All remainders of assets belong to debt holders, that is, depositors. When insolvency of bank occurs, the insurer of deposit insurance should pay the difference of the bank assets and the deposits to depositors. Therefore, the contract of deposit insurance can be viewed as a put option written on bank assets with the strike price equal to deposits. Marcus and Shaked (1984) first implement Merton's model to price insurance premium with constant proportional dividends allowed. Their empirical results show the overpriced deposit insurance premiums charged by the FDIC.

In the most recent literature, the deposit insurance premium is evaluated by barrier option models (Brockman and Turle, 2003; Episcopos, 2008). However, the barrier option model used in previous studies neglects the restrictions of the deposit insurance contacts. In hence, the structural model approach in terms of the barrier option model and the Stair Tree model is proposed to deal with bankruptcy costs, the limited indemnification for depositors, discretely monitoring banks' situations and the adjustment of the insurance premium in different financial institution based on a risk-based assessment system. We are then able to build a fair insurance premium system and calculate the reasonable implied barrier critical points to determine whether FDIC's supervisory policy is strict or forbearing.

This paper is organized as follows. In section 3.2, a structural model in terms of barrier option model and Stair Tree model is illustrated to in accordance with the restrictions of deposit insurance contracts and bankruptcy costs. The results from the simulation analysis are discussed in the subsequent section. Finally, section 3.4 includes the conclusion and the future research.

3.2 The Methodology

At the beginning, the BT model shows the classical structural model, barrier option closed form, which views the value of equity a down-and-out call (DOC):

$$\mathrm{DOC}(H,X) = VN(a) - Xe^{-rT}N\left(a - \sigma\sqrt{T}\right)$$

$$-V\left(\frac{H}{V}\right)^{2\eta}N(b) + Xe^{-rT}\left(\frac{H}{V}\right)^{2\eta-2}N\left(b - \sigma\sqrt{T}\right) \qquad (3.1)$$

V is the current market value of bank asset, X is the promised payment to depositors in T years, H is closure barrier, N is the standard normal cumulative distribution function, and r is the risk free rate of interest.

Where

$$a = \begin{cases} \dfrac{\ln(V/X) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & X \geq H \\ \dfrac{\ln(V/H) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & X < H \end{cases}$$

$$b = \begin{cases} \dfrac{\ln(H^2/VX) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & X \geq H \\ \dfrac{\ln(H/V) + (r + \sigma^2/2)T}{\sigma\sqrt{T}} & X < H \end{cases}$$

$$\eta = r/\sigma^2 + 1/2$$

According to capture bank's equity by DOC, the residual bank's asset would be equal to

$$V - DOC(H, X) = V - C(X) + DIC(H, X)$$

$$= Xe^{-rT} - P(X) + DIC(H, X) \qquad (3.2)$$

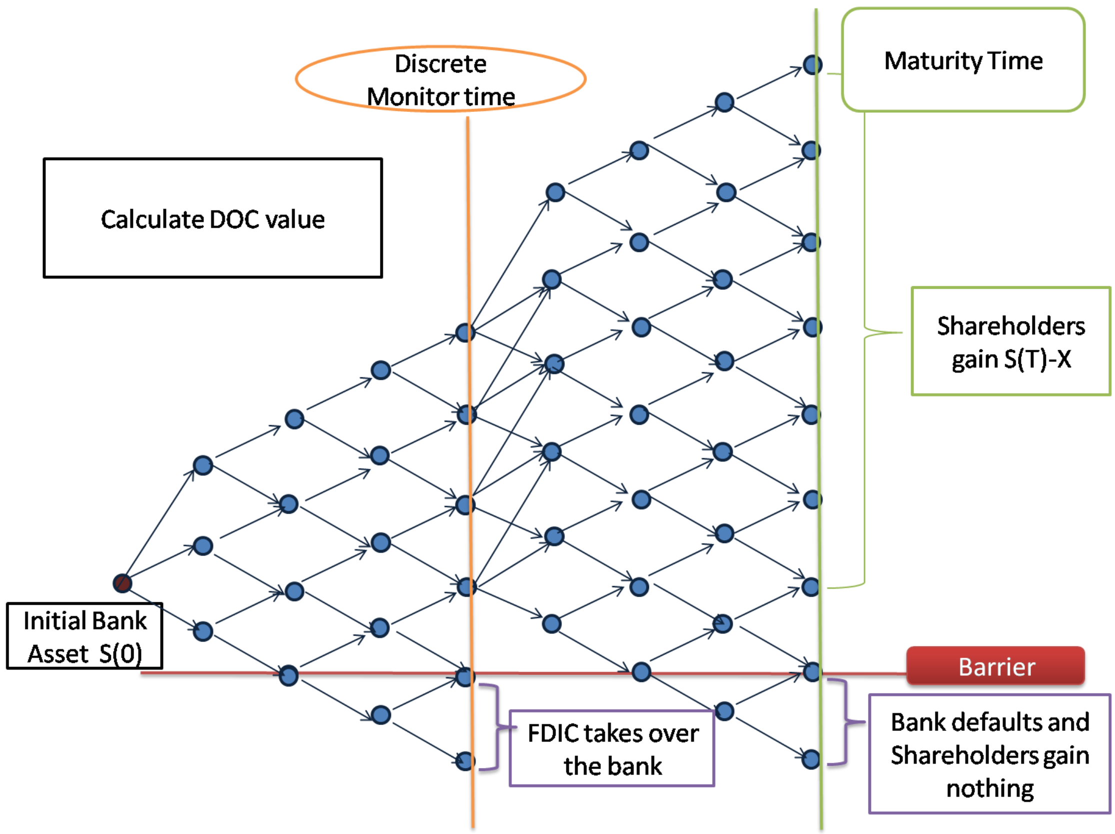
Where C(X) is a European call option and P(X) is a European put with exercise price X; DIC (H, X) is a down-and-in call (DIC) with barrier H. The first term is the present value for the insurants (the depositors) under the full insurance; the last two term is the total value of FDIC which profits DIC(H,X) by taking over the failure bank but loses P(X) due to responsibility of insurance payment for depositors at maturity date.

However, BT model is difficult to catch up all real extent of bank regulation, thus simplifying assumptions, for example, no dividends, no tax, no bankruptcy cost, no insurance premium, constant volatility and continuous monitor. For example, the contract of the FDIC deposit insurance is determined quarterly. According to the quarterly financial statement of the financial institutions, the FDIC will receive their insurance premium by assessing the level of risk-based assessment system. Therefore, the continuous assumption of the structural model doesn't seem suitable for the evaluation of deposit insurances. Another example of the contract's limitation elaborated in a practical provision is that the FDIC protects the depositors to a certain extent that the deposit insurances don't cover other financial products when a bankruptcy occurs.

Taking the aforementioned into consideration, we provide a novel discretely structural model based on the Stair Tree model and the concept of BT model to price the Federal deposit insurance in a barrier option framework. In other words, our extended structural approach can modify BT model by adding the regulation limitations. This model not only allows the adjustment of the insurance premium in different financial institution based on a risk-based assessment system, but also takes account of the loss from bankruptcy cost and the limited indemnification for depositors. We are then able to build a fair insurance premium system and calculate the reasonable implied barrier critical points to determine whether FDIC's supervisory policy is strict or forbearing.

First of all, the bank asset is only actually monitored discretely at the regular declaration of financial report and significant announcements. Therefore, we introduce the concept of the Stair Tree (Dai, 2009) to monitor the bank asset at the auditing time and to deal with the situations that the bank fails when its asset meets the closure barrier. A sample of extended structural approach illustrates the equity value (DOC) in Figure 3.1.

Figure 3.1 Evaluation of Bank's Equity Value by Structural Approach



The structure of the tree and the probability of the branches to the nodes are equal to the Stair Tree (Dai, 2009). In Figure 3.1, initial bank asset S (0) is the beginning node of the tree, connecting with a trinomial tree and then joining to a series binomial tree until next discrete monitor time. At monitor time, FDIC would take over the bank if the bank asset under the barrier, thus the shareholders holds nothing when bank failures. At the maturity date for promised payment to insurance depositors, shareholders gain residual value of bank asset after paying the deposits.

Episocopos (2008) extends the BT model via adding constant bankruptcy cost and insurance premium; however, it is not negligible that bankruptcy cost and insurance premium depend on the asset's value and barrier. The bankruptcy cost incurs when banks default. In the receivership, the FDIC only gains the proportion of the bank's asset at the time of its closure because of the cost in liquidation process. Moreover, in insurance provision, the FDIC stipulates that insured financial institutions pay insurance premium quarterly to protect the wealth of depositors' accounts. In reality, FDIC can receive insurance premium until banks failure. Therefore, the value of insurance premium is dependent on bank's asset and closure barrier. Thus, the FDIC value is given by

$$\mathrm{DIC}(\mathrm{H},\mathrm{X}) + \mathrm{IP}(\mathrm{H}) - (\mathrm{P}(\mathrm{X}) + \mathrm{BC}(\mathrm{H},\mathrm{X})) \qquad (3.3)$$

BC (H, X) is bankruptcy cost which depends on the bank asset and the closure barrier H; IP (H) means the insurance premium paid when bank's asset above barrier.

More discussions about supervisory policy, fair insurance premium and bankruptcy cost are as follows.

The previous studies investigate the assumption of bankruptcy criteria during the period of banks' auditing time. Under the prompt corrective action (PCA) and closure rules, that is, bankruptcy occurring when banks fail to meet minimum levels of capital adequacy, the Federal Deposit Insurance Corporation (FDIC) can take charge of the banks and be responsible for its liabilities. However, according to the forbearance policy, the defaulted bank can be allowed to operate under the supervision. With regard to closure policy, forbearance is granting the bank time to return to solvency before it is closed. Ronn and Verma (1986) consider that the insurer would infuse funds to the bank whose asset is below the deposit liability under the forbearing range and then the bank would not be liquidated immediately. Take account of the forbearing policy into the framework of option pricing model, Ronn and Verma (1986) state that the deposit insurance premiums are underestimated. Allen and Saunders (1993) indicate that the value of the deposit insurance can be viewed as the value of a callable perpetual American put option under the consideration of forbearance policy. They show that the deposit insurance premium increases with loose closure policy. Lee, Lee and Yu (2005) propose the formula for fair deposit insurance and state the fair value of deposit insurance decreases with the strict policy, which is consistent with the results of Allen and Saunders (1993).

Since FDIC has the power to set closure policy which makes the deposit insurance contract expire when the bank asset knock the regulatory closure point, the deposit insurance could be evaluated as a down and out barrier option that the barrier can be viewed as the regulatory closure rule. Brockman and Turtle (2003) state that the valuation of the corporate security can be viewed as a path-dependent, barrier option model (BT model). Episcopos (2008) utilize the BT model to price the deposit insurance premium. In bank regulation, the value of equity is given by a down-and-out call option with the barrier as a critical point of failure. In contrast with equity, the FDICs contingent asset value can be viewed as a down-and-in call option and the FDIC obligation to pay liabilities, generally deposits, can be viewed as an European put option on written on the asset of bank. Hwang, Shie, Wang and Lin (2009) modify the barrier option model to price the deposit insurance by adding the bankruptcy cost as a function of the bank asset return volatility. They consider the bankruptcy cost explicitly incorporated into the pricing framework of deposit insurance and make barrier option approach close to realistic closure policies and regulatory forbearance.

In the basic FDIC deposit insurance contract, the FDIC collects a deposit insurance premium from each surviving insured financial institution at the beginning of each quarter. Therefore, it is possible for the FDIC to receive the premium at this quarter but to take over the failure banks at next quarter with no the deposit insurance premium paid anymore. On the other hand, the assumption is not realistic if structural models assume continuous monitoring because the accounting information of financial institution only can be observed quarterly. Besides, in a practical provision, though the FDIC would cover insurance funds in many kinds of the deposit accounts, including checking and savings accounts, money market deposit accounts and certificates of deposit (CDs), the FDIC does not cover other financial products such as stocks, bonds or securities and only protects each depositor with limitation[2].

The purpose of this paper is to combine all above real provisions of the FDIC contract and to take account of cover limitation of insurance for depositors. Here we illustrate a simple sample of extended structural approach in Figure 3.2 to implement FDIC value in reality, concluding insurance premium and bankruptcy cost.

The assumption of insurance premium is paid quarterly as the star sign at the monitor time and the initial node in Figure 3.2. When bank asset fails to closure barrier, the FDIC would take over the bank; therefore the value of bank's shareholders transfers to FDIC. At this moment, the indirect bankruptcy cost occurs and the bank asset drops suddenly. At the maturity time, FDIC would gain the profit if the bank asset is enough to

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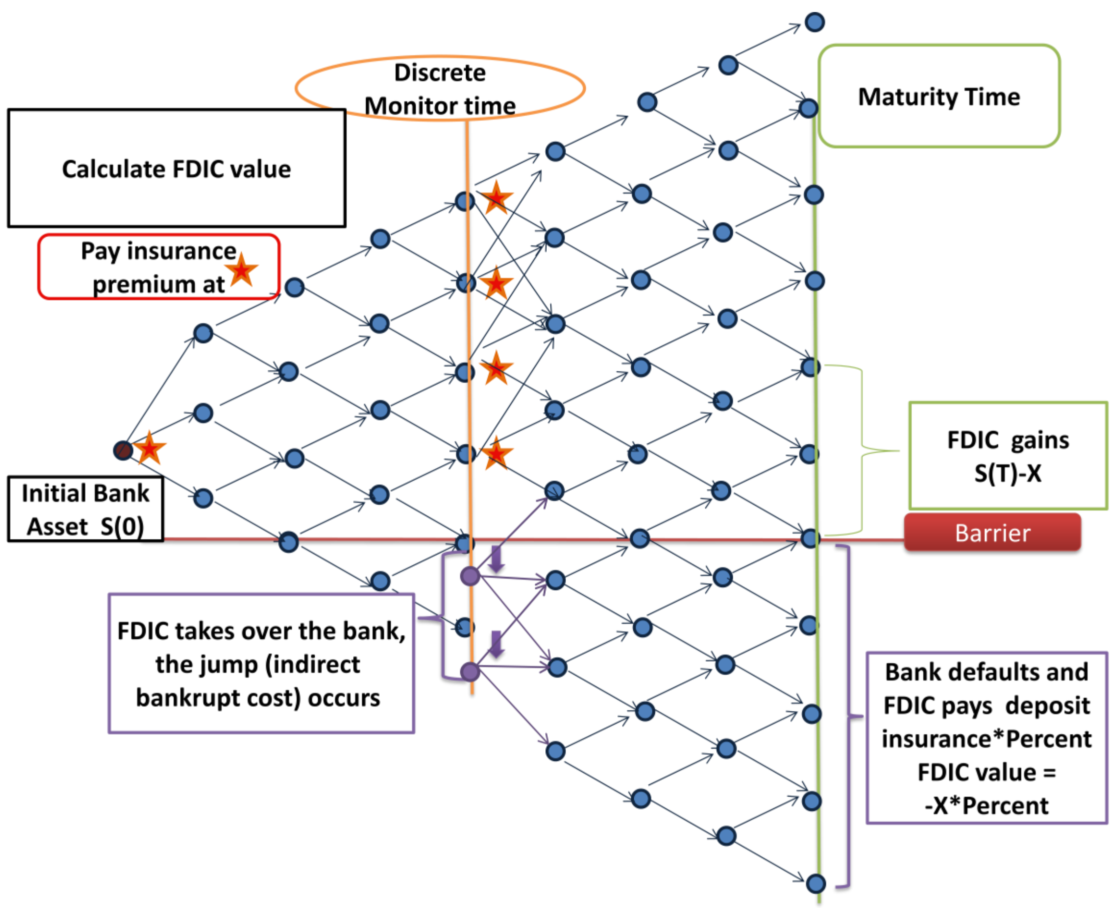
[2] Current deposit insurance coverage limit increases from \$100,000 to \$250,000 per depositor through December 31, 2009 but unlimited coverage for non-interest bearing transaction accounts. The insurance coverage limit will return to standard coverage \$100,000 for all deposit categories on January 1, 2010.

pay deposits; otherwise, FDIC would loss the insurance fund because of the proportion of promised payment to deposits insurance due to limited coverage regulation.

Figure 3.2 Estimate FDIC Value by Structural Approach



Furthermore, the future research is to find the implied barrier as the optimal barrier that does not make FDIC gain or loss on average, that is:

$$P(X) = DIC(H, X) \tag{3.4}$$

If we take account of bankruptcy and insurance premium, the determination of implied barrier follows the equation:

$$\mathrm{P(X) + BC(H, X) = DIC(H, X) + IP(H)} \qquad (3.5)$$

More discussions about supervisory policy, fair insurance premium and bankruptcy cost are in the future.

3.3 Simulation Results

In this section, we first present the accuracy of our model by the parameters analysis consistent with the results in BT model. Secondly, moral hazard problem must be considered due to the relationship between the FDIC value and the level of barrier.

3.3.1 Parameters analysis

Figure 3.3 and Figure 3.4 show the property of convergence in our extended structural model can accurately generate the value of barrier option in bank capital regulation (Episcopos, 2008).

Compared with the same parameters in Table 3.1, the value of down-and-out call options in our numerical approach converges on 15.885 (computed by linear regression) which close to the value of its closed-form formula (15.8853); the convergent value

0.5508 of failure probability of banks is also the same as its closed-form value 0.5508 calculated by BT model.

Figure 3.3 Evaluation of An Down-and-Out Call Option

Parameters are the same as general case in Table 3.4.

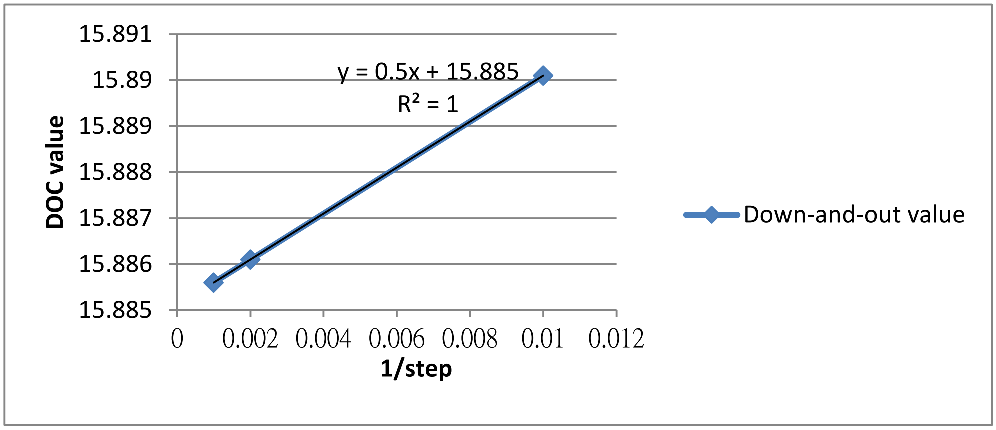
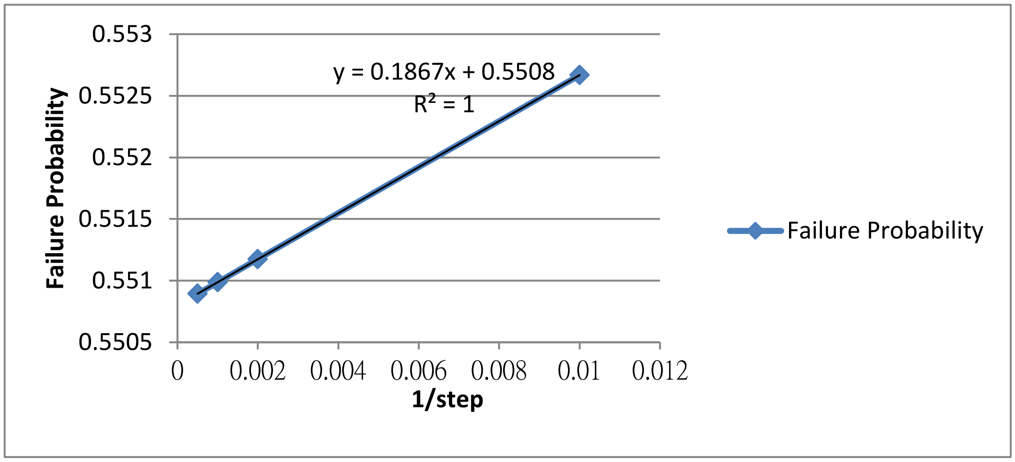


Figure 3.4 Estimation of a Bank's Failure Probability

Parameters are the same as general case in Table 3.4 except Interest rate r=0.05.



The parameters analysis is summarized in Table 3.1, concluding our numerical results and our benchmark, BT model. It is obvious that the extended structural approach exactly illustrates the value of closed-form of BT model. There is an interesting argument for elimination of moral hazard effect in Table 3.1 that the FDIC value accrues as asset volatility increasing. Episcopos (2008) also explains the negative effect of increase of volatility on actual equity value (down-and-out call option), thus claiming that the rise in “total equity” value would transform from the shareholders to FDIC. However, Episcopos (2008) doesn’t take account of default risk for FDIC. The total value of FDIC is combined contingent asset (down-and-in option) with promised payment for depositors (European put option). If the speed of transformation from shareholders’ equity is slow, the FDICs asset value cannot handle the payment of deposits but the shareholder still obtain a part of asset value; therefore moral hazard still exists.

Table 3.1 Comparison of Closed-Form Solution and Structural Approach

*General means the original parameter values, unless stated otherwise: Current market value of bank asset V=$100, promised payment to depositors X=$90, Regulation barrier for closure rule H=$90, Asset volatility σ =0.2, Interest rate r=0.1, Regulation horizon T= 1 year.

Implement BT model by extended structural approach					Closed-Form Value of BT model				
parameters		Down-and-out call (Equity value)	failure prob.	Down-and-in call -European put (FDIC value)	down-and-out call (Equity value)	failure prob.	Down-and-in call -European put (FDIC value)	European call	European put
General*		15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
V	95	8.756	0.6956	4.8085	8.7559	0.6956	4.8087	15.7856	2.2209
	100	15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
	105	22.083	0.3127	1.4819	22.0829	0.3127	1.4817	24.4573	0.8927
	110	27.751	0.2027	0.8136	27.7510	0.2027	0.8136	29.1132	0.5485
H	80	19.661	0.2163	-1.0964	19.6610	0.2163	-1.0964	19.9886	1.4239
	85	18.638	0.3036	-0.0734	18.6379	0.3036	-0.0733	19.9886	1.4239
	90	15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
	95	10.121	0.7095	8.4432	10.1213	0.7095	8.4433	19.9886	1.4239
σ	0.1	18.222	0.0845	0.3425	18.2221	0.0845	0.3425	18.6309	0.0662
	0.2	15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
	0.3	14.186	0.6775	4.3786	14.1862	0.6775	4.3784	22.5101	3.9454
	0.4	13.156	0.7817	5.4085	13.1559	0.7817	5.4087	25.4849	6.9203
T	0.5	13.487	0.3633	0.9023	13.4871	0.3633	0.9022	15.2883	0.8990
	1.0	15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
	1.5	17.873	0.5225	4.6627	17.8730	0.5225	4.6633	24.1838	1.6475
	2.0	19.616	0.5524	6.6985	19.6168	0.5524	6.6974	28.0373	1.7230
r	0.05	12.787	0.5508	1.6022	12.7872	0.5508	1.6022	16.6994	2.3101
	0.10	15.885	0.4720	2.6795	15.8853	0.4720	2.6794	19.9886	1.4239
	0.15	19.223	0.3965	3.3136	19.2231	0.3964	3.3132	23.3752	0.8389
	0.20	22.720	0.3269	3.5944	22.7208	0.3269	3.5934	26.7857	0.4715

3.3.2 Moral Hazard Problem

Figure 3.5 and Figure 3.6 show the existence of moral hazard when the supervisory policy is of forbearance. Figure 3.6, as a part of the cross-section of Figure 3.5, describes that the FDIC value declines and moral hazard happen under lower barrier when asset risk increases. In contrast, under higher barrier, the increase of FDIC value follows the raise of asset risk, that is, the strict supervision policy would diminish moral hazard.

Figure 3.5 Plot of FDIC Value versus Barrier and Volatility

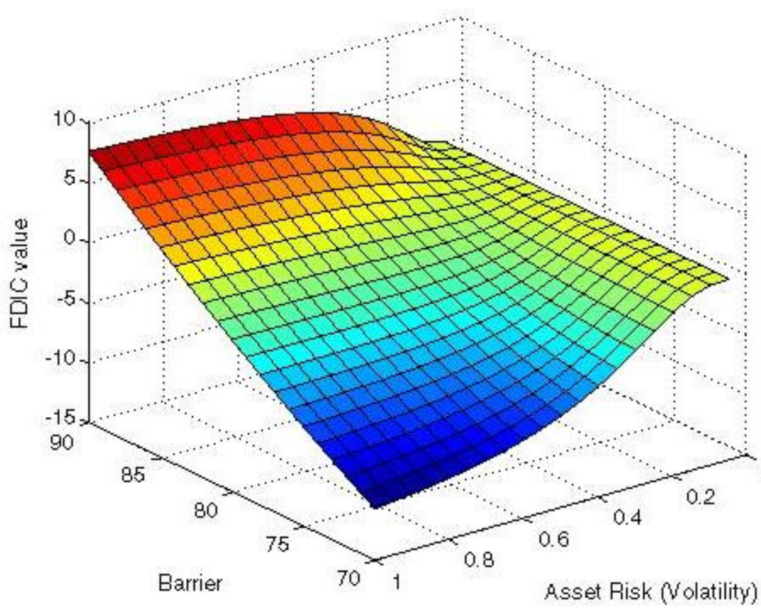
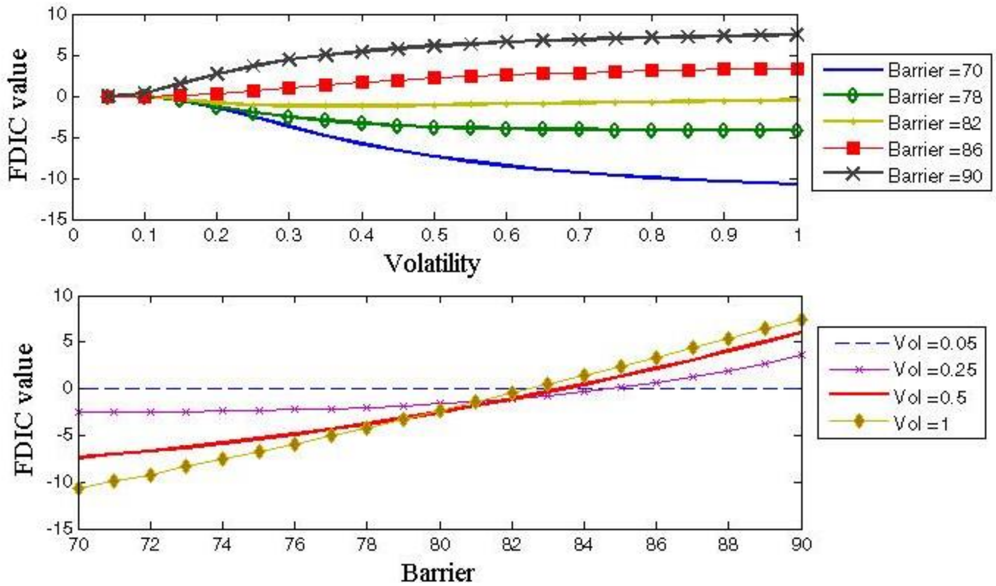


Figure 3.6 Impacts of Volatility and Barrier on FDIC Value



3.4 Conclusion

This chapter utilizes the structural model approach to price deposit insurance premium and to discuss the relationship between the forbearance policy and the closure regulation. We combine the barrier option framework with stair tree approach in which the bankruptcy cost is set as the proportion of the bank assets and the limit insurance coverage is viewed as the percentage of bank deposits. Our structural model not only deals with practical provisions and restrictions of insurance contracts in reality but also monitors financial institutions reasonably by their financial statement or accounting information.

First, the numerical results confirm the accuracy of our model and show that BT model is the special case of our structural model approach. Secondly, the interaction between closure policy and bankruptcy is incorporated in our model and the results manifest the important role of bankrupt costs in FDIC supervision. Even though the increase in regulatory barrier will lead to transfer the wealth from stockholders to the insurer, the indirectly bankrupt costs will offset this benefit. Therefore, FDIC would prefer to take forbearance closure policy to protect insurance fund from loss of bankrupt costs. Finally, the contribution of this chapter is expected to provide the suggestion for supervisory agencies how to exactly determine a barrier as a policy of taking over financial institutions. The closure policy for capital regulation can be adjusted by the setting of insurance premium and the impacts of bankruptcy cost. An appropriate deposit insurance premium can alleviate potential moral hazard problems caused by a forbearance policy.

In this essay, we cannot get the information of deposit premium for financial institutions. Therefore, we cannot test whether the current deposit insurance premium is overpriced or underpriced. For the future research, if we can obtain real data to find the fair deposit insurance premium and proper closure barrier, then we can confirm our presumption. The results are anticipated to consist with our supposition that the forbearance policy is better than restrict policy for FDIC.

CHAPTER 4

Forecasting Implied Volatilities for Options on Index Futures: Time Series and Cross-Sectional Analysis versus Constant Elasticity of Variance (CEV) Model

4.1 Introduction

Forecasting volatility is crucial to risk management and financial decision for future uncertainty. Previous studies have found that the volatility changes are predictable (Engle, 1982; Pagan and Schwert, 1990; Harvey and Whaley, 1991, 1992a, 1992b; Day and Lewis, 1992; Fleming, 1998). In perfectly frictionless and rational markets, options and their underlying assets should simultaneously and properly change prices to reflect new information. Otherwise, costless arbitrage profits would happen in portfolios combined by options and their underlying assets. However, prices in security and option markets may differently and inconsistently change to respond to news because transaction costs vary cross financial markets (Phillips and Smith, 1980). Based on trading cost hypothesis, the market with the lowest trading costs would quickly respond to new information. The price changes of options on index and options on index futures lead price changes in the index stocks because trading costs of index option markets are lower than the cost of trading an equivalent stock portfolio. (Fleming, Ostdiek, and Whaley, 1996). Therefore, the dynamic behavior of market volatility can be captured by forecasting implied volatilities in index option markets (Dumas, Fleming, and Whaley, 1998; Harvey and Whaley, 1992a).

In this paper, we use option prices instead of relying on the past behavior of asset prices to infer volatility expectations of underlying assets. The derivation and use of the implied volatility (called IV hereafter) for an option as originated by Latane and Rendleman (1976) has become a widely used methodology for variance estimation. The IV derived from option prices depends on the assumptions of option valuation formula. For example, IV in Black-Scholes-Merton option pricing model (called BSM hereafter) tends to differ across exercise price and times to maturity, which violates the assumption of the constant volatility of underlying asset in model. The fact that there are as many BSM IV estimates for an underlying asset as there are options on it, as well as the observable non-constant nature, has attracted considerable attention from practitioner and theoretician alike.

For the academician, previous studies have been proposed to capture the characteristics of implied volatility by either using statistical models or stochastic diffusion process approaches. Statistical models such as autoregressive conditional heteroskedasticity (ARCH) models (Engle, 1982) and GARCH model (Day and Lewis,

1992) have been used to capture time series nature of IV dynamic behavior. On the other hand, stochastic process models such as constant-elasticity-of-variance (CEV) model (Cox, 1975; Cox and Ross, 1976; Beckers, 1980; Chen and Lee, 1993; DelBaen and Sirakawa, 2002; Emanuel and MacBeth, 1982; MacBeth and Merville, 1980; Hsu, Lin and Lee, 2008; Schroder, 1989; Singh and Ahmad, 2011; Pun and Wong, 2013; Larguinho et al., 2013) and stochastic volatility models (Hull and White, 1987; Heston, 1993; Scott, 1997; Lewis, 2000; Lee, 2001; Jones, 2003; Medvedev and Scaillet, 2007) incorporate the interactive behaviors of an asset and its volatilities in option pricing model. From the practitioner's point of view, the implementation and computational costs are the principal criteria of selecting option pricing models to estimate IV. Therefore, we use cross-sectional time series regression and CEV model to forecast IV with less computational costs.

The two alternative approaches used in this paper give different perspective of estimating IV. The cross-sectional time series analysis focuses on the dynamic behavior of volatility in each option contracts. The predicted IV obtained from the time series model is the estimated conditional volatility based on the information of IV extracted from BSM. Although the estimated IVs in a time series model vary across option contracts, this kind of model can seize the specification of time-vary characteristic that links ex post volatility to ex ante volatility for each option contract. In addition, cross-sectional analysis can capture other trading behaviors such as week effect and in/out of the money effect. On the other hand, CEV model generalizes implied volatility surface as a function of asset price. It can reduce more computational and implementation costs rather than the complex models such as jump-diffusion stochastic volatility models because there is only one more variable compared with BSM. Although the constant estimated IV for each trading day may cause low forecast power of whole option contacts, it is more reasonable that the IVs of underlying assets are independent of different strike prices and times to expiration.

The focuses of this paper are (1) to improve the ability to forecast the IV by cross-sectional time series analysis and CEV model, (2) to explain the significance of variables in each approaches, (3) compare prediction power of these two alternative methods, and (4) test market efficiency by building an arbitrage trading strategy. If volatility changes are predictable by using cross-sectional time series analysis and CEV model, the prediction power of these two methods can draw specific implications as to how BSM might be misspecified. If the abnormal returns are impossible in a trading strategy which takes transaction costs into account, we would claim that option markets are efficient.

The structure of this paper is as follows. Section 4.2 reviews previous option pricing models and related empirical works concerning the viability and use of these models. The data and methodology are described in Section 4.3. Section 4.4 shows the empirical analysis and devise the trading and hedging strategies to determine if arbitrage profit can be obtained. Finally, in section 4.5, the implications of the results are summarized from both an academic and practitioner view.

4.2 Literature Review

The amount of option pricing research is substantial. This section briefly surveys the major studies which form the impetus for this research effect. Then we introduce previous literature using time series analysis as an alternative approach to forecast implied volatilities.

4.2.1 Black-Scholes-Merton Option Pricing Model (BSM) and CEV Model

Option pricing is a central issue in the derivatives literature. After the seminal papers by Black and Scholes (1973) and Merton (1973), there has been an explosion in option pricing models developed over the last few decades (Black, 1975; Brenner et al. 1985; Chance, 1986; Rampini and Viswanathan, 1985; Wolf, 1982, Hull, 2011). BSM formula for a European call option on a stock with dividend yield rate, q, is:

$$C_t = S_t e^{-q\tau} N(d_1) - K e^{-r\tau} N(d_2) \qquad (4.1)$$

where $d_1 = \frac{\ln\left(\frac{S_t}{K}\right) + (r - q + \frac{\sigma^2}{2})\tau}{\sigma\sqrt{\tau}}$, $d_2 = d_1 - \sigma\sqrt{\tau}$, $N(\cdot)$ is the cumulative probability distribution function for a standardized normal distribution, τ is time to maturity, r is risk free rate, S_0 is current underlying stock price, K is exercise price, σ^2 is the variance of stock returns, C_t is the theoretical BSM option price at time t.

Black's (1976) model for pricing futures call options is used in this study. His model is:

$$C_t^F = e^{-r\tau}[F_t N(d_1) - KN(d_2)]$$
$$d_1 = [\ln(F_t / K) + (\sigma_f^2 / 2)\tau] / \sigma_f \sqrt{\tau}$$
$$d_2 = d_1 - \sigma_f \sqrt{\tau} \qquad (4.2)$$

where C_t^F is the model price for a call option on future at time t, F_t is the underlying futures price at time t, K is the exercise price of the call option, τ is the option's remaining time to maturity in terms of a year, r is the continuous annualized risk-free rate, ${\sigma_f}^2$ is the instantaneous variance of returns of the underlying futures contract over the remaining life of the option, and $N(\cdot)$ is the cumulative normal density function.

The differences in valuing an option on a futures contract versus an option on a stock can be seen by contrasting Black's model with the BSM. Both models' strengths rely on the initial establishment of the riskless hedge portfolio between the option, its underlying asset and some riskless security. However, Black assumes that there are no up-front costs for entering into a futures contract as would occur if one was buying a stock. Thus in the derivation of the Black models, the interest rate term in the d_1 and d_2 components of BSM drops out. Additionally, Black implicitly assumes that the futures price series follows a submartingale; hence the futures price is an unbiased estimation of the contract's maturity price. It then follows through the derivation that the left hand portion of equation (4.2) ends up being discounted back to the present at the same rate as the exercise price (with the additional assumption that the option and futures contracts mature on the same date). Numerous studies have considered the biasing effects of dividend payments on the underlying stock which can invoke an early exercise value. Geske and Roll (1984) found that the American option variant of the BSM formula can only partially explain the bias associated with the BSM model in the theoretical value of an option.

While the two pricing models are by no means identical, the general uniformity of their assumptions and derivations will allow us to concurrently draw direct implications for the Black model and related but indirect consequences for the BSM option pricing model. While this paper is concerned primarily with the assumptions that the instantaneous variance rate is proportionally constant over time, this study also indirectly examines the model assumptions of a frictionless, liquid market that allows the costless formation and continuous adjustment of riskless hedge portfolios. The costs associated with low levels of volume are significant in option trading pits, particularly for deep-in and out-of-the money options and those with a long time to maturity. Evidence of such costs is exhibited in the wider range of bid-ask prices for these options.

While such a market reality might have some correlation with BSM poorer pricing performance for such options, a growing array of evidence is emerging which points to the observed non-constancy of the volatility parameter as a probable source of misspecification bias. Moreover, the proportionally constant variance and frictionless markets together imply that an adequately liquid level of trading volume exists for each option on a particular security. Generally, this implicit condition does not hold in the market place. As a result of these constraining assumptions, the individual risk-return characteristics between options differing by exercise price and (or) maturity date, along with the particular market climate at hand may not be sufficiently expressed in the Black or BSM model framework.

Empirical tests of the "accuracy" of Black's model are not well founded in the literature, thus we turn to the abundance of research that has been generated off of the BSM model.

Although it is well known that the BSM model exhibits biases in its pricing of deep-in and out-of-the-money options and those with a very short or very long term to maturity, the direction of the bias has not been consistent across studies. Black (1975) found that the BSM model systematically over-priced options which were deep-in-the-money and underpriced those being deep-out-of-the-money. However, MacBeth and Merville (1979) reported an exactly opposite type of systematic bias. To make matters even more imprecise, Merton (1976) notes that practitioners often claim that the BSM underprices both deep-in and out-of-the-money options. In regards to time to maturity, it is generally maintained that the BSM underprices short-maturity and overprices long-maturity options. But again, the evidence contains discrepancies, particularly when the bias relative to both exercise price and maturity are considered. All these authors conclude that, to some degree, the pricing bias is related to the volatility parameter which is typically observed not to be proportionally constant over time.

Jarrow and Rudd (1982) focus on the potential effects from distributional misspecification of the underlying return-generating process. Thus, their model takes into account pricing biases which might arise due to differences between the second, third and fourth moments of the assumed and "true" distributions. Although tests of these models are far from conclusive, the general impression from the literature is that these models explain the BSM pricing biases better intuitively than they do empirically. However, extensive testing and use of these models is somewhat restricted due to the difficulty of accurately estimating their additional input variables.

Previous studies have shown that the constant volatility assumption is inappropriate, and the evidence of our empirical results presents as well. Several more generalized models have been proposed to overcome the BSM restriction on the volatility parameter. Cox (1975) and Cox and Ross (1976) developed the "constant elasticity of variance (CEV) model" which incorporates an observed market phenomenon that the underlying asset variance tends to fall as the asset price increases (and vice versa). The advantage of CEV model is that it can describe the interrelationship between stock prices and its volatility. The constant elasticity of variance (CEV) model for a stock price, S, can be represented as follows:

$$dS = (r - q)Sdt + \delta S^{\alpha}dZ \qquad (4.3)$$

where r is the risk-free rate, q is the dividend yield, dZ is a Wiener process, δ is a volatility parameter, and α is a positive constant. The relationship between the instantaneous volatility of the asset return, $\sigma(S,t)$, and parameters in CEV model can be represented as:

$$\sigma(S,t) = \delta S^{\alpha-1} \qquad (4.4)$$

When $\alpha = 1$, the CEV model is the geometric Brownian motion model we have been using up to now. When $\alpha < 1$, the volatility increases as the stock price decreases.

This creates a probability distribution similar to that observed for equities with a heavy left tail and a less heavy right tail. When $\alpha > 1$, the volatility increases as the stock price increases, giving a probability distribution with a heavy right tail and a less left tail. This corresponds to a volatility smile where the implied volatility is an increasing function of the strike price. This type of volatility smile is sometimes observed for options on futures.

The formula for pricing a European call option in CEV model is:

$$C_t = \begin{cases} S_t e^{-q\tau}[1 - \chi^2(a, b+2, c)] - Ke^{-r\tau}\chi^2(c, b, a) & \text{when } \alpha < 1 \\ S_t e^{-q\tau}[1 - \chi^2(c, -b, a)] - Ke^{-r\tau}\chi^2(a, 2-b, c) & \text{when } \alpha > 1 \end{cases} \quad (4.5)$$

where $a = \frac{[Ke^{-(r-q)\tau}]^{2(1-\alpha)}}{(1-\alpha)^2\upsilon}, b = \frac{1}{1-\alpha}, c = \frac{{S_t}^{2(1-\alpha)}}{(1-\alpha)^2\upsilon},\ \upsilon = \frac{\delta^2}{2(r-q)(\alpha-1)}[e^{2(r-q)(\alpha-1)\tau} - 1]$,

and $\chi^2(z, k, v)$ is the cumulative probability that a variable with a non-central χ^2 distribution[1] with non-centrality parameter v and k degrees of freedom is less than z. Hsu, Lin and Lee (2008) provided the detailed derivation of approximative formula for CEV model. Based on the approximated formula, CEV model can reduce computational and implementation costs rather than the complex models such as jump-diffusion stochastic volatility model. Therefore, CVE model with one more parameter than BSM can be a better choice to improve the performance of predicting implied volatilities of

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[1] The calculation process of $\chi^2(z, k, v)$ value can be referred to Ding (1992). The complementary non-central chi-square distribution function can be expressed as an infinite double sum of gamma function, which can be referred to Benton and Krishnamoorthy (2003).

index options (Singh and Ahmad, 2011).

Beckers (1980) investigate the relationship between the stock price and its variance of returns by using an approximative closed-form formulas for CEV model based on two special cases of the constant elasticity class ($\alpha = 1 \; or \; 0$). Based on the significant relationship between the stock price and its volatility in the empirical results, Beckers (1980) claimed that CEV model in terms of non-central Chi-square distribution performs better than BC model in terms of log-normal distribution in description of stock price behavior. MacBeth and Merville (1980) is the first paper to empirically test the performance of CEV model. Their empirical results show the negative relationship between stock prices and its volatility of returns; that is, the elasticity class is less than 2 (i.e. $\alpha < 2$). Jackwerth and Rubinstein (2001) and Lee, Wu, and Chen (2004) used S&P 500 index options to do empirical work and found that CEV model performed well because it took account the negative correlation between the index level and volatility into model assumption. Pun and Wong (2013) combine asymptotics approach with CEV model to price American options. Larguinho et al. (2013) compute Greek letters under CEV model to measure different dimension to the risk in option positions and investigate leverage effects in option markets.

Merton (1976) derived a model based on a jump-diffusion process for the underlying security that allows for discontinuous jumps in price due to unexpected information flows. Geske (1979) derived a compound-option formula which considers the firm's equity to be an option underlying the exchange traded option. An interesting feature of Geske's model is that by incorporating the effects of a firm's leverage on its option the model allows for a non-constant variance. Alternative option pricing models to describe non-constant volatility is stochastic volatility models which consider the volatility of the stock as a separate stochastic factor (Scott, 1987; Wiggins, 1987; Stein and Stein, 1991; Heston, 1993; Lewis, 2000; Lee, 2001; Jones, 2003; Medvedev and Scaillet, 2007). Heston (1993) assumes the dynamics of instantaneous variance, V, as a stochastic process:

$$dS = \mu S dt + \sqrt{V} S dZ_1 \tag{4.6a}$$

$$dV = (\alpha + \beta V)dt + \sigma\sqrt{V} dZ_2 \tag{4.6b}$$

where dZ_1 and dZ_2 are Wiener processes with correlation ρ. For the complex implied volatility model without closed-form solutions, advanced techniques such as partial differential equations (PDEs) or Monte Carlo simulation are used to estimate the approximation of implied volatility under non-tractable models. Lewis (2000) and Lee (2001) estimate implied volatility under stochastic volatility model without jumps. Jones (2003) extends the Heston model and proposes a more general stochastic volatility models in the CEV class as follows:

$$dS = \mu S dt + \sqrt{V} S dZ_1 \qquad (4.7a)$$

$$dV = (\alpha + \beta V)dt + \sigma_1 V^{\gamma_1} dZ_1 + \sigma_2 V^{\gamma_2} dZ_2 \qquad (4.7b)$$

where dZ_1 and dZ_2 are independent Wiener processes under the risk-neutral probability measure. The model setting in Jones (2003) allows the correlation of the price and variance processes to depend on the level of instantaneous variance. Recently, Medvedev and Scaillet (2007) deal with a two-factor jump-diffusion stochastic volatility model where there is a jump term in stock price and volatility follows another stochastic process related to stock price's Brownian motion term with constant correlation ρ. Medvedev and Scaillet (2007) empirical results advocate the necessary of introducing jumps in stock price process. They found that jumps are significant in returns. The evidence also supports the specification of the stochastic volatility in CEV model (Jones, 2003; Heston, 1993).

The optimal selection of an option pricing model should be based on a trade-off between its flexibility and its analytical tractability. The more complicated model it is, the less applicable implementation the model has. Although jump-diffusion stochastic volatility models can general volatility surface as a deterministic function of exercise price and time, the computational costs such as parameter calibration or model implementation are high. Chen, Lee and Lee (2009) indicated that CEV model should be better candidate rather than other complex jump-diffusion stochastic volatility models because of fast computational speed and less implementation costs. Therefore, we decide to use CEV model for forecasting implied volatilities in our empirical study.

4.2.2 Time-Varying Volatility and Time Series Analysis

Several studies have attempted to improve the estimation of the volatility term required by the BSM and Black models. Harvey and Whaley (1992) stated that market volatility changes are predictable by forecasting the volatility implied in index options. Their findings are consistent with the trading cost hypothesis that the index futures and option price changes lead price changes in the stock market (Stephan and Whaley, 1990; Fleming, Ostdiek, and Whaley, 1996). Therefore, we can employ the predicted IV to do hedge strategy and risk management.

All the studies involving IV estimation point out to one degree or another that for any day, the individual IV's for all the options on a particular asset (stock or futures contract) will all be different, and will change over time. Yet as MacBeth and Merville (1979) aptly note, different exercise prices should not imply differing IV's since the IV pertains to the underlying asset itself and not the exercise price. In what might be considered a preliminary basis for this study, MacBeth and Merville (1979) relate systematic pricing differences between market and BSM option prices to the systematic differences that occur among individual IV's relative to exercise price and time to maturity.

Since Latana and Rendleman's (1976) development of the IV concept, numerous researchers have studied different weighting schemes in calculating the IV. The majority of studies, including Schmalensee and Trippi (1978) and Chiras and Manaster (1978), devise weighting schemes which aim at deriving a single weighted IV from among all individual IV's for input into the BSM model. Whaley (1981; 1982) and Park and Sears (1985) utilized an OLS regression procedure to weight and segregate IV's by maturity date. The major finding of the Park and Sears (1985) study, which used option on stock index futures data, was a "time-to-maturity" effect in the pattern of the weighted IV's over time. The authors interpreted their findings as being consistent with Merton's (1973) option pricing model with stochastic interest rate. This is, a portion of the IV's instability is due to the diminishing instantaneous variance of the riskless security.

Another rather foreshadowing study conducted by Brenner and Galai (1981) not only found significant divergence between the daily individual IV's and some time series average IV, but that the distributions of the average IV's were not invariant over time. Finally, Rubenstein (1985) used individual IV's to test five alternative option pricing models versus the BSM formulation, and attempted to explain observed pricing biases. Rubenstein (1985) reported that the direction of pricing bias changed over time. This instability could be a function not only of a time-varying volatility term, but also stochastic interest rates and a changing stock market climate. Harvey and Whaley (1992) utilized OLS regression of the change in IV on S&P 100 index option on lagged IV, week effect dummy variables, and interest rate measures to test if IV is predictable. The significant abnormal returns obtained in Harvey and Whaley (1992) indicated that the market volatility is predictable time-varying variable and can be estimated by time-series analysis.

4.3 Data and Methodology

4.3.1 Data

The data for this study of individual option IV's included the use of call options on the S&P 500 index futures which are traded at the Chicago Mercantile Exchange (CME)[2]. The Data is the options on S&P 500 index futures expired within January 1, 2010 to December 31, 2013. The reason for using options on S&P 500 index futures instead of

[2] Nowadays Chicago Mercantile Exchange (CME), Chicago Board of Trade (CBOT), New York Mercantile Exchange (NYMEX), and Commodity Exchange (COMEX) are merged and operate as designated contract markets (DCM) of the CME Group which is the world's leading and most diverse derivatives marketplace. Website of CME group: http://www.cmegroup.com/

S&P 500 index is to eliminate from non-simultaneous price effects between options and its underlying assets (Harvey and Whaley, 1991). The option and future markets are closed at 3:15pm Central Time (CT), while stock market is closed at 3pm CT. Therefore, using closing option prices to estimate the volatility of underlying stock return is problematic even though the correct option pricing model is used. In addition to no non-synchronous price issue, the underlying assets, S&P 500 index futures, do not need to be adjusted for discrete dividends. Therefore, we can reduce the pricing error in accordance with the needless dividend adjustment. According to the suggestions in Harvey and Whaley (1991, 1992), we select simultaneous index option prices and index future prices to do empirical analysis.

The risk free rate used in Black model and CEV model is based on 1-year Treasury Bill from Federal Reserve Bank of ST. LOUIS[3]. Daily closing price and trading volumes of options on S&P 500 index futures and its underlying asset can be obtained from Datastream.

There are two ways to select data in respect to two alternative methodologies used in this chapter. For time-series and cross-section analysis, we ignore transaction information and choose the futures options according to the length of trading period. The futures

[3] Website of Federal Reserve Bank of ST. LOUIS: http://research.stlouisfed.org/

options expired on March, June and September in both 2010 and 2011 are selected because they have over one year trading date (above 252 observations) while other options only have more or less 100 observations. Studying futures option contracts with same expired months in 2010 and 2011 will allow the examination of IV characteristics and movements over time as well as the effects of different market climates.

In order to ensure reliable estimation of IV, we estimate market volatility by using multiple option transactions instead of a single contract. For comparing prediction power of Black model and CEV model, we use all futures options expired in 2010 and 2013 to generate implied volatility surface. Here we exclude the data based on the following criteria:

(1) BS IV cannot be computed.

(2) Trading volume is lower than 10 for excluding minuscule transactions

(3) Time-to-maturity is less than 10 days for avoiding liquidity-related biases

(4) Quotes not satisfying the arbitrage restriction: excluding option contact if its price larger than the difference between S&P500 index future and exercise price

(5) Deep-in/out-of-money contacts where the ratio of S&P500 index future price to exercise price is either above 1.2 or below 0.8

After arranging data based on these criteria, we still have 30,364 observations of future options which are expired within the period of 2010 to 2013. The period of option prices is from March 19, 2009 to November 5, 2013.

4.3.2 Methodology

In this section, two alternative approaches to estimate IVs are introduced. We first discuss the algorithm to estimate BSM IVs and illustrate how to obtain BSM IV for each option contract in MATLAB. Then, based on BSM IVs, we forecast future BSM IVs for each option contract by time-series analysis and cross-sectional regression. Finally, the second method to estimate future IV is based on CEV model. To deal with moneyness- and maturity-related biases, we use the "implied-volatility matrix" to find proper parameters in CEV model. Then, the IV surface can be represented for predicting future IV in different moneyness and time-to-maturity categories.

4.3.2.1 Estimating BSM IV

The algorithm to calculate the daily BSM IV for options on S&P 500 index futures is an important preliminary for IV prediction by cross-sectional time-series analysis. The examination of IV for each individual option contract, broken down by maturity and exercise price, is that the estimated IV can be obtained by first choosing an initial estimate, σ_0, and then we use equation (4.8) to iterate towards the correct value as follows:

$$C^F{}_{t,j} - C^F{}_{t,j}(\sigma_0) = (\sigma_1 - \sigma_0)\left.\frac{\partial C^F{}_{t,j}}{\partial \sigma}\right|_{\sigma} \tag{4.8}$$

where

$C^F{}_{t,j}$ = market price of call option j at time t;

$C^F{}_{t,j}$ (σ_0) = theoretical price of call option j at time t given $\sigma = \sigma_0$

σ_0 = initialized estimate of the IV

σ_1 = estimate of the IV from iteration

$\left.\frac{\partial C^F{}_{t,j}}{\partial \sigma}\right|_{\sigma_0}$ = partial derivative of the market price with respect to the standard deviation evaluated at a σ_0

In the context of the Black option pricing model, the partial with respect to the standard deviation can be expressed explicitly as:

$$\frac{\partial C^F_{t,j}}{\partial \sigma} = F_t e^{-r\tau}\sqrt{\tau}N'(d1) = F_t e^{-r\tau}\frac{\sqrt{\tau}}{\sqrt{2\pi}}e^{-d_1^2/2} \tag{4.9}$$

where *d1* is defined as in equation (4.1). The partial derivative formula in equation (4.9) is also called Vega of a futures option which is represented the rate of change of the value of a futures option with respect to the volatility of the underlying futures.

The iteration proceeds by reinitializing σ_0 to equal σ_1 at each successive stage until an acceptable tolerance level is attained. The tolerance level used is:

$$\left|\frac{\sigma_1 - \sigma_0}{\sigma_0}\right| < .001$$

This paper can utilize financial toolbox in MATLAB to calculate the implied volatility for futures option that the code of function is as follows:

Volatility = blsimpv(Price, Strike, Rate, Time, Value, Limit, Tolerance, Class)

where the blsimpv is the function name; Price, Strike, Rate, Time, Value, Limit, Tolerance, and Class are input variables; Volatility is the annualized IV[4]. The advantages of this function are the allowance of the upper bound of implied volatility (Limit variable) and the adjustment of the implied volatility termination tolerance (Tolerance variable), in general, equal to 0.000001. The algorithm used in blsimpv function is Newton's method. It should be emphasized that a unique feature of this approach is the determination of "maturity-specific" and "exercise price-specific" IV. Thus, the option contract data has been disaggregated in hopes of extracting information from the IV's that might otherwise be lost. The rationale for such an approach is as follows.

Although our discussions with various commodity brokerage houses indicated that

[4] Detailed information of the function and example of calculating the implied volatility for futures option can be found on MathWorks website: http://www.mathworks.com/help/toolbox/finance/blkimpv.html

most used some type of weighting scheme for IV's, other talks with traders indicated a preference to consider each option as an individual (derivative) asset. So by utilizing a conglomerate or maturity-specific IV, those options which are not near-the-money or moderately close to maturity, will appear to be mispriced. Yet, as other studies have shown, the BSM and Black models do not price far-in or far-out-of-the-money, or longer term to maturity options nearly as well as they do the nearer term, near-the-money call options. As indicated earlier, the assumptions underlying these models do not allow for market imperfections such as low liquidity and other various market idiosyncrasies. Thus, the use of weighted IV's would seem to impute a certain degree of "homogenization" into such options. More specifically, the pricing model used in conjunction with some weighted IV would not account for such influences as differences in the level or consistency of volume on the option's actual trading price. Accordingly, all analysis and interpretation is focused on the IV's of maturity- and exercise price-specific S&P500 index futures options.

When we do the comparison of performance between CEV model and Black model, the implied volatility of Black model for each group at time t can be obtained by following steps:

(1) Let $C_{i,n,t}^{F}$ is market price of the nth option contract in category i, $\widehat{C_{i,n,t}^{F}}(\sigma)$ is the

model option price determined by Black model in equation (4.2) with the volatility parameters, σ. For nth option contract in category i at date t, the difference between market price and model option price can be described as:

$$\varepsilon_{i,n,t}^{F} = C_{i,n,t}^{F} - \widehat{C_{i,n,t}^{F}}(\sigma) \qquad (4.10)$$

(2) For each date t, we can obtain the optimal parameters in each group by solving the minimum value of absolute pricing errors (minAPE) as:

$$\text{minAPE}_{i,t} = \min_{\sigma} \sum_{n=1}^{N} \left|\varepsilon_{i,n,t}^{F}\right| \qquad (4.11)$$

Where N is total number of option contracts in group i at time t.

(3) Using MTALAB optimization function to find optimal σ_0 in a fixed interval. The function code is as follows:

$$[\sigma_0, \text{fvalBls}]=\text{fminbnd}(\text{fun}, x_1,x_2) \qquad (4.12)$$

Where σ_0 is an optimal implied volatility in Black model that locally minimize function of minAPE, fvalBls is the minimum value of minAPE, fun is MATLAB function describing equation (4.11). The implied volatility, σ_0, is constrained in the interval between x_1 and x_2, that is, $x_1 \le \sigma_0 \le x_2$. The algorithm of fminbnd function is based on golden section search and parabolic interpolation.

4.3.2.2 Forecasting IV by Cross-Sectional and Time-Series Analysis

4.3.2.2.1 Time-Series Analysis

Box and Jenkins (1970) time series model building techniques are used to identify, estimate, and check models describing particular generating processes. These models are of the form

$$x_t - \Phi_1 x_{t-1} - \cdots - \Phi_p x_{t-p} = \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{4.13}$$

where x_t is an observation from a covariance stationary series meaning that

$$\lambda_\tau = \text{cov}(x_t, x_{t-\tau}) \tag{4.14}$$

is independent of t for all τ. If stationarity conditions are not satisfied, they can typically be induced by redefining the x_t's to be the first differences between successive observations. The Φ and θ terms represent the autoregressive (AR) and moving average (MA) coefficients and ε_t is white noise. A large body of evidence is accumulating which supports the Box-Jenkins methodology, especially in cases of single series with moderate to large numbers of sample observations.

If any stage of the iterative process falls short of being incontrovertibly clear, it is the initial one. The theoretical relationships between autoregressive moving average structures and concomitant autocorrelations and partial autocorrelations are often useful in selecting a model that adequately describes a sample data set. However, detecting these theoretical patterns in practice may be considered more of an art than a science.

A developed technique motivated by Hannan and Rissanen (1982) seems to provide a good practical basis for model selection. The process involves two stages of computation. The purpose of the first stage is to obtain estimates of the innovation errors of model. This is accomplished by running successively higher order auto-regressive models and using the AIC of Akaike (1969) to determine the optimal order from among them. The innovation errors are estimated by

$$\hat{\varepsilon}_t = x_t - \hat{\Phi}_1 x_{t-1} - \cdots - \hat{\Phi}_k x_{t-k} \tag{4.15}$$

where k is the optimal autoregressive order suggested by the AIC. The second stage involves fitting all different combinations of ARMA (p, q) models where, instead of using full maximum likelihood estimation, the innovation errors estimated in stage one are used as the regressors upon which the moving average parameter estimates are based. This allows use of least squares. The different ARMA (p, q) models are then compared using the AIC of Akaike (1977) and SBC of Schwarz (1978) and the appropriate model is chosen on that basis. This procedure comes with no guarantees of consistently being able to determine "correct" model structures, yet it has been very valuable, when used in conjunction with sample autocorrelations and partial autocorrelations, in providing good first guesses.

Once the values of p and q are chosen in the initial stage, the parameters are estimated. A simulation study conducted by Ansley and Newbold (1980) has found that exact maximum likelihood estimation outperforms least squares when the series are of moderate size and moving average terms are involved. An approximation to the full maximum likelihood function has been derived by Hillmer and Tiao (1979).

The fitted models are then subjected to a series of diagnostic checks to ensure that the initially specified structures are indeed adequate. These checks may be viewed as either tests against alternative specifications involving additional AR or MA terms or tests based on the residual autocorrelations from the fitted models.

The sample autocorrelations of each of the IV series were explained they tended to die out quickly enough over successive lags that the stationarity assumption appears to be satisfied without first differencing. The series were then modeled in the manner described above. After satisfactory models were obtained, it remained to find the best use for the information afforded by the parameter estimates. Certainly the more predictable future IV's are, the more profitable hedged trading strategies become. In order to test the accuracy of the ARMA forecasts, the indicators of root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) of recursive updating forecasts were calculated for holdout periods.

In addition, alternative simple time series methods are taken into account to compare with the forecastability indicators from optimal ARMA models. They are five alternative models to generate IV indicators which are used in cross-sectional regression model in next section. These time series models are as follows:

(1) ARMA model (ARMA): $\mathrm{IV_t} = \mathrm{a_0} + \sum_{i=1}^{p} \mathrm{a_i IV_{t-i}} + \varepsilon_t + \sum_{i=1}^{q} \mathrm{b_i} \varepsilon_{t-i}$

(2) Lag IV method (LIV): $\mathrm{IV_t} = \mathrm{IV_{t-1}}$

(3) 5-day moving average method (MAV5): $\mathrm{IV_t} = \frac{\sum_{i=1}^{5} \mathrm{IV_{t-i}}}{5}$

(4) 5-day exponential moving average method (EMA5): $\mathrm{IV_t} = \frac{\sum_{i=1}^{5} 2^{i-1} \mathrm{IV_{t-i}}}{\sum_{i=1}^{5} 2^{i-1}}$

(5) Regression on lag IV (RGN): $\mathrm{IV_t} = \mathrm{a_0} + \mathrm{a_1 IV_{t-1}} + \varepsilon_t$

The optimal ARMA model is autoregressive-moving-average model with order of the autoregressive part, p, and the order of the moving average part, q where the suitable p and q are based on the goodness-of-fit indicators, AIC and SBC, and the forecastability indicators, RMSE, MAE and MAPE. The 5-day moving average and the 5-day exponential moving average methods can be expressed as the special cases of the general AR(5) model. Lag IV and the regression on lag IV methods belong to AR(1) process.

4.3.2.2.1 Cross-sectional Predictive Regression Model

A significant amount of information has been shown to exist in a time series of IV. The five alternative time series models used to describe the generating processes of the

IV series examined are all clearly preferred to random walk or "white noise" alternatives. These models do not give the final word on the subject of IV forecasting, however. There are several cross-contract effects that may exist which, if isolated properly, will provide further predictive power. To learn more about these different influences, a large cross-section time series predictive regression model was formulated. The cross-section time series predictive regression model is

$$y_{it} = \beta_0 + \beta_1 x_{1it-1} + \beta_2 x_{2it-1} + \cdots + \beta_{14} x_{14it-1} + \varepsilon_{it} \qquad (4.16)$$

where

y_{it} = IV of the i^{th} option contract at time t

x_{1it-1} = the time series predictor of i^{th} contract for time t based on information known at time t-1 and one of forecasting time-series methods

x_{2it-1} = time to maturity of the i^{th} option contract at time t-1 which is the unit of year

x_{3it-1} = proportional in-the-money that is equal to the value of (future price at time t-1 - strike price)/ (strike price) if the value is positive, otherwise is zero

x_{4it-1} = proportion out-of-the-money that is equal to the value of (strike price - futures price at time t-1)/ (strike price) if the value is positive, otherwise is zero

x_{5it-1} = standard deviation of the IV based on previous 5 observations

x_{6it-1} = standard deviation of the IV based on previous 20 observations

x_{7it-1} = skewness of IV distribution over the previous 20 observations

x_{8it-1} = kurtosis of IV distribution over the previous 20 observations

x_{9it-1} = the standard deviations of the rate of returns of the underlying future price on previous 5 observations

x_{10it-1} = the standard deviations of the rate of returns of the underlying future price on previous 20 observations

x_{11it-1} = dummy variable that equals 1 if the trading date at time t-1 is Tuesday, otherwise equal to zero

x_{12it-1} = dummy variable that equals 1 if the trading date at time t-1 is Wednesday, otherwise equal to zero

x_{13it-1} = dummy variable that equals 1 if the trading date at time t-1 is Thursday, otherwise equal to zero

x_{14it-1} = dummy, variable that equals 1 if the trading date at time t-1 is Friday, otherwise equal to zero

The optimal time series predictors are included in an attempt to deduce information contained in the past. This variable is likely to capture large portions of the expected cross-contract effects since the market influences pertaining to a particular contract today are not likely to have changed considerably since the prior trading day. The resulting IV's tend to evolve over time with a strong sense of heritage.

The time-to-maturity variable was included because, as was indicated by Park and Sears (1985), there tends to be a certain point close to maturity where the IV's begin to decrease. Of course, any general downward trend in IV's would be partially accounted for by the ARMA predictors, but it may still be the case that there is a partial influence that time-to-maturity exhibits. The third and fourth independent variables have been included to see if deep-in-the-money options and far-out-of-the-money options tend toward higher or lower than expected IV's. Previous studies have had conflicting answers to this important question (see Jarrow and Rudd, 1983). The next two independent variables are included to determine whether or not the standard deviations of the IVs have any positive or negative effect on the IVs themselves. The third and fourth moments of the distribution of 20 previous IV observations were also included in the regression equation to see what, if any, influence they have in determining current IV.

The two measures of the standard deviations of the rate of returns of the underlying future price are of great interest as regressors since these have traditionally been approximations of the variable used in the BSM model to determine the theoretical option price. One would hope to find a strong relationship between the two volatility measures; the one based on historical deviations and the one implied by the observed option price. It may be the case, however, that the implied standard deviation encompasses more than just the expected future standard deviation of the underlying asset's return. All BSM model misspecifications are represented in the IV term, which may amount to quite a large distortion. A low correlation between these historical and implied variables would indicate either that the model misspecifications manifesting themselves in the IV terms are significant or that the historical standard deviation measure is a poor proxy for the expected future standard deviation, or both.

The final four explanatory variables are weekday effect dummies which are intended to see if certain days give rise to higher IV than others. For example, certain economic announcements are regularly made on particular days of the week and this may have a weekday effect on IV. Note that only four dummy variables are needed to describe the five days of the week in order to avoid perfect multi-collinearity with the constant term.

4.3.2.3 Forecasting IV by CEV Model

To deal with moneyness- and expiration- related biases in estimating BSM IV, we use the “implied-volatility matrix” to separate option contracts and estimate parameters of CEV model in each category. The option contracts are divided into nine categories by moneyness and time-to-maturity. Option contracts are classified by moneyness level as at-the-money (ATM), out-of-the-money (OTM), or in-the-money (ITM) based on the ratio of underlying asset price, S, to exercise price, K. If an option contract with S/K ratio is between 0.95 and 1.01, it belongs to ATM category. If its S/K ratio is higher (lower) than 1.01 (0.95), the option contract belongs to ITM (OTM) category. According to the large observations in ATM and OTM, we divide moneyness-level group into five levels: ratio above 1.01, ratio between 0.98 and 1.01, ratio between 0.95 and 0.98, ratio between 0.90 and 0.95, and ratio below 0.90. By expiration day, we classified option contracts into short-term (less than 30 trading days), medium-term (between 30 and 60 trading days), and long-term (more than 60 trading days).

Since for all assets the future price equals the expected future spot price in a risk-neutral measurement, the S&P 500 index futures prices have same distribution property of S&P 500 index prices. Therefore, for a call option on index futures can be given by equation (4.5) with S_t replaced by F_t and $q = r$ as equation (4.17)[5]:

$$C_t^F = \begin{cases} e^{-r\tau}(F_t[1-\chi^2(a, b+2, c)] - K\chi^2(c, b, a)) & \text{when } \alpha < 1 \\ e^{-r\tau}(F_t[1-\chi^2(c, -b, a)] - K\chi^2(a, 2-b, c)) & \text{when } \alpha > 1 \end{cases} \tag{4.17}$$

where $a = \frac{K^{2(1-\alpha)}}{(1-\alpha)^2\upsilon}, b = \frac{1}{1-\alpha}, c = \frac{{F_t}^{2(1-\alpha)}}{(1-\alpha)^2\upsilon},\ \upsilon = \delta^2\tau$

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[5] When substituting $q = r$ into $\upsilon = \frac{\delta^2}{2(r-q)(\alpha-1)}[e^{2(r-q)(\alpha-1)\tau} - 1]$, we can use L'Hospital's Rule to obtain υ. Let $x = r - q$, then

$$\lim_{x\to 0}\frac{\delta^2[e^{2x(\alpha-1)\tau}-1]}{2x(\alpha-1)} = \lim_{x\to 0}\frac{\frac{\partial\delta^2[e^{2x(\alpha-1)\tau}-1]}{\partial x}}{\frac{\partial 2x(\alpha-1)}{\partial x}} = \lim_{x\to 0}\frac{(2(\alpha-1)\tau)\delta^2[e^{2x(\alpha-1)\tau}]}{2(\alpha-1)} = \lim_{x\to 0}\frac{\tau\delta^2[e^{2x(\alpha-1)\tau}]}{1} = \tau\delta^2$$

The procedures to obtain estimated parameters of CEV model in each category of implied-volatility matrix are as follows:

(1) Let $C^F_{i,n,t}$ is market price of the nth option contract in category i, $\widehat{C^F_{i,n,t}}(\delta_0, \alpha_0)$ is the model option price determined by CEV model in equation (4.17) with the initial value of parameters, $\delta = \delta_0$ and $\alpha = \alpha_0$. For nth option contract in category i at date t, the difference between market price and model option price can be described as:

$$\varepsilon^F_{i,n,t} = C^F_{i,n,t} - \widehat{C^F_{i,n,t}}(\delta_0, \alpha_0) \qquad (4.18)$$

(2) For each date t, we can obtain the optimal parameters in each group by solving the minimum value of absolute pricing errors (minAPE) as:

$$\text{minAPE}_{i,t} = \min_{\delta_0, \alpha_0} \sum_{n=1}^{N} \left| \varepsilon^F_{i,n,t} \right| \qquad (4.19)$$

Where N is total number of option contracts in group i at time t.

(3) Using optimization function in MATLAB to find a minimum value of the unconstrained multivariable function. The function code is as follows:

[x, fval]=fminunc(fun, x_0) (4.20)

where x is the optimal parameters of CEV model, fval is the local minimum value of minAPE, fun is the specified MATLAB function of equation (4.19), and x_0 is the initial points of parameters obtained in step (1). The algorithm of fminunc function is based on quasi-Newton method.

4.4 Empirical Analysis

In the empirical study section, we present the forecastability of S&P 500 index option price for two alternative models: time-series and cross-sectional analysis and CEV model. First, the statistical analysis for time-series futures option prices of the contracts expired on March, June and September in both 2010 and 2011 is summarized. Then we use time-series and cross-sectional models to analyze each individual contract and compare their forecastability of IV. Finally, we estimated IV by using CEV model and compare its pricing accuracy with Black model.

4.4.1 Distributional Qualities of IV time series

One difficulty in discerning the correct value for the volatility parameter in the option pricing model is due to its fluctuation over time. Therefore, since an accurate estimate of this variable is essential for correctly pricing an option, it would seem that time-series and cross-sectional analysis of this variable would be as important as the conventional study of security price movements. Moreover, by examining individual IV's over time as well as within different time sets, the unique relationships between the underlying stochastic process and the pricing influences of differing exercise prices, maturity dates and market sentiment (and indirectly, volume), might be revealed in a way that could be modeled more efficiently. This section will examine the distributional qualities of IV's as a prelude to the more quantitatively powerful ARMA and cross-sectional time series regression models presented in later sections.

A summary of individual IV distributional statistics for S&P 500 index futures call options in 2010 and 2011 appears in Table 4.1. The most noteworthy feature from this table is the significantly different mean values of IV's that occur for different exercise prices. The means and variability of the IV in 2010 and 2011 appear to be inversely related to the exercise price. More precisely conclusive evidence of the relationship of IV's to exercise price will arise from the results of the cross-sectional time series regression in the next section. Comparing the mean IV's across time periods, it is quite evident that the 2011 IV's are significantly smaller. Also, the time-to-maturity effect observed by Park and Sears (1985) can be identified. The September options in 2011 possess higher mean IV's than those maturing in June and March with the same strike price. Once again, stronger support for this effect on the IV's will be displayed in the regression results.

The other statistical measures listed in Table 4.1 are the relative skewness and relative kurtosis of the IV series, along with the studentized range. Skewness measures lopsidedness in the distribution and might be considered indicative of a series of large outliers at some point in the time series of the IV's. Kurtosis measures the peakedness of the distribution relative to the normal and has been found to affect the stability of variance (Lee and Wu, 1985). The studentized range gives an overall indication as to whether the measured degrees of skewness and kurtosis have significantly deviated from the levels implied by a normality assumption for the IV series.

Although an interpretation of the effects of skewness and kurtosis on the IV series is postponed until the regression results, a few general observations are warranted at this point. Both 2010 and 2011 IV's statistics present a very different view of normal distribution, certainly challenging any assumptions concerning normality. Using significance tests on the results of Table 4.1 in accordance with Jarque-Bera test, the 2010 and 2011 skewness and kurtosis measures indicate a higher proportion of statistical significance. We also utilize simple back-of-the-envelope test based on the studentized range to identify whether the individual IV series approximate a normal distribution. The studentized range larger than 4 in both 2010 and 2011 indicates that a normal distribution significantly understates the maximum magnitude of deviation in individual IV series.

As a final point to this brief examination of the IV skewness and kurtosis, note the statistics for MAR10 1075, MAR11 1200, and MAR11 1250 contracts. The relative size of this contract's skewness and kurtosis measures reflect the high degree of instability that its IV exhibited during the last ten days of the contract's life. Such instability is consistent across contracts.

Table 4.1 Distributional Statistics for Individual IV's

*Option series contain the name and code of futures options with information of the strike price and the expired month, for example, SEP11 1350 (B9370V) represents that the futures call option is expired on September, 2011 with the strike price $1350 and the parentheses is the code of this futures option in Datastream. **CV represents the coefficient of variation that is standard deviation of option series divided by their mean value. ***Studentized range is the difference of the maximum and minimum of the observations divided by the standard deviation of the sample.

Option Series*	Mean	Std. Dev.	CV**	Skewness	Kurtosis	Studentized Range***	Observations
Call Futures Options in 2010							
MAR10 1075 (C070WC)	0.230	0.032	0.141	2.908	14.898	10.336	251
JUN10 1050 (B243UE)	0.263	0.050	0.191	0.987	0.943	6.729	434
JUN10 1100 (B243UF)	0.247	0.047	0.189	0.718	-0.569	4.299	434
SEP10 1100 (C9210T)	0.216	0.024	0.111	0.928	1.539	6.092	259
SEP10 1200 (C9210U)	0.191	0.022	0.117	0.982	2.194	6.178	257
Call Futures Options in 2011							
MAR11 1200 (D039NR)	0.206	0.040	0.195	5.108	36.483	10.190	384
MAR11 1250 (D1843V)	0.188	0.027	0.145	3.739	25.527	10.636	324
MAR11 1300 (D039NT)	0.176	0.021	0.118	1.104	4.787	8.588	384
JUN11 1325 (B513XF)	0.165	0.016	0.095	-1.831	12.656	10.103	200
JUN11 1350 (A850CJ)	0.161	0.018	0.113	-0.228	1.856	8.653	234

SEP11 1250 (B9370T)	0.200	0.031	0.152	2.274	6.875	7.562	248
SEP11 1300 (B778PK)	0.185	0.024	0.131	2.279	6.861	7.399	253
SEP11 1350 (B9370V)	0.170	0.025	0.147	2.212	5.848	6.040	470

However, these distortions remain in the computed skewness and kurtosis measures only for these particular contracts to emphasize how a few large outliers can magnify the size of these statistics. For example, the evidence that S&P 500 future price jumped on January 18, 2010 and plunged on February 2, 2011 cause the IV of these particular contracts sharply increasing on that dates. Thus, while still of interest, any skewness and kurtosis measures must be calculated and interpreted with caution.

4.4.2 Time-Series and Cross-Sectional Analysis for IV Series

The optimal ARMA models for the IV series are based on the goodness-of-fit indicators, AIC and SBC, and the forecastability indicators, RMSE, MAE and MAPE. Here the length of the holdout periods range is 20 days because there are enough observations in the series to do so. Tables 4.2 and 4.3 represented the forecastability indicators of optimal ARMA models compared with these indicators obtained by using previous period IV's, 5-day moving averages, and 5-day exponential moving averages with the holdout periods range from five to 20 days to indicate how different predictors perform over different forecast periods.

Table 4.2 Forecastability for Different Prediction Models of Individual IV Series in 2010

*For the forecasting methods used in Table 2 are as follows: ARMA is autoregressive-moving-average model with order of the autoregressive part, p, and the order of the moving average part, q as the form $\mathbf{IV_t = a_0 + \sum_{i=1}^{p} a_i IV_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i}}$. The suitable p and q are based on the goodness-of-fit indicators, AIC and SBC, and the forecastability indicators, RMSE, MAE and MAPE. Previous IV is simply an AR(1) process of the form $\mathbf{IV_t = IV_{t-1}}$. The 5-day moving averages can be expressed as an AR(5) model of the form $\mathbf{IV_t = 0.2\, IV_{t-1} + 0.2\, IV_{t-2} + 0.2\, IV_{t-3} + 0.2\, IV_{t-4} + 0.2\, IV_{t-5}}$. The 5-day exponential moving averages is another special case of the general AR(5) model where the parameters are restricted as follows: $\mathbf{IV_t = \frac{16}{31} IV_{t-1} + \frac{8}{31} IV_{t-2} + \frac{4}{31} IV_{t-3} + \frac{2}{31} IV_{t-4} + \frac{1}{31} IV_{t-5}}$. The Regression is the general case of AR(1) as $\mathbf{IV_t = a_0 + a_1 IV_{t-1} + \varepsilon_t}$.

Forecasting Methods*		5-day moving averages			5-day exponential moving averages			Previous IV			Regression			ARMA		
Option series	Holdout period	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
MAR10 1075 (C070WC)	5	0.111	0.102	0.269	0.076	0.063	0.170	0.056	0.053	0.141	0.058	0.053	0.142	0.042	0.037	0.100
	10	0.080	0.060	0.173	0.055	0.038	0.111	0.040	0.031	0.090	0.042	0.030	0.087	0.031	0.022	0.066
	20	0.057	0.031	0.091	0.039	0.020	0.064	0.029	0.017	0.052	0.029	0.017	0.053	0.023	0.015	0.056
JUN10 1050 (B243UE)	5	0.087	0.069	0.169	0.072	0.058	0.145	0.063	0.050	0.126	0.065	0.052	0.129	0.045	0.038	0.097
	10	0.063	0.042	0.107	0.052	0.035	0.090	0.046	0.031	0.080	0.047	0.031	0.081	0.035	0.027	0.074
	20	0.061	0.042	0.112	0.058	0.041	0.109	0.059	0.038	0.102	0.059	0.038	0.100	0.049	0.035	0.094
JUN10 1100 (B243UF)	5	0.022	0.017	0.071	0.020	0.017	0.072	0.022	0.018	0.072	0.021	0.017	0.070	0.022	0.016	0.066
	10	0.017	0.012	0.048	0.017	0.014	0.057	0.019	0.015	0.059	0.018	0.015	0.059	0.018	0.013	0.051
	20	0.032	0.022	0.081	0.033	0.024	0.087	0.035	0.024	0.085	0.034	0.024	0.082	0.027	0.019	0.067

Forecasting Methods*		5-day moving averages			5-day exponential moving averages			Previous IV			Regression			ARMA		
Option series	Holdout period	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
SEP10 1100 (C9210T)	5	0.040	0.037	0.162	0.036	0.034	0.148	0.029	0.026	0.113	0.029	0.026	0.113	0.029	0.025	0.107
	10	0.040	0.034	0.156	0.041	0.036	0.166	0.046	0.034	0.154	0.044	0.034	0.155	0.039	0.030	0.137
	20	0.029	0.020	0.094	0.030	0.022	0.102	0.033	0.021	0.095	0.032	0.021	0.098	0.028	0.019	0.089
SEP10 1200 (C9210U)	5	0.036	0.031	0.116	0.027	0.020	0.070	0.025	0.014	0.052	0.025	0.015	0.054	0.018	0.013	0.048
	10	0.030	0.026	0.109	0.026	0.021	0.090	0.025	0.016	0.068	0.025	0.016	0.068	0.019	0.014	0.058
	20	0.025	0.022	0.095	0.021	0.017	0.076	0.021	0.014	0.060	0.021	0.014	0.061	0.018	0.013	0.059
MAR10 1075 (C070WC)	5	0.111	0.102	0.269	0.076	0.063	0.170	0.056	0.053	0.141	0.058	0.053	0.142	0.042	0.037	0.100
	10	0.080	0.060	0.173	0.055	0.038	0.111	0.040	0.031	0.090	0.042	0.030	0.087	0.031	0.022	0.066
	20	0.057	0.031	0.091	0.039	0.020	0.064	0.029	0.017	0.052	0.029	0.017	0.053	0.023	0.015	0.056
JUN10 1050 (B243UE)	5	0.087	0.069	0.169	0.072	0.058	0.145	0.063	0.050	0.126	0.065	0.052	0.129	0.045	0.038	0.097
	10	0.063	0.042	0.107	0.052	0.035	0.090	0.046	0.031	0.080	0.047	0.031	0.081	0.035	0.027	0.074
	20	0.061	0.042	0.112	0.058	0.041	0.109	0.059	0.038	0.102	0.059	0.038	0.100	0.049	0.035	0.094

Table 4.3 Forecastability for Different Prediction Models of Individual IV Series in 2011

*For the forecasting methods used in Table 3 are as follows: ARMA is autoregressive-moving-average model with order of the autoregressive part, p, and the order of the moving average part, q as the form $\mathbf{IV_t = a_0 + \sum_{i=1}^{p} a_i IV_{t-i} + \varepsilon_t + \sum_{i=1}^{q} b_i \varepsilon_{t-i}}$. The suitable p and q are based on the goodness-of-fit indicators, AIC and SBC, and the forecastability indicators, RMSE, MAE and MAPE. Previous IV is simply an AR(1) process of the form $\mathbf{IV_t = IV_{t-1}}$. The 5-day moving averages can be expressed as an AR(5) model of the form $\mathbf{IV_t = 0.2\,IV_{t-1} + 0.2\,IV_{t-2} + 0.2\,IV_{t-3} + 0.2\,IV_{t-4} + 0.2\,IV_{t-5}}$. The 5-day exponential moving averages is another special case of the general AR(5) model where the parameters are restricted as follows: $\mathbf{IV_t = \frac{16}{31}\,IV_{t-1} + \frac{8}{31}\,IV_{t-2} + \frac{4}{31}\,IV_{t-3} + \frac{2}{31}\,IV_{t-4} + \frac{1}{31}\,IV_{t-5}}$. The Regression is the general case of AR(1) as $\mathbf{IV_t = a_0 + a_1 IV_{t-1} + \varepsilon_t}$.

Forecasting Methods*		5-day moving averages			5-day exponential moving averages			Previous IV			Regression			ARMA		
Option series	Holdout period	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
MAR11	5	0.112	0.095	0.204	0.074	0.067	0.150	0.054	0.049	0.113	0.068	0.061	0.136	0.052	0.041	0.092
1200	10	0.080	0.057	0.132	0.053	0.036	0.084	0.039	0.027	0.067	0.049	0.037	0.091	0.037	0.023	0.055
(D039NR)	20	0.095	0.058	0.144	0.087	0.049	0.127	0.098	0.045	0.119	0.096	0.050	0.129	0.081	0.041	0.104
MAR11	5	0.051	0.040	0.129	0.044	0.042	0.142	0.044	0.042	0.148	0.048	0.043	0.144	0.025	0.023	0.079
1250	10	0.038	0.026	0.090	0.032	0.024	0.082	0.032	0.024	0.085	0.036	0.030	0.105	0.020	0.017	0.062
(D1843V)	20	0.062	0.034	0.112	0.062	0.035	0.119	0.073	0.036	0.122	0.067	0.037	0.126	0.058	0.029	0.096
MAR11	5	0.038	0.028	0.116	0.034	0.030	0.131	0.036	0.034	0.153	0.034	0.033	0.144	0.019	0.017	0.075
1300	10	0.028	0.019	0.083	0.024	0.018	0.080	0.026	0.020	0.091	0.025	0.020	0.091	0.015	0.012	0.057
(D039NT)	20	0.042	0.022	0.094	0.041	0.024	0.107	0.049	0.026	0.118	0.045	0.025	0.110	0.039	0.020	0.088

Forecasting Methods*		5-day moving averages			5-day exponential moving averages			Previous IV			Regression			ARMA		
Option series	Holdout period	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE	RMSE	MAE	MAPE
JUN11	5	0.023	0.016	0.084	0.020	0.016	0.090	0.023	0.019	0.112	0.020	0.016	0.093	0.011	0.009	0.050
1325	10	0.023	0.018	0.110	0.019	0.015	0.089	0.017	0.014	0.086	0.015	0.012	0.075	0.013	0.010	0.063
(B513XF)	20	0.027	0.017	0.167	0.027	0.017	0.169	0.030	0.018	0.168	0.027	0.017	0.168	0.024	0.014	0.149
JUN11	5	0.042	0.034	0.166	0.033	0.026	0.124	0.035	0.031	0.154	0.034	0.029	0.145	0.027	0.024	0.118
1350	10	0.033	0.027	0.152	0.025	0.019	0.103	0.026	0.020	0.109	0.025	0.019	0.104	0.021	0.017	0.094
(A850CJ)	20	0.026	0.019	0.126	0.021	0.015	0.108	0.022	0.016	0.106	0.021	0.016	0.108	0.019	0.014	0.099
SEP11	5	0.048	0.046	0.139	0.029	0.024	0.073	0.024	0.019	0.060	0.026	0.020	0.064	0.030	0.025	0.077
1250	10	0.036	0.030	0.096	0.025	0.020	0.068	0.024	0.019	0.065	0.024	0.019	0.066	0.026	0.020	0.068
(B9370T)	20	0.027	0.021	0.070	0.021	0.017	0.061	0.021	0.017	0.060	0.021	0.017	0.061	0.022	0.016	0.058
SEP11	5	0.039	0.036	0.127	0.034	0.031	0.115	0.036	0.032	0.118	0.037	0.034	0.124	0.033	0.032	0.114
1300	10	0.029	0.024	0.090	0.026	0.022	0.084	0.027	0.022	0.083	0.028	0.022	0.085	0.024	0.020	0.075
(B778PK)	20	0.027	0.023	0.094	0.025	0.023	0.094	0.026	0.021	0.085	0.026	0.021	0.085	0.022	0.019	0.076
SEP11	5	0.020	0.017	0.072	0.018	0.015	0.064	0.016	0.015	0.064	0.017	0.016	0.065	0.017	0.012	0.050
1350	10	0.023	0.018	0.074	0.019	0.017	0.069	0.018	0.016	0.065	0.018	0.016	0.063	0.017	0.013	0.052
(B9370V)	20	0.035	0.027	0.109	0.030	0.024	0.098	0.031	0.024	0.099	0.031	0.023	0.095	0.024	0.017	0.067

As Tables 4.2 and 4.3 indicate, the superior forecasting method is ARMA model based on the smallest value of RMSE, MAE, MAPE except that the previous IV method predict better than ARMA for SEP11 1250 contract. The better prediction ability of ARMA method is attributed to the same characteristic of other alternatives forecasting methods that are considered are actually specific cases of ARMA models themselves where the structural and quantitative relationships of the time series with their forecasts are predetermined. The efficiently specified and estimated ARMA models are chosen on the basis of the data and would therefore be expected to better project particular data generating processes into the future. The best explanation for the poorer prediction performance of ARMA model for SEP11 1250 contract is that the forecast periods, at times, exhibit structural change or even a sudden trend in IV's. Non-stationarity (trend behavior) was not observed in the estimation period and hence the ARMA coefficients that were derived for that time could not predict any stationarity in the holdout period. Some of the other, "naive" fore-castors are more responsive to these sudden movements. They do not have as much of a tendency to pull their forecasts toward middle ground as ARMA models do. For example, the most naive forecast in the previous IV method (i.e., $\mathrm{IV_t} = \mathrm{IV_{t-1}}$) will be better than some ordinarily superior ARMA forecast in regression method (i.e., $\mathrm{IV_t} = \widehat{a_0} + \widehat{a_1}\mathrm{IV_{t-1}}$) in times of unanticipated non-stationarity.

The forecasts were also compared with those derived from the regression model developed in the following section.

To tie together some of the results identified thus far, observe the interesting relationship that arises from an examination of RMSE, MAE, MAPE from the ARMA forecasts as shown in Tables 4.2 and 4.3, and the standard deviations of the IV series as shown in Table 4.1. While not precise, it is apparent that the accuracy of the ARMA forecasts correlates with the variability of the IV series. Hence, the more volatile the IV, the more difficult it is to forecast. While this observation might be obvious, a further implication is suggested. For instance, one could find such information valuable in deciding which particular options might be mispriced based on the use of the BSM (or Black's) option pricing model and some forecast of the IV. For example, if the forecasting models show that both SEP11 1300 and SEP11 1350 options are underpriced and SEP11 1350 option has a significantly lower standard deviation than the other one, we might confidently state that SEP11 1350 option is mispriced rather than SEP11 1300 option.

Determining the correct form of a model using pooled cross-section and time series data is an important, though often troublesome task. The difficulty arises because the error term may consist of time-series-related disturbances, cross-section disturbances, or both. The regression equation is defined with the time series predictor calculated by one of five forecasting methods in the design matrix. This insures that any possibility of autocorrelation in the time series disturbances has been mitigated. There remains the chance that contemporaneous correlation of disturbances across contracts exists. However, a majority of this cross-contract relationship will be accounted for by the in-the-money and out-of-the-money variables. These are akin to the cross-section dummy variables of the so-called covariance model. The only real difference between the two sets of variables is that the estimated dummy coefficients can take on any values whereas the in-the-money and out-of-the-money variables implicitly assume that a linear relationship exists between a contract's strike price above the underlying asset price and its IV and between a contract's strike price below the underlying asset price and its IV. If this posited linear relationship does exist, then cross-contract disturbances should not be highly correlated. The proper estimation procedure is ordinary least squares. Of course, the residuals must be checked for possible violations of the assumptions before placing confidence in the sample results.

Table 4.4 shows the results of the regression model in equation (4.16). The time series predictor variables calculated by different forecasting models are all significant, which should come as no surprise—IV depends on past IV value. However, the fact that other regressors were found to be significant indicates that not all of the variation in IV series is explained by the past. Time-to-maturity has the predicted positive effect. The closer an option is to expiration, the lower the IV. The in-the-money effect is significantly positive; however, the out-of-the-money give mixed insignificant influence on IV series. Merton (1976) shows that large deviations from the strike price tend to bias the BSM theoretical price downward. Therefore it is logical to expect the IV of the deep-in-the-money and far-out-of-the-money contracts to be higher because the writer of these calls runs a greater risk of being stuck in his position. However, in this study, the selected IV time series calculated by BSM model cannot show the downward characteristic obviously because the longest trading data is the option contract with the strike price close to the underlying asset.

The coefficients on the standard deviation of the IV variables give the significantly positive signals based on previous 20 observations, but show the negative effect based on previous 5 observations when the short term effect is of significance. The skewness and kurtosis terms have consistently slight effects over two sample periods even though sometimes the effects have statistical significance. Perhaps what can be said about the lower relationship between these two statistic measures and predicted IV is that the influence of the outliers bringing about the skewness and kurtosis is already captured by other independent variables such as the time series predictor estimated by forecasting model or the standard deviation of IV series.

Table 4.4 The Results of the Cross-section Time Series Predictive Regression Model

The time series predictor is the estimated prediction value of IV calculated by five different forecasting methods: ARMA model, the previous IV method, 5-day moving averages method, 5-day exponential moving averages method and the regression method described in Tables 2 and 3. Proportion in-the-money is equal to the value of (future price at time t-1 - strike price)/strike price if the value is positive, otherwise is zero. Proportion out-of-the-money is equal to the value of (strike price - future price at time t-1)/strike price if the value is positive, otherwise is zero. σ_{IV} (5 obs.) and σ_{IV} (20 obs.) are the standard deviations of the IV based on previous 5 and 20 observations, respectively. Skewness and Kurtosis are the skewness and kurtosis of the IV distribution over the previous 20 observations, respectively. σ_{R_future} (5 obs.) and σ_{R_future} (20 obs.) are the standard deviations of the rate of returns of the underlying future price on previous 5 and 20 observations. Tuesday, Wednesday, Thursday, and Friday are the dummy variables that equal to one if the trading date of IV observation at time t-1 is equal to that weekday and otherwise equal to zero. The value in table is represented the estimation coefficient with the t-value in parentheses. *, **, and *** in parenthesis indicate the significance at 90, 95, and 99 percent level. Total observations for 2010 and 2011 are 1530 and 2098, respectively. The chow test is therefore follow F(15, 3598) distribution with critical value 2.04 at 99 percent level.

Year	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Variable	ARMA		Previous IV		5-day moving averages		5-day exponential moving averages		Regression	
Intercept	0.0068 (3.13)***	0.0037 (1.61)	0.0146 (6.34)***	0.0260 (11.08)***	0.0049 (1.62)	-0.0067 (-2.31)**	0.0024 (0.95)	0.0016 (0.65)	0.0088 (3.70)***	0.0137 (5.51)***
Time series predictor	0.9362 (68.26)***	0.9634 (62.36)***	0.8798 (60.80)***	0.7827 (52.38)***	0.9576 (48.08)***	1.0546 (52.08)***	0.9650 (58.85)***	0.9582 (58.33)***	0.9064 (61.01)***	0.8574 (54.03)***
Time to Maturity	0.0038 (2.43)**	-0.0013 (-1.12)	0.0068 (4.03)***	0.0048 (3.67)***	0.0010 (0.48)	-0.0054 (-3.93)***	0.0007 (0.41)	-0.0013 (-1.00)	0.0057 (3.35)***	0.0023 (1.78)*
Proportion in-the-money	0.0718 (5.81)***	0.0914 (4.83)***	0.0880 (6.56)***	0.1536 (7.38)***	0.0904 (5.72)***	0.0507 (2.34)**	0.0694 (5.01)***	0.0732 (3.67)***	0.0757 (5.63)***	0.1383 (6.74)***
Proportion out-of-the-money	-0.0088 (-1.41)	0.0143 (1.84)*	-0.0160 (-2.36)**	-0.0056 (-0.65)	-0.0004 (-0.05)	0.0204 (2.34)**	-0.0029 (-0.42)	0.0048 (0.59)	-0.0141 (-2.08)**	0.0173 (2.04)**
σ_{IV} (5 obs.)	-0.0054 (-0.10)	-0.2240 (-5.61)***	0.0366 (0.61)	-0.1059 (-2.38)**	0.0273 (0.39)	-0.4047 (-9.02)***	-0.0242 (-0.40)	-0.3028 (-7.25)***	0.0308 (0.52)	-0.1324 (-3.03)***

Year	2010	2011	2010	2011	2010	2011	2010	2011	2010	2011
Variable	ARMA		Previous IV		5-day moving averages		5-day exponential moving averages		Regression	
σ_{IV} (20 obs.)	0.2355 (3.59)***	0.1244 (2.01)**	0.3268 (4.59)***	0.3887 (5.74)***	0.2889 (3.42)***	0.1995 (2.89)***	0.2123 (2.88)***	0.2498 (3.90)***	0.3385 (4.78)***	0.4061 (6.12)***
Skewness	0.0004 (1.60)	0.0005 (1.44)	0.0005 (1.79)*	0.0006 (1.80)*	0.0001 (0.24)	0.0002 (0.68)	-0.0001 (-0.19)	0.0000 (0.10)	0.0007 (2.27)**	0.0011 (3.12)***
Kurtosis	-0.0002 (-1.78)*	0.0003 (2.15)**	-0.0001 (-0.55)	0.0001 (0.63)	-0.0001 (-0.71)	0.0006 (4.65)***	-0.0001 (-0.67)	0.0003 (2.49)**	-0.0001 (-0.93)	0.0002 (1.40)
σ_{R_future} (5 obs.)	0.0450 (0.73)	-0.0885 (-1.24)	0.0212 (0.32)	-0.0959 (-1.21)	-0.0407 (-0.52)	-0.2633 (-3.31)***	-0.0146 (-0.21)	-0.1846 (-2.48)**	0.0266 (0.40)	-0.1116 (-1.43)
σ_{R_future} (20 obs.)	0.1285 (1.46)	0.2018 (1.85)*	0.3202 (3.37)***	0.7288 (6.11)***	0.0536 (0.46)	0.1396 (1.13)	0.0433 (0.43)	0.2973 (2.61)***	0.3259 (3.44)***	0.5721 (4.85)***
Tuesday	-0.0001 (-0.15)	0.0002 (0.23)	-0.0003 (-0.29)	0.0010 (0.99)	-0.0009 (-0.76)	-0.0004 (-0.42)	-0.0007 (-0.70)	0.0001 (0.12)	-0.0003 (-0.30)	0.0009 (0.91)
Wednesday	0.0014 (1.48)	0.0010 (1.12)	0.0015 (1.47)	0.0015 (1.53)	0.0001 (0.10)	0.0000 (-0.01)	0.0009 (0.82)	0.0007 (0.77)	0.0015 (1.47)	0.0015 (1.52)
Thursday	0.0009 (0.96)	0.0005 (0.55)	0.0010 (1.02)	0.0008 (0.82)	0.0000 (-0.02)	-0.0005 (-0.50)	0.0008 (0.77)	0.0004 (0.38)	0.0010 (1.02)	0.0008 (0.78)
Friday	0.0009 (0.99)	0.0025 (2.70)***	0.0010 (1.01)	0.0031 (3.08)***	0.0006 (0.49)	0.0016 (1.58)	0.0010 (0.92)	0.0026 (2.68)***	0.0010 (0.99)	0.0030 (3.05)***
R^2	0.9341	0.8313	0.9219	0.7913	0.8936	0.7899	0.9182	0.8163	0.9223	0.7986
Adjusted R^2	0.9334	0.8302	0.9211	0.7899	0.8926	0.7885	0.9175	0.8151	0.9215	0.7972
S_e	0.0116	0.0132	0.0127	0.0147	0.0148	0.0147	0.0130	0.0138	0.0126	0.0144
F-value	1532.75***	733.25***	1276.67***	564.08***	908.61***	559.51***	1214.92***	661.33***	1283.62***	589.98***
Chow test	2.125***		6.108***		3.763***		2.725***		2.985***	

The coefficient on the standard deviation of the rate of returns of the underlying future price only has significantly large positive effect on IV for the 20-day measure. The strong relationship to historical standard deviations of underlying assets seems that the IV series not only response to market deviation from the functional specification of the BSM model but also reflect the market assessment of the standard deviation of underlying assets.

The weekday effect dummies indicate a significantly small Friday effect where the IV are slightly higher. This may be related to the fact that certain economic announcements are made on Friday such as employment situation or lag response to the announcements made on Thursday such as money supply and jobless claims. These economic announcements will alter the market perception of asset price volatility, especially currently the situation of economics that just came through the financial crisis and is suffering from European sovereign-debt crisis. The Friday effect might also be related to option market inactivity the day before the weekend. Further study may investigate this apparent weekday effect to explain why Friday's market may be out of line with that of other days.

Whether the estimated models change significantly over time is an important question. The parameter estimates obtained for this cross-section time series model seems not consistent in 2010 and 2011 sample periods. A Chow test[6] statistic indicating structural change based on five forecasting methods are obtained in Table 4.4 for the 2010 and 2011 regressions and are calculated to be 2.125, 6.108, 3.763, 2.725 and 2.985,respectively .These values exceed the table value of 2.04 for an F random variable at the 99 percent level. The chow test indicated the significant change of structure in the cross-section time series predictive regression model on 2010 and 2011. It would therefore be wise for the practitioner to update parameter estimates periodically even though both 2010 and 2011 sample periods are suffering from global financial crisis.

4.4.3 Ex-Post Test for Forecastability of Time-Series and Cross-Sectional Regression Models

In the previous section, the various estimated methods such as ARMA and regression models for the "true-future" underlying IV are compared to a number of naive methods and evaluated through the conventional measure of forecast accuracy such as RMSE, MAE and MAPE. Now the practical monetary value of the IV estimates versus more naive methods is tested, to determine which might be superior from a trader's point

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[6] Chow test $F_{q,n-k} = \frac{e_*'e_*/\alpha}{e'e/(n-k)}$ where $e_*'e_*$ is restricted SSE, $e'e$ is unrestricted SSE, α represents the number of restrictions, and k is number of regression coefficients estimated in unrestricted regression.

of view. In addition, we hope that these results will further support the theoretical and practical superiority of using individual IV estimates versus some weighted-IV measure.

Discussions with traders of options on S&P 500 index futures along with various segments of the brokerage industry yielded a general view of how IV's are utilized in practice. The common methods are to look at yesterday's weighted-IV (though some sources indicated that they looked at individual IV's), or some type of moving average scheme of past IVs as being the true-future underlying volatility to use in the Black option pricing model. Changes in the option price due to the deviation in the current IV from the estimates of the true-future IV is thus deemed as mispricing by the market. Trading rule tests in this paper utilizes seven different estimates for IV as follows:

(1) a 5-day equally-weighted moving average of the IV (MAV5)

(2) a 5-day exponentially-weighted average of the IV (EMA5)

(3) a 1-day lag of the actual IV for the option (LIV)

(4) 1-day ahead simple regression forecasts of the IV (RGN)

(5) 1-day ahead ARMA forecasts of the IV (ARMA)

(6) 1-day ahead cross-section time series predictive regression forecasts of the IV based on equation (4.16) (CSTS)

(7) a simple-constant mean of an individual IV time series for the estimated IV of

that option (MEAN)

The trading rule used is simply to buy underpriced and sell overpriced options, while taking an opposite position in the underlying futures contract according to the hedge ratio computed by the estimated IV. The holdout periods for each option are twenty trading days. Here the day count convention in Black option pricing model is used actual/actual basis. Mispricing will be identified by comparing the market price for an option with the price calculated by Black option pricing model using one of the seven IV estimates. The overpriced (underpriced) options are defined as the situation that the theoretical price calculated by Black option pricing model is smaller (larger) than the market price. The trading behavior is buying (selling) the underpriced (overpriced) future option and selling (buying) S&P 500 index future for hedge. In order to magnify the mispricing as might be seen from the eyes of a trader, ten options and ten times the hedge ratio of futures are sold or bought in opposite position respectively in each transaction. Positions are closed out once the absolute value of mispricing diminishes to a predetermined minimum level equal to 0.1. If the mispricing has reversed and is of a great enough significance larger than 0.1, the trading rule is utilized again.

In order to ascribe as much realism as possible to these tests, the following market trading costs are considered. Transaction fee per transaction of $2.3 is determined by CME group which provides CME Globex trading platform for 24-hour global access to electronic markets. These costs were calculated as follows:

Total transaction fees

= transaction costs of option position + transaction costs of future position

$$= \sum_{i=1}^{n}(\$2.3\times 10)+\sum_{i=1}^{n}(\$2.3\times 10\times \text{hedge ratio}_{T_i})$$

where n is the total number of times a position is opened at time T_i .

Although a portion of the margin required of a trader enter into a futures position can be put up in the form of interest earning T-bills, a substantial portion required for maintaining the margin account by the clearinghouse must be strictly in cash even for a hedge or spread position. Consequently, there is a real interest cost involved, for which we will further reduce gross trading income:

$$\text{Margin Interest Costs} = \sum_{i=1}^{n}(RMM \times NF_{T_i} \times R_{T_i} \times \tau_i)$$

where RMM is required maintenance margin from CME group[7], NF_{Ti} indicate the number of futures contracts entered into trading which is equal to ten times hedge ratio at

[7] The minimum required maintenance for S&P 500 index futures is various in different period. For example, from Jan 28, 2008 to Oct 1st, 2008, the maintenance cost is $18,000 per future contract. However, the period during Oct 1st, 2008 to Oct 17, 2008, the required maintenance is changed to $20,250. The maintenance costs are $22,500, $24,750, $22,500, and $20,000 for other periods Oct 17, 2008-Oct 30, 2008; Oct 30, 2008-Mar 20, 2009; Mar 20, 2009-Jun 2nd, 2011; and Jun 2nd, 2011 until now.

time T_i, R_{T_i} is the risk free rate defined as the 3-month T-bill rate used in Black option pricing model, τ_i is the length of futures position holding until maturity in annual terms, and n is the total number of times a futures position is entered.

Other very real and significant market costs are those associated with liquidity and timing. Options which are deep-in-the-money for instance, are not heavily traded and therefore present additional costs for actually getting into or out of a position. Since the last reported price for the option may not have occurred at the same time as that for the underlying future, there always arises a problem with using closing prices. Furthermore, there is little assurance that one could buy or sell these contracts and expect to receive the closing prices reported in the paper when the market reopens the next morning. To approximate such market costs the position is penalized each time a futures position is entered and existed by "one tick" equal to 0.1 index points = $25 per contract[8]:

$$\text{Futures Liquidity Costs} = \sum_{i=1}^{n} (\$50 \times NF_{T_i})$$

where $50 = 2 × $25 represented the entered and existed cost by one tick, the market value of two price ticks; NF_{T_i} is defined as the number of futures contracts entered into trading which is equal to ten times hedge ratio at time T_i, and n is the number of times a

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[8] The detailed contract specifications for S&P 500 futures and options on futures can be found in CME group website: http://www.cmegroup.com/trading/equity-index/files/SxP500_FC.pdf

futures position is entered.

More severe liquidity and timing costs are calculated and deducted for each option transaction:

$$\text{Option Liquidity costs} = \sum_{i=1}^{n}[\$250 \times (\text{NEPA}_{T_i} + \text{NMMO}_{Ti})]$$

where \$250 = 10, (number of options bought or sold) × \$250 (the market value multiplier for the option premium) × 0.1 (one tick price as the correspondingly liquidity), NEPA represented the number of exercise prices in out-of-the-money options are \$5 away from underlying future prices at time T_i, and NMMO represented the percentage of maturity months out. For example, a option assumed to be expired on September 2010 and this option start to be traded on February 2010, then the NMMO on June 2010 is equal to the number of month of the period between February and June divided by the number of month of the period between February and September, that is, (6-2)/(9-2)=4/7.

The test results are summarized in Tables 4.5 through 4.7. We use seven alternative methods, a cross-sectional time-series regression and six time series models, to compute tomorrow's IV for each contract. The cross-section time series (CSTS) model utilized some of the insights of time series analysis as would be impounded in the optimal time series predictors, ARMA model. Also, it takes into account the historical 5-days and 20-days standard deviation of the continuous return for the underlying futures contract, the short-term variability and skewness and kurtosis of the IV, the time-to-maturity, and weekday effects. Tables 5a and 5b summarize the cumulative trading results for the selected options contract in Table 1. For both years, EMA5, LIV and RGN perform better than the sophisticated model such as cross-section time-series predictive regression. The results implied that the ARMA model may have over-fitting problem and thus make CSTS model perform worse. The worse prediction is using MEAN model to estimate IV. MEAN model's IV is constant for entire period of contract; thus, MEAN model neither deal with the fluctuation of option market nor response to everyday's new important information. It also implied that the constant volatility setting in BSM model may be misspecified.

In Table 4.6 and Table 4.7, the LIV forecasts do quite well overall. The outcomes of these two Tables strongly support the advantage of considering the previous day's IV to predict current IV for each option contract. Though certainly not conclusive or even completely realistic, these results do point to the fact that previous IV may include all information except the upcoming news. In addition, in Table 4.5, although the trading behaviors based on these seven alternative predictors of IV is mostly profitable; the transaction costs cancel its profit out. Therefore, the setting of trading strategy should be necessarily adjusted to the transaction costs. The possible abnormal returns in trading strategy with transaction costs imply that the future option markets may be inefficient.

Table 4.5 Cumulative Survey of Trading Results for Samples in Holdout Period

The holdout period is the last 20 days of each S&P 500 index futures option contracts. There are seven IV estimates for the trading rule test: MAV5 is the 5-day moving averages method, EMA5 is the 5-day exponential moving averages method, LIV is Previous IV method, RGN is the Regression method, ARMA is autoregressive-moving-average model, CSTS is the cross-section time series predictive regression model represented in equation (4.16) where using ARMA as predictor method, and MEAN is the constant value over the entire period equal to the mean of individual IV series. The definitions of first five IV estimates are indicated in Tables 2 and 3. The gross value of all trades are included the bought and sold price of options plus the value in the end of maturity if the trades are not closed out before maturity. Total trading costs are included the total transaction fees, margin interest costs, future liquidity costs, and option liquidity costs. The net value of all equals to gross value of all trades minus total trading costs. The net profit or loss per trade is the value of net value of all trades divided by number of trade.

a) 2010					
***IV Estimate**	Gross Value of All Trades	Total Trading Costs	Net Value of All Trades	Number of Trade Made	Net Profit or Loss Per Trade
MAV5	**1,673,339**	785,469.1	887,869.8	95	9,345.997
EMA5	1,185,108	735,197.1	449,910.6	95	4,735.901
LIV	1,325,712	**405,671**	**920,041.3**	95	**9,684.645**
RGN	1,077,990	432,747.3	645,243.1	95	6,792.033
ARMA	535,833.8	462,131	73,702.82	95	7,75.8192
CSTS	413,830.8	618,588.4	-204,758	95	-2,155.34
MEAN	454,006.3	1,714,191	-1,260,185	95	-13,265.1
b) 2011					
***IV Estimate**	Gross Value of All Trades	Total Trading Costs	Net Value of All Trades	Number of Trade Made	Net Profit or Loss Per Trade
MAV5	840,926.2	706,118.6	134,807.6	152	886.8921
EMA5	-794,276	784,070.1	-1,578,346	152	-10,383.9
LIV	2,433,862	**500,012.3**	1,933,850	152	12,722.7
RGN	**3,170,605**	1,090,987	**2,079,618**	152	**13,681.7**

ARMA	679,499.3	786,602.5	-107,103	152	-704.63
CSTS	-4,119,967	600,665.3	-4,720,633	152	-31,056.8
MEAN	4,168,410	2,752,602	1,415,807	152	9,314.522

Table 4.6 Average Absolute and Relative Differences between Model and Market Prices for 2010 Option Contracts

The holdout period is the last 20 days of each S&P 500 index futures option contracts. There are seven IV estimates for the trading rule test: MAV5 is the 5-day moving averages method, EMA5 is the 5-day exponential moving averages method, LIV is Previous IV method, RGN is the Regression method, ARMA is autoregressive-moving-average model, CSTS is the cross-section time series predictive regression model represented in equation (4.16) where using ARMA as predictor method, and MEAN is the constant value over the entire period equal to the mean of individual IV series. (a) represents the average absolute difference between the theoretical price (BP) calculated by Black model and actual market price (MP), which the formula is $\sum_{i=1}^{k}|BP_i - MP_i|/k$. (r) represents the average relative difference between the theoretical price (BP) calculated by Black model and actual market price (MP), which the formula is $\sum_{i=1}^{k}(BP_i - MP_i)/k$.

*IV Estimate		MAV5	EMA5	LIV	RGN	ARMA	CSTS	MEAN
MAR10 1075	*(a)	1.253	1.161	**0.944**	0.950	1.154	1.143	1.861
(C070WC)	*(r)	0.224	0.561	**0.076**	0.204	0.074	-0.212	0.235
JUN10 1050	*(a)	1.880	1.717	**1.356**	1.406	1.707	1.694	11.077
(B243UE)	*(r)	0.241	0.782	**0.092**	0.192	0.187	0.117	0.189
JUN10 1100	*(a)	1.754	1.581	**1.237**	1.264	1.382	1.347	10.573
(B243UF)	*(r)	0.257	0.752	0.101	**0.006**	0.022	-0.132	-0.355
SEP10 1100	*(a)	1.704	1.587	**1.317**	1.401	1.363	1.440	4.648
(C9210T)	*(r)	0.037	0.515	**0.011**	0.106	0.070	0.294	0.301
SEP10 1200	*(a)	1.250	1.126	**0.880**	0.893	0.900	0.903	3.809
(C9210U)	*(r)	0.078	0.424	**0.028**	0.130	0.068	0.179	0.500

Table 4.7 Average-Absolute and Relative Differences between Model and Market Prices for 2011 Option Contracts

The holdout period is the last 20 days of each S&P 500 index futures option contracts. There are seven IV estimates for the trading rule test: MAV5 is the 5-day moving averages method, EMA5 is the 5-day exponential moving averages method, LIV is Previous IV method, RGN is the Regression method, ARMA is autoregressive-moving-average model, CSTS is the cross-section time series predictive regression model represented in equation (4.16) where using ARMA as predictor method, and MEAN is the constant value over the entire period equal to the mean of individual IV series. (a) represents the average absolute difference between the theoretical price (BP) calculated by Black model and actual market price (MP), which the formula is $\sum_{i=1}^{k}|BP_i - MP_i|\,/k$. (r) represents the average relative difference between the theoretical price (BP) calculated by Black model and actual market price (MP), which the formula is $\sum_{i=1}^{k}(BP_i - MP_i)\,/k$.

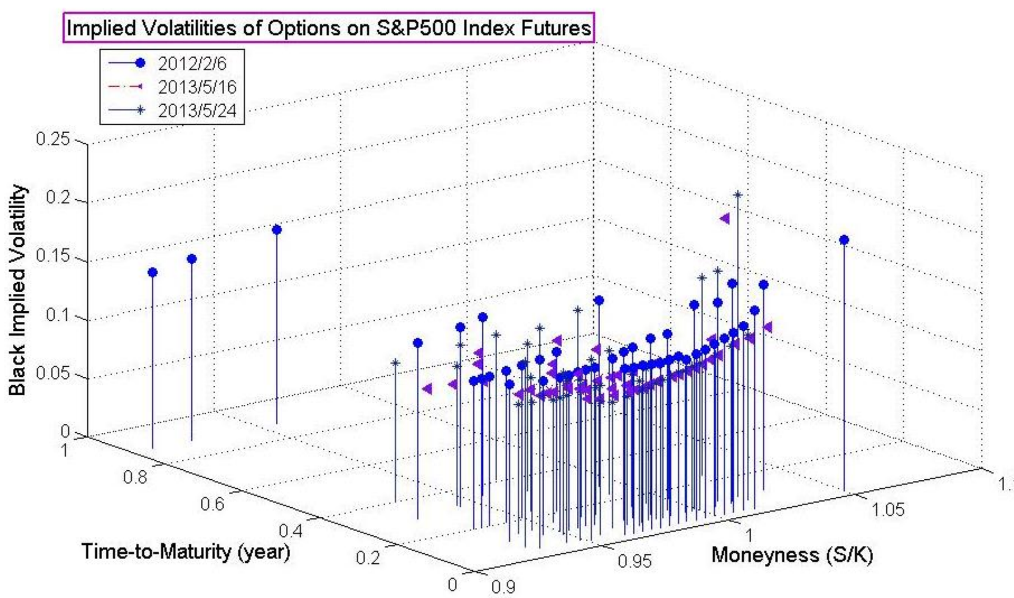
*IV Estimate		MAV5	EMA5	LIV	RGN	ARMA	CSTS	MEAN
MAR11 1200	*(a)	1.800	2.023	**1.276**	1.478	2.018	1.994	5.234
(D039NR)	*(r)	-0.041	1.353	**-0.006**	0.510	0.263	-0.166	2.735
MAR11 1250	*(a)	1.619	1.670	**1.136**	1.496	1.461	1.438	4.445
(D1843V)	*(r)	0.075	1.056	0.037	0.138	0.122	**0.002**	0.892
MAR11 1300	*(a)	1.332	1.492	**0.929**	1.125	1.090	1.119	4.087
(D039NT)	*(r)	0.041	1.005	**0.017**	0.025	0.065	0.049	0.068
JUN11 1325	*(a)	1.274	1.448	**0.927**	1.089	1.096	1.100	2.515
(B513XF)	*(r)	0.193	1.009	0.070	-0.075	0.027	**-0.007**	-0.363
JUN11 1350	*(a)	1.052	1.184	**0.753**	0.773	0.846	0.881	2.705
(A850CJ)	*(r)	0.188	0.893	0.064	0.075	0.091	0.149	**0.060**
SEP11 1250	*(a)	1.595	1.769	**1.192**	1.235	1.274	1.536	4.160
(B9370T)	*(r)	-0.081	1.135	**0.000**	0.258	0.239	0.547	2.726
SEP11 1300	*(a)	1.435	1.656	**1.016**	1.061	1.218	1.166	2.959
(B778PK)	*(r)	0.056	1.205	**0.038**	0.318	0.228	0.087	2.086

SEP11 1350	*(a)	1.228	1.424	**0.843**	0.872	1.014	1.007	2.817
(B9370V)	*(r)	0.108	1.094	**0.049**	0.260	0.099	-0.017	1.815

4.4.4 Structural Parameter Estimation and Performance of CEV Model

In Figure 4.1, we find that each contract's Black IV varies across moneyness and time-to-maturity. This graph shows volatility skew (or smile) in options on S&P 500 index futures, i.e. the implied volatilities decrease as the strike price increases (the moneyness level decreases).

Figure 4.1 Implied Volatilities in Black Model



Even though everyday implied volatility surface changes, this characteristic still exists. Therefore, we divided future option contracts into a six by four matrix based on moneyness and time-to-maturity levels when we estimate implied volatilities of futures options in CEV model framework in accordance with this character. The whole option samples expired within the period of 2010 to 2013 contains 30,364 observations. The whole period of option prices is from March 19, 2009 to November 5, 2013. The observations for each group are presented in Table 4.8.

Table 4.8 Average Daily and Total Number of Observations in Each Group

The whole period of option prices is from March 19, 2009 to November 5, 2013. Total observations is 30, 364. The lengths of period in groups are various. The range of lengths is from 260 (group with ratio below 0.90 and time-to-maturity within 30 days) to 1,100 (whole samples).

Time-to-Maturity(TM)	**TM<30**		**30≦TM≦60**		**TM>60**		**All TM**	
Moneyness (S/K ratio)	Daily Obs.	Total Obs.	Daily Obs.	Total Obs.	Daily Obs.	Total Obs.	Daily Obs.	Total Obs.
S/K ratio >1.01	1.91	844	1.64	499	1.53	462	2.61	1,805
0.98≦S/K ratio≦1.01	4.26	3,217	2.58	1,963	2.04	1,282	6.53	6,462
0.95≦S/K ratio<0.98	5.37	4,031	3.97	3,440	2.58	1,957	9.32	9,428
0.9≦S/K ratio<0.95	4.26	3,194	4.37	3,825	3.27	2,843	9.71	9,862
S/K ratio <0.9	2.84	764	2.68	798	2.37	1,244	4.42	2,806
All Ratio	12.59	12,050	10.78	10,526	7.45	7,788	27.62	30,364

Since most trades are in the futures options with short time-to-maturity, the estimated implied volatility of the option samples in 2009 may be significantly biased because we didn’t collect the futures options expired in 2009. Therefore, we only use option prices in the period between January 1, 2010 and November 5, 2013 to estimate parameters of CEV model. In order to find global optimization instead of local minimum of absolute pricing errors, the ranges for searching suitable δ_0 and α_0 are set as $\delta_0 \in [0.01,0.81]$ with interval 0.05, and $\alpha_0 \in [-0.81, 1.39]$ with interval 0.1, respectively. First, we find the value of parameters, $(\widehat{\delta_0}, \widehat{\alpha_0})$, within the ranges such that minimize value of absolute pricing errors in equation (4.19). Then we use this pair of parameters, $(\widehat{\delta_0}, \widehat{\alpha_0})$, as optimal initial estimates in the procedure of estimating local minimum minAPE based on steps (1)-(3) in section 4.3.2.3. To compare with the option pricing performance of Black model, we set the interval between 0.01 and 0.08 to find optimal implied volatility via estimation procedure in section 4.3.2.1. The initial parameter setting of CEV model is presented in Table 4.9.

Table 4.9 Initial Parameters of CEV Model for Estimation Procedure

The sample period of option prices is from January 1, 2010 to November 5, 2013. During the estimating procedure for initial parameters of CEV model, the volatility for S&P 500 index futures equals to $\delta_0 S^{\alpha_0 - 1}$.

Time-to-Maturity(TM)	**TM<30**		**30≦TM≦60**		**TM>60**		**All TM**	
Moneyness (S/K ratio)	α_0	δ_0.	α_0	δ_0	α_0	δ_0	α_0	δ_0
S/K ratio >1.01	0.677	0.400	0.690	0.433	0.814	0.448	0.692	0.429
0.98≦S/K ratio≦1.01	0.602	0.333	0.659	0.373	0.567	0.361	0.647	0.345
0.95≦S/K ratio<0.98	0.513	0.331	0.555	0.321	0.545	0.349	0.586	0.343
0.9≦S/K ratio<0.95	0.502	0.344	0.538	0.332	0.547	0.318	0.578	0.321
S/K ratio <0.9	0.777	0.457	0.526	0.468	0.726	0.423	0.709	0.423
All Ratio	0.854	0.517	0.846	0.512	0.847	0.534	0.835	0.504

In Table 4.9, the average sigma are almost the same while the average alpha value in either each group or whole sample is less than one. This evidence implies that the alpha of CEV model can capture the negative relationship between S&P 500 index future prices and its volatilities shown in Figure 4.1. The instant volatility of S&P 500 index future prices equals to $\delta_0 S^{\alpha_0 - 1}$ where S is S&P 500 index future prices, δ_0 and α_0 are the parameters in CEV model. The estimated parameters in Table 4.9 are similar across time-to-maturity level but volatile across moneyness.

Because of the implementation and computational costs, we select the sub-period from January 2012 to November 2013 to analyze the performance of CEV model. The total number of observations and the length of trading days in each group are presented in Table 4.10. The estimated parameters in Table 4.9 are similar across time-to-maturity level but volatile across moneyness. Therefore, we investigate the performance of all groups except the groups on the bottom row of Table 4.10. The performance of models can be measured by either the implied volatility graph or the average absolute pricing errors (AveAPE). The implied volatility graph should be flat across different moneyness level and time-to-maturity. We use subsample like Bakshi et al. (1997) and Chen et al. (2009) did to test implied volatility consistency among moneyness-maturity categories. Using the subsample data from January 2012 to May 2013 to test in-the-sample fitness, the average daily implied volatility of both CEV and Black models, and average alpha of CEV model are computed in Table 4.11. The fitness performance is shown in Table 4.12. The implied volatility graphs for both models are shown in Figure 4.2. In Table 4.11, we estimate the optimal parameters of CEV model by using a more efficient program. In this efficient program, we scale the strike price and future price to speed up the program where the implied volatility of CEV model equals to $\delta(\text{ratio}^{\alpha-1})$, ratio is the moneyness level, δ and α are the optimal parameters of program which are not the parameters of CEV model in equation (4.17). In Table 4.12, we found that CEV model perform well at in-the-money group.

Table 4.10 Total Number of Observations and Trading Days in Each Group

The subsample period of option prices is from January 1, 2012 to November 5, 2013. Total observations is 13, 434. The lengths of period in groups are various. The range of lengths is from 47 (group with ratio below 0.90 and time-to-maturity within 30 days) to 1,100 (whole samples). The range of daily observations is from 1 to 30.

Time-to-Maturity(TM)	**TM<30**		**30≦TM≦60**		**TM>60**		**All TM**	
Moneyness (S/K ratio)	Days	Total Obs.	Days	Total Obs.	Days	Total Obs.	Days	Total Obs.
S/K ratio >1.01	172	272	104	163	81	122	249	557
0.98≦S/K ratio≦1.01	377	1,695	354	984	268	592	448	3,271
0.95≦S/K ratio<0.98	362	1,958	405	1,828	349	1,074	457	4,860
0.9≦S/K ratio<0.95	315	919	380	1,399	375	1,318	440	3,636
S/K ratio <0.9	32	35	40	73	105	173	134	281
All Ratio	441	4,879	440	4,447	418	3,279	461	12,605

Figure 4.2 shows the IV computed by CEV and Black models. Although their implied volatility graphs are similar in each group, the reasons to cause volatility smile are totally different. In Black model, the constant volatility setting is misspecified. The volatility parameter of Black model in Figure 4.2(b) varies across moneyless and time-to-maturity levels while the IV in CEV model is a function of the underlying price

and the elasticity of variance (alpha parameter). Therefore, we can image that the prediction power of CEV model will be better than Black model because of the explicit function of IV in CEV model. We can use alpha to measure the sensitivity of relationship between option price and its underlying asset. For example, in Figure 4.2(c), the in-the-money future options near expired date have significantly negative relationship between future price and its volatility.

Table 4.11 Average Daily Parameters of In-Sample

The in-sample period of option prices is from January 1, 2012 to May 30, 2013. In the in-sample estimating procedure, CEV implied volatility for S&P 500 index futures (CEV IV) equals to $\delta(S/K \text{ ratio})^{\alpha-1}$ in according to reduce computational costs. The optimization setting of finding CEV IV and Black IV is under the same criteria.

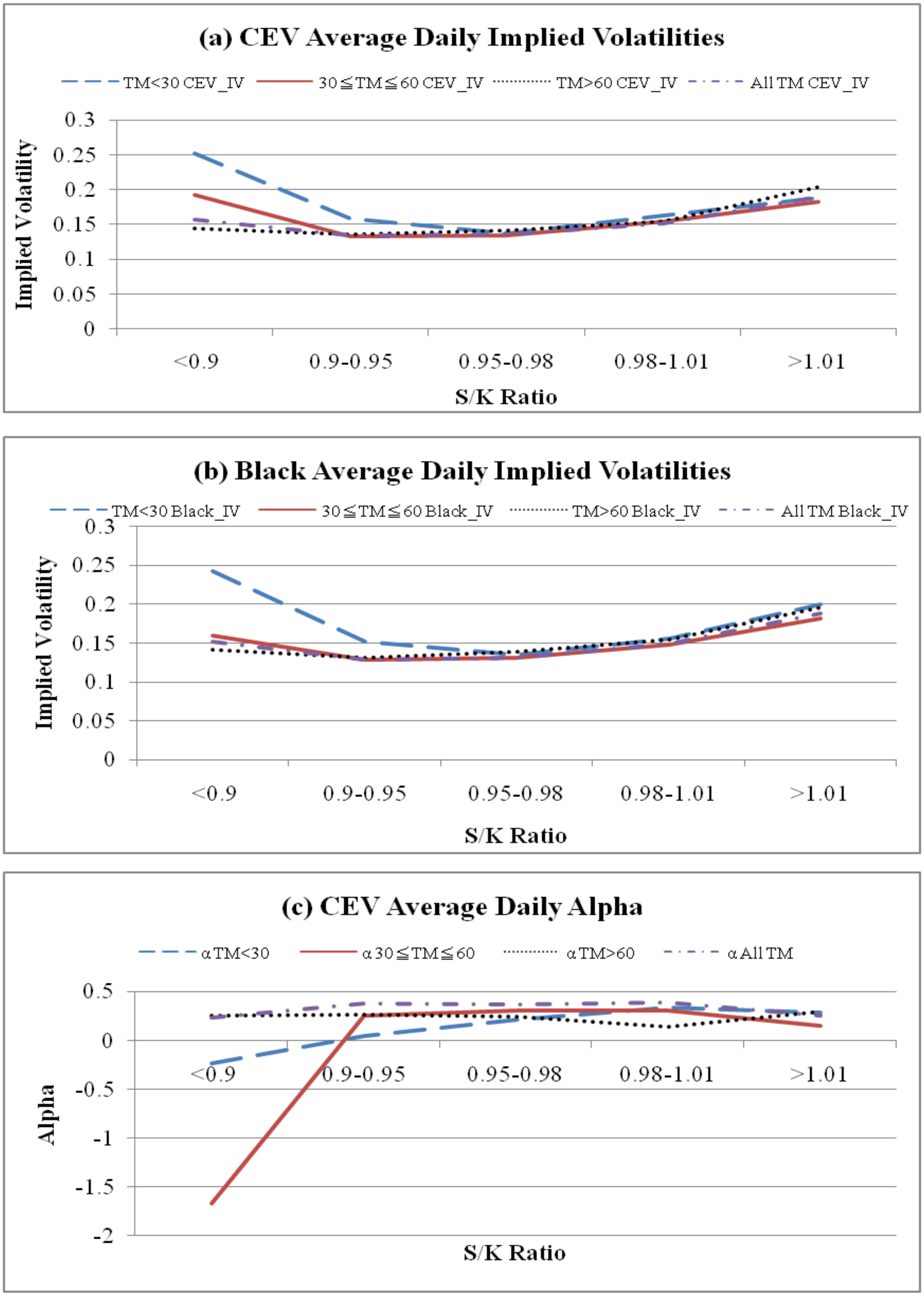
Time-to-Maturity(TM)	TM<30				30≦TM≦60				TM>60				All TM			
Moneyness (S/K ratio)	CEV			Black	CEV			Black	CEV			Black	CEV			Black
Parameters	α	δ	IV	IV	α	δ	IV	IV	α	δ	IV	IV	α	δ	IV	IV
S/K ratio >1.01	0.29	0.19	0.188	0.200	0.14	0.18	0.183	0.181	0.29	0.21	0.204	0.196	0.25	0.19	0.1890	0.1882
0.98≦S/K ratio≦1.01	0.34	0.16	0.162	0.1556	0.30	0.16	0.154	0.147	0.14	0.16	0.155	0.155	0.39	0.17	0.151	0.150
0.95≦S/K ratio<0.98	0.22	0.13	0.137	0.135	0.30	0.13	0.134	0.131	0.24	0.14	0.141	0.139	0.37	0.14	0.136	0.132
0.9≦S/K ratio<0.95	0.05	0.15	0.159	0.152	0.25	0.13	0.133	0.128	0.26	0.14	0.136	0.131	0.38	0.14	0.135	0.129
S/K ratio <0.9	-0.23	0.22	0.252	0.243	-1.67	0.14	0.193	0.159	0.25	0.15	0.145	0.142	0.23	0.15	0.157	0.152

Table 4.12 AveAPE Performance for In-Sample-Fitness

The in-sample period of option prices is from January 1, 2012 to May 30, 2013.

Time-to-Maturity(TM)	TM<30			30≦TM≦60			TM>60			All TM		
Moneyness (S/K ratio)	CEV	Black	Obs.	CEV	Black	Obs.	CEV	Black	Obs.	CEV	Black	Obs.
S/K ratio >1.01	**1.65**	1.88	202	1.81	**1.77**	142	5.10	**5.08**	115	**5.80**	6.51	459
0.98≦S/K ratio≦1.01	**6.63**	7.02	1,290	**4.00**	4.28	801	4.59	**4.53**	529	**18.54**	18.90	2,620
0.95≦S/K ratio<0.98	2.38	**2.34**	1,560	4.25	**4.14**	1,469	3.96	**3.89**	913	14.25	**14.15**	3,942
0.9≦S/K ratio<0.95	0.69	**0.68**	710	1.44	**1.43**	1,094	3.68	**3.62**	1,131	**7.08**	7.10	2,935
S/K ratio <0.9	0.01	0.01	33	**0.13**	0.18	72	0.61	**0.60**	171	0.69	**0.68**	276

Figure 4.2 Implied Volatilities and CEV Alpha Graph



The better performance of CEV model may result from the over-fitting issue that will hurt the forecastability of CEV model. Therefore, we use out-of-sample data from June 2013 to November 2013 to compare the prediction power of Black and CEV models. We use the estimated parameters in previous day as the current day's input variables of model. Then, the theoretical option price computed by either Black or CEV model can calculate bias between theoretical price and market price. Thus, we can calculate the average absolute pricing errors (AveAPE) for both models. The lower value of a model's AveAPE, the higher pricing prediction power of the model. The pricing errors of out-of-sample data are presented in Table 4.13. Here we find that CEV model can predict options on S&P 500 index futures more precisely than Black model. Based on the better performance in both in-sample and out-of-sample, we claim that CEV model can describe the options of S&P 500 index futures more precisely than Black model.

Table 4.13 AveAPE Performance for Out-of-Sample

Time-to-Maturity(TM)	**TM<30**		**30≦TM≦60**		**TM>60**		**All TM**	
Moneyness (S/K ratio)	CEV	Black	CEV	Black	CEV	Black	CEV	Black
S/K ratio >1.01	**3.22**	3.62	**3.38**	4.94	**8.96**	13.86	**4.25**	5.47
0.98≦S/K ratio≦1.01	**2.21**	2.35	2.63	**2.53**	**3.47**	3.56	**2.72**	2.75
0.95≦S/K ratio<0.98	**0.88**	1.04	**1.42**	1.46	1.97	**1.95**	**1.44**	1.45
0.9≦S/K ratio<0.95	**0.34**	0.53	**0.61**	0.62	1.40	1.40	**0.88**	0.90
S/K ratio <0.9	**0.23**	0.79	**0.25**	0.30	1.28	**1.27**	**1.03**	1.66

4.5 Conclusion

For the academician, the inconsistent cross-sectional and time series nature of the IV implies a certain and perhaps significant degree of misspecification within BSM /Black option pricing model.

The purpose of this essay has been to improve the interpretation and forecasting of individual implied volatility (IV) for call options on S&P500 index futures in 2010 to 2013. The two alternative methods used in this essay are cross-sectional time-series analysis and CEV model. These two alternative approaches give different perspective of estimating IV. The cross-sectional time series analysis focuses on the dynamic behavior of volatility in each option contracts and captures other trading behaviors such as week effect and in/out of the money effect. On the other hand, CEV model generalizes implied volatility surface as a function of asset price.

By empirically explaining the composition through time series analysis and cross-sectional time series regression models, the disadvantages to evaluating an option IV by Black model have been demonstrated. More importantly, the results based on our trading strategy provide some evidence as to how the Black option pricing model might be misspecified, or jointly, how the market might be inefficient. Though the original model implicitly assumes a frictionless market and a constant volatility term, market realities along with past studies would not be able to substantiate these types of assumptions. The forecasting performances of seven time-series regression models based on our trading strategy show that the simple regression models perform better than sophisticated cross-sectional time-series models because of over-fitting problem in the advanced models. In addition, although our trading rules based on the prediction of these models can make profit, the net profit depends on the transaction costs. Therefore, the setting of trading strategy should be necessarily adjusted to the transaction costs.

We also show that CEV model performs better than Black model in aspects of either in-sample fitness or out-of-sample prediction. The setting of CEV model is more reasonable to depict the negative relationship between S&P 500 index future price and its volatilities. The elasticity of variance parameter in CEV model captures the level of this characteristic. The stable volatility parameter in CEV model in our empirical results implies that the instantaneous volatility of index future is mainly determined by current future price and the level of elasticity of variance parameter.

In sum, we suggest predict individual option contract by using simple regression analysis instead of advanced cross-sectional time-series model. Even though the moneyness and week effect have significant influence on index future option prices, the over-fitting problem in an advanced cross-sectional time-series model will decrease its pricing forecastability. With regard to generate implied volatility surface to capture whole prediction of the future option market, the CEV model is the better choice than Black model because it not only captures the skewness and kurtosis effects of options on index futures but also has less computational costs than other jump-diffusion stochastic volatility models.

CHAPTER 5

Summary and Future Study

This thesis includes three essays in chapters 2 to 4 respectively related to capital structure, risk management in banking, and options on index futures. The first essay in chapter 2 investigates the determinants of capital structure and the joint determination of capital structure and stock rate of return by using structure equation modeling (SEM) approach. The second essay in chapter 3 proposes the structural model approach in terms of the Stair Tree model and the barrier option model to price fair deposit insurance premium in accordance with closure policy, bankrupt costs, and practical provisions and restrictions of insurance contracts. Finally, the purpose of the third essay is to improve the interpretation and forecasting of individual implied volatility for call options on S&P500 index futures by using cross-sectional time series regression and CEV models. The results of these three essays are as following.

In chapter 2, we utilize the structure equation modeling (SEM) with CFA approach estimate the impacts of unobservable attributes on capital structure. The main contribution of this essay is the comprehensive confirmation on theories in corporate finance. Based on the sample during 2001 to 2012, our empirical work only shows

“Profitability” and “Volatility & Financial Rating” are significant attributes on the decision of capital structure. However, all attributes become significant determinants of capital structure and stock returns in either market- or book- value basis. The evidence shows that the interaction of a firm’s leverage and its stock price should be necessarily considered in capital structure research. Besides the proof of trade-off between financial distress and agency costs in previous theories, our results confirm the endogenous supply relationship between public and private debts. Moreover, the interrelation between leverage ratios and stock returns verifies the signal theory under the assumption of asymmetric information between managers and investors. Only significantly negative influence of stock returns on market-value based leverage ratios supports Welch’s (2004) statement. We also do robustness check by using MIMIC model and the two-stage, least square (2SLS) estimating method. However, MIMIC model and 2SLS method cannot well identify the influences of factors on long-term leverage decisions in accordance with capital structure theories. According to comparison of these methods’ results, the setting of latent attributes is necessary to clarify and confirm theories in capital structure. Therefore, I would suggest using structural equation modeling (SEM) with confirmatory factor analysis (CFA) to capture the appropriate factors of firms’ leverage decisions.

The simulation results in chapter 3 first indicate that our structural model approach is the general model to evaluate deposit insurance and the model in Brockman and Turle (2003) (hereafter called BT) is a special case of mine. Moreover, the interaction between closure policy and bankruptcy is incorporated in our model and the results manifest the important role of bankrupt costs in FDIC supervision. Even though the increase in regulatory barrier will lead to transfer the wealth from stockholders to the insurer, the indirectly bankrupt costs will offset this benefit. Therefore, FDIC would prefer to take the forbearance closure policy rather than the strict policy to protect insurance fund from loss of bankrupt costs. The closure policy can be properly adjusted by the setting of insurance premium and the impacts of bankruptcy cost. Finally, an appropriate deposit insurance premium can alleviate potential moral hazard problems caused by a forbearance policy.

The empirical results of chapter 4 by using options on S&P 500 index futures expired in 2010 to 2013 shows that implied volatility is predictable. The two alternative approaches, cross-sectional time-series analysis and CEV model, give different perspective of estimating IV in the third essay. The cross-sectional time series analysis focuses on the dynamic behavior of volatility in each option contracts and captures other trading behaviors such as week effect and in/out of the money effect. On the other hand, CEV model generalizes implied volatility surface as a function of asset price. The abnormal returns in our trading strategy with transaction costs provide some evidence as to how the Black option pricing model might be misspecified, or jointly, how the market might be inefficient. According to the performance in terms of in-sample fitness and out-of-sample prediction, CEV model is a better option pricing model than Black model. It not only captures the skewness and kurtosis effects of options on index futures but also has less computational costs than other jump-diffusion stochastic volatility models. In addition, the setting of CEV model is more reasonable to depict the negative relationship between S&P 500 index future price and its volatilities. The stable volatility parameter in CEV model in our empirical results implies that the instantaneous volatility of index future is mainly determined by current future price and the level of elasticity of variance parameter. In sum, we suggest predict individual option contract by using time-series analysis and generate implied volatility surface by using CEV model.

In future research, personal taxes and heterogeneous beliefs between manager and outside investors can be taken into joint determinants of capital structure and stock return if the related information is available. In second essay, if we can obtain real data to find the fair deposit insurance premium and proper closure barrier, then we can confirm our supposition that the forbearance policy is better than restrict policy for FDIC. Finally, we can apply CEV model and its Greek measures to other liquid option markets to test market efficiency based on our trading rules.

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