

CHAPTER 1

Introduction

1.1 Statement of the Problem and Significance of the Study

Stock exchange market is an attractive choice for investor to make money. First, shareholders could gain a return on their investment in two ways; capital gains from the stock's price rise and dividends would have been distributed to shareholders depending on the company's annual income. Second, a variety of financial products such as common stocks, preferred stocks, bonds and warrants are offered for investment. Third, the rate of return from stocks investment is likely higher than bank deposits. Lastly, finance investment induce a company's or an economy's growth. Mostly investors often choose to invest in the company's shares that show the potential growth. However, if the market down, the stock prices can lower down than its issuing prices. Investors will face with a possible loss by selling stock before its maturity date. Since the stock prices are volatility and uncertainty, it is hard to find the best time point of buying or selling stocks. Investors who need success in financial trading should have an adequate field of knowledge to make wise investment decisions. Thus, stock price prediction is very important and challenging for individual investors, stock fund managers and financial analysts. The more accurate of stock prices forecasting, the more profitable investors gain.

The choices of econometric model have an effect on an accuracy of stock price prediction. The properties of econometric model are different in requirement. The traditional model usually based on some strong assumption that is bonded with probability theory and historical data. For example, Bayesian approach, it faces some difficulties in specifying the prior density function of the parameters to be estimated. Maximum Likelihood method requires asymptotic property and is not appropriate to use in the sense of small sample. These mentioned problems could be solved by using belief function approach. The advantages of belief function approach do not require

the statistician to arbitrarily provide a prior probability distribution when prior knowledge is not available and can forecast in both cases of low and high imprecise data.

When we deal with finance data sets of variables for prediction, we usually pay attention to time series framework. The sample is a collection of data points $(y_i), i = 1, 2, \dots, n$ or $(y_t), t = 1 \dots T$ where y_i or $y_t \in \mathbb{R}$. The finance assets such as stocks, bonds, exchange rates are collected at a very high frequency daily, weekly or monthly. It will produce a mass number of studies. Moreover, financial assets data mainly are analyzed in closing prices that consists of noise due to the incomplete of trading strategy process. Then, the variables measured with error by closing prices collection are caused to unstable ordinary least square estimators in market line or multifactor model (see, Kleper and leamer (1984)). The amount number of data be reduced by interval-valued data method is an alternative way of collecting data in a range of low and high prices in a day. Interval-valued concept is very useful and facilitative for data analysis.

In finance, risk is the main concern for financial activities in the economy. Two types of investment risks affect investors; unsystematic risk involves general market conditions, such as recessions, interest rates and war, over which investors have no control and systematic risk is inherent in individual stocks. Risk in investment is mostly end up as a huge loss on money. Not only investors face with financial risk but also investment decision problem. In order to limit their risk of loss, investors diversify their portfolio holdings. Among several possible investment portfolios, which one should they choose? The general decision is based in the contexts of social or physical sciences, the problem is on choosing "optimal" actions leading to an "optimal portfolio". In the investment choice problem, we view investment portfolios as risky projects which, in turn, are modeled as real-valued random variables. In any case, we face the problem of making-decision under uncertainty where the obviously probability theory is the language for quantitative analysis. Generally, an investment consists of several portfolio units. One of the problems of great importance is on an application of allocating (divide) the capital to its portfolio investment. Specifically,

let the investment portfolio be $I = \{1, 2, \dots, n\}$ where $i \in I$ is a portfolio unit. Let $c(I)$ be denoted as the investor capital risk. The inquiry raised is on “how to construct a vector $x = (x^1, x^2, \dots, x_n) \in R^n$, such that $\sum_{i=1}^n x_i = c(I)$, where x_i is the capital risk allocated to the portfolio unit i . There are many ways of doing these. We are really talking about "fair" allocations where the allocated amounts should reflect the contributions of corresponding portfolio units.

An investor concerns in choosing a number of assets to include in his/her portfolio. Which weight of each asset must bear for the investor to maximize some utility criterion? We deal with the concept of diversification of entire investment across assets as in the approach of Markovitz (1952), a portfolio optimization formulation with the mean-variance analysis framework. The Capital Asset Pricing Model (CAPM) is a way to measure the risk in relation to expected return. The volatility of a stock is estimated by a coefficient called beta, serves as a systemic risk. CAPM is widely used in finance for evaluation of portfolio diversification, assessment investments and choosing portfolio strategy among others. In terms of risk calculating, CAPM is more reliable and effective method than other models such as the Dividend Growth Model. Because CAPM can calculate a company's level of systematic risk against the stock market as a whole; the company can compare itself to the market. Besides, an investor can use CAPM for investment decision. Nevertheless, the assumptions of CAPM theory can be criticized that it is unrealistic and does not correspond to the practical facts, as a results many empirical studies of CAPM have been developed to overcome the unrealistic.

As the financial system becomes more complex, particularly, the stock returns are likely to show asymmetric dependence-the increasing sophistication of financial models requires equally sophisticated methods for their empirical implementation. Therefore, this study contributes the new techniques such as belief functions, interval valued-data regression, and vine copulas to improve the original capital asset pricing model are following three topics.

TOPIC 1: Forecasting risk and returns: CAPM model with belief functions.

TOPIC 2: Capital Asset Pricing Model with Interval Data.

TOPIC 3: Optimizing Stock Returns Portfolio Using the Dependence Structure Between Capital Asset Pricing Models: A Vine Copula-based approach.

1.2 Literature Review

Our econometrics approach of interest involves the financial model. We focus on the capital asset pricing model (CAPM) and its applications, namely, belief functions, interval regression, and portfolio optimization using vine copulas.

1.2.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) is foundation and important tool in finance for measure systematic risk. Since the introducing of CAPM by Sharpe (1964) and Lintner (1965) , the productive of empirical studies have been tested on the validity of the CAPM. Galagera (2007) discussed the CAPM under five categories: the single factor model, multifactor models, CAPM with higher order systematic co-moments, CAPM conditional on market movements and time-varying volatility models. The research found that a lot of empirical studies of cross-asset variation in expected returns could not be explained by the systematic risk or beta alone. Then, many models have been developed and new techniques have been incorporated with CAPM to improve asset returns prediction. Heinen and Valdesogo (2009) developed the Canonical Vine Autoregressive (CAVA) model original from CAPM that can capture non-linear and non-Gaussian behavior of the cross-section of asset returns as well as model their dependencies to the market and the respective sector. Brechmann and Czado (2013) developed the Regular Vine Market Sector model (RVMS), a regular vine copula based factor model for asset returns. The results showed that RVMS model had better than the CAVA model because it had been used to separate the systematic and idiosyncratic risk of specific

stocks. Moussa et al. (2014) found that beta estimate via the fuzzy returns were more stable than ordinary least square estimates when the return intervals and the sample size change. Zabarankin et al. (2014) studied the optimality conditions for a portfolio optimization problem with Conditional Drawdown at Risk (CDaR) yield the CAPM in both single and multiple sample-path settings. Prukumpai (2015) studied the time-varying beta behavior of eight industrial portfolios in Stock Exchange of Thailand by two- regime Markov-switching model.

1.2.2 Belief Functions

The Dempster-Shafer belief function theory is a useful tool for managing different types of imperfection. It has been developed by Dempster (1967) and later formalized by Shafer (1976). Belief functions have been used in financial and business model combination. Srivastava and Mock (1999) applied an evidential reasoning approach based on the belief framework for web trust assurance. A decision theoretical approach be used to estimate audit fee based on costs related with various risk. Srivastava and Datta (2002) used the belief functions approach to evaluate mergers and acquisitions candidates and to represent uncertainty in the evidence. McBurney and Parsons (2002) used the theory of belief functions to model financial portfolio. The studied shown new information or evidence could be modeled as independent belief functions and then be used update the predictions. Shenoy and Shenoy (2002) forecasted demand for global mobile satellite services by using belief function. Liu et al. (2002) used linear belief functions to represent for market information and financial knowledge, including complete ignorance, statistical observations, subjective speculations, distributional assumptions, linear relations, and empirical asset pricing models. Kanjanatarakul et al. (2014) used the Bass model for innovation diffusion together with past sales data and the formalism of belief functions to quantify the uncertainty on future sales. Autcharyapanitkul et al. (2014) used quantile regression and belief functions to predict stock return in CAPM. Liu et al. (2014) detected the

dependence structure between crude oil and corn returns by using belief functions-based copula quantile curves and quantified uncertainty of the corn returns at one step period. Xu et al. (2014) applied Dempster-Shafer theory to the prediction of China's stock market.

1.2.3 The Interval Regression

Interval-valued data are observed as ranges of minimum and maximum values. Many research fields adopted interval-valued data widely such as marketing, environmental sciences, medicine, meteorology economics and finance. Especially, the assets prices in financial markets usually are incomplete, uncertain and imperfect. It is collected in the range of minimum and maximum prices at daily, weekly or monthly that considered in an interval form. Several research works for analyzing interval-valued applied to various approaches. For example, Diamond (1990), Kórner and Nätzer (1998), Billard and Diday (2000), Manski (2002), Gil et al. (2002), Billard (2007), Neto and Carvalho (2008), Maia et al. (2008), Carvalho et al. (2012), Cattaneo and Wiencierz (2012). In framework of forecasting by interval -valued data with regression analysis methods, Hu and He (2006) found that stock market forecasting by interval data computing approach is better than traditional point data based on OLS estimator. Arroyo et al. (2010) used interval regression prediction method to the daily interval time series of low/high prices of the S&P500 index. Xiong et al. (2014) forecasted an interval-valued stock price index series over short and long horizons using a multi-output support vector regression with a firefly algorithm (FA-MSVR). Sun and Li (2015) applied linear regression for interval-valued data within the framework of random sets.

1.2.4 Vine Copula based Approach

Vine copula has been a popular tool for dependence modeling in financial applications. The first study of vine copula in financial risk management, De Melo Mendes et al. (2010) applied a D-Vine copula model with four different bivariate copula families for a six dimensional data set and

discussed its use in portfolio management. Hofmann and Czado (2010) found that an accuracy of VaR forecasting by D-Vine model superior to multivariate t copula model. Guegan and Maugis (2011) employed vine copula to estimate the VaR of a portfolio and showed that vine copula had offered a significant improvement as compared to a benchmark estimator based on a GARCH model. Emmanouil and Nikos (2012) used a mixed C-Vine copula to model the joint distribution of spot and futures electricity portfolios. Low et al. (2013) concluded that Clayton C-Vine and D-Vine copula have been useful for managing portfolios in high dimension because they had captured nonlinear dependence structure of stocks. So and Yeung (2014) used the time varying vine copulas based GARCH model. The results showed that Kendalls tau and linear correlation of the stock returns change over time. Zhang et al. (2014) employed vine copula methods to estimate CVaR of the portfolio based on VaR measurement. Roboredo and Ugolini (2015) employed vine-copula models to identify the dependence structure between financial and sovereign debt markets. Bekiros et al. (2015) used vine copula for modeling of changing dependence risk under three different period scenarios combined with the optimization of portfolios.

1.2.5 Financial Risk Measurement via VaR and CVaR

Value at risk (VaR) is well-known in context of risk measurement. The risk management form is defined in terms of percentiles of loss distribution. VaR is the upper percentile of loss distribution. VaR is estimated under risk factors that are assumed normal or log-normal distribution. VaR does not perform well under the non-normal distribution. For example, Burns (2002) estimated VaR by using univariate GARCH models. The results shown that the quality of the VaR estimates depended on particular used of GARCH model. DJORIĆ and NIKOLIĆ-DJORIĆ (2011) calculated VaR based on the normal and Student t innovation distribution using Risk Metrics, GARCH and IGARCH models. The results showed that IGARCH models could not outperform GARCH type

models in VaR evaluations for Belgrade Stock Exchange index. Sethapramote et al. (2014) estimated VaR by using the standard conditional volatility models (GARCH) and the GARCH model with long memory process (FIGARCH). The results from FIGARCH did not work of those the asymmetric GARCH for Stock Exchange of Thailand. Besides, VaR does not satisfy coherent risk measure. The Conditional Value at Risk (CVaR) has been proved to be a coherent risk measure by Pflug (2000). The linear programming techniques can be used for optimization of CVaR risk measure, see Rockafellar and Uryasev (2000). The approach for minimizing CVaR and optimization problems with CVaR constraints can be found in Sriboonchitta et al. (2013), Rockafellar and Uryasev (2000), Chekhlov et al. (2000), Pflug (2000). Their empirical studies showed that the optimization with CVaR is much more efficient method.

1.3 Objectives of the Study

The objectives of this study are as follows:

1.3.1 Study the CAPM model with belief functions approach for forecasting the Chesapeake Energy Corporation (CHK) stock.

1) To analyze the dependence pattern between the CHK stock and Standard and Poor's 500 (S&P 500) index.

2) To forecast the CHK stock returns using belief functions.

1.3.2 Study the CAPM model with interval data of Chesapeake Energy Corporation (CHK) stock and Microsoft Corporation (MSFT) stock.

1) To estimate the beta coefficient which represents risk in the portfolios management analysis.

2) To obtain a point valued of asset returns from the interval valued data to measure the sensitivity between the CHK stock return, MSFT stock return and the S&P 500 index return.

1.3.3 Apply the vine-copulas approach based on CAPM models to optimize the portfolios' risks and returns of selected stocks in the Stock Exchange of Thailand (SET50).

1) To use C-vine and D-vine copulas to examine the dependence structure of selected stocks.

2) To use the joint distribution which minimize expected shortfall with respect to the expected returns to show the optimal weight of stocks in portfolios.

1.4 Main Contributions of the Research

The contributions of this study are as follows:

1.4.1 The study provides an alternative method for drawing inference via a likelihood based on a belief functions approach for estimation of linear regression of CAPM.

1.4.2 The study confirms the usefulness of the concept of the interval valued data to the CAPM model by replace a single value of market returns and asset returns with the range of high and low historical data into the model which attains all desired asymptotic properties of estimator.

1.4.3 The study confirms the vine copula based on CAPM models, which can model the dependence structure from bivariate copulas of the risk in portfolio analysis, especially in context of financial economics.

1.4.4 The study is useful for the investor to make decisions and evaluations for portfolio investment. Thus, it will be beneficial to improve the portfolio's performance.