12-20-2011 12:00 AM

Socially Responsible Investment in a Changing World

Desheng Wu
The University of Western Ontario

Supervisor
Matt Davison
The University of Western Ontario

Graduate Program in Applied Mathematics
A thesis submitted in partial fulfillment of the requirements for the degree in Master of Science

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(Thesis Format: Monograph)

by

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The School of Graduate and Postdoctoral Studies
The University of Western Ontario
London, Ontario, Canada

THE UNIVERSITY OF WESTERN ONTARIO
School of Graduate and Postdoctoral Studies

CERTIFICATE OF EXAMINATION

Supervisor	Examiners
Dr. Matt Davison	Dr. David Stanford
	Dr. Adam Metzler
	Dr. Mark Reesor

The thesis by

Desheng Wu

entitled:

SOCIAL RESPONSIBLE INVESTMENT IN A CHANGING WORLD

is accepted in partial fulfillment of the
requirements for the degree of
Master of Science

Date

Chair of the Thesis Examination Board

Abstract

Socially responsible investment funds make up a growing segment of the investment world. This work considers the impact of including SRI in an investor portfolio both normally and during crisis times. Regimes are identified using Markov switching models. This study is based on return data of four indices, namely, the MSCI World Index, S&P 500, Eurostoxx 50, and the socially responsible index - Advanced Sustainable Performance Index (ASPI). The approaches used are portfolio optimization, GARCH and Markov switching models. Our work shows that a socially responsible index is a good asset to keep in a portfolio. Our simulation results suggest that a very risk-averse investor during the time period between 1992 to 2009 might allocate up to 75% of his portfolio in socially responsible index. We also present a framework which uses binary integer programming to construct a social index designed to prepare optimal diversification from a fixed given equity index.

Keywords

Socially responsible investment, Markov switching, portfolio optimization, GARCH, Finance, Performance metrics, Crisis, Monte Carlo Simulation.

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1. CHAPTER 1: Introduction

Socially responsible investments (SRI) make up a growing proportion of the investment world. This thesis investigates four main practical issues faced by a portfolio manager in dealing with the SRI market and analyzing the risk associated with a portfolio of assets including an SRI index: performance evaluation, risk analysis, portfolio selection and portfolio index design. To tackle these practical issues, data are collected from key index markets spanning about 18 years. The data are presented in Chapter 2. The first three issues are investigated using both the overall population of data and regime-levels estimated from this data from Chapter 3 to 6. Regimes are identified using the regime-switching model presented in Chapter 2. The thesis concludes with an innovative approach developed to construct new index portfolios which combine social responsibility with minimal correlation to a benchmark. To begin, this Chapter reviews both the conceptual and practical aspects of the SRI market.

1.1 The concept

Socially responsible investing (SRI) is one way to fit portfolios to various ethical goals. Mercer (2008) defines SRI as the integration of environmental, social and corporate governance (ESG) considerations into investment management processes and ownership practices with the hope that these factors can have an impact on financial performance. Investors and people all around are starting to be more socially conscious with their investments. Either if they are in the marketplace or just buying groceries, people are starting to care for the environment (Mercer, 2008). SRI investors are at the same time wondering about how to get the best return from their investment and how that investment will impact society. Investors who are socially responsible are putting increasing pressure on corporations to improve their practices on social and environmental issues. This investment strategy works to enhance the financial, social, and environmental triple bottom lines of the companies in question. In doing so, it aims to deliver better long term returns to shareholders. Socially responsible investors include individuals and corporations and comprise universities, hospitals, foundations, insurance companies, public and private pension funds and non-profit organizations. Institutional investors represent the largest and fastest growing segment of the SRI world. Generally, social investors seek to own profitable companies that make positive contributions to society (Mercer, 2008).

1.2 The market

During the last two decades the unprecedented growth in the SRI market has made it more and more important. The 2009 size of the worldwide SRI market is approximately 5 trillion dollars, with 53% market share of the SRI market based in Europe, 39% from the United States, and 8% from the rest of the world (Hross et al., 2010).

The GoodPlanet research news indicates that between 2004 and 2006, Canadian SRI market assets increased from $65bn to $504bn by June 30, 2006, growing by almost 700%. The size of the UK SRI sector was about 781 billion pounds at the end of 2005. The SRI market in the US had a size of $639 billion in 1995 and $2,159 billion in 1999 suggesting an average annual growth rate of 36%. This amount grew only to $2,290 billion from 1999 to 2005, but then it increased again resulting in $2,711 billion in 2007 (Renneboog et al. 2008). SRI is a wide range investment choice that makes up an estimated $3.07 trillion in the U.S. investment marketplace today according to Social Investment Forum (2010). The size of the European SRI Market almost doubled since 2008, in spite of the financial crisis, according to Eurosif's 2010 European SRI Study (Social Investment Forum, 2010).

1.3 Why SRI ?

All investors seek investment choices that have competitive financial returns. Studies have shown that funds with SRI perform competitively with funds that don‘t include SRI (Lydenberg, 2006; Renneboog, 2008). Also indices including SRI perform well and are designed to follow non-SRI index benchmarks such as the S&P500. Investors, institutions, professionals and individual investors are involved increasingly in the mainstream field (Swan, 2011) and investors not only invest in this type of investment because it is socially responsible, or green investment, but because it is competitive to other conventional investments on the market. Pension funds, university endowments and foundations are increasing their investment in SRI. These institutions are obligated by law to seek competitive returns for the portfolios they manage so this is a big step for the SRI field. It is essential to point out that the massive growth in the field of SRI today is a phenomenon driven by consumers. The main reasons for this rapid growth are many but the most important one is information. We see that social research organizations are providing much better information than before and investors who are well informed make much better and more responsible decisions than otherwise. Female investors seem particularly interested in SRI, with over 60 percent of SRI investors today being women (Renneboog, 2008). Those are some of main reasons for growth in this area and the reason that investors need no longer sacrifice any investment performance by thinking about social responsibility, as the thesis will show. Responsibility can now work hand in hand with prosperity.

1.4 Construction "universe" of SRI stocks

SRI investment managers have three main methods: screening, shareholder advocacy, and community investing (Social Investment Forum, 2011).

Investment screens can be positive or negative. Screening is the practice of evaluating investment portfolios or mutual funds based on social, environmental and good corporate management. In a positive screening approach, companies in which SRI investors own shares, must exhibit good employer-employee relations, strong environmental practices and companies that are manufacturing products will have to produce products that are useful and not harmful to people and the environment. Many investors think that screening only involves negative screens, in which companies involved in, for instances, tobacco are excluded from a portfolio. This is a misunderstanding because positive screening of social investments is a way to utilize screening as an integrated step within security analysis that allows for better diversification.

A second tool used by SRI managers is shareholders advocacy. This is when the shareholder keeps the company on their toes by talking to the company about issues of social, environmental or governance concerns. The issues of climate change, political contributions, gender or racial discrimination, pollution and problematic labor practices are presented for a vote to all owners of a corporation by the shareholder (Social Investment Forum, 2011). This creates pressure from investors on company management, and often receives media attention and educates the public on social, environmental and labor issues.

The third approach, community investing, directs capital from investors and lenders to communities that are supplied with inadequate social and health services. This gives the community access to credit, equity, capital and basic banking products that they lack. This makes it possible to give these communities the financial services and financial aid they need such as capital for small businesses, affordable housing, child care, and health care. By investing directly in an institution, rather than buying stock, an investor is able to create a greater social impact. That is, buying a stock merely transfers money to the stock‘s previous owner and may not generate social good, while money invested in a community institution is put to work.

1.5 Advantages and disadvantages

Table 1-1 gives the advantages and disadvantages of SRI (Social Investment Forum, 2010 and 2011; Kempf and Osthoff, 2007).

Table 1- 1 Pros and Cons of SRI

Pros	Cons
You can invest in a company that you personally believe in.	SRI investments may have higher risk because of lower gross profit margins.
Social fairness.	Hard to diversify.
Return is competitive to non SRI investments.	Always the possibility of lower investment return.
Reduces Risk.	Companies may be unable to maximize investment returns.
Creating positive ethical business environment.	investor will have to keep their money in the company for longer time period then initially planned.

1.6 Quantitative modeling of SRI

Early studies on the performance of SRI used one- or two- factor models to compute various performance metrics such as Sharpe ratio and Jensen's alpha. Hamilton (1993) compared 32 SRI funds to 320 non-SRI funds in the US between 1981 and 1990 and found no significant average abnormal returns with respect to a value-weighted NYSE index. Performance comparison between SRI and non-SRI funds with similar characteristics has also been conducted by many including Mallin et. al. (1995) and Statman (2000). Bauer (2005) applied a four factor model to investigate ethical mutual fund performance and investment style. Geczy et. al. (2005) found that SRI investors have to pay for their constrained investment style. Findings from these works seems to suggest that no consistent conclusions can be drawn: some studies find that no significant return penalties are observed as opposed to non-SRI (see Sauer, 1997; Carhart, 1997; Bauer et al., 2005; Fernandez-Izquierdo and Matallin-Saez, 2008; Luo and Bhattacharya, 2006; Mittal et al., 2008; Becchetti and Ciciretti, 2009; Cortez et al., 2009), while others report that SRI significantly outperformed non-SRI (see Guerard, 1997; Derwall et al., 2005; Jan De and

Slager, 2009).

Li et al. (2010) employed a regime-switching model to specifically divide the study period of SRI index into good and bad times. Li et al. (2010) simply analyze return and risk of SRI and non-SRI indices and do not consider portfolio analysis in an optimal frontier. Hross et al. (2010) analyzes SRI using different portfolio optimization frameworks including bond, stocks and SRI asset classes. Hross et al. (2010) find the asset class SRI to be a good substitute for the stock asset class. Our current study continues this work by analyzing various investment scenarios such as short-selling and/or investment boundaries. We also consider different market periods.

This thesis will focus on SRI index market data modeling and analysis and analyzing SRI in a portfolio context by generating optimal portfolios in different market time periods. The quantitative models include both regime-switching stochastic volatility and GARCH models in four index markets: MSCI World Index (World), S&P 500 Index(USA2), Eurostoxx 50(Europe), and SRI Advanced Sustainable Performance Index(ASPI). Various GARCH models are compared to regime-switching-GARCH models, based on which volatility forecasting is conducted. Using different forecasts, model performance is compared with each other. The Markov Switching model is employed to divide the study period into four regime periods. We then compare the risk, and return of the SRI and non-SRI indices during each identified regime. Optimal portfolios are generated in reference to a portfolio frontier constructed from four typical market indices.

1.6.1 Portfolio Optimization, Sharp ratio and Information Ratio

The most popular portfolio optimization method used in industry is due to Markowitz (1952) where mean and standard deviation are assumed to embody sufficient information about the return distribution of a portfolio when assuming normality in data returns. The idea of the Markowitz framework is quite simple: a portfolio is mean-variance efficient if there exists no other portfolio with the same (or less) risk and a higher expected return, or the same (or a higher) expected return accompanied by lower risk.

The portfolio optimization problems are formulated

$$\max \boldsymbol{w}^T \boldsymbol{\mu} - \lambda \mathrm{Risk}(\boldsymbol{w})$$
$$\text{s.t.} \quad \boldsymbol{w} \geq \boldsymbol{0} \qquad (1.1)$$
$$\boldsymbol{w}^T \boldsymbol{1} = 1,$$

where w is the vector of portfolio weights, λ the investor's risk-aversion parameter, and μ the expected return vector. $Risk(w)$ reflects a risk functional for the portfolio. In this section, we use Portfolio variance to replace $Risk(w)$, which yields the famous mean-variance framework (MV) based on the seminal work by Markowitz (1952). The popular performance metrics used in this work are the Sharpe ratio and the information ratio.

The Sharpe ratio can be formulated as:

$Sharpe = \frac{r_p - r_f}{\sigma_P}$, where r_p is the asset portfolio return, r_f is the return of a riskless asset, and σ_P is the portfolio standard deviation. The information ratio (IR) defined in more detail in Chapter 5 measures a portfolio manager's ability to generate excess returns relative to a benchmark, but also attempts to identify the consistency of the investor.

1.7 Overview of the Thesis

The structure of this thesis is as follows. Chapter 2 is on the data and the stochastic models used to describe the data in this study. Chapter 3 gives the calibration results of GARCH and regime-switching-GARCH models. Prediction results based on the calibrated models are presented in Chapter 4. Chapter 5 investigates portfolio optimization strategies from both normal and crisis markets. Chapter 6 presents various investment scenarios in employing one particular SRI index. Chapter 7 develops a model to design a social investment index based on an existing investment index market. The following flowchart gives the structure of the thesis.

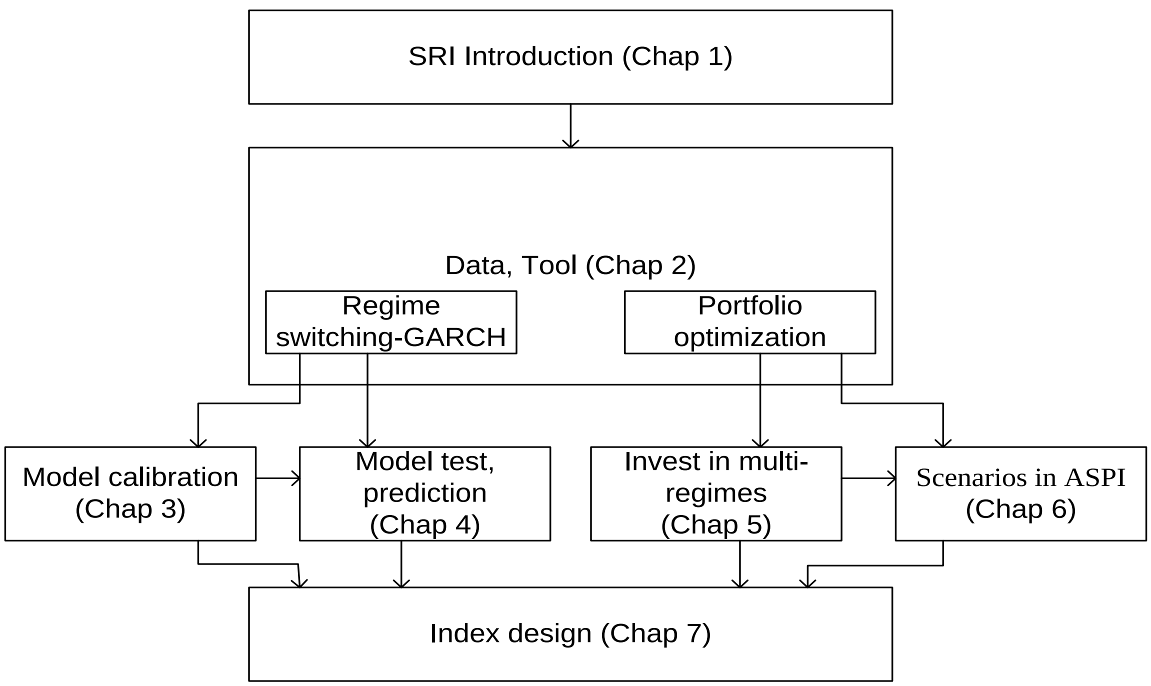


Figure 1- 1 Structure of the thesis

Note: Chap denotes Chapter;

2. CHAPTER 2: Investigating and Modelling the data

2.1 Data

This thesis uses a data of four key index markets: MSCI World Index (World), S&P 500 Index (USA), Eurostoxx 50 (Europe), and the Advanced Sustainable Performance Index (ASPI). We ignore impact of exchange rate in the calculation.

To analyze social sustainability investment (SRI), we mainly use Advanced Sustainable Performance Index (ASPI) and compare this index with typical indexes in USA, Europe, and World market. The data analyzed in this work include four daily observed indices of different markets including the MSCI World Index (World), S&P 500 Index (USA), Eurostoxx 50 (Europe), and Advanced Sustainable Performance Index (ASPI).

The samples used in MS-GARCH modeling include the Advanced Sustainable Performance Index (ASPI) and S&P 500 Index (USA).

The Advanced Sustainable Performance Indices (ASPI Index) is traded on Colombo Stock Exchange in Sri Lanka. The ASPI is an index consisting of 120 European companies and is published by Vigeo Group, a rating agency in the field of sustainable development and social responsibility. In total, the sectoral distribution of the 120 companies of the index is tracking the sector of the Eurostoxx 50 quite well. Since the Vigeo method of notation does not favor any economic sector, the distribution of ratings awarded by Vigeo remains much the same from one sector to another.

The S&P500 (USA) is a free-float capitalization-weighted index published since 1957 of the prices of 500 large-cap common stocks actively traded in the United States. The stocks included in the S&P 500 are those of large publicly held companies that trade on either of the two largest American stock market companies; the NYSE Euronext and the NASDAQ OMX. The S&P 500 is the most widely followed index of large-cap American stocks. Because of that, we use S&P500 as one of our US market benchmarks.

The data for these indices spans a continuous sequence of 4292 days from January 1992 to July 2009, showing daily closing prices for each index. In Figure 2.1 we show a plot of 4 daily indices movement, including World Index, USA Index, ASPI and SI.

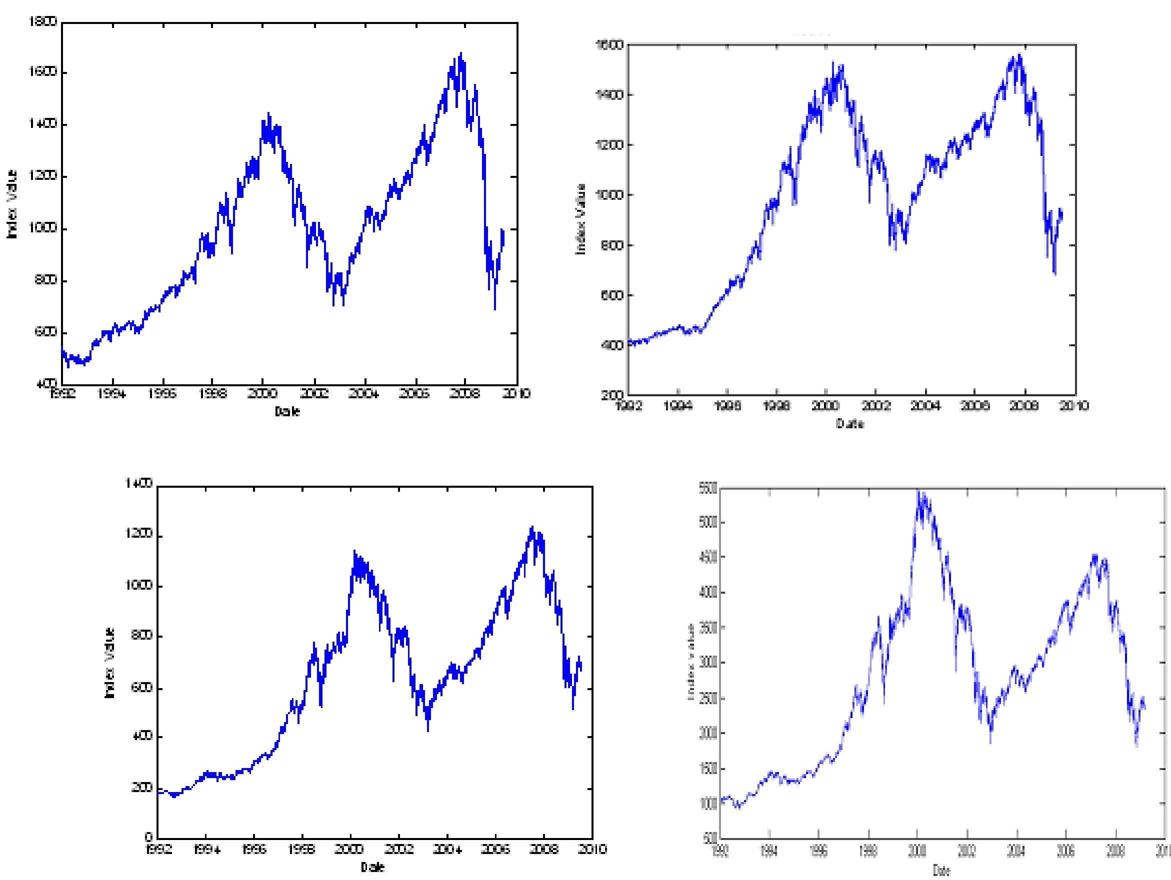


Figure 2- 1 **Indices movements (World Index, USA Index, ASPI and Eurostoxx 50)**

Note: upper left World Index closing price; upper right USA Index closing price; lower left ASPI Index closing price; Lower right Eurostoxx 50 Index closing price;

To get a preliminary view of volatility change, we show in Table 2.1 the descriptive statistics on the Daily log-returns of these 11 indices ranging from January 1992 to July 2009. The corresponding log-returns plots are given in Figure 2.2.

Table 2- 1 Empirical statistics of daily log-returns of 4 indices

Statistics	Sample Size	Mean	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis
World	4291	1.31 bp	9.09%	-7.32%	0.99%	-0.36	12.18
USA	4291	1.79 bp	10.96%	-9.47%	1.21%	-0.18	12.26
Europe	4291	1.99 bp	10.43%	-8.80%	1.25%	-0.11	8.61
ASPI	4291	3.23 bp	10.29%	-8.75%	1.36%	-0.13	8.69

Note: 1 bp (basis point) = 0.01%; Skewness is a measure of the asymmetry of the probability distribution of a random variable; Kurtosis is any measure of the "peakedness" of the probability distribution of a random variable

All the indices have a large difference between their maximum and minimum returns. High standard deviations are exhibited in the table which indicates a high level of fluctuations of daily returns. There is also evidence of negative skewness in each of the four indices, which means that the left tails of the corresponding returns are particularly extreme, and indication that the these returns are asymmetric. The returns of all the indices are leptokurtic or heavy tailed.

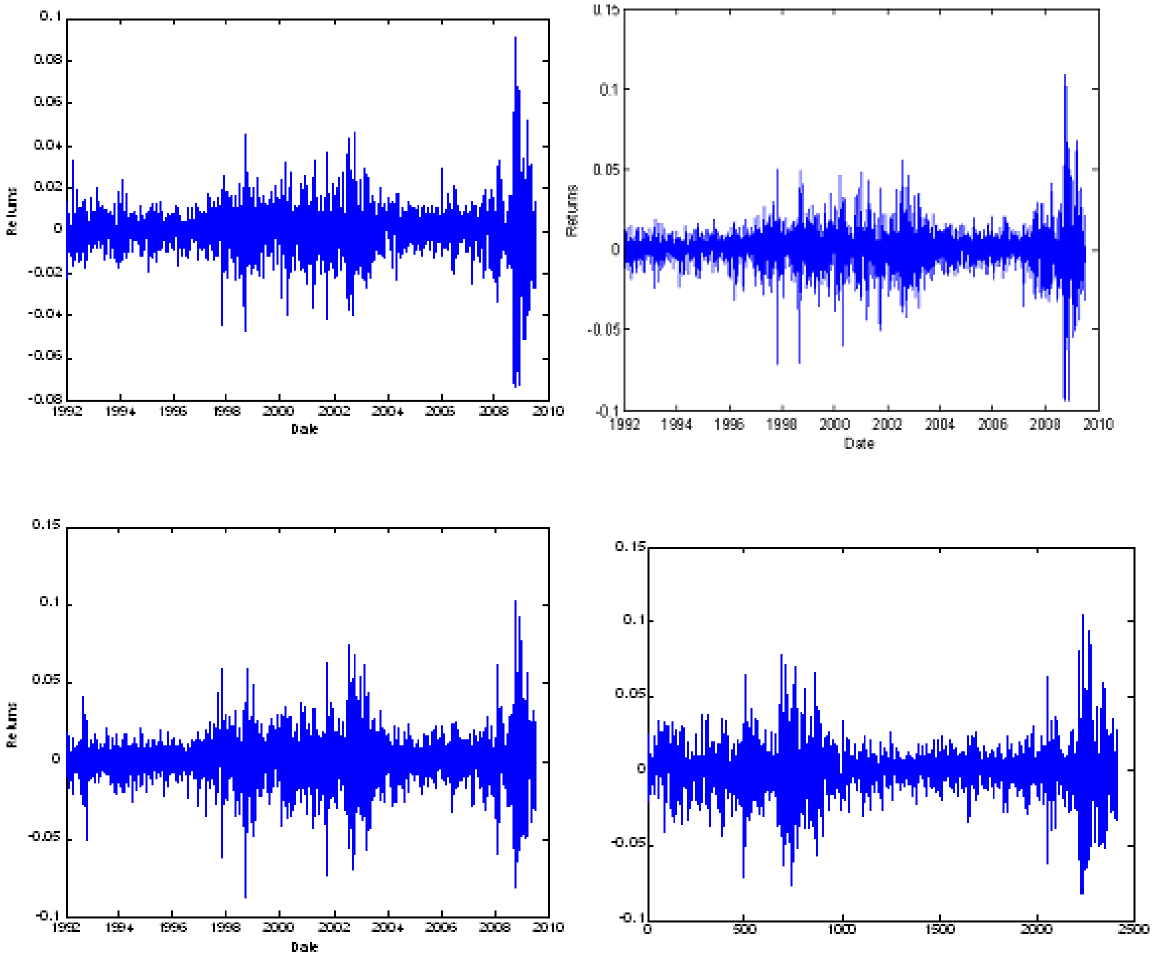


Figure 2- 2 Daily log-returns of World Index, USA Index, ASPI , and Eurostoxx50

Note: upper left World Index daily log-returns ; upper right USA Index daily log-returns ; lower left ASPI Index daily log-returns ; Lower right Eurostoxx 50 Index daily log-returns

It is clear from Figures 2.2 that fluctuations of these four returns series display volatility clustering. With volatility clustering, a turbulent trading day tends to be followed by another turbulent day, while a tranquil period tends to be followed by another tranquil period.

2.2 Distribution analysis

Figure 2.3 displays a distribution analysis of World Index, USA Index, and ASPI ranging from January 1992 up to July 2009. The data is the log-return of the daily index movements. We can see that, while the data seems to be approximately normal, perhaps a better distribution for the data is a T- Distribution shown by the blue line (Figure 3). The red line represents the normal distribution of our data. Similarly I did the same distribution test about other indices. So a T- Distribution is preferred to normal distribution in general.

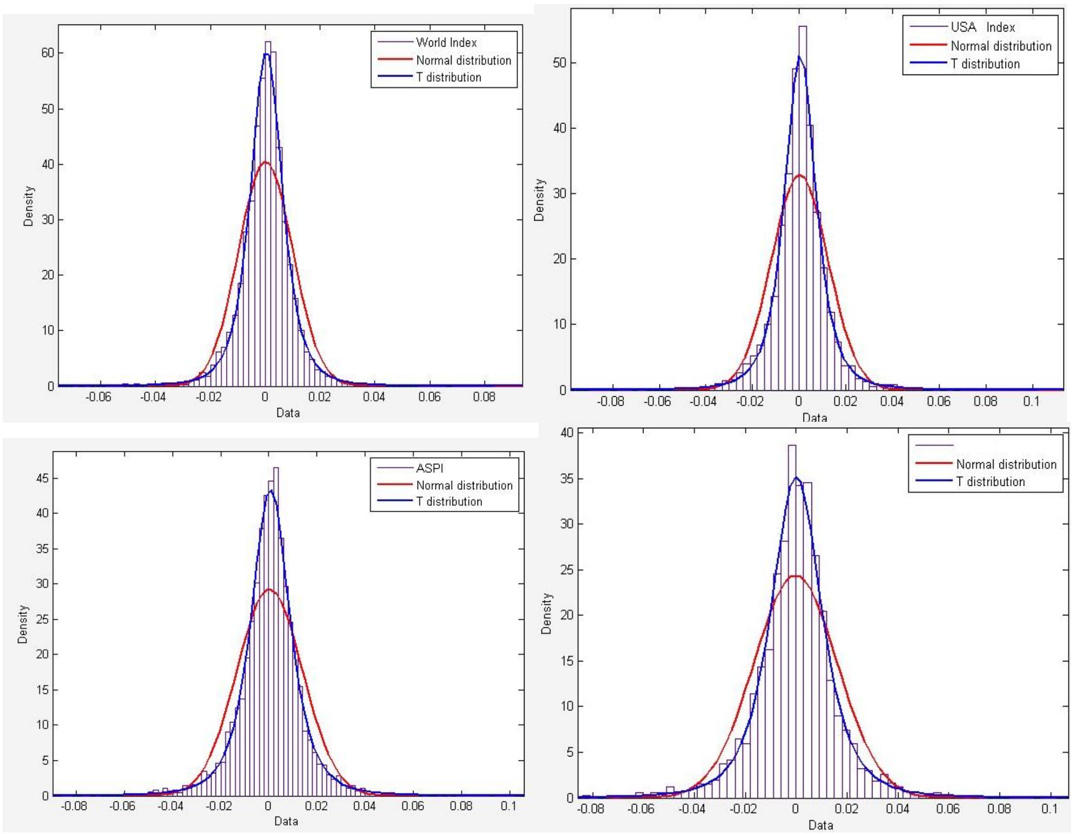


Figure 2- 3 Normal Distribution vs. T Distribution

Note: upper left World Index distribution ; upper right USA Index distribution ; lower left ASPI Index distribution ; Lower right Eurostoxx 50 Index distribution

2.3 Correlation

As correlations are essential for diversification in a portfolio context the correlations of the empirical daily log-returns are examined first. The analysis in this section emphasizes the correlation between the market of socially responsible investing indices. The correlation between ASPI and the other indices is shown in the following figure.

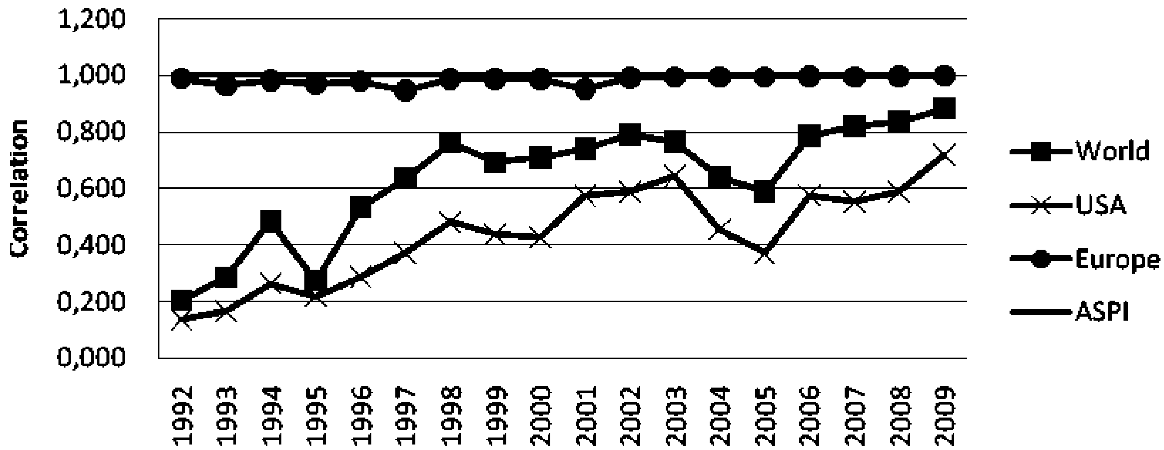


Figure 2- 4 The correlation between ASPI and the other indices

From the figure we can see that ASPI has a great correlation with Europe. This result is expected because the ASPI is an index consisting of 120 European companies. We can also see that during normal market period (1992-1996 and 2003-2006), the ASPI has a low correlation with other indices but when the market experiences crisis (1997-2003 and 2007-2009), it have a relatively high correlation with others. This high correlation in times of market turmoil is, unfortunately, all too frequent in the modern world.

2.4 Models

Both regime-switching models and GARCH are used in this work to model and explain the behavior of four market data. Both models are used to deal with different phases of volatility behavior and the dependence of the variability of the time series on its own past, allowing for heteroscedasticity. The former is very useful in modeling a unique stochastic process with conditional variance; the latter has the advantage of dividing the observed stochastic behavior of a time series into several separate phases with different underlying stochastic processes. Both types of models are widely used in practice. There is no clear evidence regarding which approach outperforms the other one (Agnolucci, 2009; Alizadeh et al. 2008; Klaassen, 2002; Aloui and Jammazi 2009). We provide a brief review and explanation of both modeling technique in this chapter. A modeling approach which integrates regime-switching and GARCH models introduced by Marcucci (2005) is also presented in this chapter.

ARMA (R, M)

Given a time series X_t, the autoregressive moving average (ARMA) model is very useful for predicting future values in time series where there are both an autoregressive (AR) part and a moving average (MA) part. The model is usually then referred to as the ARMA(R, M) model where R is the order of the first part and M is the order of the second part. The following ARMA(R, M) model contains the AR(R) and MA (M) models:

$$X_t = c + \varepsilon_t + \sum_{i=1}^{R} \varphi_i X_{t-i} + \sum_{j=1}^{M} \theta_j \varepsilon_{t-j} . \qquad (2.1)$$

where φ_i and θ_j are parameters for AR and MA parts respectively.

ARMAX(R, M, b)

To include the AR(R) and MA(M) models and a linear combination of the last b terms of a known and external time series d_t, one can have a model of ARMAX(R, M, b) with R autoregressive terms, M moving average terms and b exogenous inputs terms.

$$X_t = c + \varepsilon_t + \sum_{i=1}^{R} \varphi_i X_{t-i} + \sum_{j=1}^{M} \theta_j \varepsilon_{t-j} + \sum_{k=1}^{b} \eta_k d_{t-k} , \qquad (2.2)$$

where $\eta_1, \ldots, \eta_b$ are the parameters of the exogenous input d_t.

GARCH(p, q)

Bollerslev's Generalized Autogressive Conditional Heteroscedasticity [GARCH(p, q)] specification (1986) generalizes the volatility forecasting model by allowing the current conditional variance to depend on the first p past conditional variances as well as the q past squared innovations. That is,

$$\sigma_t^2 = L + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \qquad (2.3)$$

where L denotes the long-run volatility, σ_t^2 denote the conditional variance, α_j and β_i are parameters given to innovation term and conditional volatility term respectively. By accounting for the information in the lag(s) of the conditional variance in addition to the lagged t-i terms, the GARCH model reduces the number of parameters required. In most cases, one lag for each variable is sufficient. The GARCH(1,1) model is given by: $\sigma_t^2 = L + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2$. GARCH can successfully capture thick tailed returns and volatility clustering. It can also be modified to allow for several other stylized facts of asset returns.

EGARCH

The Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model introduced by Nelson (1991) builds in a directional effect of price moves on conditional variance. Large price declines, for instance, may have a larger impact on volatility than large price increases. The general EGARCH(p,q) model for the conditional variance of the innovations, with leverage terms and an explicit probability distribution assumption, is

$$\log \sigma_t^2 = L + \sum_{i=1}^{p} \beta_i \log \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} \right] + \sum_{j=1}^{q} L_j \left(\frac{\varepsilon_{t-j}}{\sigma_{t-j}} \right) \quad (2.4)$$

where $E\left\{| z_{t-j} |\right\} E\left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} = \sqrt{\frac{2}{\pi}}$ for the normal distribution, and

$E\left\{| z_{t-j} |\right\} E\left\{ \frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} \right\} = \sqrt{\frac{v-2}{\pi}} \frac{\Gamma\left(\frac{v-1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)}$ for the Student's t distribution with v > 2 degrees of

freedom, L_j is the parameter given to the j^{th} leverage term.

GJR(p,q)

GJR(*p*,*q*) model is an extension of an equivalent GARCH(*p*,*q*) model with zero leverage terms. Thus, estimation of initial parameter for GJR models should be identical to those of GARCH models. The difference is the additional assumption with all leverage terms being zero:

$$\sigma_t^2 = L + \sum_{i=1}^{p} \beta_i \sigma_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 + \sum_{j=1}^{q} L_j S_{t-j} \varepsilon_{t-j}^2 \quad (2.5)$$

where $S_{t-j} = 1$ if $\varepsilon_{t-j} < 0$, $S_{t-j} = 0$ otherwise, with constraints

$$\sum_{i=1}^{p} \beta_i + \sum_{j=1}^{q} \alpha_j + \frac{1}{2} \sum_{j=1}^{q} L_j < 1$$
$$L \geq 0, \beta_i \geq 0, \alpha_j \geq 0, \alpha_j + L_j \geq 0.$$

2.5 Regime switching models

Markov regime-switching models have been applied in various fields such as macroeconomic analysis (Raymond and Rich, 1997), analysis of business cycles

(Hamilton 1989), modeling stock market and asset returns and portfolio construction (Engel, 1994).

We now consider a dynamic volatility model with regime-switching. Suppose a time series X_t follows an AR (p) model with AR coefficients, together with the mean and variance, depending on the regime indicator s_t :

$$X_t = \mu_{s_t} + \sum_{j=1}^{p} \varphi_{j,s_t} X_{t-j} + \varepsilon_t, \tag{2.6}$$

$$\text{where } \varepsilon_t \sim i.i.d.\text{Normal}(0, \sigma_{s_t}^2).$$

The corresponding density function for X_t is:

$$f(X_t \mid s_t, X_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_{s_t}^2}} \cdot \exp\left[-\frac{\omega_t^2}{2\sigma_{s_t}^2} \right] = f(X_t \mid s_t, X_{t-1}, \ldots, X_{t-p}), \tag{2.7}$$

where $\omega_t = X_t - \omega_{s_t} - \sum_{j=1}^{p} \varphi_{j,s_t} X_{t-j}$.

The model can be estimated by use of straightforward maximum log likelihood estimation. A more practical situation is to allow the density function of X_t to depend on not only the current value of the regime indicator s_t but also the past values of the regime indicator s_t which means the density function should take the form of $f(X_t \mid s_t, s_{t-1}, X_{t-1})$ with $S_{t-1} = \{s_{t-1}, s_{t-2}, \ldots\}$ being the set of all the past information on s_t.

2.5.1 Regime switching-GARCH model

The regime switching-GARCH requires the specification or estimation of four elements:

the conditional mean X_t, the conditional variance, the regime process and the conditional distribution. The conditional mean equation is normally modeled by use of a random walk with or without drift. In our work, we follow Marcucci (2005) and simply use

$$X_t = E\left(X_t \mid \varsigma_{t-1}\right)^{(i)} + \varepsilon_t = \mu_t^{(i)} + \varepsilon_t \text{ (i = 1, 2)}, \qquad (2.8)$$

where $\mu_t^{(i)} = E\left(X_t \mid \varsigma_{t-1}\right)^{(i)}$ denotes the conditional mean for the ith regime,

$\varepsilon_t = \eta_t \left[h_t^{(i)}\right]^{1/2}$ and η_t is a zero mean, unit variance process, and ς_{t-1} denotes the information set at time t-1, i.e., the σ-algebra induced by all the variables observed up until t-1.

The conditional variance of X_t, given the whole regime path $\tilde{s}_t = \left(s_t, s_{t-1}, ...\right)$, is $h_t^{(i)} = V\left[\varepsilon_t \mid \tilde{s}_t, \varsigma_{t-1}\right]$. For this conditional variance the following GARCH(1,1) expression is assumed

$$(\sigma_t^2)^{(i)} = L^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta_1^{(i)}(\sigma_{t-1}^2) \qquad (2.9)$$

where σ_{t-1}^2 is a state-independent average of past conditional variances.

To integrate out the past regimes taking into account also the current one, Marcucci (2005) employs the following expression for the conditional variance from Klaassen (2002):

$$(\sigma_t^2)^{(i)} = L^{(i)} + \alpha_1^{(i)}\varepsilon_{t-1}^2 + \beta_1^{(i)} E_{t-1}\left\{(\sigma_{t-1}^2)^{(i)} \mid s_t\right\} \qquad (2.10)$$

where the expectation is computed as

$$E_{t-1}\left\{(\sigma_{t-1}^2)^{(i)} \mid s_t\right\} = \sum_{j=1}^{2} \tilde{p}_{ji,t-1}\left[\left(\mu_{t-1}^{(j)}\right)^2 + (\sigma_{t-1}^2)^{(j)}\right] - \left[\sum_{j=1}^{2} \tilde{p}_{ji,t-1}\mu_{t-1}^{(j)}\right]^2, \qquad (2.11)$$

and the transitional probabilities are calculated as

$$\tilde{p}_{ji,t-1} = \Pr\left(s_t = j \mid s_{t-1} = i, \varsigma_{t-1}\right) = \frac{p_{ji}\Pr\left(s_t = j \mid \varsigma_{t-1}\right)}{\Pr\left(s_{t-1} = i \mid \varsigma_{t-1}\right)} = \frac{p_{ji}\, p_{j,t}}{p_{i,t-1}} \text{ (i, j =1, 2)}. \qquad (2.12)$$

It is believed that Klaassen's (2002) regime-switching GARCH shows two main advantages over the other MRS-GARCH models. First, within the model, higher flexibility is allowed in capturing the persistence of shocks to volatility. Second, straightforward expressions can be yielded to compute the multi-step-ahead volatility forecasts.

The m-step-ahead volatility forecast at time T-1 can be computed

$$\sigma^2_{T,T+m} = \sum_{k=1}^{m} \sigma^2_{T,T+k} = \sum_{k=1}^{m} \sum_{i=1}^{2} \Pr(s_k = i \mid \varsigma_{T-1})(\sigma^2_{T,T+k})^{(i)}, \qquad (2.13)$$

where the k--step-ahead volatility forecast in regime i made at time T $(\sigma^2_{T,T+k})^{(i)}$ can be computed recursively:

$$(\sigma^2_{T,T+k})^{(i)} = L^{(i)} + (\alpha_1^{(i)} + \beta_1^{(i)}) E_T \left\{ (\sigma^2_{T,T+k-1})^{(i)} \mid s_{T+k} \right\}. \qquad (2.14)$$

We employ the estimation technique from Marcucci (2005).

2.6 Conclusion

This chapter provides an overview of data and process estimation tools that will be used in the remaining chapters.

3. CHAPTER 3: Model Calibration

Calibration results for both regime-switching and GARCH models are presented in this chapter based on the data described and analyzed in the previous chapter.

3.1 Calibration of GARCH Models

We focus on calibration of ASPI market, but also compare the result with the S&P 500 Index (USA) market. Note that Marcucci (2005) use Standard & Poor 100 (S&P100) data, so such a comparison can be used to validate the computation.

To facilitate computation, similar to Marcucci (2005), we take the log difference of prices indices and then multiply by 100 to yield the log return time series. The estimation is carried out on a moving (or rolling) window of 4192 observations. In this chapter we present the calibration results of GARCH and MRS-GARCH models. We will present the in-sample statistics and the out-of-sample forecast evaluation in the next chapter.

Table 3.1-3.6 shows the calibrated parameter values of the different GARCH models: GARCH(1,1), EGARCH and GJR. Three different distributions for the innovations , i.e., the Normal, the Student's t and the general error distribution (GED) are used in each model for four index markets. The in-sample period for both indices is from January 2, 1992 through February 6, 2009. The 100 observations from February 9, 2009 through July 6, 2009 are reserved for the evaluation of the out-of-sample performances for both indices. The standard errors are asymptotic standard errors in all tables. All the parameters of the various GARCH models in two markets are significant in the conditional mean model. Almost all the parameters of the various GARCH models in two markets except the L s in the GARCH and GJR models are highly significant in the conditional variance estimates. Hence GARCH models perform well at least in-sample.

The conditional kurtosis of the Student's t distribution is given by $3(\nu - 2) / (\nu - 4)$. For ASPI market, the conditional kurtosis values are 4.099, 3.97, 3.952. For USA market, the conditional kurtosis values are 4.57, 4.36, 4.285. This suggests that the conditional distribution has fatter tails than the Gaussian for both index markets assuming the models with t- innovations.

For the models with GED innovations, the hypothesis that all the shape parameters ν have values between 1 and 2 is tested with a high degree of significance. In general, when the shape parameter ν is smaller than 2, the distribution has thicker tails than the normal distribution. This suggests that the conditional distribution has fatter tails than the Gaussian for both index markets.

Table 3- 1 Parameter Estimates of Standard GARCH Models-ASPI

Para.	GARCH								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.074	0.014	5.131	0.083	0.014	5.997	0.084	0.014	6.081
L	0.028	0.003	8.946	0.027	0.004	6.514	0.027	0.004	6.648
α_1	0.106	0.007	14.399	0.106	0.011	10.055	0.106	0.01	10.369
β_1	0.871	0.008	110.387	0.872	0.011	82.257	0.871	0.011	82.201
ν	-	-	-	9.457	1.228	7.7	1.508	0.043	35.375
Log(L)	-6259.5			-6213.6			-6215.0		

Note: Each GARCH model has been estimated with a Normal (N), a Student's t and a GED distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. The conditional mean is $X_t = \delta + \varepsilon_t$. More parameters are defined in Chapter 2.

Table 3- 2 Parameter Estimates of EGARCH Models-ASPI

Para.	EGARCH								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.045	0.014	3.319	0.059	0.013	4.443	0.060	0.013	4.497
L	-0.117	0.007	-15.873	-0.117	0.011	-10.868	-0.117	0.01	-11.695
α_1	0.153	0.01	15.965	0.151	0.014	10.809	0.151	0.013	11.635
β_1	-0.076	0.006	-12.589	-0.077	0.009	-8.862	-0.075	0.008	-9.301
ξ	0.985	0.002	509.172	0.987	0.002	406.068	0.986	0.002	402.985
ν	-	-	-	10.203	1.421	7.179	1.560	0.044	35.129
Log(L)	-6186.4			-6149.5			-6153.8		

Note: Each GARCH model has been estimated with a Normal ($\mathcal{N}$), a Student's t and a GED distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. More parameters are defined in Chapter 2.

Table 3- 3 Parameter Estimates of GJR Models-ASPI

Para.	GJR								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.051	0.014	3.572	0.065	0.014	4.705	0.066	0.014	4.783
L	0.029	0.003	9.876	0.028	0.004	7.232	0.028	0.004	7.407
α_1	0.158	0.011	14.34	0.162	0.015	10.625	0.159	0.015	10.864
β_1	0.878	0.007	117.935	0.877	0.01	87.19	0.877	0.01	89.087
ξ	0.036	0.007	5.293	0.033	0.01	3.299	0.034	0.009	3.623
ν	-	-	-	10.307	1.431	7.203	1.548	0.044	35.241
Log(L)	-6217.4			-6179.4			-6181.9		

Note: Each GARCH model has been estimated with a Normal ($\mathcal{N}$), a Student's t and a GED distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009.

Table 3- 4 Parameter Estimates of Standard GARCH Models-S&P

Para.	GARCH								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.051	0.013	4.09	0.060	0.012	5.064	0.059	0.012	5.089
L	0.020	0.002	9.692	0.019	0.003	6.572	0.019	0.003	6.554
α_1	0.100	0.007	14.909	0.099	0.01	9.672	0.100	0.01	9.711
β_1	0.878	0.007	117.365	0.880	0.01	87.457	0.878	0.011	83.297
ν	-	-	-	7.822	0.8	9.772	1.394	0.035	40.265
Log(L)	-5669.2			-5593.5			- 5591.2		

Note: Each GARCH model has been estimated with a Normal ($\mathcal{N}$), a Student's t and a GED distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009.

Table 3- 5 Parameter Estimates of EGARCH Models-S&P

Para.	EGARCH								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.020	0.012	1.667	0.035	0.011	3.043	0.035	0.011	3.08
L	-0.100	0.008	-12.381	-0.096	0.01	-9.179	-0.098	0.011	-8.999
α_1	0.126	0.01	12.437	0.121	0.013	8.968	0.123	0.014	8.782
β_1	-0.104	0.007	-15.066	-0.102	0.01	-10.532	-0.101	0.01	-10.47
ξ	0.983	0.002	552.289	0.987	0.002	447.418	0.986	0.002	431.287
ν	-	-	-	8.429	0.926	9.104	1.458	0.036	40.318
Log(L)	-5561.5			-5501.5			-5505.7		

Note: Each GARCH model has been estimated with a Normal ($\mathcal{N}$), a Student's t and a $\mathcal{GED}$ distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. More parameters are defined in Chapter 2.

Table 3- 6 Parameter Estimates of GJR Models-S&P

Para.	GJR								
	N			t			GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
δ	0.028	0.013	2.179	0.042	0.012	3.55	0.042	0.012	3.587
L	0.024	0.002	11.457	0.020	0.003	7.727	0.021	0.003	7.692
α_1	0.173	0.01	16.734	0.172	0.016	10.912	0.172	0.015	11.136
β_1	0.883	0.007	120.176	0.886	0.01	90.063	0.884	0.01	86.344
ξ	0.009	0.007	1.31	0.006	0.01	0.633	0.008	0.01	0.823
ν	-	-	-	8.674	0.936	9.267	1.445	0.036	40.438
Log(L)	-5605.1			-5542.9			-5544.2		

Note: Each GARCH model has been estimated with a Normal ($\mathcal{N}$), a Student's t and a $\mathcal{GED}$ distribution. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. More parameters are defined in Chapter 2.

3.2 Calibration of MRS-GARCH Models

We present the calibrated parameter estimates of MRS-GARCH models for ASPI and S&P500 markets in Table 3- 7 and 3.8 respectively. All the parameters of the various GARCH models, in both markets, are significant in the conditional mean model. Almost all the parameters of the various MRS-GARCH models except in the $\sigma^{(2)}$ s in ASPI and

USA markets in the MRS-GARCH with normal and t distributions are highly significant in the conditional variance estimates. Hence MRS-GARCH models perform very well for in-sample estimation.

The estimates confirm the existence of two states: the first regime is characterized by a low volatility and in most cases by a lower persistence of the shocks as indicated by $\rho_i = \alpha_1^{(i)} + \beta_1^{(i)}$. On the other hand, the second regime reveals a higher volatility and, almost always, a higher persistence. The persistence of ASPI index is between 0.74 and 0.998; The persistence of S&P 500 (USA) index is between 0 and 0.999.

The transition probabilities, i.e., the value of p and q are all highly significant and close to one except for the normal case at the USA market where one of them is rather far away from unity, indicating that almost all regimes are particularly persistent. This is consistent with Marcucci's (2005) result. Table 3.4 also documents the unconditional probabilities of each MRS-GARCH model for five index markets. The unconditional probability π_1 of being in the first regime with lower volatility than the second, ranges between 18.2% for the Student's t version of the MRS-GARCH and 56.2% for the model with Gaussian innovations. On the other hand, the unconditional probability of being in the high-volatility regime ranges between 43.8% for the model with Normal innovations and 81.8% for the one with Student's t version innovations.

Table 3- 7 Maximum Likelihood Estimates of MRS-GARCH Models-ASPI

Para.	MRS-GARCH-N			MRS-GARCH-t			MRS-GARCH-GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
$\delta^{(1)}$	0.143	0.017	8.282	-0.082	0.078	-1.057	0.103	0.018	5.862
$\delta^{(2)}$	-0.146	0.037	-3.93	0.098	0.015	6.527	0.049	0.023	2.109
$\sigma^{(1)}$	0.043	0.006	6.691	0.188	0.072	2.607	0.109	0.031	3.459
$\sigma^{(2)}$	0.075	0.016	4.789	0.009	0.003	3.305	0.034	0.012	2.703
$\alpha_1^{(1)}$	0	0.016	0	0.175	0.046	3.762	0.012	0.02	0.622
$\alpha_1^{(2)}$	0.062	0.012	5.326	0.057	0.011	5.32	0.093	0.012	7.65
$\beta_1^{(1)}$	0.867	0.017	50.058	0.759	0.053	14.264	0.728	0.075	9.747
$\beta_1^{(2)}$	0.936	0.016	58.852	0.931	0.01	91.225	0.895	0.014	64.006
p	0.961	0.008	125.308	0.989	0.006	154.057	0.996	0.002	480.645
q	0.950	0.011	88.667	0.997	0.002	654.089	0.998	0.001	779.595
$\nu^{(1)}$	-	-	-	9.731	1.412	6.893	1.575	0.049	32.291
$\nu^{(2)}$	-	-	-	-	-	-	-	-	-
Log(L)	- 6197.6			-6188.1			-6175.2		
N. of P.	10			11			11		
π_1	0.562			0.214			0.333		
π_2	0.438			0.786			0.667		
ρ_1	0.867			0.934			0.74		
ρ_2	0.998			0.988			0.988		

Note: Each MRS-GARCH model has been estimated with different conditional distributions. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. The superscripts indicate the regime. The conditional mean is $X_t = \delta^{(i)} + \varepsilon_t$, whereas the conditional variance is where the expectation is calculated as in (3.12). Instead of $L^{(i)}$, we report $\sigma^{(i)} = \sqrt{L^{(i)} / (1-\alpha_1^{(i)} - \beta_1^{(i)})}$ for each regime which is the standard deviation conditional to the volatility regime. π_i is the unconditional probability of being in regime i, while $\rho_i = \alpha_1^{(i)} + \beta_1^{(i)}$ is the persistence of shocks in the i-th regime. Asymptotic standard errors are in parentheses.

3.3 Conclusion

The calibration result presented in this chapter is consistent with existing work. In the next chapter, the calibrated models in this chapter will be further tested and the resulting predictions analyzed.

4. CHAPTER 4: Testing, Prediction

In this chapter we present the both the In-Sample and out-of-Sample results of GARCH and MRS-GARCH models for both the S&P500 and ASPI index markets. We will present the in-sample statistics and the out-of-sample forecast evaluation in the next chapter. We employ the statistic measures used by Marcucci (2005). Our empirical results in S & P 500 market is completely consistent with Marcucci (2005) who used US stock market data to point out that MRS-GARCH models significantly outperform usual GARCH in forecasting volatility at shorter horizons, while at longer horizons, standard asymmetric GARCH fare better. Our empirical results also indicate that none of the models seems to be uniformly superior in forecasting two index markets, which also agrees with Marcucci (2005)'s result on US stock market volatility forecasting.

To conduct effective forecasting, we must evaluate model performance by use of various metrics. In general, the evaluation of different volatility forecast models can be very difficult because there is no unique criterion capable of choosing the best model (see Bollerslev *et al.* 1994 and Lopez, 2001).

Similar to Marcucci (2005), instead of choosing a particular statistical loss function as the best and unique criterion, this study adopts seven different statistical metrics, each with different interpretations, so leading to a more complete forecast evaluation of the competing models. These statistical functions are:

AIC is the Akaike information criterion

AIC = $-2\ \log(L)/T + 2k/T$, where k is the number of parameters and T the number of observations.

$$\text{BIC} = -2\,\log(L)/T + 2k/T\log(T).$$

$$\text{MSE}=\frac{1}{n}\sum_{t=1}^{n}(\sigma_{t+m} - h^{0.5}_{t,t+m})^2$$

$$\text{R2LOG} = \frac{1}{n}\sum_{t=1}^{n}[\log(\sigma^2_{t+m}h^{-1}_{t,t+m})]^2 ,$$

$$MAD1 = \frac{1}{n}\sum_{t=1}^{n}\left|\sigma_{t+m} - h^{0.5}_{t,t+m}\right| ,$$

$$MAD2 = \frac{1}{n}\sum_{t=1}^{n}\left|\sigma^2_{t+m} - h_{t,t+m}\right| ,$$

$$\text{HMSE} = \frac{1}{n}\sum_{t=1}^{n}[(\sigma^2_{t+m}h^{-1}_{t,t+m} - 1)]^2 .$$

Note that rather than using typical mean squared error metrics, we employ the heteroscedasticity-adjusted MSE proposed by Bollerslev and Ghysels (1996). The $R2LOG$ metric is a particular R^2 metric when the forecasts are unbiased and has the particular feature of penalizing volatility forecasts asymmetrically in low and high volatility periods. The Mean Absolute Deviation (MAD) criteria are believed to be more robust to the possible presence of outliers than the MSE criteria, but they impose the same penalty on over- and under-predictions and are not scale invariant.

Both regime-switching models and GARCH are used in this paper to model and explain the behavior of four key index markets.

4.1 In-Sample statistics

Table 4.1 and 4.2 in the appendix document some in-sample goodness-of-fit statistics results, which are used as model selection criteria.

Overall, the EGARCH model with t innovations has the largest log-likelihood value among the state-independent GARCH models, while for the MRS-GARCH models, the best result is from the MRS-GARCH with Student's t distribution, where the degrees of freedom switch across the two volatility regimes; for the ASPI index, the best model is shown to be MRS-GARCH with GED innovations.

The Akaike Information Criterion (AIC) and the Schwarz Criterion (BIC) both indicate that the best model among the standard GARCH and overall is the EGARCH model with t innovations, while among the MRS-GARCH models is the MRS-GARCH-t that fits the best. Overall, it is hard to justify which model outperforms the other.

4.2 Out-of-Sample forecast evaluation

Table 4.3-4.10 in the appendix show the results of the out-of-sample evaluation of the one-, five-, ten-, and twenty-two-step-ahead volatility forecasts, where the statistical loss functions of Marcucci (2005) are employed. The volatility proxy in the table is given by the realized volatility.

Almost all models yield high success ratio (SR) values of more than 70% and highly significant DA test at all forecast horizons with the sole exception being the

S&P500 market using MRS-GARCH-t model.

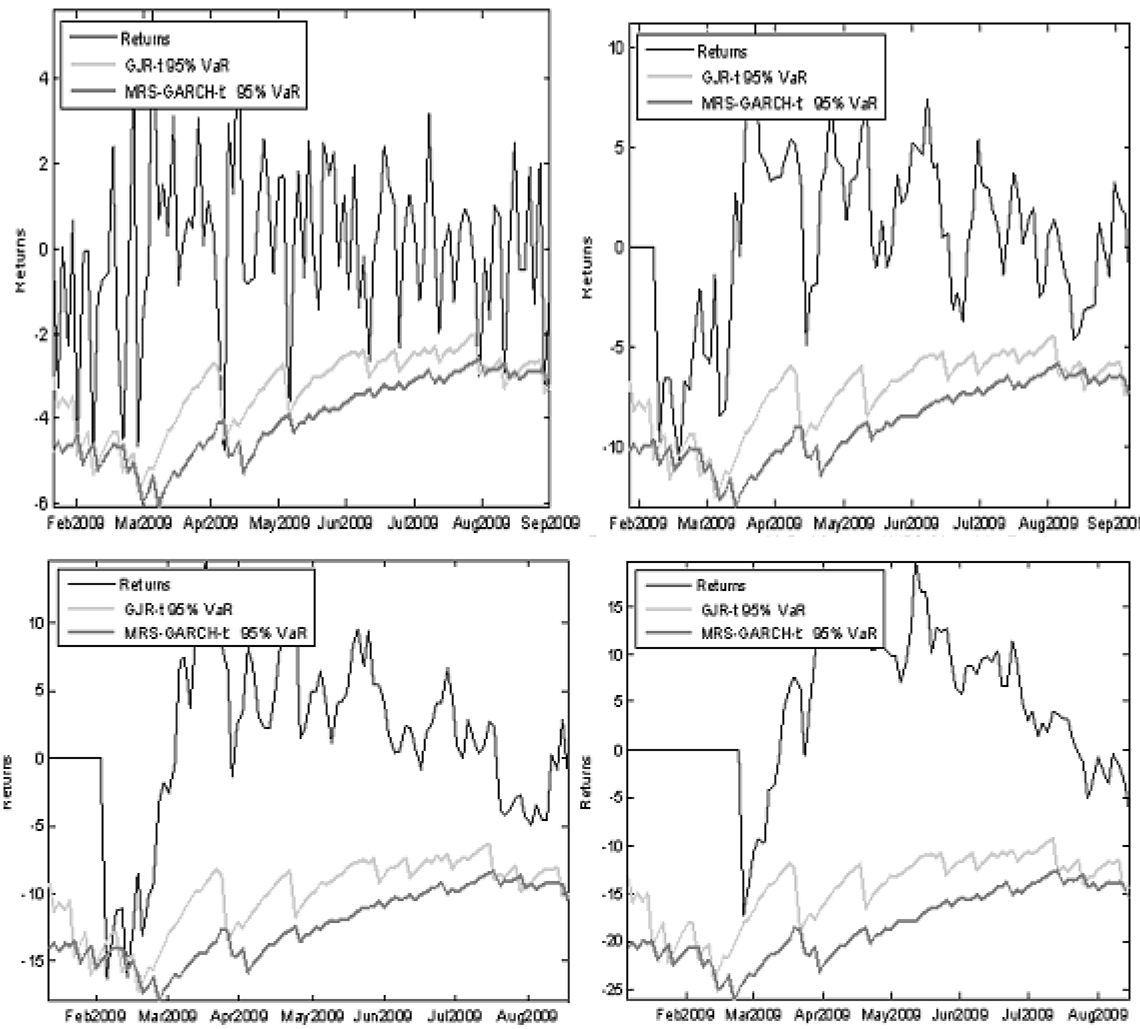
At one-day forecasting, the best model for the market of ASPI is the GARCH-GED and the MRS-GARCH-N is the best model among the MRS-GARCH; however, the ranking order of MRS-GARCH models are in general smaller than GARCH models. At each of the one-week, two-week and one-month forecast horizons, the best model is EGARCH-N, while the MRS-GARCH-N is only the best model among the MRS-GARCH. In general, MRS-GARCH performs worse than GARCH models.

For the S&P500 market, in terms of one-day, one-week and two-week forecasting, the best model turns out to be the MRS-GARCH-t, and the best model among the single-regime GARCH models is GARCH-GED ranking the third. For the one-week and two-week forecasts, the best model is again the MRS-GARCH-t model, while the best model among the single-regime GARCH models is EGARCH-N which ranks the second and the third. At the one-month forecasting, the best model is the EGARCH-N, and the best model among the MRS-GARCH is the MRS-GARCH-N or MRS-GARCH-t. Meanwhile, one can notice that for each forecast horizon, the MRS-GARCH-N performs well and it always ranks top four among the 12 models. Such results agree with Marcucci (2005) which shows that for the US stock market (here with the S&P 100) MRS-GARCH models significantly outperform usual GARCH in forecasting volatility at shorter horizons, while at longer ones, standard asymmetric GARCH fare better.

It can be seen from our empirical results that none of the models seems to be uniformly superior in forecasting the two index markets, which also agrees with Marcucci (2005)'s result on US stock market volatility forecasts.

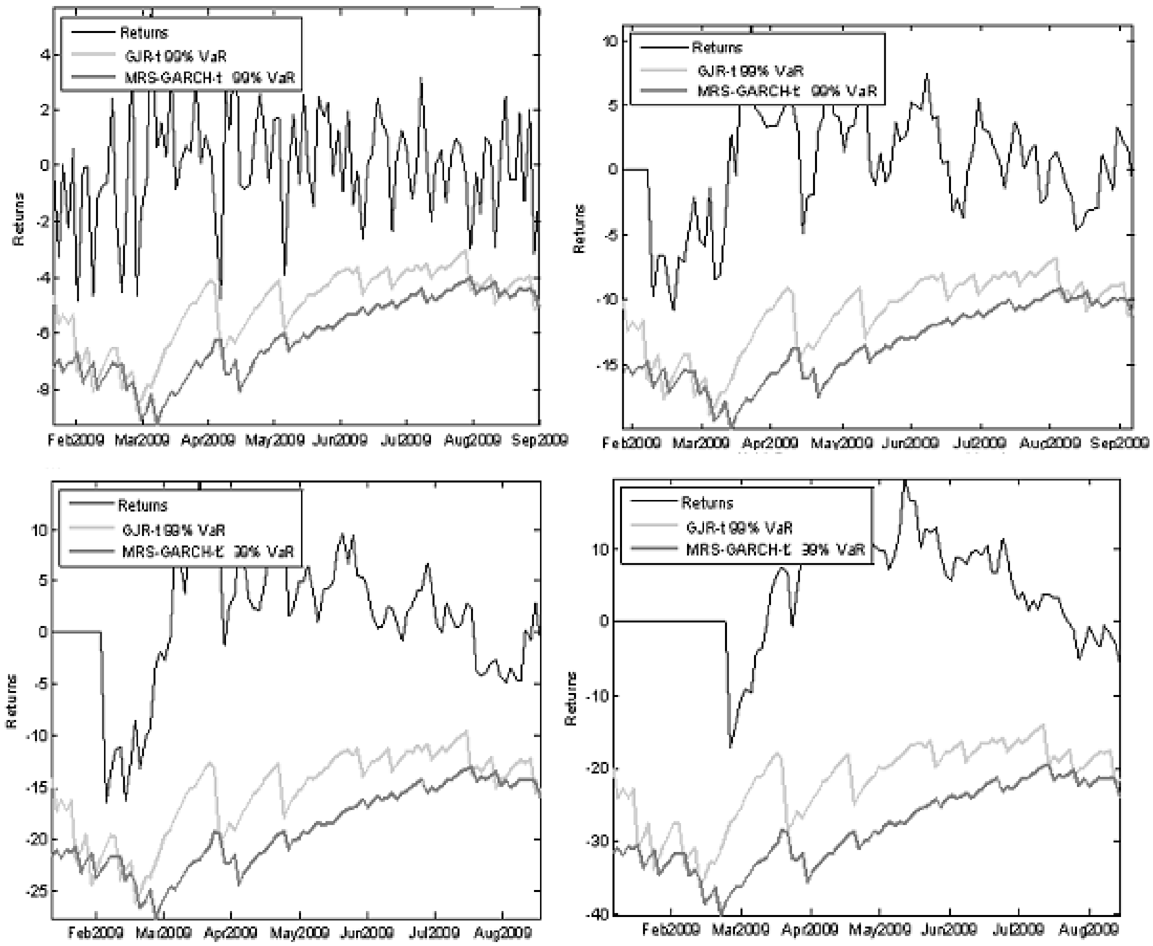
Figure 4.1 and 4.2 depict the excessive losses of 95% and 99% VaR estimates from the GJR-t and MRS-GARCH-t models for ASPI market. Both figures indicate that MRS-GARCH-t model seems worse than GJR-t to quickly capture the changes in the volatility of returns for ASPI market. The patterns are similar to Marcucci (2005).

Figure 4- 1 95% VaR estimates from the best models-ASPI



Note: upper left excess loss for 95% VaR of GJR-t and MRS-GARCH-t 1-step ahead; upper right excess loss for 95% VaR of GJR-t and MRS-GARCH-t 5-step ahead; lower left excess loss for 95% VaR of GJR-t and MRS-GARCH-t 10-step ahead; Lower right excess loss for 95% VaR of GJR-t and MRS-GARCH-t 22-step ahead;

Figure 4- 2 99% VaR estimates from the best models.-ASPI



Note: upper left excess loss for 95% VaR of GJR-t and MRS-GARCH-t 1-step ahead; upper right excess loss for 95% VaR of GJR-t and MRS-GARCH-t 5-step ahead; lower left excess loss for 95% VaR of GJR-t and MRS-GARCH-t 10-step ahead; Lower right excess loss for 95% VaR of GJR-t and MRS-GARCH-t 22-step ahead;

4.3 Conclusions

Models are carefully tested and validated models are used in another prediction task. Results presented in this chapter coincide with existing work. Based on the regime switching modeling in this chapter, we estimated regime-level data used for investment analysis in the next two chapters.

5. CHAPTER 5: Investment in Different Regimes

This chapter investigates portfolio optimization strategies using a portfolio composed of four index markets during both normal and crisis market times. Identification of normal market and the crisis market are based on results from regime-switching models.

5.1 Regime identification

As described in Chapter 2-4, we assume two distinct states or regimes 1 and 2 in our model. State 1 represents a low risk state. State 2 represent the opposite, i.e. high conditional volatility and low or even negative returns. State 1 can be expected during a “bull market” and state 2 can be expected during a “bear market”.

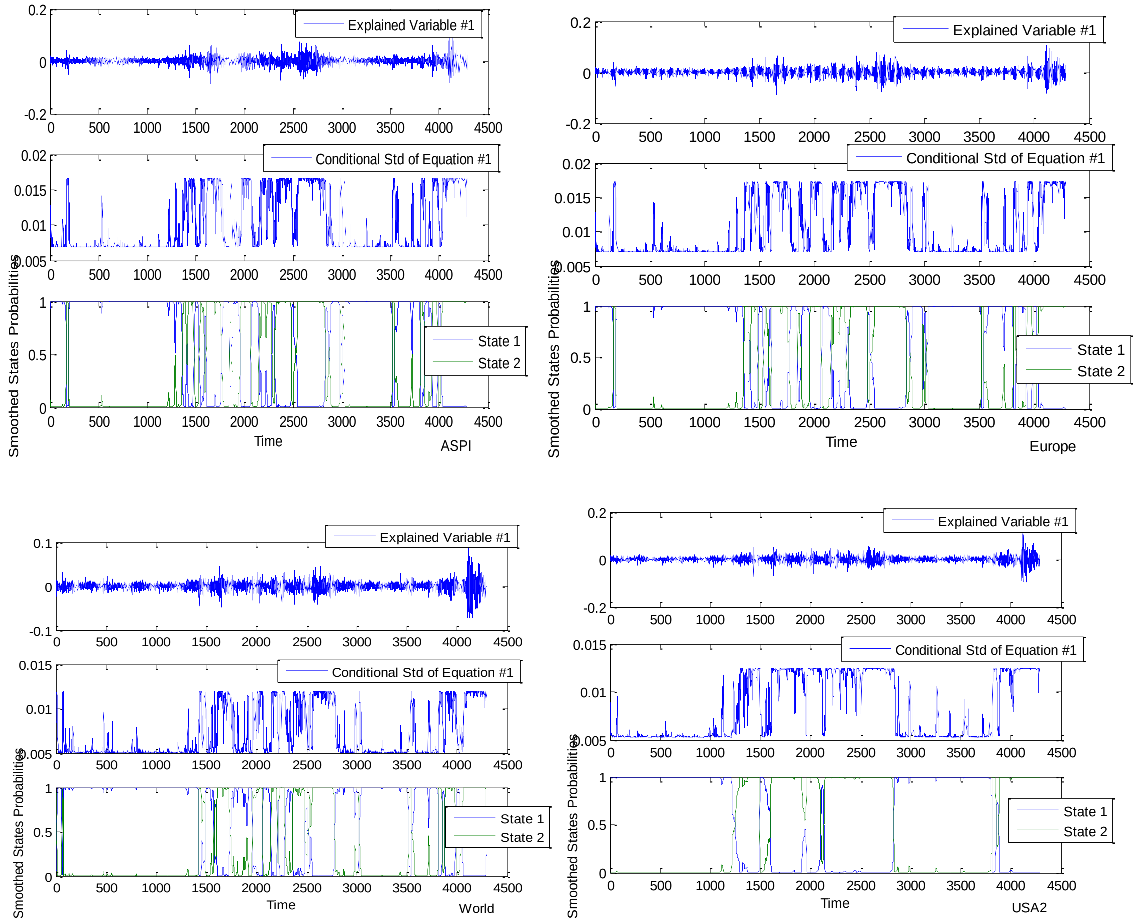


Figure 5- 1 Transitional probability evolution for index markets

Note: upper left World Index transitional probability; upper right USA Index transitional probability; lower left ASPI Index transitional probability; Lower right Eurostoxx 50 Index transitional probability; “0“ at the x-axis denotes Jan. 1992; “500“ denotes Jan. 1994; “1000“ denotes Jan. 1996; “1500“ denotes Jan. 1998; “2000“ denotes Jan. 2000; “2500“ denotes Jan. 2002; “3000“ denotes Jan. 2004; “3500“ denotes Jan. 2006; “4000“ denotes Jan. 2008;

Figure 5.1 presents explained (dependent) variable, conditional standard deviation and transitional probabilities in Markov Regime Switching with t distribution: fitted state probabilities and smoothed state probabilities. It is not surprising to see that the ASPI curves are very similar to European curves and the world curves are similar to S&P500 curves. Based on the conditional standard deviation of all indices, transitional probability and referring to the fact of an economic crisis occurring, we can classify the historical data into two types: the normal market (Jan. 1992-Mar. 1997 and Mar. 2003-Jul. 2007) and the crisis market (Mar. 1997- Mar. 2003 and Jul. 2007- Jul. 2009). After the classification of historical market states, the associated mean and standard deviation of daily returns are computed in the following table for these four market periods.

Table 5- 1 return and standard deviation during different periods

statistic	Period	World	USA	Europe	ASPI
mean	92-97	3.5bp	5.0bp	5.8bp	7.3bp
	97-03	-0.73bp	0.42bp	0.21bp	0.91bp
	03-07	7.07bp	5.44bp	6.93bp	8.54bp
	07-09	-11bp	-10bp	-13bp	-12bp
St.d.	92-97	0.5%	0.6%	0.8%	0.7%
	97-03	1.1%	1.4%	1.8%	1.7%
	03-07	0.7%	0.8%	1.0%	1.0%
	07-09	1.8%	2.2%	2.2%	2.1%

Note: 1 bp(basis point) = 0.01%;

5.2 Sharpe ratio and Information ratio

As described in Chapter One, the Sharpe ratio is defined as the ratio of the difference between the asset portfolio return and the return of a riskless asset divided by the portfolio standard deviation. The information ratio (IR) measures a portfolio manager's ability to generate excess returns relative to a benchmark, but also attempts to identify the consistency of the investor. Given an asset or portfolio of assets with random returns designated by Asset i and a benchmark with random returns designated by Benchmark i, the information ratio is defined as the ratio of the mean of Asset minus Benchmark returns divided by the standard deviation of Asset minus Benchmark returns, i.e., IR= (E[Asset *i*]-E[Benchmark *i*])/ σ (Asset *i* - Benchmark *i*). A higher information ratio is considered better than a lower information ratio. All index markets have positive IR values during the first three regimes and negative IR values in the last regime, which is very good.

Table 5-2 also indicates that during the normal market period of 1992~1997 and 2003~2007, the performance of ASPI are better than other indices; however during crisis, the ASPI performance is not better than the rest.

Table 5- 2 Sharpe ratio and Information ratio during different periods

statistic	Period	World	USA2	Europe	ASPI
Sharpe ratio	92-97	7.80%	9.30%	8.50%	10.90%
	97-03	1.70%	2.20%	1.60%	2.10%
	03-07	9.50%	6.10%	5.80%	7.70%
	07-09	-4.00%	-3.20%	-4.60%	-4.10%
Information ratio	92-97	4.20%	5.00%	5.70%	7.20%
	97-03	1.40%	2.00%	1.50%	2.00%
	03-07	5.60%	4.00%	4.80%	6.20%
	07-09	-3.50%	-3.00%	-4.30%	-3.80%

Note : T-bill is used as a bench mark because it is backed by the full taxing power of the US government and therefore the risk of default is essentially zero, besides it is subject to interest rate risk, T-bill is the most common example of a riskless investment.

5.3 Portfolio Optimization

When constructing a portfolio for clients, a portfolio manager faces many constraints to meet the objectives of the particular investor he or she serves. Different investor risk appetite, different diversification preferences, industry regulation and so on, result in different constraints that the portfolio manager must use to find an optimal portfolio. The optimal portfolio is the portfolio that maximizes the return for a given risk, or minimizes the risk for a given return. Optimal portfolios define a line in the risk/return plane called the efficient frontier. The efficient frontier builds optimal portfolios that optimize risk adjusted return.

The data set consisted of yearly prices of one World index, one North American index, S&P 500, and two European indices, ASPI and Eurostoxx 50. Note that we may deem World indices as both European and North American markets.

In this section, we will compute portfolios along the efficient frontier for the whole group of indices by minimizing the risk for given values of the expected returns of each index during the four periods mentioned above. We will examine some different scenarios to see how efficient frontiers may change when we apply different constraints. In some scenarios we look at what will happen if we divide the indexes into two different groups or regions and put some constraints on the weights that these regions can contain. Matlab was used for all calculations.

5.3.1 Portfolio optimization for overall period

We now look at the efficient frontier according to different scenarios where we change the investment strategy in different index markets according to real situation.

Scenario 1 – No short selling allowed

First we look at the scenario if no short selling is allowed (or if the investor does not want to short sell). Short selling involves the investor borrowing and selling a security which he must later repay. Many investors are either forbidden to short sell (for example mutual funds and many pension funds) or are uncomfortable investing with money that they have borrowed so this scenario is important to examine. The following table shows 10 portfolios that lie on the efficient frontier.

Table 5- 3 Scenario 1 No short selling allowed

	Preturn	Prisk	%World	%S&P500	%Euro	%ASPI	%T-bill
P1	0.081%	13.69%	0	40.17%	0	0	59.83%
P2	1.38%	13.94%	0	52.15%	0	0	47.85%
P3	2.68%	14.62%	0	57.83%	0	4.25%	37.91%
P4	3.97%	15.57%	0	55.80%	0	13.72%	30.48%
P5	5.27%	16.73%	0	53.77%	0	23.19%	23.04%
P6	6.57%	18.05%	0	51.73%	0	32.66%	15.61%
P7	7.87%	19.49%	0	49.7%	0	42.13%	8.17%
P8	9.17%	21.04%	0	47.67%	0	51.6%	7.4%
P9	10.46%	22.79%	0	24.97%	0	75.03%	0
P10	11.76%	24.85%	0	0	0	1	0.00%

Note : Preturn denotes returns of portfolio; Prisk denotes risk of portfolio; P1-P10 denotes portfolio1-portfolio10;

Scenario 2 – 10% short selling in US indexes allowed and 80% and 70% upper bound on portfolio value in USA and Europe respectively

Next we look at the scenario where we have two constraints: only 10% short selling allowed in the US indexes and 80% and 70% upper bound on portfolio in USA and Europe indices respectively. The following table shows 10 portfolios that lie on the efficient frontier in this scenario.

Table 5- 4 Scenario 2 10% short selling in US

	Preturn	Prisk	%World	%S&P500	%Euro	%ASPI	%T-bill
P1	0.081%	13.69%	0.00%	40.17%	0	0	59.83%
P2	1.28%	13.90%	-0.18%	51.11%	0	0.18%	48.89%
P3	2.48%	14.42%	-10%	56.23%	0	10%	43.77%
P4	3.67%	15.22%	-10%	61.80%	0	13.71%	34.5%
P5	4.87%	16.23%	-10%	59.92%	0	22.44%	27.64%
P6	6.07%	17.39%	-10%	58.05%	0	31.18%	20.78%
P7	7.26%	18.67%	-10%	56.17%	0	39.91%	13.92%
P8	8.46%	20.05%	-10%	54.30%	0	48.65%	7.06%
P9	9.66%	21.51%	-10%	52.42%	0	57.38%	0.2%
P10	10.86%	23.14%	-10%	30%	0	80%	0%

Note : Preturn denotes returns of portfolio; Prisk denotes risk of portfolio; P1-P10 denotes portfolio1-portfolio10;

If we plot these two scenarios together we get the following graph.

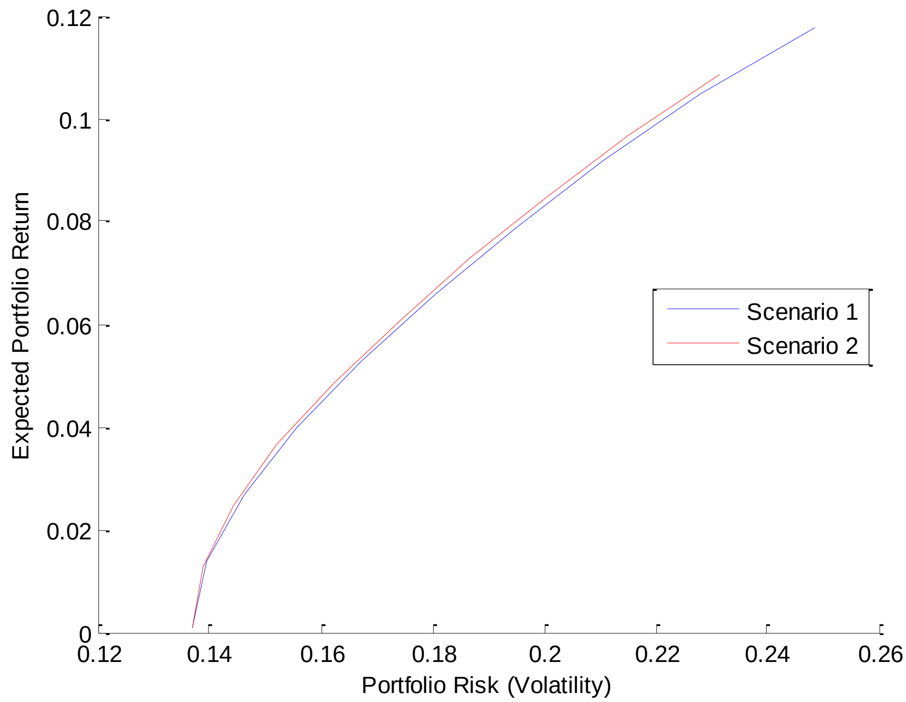


Figure 5- 2 Scenario 1 and 2

Note: upper curve scenario 2; lower curve scenario 1

As we can see the two efficient frontiers are very similar but scenario 2 is slightly better in terms of return and risk.

We also conduct various scenario analysis, i.e., Scenario 3-10 and present the results in the appendix. It is suggested that the scenario that allows the most short selling dominates all the other efficient frontiers. It also extends further than the other frontiers. There is no regional constraint for Scenario 3-6 while investment constraints are added to allow limited investment either in USA or in Europe for Scenario 7-10. Scenario 7-10 in the appendix suggests that it is not wise to stick to only one region (only USA or only Europe) because then we are constraining the frontier and getting less return for the same amount of risk. If people are concerned with regional market risk their efficient frontier will not be greatly affected if they constrain their portfolio value to 50% in each region.

5.3.2 Portfolio optimization for different regimes

Figure 5- 3 represents the efficient frontier curve of these four periods.

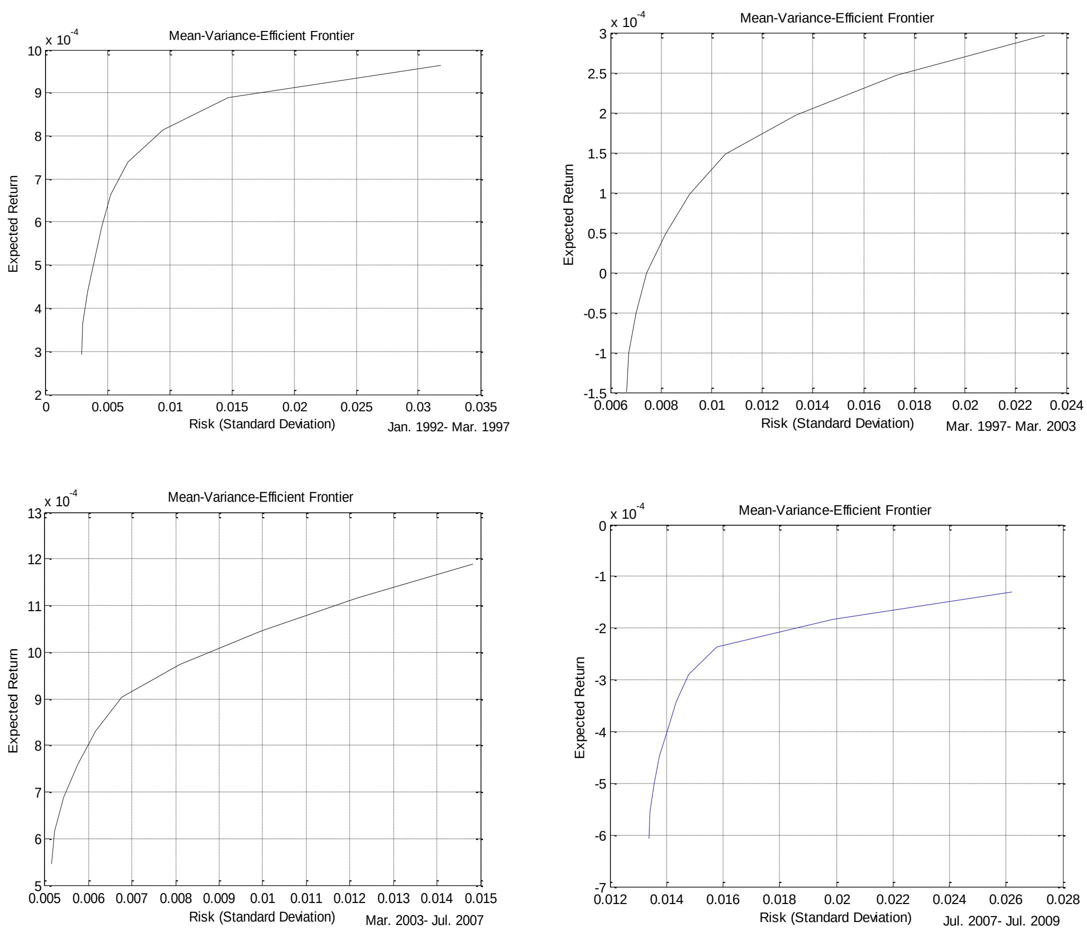


Figure 5- 3 Efficient frontier curve for four period markets

Note: upper left efficient frontier based on the data from January 1992-March 1997; upper right efficient frontier based on the data from March 1997-March 2003; lower left efficient frontier based on the data from March 2003-July 2007; Lower right efficient frontier based on the data from July 2007- July 2009;

The risk and return for each of the 10 portfolios computed along the efficient frontier are shown in Table 5- 5 . It is worth remarking that for given risk, the optimal portfolio under normal market gives a larger return than the one under crisis market. For example, we can see from these results that in the normal market during the period

1992-1997, given the risk of 0.0147, the 9th portfolio has a higher expected return of 0.09% comparing to the 9th portfolio in the crisis market during the period 1997-2003, which has an expected return of 0.02%, given a higher risk of 0.0173.

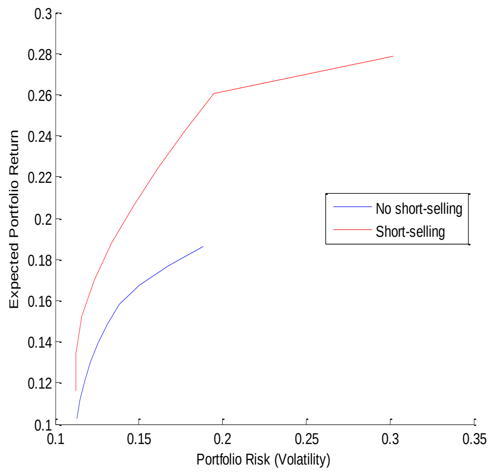
Table 5- 5 The returns of optimal portfolio given risk

Normal Market 1992-1997		Crisis Market 1997-2003		Normal Market 2003-2007		Crisis Market 2007-2009	
PortRisk	PortReturn	PortRisk	PortReturn	PortRisk	PortReturn	PortRisk	PortReturn
0.290%	0.030%	0.660%	-0.010%	0.510%	0.050%	1.340%	-0.060%
0.310%	0.040%	0.670%	-0.010%	0.520%	0.060%	1.340%	-0.060%
0.340%	0.040%	0.700%	-0.010%	0.540%	0.070%	1.360%	-0.050%
0.400%	0.050%	0.750%	0.000%	0.570%	0.080%	1.380%	-0.040%
0.460%	0.060%	0.820%	0.000%	0.620%	0.080%	1.400%	-0.040%
0.530%	0.070%	0.910%	0.010%	0.680%	0.090%	1.440%	-0.030%
0.670%	0.070%	1.060%	0.010%	0.810%	0.100%	1.480%	-0.030%
0.940%	0.080%	1.330%	0.020%	1.000%	0.100%	1.580%	-0.020%
1.470%	0.090%	1.730%	0.020%	1.220%	0.110%	1.990%	-0.020%
3.180%	0.100%	2.310%	0.030%	1.480%	0.120%	2.620%	-0.010%

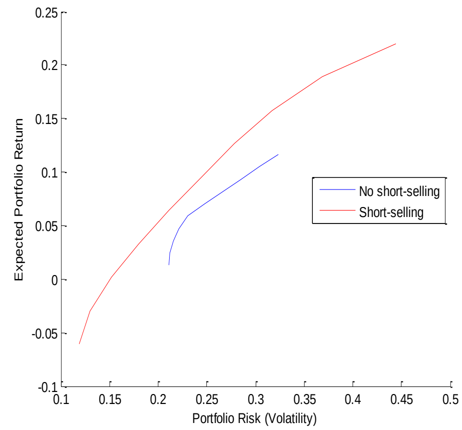
Note : the PortRisk in the table represents the standard deviation of each portfolio and the PortReturn represents the expected return of each portfolio.

5.3.3 Portfolio optimization with short selling for different regimes

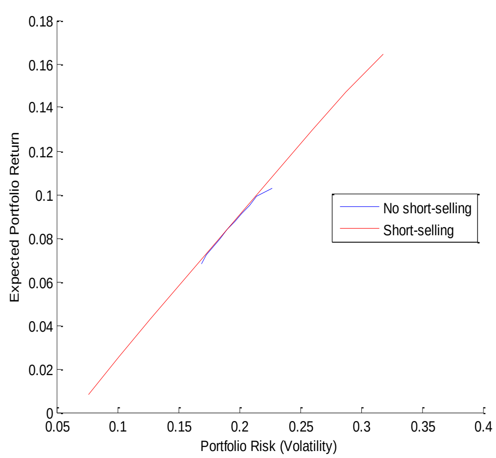
When looking at these four periods we should rerun the portfolio optimization and show how short selling changes our optimal investment in these four periods. We plot the efficient frontiers for the four periods, one where short selling is not allowed and another when short selling is allowed.



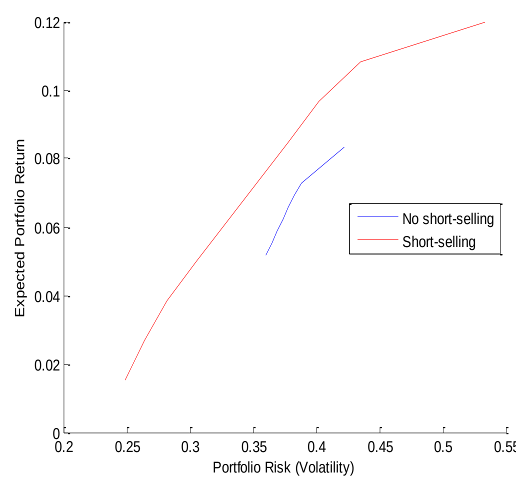
Period 1: 1992-1997



Period 2: 1997-2003



Period 3: 2003-2007



Period 4: 2007-2009

Figure 5- 4 All periods – Short selling not allowed

Note: upper left efficient frontier based on the data from January 1992-March 1997; upper right efficient frontier based on the data from March 1997-March 2003; lower left efficient frontier based on the data from March 2003-July 2007; Lower right efficient frontier based on the data from July 2007- July 2009;

We can see from the graphs that allowing short selling results in a big difference in terms of the efficient frontier. The difference is quite big in period 1, 2 and 4 but small in period 3. Let ́s now plot the four efficient frontiers where short selling is allowed on one graph:

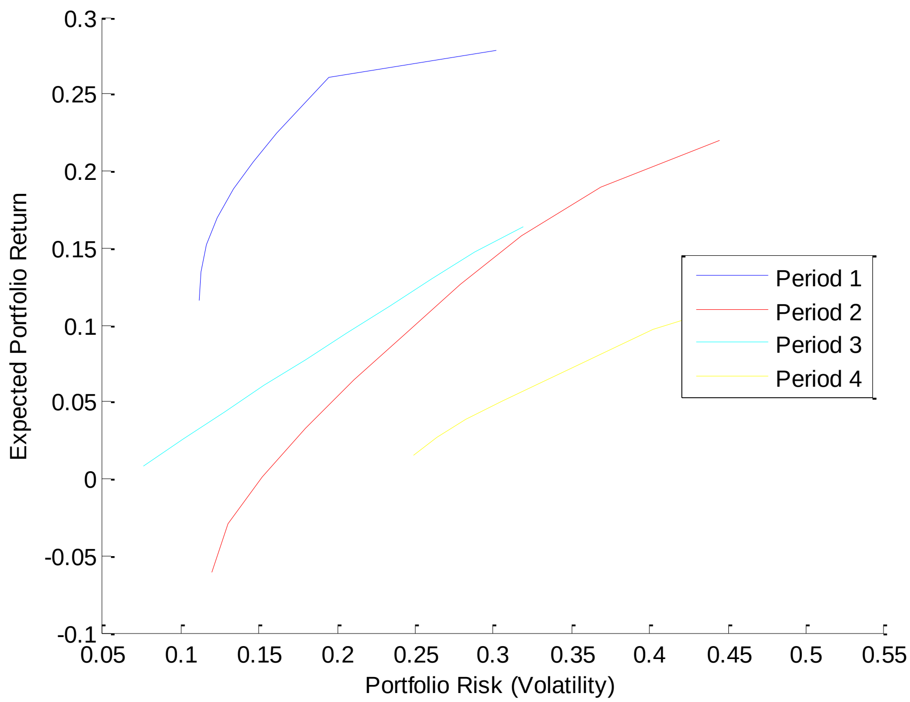


Figure 5- 5 All periods – Short selling allowed

From Figure 5.5 we see that period 1 gives us the best result and period 4 the worst. When looking at our data and the graph we are inclined to think that period 1 and 3 are bull markets, period 4 is bear market and period 2 is somewhere between.

5.4 Conclusion

During normal market conditions ASPI is a good asset to keep in a portfolio. By including it, it can give us a higher return and lower risk. It is hard to say how big a portion ASPI should be of a portfolio, because that depends on investor risk aversion and investment constraints. A very risk-averse investor during the total time period of approximately 17 years, from 1992 to 2009, compared to the optimization results, could have approximately 75% of his portfolio in ASPI. That is of course only dependent on the assets we are considering.

6. CHAPTER 6: Investment scenarios in ASPI Market

This chapter investigates whether an investor can be better off by including ASPI in her portfolio. We check four cases: including ASPI in the portfolio in a normal sense; when facing regional constraints; when allowing short-selling and when investing in different market regimes. Again, identification of normal market and the crisis market are based on results from regime-switching models.

6.1 Including ASPI in your portfolio?

The expected return and volatility for each asset can be seen in the table below:

Table 6- 1 The expected return and volatility for each asset

Asset	World	S&P500	Eurostoxx 50	ASPI
return	5.22%	6.56%	8.58%	11.76%
Volatility	19.41%	18.82%	24.46%	24.85%

Note: annualized data over whole period.

As we can see, the ASPI index outperforms the other indexes with regards to expected return but on the other hand it also bears the highest risk. As we can see from Table 6- 1 some of the portfolios bear high risk and are often not well diversified over the 4 indexes (ASPI index with high weight in the riskier portfolios). We now look at some scenarios where we put some constraints on the allowed weight of the ASPI index. We look at 4 scenarios where the allowed weight of the ASPI index is 0%, 20%, 40% and 60%. The following table shows 10 portfolios that lie on the efficient frontier when the allowed weight is 0%.

We plot these 4 scenarios on one figure as well as the scenarios when all assets are included. This figure can be seen below:

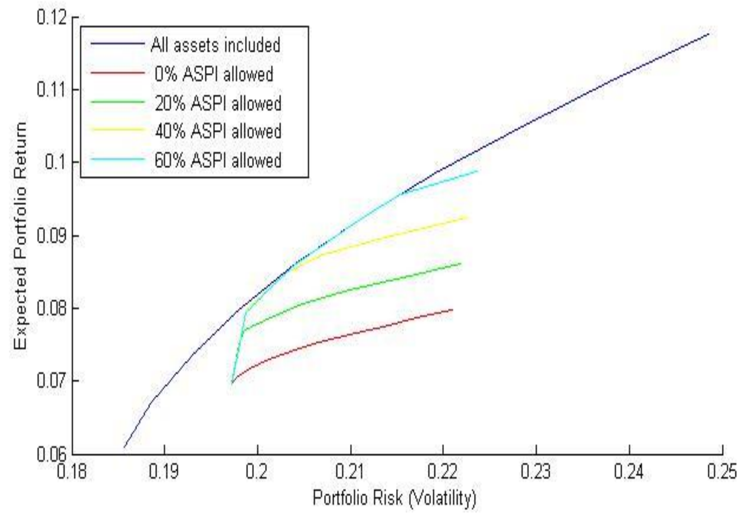


Figure 6- 1 All assets included and constraints on the ASPI index

As we can see, constraint on the weight of ASPI index reduces expected portfolio return as well as the portfolio risk.

6.2 Including ASPI when facing regional constraints ?

Constraint 1: The sum of weights for each portfolio must equal to 1, and investment in individual asset must be more than 0.

Constraint 2: Divide the assets in to two groups, North America (NA) and EU and put min and max weight on those groups. NA [0.3, 0.7] and EU [0.4, 0.8].

In Figure 6.2, we can see the efficient frontier for the case with and without ASPI. From Table 6- 2 Table 6- 3 , we can see the risk, return and weights of those portfolios plotted in Figure 6.2:

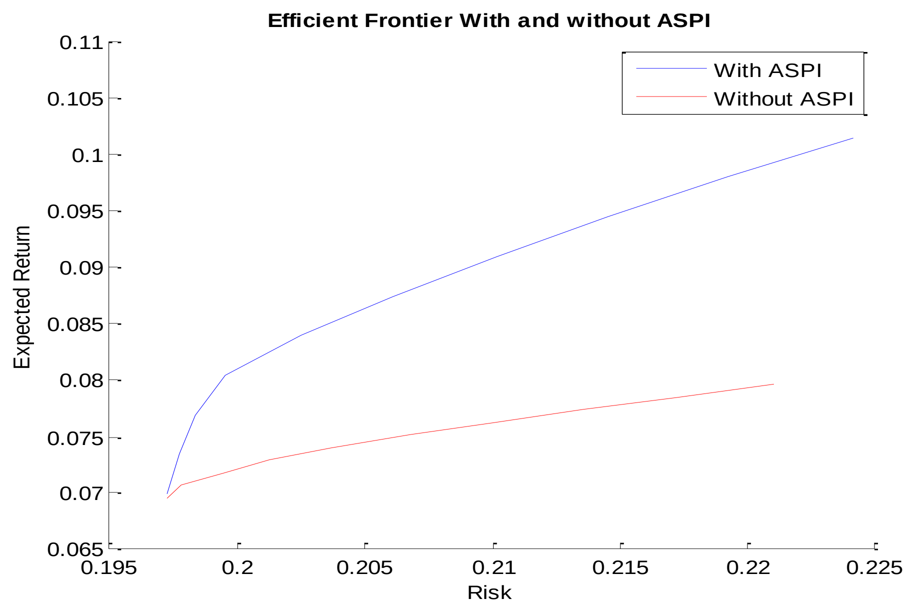


Figure 6- 2 Efficient frontier with and without ASPI

Note: upper curve with ASPI; lower curve without ASPI

Table 6- 2 shows risk, return and weights of the portfolios which include ASPI. Table 6- 3 shows the same thing but without ASPI.

Table 6- 2 risk, return and weights of the portfolios with ASPI

	Preturn	Prisk	W-World	W-S&P500	W-Euro	W-ASPI
P1	6.99%	19.73%	15.52%	54.48%	29%	1%
P2	7.43%	19.78%	10.13%	59.87%	20.23%	9.77%
P3	7.69%	19.83%	10.08%	59.92%	9.19%	20.81%
P4	8.05%	19.95%	8.63%	60%	1%	30.37%
P5	8.40%	20.25%	3.25%	60%	**1%**	35.75%
P6	8.75%	20.61%	1%	56.07%	1%	41.93%
P7	9.10%	21.02%	1%	49.30%	1%	48.7%
P8	9.45%	21.45%	1%	42.53%	1%	55.47%
P9	9.80%	21.92%	1%	35.77%	1%	62.23%
P10	10.16%	22.41%	1%	29%	1%	69%

Note : Preturn denotes portfolio returns; Prisk denotes portfolio risk; P1-P10 denotes portfolio1-portfolio10; W-X denotes weights given to X,where X represents World, S&P500, Europe, and ASPI

Table 6- 3 risk, return and weights of the portfolios without ASPI

	Preturn	Prisk	W-World	W-S&P500	W-Euro
P1	6.96%	19.72%	15.50%	54.50%	30%
P2	7.07%	19.78%	8.89%	60%	31.11%
P3	7.18%	19.95%	5.58%	60%	34.42%
P4	7.29%	20.12%	2.28%	60%	37.72%
P5	7.40%	20.37%	1%	56.61%	**42.39%**
P6	7.52%	20.68%	1%	51.09%	47.91%
P7	7.63%	21.01%	1%	45.56%	53.44%
P8	7.74%	21.35%	1%	40.04%	58.96%
P9	7.85%	21.72%	1%	34.52%	64.48%
P10	7.96%	22.10%	1%	29%	70%

Note : Preturn denotes portfolio returns; Prisk denotes portfolio risk; P1-P10 denotes portfolio1-portfolio10; W-X denotes weights given to X,where X represents World, S&P500, Europe

From Figure 6.2 and Table 6- 2 Table 6- 3 , we can clearly see that we can make a better portfolio by including ASPI in it. That gives us higher return compared to the same volatility. Of course a better investment might arise from adding a different new index without lower correlation to existing indices, which is the main goal of Chapter 7.

6.3 Including ASPI when allowing short-selling?

To address this question, I used the short selling bounds for both NA and EU. When I had short selling in NA, I kept the original lower bound for EU (min 0.4) and vice versa. Then I compared the scenarios, with and without ASPI to find out if that asset should be included in our investment.

Short selling in NA

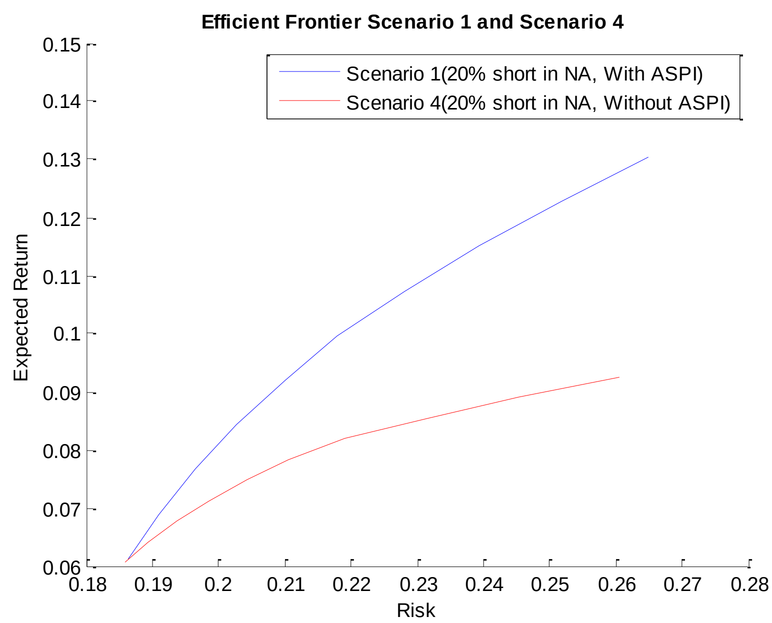


Figure 6- 3 Efficient frontier Scenario 1 and 4

Note: upper curve 20% short in NA with ASPI; lower curve 20% short in NA without ASPI

In Figure 6.3, we have two efficient frontiers. Both have allowable short selling up to 20% in NA indices, but one of them does not include ASPI. It can clearly be seen that it is better to include ASPI in our portfolio. The reason is that, the return is higher compare to the same volatility.

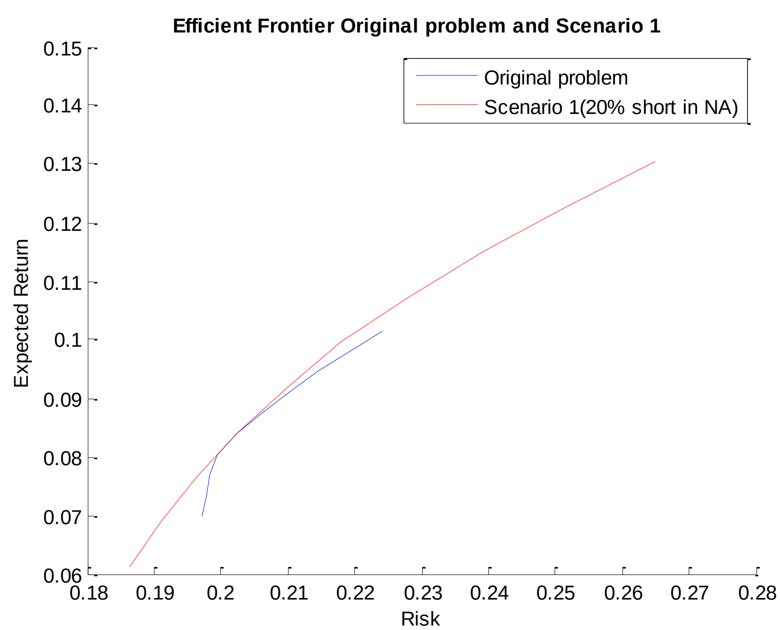


Figure 6- 4 Efficient frontier-original problem and Scenario 1

Note: upper curve 20% short in NA; lower curve original problem

In Figure 6.4, we can see the original problem with the original constraints and the scenario where we have 20% allowable short selling in NA market. When short selling is allowed, we are able to make a better portfolio with less risk and higher return. Both portfolios have ASPI included.

Short selling in EU

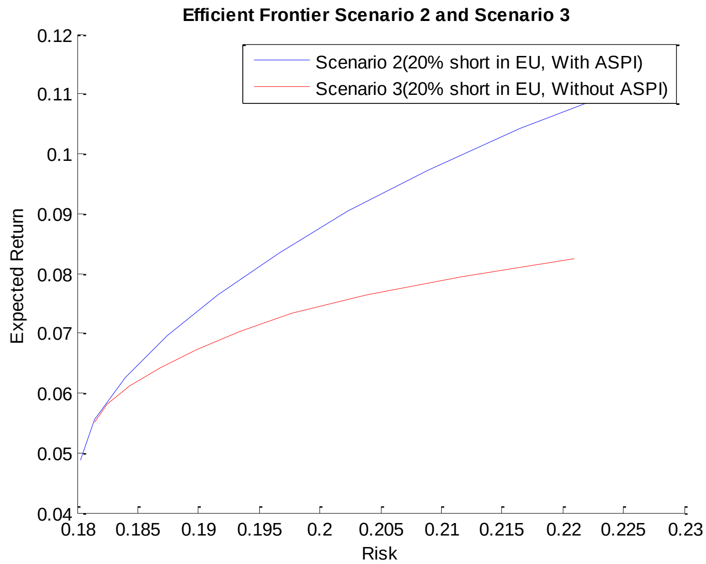


Figure 6- 5 Efficient frontier Scenario 2 and 3

Note: upper curve 20% short in EU with ASPI; lower curve 20% short in EU without ASPI

In Figure 6.5, we have two efficient frontiers. Both have allowable short selling up to 20% in EU indices, but one of them does not include ASPI. It can clearly be seen that it is better to include ASPI in our portfolio. The reason is that the return is higher compare to the same volatility. In Tables 6.10 and 6.11 in the appendix, we can see the risk, return and weights of the optimal portfolios.

Short selling in NA and EU

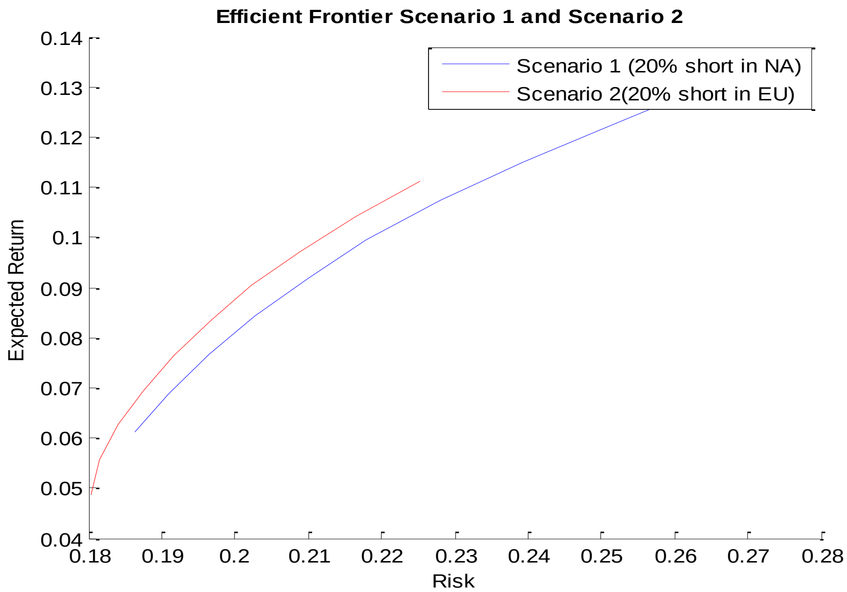


Figure 6- 6 Efficient frontier Scenario 1 and 2

Note: upper curve 20% short in EU; lower curve 20% short in NA

In Figure 6.6, we compare the scenarios where 20% short selling is allowed in NA and then where 20% short selling is allowed in EU. From this figure we can see that the return is higher for investing in EU market. Still, you can get higher return for investing in NA market if you are risk seeking investor, but then you would have to increase your risk quite much for a little increase in expected return.

The above analysis indicates that it is always better to have ASPI included in the portfolios. It gives us higher return compared to the portfolio risk. This means socially responsible investment is preferred.

6.4 Including ASPI when investing in different regimes ?

This section looks into investment strategies in different regimes. Again, optimal portfolios along the efficient frontier are computed and the expected returns of optimized portfolios are compared for the cases with and without ASPI during different periods. Annual return data are used except for the last period, 2007~2009, where quarterly returns are used to generate the optimized portfolio. The risk, return and weights allocated to each index of the 10 portfolios computed along the efficient frontier are shown in Table 6- 4 , where each row represents a portfolio.

Table 6- 4 **Risk, Return and Weights for each optimized portfolio from 92-97**

	PortRisk	PortReturn	W-World	W-USA	W-Europe	W-ASPI
without ASPI	10.35%	9.51%	65.72%	34.28%	0.00%	NA
	10.40%	9.82%	55.78%	41.17%	3.05%	
	10.49%	10.13%	46.48%	45.45%	8.07%	
	10.64%	10.44%	37.19%	49.73%	13.08%	
	10.82%	10.75%	27.89%	54.01%	18.10%	
	11.04%	11.06%	18.60%	58.29%	23.11%	
	11.30%	11.37%	9.30%	62.57%	28.13%	
	11.59%	11.69%	0.01%	66.85%	33.14%	
	13.04%	12.00%	0.00%	33.44%	66.56%	
	16.23%	12.31%	0.00%	0.00%	100.00%	
with ASPI	10.35%	9.51%	65.72%	34.28%	0.00%	0.00%
	10.42%	10.24%	53.01%	39.16%	0.00%	7.83%
	10.59%	10.97%	40.96%	42.97%	0.00%	16.07%
	10.85%	11.70%	28.92%	46.78%	0.00%	24.30%
	11.20%	12.42%	16.87%	50.59%	0.00%	32.54%
	11.62%	13.15%	4.82%	54.41%	0.00%	40.77%
	12.18%	13.88%	0.00%	46.62%	0.00%	53.38%
	13.15%	14.61%	0.00%	31.08%	0.00%	68.92%
	14.47%	15.34%	0.00%	15.54%	0.00%	84.46%
	16.06%	16.06%	0.00%	0.00%	0.00%	100.00%

Note : the PortRisk in the table represents the standard deviation of each portfolio and the PortReturn represents the expected return of each portfolio; W-X represents weight given to “X“, where X denotes World, USA, Europe and ASPI.

Table 6- 5 Risk, Return and Weights for each optimized portfolio from 97-03

	PortRisk	PortReturn	W-World	W-USA	W-Europe	W-ASPI
without ASPI	21.02%	-0.03%	86.58%	13.42%	0.00%	NA
	21.04%	0.54%	72.42%	27.58%	0.00%	
	21.11%	1.12%	58.26%	41.74%	0.00%	
	21.21%	1.70%	44.10%	55.90%	0.00%	
	21.35%	2.28%	29.94%	70.06%	0.00%	
	21.53%	2.85%	15.77%	84.23%	0.00%	
	21.75%	3.43%	1.61%	98.39%	0.00%	
	24.58%	4.01%	0.00%	69.30%	30.70%	
	28.05%	4.59%	0.00%	34.65%	65.35%	
	31.74%	5.16%	0.00%	0.00%	100.00%	
with ASPI	21.020%	-0.035%	86.584%	13.420%	0.000%	0.000%
	21.060%	0.770%	66.838%	33.160%	0.000%	0.000%
	21.180%	1.576%	47.093%	52.910%	0.000%	0.000%
	21.380%	2.381%	27.347%	72.650%	0.000%	0.000%
	21.660%	3.186%	7.602%	92.400%	0.000%	0.000%
	22.890%	3.992%	0.000%	86.670%	0.000%	13.330%
	24.760%	4.797%	0.000%	65.010%	0.000%	34.990%
	26.710%	5.602%	0.000%	43.340%	0.000%	56.660%
	28.720%	6.407%	0.000%	21.670%	0.000%	78.330%
	30.780%	7.213%	0.000%	0.000%	0.000%	100.000%

Note : the PortRisk in the table represents the standard deviation of each portfolio and the PortReturn represents the expected return of each portfolio; W-X represents weight given to “X“, where X denotes World, USA, Europe and ASPI.

Table 6- 6 **Risk, Return and Weights for each optimized portfolio from 03-07**

	PortRisk	PortReturn	W-World	W-USA2	W-Europe	W-ASPI
without ASPI	3.19%	11.87%	0.00%	50.16%	49.84%	NA
	3.31%	12.29%	8.64%	39.50%	51.86%	
	3.43%	12.72%	17.76%	29.80%	52.44%	
	3.55%	13.14%	26.87%	20.11%	53.03%	
	3.68%	13.57%	35.98%	10.41%	53.61%	
	3.81%	13.99%	45.09%	0.71%	54.19%	
	4.14%	14.42%	58.56%	0.00%	41.44%	
	4.87%	14.85%	72.37%	0.00%	27.63%	
	5.85%	15.27%	86.19%	0.00%	13.81%	
	6.98%	15.70%	100.00%	0.00%	0.00%	
with ASPI	3.19%	11.87%	0.00%	50.16%	49.84%	0.00%
	3.30%	12.31%	0.00%	49.28%	37.47%	13.24%
	3.42%	12.76%	1.63%	47.94%	25.68%	24.75%
	3.54%	13.21%	6.53%	43.00%	18.92%	31.55%
	3.65%	13.66%	11.43%	38.05%	12.16%	38.36%
	3.77%	14.11%	16.34%	33.10%	5.40%	45.16%
	3.89%	14.56%	22.08%	27.19%	0.00%	50.74%
	4.01%	15.01%	31.13%	17.41%	0.00%	51.45%
	4.13%	15.46%	40.19%	7.64%	0.00%	52.17%
	6.56%	15.91%	0.00%	0.00%	0.00%	100.00%

Note : the PortRisk in the table represents the standard deviation of each portfolio and the PortReturn represents the expected return of each portfolio; W-X represents weight given to "X", where X denotes World, USA, Europe and ASPI.

Table 6- 7 **Risk, Return and Weights for each optimized portfolio from 07-09**

	PortRisk	PortReturn	W-World	W-USA2	W-Europe	W-ASPI
without ASPI	29.44%	-10.41%	0.00%	100.00%	0.00%	NA
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
	29.44%	-10.41%	0.00%	100.00%	0.00%	
with ASPI	29.44%	-10.41%	0.00%	100.00%	0.00%	0.00%
	30.24%	-10.21%	0.00%	88.89%	0.00%	11.11%
	31.05%	-10.00%	0.00%	77.78%	0.00%	22.22%
	31.86%	-9.79%	0.00%	66.67%	0.00%	33.33%
	32.66%	-9.59%	0.00%	55.56%	0.00%	44.44%
	33.47%	-9.38%	0.00%	44.44%	0.00%	55.56%
	34.28%	-9.18%	0.00%	33.33%	0.00%	66.67%
	35.08%	-8.97%	0.00%	22.22%	0.00%	77.78%
	35.89%	-8.76%	0.00%	11.11%	0.00%	88.89%
	36.70%	-8.56%	0.00%	0.00%	0.00%	100.00%

Note: the PortRisk in the table represents the standard deviation of each portfolio and the PortReturn represents the expected return of each portfolio; W-X represents weight given to "X", where X denotes World, USA, Europe and ASPI.

Table 6.4, 6.5, 6.6. and 6.7 show that during difference periods, the portfolio including ASPI has a better return than the one without it for a given risk. For example, in the crisis market during the period 1997-2003, given the risk of 0.3174, the 10th portfolio which excludes ASPI has a lower expected return of 5.16% comparing to the 10th portfolio in the same period with ASPI included, which has an expected return of 7.21%, under the conditional risk of 30.78%. This result attracts investors to invest in ASPI, which means the investors should add SRI investments to their portfolio.

6.5 Risk management - Simulated VaR

Value at Risk (VaR) is a widely accepted risk measure in practice. It gives answers to a practical question facing all investors: what is the worst-case loss given a confidence level and within some time horizon? VaR is defined as a threshold value such that the probability that the mark-to-market loss on the portfolio over a given time horizon exceeds this value for the given probability level (Jorion, 2006).

Table 6- 8 shows the simulated Value-at-Risk (VaR) of the portfolio at various confidence levels of 90%, 95% and 99%.

Table 6- 8 The simulated VaR of the hypothetical portfolio over one month horizon

		90% VaR	95% VaR	99% VaR
Normal Market 1992-1997	with ASPI	-2.13%	-3.00%	-4.73%
	w/o ASPI	-2.28%	-3.35%	-5.11%
Normal Market 2003-2007	with ASPI	-2.08%	-3.22%	-6.02%
	w/o ASPI	-2.28%	-3.52%	-6.59%
Crisis Market 1997-2003	with ASPI	-5.54%	-8.08%	-12.61%
	w/o ASPI	-5.30%	-7.38%	-11.17%
Crisis Market 2007-2009	with ASPI	-9.93%	-13.31%	-22.20%
	w/o ASPI	-9.50%	-12.85%	-20.14%

Note: w/o represents “without”; time horizon is one month

During the normal market period, for the same confidence level over one month horizon, the simulated return which includes ASPI is greater than the return without ASPI. For example, in 2003~2007 which is normal market period, the simulated 95% VaR of the portfolio including ASPI over one month horizon is -3.22% which is higher than the simulated 95% VaR value of -3.52% excluding ASPI and SI. On the other hand, during the crisis period, the simulated return in the case with ASPI over one month horizon, is less than the simulated return in the case without ASPI at the same level of VaR. Such an observation seems to suggest that in normal period the portfolio with SRI has a lower risk than the one without SRI; however, in crisis period, including SRI does not help to reduce the investment risk.

6.6 Conclusion

Results in this chapter shows that in normal period the portfolio including SRI has a lower risk than the one without SRI, however, in crisis period, including SRI does not help to reduce the investment risk. It also indicates that for given risk, the optimal portfolio under normal market gives a larger return than the one under crisis market. It can be also found that during different periods, the portfolio including ASPI has a better return than the one without it for a given risk which attracts the investors to invest on ASPI.

Given various benefits of investing ASPI market shown in both Chapter 5 and 6, it will be very appealing to design new SRI indices based on existing markets. The next Chapter 7 will discuss an index design problem.

7. CHAPTER 7: Index Design in Social Investment Market

This chapter proposes a new idea for designing a social sustainability index. An innovative model is created to compute SRI portfolio based on existing SRI index component companies. The idea is to improve investor appetite for SRI portfolios by choosing them to be optimally uncorrelated with another popular equity index. This will maximize not only the social benefit of the investment to the investor but also the positive effect of diversification on the investor portfolio. The new portfolio or fund can outperform an existing SRI index if the portfolio size is appropriately chosen.

We consider the problem of reproducing the performance of the Jantzi Social Index, but without purchasing all the component stocks in the index, in other words, index tracking. The Jantzi Social Index is a Canadian stock market index created in 2000. It is based on a modified S&P/TSX Composite Index with the purpose of measuring the effect of a socially and environmentally conscious stock market index on market behavior.

7.1 index tracking model

This section presents a basic model from Cornuejols and Tütüncü (2007), which is adopted in Chen and Kwon (2010). Suppose the values of N stocks as well as the index value are observed over time 0,1,2,…,T. We must choose a set of L stocks to hold (where L<N), as well as their appropriate quantities.

Let x_{ij} be the indicator function such that stock j is a representative of stock i, x_{ij} is 1 if j is the most similar asset in the portfolio to i, 0 otherwise. Let y_j represent if asset j is selected to be in the portfolio (1 if true, 0 otherwise), i.e.,

$$x_{ij} = \begin{cases} 1 & if \quad stock \quad j \quad is \quad most \quad similar \quad to \quad stock \quad i \\ 0 & otherwise \end{cases}$$

$$y_j = \begin{cases} 1 & if \quad stock \quad j \quad is \quad selected \quad to \quad represent \quad any \quad stock \\ 0 & otherwise \end{cases}$$

The following binary (zero-one) integer programming model selects a portfolio of L stocks that has the highest correlation to the index (see Chen and Kwon, 2010).

$$\max \sum_{i=1}^{N} \sum_{j=1}^{N} \rho_{ij} x_{ij} \qquad (7.1)$$

S.t.

$$\sum_{j=1}^{N} y_j = L$$

$$\sum_{j=1}^{N} x_{ij} = 1 \quad \forall i = 1, \ldots, N$$

$$x_{ij} \le y_j \quad \forall i = 1, \ldots, N; \quad j = 1, \ldots, N$$

$$x_{ij}, y_j \in \{0,1\}$$

here ρ_{ij} is the correlation coefficient that represents the similarity between asset i and asset j; and L denotes portfolio size. The first constraint ensures that there are exactly L stocks in the new constructed portfolio; the second constraint means each stock has exactly one representative in the portfolio; the third constraint means any stock must be in the portfolio to be a representative. After solving the model, a weight can be calculated for each selected asset j using sum of the market value, of each stock from the index it is representing.

7.2 SRI index tracking model

This section presents two ideas for constructing a SRI index portfolio. The first idea is to adopt the index tracking model in Section 7.1 based on the Jantzi Social Index. The second idea is to construct a portfolio having the largest similarity to the Jantzi Social Index but the least similarity to another index such as S&P100.

Suppose there are k clusters of indexes under consideration. Specifically k=2 in our case here. The following zero-one integer programming model selects a portfolio of L stocks that has the highest correlation to the first but lowest correlation to the second index.

$$Z = \max \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} (\rho_{ij1} x_{ij1} + \rho_{ij2} x_{ij2}) - \sum_{i=n_1}^{n_1+n_2} \sum_{j=1}^{n_1} \sum_{k=1}^{2} (\rho_{ij1} x_{ij1} + \rho_{ij2} x_{ij2}) \qquad (7.2)$$

Subject to:

$$\sum_{j=1}^{n_1} y_{jk} = L_k \quad k = 1,2$$

$$l_k \leq L_k \leq u_k \quad k = 1,2$$

$$\sum_{k=1}^{2} L_k = L$$

$$\sum_{j=1}^{n} x_{ijk} = 1 \quad \forall i = 1,\dots,n_1; \quad k = 1,2$$

$$x_{ijk} \leq y_{jk} \quad \forall i = 1,\dots,n_1; \quad j = 1,\dots,n_1, \quad k = 1,2$$

$$y_{jk} = 0 \quad if \quad j \notin group \quad k$$

$$x_{ij1}, x_{ij2}, y_{j1}, y_{j2} \in \{0,1\}$$

Here ρ_{ijk} represents the similarity between asset i and asset j in group k; L_k denotes portfolio size in group k. $Z_1 = \sum_{i=1}^{n_1} \sum_{j=1}^{n_1} \sum_{k=1}^{2} (\rho_{ij1} x_{ij1} + \rho_{ij2} x_{ij2})$ and $Z_2 = \sum_{i=n_1}^{n_1+n_2} \sum_{j=1}^{n_1} \sum_{k=1}^{2} (\rho_{ij1} x_{ij1} + \rho_{ij2} x_{ij2})$ denote the portfolio similarity to the first and second cluster respectively.

7.3 Data and computation

Historical data for the Jantzi Social Index and S&P100 are obtained from 2000 to 2010 using Bloomberg. The following figure gives seasonal rolling window correlation between the Jantzi Social Index and S&P100. From Figure 7.1, we can see that these two indices are highly correlated on average.

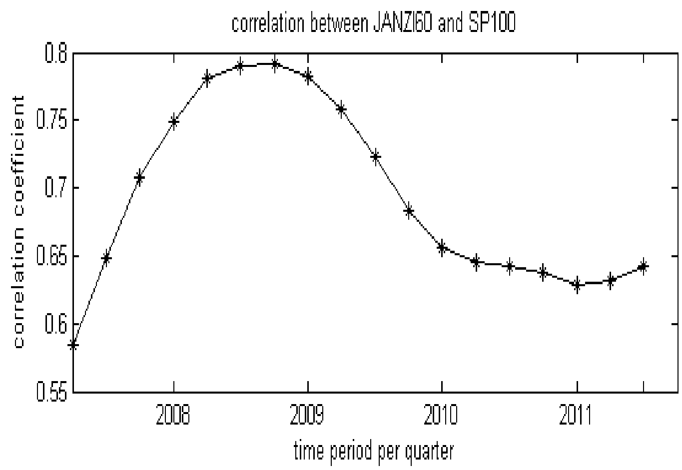


Figure 7- 1 **seasonal correlation dynamics**

Daily returns from January 1, 2000 until December 31, 2009, i.e., 2514 days, were used to generate portfolio by using model (7.1) and (7.2); Performance was tracked out of sample from January 1, 2010 to February 28, 2011. We set portfolio size q to range from 2 to 60 using a step size of 2, and solve the problem one by one.

Model (1) is run using 60 companies daily return data in the Jantzi Social Index. Model (2) is run using 60 companies daily return data in the Jantzi Social Index and 100 companies daily return data in S&P100. Selected stocks in the optimal portfolio using

Model (1) and (2) are presented in Appendix E.

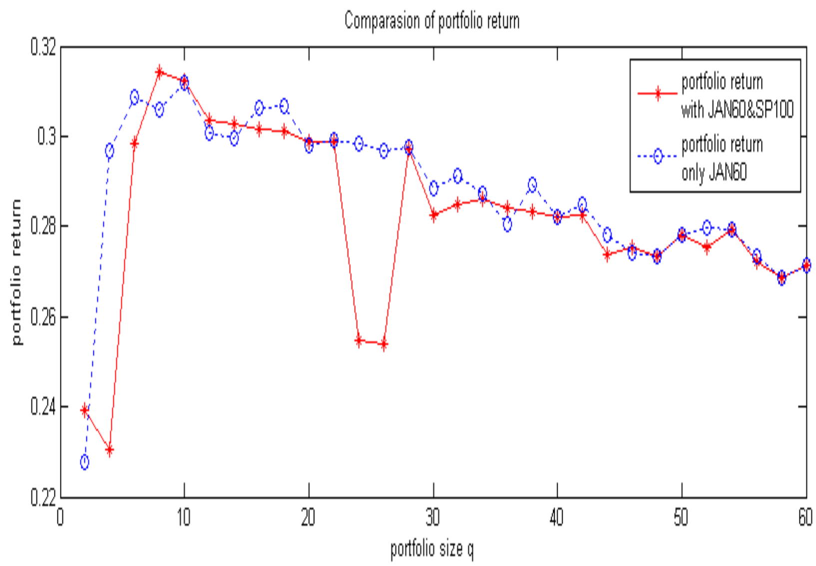
The following table presents computational results by use of both Model (1) and (2), where portfolio return, standard deviation (Std) and optimal objective values are given. Table 7.1 indicates that results based on Model (2) can generate higher return and lower standard deviation when portfolio size is appropriately selected. For example, when the portfolio size is 2 or 36, return generated from Model (2) is 0.239 and 0.284, higher than 0.228 and 0.2806 generated by Model (1). The portfolio Std values are 0.317 and 0.264, which are lower than 0.33 and 0.265 generated by Model (1) respectively.

Table 7- 1 **result comparison between Model (1) and (2)**

Port size	2	6	10	14	18	20	26	30	32	36	40	44	48	52	56	60
Only Janz Z1	22.79	26.64	30.021	33.31	36.48	38.04	42.56	45.465	46.89	49.669	52.16	54.281	56.147	57.72	58.95	60
Z1-Z2	16.17	25.96	29.634	32.98	36.2	37.77	42.35	45.27	46.7	49.482	51.98	54.095	55.96	57.533	58.76	59.81
Z1	19.4	26.49	29.901	33.19	36.41	37.98	42.54	45.457	46.89	49.669	52.16	54.281	56.147	57.72	58.95	60
PortRet	0.228	0.309	0.312	0.3	0.307	0.298	0.297	0.2883	0.291	0.2806	0.282	0.2783	0.2734	0.2799	0.273	0.272
Retwith100	0.239	0.298	0.3123	0.303	0.301	0.299	0.254	0.2824	0.285	0.284	0.282	0.2737	0.2734	0.2753	0.272	0.272
PortStd	0.33	0.308	0.302	0.287	0.289	0.281	0.279	0.274	0.27	0.265	0.257	0.255	0.2519	0.251	0.246	0.244
Stdwith100	0.317	0.298	0.297	0.288	0.284	0.278	0.272	0.271	0.268	0.264	0.257	0.253	0.2519	0.252	0.246	0.244

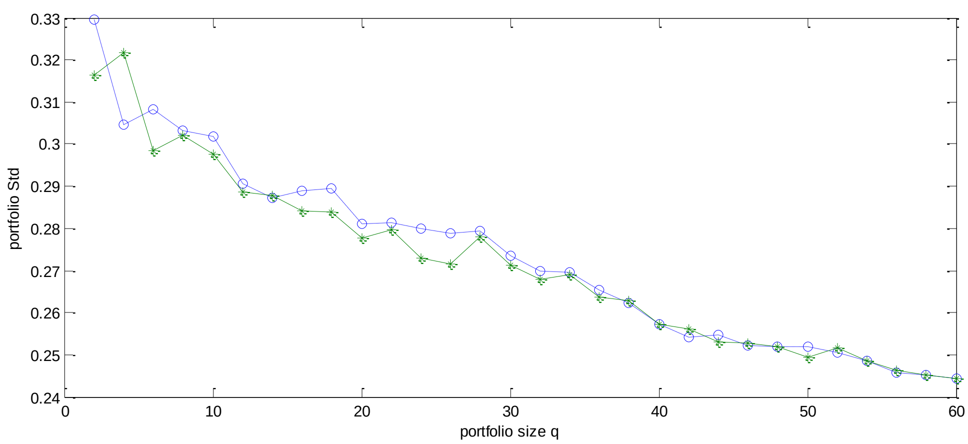
Note: Port size denotes Portfolio size; PortRet denotes Portfolio return; PortStd denotes Portfolio standard deviation; Retwith100 and Stdwith100 denote return with S&P100 and standard deviation with S&P100 respectively

Detailed results are further depicted in Figure 7- 2 Figure 7- 3 Figure 7- 4 .



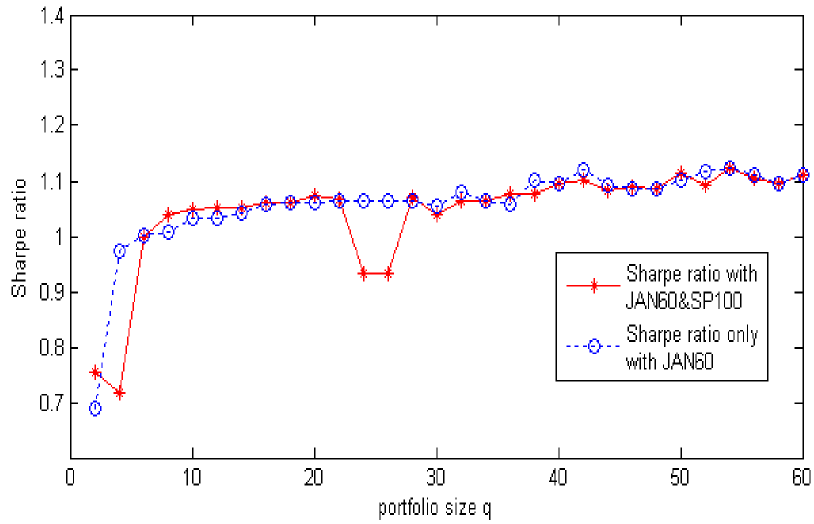
Note: the dash line is for only JAN60; the solid line is for JAN60&SP100

Figure 7- 2 portfolio return in Model (1) and (2)



Note: the dash line is for JAN60&SP100; the solid line is for only JAN60

Figure 7- 3 portfolio variance in Model (1) and (2)



Note: the dash line is for only JAN60; the solid line is for JAN60&SP100

Figure 7- 4 Sharpe ratio in Model (1) and (2)

7.4 In-sample and out-of-sample correlation between new index and S&P100

This section presents both in-sample and out-of-sample correlation values between the new index we have constructed and the S&P100. Table 7.2 gives in-sample and out-of-sample correlation coefficient values generated from Model (1) and (2) between new index portfolio and S&P100. As can be expected, in-sample correlation coefficient values from Model (1) are greater than those from Model (2). When conducting out-of-sample prediction test using real market data, this trend remains unchanged for five new indexes: the portfolio with size of 2, 10, 20, 30 and 50. There is no difference between the two model test results when the portfolio size is 40. This indicates that the new model (2) does indeed allow the creation of a new portfolio index having the best similarity with Jantzi

Social Index but least similarity with S&P100. However, when fixing the portfolio size to 60, Out-of-sample correlation coefficient values from Model (1) can be smaller than those from Model (2). For example, when the portfolio size is 60, correlation coefficient values generated from Model (2) are 0.642, 0.638, and 0.631 respectively, higher than 0.641, 0.637, 0.63 generated by Model (1). This may suggest that portfolio size needs to be carefully decided when using our proposed model to design a new index.

Table 7- 2 In-sample and Out-of-sample correlation between new index portfolio and S&P100

	Portfolio size	q=2		q=10		q=20		q=30		q=40		q=50		q=60	
	time	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
In sample	07-12-3	0.762	0.669	0.797	0.794	0.806	0.803	0.823	0.823	0.825	0.824	0.805	0.805	0.773	0.773
	08-12-1	0.769	0.671	0.76	0.756	0.766	0.761	0.795	0.792	0.786	0.786	0.795	0.789	0.764	0.764
	09-12-1	0.72	0.515	0.581	0.559	0.627	0.595	0.688	0.661	0.665	0.665	0.698	0.682	0.648	0.648
Out of sample	10-1-4	0.719	0.509	0.577	0.556	0.623	0.592	0.686	0.658	0.662	0.662	0.697	0.681	0.646	0.646
	10-2-1	0.718	0.506	0.575	0.554	0.621	0.59	0.685	0.657	0.661	0.661	0.696	0.68	0.644	0.645
	10-3-1	0.717	0.5	0.57	0.55	0.617	0.586	0.682	0.653	0.658	0.658	0.694	0.677	0.642	0.642
	10-4-1	0.717	0.497	0.569	0.549	0.615	0.585	0.681	0.652	0.657	0.657	0.694	0.677	0.642	0.642
	10-5-3	0.718	0.499	0.57	0.551	0.617	0.587	0.682	0.653	0.659	0.659	0.695	0.678	0.643	0.643
	10-6-1	0.717	0.493	0.567	0.548	0.614	0.585	0.68	0.652	0.657	0.657	0.693	0.677	0.641	0.642
	10-7-2	0.714	0.487	0.563	0.544	0.61	0.581	0.676	0.648	0.653	0.653	0.69	0.674	0.637	0.638
	10-8-3	0.712	0.481	0.559	0.54	0.607	0.578	0.673	0.645	0.65	0.65	0.687	0.671	0.634	0.634
	10-9-1	0.71	0.476	0.556	0.537	0.604	0.575	0.67	0.641	0.645	0.645	0.684	0.667	0.63	0.631
	10-10-1	0.709	0.474	0.555	0.536	0.602	0.573	0.667	0.639	0.642	0.642	0.683	0.665	0.628	0.628
	10-11-1	0.708	0.474	0.555	0.536	0.602	0.573	0.667	0.638	0.64	0.64	0.682	0.664	0.628	0.628
	10-12-1	0.709	0.476	0.557	0.538	0.603	0.574	0.667	0.637	0.64	0.64	0.682	0.664	0.629	0.629
	11-1-4	0.71	0.48	0.56	0.541	0.606	0.577	0.669	0.639	0.642	0.642	0.684	0.666	0.631	0.631
	11-2-1	0.713	0.485	0.565	0.546	0.61	0.582	0.672	0.643	0.646	0.646	0.687	0.669	0.635	0.635
	11-3-1	0.717	0.492	0.571	0.552	0.616	0.588	0.677	0.648	0.651	0.651	0.692	0.674	0.64	0.64

Note: M1 and M2 denote Model (1) and (2) respectively.

7.5 Conclusion

This chapter proposes an idea to construct new SRI portfolio index that could outperform existing such indices. The proposed new SRI portfolio index is expected to be less correlated with normal equity index markets. In the context of this study, we take two indices from North America markets as an example: the Jantzi Social Index and S&P100. We extract stocks from the Jantzi Social Index to construct new portfolio index and let it has the least correlation with S&P100. Results in this chapter shows that when portfolio size is appropriately selected, the designed new SRI portfolio index outperforms the Jantzi Social Index in terms of return.

It must be pointed out that the example here is only used for demonstration purpose. Should data be available, one can easily construct different types of SRI indexes.

There are two further considerations of using this index design approach for an investor mentioned in Chapter 5 and 6. First, if data of all member companies forming the ASPI index became available, we can construct a new index similar to ASPI but with lower risk than ASPI. Performance from different regime periods can be compared among both indices. Second, results in Chapter 5 and 6 indicate that in crisis period, including SRI, e.g., ASPI index, does not help to reduce the investment risk. Since the new designed ASPI-like index will have lower risk, it may be valuable to check how the portfolio performance will be affected after including the new designed ASPI-like index.

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A Appendix to Chapter 3

Table 3.8: Maximum Likelihood Estimates of MRS-GARCH Models- S&P

Para.	MRS-GARCH-N			MRS-GARCH-t			MRS-GARCH-GED		
	Value	StE	T Statistic	Value	StE	T Statistic	Value	StE	T Statistic
$\delta^{(1)}$	-1.948	0.098	-19.858	0.026	0.016	4.061	0.038	0.027	1.409
$\delta^{(2)}$	0.054	0.012	4.609	0.067	0.018	2.290	0.063	0.014	4.681
$\sigma^{(1)}$	0.109	0.074	1.481	0.334	0.003	2.408	0.051	0.015	3.328
$\sigma^{(2)}$	0.016	0.003	5.716	0.006	0.178	1.253	0.052	0.013	4.153
$\alpha_1^{(1)}$	0.128	0.149	0.861	0	0.009	8.015	0.084	0.015	5.524
$\alpha_1^{(2)}$	0.056	0.008	6.605	0.072	0.029	0.000	0.056	0.017	3.306
$\beta_1^{(1)}$	0.861	0.186	4.635	0	0.009	107.482	0.895	0.020	45.882
$\beta_1^{(2)}$	0.877	0.01	90.114	0.927	0.578	0.473	0.809	0.039	20.744
p	0.159	0.078	2.047	0.999	0.000	4062.632	0.999	0.001	1403.259
q	0.982	0.002	403.943	1.000	0.001	1533.871	0.999	0.001	1906.859
$\nu^{(1)}$	-	-	-	7.590	0.804	9.363	1.429	0.039	36.198
$\nu^{(2)}$	-	-	-	-	-	-	-	-	-
Log(L)	-5589.6			-5544.5			-5546.0		
N. of P.	10			11			11		
π_1	0.021			0.000			0.500		
π_1	0.979			1.000			0.500		
ρ_1	0.989			0			0.979		
ρ_2	0.933			0.999			0.865		

Note: Each MRS-GARCH model has been estimated with different conditional distributions. The in-sample data consist of S&P500 returns from January 2, 1992 through February 6, 2009. The superscripts indicate the regime. The conditional mean is $X_t = \delta^{(i)} + \varepsilon_t$, whereas the conditional variance is where the expectation is calculated as in (3.12). Instead of $L^{(i)}$, we report $\sigma^{(i)} = \sqrt{L^{(i)} / (1-\alpha_1^{(i)} - \beta_1^{(i)})}$ for each regime which is the standard deviation conditional to the volatility regime. π_i is the unconditional probability of being in regime i, while $\rho_i = \alpha_1^{(i)} + \beta_1^{(i)}$ is the persistence of shocks in the i-th regime. Asymptotic standard errors are in parentheses.

B: Appendix to Chapter 4

Table 4.1 In-sample goodness-of-fit statistics-ASPI

	N. of Par.	PERS	AIC	Rank	BIC	Rank	LOGL	Rank	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank
GARCH-N	4	0.978	2.988	12	2.994	12	-6259.5	12	7.321	12	1.892	12	0.67	12	3.09	9
GARCH-t	5	0.978	2.967	9	2.974	8	-6213.6	9	7.296	10	1.89	11	0.67	10	3.13	11
GARCH-GED	5	0.977	2.968	10	2.975	9	-6215	10	7.303	11	1.887	10	0.67	11	3.12	10
EGARCH-N	5	0.985	2.954	6	2.961	5	-6186.4	6	7.16	3	1.793	1	0.65	1	2.9	2
EGARCH-t	6	0.987	2.937	1	2.946	1	-6149.5	1	7.159	2	1.804	3	0.66	3	2.93	4
EGARCH-GED	6	0.986	2.939	2	2.948	2	-6153.8	2	7.156	1	1.798	2	0.66	2	2.93	3
GJR-N	5	0.974	2.969	11	2.976	10	-6217.4	11	7.235	8	1.863	7	0.66	7	2.99	6
GJR-t	6	0.974	2.951	3	2.96	3	-6179.4	4	7.219	5	1.862	6	0.66	6	3.04	8
GJR-GED	6	0.974	2.952	5	2.961	4	-6181.9	5	7.224	6	1.86	5	0.66	5	3.02	7
MRS-GARCH-N	10	0.998	2.962	8	2.977	11	-6197.6	8	7.177	4	1.855	4	0.66	4	3.22	12
MRS-GARCH-t	11	0.988	2.951	4	2.968	6	-6175.2	3	7.235	7	1.871	8	0.67	8	2.87	1
MRS-GARCH-GED	11	0.988	2.958	7	2.974	7	-6188.1	7	7.282	9	1.886	9	0.67	9	2.96	5

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.2 In-sample goodness-of-fit statistics-USA2

	N. of Par.	PERS	AIC	Rank	BIC	Rank	LOGL	Rank	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank
GARCH-N	4	0.978	2.707	12	2.713	12	-5669.2	12	7.692	12	1.494	11	0.6	11	3.86	9
GARCH-t	5	0.979	2.671	9	2.679	9	-5593.5	10	7.645	10	1.492	10	0.59	9	3.98	11
GARCH-GED	5	0.978	2.67	8	2.677	8	-5591.2	9	7.657	11	1.49	9	0.59	10	3.95	10
EGARCH-N	5	0.983	2.656	7	2.663	5	-5561.5	7	7.457	4	1.366	1	0.57	1	3.55	2
EGARCH-t	6	0.987	2.628	1	2.637	1	-5501.5	1	7.445	3	1.382	4	0.57	4	3.67	4
EGARCH-GED	6	0.986	2.63	2	2.639	2	-5505.7	2	7.444	2	1.375	2	0.57	2	3.63	3
GJR-N	5	0.974	2.677	11	2.684	10	-5605.1	11	7.569	7	1.459	6	0.58	7	3.68	5
GJR-t	6	0.975	2.647	3	2.656	3	-5542.9	3	7.53	5	1.465	8	0.58	6	3.81	8
GJR-GED	6	0.974	2.648	4	2.657	4	-5544.2	4	7.544	6	1.461	7	0.58	5	3.76	7
MRS-GARCH-N	10	0.989	2.672	10	2.687	11	-5589.6	8	7.426	1	1.377	3	0.57	3	4.66	12
MRS-GARCH-t	11	0.973	2.651	6	2.668	7	-5546	6	7.579	8	1.441	5	0.59	8	3.37	1
MRS-GARCH-GED	11	1	2.651	5	2.667	6	-5544.5	5	7.579	9	2.049	12	0.6	12	3.69	6

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.3 Out-of-sample evaluation of the 1-step-ahead volatility forecasts.-ASPI

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	13.4921	3	1.8197	3	4.0379	3	1.1784	3	0.87	7.5530**
GARCH-t	13.4345	2	1.8121	2	4.012	2	1.1775	2	0.87	7.5530**
GARCH-GED	13.408	1	1.8085	1	3.9988	1	1.1772	1	0.86	7.3857**
EGARCH-N	14.382	7	1.9351	5	4.476	4	1.1879	7	0.8	6.5389**
EGARCH-t	14.6146	9	1.9692	9	4.6199	10	1.1902	9	0.8	6.5389**
EGARCH-GED	14.4921	8	1.9513	8	4.5445	5	1.189	8	0.8	6.5389**
GJR-N	14.3499	6	1.9408	7	4.5755	9	1.1846	6	0.82	6.8427**
GJR-t	14.3182	5	1.9372	6	4.5733	8	1.1837	5	0.81	6.6901**
GJR-GED	14.2998	4	1.9342	4	4.5566	7	1.1837	4	0.82	6.8427**
MRS-GARCH-N	14.6989	10	1.9714	10	4.5535	6	1.1926	10	0.84	7.0578**
MRS-GARCH-t	15.6234	11	2.1088	11	5.1129	11	1.2028	11	0.88	7.7226**
MRS-GARCH-GED	15.6508	12	2.1136	12	5.1369	12	1.2028	12	0.89	7.8418**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.4 Out-of-sample evaluation of the 5-step-ahead volatility forecasts.-ASPI

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	17.4797	6	4.0407	6	19.6532	6	1.1814	6	0.82	6.9729**
GARCH-t	17.4078	5	4.0209	5	19.5023	5	1.1804	5	0.82	6.9729**
GARCH-GED	17.3773	4	4.0119	4	19.4286	4	1.18	4	0.81	6.8362**
EGARCH-N	16.564	1	3.7341	1	17.2111	1	1.1674	1	0.73	5.8101**
EGARCH-t	16.8231	3	3.8108	3	17.848	3	1.1705	3	0.73	5.8101**
EGARCH-GED	16.6927	2	3.7725	2	17.5309	2	1.169	2	0.73	5.8101**
GJR-N	18.4386	9	4.2893	9	22.0955	10	1.1864	9	0.75	6.0570**
GJR-t	18.3933	8	4.2764	8	22.04	9	1.1853	8	0.74	5.9328**
GJR-GED	18.3677	7	4.2683	7	21.947	7	1.1853	7	0.75	6.0570**
MRS-GARCH-N	18.7998	10	4.3502	10	21.9744	8	1.1932	10	0.79	6.5691**
MRS-GARCH-t	19.9306	11	4.7293	11	25.3616	11	1.2063	12	0.83	7.1119**
MRS-GARCH-GED	19.9377	12	4.7345	12	25.4271	12	1.2063	11	0.86	7.5440**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.5 Out-of-sample evaluation of the 10-step-ahead volatility forecasts.-ASPI

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	24.06	6	5.6716	6	38.0577	6	1.1851	6	0.84	7.2688**
GARCH-t	23.9687	5	5.6391	5	37.7083	5	1.1841	5	0.84	7.2688**
GARCH-GED	23.9339	4	5.6249	4	37.5455	4	1.1837	4	0.83	7.1261**
EGARCH-N	20.8491	1	4.5026	1	25.8777	1	1.1424	1	0.75	6.0543**
EGARCH-t	21.1269	3	4.6043	3	26.9191	3	1.1465	3	0.75	6.0543**
EGARCH-GED	20.9898	2	4.5551	2	26.4159	2	1.1445	2	0.75	6.0543**
GJR-N	25.0719	9	5.9868	9	42.3868	10	1.1892	9	0.77	6.3122**
GJR-t	25.0081	8	5.9605	8	42.1775	9	1.1879	8	0.76	6.1825**
GJR-GED	24.9718	7	5.9471	7	41.9723	7	1.1878	7	0.77	6.3122**
MRS-GARCH-N	25.4848	10	6.0598	10	42.0824	8	1.1946	10	0.79	6.5762**
MRS-GARCH-t	26.9047	12	6.7151	12	50.2362	12	1.2108	12	0.85	7.4140**
MRS-GARCH-GED	26.8836	11	6.7131	11	50.2344	11	1.2107	11	0.88	7.8653**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.6 Out-of-sample evaluation of the 22-step-ahead volatility forecasts.-ASPI

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	41.9138	6	8.2982	6	77.9549	6	1.1996	8	0.81	6.8273**
GARCH-t	41.7542	5	8.2361	5	76.9839	5	1.1985	7	0.81	6.8273**
GARCH-GED	41.7087	4	8.2116	4	76.5722	4	1.1981	4	0.81	6.8273**
EGARCH-N	33.3111	1	4.9938	1	33.3496	1	1.0969	1	0.72	5.6900**
EGARCH-t	33.5905	3	5.1112	3	34.7381	3	1.1027	3	0.73	5.8101**
EGARCH-GED	33.4486	2	5.0551	2	34.078	2	1.1	2	0.72	5.6900**
GJR-N	43.1864	9	8.653	9	85.0368	10	1.2	9	0.74	5.9315**
GJR-t	43.0538	8	8.5903	8	84.1703	9	1.1984	6	0.73	5.8101**
GJR-GED	42.9941	7	8.5647	7	83.6517	7	1.1982	5	0.73	5.8101**
MRS-GARCH-N	43.8038	10	8.7209	10	84.0037	8	1.2026	10	0.76	6.1786**
MRS-GARCH-t	46.1855	12	10.0632	12	108.0961	12	1.2232	12	0.82	6.9633**
MRS-GARCH-GED	46.0765	11	10.0293	11	107.4628	11	1.2231	11	0.85	7.3861**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.7 Out-of-sample evaluation of the 1-step-ahead volatility forecasts.-USA2

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	13.8204	5	1.9639	6	4.7096	6	1.1804	8	0.89	8.0288**
GARCH-t	13.8024	4	1.9617	5	4.7016	5	1.1801	7	0.89	8.0288**
GARCH-GED	13.7736	3	1.9576	3	4.6868	4	1.1796	6	0.89	8.0288**
EGARCH-N	13.8625	6	1.958	4	4.6733	3	1.1814	9	0.84	7.2737**
EGARCH-t	14.5715	11	2.0634	11	5.1133	11	1.1892	11	0.85	7.4195**
EGARCH-GED	14.3082	10	2.024	10	4.9447	10	1.1865	10	0.84	7.2737**
GJR-N	13.9251	7	1.9781	7	4.8492	7	1.1777	3	0.8	6.7119**
GJR-t	13.9876	9	1.9877	9	4.8934	9	1.1782	5	0.79	6.5762**
GJR-GED	13.9586	8	1.9832	8	4.8712	8	1.178	4	0.79	6.5762**
MRS-GARCH-N	12.6412	2	1.7717	2	3.8626	2	1.1693	2	0.88	7.8722**
MRS-GARCH-t	11.537	1	1.5851	1	3.1757	1	1.1448	1	0.26	-4.3553
MRS-GARCH-GED	15.3898	12	2.1805	12	5.5328	12	1.1999	12	0.9	8.1884**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.8 Out-of-sample evaluation of the 5-step-ahead volatility forecasts.-USA2

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	17.5257	8	4.3494	8	22.843	8	1.1852	11	0.91	8.3623**
GARCH-t	17.495	7	4.3427	7	22.7916	7	1.1849	10	0.91	8.3623**
GARCH-GED	17.4622	6	4.3328	6	22.7083	6	1.1845	9	0.91	8.3623**
EGARCH-N	16.0982	3	3.8477	3	18.5156	3	1.1651	3	0.86	7.5747**
EGARCH-t	16.9018	5	4.093	5	20.5789	5	1.1756	5	0.87	7.7268**
EGARCH-GED	16.5935	4	3.9995	4	19.7747	4	1.1718	4	0.87	7.7268**
GJR-N	17.8355	9	4.3614	9	23.3269	9	1.1801	6	0.82	6.9887**
GJR-t	17.9012	11	4.3827	11	23.549	11	1.1806	8	0.81	6.8472**
GJR-GED	17.8599	10	4.3698	10	23.4123	10	1.1803	7	0.81	6.8472**
MRS-GARCH-N	15.8722	2	3.7325	2	17.2385	2	1.1632	2	0.9	8.1990**
MRS-GARCH-t	12.7349	1	2.6693	1	11.0633	1	1.0033	1	0.01	-9.8022
MRS-GARCH-GED	19.4301	12	4.8578	12	27.1112	12	1.204	12	0.92	8.5287**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.9 Out-of-sample evaluation of the 10-step-ahead volatility forecasts.-USA2

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	23.8819	8	6.0849	10	44.0353	8	1.1901	11	0.91	8.3623**
GARCH-t	23.8342	7	6.0726	8	43.9045	7	1.1897	10	0.91	8.3623**
GARCH-GED	23.7985	6	6.0572	6	43.7192	6	1.1893	9	0.91	8.3623**
EGARCH-N	20.4891	2	4.7289	2	28.7039	2	1.1461	2	0.86	7.5747**
EGARCH-t	21.3801	4	5.0709	5	32.3229	5	1.1596	5	0.87	7.7268**
EGARCH-GED	21.0242	3	4.9375	4	30.8837	4	1.1547	3	0.87	7.7268**
GJR-N	24.3006	9	6.07	7	44.5308	9	1.1835	6	0.83	7.1321**
GJR-t	24.367	11	6.0997	11	44.9713	11	1.1839	8	0.81	6.8472**
GJR-GED	24.3103	10	6.077	9	44.6442	10	1.1835	7	0.82	6.9887**
MRS-GARCH-N	21.5589	5	4.9314	3	30.1805	3	1.1557	4	0.9	8.1990**
MRS-GARCH-t	18.9177	1	3.4955	1	20.4046	1	0.9177	1	0.01	-9.8022
MRS-GARCH-GED	26.1677	12	6.8452	12	52.9277	12	1.2087	12	0.92	8.5287**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

Table 4.10 Out-of-sample evaluation of the 22-step-ahead volatility forecasts.-USA2

Model	R2LOG	Rank	MAD2	Rank	MAD1	Rank	HMSE	Rank	SR	DA
GARCH-N	41.3486	8	8.8328	11	89.1519	10	1.2068	11	0.85	7.3861**
GARCH-t	41.2396	7	8.805	10	88.7282	9	1.2065	10	0.85	7.3861**
GARCH-GED	41.1864	6	8.7786	9	88.2531	6	1.2061	9	0.85	7.3861**
EGARCH-N	33.3735	1	5.4128	2	38.8784	1	1.1145	2	0.8	6.6936**
EGARCH-t	34.4296	3	5.854	4	44.4026	4	1.1333	4	0.81	6.8273**
EGARCH-GED	33.9778	2	5.6745	3	42.1176	2	1.1263	3	0.81	6.8273**
GJR-N	41.7265	10	8.7161	7	88.2776	8	1.1987	7	0.77	6.3046**
GJR-t	41.7639	11	8.7559	8	89.1742	11	1.1991	8	0.75	6.0543**
GJR-GED	41.6753	9	8.71	6	88.2598	7	1.1986	6	0.77	6.3046**
MRS-GARCH-N	36.6518	4	6.3874	5	50.1899	5	1.1513	5	0.84	7.2425**
MRS-GARCH-t	38.1672	5	5.1059	1	43.306	3	0.8508	1	0.07	-8.6528
MRS-GARCH-GED	45.1047	12	10.0969	12	110.3909	12	1.221	12	0.86	7.5325**

Note: PERS is the persistence of shocks to volatility; AIC and BIC are the Akaike information criterion and Schwarz criterion respectively; LOGL is logliklihood; MAD is Mean Absolute Deviation; HMSE is the heteroscedasticity adjusted mean squared error

C: Appendix to Chapter 5

The computation for Scenario 3-6 simply repeats that from Scenario 1 and 2.

Scenario 3 – 100% short selling allowed and no regional constraint

Scenario 4 – 75% short selling allowed and no regional constraint

Scenario 5 – 50% short selling allowed and no regional constraint

Scenario 6 – 25% short selling allowed and no regional constraint

If we plot these four last scenarios we get Figure 5.6:

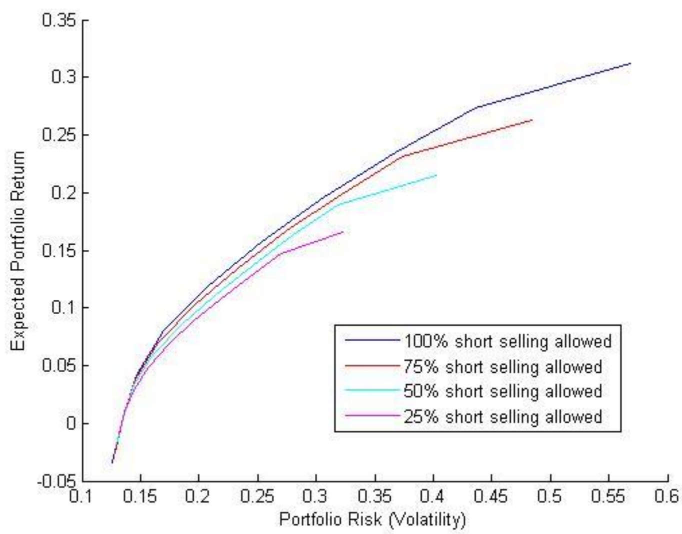

Figure 5.6: Scenario 3, 4, 5 and 6

As we clearly see it is better to have more flexibility in our efficient frontier calculation.

We now check the following four scenarios.

Scenario 7 – No short selling and 0% and 100% upper bound on portfolio value in USA and Europe respectively

Scenario 8 – No short selling and 100% and 0% upper bound on portfolio value in USA and Europe respectively

Scenario 9 – No short selling and 50% and 50% upper bound on portfolio value in USA and Europe respectively

Scenario 10 – No short selling and 100% upper bound on portfolio value in USA and Europe.

We plot these four last scenarios in the following graph of Figure 5.7:

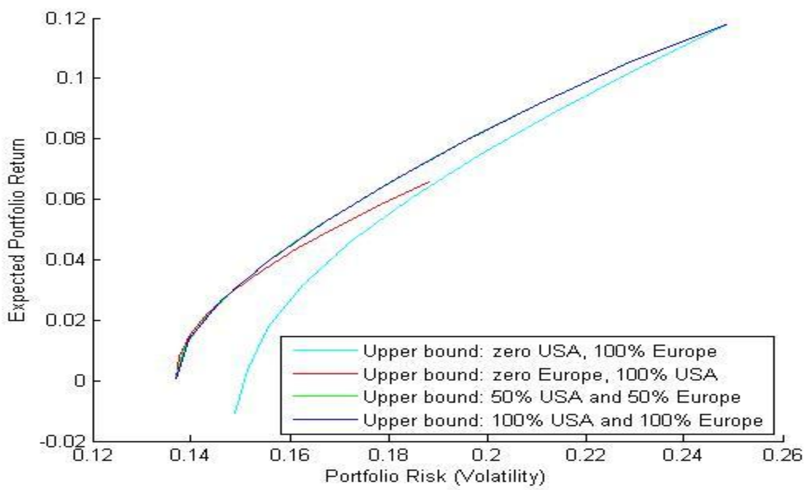

Figure 5.7: Scenario 7, 8, 9 and 10

As we can see the efficient frontiers in scenario 9 and 10 are very similar as well as the scenario 8 in the less risky portfolios. The three efficient frontiers keep overlapping each other in the beginning until the frontiers in scenario 9 and 10 become better than the others (we can also see that frontier 9 and 10 are almost the same).

D: Appendix to Chapter 6

Table 6.10: 20% allowable short in EU

	Preturn	Prisk	W-World	W-S&P500	W-Euro	W-ASPI
P1	4.87%	18.03%	48.21%	71.79%	0%	-20%
P2	5.57%	18.15%	42.62%	77.38%	-19.40%	-0.6%
P3	6.26%	18.40%	28.58%	82.10%	-20%	9.32%
P4	6.95%	18.74%	17.56%	82.66%	-20%	19.79%
P5	7.64%	19.16%	6.54%	83.21%	-20%	30.25%
P6	8.34%	19.66%	-4.48%	83.76%	-20%	40.72%
P7	9.03%	20.23%	-15.51%	84.32%	-20%	51.19%
P8	9.72%	20.88%	-20%	76.65%	-20%	63.35%
P9	10.41%	21.65%	-20%	63.33%	-20%	76.67%
P10	11.11%	22.52%	-20%	50%	-20%	90%

Note : Preturn denotes portfolio of returns; Prisk denotes portfolio of risk; P1-P10 denotes portfolio1-portfolio10; W-X denotes weights given to X,where X represents World, S&P500, Europe, and ASPI

Table 6.11: 20% allowable short in EU, without ASPI

	Preturn	Prisk	W-World	W-S&P500	W-Euro
P1	5.51%	18.15%	48.57%	71.43%	-20%
P2	5.81%	18.24%	29.86%	87.55%	-17.41%
P3	6.11%	18.43%	18.49%	91.43%	-9.92%
P4	6.42%	18.68%	7.12%	95.31%	-2.43%
P5	6.72%	18.98%	-4.25%	99.19%	5.06%
P6	7.03%	19.34%	-15.62%	103.07%	12.551%
P7	7.33%	19.77%	-20%	95.28%	24.72%
P8	7.64%	20.38%	-20%	80.19%	39.81%
P9	7.94%	21.16%	-20%	65.09%	54.91%
P10	8.24%	22.09%	-20%	50%	70%

Note : Preturn denotes portfolio of returns; Prisk denotes portfolio of risk; P1-P10 denotes portfolio1-portfolio10; W-X denotes weights given to X,where X represents World, S&P500, Europe

E: Appendix from Chapter 7

Table 7.3: selected stocks in the optimal portfolio using Model (1)

Port size	2	4	8	10	14	18	20	24	28	30	34	38	40	44	48	50	54	58	60
S1	0	0	0	0	1	1	1	1	1	1	1	0	0	0	0	1	1	1	1
S2	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1
S4	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S5	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S7	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
S8	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
S9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
S10	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S11	0	0	0	0	0	0	0	0	0	1	1	1	1	0	0	1	1	1	1
S12	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1
S13	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1	1	1
S14	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S15	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S16	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S17	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S18	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
S20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S21	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S22	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S23	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S24	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
S25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S26	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S27	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S28	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1

S29	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
S30	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S31	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
S33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S34	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S35	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
S37	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	0	1	1	1
S38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S39	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S40	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S41	0	0	0	0	0	1	0	1	1	1	1	0	0	1	1	1	1	1	1
S42	0	1	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1
S43	0	0	1	1	1	0	1	0	0	0	0	1	1	1	1	1	1	1	1
S44	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S45	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S48	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
S49	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S50	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S51	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S52	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
S53	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S55	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S56	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S57	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
S58	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S59	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S60	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1

Note: S# denotes the alternative stock # in the portfolio; if S# yields an integer value “1” in the table, then # is selected; otherwise not selected.

Table 7.4: selected stocks in the optimal portfolio using Model (2)

Port size	2	4	8	10	14	18	20	24	28	30	34	38	40	44	48	50	54	58	60
S1	0	0	0	0	1	1	1	1	1	1	0	0	0	0	0	0	1	1	1
S2	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S3	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
S4	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
S5	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S7	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1
S8	0	0	0	0	0	0	1	1	0	1	1	1	1	1	1	1	1	1	1
S9	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1
S10	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S11	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1
S12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
S13	0	0	0	0	0	0	0	0	0	1	1	1	0	1	1	0	1	1	1
S14	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S15	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S16	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S17	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S18	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1
S20	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S21	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S22	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S23	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S24	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
S25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S26	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S27	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S28	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S29	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1

S30	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S31	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
S33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S34	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S35	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1
S37	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1
S38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S39	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S40	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
S41	0	0	0	1	1	1	1	1	1	0	1	0	0	1	1	1	1	1	1
S42	1	0	1	1	1	1	1	1	1	0	0	0	0	0	0	0	0	0	1
S43	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1
S44	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S45	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S46	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
S47	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S48	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
S49	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1
S50	0	0	0	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1
S51	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S52	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1
S53	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1
S54	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
S55	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1
S56	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S57	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1
S58	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S59	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
S60	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1

Note: S# denotes the alternative stock # in the portfolio; if S# yields an integer value "1" in the table, then # is selected; otherwise not selected.

Curriculum Vitae

Name: Desheng Wu

Post-secondary Education and Degrees:

HF University of Tech.
Hefei, China
1997-2002 B.Math.

The University of Western Ontario
London, Ontario, Canada
2010-2011 M.Sc.

University of Science &Tech of China (USTC) and University of Toronto
Joint program
2002-2006 Ph.D. (Degree from USTC)

Honours and Awards:

CAS Scholarship
2002-2006

Related Work Experience

Teaching Assistant
University of Science &Tech of China (USTC)
2002-2006

Managing Director
Risklab
2008-2010