南 華 大 學

財 務 管 理 研 究 所 碩 士 論 文

A THESIS FOR THE DEGREE OF MASTER OF BUSINESS ADMINISTRATION

INSTITUTE OF FINANCIAL MANAGEMENT

NAN HUA UNIVERSITY

下方風險對報酬績效之影響分析：

以美國社會責任投資及反社會投資為例

DISENTANGLING THE EFFECT OF DOWNSIDE RISK ON PERFORMANCE: EVIDENCE FOR SOCIALLY RESPONSIBLE AND ANTI-SOCIAL INVESTING IN THE UNITED STATES

指導教授：張簡彰程 博士

ADVISOR: PH.D. CHANG-CHENG CHANG CHIEN

共同指導教授： 張瑞真 博士

CO-ADVISOR: PH.D. JUI-CHEN CHANG

研 究 生： 陳易佐

GRADUATE STUDENT: YI-TSO CHEN

中華民國九十八年七月

南　華　大　學

財務管理研究所

碩 士 學 位 論 文

下方風險對報酬績效之影響分析：以美國社會責任投資及反社會投資為例

Disentangling the Effect of Downside Risk on Performance: Evidence for Socially Responsible and Anti-social Investing in the United States

研究生：陳易佐

經考試合格特此證明

口試委員：

白宗民

羅進水

張簡彰程

指導教授：張簡彰程

系主任(所長)：張瑞真

口試日期：中華民國 九十八 年 五 月 二十五 日

謝辭

本論文之完成，首先要感謝的是指導老師張簡彰程博士。在論文的撰寫過程中，每當在實證的程式部分遇到挫折時，張簡老師總是毫不吝嗇地給予鼓勵與建議，並介紹一些相當實用的軟體和書籍讓我們學習，使得原本對於程式撰寫毫無頭緒的我，逐漸地可以自我學習；而在研討會的投稿過程中，張簡老師不厭其煩地修改文章，事後的討論和建議都給予我極大的助益，唯一比較可惜的是研二時張簡老師到其他學校服務了(這真是系上一大損失!)，因而少了很多可以跟老師學習的機會。另外還要感謝的是白宗民博士。在實證結果的細部解讀以及論文方向的定位上，白老師曾多次給予實質寶貴的建議；而在投資實務上，白老師樂於分享個人的系統和經驗，使我了解在進行投資或投機前一些必要的準備工作，包括目標設定以及個人中心思想的建立，這些觀念也都適用於往後的人生歷練。同時也要謝謝口試委員羅進水博士所提供的寶貴意見，包括論文架構編排以及細部數字計算過程的說明等等。還有要謝謝的是我的共同指導老師張瑞真博士，在修習張老師的不動產相關課程中，老師提供了許多優質的國外期刊文獻，讓我在使用英文撰寫這篇論文的時候擁有許多可茲參考的對象。

此外，我要特別謝謝同門的雅蕾和國城，在跟老師 meeting 的過程中時常麻煩你們當司機，每次坐車時聽你們在聊工作實務或社會經驗時真的讓我受益匪淺。不管是在撰寫論文或者是參與團體活動的過程中，班上的同學們彼此之間互相扶持和鼓勵，感謝大家讓我在就讀研究所的期間有個美好的求學回憶。另外也謝謝素英姐的協助，讓我能夠做好在所辦的值班工作。最後謝謝我的父母與家人，謝謝你們無私的奉獻與關懷，讓我能夠無後顧之憂地完成研究所的學業，謝謝你們!

陳易佐　謹致於　嘉義大林

中華民國九十八年六月

南華大學財務管理研究所九十七學年度第二學期碩士論文摘要

論文題目：下方風險對報酬績效之影響分析：以美國社會責任投資及反社會投資為例

研 究 生：陳 易 佐　　**指導教授：**張 簡 彰 程 博士
共同指導：張 瑞 真 博士

論文摘要內容：

社會責任投資(Socially Responsible Investing, SRI)的概念在過去十年來快速地形成，過去的學術文獻主要集中在探討社會責任投資的發展以及績效表現，然而與其對應的反社會投資(Anti-Social Investing, ASI)之研究則相對較少。本文以風險值(Value-at-Risk)的角度進一步衡量這兩種投資策略的下方風險，樣本資料包括十支美國社會責任投資基金、一支美國反社會投資基金以及兩個相關指數的日報酬資料，研究期間為 2002 年 9 月 16 日至 2007 年 9 月 16 日。除了使用傳統資本資產定價模型的績效衡量方法，本研究使用風險值修正夏普指數以及風險值調整後超額報酬來衡量樣本投資組合的績效表現。實證結果顯示，社會責任投資樣本組相較於反社會投資樣本組普遍具有較高的下方風險以及較低的年化平均報酬，而資料型態的差異(基金或指數)會影響其績效和下方風險的推論。此外， Wilcoxon 符號等級檢定結果顯示風險值修正後之績效與修正前之績效存在顯著差異。在風險值調整後報酬之架構下，以國際證券交易所編制的 SINdex 指數之績效表現最佳。在風險值模型的實證結果部份，根據 Kupiec (1995)非條件涵蓋比率檢定以及平均失敗誤差之統計結果，經 Gram-Charlier 展開式調整的風險值模型在各種風險值估計方法中具有最佳的準確性並保有效率性，此方法同時亦可解決常態分配尾部風險值低估問題而對金融資產報酬具有較佳的厚尾捕捉能力。

關鍵字：社會責任投資、風險值、Gram-Charlier 展開式

Title of Thesis: Disentangling the Effect of Downside Risk on Performance: Evidence for Socially Responsible and Anti-social Investing in the United States

Name of Institute: Institute of Financial Management, Nan Hua University

Graduate date: July 2009 **Degree Conferred**: M.B.A.

Name of student: Yi-Tso Chen **Advisor**: Ph.D. Chang-Cheng Chang Chien

Co- Advisor: Ph.D. Jui-Chen Chang

Abstract

The concept of socially responsible investing (SRI) has escalated rapidly over the past decade. Considerable interest in the evolution and performance of socially responsible investing continues to be widened in academic literature while the studies pertaining to its antithetical counterpart, anti-social investing (ASI), are relatively underappreciated. This article sheds further light on the downside risk of the two antipodal investment strategies, introducing a more robust measure of risk in the form of Value-at-Risk (VaR). The data are sourced from daily closing prices of ten U.S. SRI mutual funds, one U.S. ASI mutual fund and two relevant indices. The sample spans the period from September 16th, 2002 to September 16th, 2007. Apart from the traditional performance measurement of capital asset pricing model (CAPM), the VaR-modified Sharpe index and excess VaR-adjusted return are employed to conduct performance assessment for the correspondingly screened portfolios. The empirical evidence indicates that generally the SRI sample group embraces higher permeation of downside risks and lower annualized returns compared with the ASI sample group, whereas different data type (mutual fund or index) leads to variant downside risk and performance inferences. Furthermore, the result of the Wilcoxon signed-rank test indicates that the VaR-modified performance differs from the non-modified one significantly. Under the framework of the VaR-adjusted return the SINdex constructed by International Securities Exchange outperforms the rest of the reference portfolios. The empirical result from VaR modelling suggests that the VaR model adjusted by Gram-Charlier expansions is the most accurate measurement and maintains model efficiency among various estimation models in terms of Kupiec's (1995) unconditional coverage test and average failure bias. Simultaneously the model can address the VaR underestimation problem beneath the normality assumption, possessing superior competence for capturing heavy-tailed idiosyncrasy of financial asset returns.

Keywords: Socially Responsible Investing, Value-at-Risk, Gram-Charlier Expansions

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter 1 Introduction

Socially responsible investing (SRI), interchangeably termed ethical investing, social investing or sustainable investing, has been experiencing dramatic growth over the past decade. According to the statistics from Social Investment Forum (SIF), American SRI assets reached $2.71 trillion by the end of 2007, growing more than 324 percent from $639 billion a decade earlier, roughly 11 percent of the $25.1 trillion in total assets under management in the United States are involved in socially responsible investing. European Sustainable and Responsible Investment Forum (Eurosif) compiled that SRI assets in Europe amounted to $1.4 trillion as of 2005. At the end of June 2006 there were $503.6 billion SRI assets under management in Canada as indicated by Social Investment Organization (SIO). Australia SRI assets have been surging from $13.9 billion to $19.4 billion during the period 2002-2007 surveyed by Responsible Investment Association Australasia (RIAA). Incepted on 1st March 1990, The TIAA-CREF Social Choice Account aggregated $8.02 billion as of September 30th, 2008, contrasting sharply with $273 million as of September 1992. Figure 1.1 and Figure 1.2 chart the scale of SRI assets in the United States and the Global market, respectively.

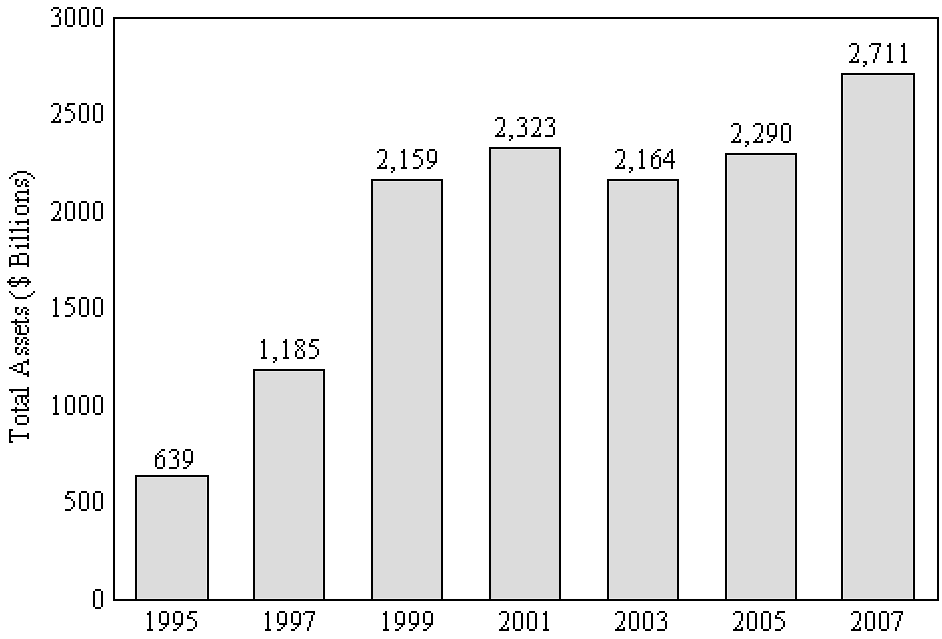


Figure 1.1

Socially Responsible Investing in the United States, 1995-2007

Source: Social Investment Forum Foundation

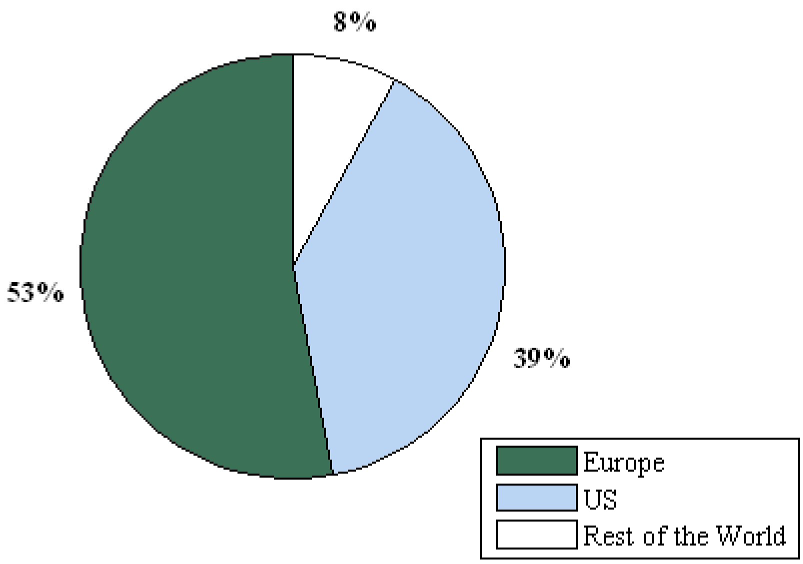


Figure 1.2

Global SRI market (approx €5 trillion), as of September, 2008

Source: Social Investment Forum, RIAA, SIO, Eurosif, SIF-Japan

To a certain extent the proliferation of modern socially responsible investing can be attributed to the establishment of SRI related regulations, especially in western countries. In the United States, Section 406 of the Sarbanes-Oxley Act came into force in July 2002, requiring the listed companies to disclose a code of ethics for senior financial officers, applicable to principal financial officers and comptrollers or principal accounting officers. In 2006, the United Nations Environment Programme announced the 'Principles for Responsible Investment', providing signatories with a framework to facilitate incorporation of environmental, social, and governance (ESG) factors into their investment decision making process. For more SRI regulations see Renneboog et al. (2008a) cited in Table 1.1. Given the growing social awareness of investors and the evolvement of international agendas such as global warming, sustainable business, corporate governance, microfinance and so forth, it is unnegligible to reexamine the arena for socially responsible investing.

Table 1.1
SRI regulations

Country	SRI related regulations
Australia	In a 2001 bill it is stated that all investment firms' product disclosure statements should include a description of ''the extent to which labor standards or environmental, social or ethical considerations are taken into account". Since 2001, all listed companies on the Australian Stock Exchange are required to make an annual social responsibility report.
Belgium	In 2001, Belgium passed the 'Vandebroucke' law, which requires pension funds to report the degree to which their investments take into account social, ethical and environmental aspects.
France	In May 2001, the legislation ''New Economic Regulations" came into force requiring listed companies to publish social and environmental information in their annual reports. Since February 2001 managers of the Employee Savings Plans are required to consider social, environmental or ethical considerations when buying and selling shares.

Table 1.1 (continued)

Country	SRI related regulations
Germany	Since 1991, the Renewable Energy Act gives a tax advantage to closed-end funds to invest in wind energy. Since January 2002, certified private pension schemes and occupational pension schemes 'must inform the members in writing, whether and in what form ethical, social, or ecological aspects are taken into consideration when investing the paid-in contributions'.
Italy	Since September 2004 pension funds are required to disclose non-financial factors (including social, environmental and ethical factors) influencing their investment decisions.
Netherlands	In 1995, the Dutch Tax Office introduced a 'Green Savings and Investment Plan', which applies a tax deduction for green investments, such as wind and solar energy, and organic farming.
Sweden	Since January 2002, Swedish national pension funds are obliged to incorporate environmental and ethical aspects in their investment policies.
UK	In July 2000, the Amendment to 1995 Pensions Act came into force, requiring trustees of occupational pension funds in the UK to disclose in the Statement of Investment Principles ''the extent (if at all) to which social, environmental and ethical considerations are taken into account in the selection, retention and realization of investments". The Trustee Act 2000 came into force in February 2001. Charity trustees must ensure that investments are suitable to a charity's stated aims, including applying ethical considerations to investments. In 2002, The Cabinet Office in the UK published the Review of Charity Law in 2002, which proposed that all charities with an annual income of over £1 m should report on the extent to which social, environmental and ethical issues are taken into account in their investment policy. The Home Office accepted theses recommendations in 2003. The Association of British Insurers (ABI) published a disclosure guideline in 2001, asking listed companies to report on material social, environmental and ethical risks relevant to their business activities.
US	Section 406 of the Sarbanes-Oxley Act, which came into effect in July 2002, requires companies to disclose a written code of ethics adopted by their CEO, chief financial officer and chief accountant.

Cited from Renneboog, L. et al., Socially responsible investments: Institutional aspects, performance, and investor behavior, Journal of Banking and Finance (2008), pp. 5.

The focal issues of social concern embrace time-varying nature per se. The root of socially responsible investing can be stretched back to the ancient religious paradigms such as Jewish, Christian and Islamic doctrines. In ancient times, many religions like Judaism, Christianity or Islam instructed people in the ethical use of public wealth, such as imposing ethical constraints on loans, the forbiddance of devouring usury as well as the avoidance in sinful tradings. In the 20th century, a series of social campaigns revealed that investors had become incrementally conscious of the influence from their investments on the society. The Pax World Fund, which was the first antiwar mutual fund launched in 1971, materialized the desire for antimilitarism of social investors under the context of opposing against the Vietnam War. By the late 1980s attention had been drawn to the apartheid in South Africa, ending up indirectly in the large-scale divestment campaigns in South Africa. Afterward social investors' cravings for antiracism were incorporated into the launching of the Calvert Social Investment Funds, which excluded investment targets that operate or have subsidiaries in South Africa. More recently, modern socially responsible investing has attached enormous importance to the environmental stewardship, business sustainability and corporate governance factors, particularly with aspects on investments in eco-friendly industries, human rights and stakeholder relations.

The remainders of this article are structured as follows. Chapter 2 summarizes reviewed literature. Chapter 3 describes the data extraction process and methodology. Chapter 4 reports the empirical results. Finally, some concluding remarks are given in Chapter 5.

Chapter 2 Literature Review

2.1 Literature on the performance of socially responsible and anti-social investing

In a nutshell, there are two principal hypotheses to account for the performance relationship between socially responsible investing and conventional non-SRI investments.[1] The first hypothesis is that the expected returns of socially responsible portfolios are lower than those of their conventional peers, implying that the unique social responsibility characteristics for socially screened portfolios are priced negatively. Renneboog et al. (2008a) document that believers in the efficient market hypothesis contend that screening portfolios based on public information such as corporate social responsibility (CSR) cannot generate abnormal returns. The perspective of market efficiency is also shared with Diltz (1995). Renneboog et al. (2008a) provide a further supplement with owing to the multi-task nature of SRI portfolios, managers may weaken the incentives to pursue high risk-adjusted returns and consequently augment potential agency costs. Furthermore, some argue that socially oriented portfolios might suffer spiraling costs from limited diversification paralleled with conventional portfolios (Geczy et al., 2005). The second hypothesis is that socially responsible portfolios can outperform their conventional counterparts. Sustainers of this hypothesis consider that companies would benefit from the signaling effect of social soundness that could be transformed into

[1] Three alternative hypotheses as posited by Hamilton et al. (1993) are: (1) the expected returns of socially responsible portfolios are equal to those of conventional ones, (2) the expected returns of socially responsible portfolios are lower than those of conventional ones and (3) the expected returns of socially responsible portfolios are higher than those of conventional ones, respectively.

sustainable competitive advantage (Dillenburg et al., 2003). Renneboog et al. (2008a) summarize another argument with reference to this outperformance hypothesis: social and environmental screening reduces the possibility of inviting high costs during corporate social crises or environmental disasters, hence increasing the financial performance implicitly.

The continuing debate around the performance of socially responsible investing will ultimately fail to be settled without resorting to empirical investigations. As for the empirical evidence from the United States, Hamilton et al. (1993) exploit CAPM one-factor model using monthly data to measure the excess returns of 32 SRI mutual funds compared with 320 randomly selected conventional mutual funds during the period 1981-1990. Their findings revel that the mean monthly excess return of the 17 SRI funds established before 1985 is higher than the 170 conventional funds while the mean monthly excess return of the 15 SRI funds established 1986 or later is lower than the other 150 conventional funds, both the differences above are statistically insignificant. Using the event study methodology Hamilton (1995) examines the information content of the announcements of Toxics Release Inventory (TRI) pollution releases and statistically significant negative abnormal returns are observed on the day the pollution figures are first released. Statman (2000) assesses the performance difference between 31 SRI funds and 62 conventional funds matched by asset size over the 1990-1998 period. The empirical result shows that the average yearly alpha of the 31 SRI funds is higher than that of the 62 conventional counterparts of similar asset size, whereas the mean excess standard-deviation-adjusted return of the 62 conventional funds trails the 31 SRI funds by 1.06% on average per annum. No significant difference is found in the performance between the two distinct categories of funds. Dowell et al. (2000) identify U.S.-based multinational enterprises with a single stringent global environmental standard have much higher market values proxied by Tobin's q. Geczy et al. (2005) spotlight the diversification costs from which the investors imposing the SRI constraint on their optimal mean-variance portfolios might suffer for the period 1963-2001. They argue that the magnitude of financial costs hinges chiefly upon the investor's attitude toward assets pricing models and manager skills. They point out the financial costs ranging from 5 to 150 basis points at least per month have been charged once the SRI constraint is imposed. On the part of international surveys, after controlling for the exposures to market risk premium, size, book-to-market and momentum factors Bauer et all. (2005) uncover the difference in risk-adjusted excess returns between SRI funds and regional indices is verified to be marginally significant and no significant performance difference is found between SRI funds and conventional peers in Germany, the United Kingdom and the United States over the period 1990-2001. German and UK SRI funds are heavily exposed to small caps while US SRI funds are more invested in large caps. Bauer et all. (2005) further divide the study period into three sub-periods and discern that SRI funds were undergoing a performance enhancement process across the researched countries throughout the 1990s. Renneboog et al. (2008b) ascertain that socially responsible investors pay a price for ethics in response to the significant underperformance to their domestic benchmarks in the United States, the United Kingdom and most continental European and Asia-Pacific countries during the 1991-2003 period. A so-called 'smart money effect', in addition, gains mixed reviews in the SRI fund industry. Renneboog et al. (2008b) clarify the phenomenon that SRI investors' selection capability for funds outperforming in the future is less pronounced, albeit that they do show some sophisticated aptitude for identifying poorly performing ethical funds.

On the other hand, anti-social investing (ASI), namely vice-based investing (Waxler, 2004), does not have a savory reputation and is frequently deemed to be morally irresponsible or politically incorrect to the detriment of the environment and human society. Simultaneously anti-social investing has been seldom regarded in academic research in comparison with social responsible investing. Using CAPM one-factor model Shank et al. (2005) compare the risk-adjusted return of a most socially responsible firms (MostSRF) portfolio with a naughty firm portfolio (NFP), where MostSRF is defined as the common top ten holdings owned by at least one third of the SIF identified funds and NFP represents the top ten stock holdings of the Vice Fund weighted with market value. Over the relatively short term of three years, both the MostSRF and NFP exhibit no statistically distinguishable performance differences against the S&P 500 index. During the mid and longest sample horizons for five and ten years, the MostSRF outperforms the benchmark index significantly while NFP exists no performance difference against the S&P 500 index. The foremost research utilizing GJR model from generalized autoregressive conditional heteroscedasticity (GARCH) family to capture the dynamic volatility for the Vice Fund is rendered by Chong et al. (2006). Over the period from September 2002 to September 2005 they not only detect the fact that the conditional Sharpe ratio of Vice Fund surpasses both the S&P 500 index and the Domini Social Equity Fund but the circumstance that the average conditional beta of the Vice Fund is evidently lower than the others, both enabling the Vice Fund to resemble a hedge fund further closely.

Overall there seems to be no definitive consensus pertinent to the performance difference between SRI portfolios, ASI portfolios and conventional equivalents. We supposedly ascribe the performance puzzle to mutual fund data contaminated by diversification requirements and expense ratio differentials, conventional funds gradually converge to SRI funds since the SRI legislations, performance regression models suffer randomness endogenous in data and the constraint of different sample periods and regions. In view of the significance of data purity, we accordingly adopt two relevant indices to mitigate these perturbations. Comparisons using indices also have the advantage without allowing for the transaction costs of funds, market timing and stock-picking ability of fund managers, hence the effect of specific screens on portfolio performance can be measured relatively directly (Schröder, 2007).

2.2 Literature on Value-at-Risk (VaR) methodologies

We utilize Value at Risk (VaR) as a downside risk proxy to examine its effects on the performance of SRI and ASI portfolios. According to Jorion (2000), VaR is defined as the maximum potential losses on specific portfolios at a given confidence level and time horizon. The most prevailing VaR models are classified into three major categories: (1) the Variance-Covariance approach or Delta-Normal approach, (2) the Historical Simulation, and (3) the Monte Carlo Simulation. Each methodology has its own prerequisites and disadvantages, which is itemized as follows.

Using the Variance-Covariance approach and the Historical Simulation Hendrics (1996) examines the performance of the two methods with twelve different parameters applied to eight types of foreign exchange rate over the period 1978-1995. He points out that the selection of confidence level can influence the performance of Value-at-Risk approaches substantially. At the 95% confidence level almost all of the selected twelve approaches generate accurate risk measures while these approaches can not provide adequate risk coverage at the 99% confidence level, which implicitly means that both the Variance-Covariance approach and the Historical Simulation have the tendency toward underestimating risks at high confidence levels. Duffie and Pan (1997) also indicate that the Variance-Covariance approach suffers from the risk underestimation at high confidence levels since the heavy-tailed idiosyncrasy of financial asset returns. Several researches manifest the disadvantages of the Historical Simulation. Beder (1995), Pritsker (1997), and Jackson et al. (1997) caveat that the Historical Simulation is very subject to the amount of historical data. The insufficiency of historical data will result in severe out-of-sample forecasting biases whereas the redundancy of historical data may envelop too much irrelevant information, diluting the current information's influence (Hull and White, 1998). Goorbergh and Vlaar (1999) apply various VaR techniques to Dutch stock market index (AEX) and indicate the length of window size is greatly responsible for the variability of VaR estimated with the Historical Simulation. The longer the specified window size is, the less volatile the VaR estimates will be. Vlaar (2000) exploit VaR standards including the Variance-Covariance approach, the Historical Simulation and the Monte Carlo Simulation to investigate the corresponding model accurateness in the term structure of Dutch interest rates. He concludes that the Historical Simulation performs satisfactorily only if a long history is included and the Monte Carlo Simulation requires a very great number of samplings to achieve its theoretical accurateness, which could potentially give rise to the inclusion of irrelevant information and generate immense computing time and costs, respectively. Linsmeier and Pearson (2000) state that the Variance-Covariance approach is incapable of capturing the risks of portfolios which include options and the scenario analysis is not suitable for the Historical Simulation despite its easiness to compute and explain the VaR compared with the others. Furthermore, the common ground of the three VaR models shares the deficiency of misleading market risk exposures at any atypical fluctuating market.

Given the prevalent VaR methodologies have their own disadvantages, the goal of providing another suitable VaR model is pursued in this research.

Table 2.1

Literature Review Summary

Panel A: SRI performance

Study	Country	Period	Findings	SRI Influence
Hamilton et al. (1993)	US	1981-1990	The mean monthly excess return of the 17 SRI funds established before 1985 is higher than the 170 conventional funds while the mean monthly excess return of the 15 SRI funds established 1986 or later is lower than the other 150 conventional funds, both the differences above are statistically insignificant.	Non
Hamilton (1995)	US	1989	Statistically significant negative abnormal returns are found on the day the pollution figures are first released.	+
Statman (2000)	US	1990-1998	The average yearly alpha of the 31 SRI funds is higher than that of the 62 conventional counterparts of similar asset size, whereas the mean excess standard-deviation-adjusted return of the 62 conventional funds trails the 31 SRI funds by 1.06% on average per annum. No significant difference is found in the performance between the two distinct categories of funds.	Non
Dowell et al. (2000)	US	1994-1997	US-based multinational enterprises with a single stringent global environmental standard have much higher market values proxied by Tobin's q.	+
Geczy et al. (2005)	US	1963-2001	Financial costs (diversification costs) ranging from 5 to 150 basis points at least per month have been charged once the SRI constraint is imposed.	−
Bauer et all. (2005)	Germany, UK and US	1990-2001	The difference in risk-adjusted excess return between SRI funds and regional indices is marginally significant in Germany, the United Kingdom and the United States. No significant performance difference is found between SRI funds and conventional peers.	Non
Renneboog et al. (2008b)	17 countries worldwide	1991-2003	SRI investors pay a price for ethics in response to the significant underperformance to their domestic benchmarks in the United States, the United Kingdom and most continental European and Asia-Pacific countries. Smart money effect in the SRI industry is mixed.	−

Table 2.1 (continued)

Panel B: ASI performance

Study	Country	Period	Findings	ASI Influence
Shank et al. (2005)	US	1994-2003	Over the three-year period, both the most socially responsible firms (MostSRF) portfolio and naughty firm portfolio (NFP) exhibit no statistically distinguishable performance differences against the S&P 500 index. During the five- and ten-year periods, the MostSRF outperforms the benchmark index significantly while NFP exists no performance difference against the S&P 500 index.	Non
Chong et al. (2006)	US	2002-2005	The conditional Sharpe ratio of Vice Fund (ticker VICEX) surpasses both the S&P 500 index and the Domini Social Equity Fund (ticker DSEFX), and the average conditional beta of the Vice Fund is evidently lower than the others.	+

Panel C: Literature on Value-at-Risk (VaR) methodologies

Study	Findings
Hendrics (1996)	The selection of confidence level can influence the performance of Value-at-Risk approaches substantially. At the 95% confidence level almost all of the selected twelve approaches generate accurate risk measures while these approaches can not provide adequate risk coverage at the 99% confidence level, which implicitly means that both the Variance-Covariance approach and the Historical Simulation have the tendency toward underestimating risks at high confidence levels.
Duffie and Pan (1997)	The Variance-Covariance approach suffers from the risk underestimation at high confidence levels since the heavy-tailed idiosyncrasy of financial asset returns.
Beder (1995) Pritsker (1997) Jackson et al. (1997) Hull and White (1998)	The Historical Simulation is very subject to the amount of historical data. The insufficiency of historical data will result in severe out-of-sample forecasting biases whereas the redundancy of historical data may envelop too much irrelevant information, diluting the current information’s influence.

Table 2.1 (continued)

Panel C: Literature on Value-at-Risk (VaR) methodologies

Study	Findings
Goorbergh and Vlaar (1999)	The length of window size is greatly responsible for the variability of VaR estimated with the Historical Simulation. The longer the specified window size is, the less volatile the VaR estimates will be.
Vlaar (2000)	The Historical Simulation performs satisfactorily only if a long history is included and the Monte Carlo Simulation requires a very great number of samplings to achieve its theoretical accurateness, which could potentially give rise to the inclusion of irrelevant information and generate immense computing time and costs, respectively.
Linsmeier and Pearson (2000)	The Variance-Covariance approach is incapable of capturing the risks of portfolios which include options and the scenario analysis is not suitable for the Historical Simulation despite its easiness to compute and explain the VaR compared with the others. The common ground of the three VaR models shares the deficiency of misleading market exposures at any atypical fluctuating market.

Chapter 3 Data and Methodology

3.1 Data

Extracting from the Natural Capital Institute SRI Database, we execute the negative screening strategy filtering out portfolios involving with alcohol, firearms, defense/military weapons, gambling and tobacco industries to single out ten American SRI mutual funds compatible with the study period from September 16th, 2002 to September 16th, 2007.[2] Figure 3.1 illustrates the screen criteria practiced by US SRI funds in 2005. The SRI fund sample is constituted by Citizens Emerging Growth Institutional Fund (ticker CEGIX), Citizens Emerging Growth Standard Fund (ticker WAEGX), Domini Social Equity Fund (ticker DSEFX), Dow Jones Islamic Fund Class K (ticker IMANX), Neuberger Berman Socially Responsive Fund Class I (ticker NBSRX), Neuberger Berman Socially Responsive Fund Trust Class (ticker NBSTX), New Alternatives Fund (ticker NALFX), Parnassus Equity Income Fund (ticker PRBLX), PAX World Balanced Fund (ticker PAXWX) and PAX World Growth Fund (ticker PXWGX). All the daily closing prices are compiled form Yahoo Finance Database and adjusted for dividends and splits if any. Vice Fund (ticker VICEX), incepted on 30th August 2002, is designated to proxy the antithetic sample for screened SRI funds. According to the Vice Fund's prospectus (2007), the prerequisite for 25 percent at least of sales revenues from products or services in alcohol, tobacco, gambling, aerospace and defense must be fulfilled in its target selection process. In addition, the Domini 400 Social Index (ticker KLDDSI) and the SINdex (ticker SIN) are

[2] The most widely adopted policy of SRI mutual funds is negative screening. Approximately 87 percent of the American SRI mutual funds stick to the negative screening strategy (SIF, 2003).

infused into their corresponding sample group to ameliorate the perturbations arising from mutual fund data. The Domini 400 Social Index is elaborated by Kinder, Lydenberg, Domini & Company in May 1990, intercepting approximate 250 companies from the S&P 500 index, 100 supplemental companies meeting specific social criteria for diversification purposes and 50 small cap companies with excellent social and environment records. Specific thresholds into alcohol, tobacco, firearms, gambling, nuclear power and military weapons are automatically ineligible for KLDDSI. Constructed by International Securities Exchange (ISE), the equiweighted SINdex comprises 30 operators engaging in casinos and gambling facilities, producers of alcoholic beverages and manufactures of tobacco products.

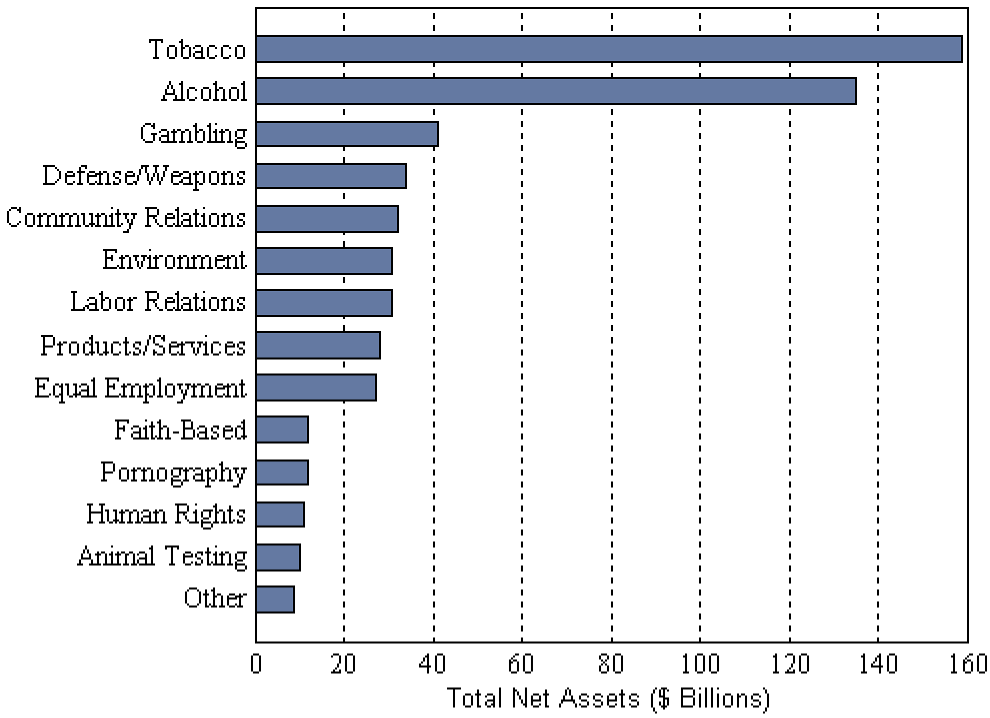


Figure 3.1
Mutual Fund Assets by Screen Types, 2005
Source: Social Investment Forum Foundation

3.2 Methodology

3.2.1 Downside Risk Proxy: Value at Risk

Kahneman and Tversky (1979) propose the prospect theory to account for the market anomalies the market efficiency hypothesis and the expected utility theory fail to explain. The value function thereof reflects the phenomenon that the value generated from marginal losses is asymmetric and more sensitive to that of marginal gains. They indicate the losses or downside risks have greater influence on the sentiment and behavior of examinees through psychological experiments. Schwager (1985) criticize the traditional risk indicators such as standard deviations or variances for incapability of discriminating downside risks from upside risks. Not only a reference basis for financial intermediaries to scrutinize capital adequacy, Value at Risk (VaR) is also a reasonable instrument to capture the magnitude of downside risks, which is defined as the maximum potential losses on specific portfolios at a given confidence level and time horizon. The most prevailing model specifications for VaR are the Variance-Covariance approach, the Historical Simulation and the Monte Carlo Simulation, respectively. The Variance-Covariance approach, called likewise parametric methods, specifies the return distributions of financial assets as asymptotically normally distributed, hence the VaR can be speedily simplified to the product of normal quantiles and corresponding standard deviations or covariances. The unconditional standard deviation is set as volatility proxy throughout this article, which is expressed as follows:

$$\sigma_t = \sqrt{\frac{\sum_{t=1}^{T}\left(R_{t-1}-\mu\right)^2}{T-1}} \tag{3-1}$$

where σ_t is the standard deviation at period t, R_{t-1} the portfolio return at period t-1, μ the mean return over the sample period and T the sample numbers.

Both the historical simulation and the Monte Carlo simulation are likewise termed as non-parametric methods, wherein the historical simulation uses no pre-specified probability distributions and hypothesizes the sample path of past financial return series will be reproducibly distributed in the future, hence VaR could be intuitively calculated based on quantiles of past return distributions. Massively different to the single sample path the historical simulation complies with, the Monte Carlo simulation supposes a plausible stochastic process for asset prices or financial returns, substantially simulating the sample path to depict asymptotic parent probability distributions of financial series under varieties of scenarios. The most widely specified stochastic process in VaR literature is the Geometric Brownian Motion (GBM), whose continuous form of stochastic differential equation is defined as follow:

$$dS_t = \mu_t S_t dt + \sigma_t S_t dW_t \quad \text{or} \quad \frac{dS_t}{S_t} = \mu_t dt + \sigma_t dW_t, \quad dW_t \sim N(0, dt) \qquad (3\text{-}2)$$

where S_t is the asset price at time t, μ_t and σ_t denote the expected return and standard deviation of financial series over the time interval, respectively. dW_t stands for instantaneous variations in a Wiener process over the time interval and is normally distributed with naught mean and variance of transient time variations.

3.2.2 Gram-Charlier Parametric Density Estimation

In this research we additionally provide Gram-Charlier parametric density estimation to compute the VaR for our sample. Advanced by a Danish mathematician named J. P. Gram (1884) as well as a Swedish astronomer named C. V. L. Charlier (1905), Gram-Charlier expansions are comprehensively applied in the fields of mathematics, statistics and physics. Sargan (1975) firstly accommodate the expansions into the arena of econometrics. Corrado and Su (1996) and Rubinstein (1998) marshal the expansions into the derivatives pricing models. Mauleón and Perote (2000) and Verhoeven and McAleer (2004) use the Gram-Charlier density to mimic high-frequency financial series characterized by skewness and leptokurtosis. Mauleón and Perote (2000) share the evidence that the Gram-Charlier density or Edgeworth-Sargan density possesses superior goodness of fit in comparison with Student's t distribution using 25-year length of daily return distributions for Dow Jone industrial average index and UK financial times index. The Gram-Charlier probability density function is parameterized by

$$f_n(x) = \sum_{i=0}^{n} c_i \cdot H_i(x) \cdot \phi(x) \tag{3-3}$$

where $f_n(x)$ represents nth-order Garm-Charlier probability density function. c_i the constants pertaining to ith-order moments around the mean. $H_i(x)$ are Hermite polynomials, which can be derived from successive differentiations of standard normal density function with respect to x and hold the orthogonal property.[3] $\phi(x)$ denotes the standard normal density. In practice the Gram-Charlier probability density function is predominantly

[3] The first four Hermite polynomials have the following sequences: $H_0(x) = 1$, $H_1(x) = x$, $H_2(x) = x^2 - 1$, $H_3(x) = x^3 - 3x$ and $H_4(x) = x^4 - 6x^2 + 3$. The constants c_i can be formally expanded into: $c_0 = 1$, $c_1 = 0$, $c_2 = 1/2(\mu_2 - 1)$, $c_3 = \mu_3/6$ and $c_4 = 1/24(\mu_4 - 6\mu_2 + 3)$, where μ_2, μ_3 and μ_4 denote the second, the third and the fourth moments around the mean, separately.

truncated into the fourth-order form, enveloping the first four moments as crucial parameters straightforwardly for the avoidance of multicollinearity between tedious parametric estimators (Jarrow and Rudd, 1982; Corrado and Su, 1996) and narrowing the parameter spaces defining the positive density (Barton and Dennis, 1952; Rubinstein,1998). The fourth-order truncated Gram-Charlier probability density function can be parsimoniously rearranged into

$$f_4(z) = \phi(z) \cdot \left[1 + \frac{SK}{6}(z^3 - 3z) + \frac{KU}{24}(z^4 - 6z^2 + 3) \right] \tag{3-4}$$

Equation (3-4) is empirically manipulated in our case, where z denotes a standardized random variable with naught mean and unit variance. *SK* and *KU* notate the coefficients of skewness and excess kurtosis. The standardized fourth-order truncated Gram-Charlier density nests the standard normal density under the specific circumstance *SK* and *KU* are tantamount to naught contemporaneously. In virtue of being polynomial approximations, the Gram-Charlier probability density curve varies dynamically with the corresponding parameter spaces and hence might suffer from the disadvantage generating negative probability and multimodality. Jondeau and Rockinger (2001) implement analytical geometry algorithm to guarantee the Gram-Charlier density of being positive and unimodal definite in compliance with probability postulates. They contribute to the steady Gram-Charlier density with excess kurtosis inside the interval [0, 4] and symmetric skewness within [1.0493, -1.0493] to the excess kurtosis. Following the algorithm Jondeau and Rockinger (2001) provide, we impose the positive and unimodal definiteness on the VaR parametric estimation. Simpson's Rule is embedded into the process proceeding numerical integration for the Gram-Charlier density, expressed mathematically as:

$$\int_{-\infty}^{\Im_{GC}(\alpha)} f_4(z)\,\mathrm{d}z = \alpha \tag{3-5}$$

where $\Im_{GC}(\alpha)$ denotes α-quantiles of the fourth-order Gram-Charlier density, i.e. VaR of standardized return distributions at the confidence level of 100(1-α)%. Since the standardized density, $\Im_{GC}(\alpha)$ is inevitably destandardized and retrieved to its archetype using

$$VaR(\alpha) = \Im_{GC}(\alpha) \times \sigma_i + \mu_i \tag{3-6}$$

where $VaR(\alpha)$ is the destandardized Value-at-Risk with α percent thresholds. σ_i and μ_i correspond to the standard deviation and the mean from sampling distributions, separately.

3.2.3 Model Backtesting

Resorting to much rigorous empirical scrutiny, the window size is conformably stiffened with 1000-day rolling windows to conduct 250 out-of-sample VaR one-day-ahead forecasting for the sake of sufficing the parametric requirement the Gram-Charlier density signifies. Furthermore, Kupiec's (1995) unconditional coverage test and average failure bias (*AFB*) are quantified as the accuracy and efficiency criteria in VaR modelling. The exception or failure is marked when the realized losses exceed the VaR preliminarily estimated. Kupiec's (1995) unconditional coverage test or proportion of failure test, the essential backtesting procedure in the internal model analysis regularized by the Basel Committee, is utilized to examine whether the ex-post violation rate equals the predetermined threshold level or not.[4] Using the binomially-distributed violation rate variables to access a log-likelihood ratio statistics given by

$$LR_{uc} = 2 \times \ln\left[\frac{(1-(x/T))^{T-x}(x/T)^{x}}{(1-\alpha)^{T-x}\alpha^{x}}\right] \sim \chi_1^2 \tag{3-7}$$

The null hypothesis is established by $\mathrm{H}_0 : \alpha = (x/T)$, where LR_{uc} is the log-likelihood ratio statistics chi-square distributed with one degree of freedom, α the predetermined threshold level, T the out-of-sample forecasting observations and x the number of VaR violations or exceptions.

Not only should meet the accuracy criteria, a robust VaR model ought to stand seized of efficiency. We define the efficiency criteria in VaR modelling with average failure bias (*AFB*) listed as follows:

$$AFB = \sqrt{\frac{\sum_{t=1}^{T}(R_t - VaR_t)^2}{T}} \tag{3-8}$$

where R_t refers to realistic loss at period t in the backtesting term, VaR_t the Value-at-Risk estimated with omnigenous models in advance and T the VaR exceptions. Analogous to Root Mean Squared Error (*RMSE*) utilized by Alexander and Leigh (1997), the average failure bias serves as a barometer detecting the average dimension between realized losses and VaR in the presence of exceptions. The lower scalar the *AFB* indicates, the smaller unexpected loss and the more efficiency the VaR model possesses.

[4] Violation rate is defined as the ratio of the aggregate exceptions against the out-of-sample forecasting observations.

3.2.4 Performance Evaluation Model

On the one hand, given the traditional CAPM one-factor model initiated by Sharpe (1964) and Lintner (1965) has been persistently infused into the financial performance evaluation process, this article is also equipped with the traditional performance measure delineated by

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it} \tag{3-9}$$

where R_{it} is the daily return on portfolio i at period t, R_{ft} the daily geometric average coupon equivalent rate of 13-week treasury bill sourced from the Federal Reserve Bank of New York, α_i-coefficient the returns adjusted for systematic risks or the Jensen's (1968) alpha, β_i-coefficient the risk factor loading exposed to market risk premium, R_{mt} the daily return of the market benchmark and ε_{it} the idiosyncratic return.

On the other hand, we further incorporate the VaR into the Sharpe index, forming the VaR-modified Sharpe index initially introduced by Dowd (1999) as formulized below:

$$VaR\text{-}modified\ Sharpe\ index = \frac{\overline{R_i} - \overline{R_f}}{VaR_i} \tag{3-10}$$

where $\overline{R_i}$ denotes annualized geometric average return on portfolio i, $\overline{R_f}$ the annual geometric average risk-free rate and VaR_i the annualized Value-at-Risk of portfolio i throughout the sample period.

Refining the excess standard-deviation-adjusted return (*eSDAR*)[5] put forth by Statman (1987; 2000; 2006), we advance the excess VaR-adjusted return (*eVaRAR*) serving as the modified version of the VaR-modified Sharpe index in the form of

$$eVaRAR = \overline{R_f} + \left(\frac{\overline{R_i} - \overline{R_f}}{VaR_i}\right)VaR_{bench} - \overline{R_m} \tag{3-11}$$

where VaR_{bench} and $\overline{R_m}$ indicate the annualized Value-at-Risk and the annualized geometric average return of the market benchmark throughout the sample period, respectively. Being leveraged to have the market benchmark's VaR, the *eVaRAR* of any portfolio diagnoses the excess return on a specific portfolio beyond the return of the selected market benchmark.

[5] The formula of *eSDAR* is specified as follows: $eSDAR = \overline{R_f} + \left(\frac{\overline{R_i} - \overline{R_f}}{SD_i}\right)SD_{bench} - \overline{R_m}$, where SD_i is the standard deviation of the return of portfolio *i* and SD_{bench} the standard deviation of the market benchmark.

Chapter 4 Empirical Analysis

Table 4.1 summarily presents the descriptive statists for the daily log-return series of research samples. Generally, the SRI sample group has lower annualized returns and higher annualized standard deviations in comparison with those of the ASI sample. Consistent with the common characteristics of most high-frequency financial series, skewness and leptokurtosis clustering around zero define the daily return distributions of the two samples, for all the coefficients of skewness and excess kurtosis synchronously deviate from zero significantly and the entire ASI sample group has a higher proportion of positive returns. All the return series are stationary and conspicuously non-normal distributed.

Table 4.1
Summary statistics

Ticker Symbol	Type	Mean (%)	Std. Dev. (%)	Skewness	Excess Kurtosis	Jarque-Bera	Observations	P-P
SRI sample group								
CEGIX	Fund	10.43	17.28	-0.0373	0.8031	33.43***	1258	-36.29***
WAEGX	Fund	9.85	17.28	-0.0371	0.8043	33.52***	1258	-36.27***
DSEFX	Fund	8.70	14.28	0.0683	2.3801	294.37***	1258	-39.60***
IMANX	Fund	9.90	14.05	0.0466	1.7745	163.31***	1258	-39.95***
NBSRX	Fund	13.40	13.32	0.0521	1.4828	114.16***	1258	-38.22***
NBSTX	Fund	13.20	13.32	0.0625	1.5162	119.60***	1258	-38.26***
NALFX	Fund	17.70	13.55	-0.1736	1.4293	111.74***	1257	-32.94***
PRBLX	Fund	10.40	11.70	0.1304	3.0138	465.42***	1257	-37.51***
PAXWX	Fund	9.95	9.02	-0.1320	0.7167	30.00***	1258	-38.31***
PXWGX	Fund	10.25	16.28	-0.1581	0.4432	15.22***	1258	-34.51***
KLDDSI	Index	8.25	14.20	0.1478	2.2855	275.05***	1258	-40.28***
ASI sample group								
VICEX	Fund	16.00	12.79	-0.1815	0.6050	25.62***	1258	-35.18***
SIN	Index	19.23	13.88	-0.0945	1.2347	80.47***	1257	-36.69***

Notes: All the mean and the standard deviation are annualized. Jarque-Bera test serves to examine the distributional normality. P-P stands for Phillips-Perron unit root test. *** denotes significance at the 1% level.

4.1 Backtesting Results in VaR Modelling

Table 4.2 reports the statistical results of VaR exceptions and violation rate at the 90%, 95%, 99% and 99.5% confidence levels within the out-of-sample period. Under the probabilistic specification of these four confidence levels, the theoretical VaR exceptions should be successively equal to 25, 12.5, 2.5 and 1.25 over the 250 out-of-sample forecasts. In Table 4.2 the Gram-Charlier parametric density model is substantiated to be able to pertinently provide for conservativeness by suggesting comparatively small excess exception deviations at high confidence levels (99% and 99.5%), possessing superior competence for capturing heavy-tailed idiosyncrasy of financial asset returns. In addition, 75 percent of the SRI sample generates more exceptions than those of the ASI sample under the same VaR methodology and confidence level, which implies that higher downside risks probably exist in the SRI sample group.

Table 4.3 provides the applied VaR models with a formal statistical test for the accuracy. In summary, approximately 79 percent, 56 percent, 23 percent and 54 percent of VaR forecasts estimated by the Gram-Charlier parametric density estimation, Variance-Covariance approach, Historical Simulation and Monte Carlo simulation could pass through the accuracy inspection, hence Gram-Charlier parametric density estimation possesses preferable model accuracy among VaR models effectuated herein. Furthermore, the Gram-Charlier parametric density model exceptionally maintains model accuracy at high confidence levels (99% and 99.5%) compared with other VaR models, reconfirming its superiority in capturing heavy-tailed idiosyncrasy of financial asset returns.

Table 4.2

Overview of VaR exceptions and violation rate

Panel A: Gram-Charlier parametric density estimation

SRI sample group

Ticker Symbol	α = 10% exceptions	α = 10% VR	α = 5% exceptions	α = 5% VR	α = 1% exceptions	α = 1% VR	α = 0.5% exceptions	α = 0.5% VR
CEGIX	24†	9.60%	16†	6.40%	4	1.60%	3	1.20%
WAEGX	25†	10.00%	16†	6.40%	4	1.60%	3	1.20%
DSEFX	29†	11.60%	20†	8.00%	8†	3.20%	5†	2.00%
IMANX	26†	10.40%	17†	6.80%	6	2.40%	4†	1.60%
NBSRX	27†	10.80%	16†	6.40%	7†	2.80%	4†	1.60%
NBSTX	27†	10.80%	16†	6.40%	6	2.40%	4†	1.60%
NALFX	35†	14.00%	19†	7.60%	5	2.00%	4†	1.60%
PRBLX	32†	12.80%	24†	9.60%	9†	3.60%	6†	2.40%
PAXWX	27†	10.80%	20†	8.00%	7†	2.80%	4†	1.60%
PXWGX	26†	10.40%	17†	6.80%	1	0.40%	1	0.40%
KLDDSI	26	10.40%	19	7.60%	7†	2.80%	4†	1.60%
ASI sample group								
VICEX	23	9.20%	14	5.60%	6	2.40%	3	1.20%
SIN	27	10.80%	19	7.60%	4	1.60%	1	0.40%

Panel B: Variance-Covariance approach

SRI sample group

Ticker Symbol	α = 10% exceptions	α = 10% VR	α = 5% exceptions	α = 5% VR	α = 1% exceptions	α = 1% VR	α = 0.5% exceptions	α = 0.5% VR
CEGIX	22†	8.80%	14†	5.60%	7	2.80%	6†	2.40%
WAEGX	22†	8.80%	15†	6.00%	7	2.80%	6†	2.40%
DSEFX	25†	10.00%	18†	7.20%	11†	4.40%	9†	3.60%
IMANX	23†	9.20%	15†	6.00%	10†	4.00%	6†	2.40%
NBSRX	24†	9.60%	14†	5.60%	9†	3.60%	6†	2.40%
NBSTX	25†	10.00%	13†	5.20%	9†	3.60%	5†	2.00%
NALFX	29†	11.60%	19†	7.60%	8†	3.20%	6†	2.40%
PRBLX	27†	10.80%	21†	8.40%	12†	4.80%	9†	3.60%
PAXWX	26†	10.40%	20†	8.00%	9†	3.60%	7†	2.80%
PXWGX	21†	8.40%	17†	6.80%	4	1.60%	1	0.40%
KLDDSI	22	8.80%	17†	6.80%	9†	3.60%	8†	3.20%
ASI sample group								
VICEX	20	8.00%	12	4.80%	7	2.80%	4	1.60%
SIN	22	8.80%	13	5.20%	6	2.40%	3	1.20%

Table 4.2 (continued)

Panel C: Historical Simulation

SRI sample group

Ticker Symbol	α = 10% exceptions	α = 10% VR	α = 5% exceptions	α = 5% VR	α = 1% exceptions	α = 1% VR	α = 0.5% exceptions	α = 0.5% VR
CEGIX	29	11.60%	22	8.80%	10	4.00%	5	2.00%
WAEGX	29	11.60%	22	8.80%	10	4.00%	5	2.00%
DSEFX	30	12.00%	25†	10.00%	14†	5.60%	9†	3.60%
IMANX	28	11.20%	21	8.40%	11	4.40%	9†	3.60%
NBSRX	33†	13.20%	26†	10.40%	13†	5.20%	8†	3.20%
NBSTX	32†	12.80%	25†	10.00%	13†	5.20%	9†	3.60%
NALFX	47†	18.80%	35†	14.00%	15†	6.00%	6	2.40%
PRBLX	36†	14.40%	27†	10.80%	14†	5.60%	10†	4.00%
PAXWX	29	11.60%	25†	10.00%	11	4.40%	8†	3.20%
PXWGX	28	11.20%	20	8.00%	3	1.20%	2	0.80%
KLDDSI	29	11.60%	21	8.40%	13†	5.20%	8†	3.20%
ASI sample group								
VICEX	30	12.00%	23	9.20%	12	4.80%	6	2.40%
SIN	41	16.40%	29	11.60%	12	4.80%	7	2.80%

Panel D: Monte Carlo Simulation

SRI sample group

Ticker Symbol	α = 10% exceptions	α = 10% VR	α = 5% exceptions	α = 5% VR	α = 1% exceptions	α = 1% VR	α = 0.5% exceptions	α = 0.5% VR
CEGIX	24†	9.60%	16†	6.40%	8†	3.20%	4	1.60%
WAEGX	24†	9.60%	15†	6.00%	9†	3.60%	5†	2.00%
DSEFX	27†	10.80%	19†	7.60%	10†	4.00%	8†	3.20%
IMANX	23	9.20%	16†	6.40%	11†	4.40%	6†	2.40%
NBSRX	26†	10.40%	14†	5.60%	10†	4.00%	6†	2.40%
NBSTX	26†	10.40%	15†	6.00%	10†	4.00%	5†	2.00%
NALFX	34†	13.60%	24†	9.60%	9†	3.60%	6†	2.40%
PRBLX	28†	11.20%	22†	8.80%	12†	4.80%	11†	4.40%
PAXWX	27†	10.80%	20†	8.00%	9†	3.60%	7†	2.80%
PXWGX	23	9.20%	18†	7.20%	3	1.20%	2	0.80%
KLDDSI	24	9.60%	17	6.80%	9†	3.60%	6†	2.40%
ASI sample group								
VICEX	23	9.20%	12	4.80%	7	2.80%	4	1.60%
SIN	24	9.60%	17	6.80%	7	2.80%	4	1.60%

Notes: VR is the violation rate. Exceptions are the number of realized losses exceeding estimated VaR. Each VaR estimated by the Monte Carlo simulation is simulated 1000 times. † denotes that exceptions of SRI sample group exceed those of ASI sample group (comparison by type).

Table 4.3

Model accuracy: Kupiec's (1995) unconditional coverage test results

Panel A: Gram-Charlier parametric density estimation

SRI sample group

Ticker Symbol	Threshold level α = 10% LR_{uc}	α = 5% LR_{uc}	α = 1% LR_{uc}	α = 0.5% LR_{uc}
CEGIX	0.0450	0.9514	0.7691	1.7652
WAEGX	0.0000	0.9514	0.7691	1.7652
DSEFX	0.6799	4.0395**	7.7336***	6.4198**
IMANX	0.0439	1.5403	3.5554	3.8357
NBSRX	0.1737	0.9514	5.4970**	3.8357
NBSTX	0.1737	0.9514	3.5554	3.8357
NALFX	4.0042**	3.0905	1.9568	3.8357
PRBLX	2.0191	8.8777***	0.2290***	9.4147***
PAXWX	0.1737	4.0395**	5.4970**	3.8357
PXWGX	0.0439	1.5403	1.1765	0.0540
KLDDSI	0.0439	3.0905	5.4970**	3.8357
ASI sample group				
VICEX	0.1822	0.1827	3.5554	1.7652
SIN	0.1737	3.0905	0.7691	0.0540

Panel B: Variance-Covariance approach

SRI sample group

Ticker Symbol	Threshold level α = 10% LR_{uc}	α = 5% LR_{uc}	α = 1% LR_{uc}	α = 0.5% LR_{uc}
CEGIX	0.4152	0.1827	5.4970**	9.4147***
WAEGX	0.4152	0.4961	5.4970**	9.4147***
DSEFX	0.0000	2.2555	15.8906***	20.2775***
IMANX	0.1822	0.4961	12.9555***	9.4147***
NBSRX	0.0450	0.1827	10.2290***	9.4147***
NBSTX	0.0000	0.0208	10.2290***	6.4198**
NALFX	0.6799	3.0905	7.7336***	9.4147***
PRBLX	0.1737	5.0972**	19.0162***	20.2775***
PAXWX	0.0439	4.0395**	10.2290***	12.7527***
PXWGX	0.7479	1.5403	0.7691	0.0540
KLDDSI	0.4152	1.5403	10.2290***	16.3856***
ASI sample group				
VICEX	1.1846	0.0213	5.4970**	3.8357
SIN	0.4152	0.0208	3.5554	1.7652

Table 4.3 (continued)

Panel C: Historical Simulation				
SRI sample group				
	Threshold level			
Ticker	α = 10%	α = 5%	α = 1%	α = 0.5%
Symbol	LR_{uc}	LR_{uc}	LR_{uc}	LR_{uc}
CEGIX	0.6799	6.2590**	12.9555***	6.4198**
WAEGX	0.6799	6.2590**	12.9555***	6.4198**
DSEFX	1.0512	10.3271***	25.7803***	20.2775***
IMANX	0.3866	5.0972**	15.8906***	20.2775***
NBSRX	2.6116	11.8655***	22.3170***	16.3856***
NBSTX	2.0191	10.3271***	22.3170***	20.2775***
NALFX	17.5644***	29.2756***	29.3950***	9.4147***
PRBLX	4.8011**	13.4897***	25.7803***	24.4003***
PAXWX	0.6799	10.3271***	15.8906***	16.3856***
PXWGX	0.3866	4.0395**	0.0949	0.3823
KLDDSI	0.6799	5.0972**	22.3170***	16.3856***
ASI sample group				
VICEX	1.0512	7.5204***	19.0162***	9.4147***
SIN	9.7308***	16.9847***	19.0162***	12.7527***

Panel D: Monte Carlo Simulation				
SRI sample group				
	Threshold level			
Ticker	α = 10%	α = 5%	α = 1%	α = 0.5%
Symbol	LR_{uc}	LR_{uc}	LR_{uc}	LR_{uc}
CEGIX	0.0450	0.9514	7.7336***	3.8357
WAEGX	0.0450	0.4961	10.2290***	6.4198**
DSEFX	0.1737	3.0905	12.9555***	16.3856***
IMANX	0.1822	0.9514	15.8906***	9.4147***
NBSRX	0.0439	0.1827	12.9555***	9.4147***
NBSTX	0.0439	0.4961	12.9555***	6.4198**
NALFX	3.2739	8.8777***	10.2290***	9.4147***
PRBLX	0.3866	6.2590**	19.0162***	28.7318***
PAXWX	0.1737	4.0395**	10.2290***	12.7527***
PXWGX	0.1822	2.2555	0.0949	0.3823
KLDDSI	0.0450	1.5403	10.2290***	9.4147***
ASI sample group				
VICEX	0.1822	0.0213	5.4970**	3.8357
SIN	0.0450	1.5403	5.4970**	3.8357

Notes: LR_{uc} is the log-likelihood ratio statistics. *** and ** denote significant at the 1% and 5% level under the null hypothesis the ex-post violation rate equals the predetermined threshold level. The critical values corresponding to the 1% and 5% significance level are 6.6349 and 3.8415, separately.

The efficiency of VaR methodologies are quantified and tabulated in Table 4.4. Firstly, the inefficiency of the Historical Simulation could be evidently observed in consequence of the largest dimensions between the actual losses and the VaR forewarned. Secondly, under the same VaR methodology and confidence level the *AFB* of the SRI sample group is generally greater than that of the ASI sample group, especially for the index-type data (KLDDSI and SIN) even though the fund-type data exhibits slight discrepancies, which respectively suggests that the SRI sample group is more prone to engender unexpected losses and that the data type could potentially affect relevant inferences about the downside risk properties of the two sample groups.

Table 4.4

Model efficiency: average failure bias (*AFB*) statistics

Panel A: Gram-Charlier parametric density estimation

SRI sample group

Ticker Symbol	Threshold level α = 10% *AFB*	α = 5% *AFB*	α = 1% *AFB*	α = 0.5% *AFB*
CEGIX	1.0341†	0.9141†	0.7692†	0.5827
WAEGX	1.0180†	0.9179†	0.7746†	0.5901
DSEFX	1.1029†	1.0604†	0.9724†	1.0125†
IMANX	1.0229†	0.9920†	0.9231†	0.9119†
NBSRX	0.8151	0.8784	0.6048	0.6077
NBSTX	0.8168	0.8080	0.6751	0.6334
NALFX	0.9446†	0.9137†	0.8794†	0.7819
PRBLX	0.8641	0.7666	0.6554	0.6400
PAXWX	0.6742	0.5943	0.5337	0.5561
PXWGX	0.8397	0.6618	1.1435†	0.8087
KLDDSI	0.9709†	0.8850†	0.7475†	0.7566
ASI sample group				
VICEX	0.9079	0.8958	0.7657	0.8616
SIN	0.8338	0.7160	0.6808	1.0332

Panel B: Variance-Covariance approach

SRI sample group

Ticker Symbol	Threshold level α = 10% *AFB*	α = 5% *AFB*	α = 1% *AFB*	α = 0.5% *AFB*
CEGIX	1.0100†	0.9619†	0.7239	0.5913
WAEGX	1.0176†	0.9359†	0.7305	0.5981
DSEFX	1.1100†	1.1006†	1.0037†	0.9723†
IMANX	1.0107†	1.0329†	0.8521†	0.9446†
NBSRX	0.8034	0.8272	0.6013	0.5939
NBSTX	0.7878	0.8624	0.6139	0.6717
NALFX	0.9164†	0.9070	0.9218†	0.9041†
PRBLX	0.8648	0.8009	0.7001	0.6869
PAXWX	0.6339	0.5750	0.5437	0.5128
PXWGX	0.8631	0.6594	0.6820	1.0913†
KLDDSI	0.9797†	0.9031†	0.8121†	0.7268
ASI sample group				
VICEX	0.8893	0.9200	0.7698	0.8550
SIN	0.7897	0.7733	0.6466	0.7435

Table 4.4 (continued)

Panel C: Historical Simulation

SRI sample group

Ticker Symbol	Threshold level α = 10% AFB	α = 5% AFB	α = 1% AFB	α = 0.5% AFB
CEGIX	1.1036†	0.9889†	0.8177	0.9206
WAEGX	1.1020†	0.9919†	0.8091	0.9132
DSEFX	1.1573†	1.0898†	1.0353†	1.0138†
IMANX	1.0838†	1.0508†	1.0560†	0.9966
NBSRX	0.8616	0.7875	0.7436	0.7162
NBSTX	0.8690	0.8040	0.7646	0.6987
NALFX	1.0164†	0.9805†	0.8165	0.9018
PRBLX	0.9024	0.8495	0.7559	0.7120
PAXWX	0.7217	0.6067	0.6337	0.5571
PXWGX	0.9219	0.7636	0.8553†	0.8827
KLDDSI	0.9812†	0.9828†	0.8430†	0.8546†
ASI sample group				
VICEX	0.9509	0.8878	0.8419	1.0042
SIN	0.8548	0.8298	0.6961	0.7643

Panel D: Monte Carlo Simulation

SRI sample group

Ticker Symbol	Threshold level α = 10% AFB	α = 5% AFB	α = 1% AFB	α = 0.5% AFB
CEGIX	1.0155†	0.9308	0.7421	0.8624†
WAEGX	1.0128†	0.9456	0.5936	0.5650
DSEFX	1.0946†	1.1014†	1.0544†	1.0343†
IMANX	1.0251†	1.0096†	0.8005†	0.9282†
NBSRX	0.8113	0.8516	0.5597	0.5985
NBSTX	0.8130	0.8428	0.6114	0.7113
NALFX	0.8953†	0.8490	0.8875†	0.8970†
PRBLX	0.8808	0.8182	0.7360	0.6916
PAXWX	0.6502	0.5993	0.5550	0.5229
PXWGX	0.8653	0.6804	0.7236	0.7678
KLDDSI	0.9699†	0.9492†	0.8562†	0.8565†
ASI sample group				
VICEX	0.8911	0.9678	0.7846	0.8426
SIN	0.8150	0.7312	0.6474	0.6275

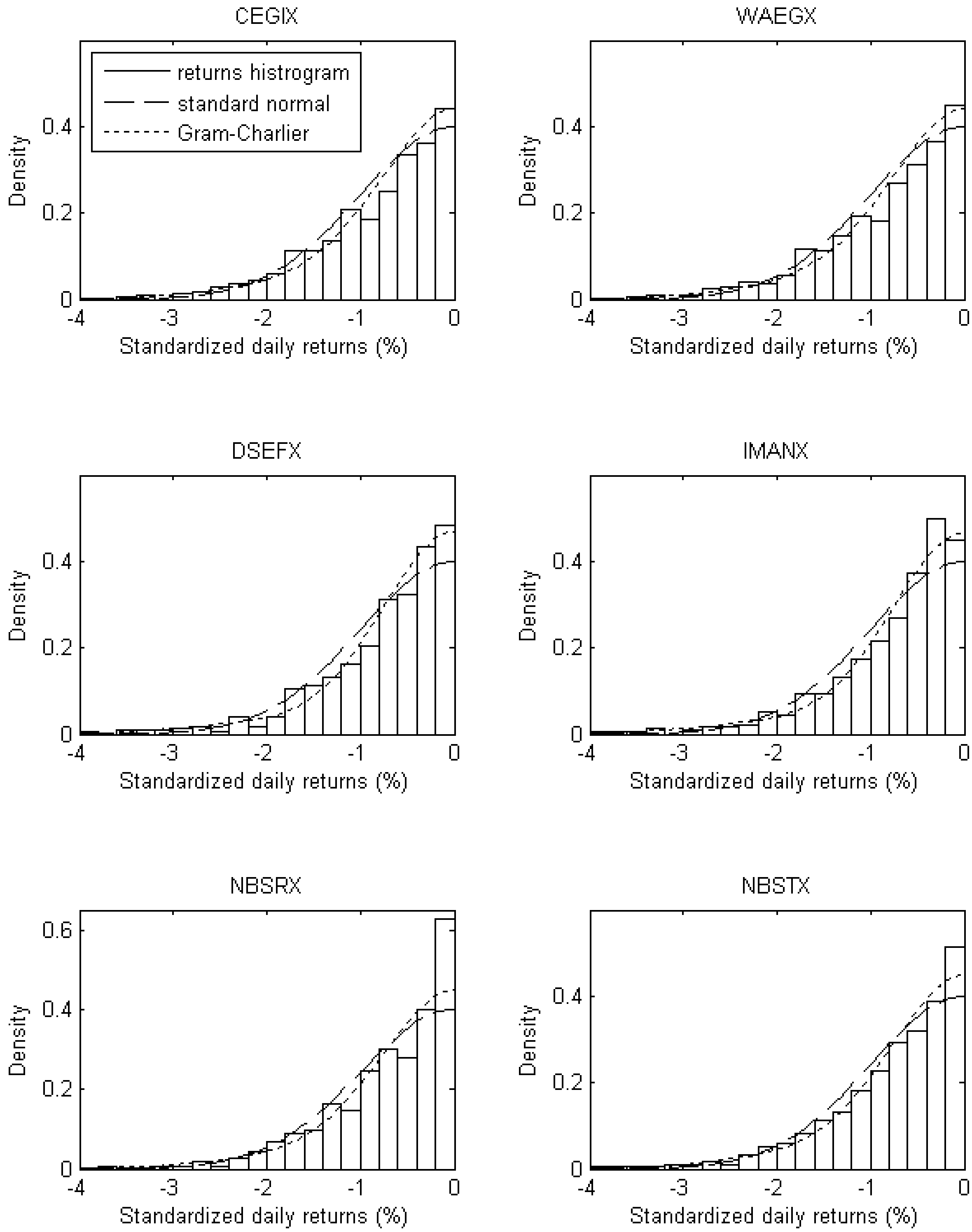
Notes: All the figures in this table are expressed in percentage. † denotes that the *AFB* of the SRI sample group exceeds that of the ASI sample group (comparison by type).

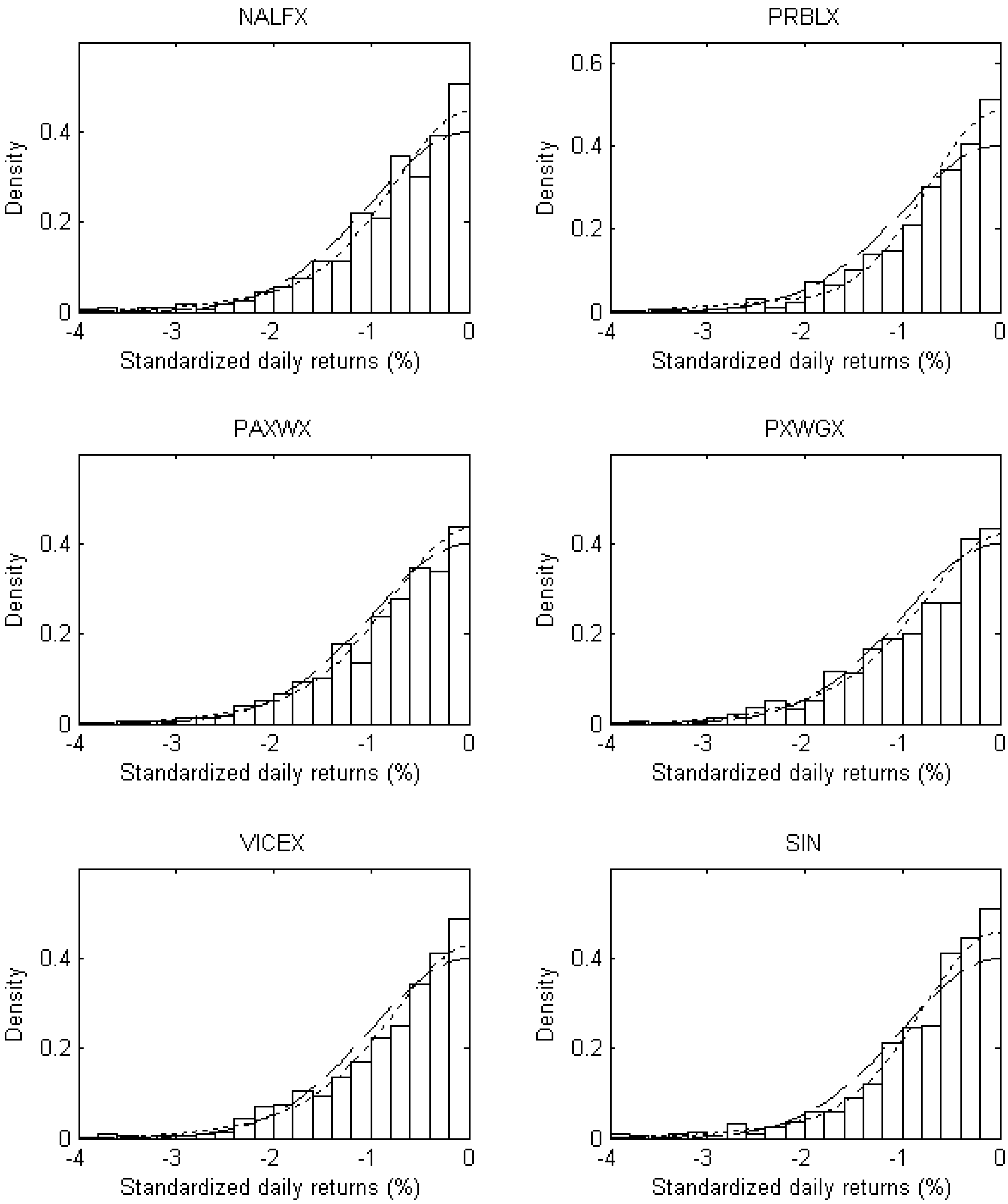
Table 4.5 shows the maximum likelihood estimates and 95% confidence interval estimates of the Gram-Charlier density for the standardized return distributions of reference portfolios. Virtually the estimated return distributions turn out to be negatively skewed (with the exception of ISE SINdex) and leptokurtic. Figure 4.1 visualizes the corresponding left-tailed distributions with ML parameter estimates. Consensus can be achieved by the graphical evidence that the Gram-Charlier density more adequately portrays the heavy-tailed idiosyncrasy the standard normal density renounces and further alleviates the spontaneous VaR underestimation phenomena inherent in the normality assumption efficaciously.

Table 4.5
Maximum likelihood estimates of the Gram-Charlier parameters

Ticker Symbol	*SK*	*KU*	95% confidence intervals *SK*	95% confidence intervals *KU*
SRI sample group				
CEGIX	-0.1385 (-1.6567)	0.8815 (5.0458)	[-0.3023, 0.0252]	[0.5390, 1.2240]
WAEGX	-0.1416 (-1.6958)	0.8740 (4.9914)	[-0.3052, 0.0220]	[0.5308, 1.2172]
DSEFX	-0.0379 (-0.4133)	1.4092 (8.1551)	[-0.2176, 0.1418]	[1.0706, 1.7478]
IMANX	-0.0440 (-0.4916)	1.3303 (7.5714)	[-0.2193, 0.1314]	[0.9860, 1.6746]
NBSRX	-0.1057 (-1.1876)	1.0114 (5.9146)	[-0.2802, 0.0687]	[0.6762, 1.3465]
NBSTX	-0.0792 (-0.8899)	1.0203 (5.9079)	[-0.2536, 0.0953]	[0.6819, 1.3587]
NALFX	-0.1344 (-1.5556)	0.9703 (5.5099)	[-0.3038, 0.0350]	[0.6252, 1.3155]
PRBLX	-0.0290 (-0.3190)	1.6973 (9.8110)	[-0.2071, 0.1491]	[1.3583, 2.0364]
PAXWX	-0.1214 (-1.4539)	0.7106 (4.0652)	[-0.2851, 0.0423]	[0.3680, 1.0533]
PXWGX	-0.2368 (-3.0127)	0.4694 (2.8414)	[-0.3907, 0.1457]	[-0.0828, 0.7931]
KLDDSI	-0.0071 (-0.0779)	1.3947 (8.0386)	[-0.1859, 0.1717]	[1.0547, 1.7347]
ASI sample group				
VICEX	-0.1861 (-2.2667)	0.5923 (3.4416)	[-0.3471, -0.0251]	[0.2549, 0.9297]
SIN	0.0153 (0.1777)	1.1541 (6.4619)	[-0.1535, 0.1841]	[0.8041, 1.5041]

This table displays the maximum likelihood estimates with asymptotic *t*-statistics in parentheses and the 95% confidence interval estimates of the Gram-Charlier density for the standardized daily return distributions of the reference portfolios. *SK* and *KU* are the estimated coefficients of skewness and excess kurtosis, respectively.


CEGIX
WAEGX
DSEFX
IMANX
NBSRX
NBSTX
returns histrogram
standard normal
Gram-Charlier
Density
Standardized daily returns (%)
0
0.2
0.4
0.6
-4
-3
-2
-1
0


NALFX
PRBLX
PAXWX
PXWGX
VICEX
SIN
Density
Standardized daily returns (%)
0
0.2
0.4
0.6
-4
-3
-2
-1
0

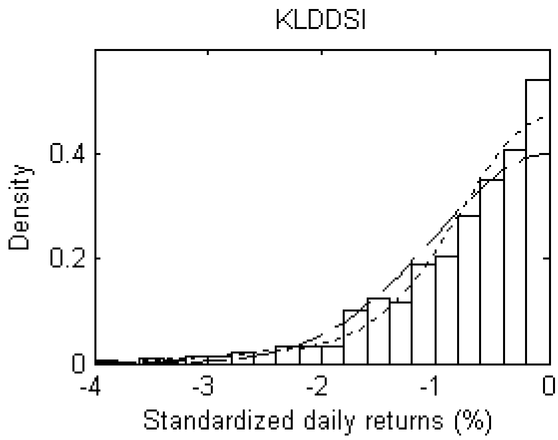


Figure 4.1
Graphical presentation of the left-tailed distributions using ML estimates

4.2 Empirical Performance Results

Table 4.6 draws forth the empirical performance correlation between reference portfolios and benchmark indices by conducting one-factor CAPM regression analysis. We find that 7 out of 11 SRI portfolios in the SRI sample group exhibit no statistically difference in beta-adjusted performance against the S&P 500 index whereas the entire ASI sample group outperforms the S&P 500 index significantly. The construction of a 'difference' portfolio, whose returns are synthesized by subtracting returns of the ASI sample group from those of the SRI sample group (subtraction by type), further reinforces the comparability between the two antithetic samples. The 'difference' portfolio unveils that the ASI sample group significantly achieves the average outperformance transcending its SRI opponent by approximately 8.08 percentage points per annum within the sample period. In line with previous researches the ASI sample group exhibits comparatively less exposure to the market fluctuations with its smallish beta coefficients. In the last column, we execute the joint test under the null hypothesis H_0: ($\alpha_i = 0$ and $\beta_i = 1$), equivalent to the spanning test proposed by Huberman and Kandel (1987), to investigate whether the returns on sample portfolios could be analogously attained by investing in their benchmark indices. The high degree of homogeneity amid the holding components justifies the non-rejection test outcomes for the Domini 400 Social Index and the Domini Social Equity Fund against the S&P 500. Another non-rejection result emerges from the PAX World Growth Fund. Additionally, we utilize the relevant industry indices for the two sample groups instead for the sake of preventing possible small-cap bias. Panel B of Table 4.6 presents this robustness-check result, where the return variations of Domini Social Equity Fund and Vice Fund are more progressively explained with the inclusion of relevant indices but others are inconspicuous.

Table 4.6

One-factor CAPM regression results

Panel A. Benchmark: S&P 500 Index

SRI sample group

Ticker Symbol	Alpha (%)		Beta		Adjusted R^2		Spanning test H$_0$: ($\alpha_i = 0$ and $\beta_i = 1$)	
	S&P 500	Difference	S&P 500	Difference	S&P 500	Difference	S&P 500	Difference
CEGIX	0.87	-7.63*	1.10***	0.35***	0.80	0.22	**	***
WAEGX	0.31	-8.18**	1.10***	0.35***	0.79	0.22	**	***
DSEFX	-0.54	-9.03**	1.00***	0.25***	0.97	0.18	not rejected	***
IMANX	1.18	-7.30**	0.96***	0.21***	0.92	0.12	**	***
NBSRX	4.95**	-3.55	0.89***	0.14***	0.87	0.05	***	***
NBSTX	4.70**	-3.78	0.88***	0.13***	0.87	0.05	***	***
NALFX	10.83**	2.46	0.68***	-0.07**	0.50	0.01	***	***
PRBLX	3.05	-5.30	0.77***	0.02	0.86	0.00	***	***
PAXWX	3.38**	-5.13*	0.61***	-0.14***	0.89	0.08	***	***
PXWGX	1.96	-6.43	0.96***	0.21***	0.68	0.08	not rejected	***
KLDDSI	-0.92	-13.18***	1.00***	0.26***	0.98	0.13	not rejected	***
ASI sample group								
VICEX	8.48**		0.75***		0.68		***	
SIN	12.58***		0.74***		0.56		***	

Panel B. Benchmark: Domini 400 Social Index and ISE SINdex

Ticker Symbol	Alpha (%)		Beta		Adjusted R^2		Spanning test H$_0$: ($\alpha_i = 0$ and $\beta_i = 1$)	
	KLDDSI	SIN	KLDDSI	SIN	KLDDSI	SIN	KLDDSI	SIN
CEGIX	2.00		1.08***		0.79		**	
WAEGX	1.45		1.08***		0.78		**	
DSEFX	0.40		1.00***		0.99		not rejected	
IMANX	2.19		0.94***		0.91		***	
NBSRX	5.88***		0.87***		0.86		***	
NBSTX	5.65**		0.87***		0.86		***	
NALFX	11.63**		0.66***		0.47		***	
PRBLX	3.85*		0.76***		0.85		***	
PAXWX	4.03***		0.59***		0.87		***	
PXWGX	2.98		0.93***		0.67		not rejected	
VICEX		-0.24		0.81***		0.77		***

This table presents the OLS estimates corrected with Newey–West heteroskedasticity and autocorrelation consistent standard errors over the 2002:09 – 2007:09 period using CAPM one-factor model. Difference stands for a portfolio whose returns are constructed by subtracting returns of the ASI sample group from those of the SRI sample group (subtraction by type). Spanning testing (Huberman and Kandel, 1987) is implemented to test the joint hypothesis H$_0$: ($\alpha_i = 0$ and $\beta_i = 1$). All the alphas are annualized via multiplying the daily alphas by 250. *, ** and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

Figure 4.2 illustrates the performance difference between the Domini 400 Social Index and the ISE SINdex by plotting its one-factor CAPM regression line. Through the illustration one can observe that the extent the ISE SINdex outperforms the Domini 400 Social Index will be linearly strengthened in a bear market and the outperformance will be linearly diminished as the market rallies into a bull one. When the annualized market risk premium is equal to zero, the ISE SINdex significantly achieves the average outperformance of 13.18 percentage points per annum beyond that of the Domini 400 Social Index. Once the annualized market risk premium is equal to 50.69 percentage points, there exists no performance difference between the two sample indices.

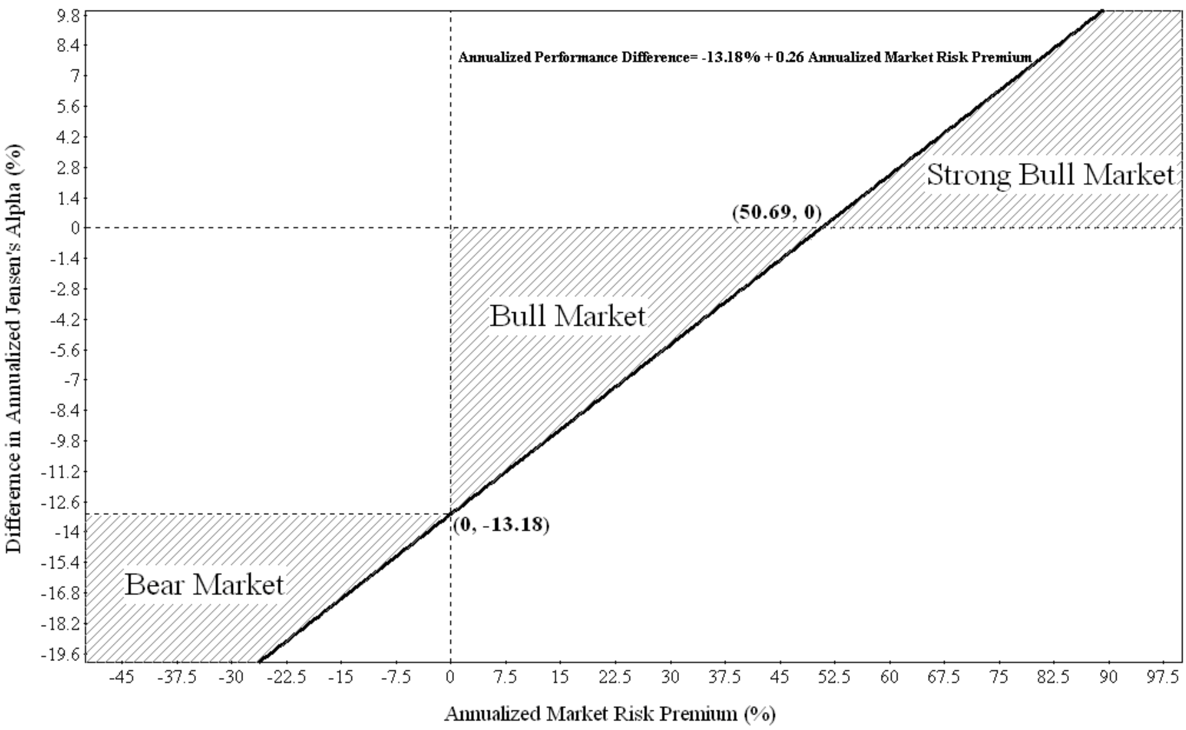


Figure 4.2
One-factor CAPM regression line —
Performance difference between Domini 400 Social Index and ISE SINdex

Table 4.7 reports the Sharpe performance result of the research samples using the traditional Sharpe index and the VaR-modified Sharpe index at four confidence levels. From Table 4.7 two conclusions can be drawn. Firstly, the traditional Sharpe index has a tendency to inflate the risk-adjusted returns on the research samples owing to the involvement of upside risks. The extrication of downside risk effects is conducive to bringing forth a more conservative and objective performance evaluation. The result of the Wilcoxon signed-rank test indicates that all the VaR-modified Sharpe index differs from the non-modified one significantly. In addition, under the framework using VaR to measure downside risks the magnitude of VaR-modified Sharpe index will vary with the selected VaR methodology and confidence levels. Secondly, regardless of how the Sharpe index is formularized the ISE SINdex in the index-type data coherently outperforms its counterpart, the Domini 400 Social Index, whereas some discrepancies exit in the performance inferences of the fund-type samples, which implies that the data type could potentially affect relevant inferences about the risk-adjusted performance of the two sample groups.

Table 4.8 summarizes the excess returns on the reference portfolios relative to the S&P 500. The *eVaRAR* at the four confidence levels calculated by the Variance-Covariance approach is equal to the *eSDAR* since the reduction fraction of normal quantiles in equation (3-11). The Wilcoxon signed-rank test indicates that the *eVaRAR* calculated by the Gram-Charlier parametric density estimation and the Monte Carlo Simulation at the 95% and 99% confidence level significantly differs from the *eSDAR* accommodating both upside risks and downside risks. After equalizing the risk loadings between reference portfolios and S&P 500, we find that the ISE SINdex in the index-type data still demonstrates consistent outperformance whereas some discrepancies exit in the outperformance of Vice Fund in the fund-type samples. Figure 4.3 exemplifies the ISE SINdex's case.

Table 4.7

Sharpe performance summary

Annualized Sharpe performance index																	
Mutual fund																	
		VaR-modified Sharpe index															
Ticker	Sharpe	Gram-Charlier				Variance-Covariance				Historical Simulation				Monte Carlo			
Symbol	index	α = 10%	α = 5%	α = 1%	α = 0.5%	α = 10%	α = 5%	α = 1%	α = 0.5%	α = 10%	α = 5%	α = 1%	α = 0.5%	α = 10%	α = 5%	α = 1%	α = 0.5%
CEGIX	0.4686	0.3963	0.2930	0.1845	0.1624	0.3657	0.2849	0.2015	0.1819	0.5119	0.3884	0.2418	0.2112	0.3729	0.2889	0.1973	0.1779
WAEGX	0.4352	0.3675	0.2717	0.1712	0.1507	0.3396	0.2646	0.1871	0.1690	0.4783	0.3581	0.2227	0.1955	0.3318	0.2718	0.1997	0.1816
DSEFX	0.4462	0.4383	0.3035	0.1541	0.1378	0.3482	0.2713	0.1918	0.1732	0.4800	0.3698	0.2263	0.1918	0.3614	0.2868	0.1998	0.1749
IMANX	0.5390	0.5008	0.3545	0.1953	0.1729	0.4206	0.3277	0.2317	0.2092	0.6091	0.4732	0.2830	0.2536	0.4727	0.3286	0.2181	0.2030
NBSRX	0.8314	0.7655	0.5486	0.3129	0.2750	0.6487	0.5055	0.3574	0.3228	1.0297	0.7404	0.4514	0.3885	0.6985	0.5453	0.3901	0.3528
NBSTX	0.8164	0.7537	0.5404	0.3068	0.2696	0.6370	0.4963	0.3509	0.3169	0.9676	0.7391	0.4404	0.3945	0.6487	0.5150	0.3661	0.3399
NALFX	**1.1345**	**1.0416**	**0.7111**	0.4134	0.3681	**0.8853**	**0.6897**	**0.4877**	**0.4404**	**1.8207**	**1.2050**	0.5743	0.4621	**0.9285**	**0.6981**	**0.5011**	**0.4714**
PRBLX	0.6896	0.7392	0.5116	0.2318	0.2087	0.5381	0.4193	0.2964	0.2677	0.8200	0.6143	0.3500	0.2862	0.5889	0.4534	0.3202	0.3080
PAXWX	0.8453	0.7237	0.5270	0.3318	0.2931	0.6596	0.5139	0.3634	0.3282	0.9089	0.6558	0.4207	0.3519	0.7270	0.5503	0.3933	0.3180
PXWGX	0.4866	0.3974	0.2954	0.1932	0.1715	0.3797	0.2958	0.2092	0.1889	0.5106	0.3597	0.2304	0.2119	0.3915	0.3070	0.2130	0.1902
VICEX	1.0690	0.9105	0.6621	**0.4210**	**0.3727**	0.8342	0.6499	0.4595	0.4150	1.4636	1.0558	**0.6318**	**0.5193**	0.8655	0.6870	0.4755	0.4352
Index																	
KLDDSI	0.4168	0.4057	0.2880	0.1466	0.1303	0.3253	0.2534	0.1792	0.1618	0.4498	0.3501	0.2136	0.1943	0.3260	0.2499	0.1859	0.1663
SIN	**1.2171**	**1.1088**	**0.7801**	**0.4592**	**0.4058**	**0.9497**	**0.7399**	**0.5232**	**0.4725**	**1.8560**	**1.2916**	**0.7366**	**0.6240**	**0.9908**	**0.7966**	**0.5678**	**0.5295**
Wilcoxon signed-rank test																	
Test statistics		4^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	9^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}	0^{***}

This table summarizes the Sharpe performance using the traditional Sharpe index and the VaR-modified Sharpe index at the 90%, 95%, 99% and 99.5% confidence level. The highest Sharpe index is marked in boldface under individual methodologies and data types. Wilcoxon signed-rank test serves to examine the null hypothesis that the difference between traditional Sharpe index and VaR-modified Sharpe index comes from a distribution with zero median. *** denotes significant at the 1% level.

Table 4.8

Relative excess performance summary

Ticker Symbol	*eSDAR*	*eVaRAR* Gram-Charlier α = 10%	Gram-Charlier α = 5%	Gram-Charlier α = 1%	Gram-Charlier α = 0.5%	Variance-Covariance α = 10%	Variance-Covariance α = 5%	Variance-Covariance α = 1%	Variance-Covariance α = 0.5%	Historical Simulation α = 10%	Historical Simulation α = 5%	Historical Simulation α = 1%	Historical Simulation α = 0.5%	Monte Carlo α = 10%	Monte Carlo α = 5%	Monte Carlo α = 1%	Monte Carlo α = 0.5%
Annualized *eSDAR* and *eVaRAR* relative to the S&P 500																	
Mutual fund																	
CEGIX	-0.25%	-1.17%	-0.81%	0.64%	0.53%	-0.25%	-0.25%	-0.25%	-0.25%	-0.45%	-0.41%	-0.22%	-0.01%	-0.35%	-0.15%	-0.40%	-0.61%
WAEGX	-0.72	-1.58	-1.25	0.10	0.00	-0.72	-0.72	-0.72	-0.72	-0.87	-0.91	-0.75	-0.51	-1.06	-0.54	-0.32	-0.49
DSEFX	-0.57	-0.57	-0.59	-0.59	-0.58	-0.57	-0.57	-0.57	-0.57	-0.85	-0.72	-0.65	-0.63	-0.55	-0.20	-0.32	-0.72
IMANX	0.74	0.32	0.46	1.08	1.01	0.74	0.74	0.74	0.74	0.76	0.99	0.90	1.36	1.38	0.77	0.28	0.26
NBSRX	4.84	4.10	4.44	5.84	5.64	4.84	4.84	4.84	4.84	6.00	5.40	5.50	5.72	5.31	5.78	5.88	5.49
NBSTX	4.63	3.93	4.27	5.59	5.39	4.63	4.63	4.63	4.63	5.23	5.38	5.20	5.91	4.44	5.08	5.10	5.04
NALFX	**9.09**	**8.04**	**7.78**	9.91	9.85	**9.09**	**9.09**	**9.09**	**9.09**	**15.85**	**13.08**	8.86	8.10	**9.30**	**9.31**	**9.50**	**9.64**
PRBLX	2.85	3.72	3.68	2.56	2.63	2.85	2.85	2.85	2.85	3.39	3.32	2.73	2.41	3.40	3.65	3.60	3.93
PAXWX	5.04	3.50	4.00	6.60	6.45	5.04	5.04	5.04	5.04	4.50	4.01	4.66	4.53	5.80	5.89	5.99	4.28
PXWGX	0.00	-1.16	-0.76	1.00	0.94	0.00	0.00	0.00	0.00	-0.47	-0.89	-0.54	0.01	-0.03	0.27	0.11	-0.18
VICEX	8.18	6.17	6.77	**10.22**	**10.06**	8.18	8.18	8.18	8.18	11.40	10.6	**10.42**	**9.94**	8.21	9.05	8.67	8.37
Index																	
KLDDSI	-0.98	-1.04	-0.91	-0.89	-0.92	-0.98	-0.98	-0.98	-0.98	-1.22	-1.04	-0.99	-0.55	-1.16	-1.05	-0.77	-1.02
SIN	**10.25**	**9.00**	**9.20**	**11.76**	**11.56**	**10.25**	**10.25**	**10.25**	**10.25**	**16.29**	**14.51**	**13.29**	**13.32**	**10.38**	**11.59**	**11.67**	**11.66**
Wilcoxon signed-rank test																	
Test statistics		6***	11**	4***	4***	-	-	-	-	27.5	29	37	25	28	2***	9***	31

This table displays the annualized *eSDAR* and *eVaRAR* at the 90%, 95%, 99% and 99.5% confidence level. The highest *eSDAR* or *eVaRAR* is marked in boldface under individual methodologies and data types. Wilcoxon signed-rank test serves to examine the null hypothesis that the difference between *eSDAR* and *eVaRAR* comes from a distribution with zero median. ** and *** denote significant at the 5% and 1% level, respectively.

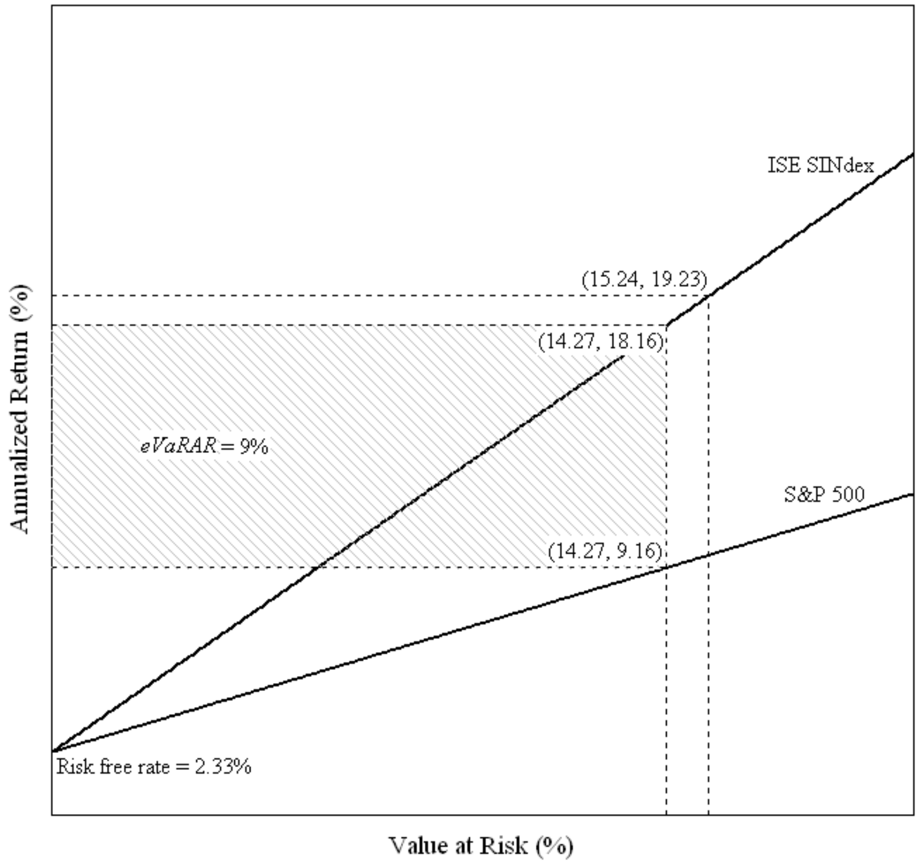


Figure 4.3
The *eVaRAR* of the ISE SINdex relative to the S&P 500

The figure illustrates the *eVaRAR* measured by the Gram-Charlier parametric density model at the 90% confidence level relative to the S&P 500. When the SINdex return is deleveraged to have the S&P 500's VaR (14. 27 percent), its annualized return declines form 19.23 percent to 18.16 percent, approximately 9 percent higher than the 9.16 percent return the S&P 500 renders per annum averagely.

Chapter 5 Conclusions

Socially responsible investing has gained its popularity whether in the global asset management industry or academic communities. This paper contributes to the literature's scarcity on socially responsible investing versus anti-social investing as it explores the downside risk and return properties of related portfolios in the United States. Furthermore, it provides for a more accurate VaR estimation technique, bolstering the prevalent VaR methodology.

Through the analysis of VaR exceptions and average failure bias, the SRI sample group generally embraces higher permeation of downside risks, whereas the ASI sample group possesses superior returns and comparatively lower downside risks. In the risk-adjusted performance analysis, Jensen's (1968) alpha, VaR-modified Sharpe index and excess VaR-adjusted return are taken into the performance assessment process. The empirical result from the CAPM regression shows that the entire ASI sample group outperforms the S&P 500 index significantly while 7 out of 11 SRI portfolios in the SRI sample group exhibit no statistically difference in beta-adjusted performance against the S&P 500 index. Moreover, the outperformance of the ISE SINdex against the Domini 400 Social Index will be linearly strengthened in a bear market and be linearly diminished as the market rallies into a bull one.

The empirical result from the Sharpe performance index and the relative excess performance shows that the ISE SINdex in the index-type data consistently demonstrates risk-adjusted outperformance regardless of how the performance evaluation formula are specified, whereas there exist some discrepancies about risk-adjusted performance inferences in the fund-type data, indicating that different data type leads to variant downside risk and performance inferences. Given the pure properties of index data, using representative indices to conduct empirical research is recommended. Furthermore, traditional performance indicators taking downside risks and upside risks into consideration are more prone to performance inflation. Specifically, the result of the Wilcoxon signed-rank test indicates that the VaR-modified performance differs from the non-modified one significantly.

Viewed with aspects on VaR modelling, the Gram-Charlier parametric density model is confirmed to be immune from risk underestimation the Variance-Covariance approach suffers, misspecified single scenario the Historical Simulation incurs and time-consuming computations the Monte Carlo simulation requests without being deprived of model accuracy and efficiency at high confidence levels, possessing superior competence for capturing heavy-tailed idiosyncrasy of financial asset returns.

Attendant restrictions on the sample period and methodology lead to some noteworthy questions: Does the predominant performance persist with the anti-social investing strategy in a market downturn? Do the specification of dynamic parameters such as conditional moments in the Gram-Charlier parametric density model and the use of other types of Gram-Charlier density provide the icing on the cake? Further investigation and research agenda are warranted.

References

Alexander, C. O. and C. T. Leigh (1997), "On the Covariance Matrices Used in Value at Risk Models," *Journal of Derivatives*, Vol. 4, pp. 50-62.

Barton, D. E. and K. E. R. Dennis (1952), "The Conditions under which Gram-Charlier and Edgeworth Curves are Positive Definite and Unimodal," *Biometrika*, Vol. 39, PP. 425-427.

Bauer, R., K. Koedijk and R. Otten (2005), "International Evidence on Ethical Mutual Fund Performance and Investment Style," *Journal of Banking and Finance*, Vol. 29, pp. 1751-1767.

Beder, T. S. (1995), "VaR: Seductive but Dangerous," *Financial Analysts Journal*, Vol. 51, pp. 12-24.

Charlier, C. V. L. (1905), "Uber Die Darstellung Willkurlicher Funktionen," *Arvik fur Mathematik Astronomi och Fysik*, Vol. 9, pp. 1-13.

Chong, J., M. Her and M. Philips (2006), "To Sin or Not to Sin? Now That's the Question," *Journal of Asset Management*, Vol. 6, pp. 406-417.

Corrado, C. J. and T. Su (1996), "Skewness and Kurtosis in S&P 500 Index Returns Implied by Option Prices," *Journal of Financial Research*, Vol. 19, pp. 175-192.

Dillenburg, S., T. Greene and H. Erekson (2003), "Approaching Socially Responsible Investment with a Comprehensive Ratings Scheme: Total Social Impact," *Journal of Business Ethics*, Vol. 43, pp. 167-177

Diltz, J. D. (1995), "The Private Cost of Socially Responsible Investing," *Applied Financial Economics*, Vol. 5, pp. 69-77.

Dowd, K. (1999), "A Value at Risk Approach to Risk-Return Analysis," *Journal of Portfolio Management*, Vol. 25, pp. 60-67.

Dowell, G., S. Hart and B. Yeung (2000), "Do Corporate Global Environment Standards Create or Destroy Market Value?," *Management Science*, Vol. 46, pp. 1059-1074.

Duffie, D. and J. Pan (1997), "An Overview of Value at Risk," Journal of Derivatives, Vol. 4, pp. 7-49.

Geczy, C., R. Stambaugh and D. Levin (2005), "Investing in Socially Responsible Mutual Funds," *Working paper*, Wharton School.

Goorbergh, R.V.D., and P. Vlaar (1999), "Value-at-Risk Analysis of Stock Returns Historical Simulation, Variance Techniques or Tail Index Estimation," *DNB Staff Reports 40*, Netherlands Central Bank

Gram, J. P. (1884), "Undersøgelser angaaende Maengden af Primtal under en given Graeense," *Det K. Videnskabernes Selskab*, Vol. 2, pp. 183-308.

Hamilton, J. (1995), "Pollution as News: Media and Stock Market Reactions to the Toxics Release Inventory Data," *Journal of Environmental Economics and Management*, Vol. 28, pp. 98-113.

Hamilton, S., H. Jo and M. Statman (1993), "Doing Well While Doing Good? The Investment Performance of Socially Responsible Mutual Funds," *Financial Analysts Journal*, Vol. 49, pp.62-66.

Hendricks, D. (1996), "Evaluation of Value-at-Risk Models Using Historical Data," *Economic Policy Review*, Vol. 2, pp. 39-69.

Huberman, G. and S. Kandel (1987), "Mean-Variance Spanning," *Journal of Finance*, Vol. 42, pp. 873-888.

Hull, J. and A. White (1998), "Value at Risk When Daily Changes in Market Variables Are Not Normally Distributed," *Journal of Derivatives*, Vol. 5, pp. 9-19.

Jarrow, R. and A. Rudd (1982), "Approximate Option Valuation for Arbitrary Stochastic Process," *Journal of Financial Economics*, Vol. 10, pp. 347-369.

Jackson, P., D. Maude, and W. Perraudin (1997), "Bank Capital and Value-at-Risk," *Journal of Derivatives*, Vol. 4, pp. 73-90.

Jensen, R. D. (1968), "The Performance of Mutual Funds in the Period 1945-64," *Journal of Finance*, Vol. 23, pp. 389-416.

Jondeau, E. and M. Rockinger (2001), "Gram-Charlier Densities," *Journal of Economic Dynamics and Control*, Vol. 25, pp. 1457-1483.

Jorion, P. (2000), *Value at risk*: *The New Benchmark for Managing Financial Risk*, McGraw-Hill.

Kahneman, D. and A. Tversky (1979), "Prospect Theory: An Analysis of Decision under Risk," *Econometrica*, Vol.47, pp. 263-291.

Kupiec, P. H. (1995), "Techniques for Verifying the Accuracy of Risk Measurement Models," *Journal of Derivatives*, Vol. 3, pp. 73-84.

Lintner, J. (1965), "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets," *Review of Economics and Statistics*, Vol. 47, pp. 13-37.

Mauleón, I. and J. Perote (2000), "Testing Densities with Financial Data: An Empirical Comparison of the Edgeworth-Sargan Density to the Student's t," *European Journal of Finance*, Vol. 6, pp. 225-239.

Pritsker, M. (1997), "Evaluating Value at Risk Methodologies: Accuracy versus Computational Time," *Journal of Financial Services Research*, Vol. 12, pp. 201-242.

Renneboog, L., J. Ter Horst and C. Zhang (2008a), "Socially Responsible Investments: Institutional Aspects, Performance, and Investor Behavior," *Journal of Banking and Finance*, Vol. 32, pp. 1723-1742.

Renneboog, L., J. Ter Horst and C. Zhang (2008b), "The Price of Ethics and Stakeholder Governance: The Performance of Socially Responsible Mutual Funds," *Journal of Corporate Finance*, Vol. 14, pp. 302-322.

Rubinstein, M. (1998), "Edgeworth Binomial Trees," *Journal of Derivatives*, Vol. 5, pp. 20-27.

Sargan, J. D. (1975), "Gram-Charlier Approximations Applied to t Ratios of k-Class Estimators," *Econometrica*, Vol. 43, pp. 327-347.

Schröder, M. (2007), “Is There a Difference? The Performance Characteristics of SRI Equity Indices,” *Journal of Business Finance and Accounting*, Vol. 34, pp. 331-348.

Schwager, J. (1985), “Alternative to Sharpe Ratio Better Measure of Performance,” *Futures: The Magazine of Commodities & Options*, Vol. 14, pp. 56-58.

Shank, T., D. Manullang and R. Hill (2005), “Is it Better to be Naughty or Nice?,” *Journal of Investing*, Vol. 14, pp. 82-87.

Sharpe, W. F. (1964), “Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk,” *Journal of Finance*, Vol.19, pp. 425-442.

Statman, M. (1987), “How Many stocks Make a Diversified Portfolio?,” *Journal of Financial and Quantitative Analysis*, Vol. 22, pp. 353-363.

Statman, M. (2000), “Socially Responsible Mutual Funds,” *Financial Analysts Journal*, Vol. 56, pp. 30-39

Statman, M. (2006), “Socially Responsible Indexes,” *Journal of Portfolio Management*, Vol. 32, pp. 100-109.

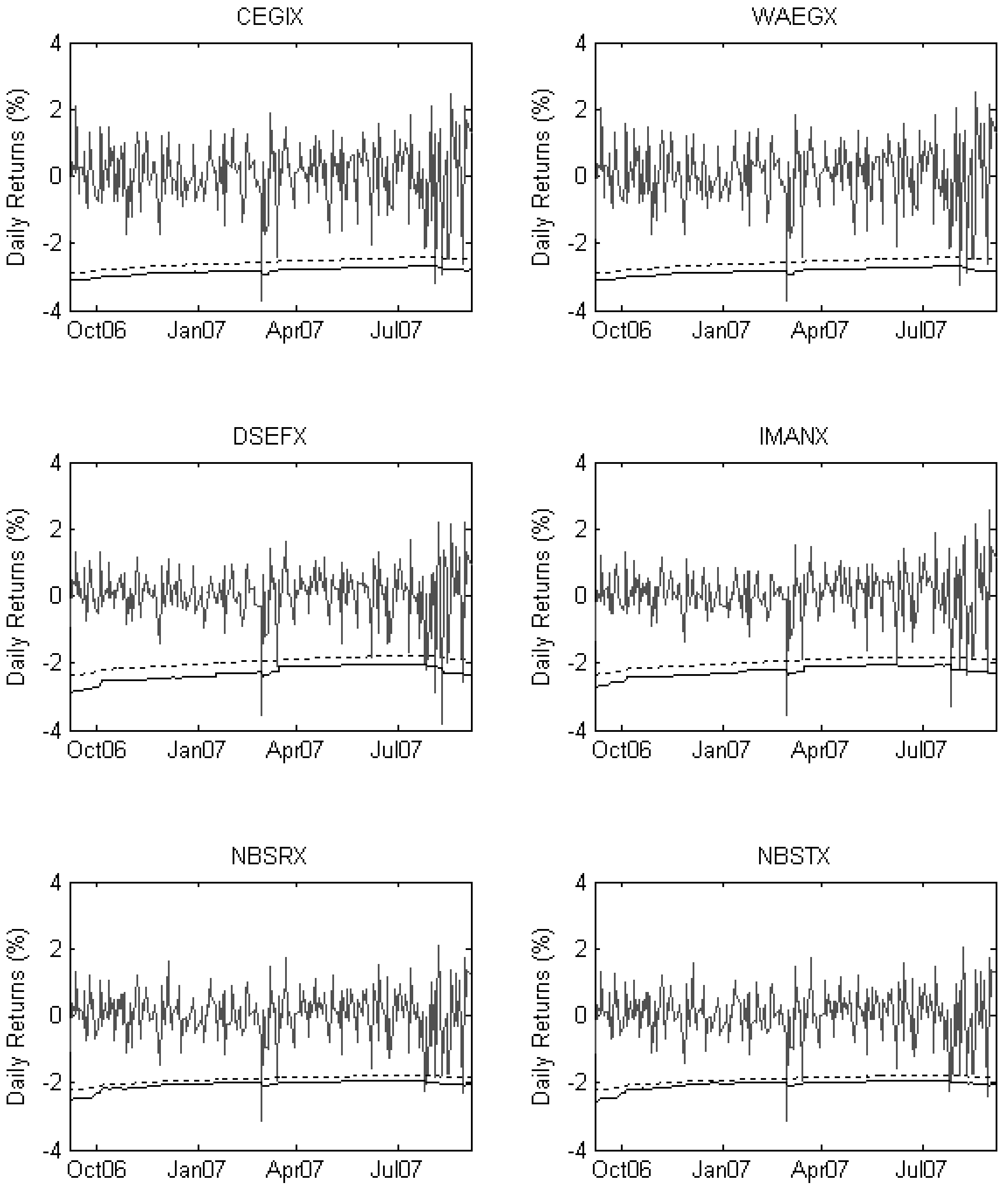
Verhoeven, P. and M. McAleer (2004), “Fat Tail and Asymmetry in Financial Volatility Models,” *Mathematics and Computers Simulation*, Vol. 64, pp. 351-362.

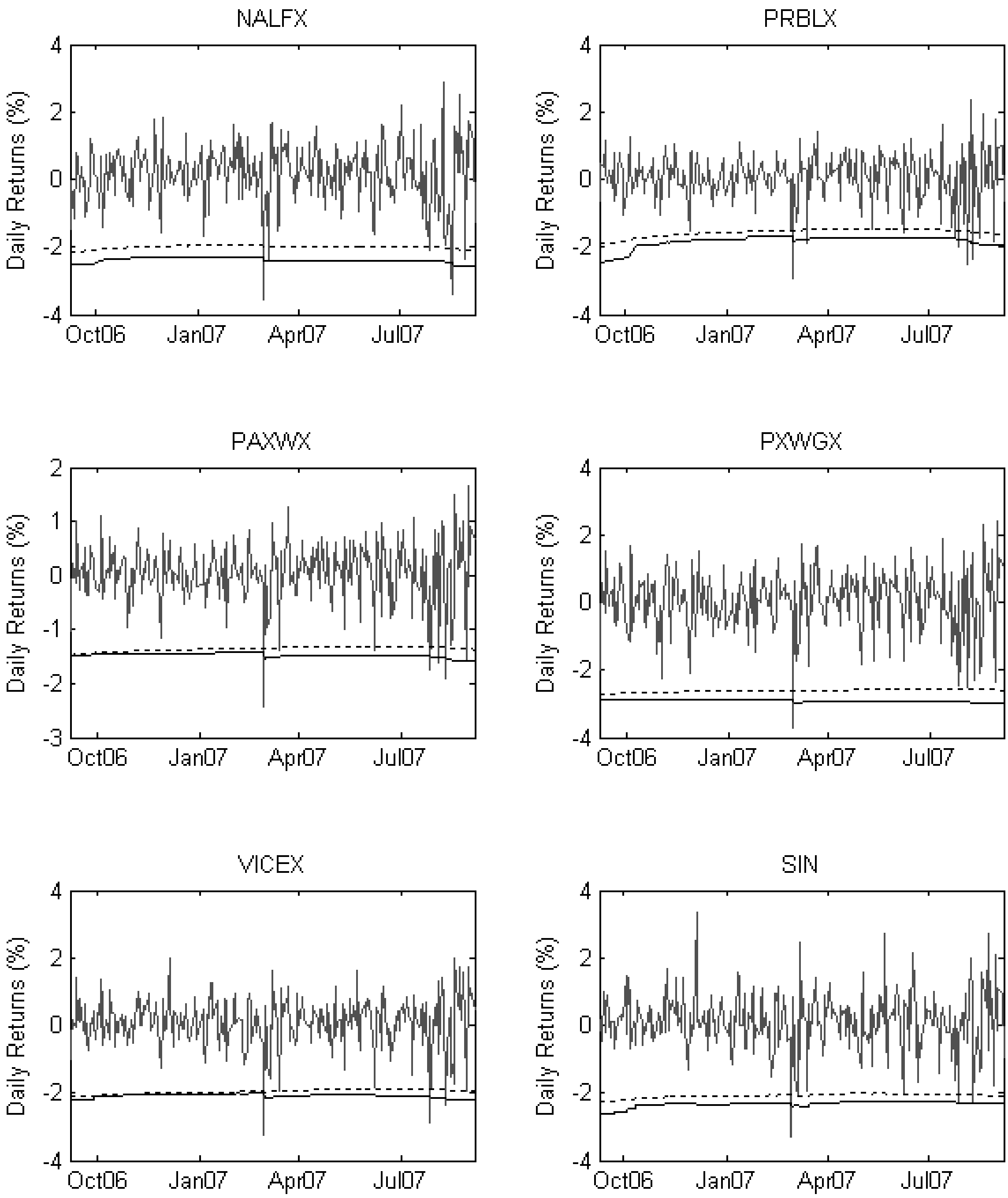
Vlaar, P. (2000), “Value at Risk Models for Dutch Bond Portfolios,” *Journal of Banking and Finance*, Vol. 24, pp. 1131-1154.

Waxler, C. (2004), *Stocking Up on Sin: How to Crush the Market with Vice-based Investing*,

John Wiley and Sons.

Appendix


CEGIX
WAEGX
DSEFX
IMANX
NBSRX
NBSTX
Daily Returns (%)
4
2
0
-2
-4
Oct06
Jan07
Apr07
Jul07


NALFX
PRBLX
PAXWX
PXWGX
VICEX
SIN
Daily Returns (%)
Oct06
Jan07
Apr07
Jul07

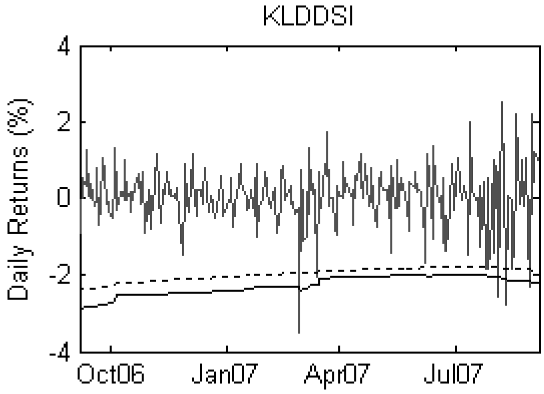
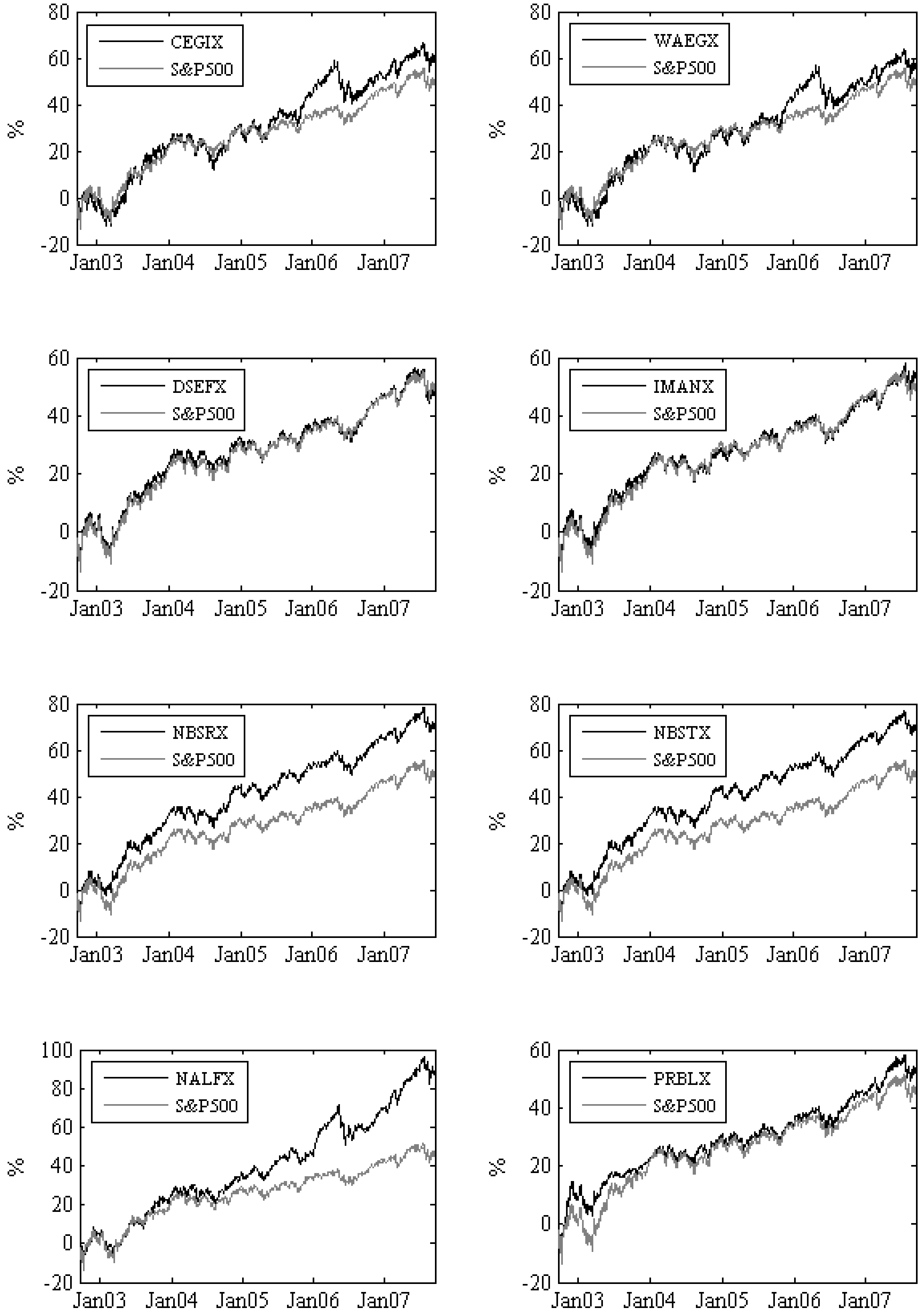


Figure A.1

The comparison of Gram-Charlier VaR forecasts (solid line) and Variance-Covariance VaR forecasts (dashed line) at the 99.5% confidence level


CEGIX
S&P500
WAEGX
S&P500
DSEFX
S&P500
IMANX
S&P500
NBSRX
S&P500
NBSTX
S&P500
NALFX
S&P500
PRBLX
S&P500
%
Jan03 Jan04 Jan05 Jan06 Jan07

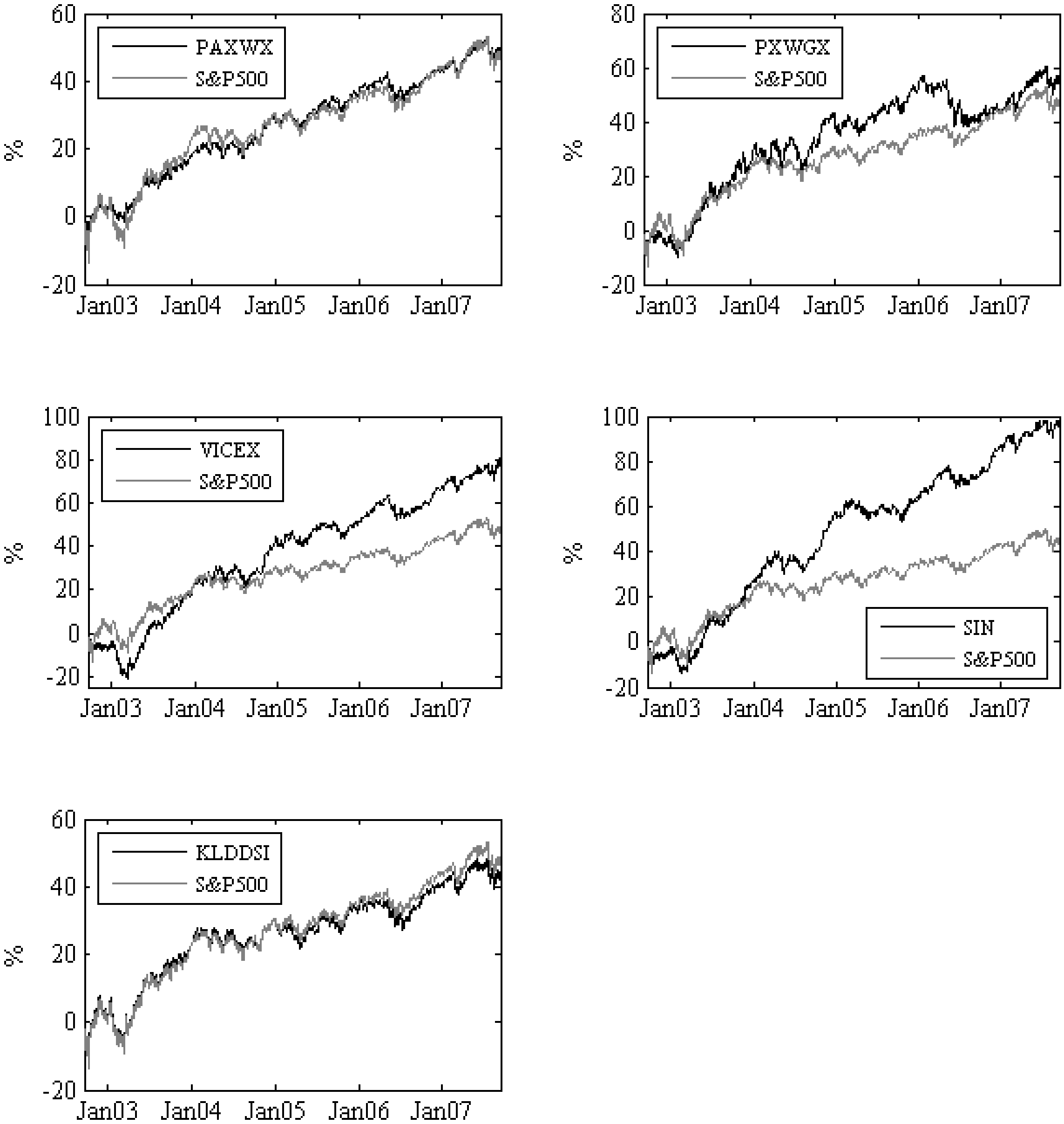


Figure A.2

Cumulative daily log returns, 16th September, 2002 –16th September, 2007