ความสามารถในการทำนายความสามารถกองทุน
และ ความต่อเนื่องระยะสั้นของความสามารถกองทุน
โดยเบเซียนแอลฟา ในตลาดสหราชอาณาจักร

นาย ธาริน อรรถจริยา

วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2552

Bayesian Alphas Predictability and Short-run Persistence of the UK market

Mr. Tarrin Attachariya

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science Program in Finance
Department of Banking and Finance
Faculty of Commerce and Accountancy
Chulalongkorn University
Academic Year 2009

Thesis Title	BAYESIAN ALPHAS PREDICTABILITY AND SHORT-RUN PERSISTENCE OF THE UK MARKET
By	Tarrin Attachariya
Field of Study	Finance
Thesis Advisor	Associate Professor Sunti Tirapat, Ph.D

Accepted by the Faculty of Commerce and Accountancy, Chulalongkorn University in Partial Fulfillment of the Requirements for the Master's Degree

.... Dean of the Faculty of Commerce and Accountancy

(Associate Professor Annop Tanlamai Ph.D.)

THESIS COMMITTEE

.... Chairman

(Assistant Professor Seksan Kiatsupaibul Ph.D.)

.... Thesis Advisor

(Associate Professor Sunti Tirapat Ph.D.)

.... External Examiner

(Sanphet Sukhapesna Ph.D.)

ธาริน อรรถจริยา : ความสามารถในการทำนายความสามารถกองทุน และ ความต่อเนื่องระยะสั้นของความสามารถกองทุน โดยเบเซียนแอลฟา ในตลาดสหราชอาณาจักร. (BAYESIAN ALPHAS PREDICTABILITY AND THE SHORT-RUN PERSISTENCE OF THE UK MARKET) อ.ที่ปรึกษาวิทยานิพนธ์หลัก : รศ.ดร.สันติ ถิรพัฒน์, 46 หน้า.

วิทยานิพนธ์ฉบับนี้ทำการทดสอบว่า การวัดประสิทธิภาพของการจัดการกองทุนด้วยเบเซียนแอลฟาซึ่งคำนวณโดยวิธีการแบบเบเซียนสามารถทำนายประสิทธิภาพการจัดการกองทุนล่วงหน้าในระยะสั้นๆได้ดีกว่าวิธีการแบบดั้งเดิมหรือไม่ ภายใต้ข้อมูลของตลาดกองทุนรวมในสหราชอาณาจักร อนึ่ง วิธีการวัดประสิทธิภาพที่กล่าวถึงนี้ ได้นำข้อมูลผลตอบแทนของปัจจัยนอกเหนือจากปัจจัยอ้างอิงที่ใช้กันทั่วไปแต่มีความเกี่ยวพันกับผลตอบแทนของกองทุนรวมมาร่วมในคำนวณ และข้อมูลของค่าใช้จ่ายของกองทุนมาประกอบในสมมติฐานสำหรับการคำนวณแบบเบเซียนด้วย ด้วยวิธีการเช่นนี้เบเซียนแอลฟาควรจะเพิ่มความสามารถในการทำนายให้มากกว่าแบบดั้งเดิมได้ อย่างไรก็ตามผลจาการทดสอบก็พบว่า ทั้งวิธีการแบบเบเซียน และแบบดั้งเดิมนั้น กลับให้ผลที่ไม่แตกต่างกันมาก นอกจากนี้ เมื่อทดลองนำประสิทธิภาพการจัดการกองทุน ที่วัดได้ด้วยวิธีการทั้งแบบเบยส์และแบบดั้งเดิมมาใช้เป็นมาตรฐานในการจัดพอร์ตการลงทุน ผลปรากฏว่า ประสิทธิภาพในการบริหารพอร์ตการลงทุนที่อ้างอิงทั้งสองวิธีนั้นกลับมีค่าเป็นลบ ทั้งที่มีผลการศึกษาก่อนหน้านี้ระบุว่า เบเซียนแอลฟาสามารถเพิ่มความสามารถในการทำนายประสิทธิภาพการจัดการกองทุนล่วงหน้าได้อย่างมีนัยสำคัญภายใต้ตลาดสหรัฐอเมริกา แต่เมื่อนำมาปรับใช้ในตลาดสหราชอาณาจักรแล้ว ผลที่ได้กับไม่ดีนัก ซึ่งน่าจะเป็นผลมาจากสภาพตลาดที่ต่างกัน โดยหลักฐานอันน่าจะบ่งชี้ถึงความต่างนี้ก็คือ ในตลาดสหรัฐอเมริกา ข้อมูลค่าใช้จ่ายของกองทุนสามารถบทำนายประสิทธิภาพการจัดการกองทุนล่วงหน้าในระยะสั้นได้ดีในระดับหนึ่ง แต่กลับไม่มีความสามารถนี้ในตลาดอังกฤษ โดยสรุปแล้วเมื่อพิจารณาจากผลการทดสอบ การวัดประสิทธิภาพในการจัดการกองทุนของกองทุนรวมด้วยเบเซียนแอลฟา ซึ่งมีวิธีการคำนวณที่ซับซ้อนกว่าแบบดั้งเดิมนั้น จึงไม่คุ้มค่าที่จะทำ

ภาควิชาการธนาคารและการเงิน	ลายมือชื่อนิสิต
สาขาวิชาการเงิน	ลายมือชื่ออ.ที่ปรึกษาวิทยานิพนธ์หลัก
ปีการศึกษา 2552	

5082154926 : MAJOR FINANCE
KEYWORDS : BAYESIAN / ALPHA / UNIT TRUST / MUTUAL FUND / PERFORMANCE PERSISTENCE / PERFORMANCE PREDICTABILITY / UNITED KINGDOM / ENGLAND

TARRIN ATTACHARIYA : BAYESIAN ALPHAS PREDICTABILITY AND THE SHORT-RUN PERSISTENCE OF THE UK MARKET. THESIS ADVISOR: ASSOC. PROF SUNTI TIRAPAT, 46 pp.

This thesis examines the ability of the Bayesian alpha, as an alternative of the frequentist alpha, to predict the UK unit trust short-run future performance. By incorporating the returns on passive non-benchmark assets that correlate with the unit trust holding and an additional information—the fund expense given to the prior distribution, the Bayesian alpha is expected to improve the predictability from the frequentist one. However, the results show that the difference in predictabilities of the Bayesian and frequentist measures is small. An additional test also shows that portfolios formed using either the Bayesian or the frequentist alpha as the selection criteria tend to similarly have abnormal losses in the subsequent years. While earlier studies suggest that using the Bayesian alpha can significantly improve the performance predictability in the US market, this study finds that, when applied to the UK market, the improvement is poor. The difference in the improvement between the US and the UK market might be due to the different environments of the two markets. A possible evidence that demonstrates the difference between the market environments is the fund expense that can provide a moderate short-run performance predictability in the US market but not in the UK market. The results from this study suggest that the Bayesian alpha is not suitable to be used to measure the unit trust performance in the UK.

Department : Banking and Finance	Student's Signature
Field of Study : Finance	Advisor's Signature
Academic Year : 2009	

Acknowledgements

This thesis would not have been accomplished without suggestions and supervisations from the following individuals: my thesis advisor, Associate Professor Dr. Sunti Tirapat; Assistant Professor Dr. Seksan Kiatsupaibul, who gave me a lot of wonderful advices about Bayesian econometrics.

I am grateful for Mr. Jaturachet Niltawat for many useful suggestions about fund performance especially in UK, and prove reading my thesis report. Mr. Than Kotchasansaeree, and my friend, Mr. Benz Sudta also helped me a lot in teaching me how to use VBA and gathering essential data in this thesis. Sudta

Lastly, I would like to thank my family included parents, who always encourage me to be hard working and never give up on any impediments on this path to success. I am thankful for my brother, Kiattipong, who have never complained when helping me prove read my thesis proposal.

Contents

List of Tables

List of Figures

Chapter 1
Introduction

1.1 Background and problem review

Performance measurement is an essential constituent of the asset management industry. From thousands of mutual funds in the market, investors will seek the best performing mutual funds to allocate their assets. Since late 1960s, funds performance had been measured by alpha, the intercept from the linear regression of asset excess return against factors, which indicate the abnormal return apart from returns from taking risk. The performance literature generally believes that this abnormal return can represent fund managerial skill. The age of modern finance literatures starts with Jensen (1968, 1969)'s concept of the alpha, regressing an asset return against market (return) factor. Then, Fama and French (1993) showed that their three-factor model with additional risk factors; size and book-to-market equity outperforms the existing CAPM model. Jeegadeesh and Titman (1993), and Carhart (1997) added more risk factors to the model, making it the "four-factor model".

Later, many of advanced measures of mutual funds performance are invented. Daniel, Grinblatt, Titman and Wermers (1997) decompose the abnormal return into timing and stock picking skills and find some stock selection ability from their fund samples. Wermers (2000), again, breaks down the mutual fund abnormal return into stock holding, expensed ratio, and transaction cost and finds evidence that supports the value of active mutual fund management. Determination of above fund performance is based on OLS estimation of factors model regression. Anyway, Baks, Metrick and Wachter (2001) introduce Bayesian estimation to measure alphas. Then, Pástor and Stambaugh (2002) incorporate "seemingly unrelated assets" through the Bayesian framework to create a new advanced mutual fund performance measure named "Bayesian Alpha". Consequently, many academic researches amend the Bayesian methodology to investigate other issues in mutual fund performance. Busse and Irvine (2006) examine the contribution of Pástor and Stambaugh framework adding to performance predictability, while Jones and Shanken (2005) use the Bayesian framework to incorporate prior beliefs about the aggregate performance of mutual fund manager to estimate fund performance.

It is obvious that measuring the persistence of mutual funds performance had been the goal of many academic researches for many decades. Active management fund managers are expected to consistently outperform a benchmark. Investors have to rely on the past performance to make their investment choice. The asset managers also rely on this past performance to demonstrate their abilities to generate excess return, i.e. positive alpha. But only alpha is insufficient to satisfy investing in any funds since the performance of the fund may not persist through time. This is because, apart from alpha, investors also care about the mutual fund performance persistence that evaluates an ability to carry on the performance. Issues surrounding the mutual funds performance persistence have been investigated by Brown and Goetzmann (1995), Carhart (1997), Elton, Gruber, and Blake (1996), Goetzmann and Ibbotson (1994), Grinblatt and Titman (1992), Hendrick, Patel, and Zeckhauser (1993), and Malkiel (1995), for the total returns persistency over time periods ranging from 10 to 31 years. Brown and Goetzmann (1995) find that relative risk-adjusted performance of mutual funds persists but that the persistence is mostly due to funds that lag the S&P 500. Malkiel (1995) finds that funds in the aggregate have underperformed benchmark portfolios even before deduction of expenses. Elton, Gruber, and Blake (1996) find that risk-adjusted performance tends to persist. Carhart demonstrates that common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted returns. On the other hand, Sirri and Tufano (1998), and Berk and Green (2004) found the relationship between the past performance and the subsequent fund flows that cause the performance persistence to dissipate quickly. More recently, Bollen and Busse (2005) examine the relationship between past and future performance, after that, they found the short-run persistence in superior performance beyond expense and momentum across quarterly period. Huij and Verbeek (2007) incorporate the empirical Bayes approach, using monthly data to support the existence of the short-run persistence.

However, the studies discussed above only focus on US market which is the largest market. Empirical evidence of persistence is still limited outside USA. Nonetheless, a number of studies have emerged to examine the persistence of the UK fund performance. The importance question is whether the mutual fund performance persistence also exists in other markets. In 2002, Charles River Associate's report, "Performance persistence in UK equity funds", demonstrates that the answer is inconclusive by reviewing contemporary academic literatures about the existence of the performance persistence in UK. The report briefs that Quigley and Sinquefield (1998), Blake and Timmerman (1998), Allen and Tan (1999) find evidences of performance persistence, while Fletcher (1999) and Rhode (2000) find no persistence in UK market. The question about the existence of fund performance persistence in the UK still remains. More recently, Fletcher and Forbes (2002) find significant persistence of UK unit trusts, when performance is evaluated relatively to a model based on CAPM (the Capital Asset Pricing Model, introduced by Jensen), but the persistence is eliminated when performance is evaluated relatively to the Four-Factor model. They also sum up an interesting difference between UK and US researches. In the UK, the persistence is largely from repeated underperformance relative to the benchmark.

Ones could notice that the literatures investigating the persistence in UK unit trusts performance prior to 2003 mostly use the methodology of Brown's and Goetzmann's (1995) as well as Carhart's (1997). Even though researchers start using more Bayesian econometrics in fund performance measurement, there has not been any study which employs this technique to recheck the fund performance persistence in the UK. Therefore, my question is whether the use of Bayesian frameworks, instead of ordinary econometrics methodology, can also provide a better results in the UK market even though the nature of the market is different from the US.

This dissertation attempts to re-examine the unit trust performance persistence in the UK. I begin by constructing daily eight passive assets which will be used in calculating both Bayesian and frequentist alphas. Using the methodology of Busse and Irvine (2006), the Bayesian and frequentist alphas are calculated and sorted into decile ranks. Then, the performance predictabilities of the Bayesian and frequentist alphas are examined. Also, to support the results from the above test, whether the performance persistence exists or not, I also assess the abnormal return of the decile portfolios which annually constructed based on Bayesian and frequentist alphas.

1.2 Objectives

1. To apply Busse and Irvine (2006) procedure to determine the Bayesian alpha in the UK market.
2. To test whether Bayesian alpha predicts the future funds performance more precisely than the frequentist one.
3. To examine whether portfolios constructed based on the Bayesian alpha provide higher abnormal returns than portfolio based on the frequentist alpha.

1.3 Scope of the study

This thesis focuses on only domestic unspecialized equity unit trusts sold in London Stock Exchange (LSE), using their historical data of 10 years. For the data on factors used to estimate the alphas, I use the historical data of all shares sold in the UK for the past 15 years to take an advantage of using the Bayesian estimation.

1.4 Contributions

Using the data of domestic equity unit trusts of the UK market and the same methodology from Busse and Irvine (2006), this paper seeks to strengthen the international out-of-sample evidence of the benefit of using Bayesian framework to estimate the fund excess returns compared to the frequentist measurement, as well as to re-examine the existence of fund performance persistence in the UK market.

Chapter 2
Literature Review

The academic literatures related to mutual fund mostly concern with the performance measurement and whether the performance continues in the future. In the early time of researching fund performances, academic literatures pay focus on the pricing model as well as the risk factors that contribute to fund returns. Then, the attention moves to whether the performance persists. Recently, several studies demonstrate the benefit of applying Bayesian technique to estimates the fund performance. However, the academic literatures mostly focus on US markets, while the number of the unit trust performance persistence studies in UK is still limited. Using UK data, there are several papers which examine the UK unit trust performance persistence, but the literatures are now outdated. The benefits of using the Bayesian technique in fund performance measurement are still not explored as well.

2.1 The mutual fund performance

Initially, Jensen (1968) offers the standard indices to measure risk adjusted mutual fund returns comparing to market return, the Capital Asset Pricing Model (CAPM). The intercept of linear regression of asset excess return against market return, denoted as alpha, was widely used as mutual fund performance measure. Using CAPM, mutual fund excess return is affected by two factors, the market risk (beta) and fund's manager skill, which is the alpha. Later, Fama and French (1993) develop the model adding size and book-to-market factors so that the alpha reflects the fund performance more precisely. After that, Jeegadeesh and Titman (1993) explore a momentum factor that inspires the work of Carhart (1997) to extend the Fama and French model into the widely cited "four-factor model".

Since the study conducted by Grinblatt and Titman (1992) did not take size, book-to-market and momentum effects into account, Daniel, Grinblatt, Titman and Wermers (Daniel et al 1997) propose to conduct the same type of study, but using a database containing a more significant number of firms (almost ten times the number of firms used by Grinblatt and Titman (1992)), taking size, book-to-market and momentum effects into account, and considering a longer time period (twenty years instead of ten). The performance measurement method used by Daniel et al (1997) forms benchmarks by directly matches the characteristics of the component stocks of the portfolio being evaluated. Using this approach, Daniel et al (1997) decompose fund returns into three components that describe the different aspects of performance: average style (AS), characteristic selectivity (CS) and characteristic timing (CT) components. They find that funds exhibit some stock selection ability, but no characteristic timing ability. The sum of CS and CT components appears statistically significant, but is in fact of the same order as the difference in fees between active and passive funds. However, using Carhart four-factor model, they conclude that performance persistence in funds is due to the use of momentum strategies by the fund managers, rather than the managers being particularly skilful at picking winning stocks. Then, Wermers (2000) extends his work from Daniel et al (1997) using a new database which was not previously available. Merging a database of mutual fund holdings with a database of mutual fund net returns, expenses, turnover levels, and other characteristics creates this database. The results over the 1975 to 1994 period indicate that mutual funds held stock portfolios that outperform a broad market index by 1.3 percent per year. About 60 basis points is due to the higher average returns associated with the characteristics of stocks held by the funds, whereas the remaining 70 basis points is due to talents in picking stocks that beat their characteristic benchmark portfolios.

In summary, the concept of using an alpha as a fund performance measure is quite simple; if the mutual fund excess return can be explained by taking risks (the factors), the residual part of return should then represent an abnormal return provided by performance of the fund's manager. The literatures intend to demonstrate the risk factors that contribute to fund excess return, as well as, construct pricing model that most accurate measure fund performance.

2.2 The performance persistence

Brown and Goetzmann (1995), Carhart (1997), Elton, Gruber, and Blake (1996), Goetzmann and Ibbotson (1994), Grinblatt and Titman (1992), Hendricks, Patel, and Zeckhauser (1993), and Malkiel (1995) test the persistence of mutual fund total returns over time periods ranging from 10 to 31 years. Grinblatt and Titman

(1992) find evidence that differences in performance between funds persist over time and that this persistence is consistent with the ability of fund managers to earn abnormal returns. Hendricks, Patel, and Zeckhauser (1993) find that the relative performance of no-load, growth-oriented mutual funds persists in the near term, with the strongest evidence for a 1-year time horizon. Goetzmann and Ibbotson (1994) find strong evidence that past mutual fund performance predicts future performance. Their data suggest that both 'winners' (funds with returns above the median) and 'losers' (funds with returns below the median) are likely to repeat, even when performance is adjusted for relative risk. Brown and Goetzmann (1995) find that relative risk-adjusted performance of mutual funds persists but that persistence is mostly due to funds that lag the S&P 500; the implication of their results for investors is that the persistence phenomenon is a useful indicator of which funds to avoid. Malkiel (1995) finds that funds in aggregate have underperformed benchmark portfolios even before deduction of expenses and that while considerable performance persistence existed during the 1970s, there was no consistency of performance during the 1980s. Elton, Gruber, and Blake (1996) find that risk-adjusted performance tends to persist; funds that did well in the past tend to do well in the future. Using Jensen's alpha as a measure of risk adjusted performance, their paper shows that, primarily, 1-year alphas provide information about future performance and that portfolios based on past performance significantly outperform equally weighted portfolios of funds. Carhart (1997) develops a 31-year data sample free of survivorship bias and demonstrates that common factors in stock returns and investment expenses almost completely explain persistence in equity mutual funds' mean and risk-adjusted returns; his results do not support the existence of skilled or informed mutual fund managers.

Nevertheless, another stream of literature shed the light on the relationship between the past and the subsequent cash flows or the future performance (e.g. alpha). Sirri and Tufano (1998) investigate the mutual funds past performance and subsequent cash flows. The result indicates that consumers of equity funds disproportionately flock to high performing funds while failing to flee lower performing funds at the same rate. Although consumers of equity funds disproportionately flock to high performing funds while failing to flee lower performing funds at the same rate, Berk and Green (2004) develop a model showing that investments with active managers are unable to outperform the passive benchmarks since investors competitively supply funds to managers and there are decreasing returns for managers in deploying their superior ability. They claim that this evidence explains the absence of performance persistence across the mutual fund universe. Bollen and Busse (2005) use an argument similar to that of Berk and Green (2004) and ask, "What if the documented absence of long-term persistence in mutual fund performance is due to the fact that investors increase their capital investment to the best performing funds?" In their investigation of 230 domestic equity growth funds, they employ both the stock selection four-factor model and the market timing models developed by Treynor and Mazuy (1966) and Henriksson and Merton (1981), and combine stock selection and timing models by including the three additional Carhart factors (size, book-to-market, and momentum) in the two market timing models. The result shows that the top decile of funds generates a statistically significant abnormal return in the post-ranking quarter of 25 to 39 basis points. When modifying the tests, the short-term persistence phenomenon disappears.

In summary, to explain the true performance of the mutual funds, many academic researches investigate on whether the performance persistence exists and how long the persistence maintained. Testing methodology usually based on principal that, from time to time, the winner should still be the winner, the loser should still be the loser, in other word, the difference between winner and loser portfolio return must be positive. Alternatively, some literatures sort fund into quintile portfolios then regress the portfolio returns with pricing model looking for positive alpha as an evidence of fund performance persistence.

2.3 The application of Bayesian to fund performance measurement and persistence

Pástor and Stambaugh (2002) demonstrate that an estimate of either alpha or the Sharpe ratio could be improved with the use of non-benchmark assets, including a book-to-market factor and Carhart momentum factor. Results indicate that, when including the non-benchmark assets, new Sharpe ratio estimates are typically four to five times more precise than usual estimates. Furthermore, 30% of funds that rank in the top Sharpe ratio deciles based on the benchmark estimates fall into the bottom two-thirds of the rankings based on the new estimates. Also, the difference between Fama-French and CAPM alphas is substantially reduced when the non-benchmark assets are included. Empirically, however, estimated alphas for the majority of equity funds are negative when the non-benchmark assets are either included or excluded, confirming previous findings in the literature.

For the benefit of using a Bayesian estimate, Baks, Metrick and Wachter (2001), and Busse and Irvine (2006) offer new models to assess mutual fund performance. Baks, Metrick and Wachter (2001) focuses on an investor's prior belief about fund manager skill using Bayesian performance evaluation wherein an investor chooses to invest in an active fund when the prior point estimate of alpha is positive. For 1,437 domestic equity funds in 1996, the authors calculate the posterior expectation of alpha over a range of prior beliefs. They conclude that a mean-variance investor would require extremely skeptical beliefs about the possibility of managerial skill to be induced not to invest in an actively managed fund. Busse and Irvine (2006) integrate Bayesian estimation and the techniques of Pástor and Stambaugh (2002) to produce a new fund performance measure. Including passive non-benchmark assets returns leads to a more precise method of predicting future performance compared to the standard frequentist measures. Moreover, using of time-varying parameter models improves predictability of both Bayesian and frequentist setting.

For the application to the persistency test, Huij and Verbeek (2007) incorporate Bayesian estimation to strengthen the short-run performance persistence as describe in Bollen and Busse (2005). Using the entire sample of US equity fund over the period of 1984-2003, the result supports the idea that past performance of mutual funds has predictive power for future performance. When funds are ranked on Bayesian four-factor alphas, estimated over horizons of 36 or 12 months, the top deciles subsequently outperform the bottom deciles across all subsamples, and they also found the short-run persistence in abnormal performance as documented by Bollen and Busse (2005). Furthermore, the result also supports the benefit of the Bayesian estimation rather than the OLS.

Besides, Jones and Shanken (2005) investigate whether learning across funds relates to mutual fund performance or not. They use Markov Chain Monte Carlo method to explore the beliefs an investor might arrive at under different assumptions about actual management skill, an investor's initial level of skepticism about abnormal performance, and the number of funds observed. The result indicates a substantial learning across funds with significant on investment decision.

In summary, Bayesian framework contributes to a jump in mutual fund performance measurement. Using this technique, fund performance is measured more accurately. However, since Bayesian econometrics itself has various techniques, each literatures use unique technique that only suited to their research.

2.4 Performance and persistence in UK market environment

About the International relevance, Ramchand and Susmel (1998) examine that the world-betas is a non-linear function of domestic volatility. They also find that Pacific and North America market have a time-varying beta coefficient, while the European markets, especially UK, volatility are not related to international CAPM beta. This indicates that, based on the international CAPM, UK and US have different risk component.

For the performance persistence in UK, Allen and Tan (1999) find evidence of raw return persistence in UK managed funds. Using 131 funds from 1989-1995 and four different test; winners and losers, chi-square, OLS, and Spearman rank correlation coefficient. Their findings imply that performance persists for longer than one year. Fletcher and Forbes (2002) examine the persistence in performance of UK unit trusts between January 1982 and December 1996. Consistent with the prior research of mutual funds and unit trusts, the paper finds evidence of significant persistence in the performance of portfolios, which are formed on the basis of prior year excess returns; when performance is evaluated with mean monthly excess returns and various factor models such as the CAPM or APT. These results are consistent with prior research. However, when performance is evaluated relative to the Carhart model, this persistence in performance is eliminated.

Furthermore, Fletcher and Forbes (2002) also sum up interesting differences between UK and US fund research. The first main finding is that there is significant persistence in the relative rankings of trusts over consecutive 1-year and 2-year intervals, which is fairly robust to the performance measure used. However when persistence is examined by comparing trust performance to an absolute benchmark, the persistence is largely driven by repeat underperformance. The second main finding is that there is significant persistence in the performance of portfolios formed on the basis of prior year excess returns which cannot be explained by evaluating performance on the basis of factor models based on the CAPM or APT. The third main finding is that the persistence in performance is eliminated when performance is estimated relative to the Carhart (1997) model. When the conditional performance measure is used, this leads to significant reversals in performance. The evidence in the paper suggests that the persistence in performance of UK trusts is not a manifestation of superior stock selection strategy and can be explained by factors that are known to capture cross-sectional differences in stock returns.

Keswani and Stolin (2006) examine whether performance persistence within a peer group of competing mutual funds depends on the group's composition. The U.K. mutual fund industry is ideal for such an examination because funds compete within strictly defined sectors. They consider several attributes related to the intensity of competition within a sector and use them to explain sector-level persistence. The choice of variables is based on the notion that the more competitive a sector is, the less likely it is to be characterized by persistence in its funds' performance. The variables used to capture intra-sector rivalry are: the number of funds in the sector, the concentration of fund family assets under management in the sector, and the proportion of mature funds in the sector. The paper finds robust evidence that persistence is higher in sectors where concentration of assets under management is higher.

In summary, although the literatures examine the existence of unit trust performance persistence in UK, the conclusion about the existence is still inconclusive while the evidences of the difference between US and UK have been spotted. Therefore, the question remains whether the fund performance measurement which applies well in the US will have the same ability in the UK?

2.5 Problem summary

Over the years, there have been many improvements to the alpha determination as well as evidences of performance persistence existence. Nevertheless, these strong literatures were done mostly using the data on the US market. For other markets, the evidence of practicality and an existence of persistency are still ambiguous especially in the UK where the environment of the market is not quite the same as the US. Hence, the advanced method to determine the alpha using Bayesian framework as initiated by Pástor and Stambaugh (2002) needs to be tested before it can be generalized across countries. Besides, since the existence of mutual fund performance persistence in the UK is still inconclusive, using this Bayesian alpha could provide a conclusive one.

Chapter 3
Data and Methodology

3.1 Data

This thesis uses the daily data for all calculations in order to optimize the benefits of Bayesian estimation. The required data includes risk free return, share returns, market return, unit trust returns and expense ratios.

The unit trust samples daily total return index (RI) is taken from the Datastream consists of daily total return index on 959 unit trusts from July 1, 1997 to June 30, 2007. To be included in the sample, funds must be non-specialized fund, in the following Investment Management Associate (IMA) sectors: UK All Companies, UK Equity Income, UK Smaller Companies, and UK Zero. Table I shows quantity of included unit trusts for each annual period.

The share database covers all shares listed in the DataStream's FBRIT list (2293 shares) using the total return index, market value, and market to book value from July 1, 1992 to June 30, 2008. To compute the industry factors, I use the total return index of 48 sectors that Datastream provides.

To compute daily excess returns on the funds and on the market returns, I use the UK one-month Treasury bill rate, divided equally over the trading days in the month, as the risk free rate. For the market portfolio returns, I use FTSE all share returns from the DataStream.

The prior for δ_A in equation (6) incorporates fund expenses. I take annual fund expenses ratios from the www.morningstar.co.uk. They are assumed to be equal for all periods. The descriptive statistics of Total Expense Ratio reported is also included in the appendix.

3.2 Variable preparations

From the raw data, a daily passive assets return database are constructed covering July1 1992 to June30 2008 by following procedures.

As in Busse and Irvine (2006), the three models include eight passive assets, including the market portfolio, the size, the book-to-market, the momentum, the stock characteristic-balanced measure, and three industry factors. Daily data are used for these factors.

<u>The first four factors</u>

The total return index of the FTSE all shares return proxies for the market factor (MKT). For the size factor (SMB) and the book-to-market factor (HML), I employ the value-weight methodology provided in Ken French's website to construct these three passive portfolios. For daily series of the momentum factor (UMD), I also follow the monthly procedure described on Ken French's website, except with daily returns.

<u>The Characteristic-balanced Measure</u>

I construct the characteristic-balanced measure, denoted CMS, as described in Pástor and Stambaugh (2002), but with a daily frequency instead of a monthly. The factor captures the return difference between stocks with low HML betas and stocks with high HML betas in a multiple regression that also includes MKT and SMB as independent variables. At the end of June each year, all FBRIT stocks are sorted and assign to three size groups and three book-to-market groups. Then, nine combination groups are constructed denote by two letters, designating increasing values of size (S, M, B) and book-to-market (H, M, L). I construct beta spread within four groups, which include SL, SH, BL, and BH. In each group, the stocks are sorted by HML betas and assigned to one of three value-weighted portfolios. The daily spread of each group is constructed by going long £1 of low-beta portfolio and short £1 of the high-beta portfolio, and the daily CMS is the equally-weighted average of the four spread payoffs on that particular day.

<u>The Three Industry Factors</u>

I use the 48 industry sectors' total return index provided by the DataStream to construct three industry factors (IND1-3) which is the first three principal component vectors, at a daily frequency. I first compute the cross-product matrix from the residuals obtained by regressing the excess returns of the 48 industry portfolios on the other benchmark and non-benchmark assets. I extract the three eigenvectors corresponding to the three largest Eigenvalues from the cross-product matrix to form the principal components matrix. To form the three industry factors, IND1-3, I then normalize the rows of the principal components matrix to a mean square of one.

3.3 The alpha computation

Bayesian estimates are proved for its worth in mutual fund performance measurement in the US, as shown in Busse in Irvine (2006). In this UK study, to assess the distinction between Bayesian and frequentist estimation outcome, the alpha estimations are performed in two manners, using the frequentist approach and the Bayesian approach in each model. Then, the two types of alphas in unit trust performance prediction are compared.

Using the framework developed by Pástor and Stambaugh (2002), the mutual fund alpha estimations are then conducted in three models based on the eight variables specified in the previous section. For each model, the eight variables are separated into benchmark and non-benchmark assets. Pástor and Stambaugh (2002) conclude that the alpha can be estimated more precisely by using information in returns on non-benchmark passive assets, whether or not one believes those assets are priced by the benchmark.

The choice of benchmark assets to be used depends on the pricing model. As in Pástor and Stambaugh (2002) and Busse and Irvine (2006), this study uses one, three, and four passive assets in CAPM, Fama-French, and Carhart four-factor models as benchmark assets. Apart from benchmark assets, the unit trusts return might be exposed to non-benchmark assets return that are not used in general regression. Like Pástor and Stambaugh (2002), this thesis uses four additional passive assets as non-benchmark assets in each pricing model. The first is the differential return between stocks with low betas with respect to the book-to-market factor (i.e., growth stocks) and stocks with high book-to-market betas, similar to the factor used by Daniel and Titman (1997). The other three passive assets capture the dynamics of industry specific returns and are related to the industry portfolios.

For the models used in this thesis, CAPM, Fama-French, and Four-factor model, the choice of being used as a benchmark or a non-benchmark asset is different for each factor. For the CAPM, the only benchmark asset is the market factor while the remaining seven factors are non-benchmark assets. For the Fama-French model, the three benchmark assets are the market factor, the size factor, and the book-to-market factor while the other five factors are non-benchmark assets. For the Four-Factor model, the four benchmark assets are the market factor, the size factor, the book-to-market, and the momentum factor while the other four are non-benchmark assets.

3.3.1 The frequentist alphas

Alpha is often used to measure fund performance. Normally the alpha is computed by regressing the unit trusts excess returns on the returns of any passive assets, or in this case the benchmark and non-benchmark assets.

$$r_{A,t} = \alpha_A + \beta'_A r_{B,t} + \varepsilon_{A,t} \tag{1}$$

Where $r_{A,t}$, is the excess return of fund A at time t, $r_{B,t}$, is a $k \times 1$ vector containing the excess return of the passive asset(s) at time t, and α_A is the fund's alpha.

The role of seemingly unrelated assets begins with regressing the non-benchmark assets on the benchmark assets to calculate the alpha for each non-benchmark passive asset. Let $r_{N,t}$ denote the $m \times 1$ vector of returns in time t on m non-benchmark passive assets, so the regression model for non-benchmark passive assets is written as

$$r_{N,t} = \alpha_N + \beta'_N r_{B,t} + \varepsilon_{N,t} \tag{2}$$

Where $r_{B,t}$ are the excess returns of the benchmark asset(s), α_N is the non-benchmark alpha that can be interpreted as general abnormal returns due to the non-benchmark assets.

Then, I extract the exposure of unit trust returns to all passive assets by regressing excess fund returns on both benchmark and non-benchmark assets. The regression of the fund's return on all $p = (m + k)$ passive assets is defined as

$$r_{A,t} = \delta_A + c'_{A,N} r_{N,t} + c'_{A,B} r_{B,t} + u_{A,t}, \quad (3)$$

Where δ_A can be interpreted as a unit trust A's stock selection skill, and $c'_{A,N}$ are the fund's exposures to the non-benchmark assets.

Substituting the right-hand side of (2) for $r_{N,t}$ in (3) gives

$$r_{A,t} = \delta_A + c_{A,N}\alpha_N + (c_{A,N}\beta_N + c_{A,B}) r_{B,t} + c_{A,N}\varepsilon_{N,t} + u_{A,t} \quad (4)$$

Lastly, the alpha can be written as a sum of two parts, the δ_A , selectivity, and the influence from the non-benchmark assets.

$$\alpha_A = \delta_A + c'_{A,N}\alpha_N \quad (5)$$

The equality in (5) provides the key to understanding how additional information about α_A is provided by the m non-benchmark assets, which are seemingly unrelated to α_A because they are not directly related by a definition. Further, alpha can be decomposed into the fund's stock selection skill and the model mispricing from the non-benchmark assets. The equation (5)'s first term (δ_A) is the selection skill part. The second term ($c'_{A,N}\alpha_N$) from the equation represents the model mispricing part, which is determined by weighing the alpha of the non-benchmark assets (obtained from equation (2)) with the exposure of the unit trust's return to particular non-benchmark asset (obtained from equation (3)).

Typically, standard performance measures above are estimated directly from the time series of returns for the unit trust and for the benchmark and non-benchmark assets, all over the same time period. However, Stambaugh (1997) indicates the advantages of using prior-period passive asset returns. The paper suggests that long-horizon returns provide more precise estimates of the moments of correlated short-horizon returns. Since the unit trust history is relatively short compared to the data on non-benchmark assets that uses the long-period estimates of the non-benchmark asset returns, α_N in equation (5) should provide better accuracy of the performance predictions associated with unit trust sector. Pástor and Stambaugh (2002) explain that a more precise estimator of α_A could be obtained by evaluating the right-hand side of equation (5) and a more precise estimator of α_N could be obtained by using a longer sample period. Therefore this thesis also estimate frequentist measures that use long-history passive asset in addition to the frequentist alphas from passive asset returns contemporary to the unit trust returns.

For each annual ranking period, I will examine two different frequentist measures for each model, the standard measure that uses only benchmark assets over the contemporary period as the unit trust returns and the long-history measure explained earlier.

Regarding long-history measure, the entire time history of benchmark and non-benchmark asset returns is used to estimate equation (2). Then, equation (3) is estimated using only the passive asset returns in the contemporary time with the unit trusts. After that, equation (5) combines the non-benchmark alphas in equation (2) with the stock selectivity, δ_A , and non-benchmark asset impacts in equation (3).

Both of frequentist alphas for every unit trust are estimated yearly in every annual period from July 1997 to the end of June 2008, using benchmark and non-benchmark passive assets returns since July 1997 for the standard version and since July 1992 for the long-history version.

3.3.2 The Bayesian alpha

Pástor and Stambaugh (2002) adopt Bayesian estimation to estimate the fund performance. The passive asset returns used in this method spans across the whole time-history, not restricted to the period that the funds exist. In addition, the Bayesian measure incorporates a flexible set of prior beliefs about managerial skill and the validity of the assets pricing model. Then, Busse and Irvine (2006) test for the predictability of Bayesian alpha and conclude that the method provides better predictability on fund's future performance. For continuity, this thesis also uses the same set of notations as Pástor and Stambaugh (2002) and Busse and Irvine (2006). The benchmark and non-benchmark assets used in this part are the ones used to calculate the frequentist alpha.

The Bayesian measure uses the entire time history of the same benchmark and non-benchmark asset returns to estimate the posterior distributions of the elements of equation (5), similar to the long-history frequentist measure.

For the Bayesian estimation method, the similar framework from the frequentist alpha estimation is used. However, Bayesian alphas are estimated using the Bayesian estimation instead of the OLS regression. In general, to use the Bayesian estimation, the prior distribution needs to be specified. Therefore, the regression in equation (2), (3) and (5) needed for the specification of their prior distribution, as follow. A conditional prior distribution of α_N for equation (2) is specified as

$$\alpha_N|\Sigma \sim N\left(0, \sigma^2_{\alpha_N}\left(\frac{1}{s^2}\right)\right) \tag{6}$$

Where Σ is the variance-covariance matrix for $\varepsilon_{N,t}$, $\sigma^2_{\alpha_N}$ is the marginal model mispricing prior variance of each element in α_N, and s^2 is the average of the diagonal element of Σ (the average variance across non-benchmark assets in each model).

For equation (3), the prior for the estimation of the skill of the benchmark and non-benchmark asset loading conditional on σ^2_u are specified as

$$\delta_A|\sigma^2_u \sim N\left(\delta_0, \left(\frac{\sigma^2_u}{E(\sigma^2_u)}\right)\sigma^2_\delta\right) \tag{7}$$

And

$$c_A|\sigma^2_u \sim N\left(c_0, \left(\frac{\sigma^2_u}{E(\sigma^2_u)}\right)\Phi_c\right) \tag{8}$$

Where σ^2_u is the variance of $u_{A,t}$, $E(\sigma^2_u)$ is the cross-sectional mean of $\hat{\sigma}^2_u$ from OLS regression for each IMA sector, σ^2_δ is the skill prior variance,

$\delta_0 = -\frac{\text{Total Expense Ratio}}{\text{Number of observation in each period}}$. $c_A = \begin{bmatrix} c'_{A,N} \\ c'_{A,B} \end{bmatrix}$ refers to the exposure of unit trust to all passive assets classified to benchmark and non-benchmark assets, c_0 and Φ_c equal to the OLS estimate of the sample cross-sectional moment of $\hat{c}_A$, separately for each IMA sector. In details, c_0 equals to average factor loading of the sector, and Φ_c equals to the cross-sectional deviation of loading across that sector.

Then, combining the prior specified in equation (6)-(8) with fund, benchmark, and non-benchmark returns produces the estimates of the posterior distributions of the elements of equation (5). The posterior distribution of α_N is independent of δ_A and $c_{A,N}$, so the posterior mean of α_A in equation (5) by simply evaluating the right-hand side of (5) at the posterior mean of α_N, δ_A and $c_{A,N}$.

To determine the posterior mean of α_N, δ_A and $c_{A,N}$, Busse and Irvine (2006) use the following method. The posterior moments of α_N are

$$(\tilde{\alpha}_N, \tilde{\beta}_N)' = (I \otimes (D + Z'Z)^{-1} Z'Z) vec(\hat{G}). \tag{9}$$

Where $(\tilde{\alpha}_N, \tilde{\beta}_N)'$is a vector which the first element is the estimated posterior of non-benchmark alpha obtained from regressing non-benchmark asset returns against benchmark asset returns according to each model while other elements is the estimated posterior of non-benchmark factor loading, *I* is an identical matrix.

$D = \begin{bmatrix} \frac{s^2}{\sigma^2_{\alpha_N}} & 0 \\ 0 & 0 \end{bmatrix}$ with *(k+1)×(k+1)* dimension. $Z = (i \quad r_B)$ with *S×(k+1)* dimension, let i equals to a column of 1 with *S* rows and r_B equal to columns of benchmark asset returns with *S* observations in a period. $\hat{G} = (Z'Z)^{-1} Z' r_N$, define r_N as a column of non-benchmark asset returns. ⊗ is a Kronecker product operator. *vec(A)* is an operator that stack column of matrix A below another.

The posterior moments of δ_A and $c_{A,N}$ are

$$(\delta_A \quad c'_{A,N} \quad c'_{A,B})' = (\Lambda_0 + Z'_A Z_A)^{-1} (\Lambda_0 \phi_0 + Z'_A r_A), \tag{10}$$

Where $(\delta_A \quad c'_{A,N} \quad c'_{A,B})'$ is 9×1 matrix that contains the estimated posterior of the unit trust skill, and the exposure to passive assets that can be classified as the exposure to non-benchmark and benchmark passive assets depended on the each model. $\Lambda_0 = \mathrm{E}(\sigma^2_u) \begin{bmatrix} \sigma^2_\delta & 0 \\ 0 & \phi_c \end{bmatrix}$, where the matrix on the right is 9×9 dimensioned. $Z_A = (i \quad r_N \quad r_B)$ with $s \times 9$ dimension let i equals to a column of 1 with *9* rows and r_N and r_B are columns of non-benchmark and benchmark, accordingly, asset returns vector with m observations in a period. $\phi_0 = \begin{bmatrix} \delta_0 \\ c_0' \end{bmatrix}$ with 9×1 dimention.

Finally, the estimates of the posterior distributions of the elements of equation (5) designating the posterior means by tilde (~) is

$$\tilde{\alpha}_A = \tilde{\delta}_A + \tilde{c}_{A,N}\tilde{\alpha}_N. \tag{11}$$

This posterior mean estimates in equation (11) is used as the Bayesian estimates of alpha, $\tilde{\alpha}_A$. Bayesian alphas for every unit trust are estimated of every period (yearly) from July 1997 to end of June 2008, using benchmark and non-benchmark passive assets returns since July 1992, similar to the long-history frequentist alpha.

I estimate the Bayesian alphas using the daily benchmark and non-benchmark asset data from July 1997 through the end of that ranking period and using eleven different skill prior variances ranging from 10^{-13} to 10^{-3} and eight model mispricing prior variances ranging from 10^{-11} to 10^{-4} for the three benchmark model as describe earlier. The intuition of varying skill prior and model mispricing variance is discussed in chapter 4.

3.4 Performance persistence tests

Using alphas obtained from the calculation described in section 3.3, this subsection describes the empirical analysis methodology to test whether Bayesian alpha described in Busse and Irvine (2006) can improve the accuracy of unit trust's alpha prediction, as well as to seek for the evidence of the persistence of the unit trusts in UK market.

3.4.1 The Predictability test

The predictability test intends to examine whether the Bayesian alphas contribute to the unit trust ranking that dominate the ranking based on the frequentist alphas in predicting future (subsequent quarter) performances, also known as performance persistence. Since Bollen and Busse (2005) found the short-run persistence in superior performance mutual funds by using the Bayesian alphas short-run predictability test from Busse and Irvine (2006), this study also conduct the same test—the test for the performance predictability in a short interval (3 month).

To evaluate the statistical significance of the performance persistence, The Spearman's rank correlation explains the relationship between the ranking and the post-ranking period, and indicates the statistical significance of the short-run predictability. To avoid induced correlation between the ranking- and post-ranking-period measures that would arise from using some of the same historical passive asset returns in both Bayesian measures, I sort unit trust alpha based on the mean of the Bayesian posterior alpha distribution and examine the subsequent ordinary OLS alpha rather than the subsequent Bayesian alpha. I use the same benchmark model in both the ranking-period Bayesian measure and the post-ranking-period ordinary measure. This procedure is duplicated from Busse and Irvine (2006). Note that ordinary alpha is calculated easily by performing OLS regression between particular unit trust and the factor(s) associated with each model.

In earlier performance persistence literatures, researchers generally focus on two features in assessing persistence. First, post-period ranking tests determine whether relative performance is consistence across the period. The second feature is the significant positive performance in the top decile. To examine whether unit trusts have performance persistence, I examine the difference in post-ranking period alpha between the top and bottom deciles (d1–d10) and the post-ranking-period alpha for the top decile (d1).

Every end of June, unit trusts are sorted into deciles rank (rank1-rank10) based on the mean of the Bayesian posterior alpha distribution or frequentist alpha estimated during an annual ranking period, and then I examine the decile rank based on the ordinary alphas during the following quarter.

Having deciles rank for all unit trusts, I examine the difference in post-ranking period alpha between the top and bottom deciles (d1–d10) and the post-ranking-period alpha for the top decile (d1); while the relationship between the ranking-period Bayesian or frequentist alpha and post-ranking-period ordinary alpha are evaluated via the Spearman rank correlation coefficients between the ranking-period decile ranks and the post-ranking-period alpha decile ranking. The result will be shown and analyzed in the chapter 4.

However, to examine whether Bayesian or frequentist alpha contributes to persistence, the performance persistence test methodology used in this section created by Busse and Irvine 2006 is just one of many accepted methodologies. The advantages of this methodology are that it examines the persistence relatively and also specifically serves the purpose to examine for the persistence in short-run. Alternatively, the performance persistence can be examined in an absolute manner simply by regressing the excess returns of portfolio constructed based on Bayesian or frequentist alphas; and then consider the alpha as well as its significance as the proof of performance persistence. The alternative test will be described in the next subsection.

3.4.2 The abnormal return of the decile portfolios based on Bayesian and frequentist alpha

The study in this subsection employ the methodologies of Hendrick et al, Brown and Goetzmann (1995) and Carhart (1997) to evaluate the persistence in unit trust performance measured by Bayesian or frequentist alphas. The famous Brown and Goetzmann (1995) use 2×2 contingency tables to evaluate performance persistence which are portfolio constructed from combinations of the winner and loser, and then looking for statistic significant alpha of each portfolio. To make a consistent with the previous test, the performance persistence test in this subsection use 10 deciles portfolio constructed based on Bayesian or frequentist alpha instead of the 2×2 combinations. An alpha of the decile portfolio exhibit whether investment portfolio using Bayesian alphas as a ranking criteria delivers abnormal return and whether Bayesian estimates contribute evidences of unit trust performance persistence in UK, I construct decile portfolios and then examine whether any portfolio produces significant alpha in the absolute manner or not.

Every end of June, unit trusts are sorted into decile portfolios on their Bayesian alphas or standard frequentist alphas, determined from section 3.2 based on 12-months ranking period. In detail, Bayesian alpha estimated using the four-factor model with the skill prior or mispricing prior that provide best result in the section 3.2. Then, I gather unit trusts in each decile to form ten equally weighted portfolios of ten deciles named "decile portfolio" and evaluate the portfolio's post-ranking performance.

Using the monthly data from July 1997 to June 2007 (10 years, unit trusts are sorted into deciles), I examine the persistence by, first, calculate the monthly (decile) portfolios' equally-weight returns over the subsequent 12 months for all decile portfolios, then, estimate the alpha for the entire time series of the portfolio returns using OLS regression against the ordinary four-factor model. The result will be shown and analyzed in the next chapter. If the ordinary alpha of the decile portfolio is positive and statistically significant, this should be another evidence of the performance persistence.

Table 1: The Number of unit trust included in the calculation separated by IMA sector.

The sectors are UK All Companies, UK Equity Income, UK Smaller Companies, and UK Zero. This excludes preference shares which produce an income. The following are definitions for each sector provided by the Investment Management Association. "UK All Companies" are funds which invest at least 80% of their assets in UK equities which have a primary objective of achieving capital growth, "UK Equity Income" is funds which invest at least 80% in UK equities and which aim to achieve a yield on the distributable income in excess of 110% of the FTSE All Share yield, "UK Smaller Companies" is funds which invest at least 80% of their assets in UK equities of companies which form the bottom 10% by market capitalization, "UK Zeros" are funds investing at least 80% of their assets in Sterling denominated, and at least 80% of their assets in zero dividend preference shares or equivalent instruments. Since all calculation in this thesis are performed in daily frequency, each period contains about 260-262 observations, therefore the unit trust calculation contains 1,672,571 observations.

Period	Total	UK All Companies	UK Equity Income	UK Smaller Companies	UK Zero
1997-1998	292	169	75	48	0
1998-1999	320	193	77	50	0
1999-2000	363	219	86	58	0
2000-2001	419	260	96	63	0
2001-2002	472	296	102	73	1
2002-2003	533	339	114	76	4
2003-2004	622	400	130	88	4
2004-2005	682	441	143	94	4
2005-2006	743	481	158	100	4
2006-2007	859	562	185	107	5
2007-2008	921	602	198	112	9
sum	6226	3962	1364	869	31

Chapter 4
Empirical Results

This chapter exhibits the statistic results of the alphas predictability test and the test for abnormal return of the decile portfolios using Bayesian and frequentist alpha as a criteria. The results for the predictability test are reported in section 4.1; and the results for the test for abnormal return of the decile portfolios are reported in section 4.2.

4.1 The predictability test results

4.1.1 Bayesian alpha predictability

There are three statistic results concerned in this section i.e. the difference between, bottom decile alphas and the top decile alpha and the Spearman rank correlation. The Spearman rank correlation coefficient in Table 2 indicate the relationship between the ranks of the deciles sorted on ranking-period Bayesian alpha and the ranks in post-ranking-period which based on ordinary alpha. The relationship evaluated by the Spearman rank correlation also indicates the statistic significance. The difference between top and bottom deciles alpha (d1-d10) and top decile alpha (d1) in Table 3 and 4 indicate the economic significance of the relationship that is the ability of the unit trusts in deciles which are sorted on Bayesian alpha to persist their performance over subsequent quarter, in this case is the alpha. The tables report the average, by skill prior variances, σ_{δ}^2, and model mispricing prior variance, $\sigma_{\alpha_N}^2$, of the statistics for the combination of the two type prior variance. Skill prior variance ranges from 10^{-13}, which precludes the possibility that managerial skill exists, to the relatively diffuse 10^{-3}. Model mispricing prior variance ranges from 10^{-11}, which preclude the worth of the non-benchmark assets to produce abnormal returns for each model, to relatively diffuse 10^{-4}.

For Table 2, 3, 4 and Figure1, Panel A uses the CAPM single factor model, Panel B uses the Fama-French three-factor model, and Panel C uses the Carhart four-factor model. The Bayesian results in Table 3 and 4 are determined by equally weighting the ordinary alphas in post-ranking period deciles for particular prior variance.

The results in Table 2 report that the Spearman Rank Correlation coefficients averaged by each Bayesian prior variance or each version are statistically insignificant for all three pricing models. Two-tailed Spearman test based on decile rankings are significant at the 10% and 5% levels for correlations of 0.564 and 0.648, respectively. This result denotes a weak rank predictability between Bayesian Alpha and subsequent quarter risk-adjusted performance ranking.

The Spearman, which imply for the predictability, is greater for the Fama-French and Carhart models than for the CAPM model, since they remove more of the abnormal performance associated with passive assets. Therefore the greater predictability in the multifactor models might suggest that managerial stock selections skill persists more than the abnormal return associated with passive assets.

Although the skill prior variance of 10^{-6} brings up the largest d1-d10 in Table3 and Figure1, it brings about the lowest Spearman correlation in Table2. This result holds for all three models. Recall that as the skill prior becomes more diffuse, the Bayesian measure of managerial skill moves closer to a multifactor alpha (estimated using both benchmark and non-benchmark assets). The similar predictability associated with a range of skill prior indicates some amount of managerial skill for among included unit trusts. Anyway, as the skill prior variance decreases, the Bayesian measure of managerial skill shrinks toward the prior mean of -1 multiplied by the fund's expense ratio, so the investors should not rely on the fund expense as fund selection criteria.

By varying the model mispricing prior variance, the relationship between mispricing uncertainty and Spearman are identical in all three models. The results in Panel A, B and C of Table 2 show that Bayesian alphas most accurately predict future ordinary alphas for the mispricing prior variance of 10^{-6} and tend to predict more accurately for precise model mispricing priors, that is, stronger priors that the non-benchmark assets do not produce abnormal returns.

For the difference between top and bottom deciles alpha, the relationship between mispricing uncertainty and d1-10 contrast to the previous relationship i.e. the Spearman correlation. The results in Table3 and Panel B and C of Figure 1 show that, for Fama-French and Four-factor model, Bayesian alphas tend to better predict future ordinary alphas for more diffuse model mispricing priors.

In the relationship results of Table2, and 3, the Spearman and d1-d10, the Four-factor brings in the largest magnitude, followed by Fama-French and CAPM. This trend holds for all skill prior variance and model mispricing prior variance combination.

The weak relationship contradicts the existing results from Busse and Irvine (2006), which reports greater magnitude of Spearman correlation in US mutual fund market. These weak relationships, represented by the Spearman, have the magnitudes that are close to the relationship from frequentist alphas, which will be discussed later. Furthermore, Keswani and Stolin (2006) also report the same level of spearman correlation among raw returns.

The performance in the top deciles, in Table4, depends on the pricing model. The CAPM results in Panel A of Table 4 show significant negative performance, emphasis that the non-benchmark assets do not produce abnormal returns in a CAPM context; while the Fama-French and the Four-factor model results in Panel B and C show significant positive performance. The positive significant alpha of the top decile also indicates the unit trust performance persistence. The negative abnormal returns from CAPM conforms with the result from Ramchand and Susmel (1998) which reports a negative alpha for UK stock returns when estimates using international CAPM as a benchmark.

4.1.2 Frequentist alpha predictability

This section also concerns for the results as same as the results from Bayesian alpha in section 4.1.1. Table5 reports relationships between frequentist alphas in ranking-period and the ordinary alpha in post-ranking-period, in cases of the frequentist alpha that use and do not use long-history passive asset, and subsequent quarter standard alphas.

The frequentist alphas in Panel A, B, C of Table5 also indicates a weak relationship between past and future performance, but shows economic significant stronger than Bayesian alpha. The magnitude of predictability depends on the pricing model and whether long-history passive assets are used. In all three models, the Bayesian alpha generally predict future ordinary alpha more accurately than both standard and long-history frequentist predicts future performance.

In contrast to Busse and Irvine (2006), the long-history results, for all three models, indicate weaker relationship between past and future performance than the standard alpha predict future performance. The Spearman and d1-d10 of the long-history frequentist results in all three Panels are lower than the results of the standard frequentist. In theory, incorporating the longer history data to make estimation should yield more precise results. Anyway, these disagreed results cannot reject the theory since the Bayesian results, which also incorporate long-history data, bring larger predictability than the standard produced. This may be implied that Pástor and Stambaugh (2002) framework is still improve the measurement of UK unit trusts, but the persistency in UK unit trust market itself are really weak.

The frequentist alphas associated with Four-factor model in Panel C and the Fama-French model in Panel B predict future performance more accurately than the CAPM frequentist measures, which is the same pattern noted earlier with the Bayesian alphas.

4.2 The abnormal return of the decile portfolios based on Bayesian and frequentist alpha

The important content provided by the results in this section is the alpha, which communicates the absolute performance persistence of asset allocation in UK unit trust, together with their statistics that indicate whether the alpha estimation is statistic significant.

Since from section 4.1, there is no significant outstanding performance predictability, I use the Bayesian alpha at skill prior variance of 10^{-6} and model mispricing prior variance of 10^{-6} which mostly contribute the best relationship to sort unit trusts into decile portfolios for the Bayesian ranking, as well as use the standard frequentist to sort unit trusts into decile portfolios for the frequentist ranking.

Table III reports negative alpha for all decile portfolios in both Bayesian and frequentist ranking. Furthermore, the results almost show negatively statistic significance, except the top decile portfolio when sorted by Bayesian alpha. This indicates abnormal loss from investment in UK unit trusts formed using either the Bayesian or the frequentist alpha as the selection criteria within one year interval. Anyway, the results show the less negative abnormal return in the superior decile portfolios. This kind of result supports the finding of Fletcher and Forbes (2002) who reports significantly negative abnormal returns for all quartile portfolios, by sorting UK unit trusts into quartile portfolio based on prior year excess return, then examine the returns of the portfolios, and make OLS regression between the portfolios returns and the Four-Factor model.

Table 2: Spearman Rank Correlation Coefficient

The Spearman correlation measures the statistical significance of the relationship between the ranking-period Bayesian alpha posterior mean decile ranking and the post-ranking-period ordinary alpha decile ranking. The Spearman correlation also describes the extent of Bayesian alphas to predict subsequent ordinary alphas. In Panel A, B and C, for each combination of skill prior variance and model mispricing prior variance, unit trusts are sorted into deciles based on their Bayesian alpha posterior mean during an annual ranking period. For the results in this table, the ranking-period Bayesian alphas are estimated using benchmarks and non-benchmarks depends on estimates model in particular Panel. Then, compute the average within the ordinary alpha in each decile over the following quarter post-ranking period using the same set of benchmarks that I use in the Bayesian without the non-benchmarks. Each statistics in the table represents the mean associated with that parameter (skill or model mispricing prior variance) over all combination of the other parameter. I estimate all alphas using daily returns. The estimation of ranking-period Bayesian alphas in Panel A uses one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3). The estimation of ranking-period Bayesian alphas in Panel B uses three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1– 3). Finally, the estimation of ranking-period Bayesian alphas in Panel C uses four benchmarks (MKT, SMB, HML and UMD) and four non-benchmarks (CMS, and IND1– 3). A two-tailed Spearman test based on decile rankings is significant at the 10%, 5%, and 1% levels for correlations of 0.564, 0.648, and 0.794, respectively.

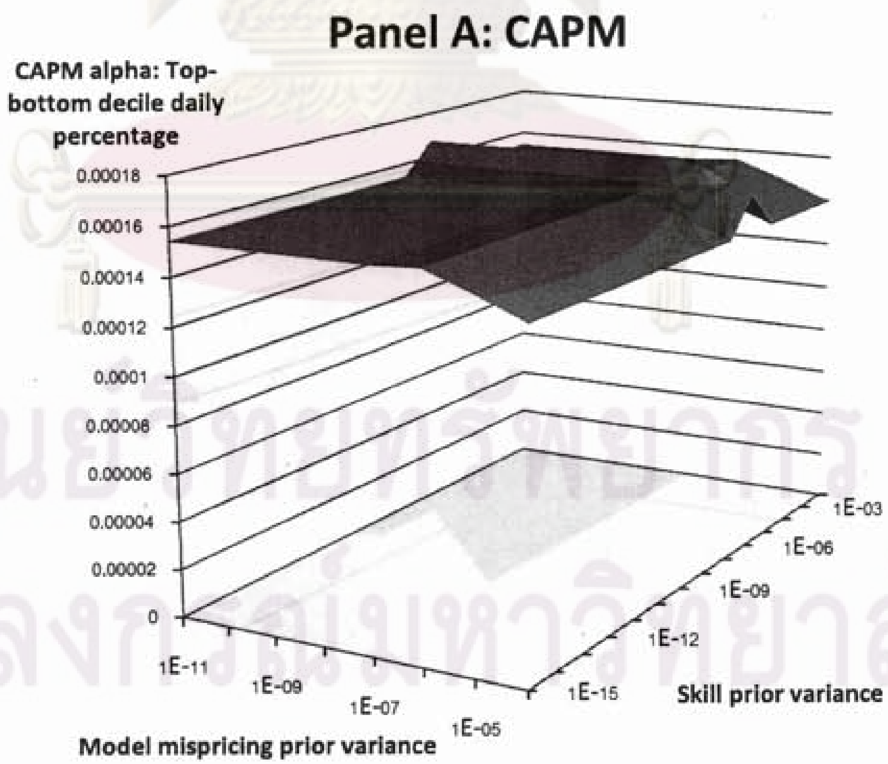
	Panel: A CAPM	**Panel: B Fama-French**	**Panel: C Four Factor**
Bayesian by skill prior variance			
1E-13	0.1626	0.1745	0.1894
1E-10	0.1626	0.1746	0.1895
1E-07	0.1626	0.1746	0.1895
1E-06	0.1527	0.1669	0.1795
1E-05	0.1626	0.1746	0.1895
1E-02	0.1627	0.1748	0.1895
Bayesian by model mispricing prior variance			
1E-11	0.1639	0.1755	0.1900
1E-08	0.1639	0.1755	0.1900
1E-07	0.1640	0.1755	0.1900
1E-06	0.1646	0.1757	0.1902
1E-05	0.1595	0.1737	0.1882
1E-04	0.1514	0.1657	0.1816

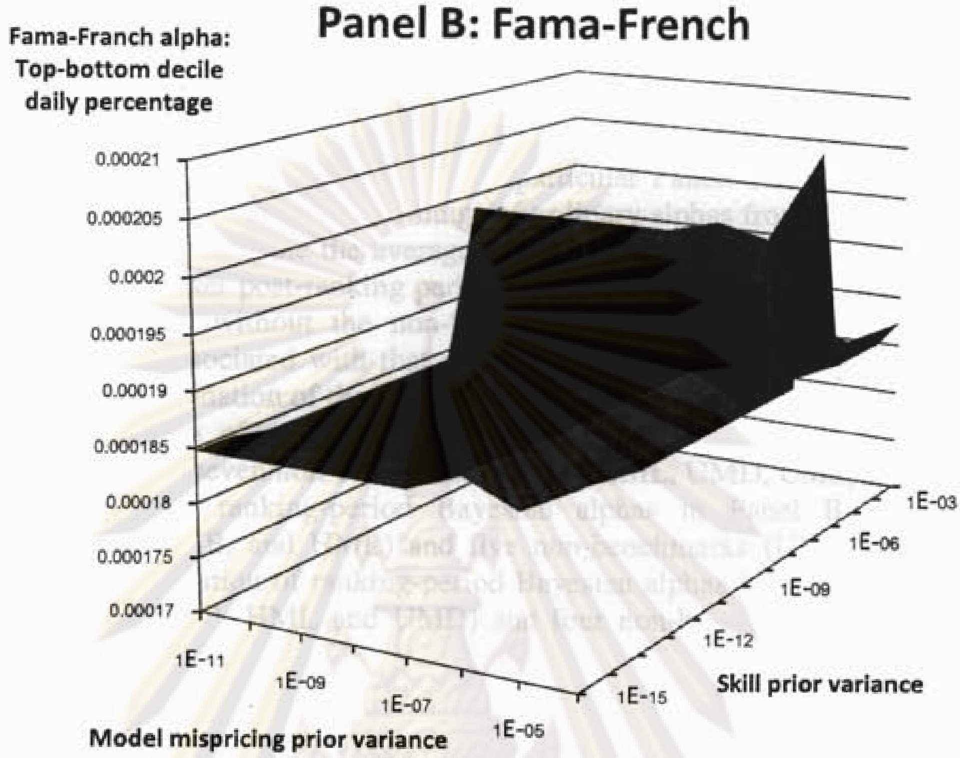
Table 3: The difference between the post-ranking-period ordinary alpha (daily percentage) for the top and bottom ranking-period deciles (d1-d10)

D1-D10 indicates the economic significance of using Bayesian alpha as fund selection tool as well as the evidence of unit trust performance persistence. For the results in this table, the ranking-period Bayesian alphas are estimated using benchmarks and non-benchmarks depending on estimates model in the particular Panel. The statistic in the tables report the post-ranking difference between the 10-year average of ordinary alphas from every unit trusts within the top decile deduct with the 10-year average of ordinary alphas from every unit trusts within the bottom decile. I compute the average within the ordinary alpha in each decile over the following quarter post-ranking period using the same set of benchmarks that I use in the Bayesian without the non-benchmarks. Each statistics in the table represents the mean associated with that parameter (skill or model mispricing prior variance) over all combination of the other parameter. I estimate all alphas using daily returns. The estimation of ranking-period Bayesian alphas in Panel A uses one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3). The estimation of ranking-period Bayesian alphas in Panel B uses three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1– 3). Finally, the estimation of ranking-period Bayesian alphas in PanelC uses four benchmarks (MKT, SMB, HML and UMD) and four non-benchmarks (CMS, and IND1– 3).

	Panel: A CAPM	**Panel: B Fama-French**	**Panel: C Four Factor**
Bayesian by skill prior variance			
1E-13	0.0152	0.0185	0.0195
1E-10	0.0152	0.0185	0.0195
1E-07	0.0152	0.0185	0.0195
1E-06	0.0166	0.0200	0.0198
1E-05	0.0152	0.0185	0.0195
1E-02	0.0152	0.0185	0.0195
Bayesian by model mispricing prior variance			
1E-11	0.0155	0.0185	0.0194
1E-08	0.0155	0.0185	0.0194
1E-07	0.0155	0.0185	0.0194
1E-06	0.0156	0.0187	0.0196
1E-05	0.0149	0.0185	0.0193
1E-04	0.0141	0.0188	0.0197

Figure 1: Performance predictability of Bayesian alphas with non-benchmarks. The figure shows statistics that describe the extent to which Bayesian alphas predict subsequent ordinary alphas. For each combination of skill prior variance and model mispricing prior variance, unit trusts are sorted into deciles based on their Bayesian alpha posterior mean during an annual ranking period. For each decile, I compute the ordinary alpha over the following quarterly post-ranking period. The vertical axis in the figure shows the difference between the post-ranking-period ordinary alpha (daily percentage) for the top and bottom ranking-period deciles. I estimate the ranking-period Bayesian alphas using one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3) in Panel A, using three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1–3) in Panel B, and using four benchmarks (MKT, SMB, HML, and UMD) and four non-benchmarks (CMS and IND1–3) in Panel C. I estimate the post-ranking-period ordinary alphas using the same set of benchmarks that I use in the Bayesian alpha estimation, but no non-benchmarks. I estimate the alphas using daily returns. I weight the standard alphas in the post-ranking-period deciles equally. The estimation of ranking-period Bayesian alphas in Panel A uses one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3). The estimation of ranking-period Bayesian alphas in Panel B uses three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1– 3) and the estimation of ranking-period Bayesian alphas in Panel C uses four benchmarks (MKT, SMB, HML and UMD) and four non-benchmarks (CMS, and IND1– 3).




Panel B: Fama-French
Fama-Franch alpha: Top-bottom decile daily percentage
0.00021
0.000205
0.0002
0.000195
0.00019
0.000185
0.00018
0.000175
0.00017
1E-11
1E-09
1E-07
1E-05
Model mispricing prior variance
1E-03
1E-06
1E-09
1E-12
1E-15
Skill prior variance

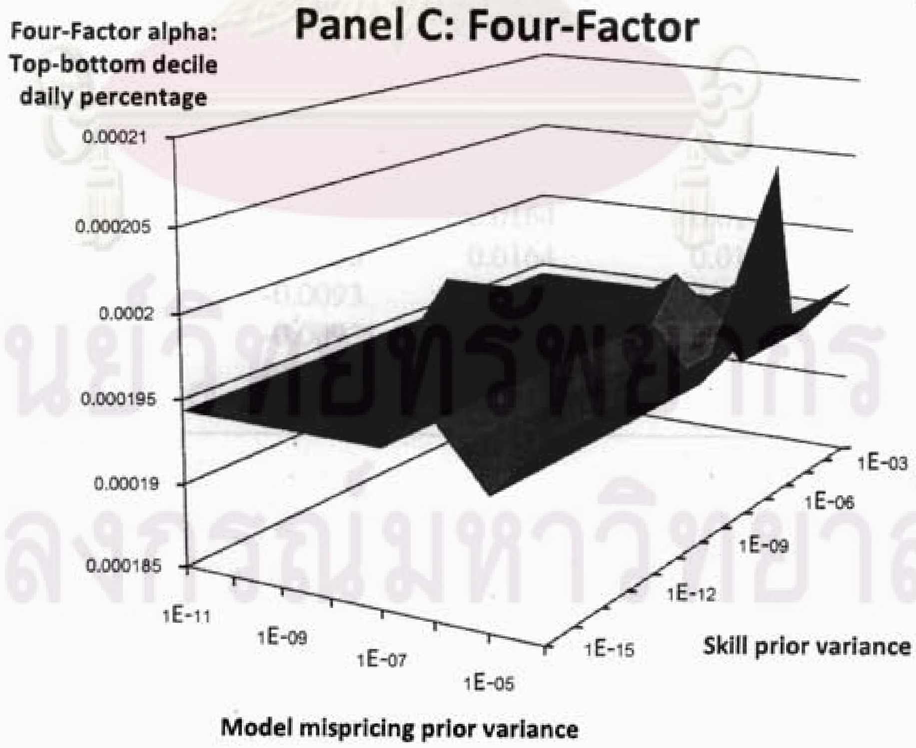

Panel C: Four-Factor
Four-Factor alpha: Top-bottom decile daily percentage
0.00021
0.000205
0.0002
0.000195
0.00019
0.000185
1E-11
1E-09
1E-07
1E-05
Model mispricing prior variance
1E-03
1E-06
1E-09
1E-12
1E-15
Skill prior variance

Table 4: The post-ranking period ordinary alphas (daily percentage) for the top ranking-period decile (d1)

The d1 are also evidence of unit trust performance persistence. For the results in this table, the ranking-period Bayesian alphas are estimated using benchmarks and non-benchmarks depending on estimates model in particular Panel. The statistics in the tables report the 10-year post-ranking average of ordinary alphas from every unit trust within the top decile. I compute the average within the ordinary alpha in each decile over the following quarter post-ranking period using the same set of benchmarks that I use in the Bayesian without the non-benchmarks. Each statistics in the table represents the mean associated with that parameter (skill or model mispricing prior variance) over all combination of the other parameter. I estimate all alphas using daily returns. The estimation of ranking-period Bayesian alphas in Panel A uses one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3). The estimation of ranking-period Bayesian alphas in Panel B uses three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1– 3) and the estimation of ranking-period Bayesian alphas in Panel C uses four benchmarks (MKT, SMB, HML and UMD) and four non-benchmarks (CMS, and IND1– 3).

	Panel A: CAPM	**Panel B: Fama-French**	**Panel C: Four Factor**
Bayesian by skill prior variance			
1E-13	-0.0094	0.0163	0.0170
1E-10	-0.0094	0.0163	0.0170
1E-07	-0.0094	0.0163	0.0170
1E-06	-0.0077	0.0181	0.0176
1E-05	-0.0094	0.0163	0.0170
1E-03	-0.0094	0.0163	0.0170
Bayesian by model mispricing prior variance			
1E-11	-0.0093	0.0164	0.0170
1E-08	-0.0093	0.0164	0.0170
1E-07	-0.0093	0.0164	0.0170
1E-06	-0.0093	0.0164	0.0170
1E-05	-0.0094	0.0164	0.0169
1E-04	-0.0095	0.0171	0.0177

Table 5: Performance persistence of the frequentist, including non-benchmark assets

The table reports the statistic that describes the extent to which frequentist alphas predict subsequent ordinary alphas. Unit trusts are sorted into decile based on their frequentist alphas and long-history frequentist alphas using one benchmark (MKT) and seven non-benchmarks (SMB, HML, UMD, CMS, and IND1–3) for CAPM, using three benchmarks (MKT, SMB, and HML) and five non-benchmarks (UMD, CMS, and IND1– 3) for Fama-French model, and using four benchmarks (MKT, SMB, HML, and UMD) and four non-benchmarks (CMS and IND1–3) for Four-factor model. I estimate the ranking-period standard frequentist alphas and all post ranking-period ordinary alphas using the same set of benchmarks that I use in the Bayesian and long-history frequentist alpha estimation, but no non-benchmarks. The two different frequentist measures for each model, namely, the standard measure that uses only benchmark assets over the contemporary period as the unit trust returns, and the long-history measure described earlier. The long-history measure uses the same set of benchmark and non-benchmark assets as the Bayesian measure. I estimate all alphas using daily returns. Then, I compute the average within the ordinary alpha in each decile over the following quarter post-ranking period using the same set of benchmarks that I use in the Bayesian without the non-benchmarks. I estimate all alphas using daily returns. A two-tailed Spearman test based on decile rankings is significant at the 10%, 5%, and 1% levels for correlations of 0.564, 0.648, and 0.794, respectively.

		Standard	**Long-history**
CAPM	Spearman	0.1579	0.1503
	d1-d10	0.0173	0.0152
	d1	-0.0082	-0.0085
Fama-French	Spearman	0.1711	0.1637
	d1-d10	0.0223	0.0200
	d1	0.0177	0.0179
Four-Factor	Spearman	0.1817	0.1710
	d1-d10	0.0227	0.0208
	d1	0.0187	0.0186

Table 6: Alpha (abnormal return) of decile portfolios sorted based on Bayesian and standard frequentist alpha.

At the end of June for each period from 1998-2007, unit trusts are sorted into equally weighted decile portfolios as annual ranking periods. The sorting criteria are Bayesian and standard frequentist alphas. Then, I calculate the average returns of the portfolios for every month. The table shows the parameter estimates of Carhart (1997) model for each decile portfolio. The deciles' post-ranking alphas are estimated using standard OLS over the entire time series of portfolio returns.

Panel A: Bayesian Ranking

Ranking period performance is measured using Bayesian alpha.

Portfolio	α	α t-stat	α Pr(>/t/)	MKT	SMB	HML	UMD	R-squared
D1	-0.0005	-0.8542	0.3948	0.4302	0.1441	-0.0020	0.0226	0.9099
D2	-0.0016	-3.5136	0.0006	0.4373	0.1216	-0.0023	0.0195	0.9351
D3	-0.0011	-2.5992	0.0106	0.4182	0.0857	0.0060	0.0171	0.9361
D4	-0.0015	-3.8781	0.0002	0.4306	0.0522	-0.0006	0.0043	0.9500
D5	-0.0013	-4.0179	0.0001	0.4305	0.0591	0.0012	0.0092	0.9610
D6	-0.0014	-3.6851	0.0004	0.4400	0.0483	0.0000	0.0073	0.9526
D7	-0.0016	-4.1157	0.0001	0.4311	0.0527	0.0030	0.0041	0.9492
D8	-0.0017	-3.7474	0.0003	0.4396	0.0564	-0.0067	0.0020	0.9344
D9	-0.0017	-3.4608	0.0008	0.4463	0.0542	-0.0086	0.0055	0.9227
D10	-0.0023	-3.8426	0.0002	0.4659	0.0976	-0.0073	0.0036	0.9003

Panel B: Standard Frequentist Ranking

Ranking period performance is measured using standard frequentist alpha.

Portfolio	α	α t-stat	α Pr(>/t/)	MKT	SMB	HML	UMD	R-squared
D1	-0.0014	-2.9414	0.0040	0.4410	0.1526	0.0042	0.0237	0.9317
D2	-0.0011	-2.5012	0.0138	0.4321	0.1137	-0.0006	0.0190	0.9299
D3	-0.0011	-2.5010	0.0138	0.4299	0.1039	0.0040	0.0163	0.9324
D4	-0.0015	-4.0201	0.0001	0.4301	0.0742	-0.0014	0.0088	0.9525
D5	-0.0015	-3.9739	0.0001	0.4277	0.0490	-0.0048	0.0044	0.9496
D6	-0.0014	-3.5805	0.0005	0.4267	0.0464	-0.0004	0.0075	0.9434
D7	-0.0012	-2.9173	0.0042	0.4334	0.0493	-0.0034	0.0033	0.9418
D8	-0.0015	-3.1977	0.0018	0.4332	0.0438	-0.0010	0.0019	0.9276
D9	-0.0018	-3.5954	0.0005	0.4540	0.0647	-0.0074	0.0031	0.9249
D10	-0.0022	-3.4636	0.0008	0.4654	0.0820	-0.0017	0.0056	0.8887

Chapter 5
Analysis and Conclusion

5.1 Result analysis

This thesis applies the methodology of Busse and Irvine (2006), which demonstrates superb short-run future performance predictability from Bayesian alpha in the US market developed by Pástor and Stambaugh (2002), to examine the worth of the Bayesian alpha in the UK market. However, the results show neither improvement in future performance predictability nor the performance perisistence for the unit trust in the UK. For the future performance predictability comparison between frequentist and Bayesian alpha, there is not much difference between the two types of alpha. The source of indifference may come from the Bayesian alpha estimation methodology developed by Pástor and Stambaugh (2002) that may not be suitable for the performance measurement in the UK.

From the Bayesian alpha methodology, most of the prior supply to Bayesian calculation is outputs of the frequentist estimation. So, if there is any enhancement from application of the Bayesian alpha, the improvement should come from the Bayesian framework and the additional information added to the prior assumption, and the only additional information is the fund expense that is expected to improve the preciseness of the measure. However, even though the empirical results of the spearman correlation coefficient in the predictability test indicate that the Bayesian framework does improve the predictability; it is not a major improvement. So it is still inconclusive whether the additional information really enhances the predictability or not. To examine whether the additional information, the fund expense, provides some performance prediction, I also performed a test for the relationship between funds expense and the subsequent performance, using the same methodology as the predictability test except using fund expense as a ranking criteria in the ranking periods. The results of the predictive power of the fund expense are reported in Table 7. The results in Panel A show very small Spearman correlation coefficients, suggesting that fund expense itself provides no predictability. When compared to the similar results from the US in Panel B which reports a lot bigger Spearman correlation results at 0.612, 0.188 and 0.552 for Model CAPM, Fama-French and Four-factor respectively, the UK figures are all less than 0.1. This should be noted as a dissimilarity between an environment in the UK and US.

Considering the US results, including a fund expense as additional information giving to the prior distribution in the Bayesian alpha calculation is appropriate to enhance the predictability of Bayesian alpha since the fund expense itself can provide some predictability; on the other hand, using the same Bayesian alpha prior assumption for the UK might not provide the same enhancement as it can in the US since the fund expense have very little performance predictability for the UK market

Table7: The performance predictability of fund expenses.

Panel A, with the UK data, reports that statistics that describe the extent to which fund expenses predict subsequent ordinary alpha. I sort funds into deciles during an annual ranking period based on 1/expense ratio. For each decile, the mean ordinary alphas of the following quarterly period are computed. Panel B shows the results from the same test as in Panel A but perform under US market by Busse and Irvine (2006). A two-tailed Spearman test based on decile rankings is significant at the 10%, 5%, and 1% levels for correlations of 0.564, 0.648, and 0.794, respectively.

	Panel A: UK		**Panel B: US**	
Model	**Spearman**	**d1-d10**	**Spearman**	**d1-d10**
CAPM	0.063	0.0001	0.612	0.0085
Fama-French	0.059	0.0001	0.188	0.0060
Four-Factor	0.062	0.0046	0.552	0.0090

5.2 Conclusion

There has been a development in fund performance measurement which uses Bayesian technique to estimate the fund alpha. Using the Bayesian framework can lead to a more accurate performance predictability in the US market, as described in Busse and Irvine (2006). Since the existing literature suggests that there are several differences between the UK and the US market, especially the inconclusive existence of unit trust performance persistence in the UK, a question emerges whether applying Bayesian technique to measure the unit trust performance could provide a more accurately performance measure and predictability in the UK.

This thesis extends the methodology of Pástor and Stambaugh (2002) to calculate both Bayesian and frequentist alpha, and then examine whether Bayesian estimates improve unit trusts performance predictability or persistence from frequentist measures in the UK unit trust market. The tests for the performance and the persistence are conducted in two manner i.e. a relative manner and an absolute manner. For the relative manner, Busse and Irvine (2006) test methodology is employed to evaluate the relationship between the ranks of the deciles sorted on ranking-period Bayesian or frequentist alpha and the ranks in post-ranking-period which is based on an ordinary alpha. For the absolute manner, the abnormal returns of portfolios constructed based on Bayesian or frequentist alpha are estimated to test for the performance persistence of each portfolio.

The empirical results from Busse and Irvine (2009) methodology indicate that incorporating history data of these returns with Bayesian estimates produces a better method for predicting future performances, when the returns on passive non-benchmark assets are correlated with unit trust holding. Anyway, there is no outstanding difference between the Bayesian and frequentist performance measures. Moreover, according to the results, the relationships between the ranking-period performance and future performance are weak and insignificant. Although the predictability is weak, the empirical results indicate an economic significance of the short-run investment that uses either the Bayesian or the frequentist estimates. Anyway the significance of the Bayesian performance measures is a little dominated by the frequentist one.

In the test for the abnormal returns of portfolios formed using either the Bayesian or the frequentist alpha as the selection criteria tend to similarly have abnormal losses in the subsequent years. The results emphasize the indifference between the persistence of the Bayesian and the frequentist results.

The reason that the Bayesian alpha cannot make a significant improvement in the future unit trust performance prediction might come from the Bayesian alpha calculation methodology that uses fund expense as an additional information, while the fund expense itself has no predictability. Therefore, the fund expense would not be an appropriate prior for Bayesian performance estimation in the UK.

At this point, the investors have no point to apply the Bayesian alpha as a selection criterion when investing in UK unit trust. Since performing Bayesian estimation needs more workload than performing a frequentist one and the results show that the outcomes from both methods are quite similar to each other.

References

Allen, D. E.; and Tan, M. L. 1999. " A test of the persistence in the performance of UK managed funds", Journal of Business Finance and Accounting 26: 559–93.

Baks, Klaas; Metrick Andrew; and Wachter, Jessica. 2001. "Should investors avoid all actively managed mutual funds? A study in Bayesian performance evaluation". Journal of Finance 56: 45–85.

Berk, J.B.; and Green, R.C. 2004. " Mutual fund flows and performance in rational markets". Journal of Political Economy 112: 1269–1295.

Blake, David ; and Timmerman, Alan.1998. "Mutual Fund Performance: Evidence from the UK". European Finance Review 2;57-77.

Bollen, Nicolas; and Busse, Jeffrey. 2005. "Short-term persistence in mutual fund performance". Review of Financial Studies 18: 569–597.

Brown, Stephen, and Goetzmann, William. 1995. "Performance persistence". Journal of Finance 50: 679–698.

Busse, Jeffrey; and Irvine, Paul. 2006. "Bayesian alpha and mutual fund persistence". Journal of Finance 56: 2251-2287.

Carhart, Mark. 1997. "On persistence in mutual fund performance". Journal of Finance 52: 57–82.

Daniel, Kent; Grinblatt, Mark; Titman, Sheridan; and Wermers, Russ .1997. "Measuring mutual fund performance with characteristic-based benchmarks". Journal of Finance 52: 1035-1058.

Elton, Edwin; Gruber, Martin; and Blake, Christopher. 1996. "The persistence of risk-adjusted mutual fund performance". Journal of Business 69: 133–157.

Fama, Eugene; and French, Kenneth.1993. "Common risk factors in the returns on stocks and bonds". Journal of Financial Economics 33: 3–56.

Fletcher, J.; and Forbes, D. 2002. "An exploration of the persistence of UK unit trust performance", Journal of Empirical Finance 9: 475–93.

Fletcher, Jonathan. 1999. "An examination of UK Unit Trust Performance within the Arbitrage Pricing Framework". Review of Quantitative Finance and Accounting 8; 91-107.

Goetzmann, William; and Ibbotson, Roger. 1994. "Do winners repeat? Patterns in mutual fund performance". Journal of Portfolio Management 20: 9–18.

Grinblatt, Mark; and Titman, Sheridan. 1992. "The persistence of mutual fund performance". Journal of Finance 47: 1977–1984.

Hendricks, Darryll; Patel, Jayendu; and Zeckhauser. 1993. "Hot hands in mutual funds: Short-run persistence of performance, 1974–1988". Journal of Finance 48: 93–130.

Henriksson, Roy D.; and Merton, Robert C. 1981. "On Market Timing and Investment Performance". Journal of Business 54:513-533

Huij, Joop; and Verbeek, Marno. 2007. "Cross-sectional learning and short-run persistence in mutual fund perpormance", Journal of Banking and Finance 31: 937-997.

Jegadeesh, Narasimhan; and Titman, Sheridan. 1993. "Returns to buying winners and selling losers: Implications for stock market efficiency", Journal of Finance 48: 65–91.

Jensen, Michael. 1968. "The performance of mutual funds in the period 1945–1964". Journal of Finance 23: 389–416.

Jensen, Michael. 1969. "Risk, the pricing of capital assets, and the evaluation of investment portfolios". Journal of Business 42: 167–247.

Jones, Christopher; and Shanken, Jay. 2005. "Mutual fund performance with learning across funds". Journal of Financial Economics 78: 507–552.

Keswani, Aneel; and Stolin, David. 2006. "Mutual fund performance persistence and competition: a cross-sector analysis", Journal of Financial Research 26: 349-366

Malkiel, Burton. 1995. "Returns from investing in equity mutual funds 1971 to 1991". Journal of Finance 50: 549–572.

Pástor, Lubos; and Stambaugh, Robert. 2002. "Mutual fund performance and seemingly unrelated assets". Journal of Financial Economics 63: 315–349.

Quigley, Garrett; and Sinquefield, Rex A.1998. "Performance of UK unit trusts". Journal of Asset Management 1:72-92

Ramchand, Latha; and Susmel, Raul. 1998. "Variances and covariances of international stock returns: the international capital asset pricing model revisited". Journal of International Financial Markets, Institutions and Money 8: 39-57.

Rhode, M. 2000. "Past Imperfect? The performance of UK equity managed funds". FSA Occasional Paper 9; 1-58.

Sirri, Erik, and Tufano, Peter. 1998. "Costly search and mutual fund flows", Journal of Finance 53: 1589–1622.

Stambaugh, Robert. 1997. "Analyzing investments whose histories differ in length". Journal of Financial Economics 45: 285–331.

Treynor,J.; and Mazuy,F. 1966. "Can mutual funds outguess the market?". Harvard Business Review 44: 131-136

Wermers, Russ. 2000. "Mutual fund performance: An empirical decomposition into stock picking talent, style, transaction cost and expense". Journal of Finance 55: 1655-1695.

Appendix

Appendix

The descriptive statistic of 'Total Expense Ratios' in UK All Companies sector, UK Equity Income sector, UK Smaller Companies sector, UK Zero sector, and overall across the four sector.

Descriptive statistic	Overall	UK All Companies	UK Equity Income	UK Smaller Companies	UK Zero
mean	1.3695	1.3324	1.4970	1.3665	1.0577
standard dev	0.4939	0.5161	0.3975	0.4799	0.5976
kurtosis	0.5597	0.2423	1.7639	0.7084	0.0580

Biography

I am Tarrin Attachariya, born in December 22, 1984 at Nakornratchasima. In 2007, I graduated for Bachelor of Engineering, major in mechanical engineering, from Thammasat University. Present, I work as an analyst for the Risk Management Department of TMB Asset Management Co. Ltd.