The UK Equity Unit Trusts: Time-Varying Market Risk and Idiosyncratic Risk

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Abstract

This thesis empirically investigates the risk of UK equity unit trusts by breaking down the total risk of trusts into market risk and idiosyncratic risk. This thesis constructs a research sample of 478 UK-authorized equity unit trusts from July 1990 to June 2015, exploring three research questions: the investment abilities of stock-picking and market return-timing; the investment ability of market volatility-timing and joint market timing; the idiosyncratic risk at the individual trust level.

This thesis uses daily data to capture intermittent timing behavior and employs GARCH-type models to address the econometric problems of autocorrelation and heteroscedasticity owing to the employment of daily returns. This thesis documents how trust managers can time the market volatility successfully, whereas this is less the case with how they time the market returns. Moreover, data frequency cannot explain the empirical findings of reverse return-timing behavior. Volatility-timing evaluation is sensitive to data frequency, indicated by the opposite results obtained from daily and monthly data analysis.

Trust managers select stocks to construct their portfolios. Stock's idiosyncratic risk related to firm news and unpriced by market returns deserve as much attention as market risk. Our last study concentrates on the idiosyncratic risk of unit trusts' portfolio that highly depends on trust managers stock-picking decisions. The study breaks down each trust's total idiosyncratic risk into aggregate idiosyncratic risk capturing typical responses of trust managers to the public firm news and trust-specific unique risk assessing the risk-taking decision of each unit trust manager.

We emphasise the relationship between realized returns of the unit trust and its unique risk exploring whether trust managers can produce high returns for trust investors when they take relatively high additional risk comparing to peers. The finding of significant positive relationship in the short-term across all trusts is favourable, supporting that managers are rewarded for their aggressive investment. Our finding can advise trust investors to invest in unit trusts with relatively high risk within their risk tolerance and capability. The positive relationship, nevertheless, is not consistent; thus, it is essential for investors to timely switch unit trusts timely.

Dedication

This thesis is dedicated to my father and my mother. They never doubted my potential ability. My father always faithfully guided me at every stage and in all aspects of my life. My mother has loved and cared for me every day. My dearest mum and dad, I love you and am grateful for your love, always and forever!

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I am most grateful to my grandparents, my parents and my brother for loving me, supporting me, inspiring me, making me appreciate the value of education, and showing me to be a kind person. The first day of my undergraduate, my dad told me “your journey of learning has just begun …”, letting me know that learning is a life-long process.

Last but not least, I would like to thank my friends for being here with me, watching films with me, having meals with me, playing squash and badminton with me, looking after me … All my dear friends give my monotonous research life a colour. I am especially grateful to one of my best friends Elaine Wood who shows me how to live as an elegant artist.

Thank you, all people in my life, for letting me be me and accepting my mistakes, ignorance, and even stubbornness. As a simple thank you would not be enough to express my gratitude, please multiply my thanks infinitely!

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Chapter 1: Introduction

1.1 Introduction

Research on mutual fund performance has experienced a long history since the 1960s. The attraction of fund performance evaluation has continued to the present for three reasons. Firstly, actively managed mutual funds have witnessed dramatic growth around the world. For example, the total net assets of worldwide regulated open-ended funds have reached more than $46 trillion by the end of 2018 since $26.7 trillion in 2009 (Investment Company Institute[1], 2019).

Secondly, although mutual funds play an essential role for investors, previous studies debate whether actively managed mutual funds can beat the financial market. On the one hand, under the assumption of the efficient or semi-efficient market, all available and relevant information is incorporated into prices; therefore, there is no way to beat the market because there are no under- or over-valued securities available. On the other hand, as investors pay large management fees to fund managers, investors have deserved to receive additional value produced by managers; otherwise, the mutual funds should not have survived.

Thirdly, empirical studies find mixed results referring to the performance of active mutual funds concerning different benchmark and estimation methods. More specifically, Jensen, (1968); Cumby and Glen (1990); Malkiel (1995); Carhart (1997); Daniel *et al.* (1997); Blake and Timmermann (1998); Busse, Goyal and Wahal (2010); Fama and French (2010); Blake *et al.* (2017) among others document an average underperformance of actively managed mutual funds after fees and expenses. By contrast, Fletcher (1995) demonstrates a positive abnormal return to the benchmark with time-varying market exposure. Ferson and Warther (1996) reveal that the distribution of alphas shifts to the right and is centred near zero from negative, after using a benchmark conditional on macro-economic public information variables. Kosowski *et al.* (2006) exhibit superior performance among growth-oriented funds using a bootstrap inference test. Overall, the cloudy findings for active fund performance motivate researchers

[1] The Investment Company Institute (ICI) is the leading global association of regulated funds in the US. Regulated funds are defined as collective investment pools that are substantively regulated, open-end investment funds, including mutual funds, exchange-traded funds, closed-end funds, and unit investment trusts in the US. ICI is the primary source of analysis and statistical information on the investment company industry. Economists and research analysts employed by the ICI research department collects and disseminates data for all types of registered investment companies, offering detailed analyses of fund shareholders, the economics of investment companies, and the retirement and education savings markets.

to improve benchmark specification and parameter estimation methods, in order to shed light on the information transparency in the financial market and investment ability of professional investors.

This thesis attempts to enrich the literature on fund performance evaluation through an emphasis on the UK-authorized equity unit trusts. Unit trusts are established for emulating the US mutual funds. We choose this subject for four reasons. Initially, the UK fund market exhibits fast growth but gets rare academic attention. UK asset management market has been the second-largest asset management centre in the world after the US and dominates the asset management industry within Europe (TheCityUK[2], 2018). Thus, it is worth undertaking deeper consideration of this booming market from an academic perspective.

Secondly, unit trusts represent a substantial proportion of the UK fund market and have a long history. Municipal & General, for example, launched the first unit trust (i.e., 'First British Fixed Trust') in 1931. The extended history permits of large dataset and long research period of UK unit trusts, ensuring enough observations in the empirical analysis.

Thirdly, UK-authorized unit trusts are free to allocate their underlying assets in either domestic or foreign equity markets, as long as the unit trust is authorized and available for trading in the UK market. We construct this integrated sample because the international fund industry plays an increasingly important role in the UK fund market. For example, TheCityUK (2015) reports that assets of the international fund management industry have increased to $108.5 trillion from $48.1 trillion from 2004 to 2014. Moreover, unit trusts with global investment objective have an attraction to UK retail investors, as these trusts can satisfy retail investors who are interested in foreign financial markets but short of costly and reliable information. We, therefore, make an effort to extend the research sample from a domestic to an international perspective.

Last but not least, equity unit trusts restrict the underlying assets of allocating to equities at least 80%. We consider equity trusts mainly attribute to the requirement that an appropriate benchmark portfolio should use asset holdings with the same characteristic by unit trusts (Roll, 1978). If unit trusts in research samples held not only equities but also a large proportion of properties and commodities, we would have to form a comprehensive benchmark portfolio,

[2] TheCityUK is the industry-led body representing UK-based financial and related professional services. TheCityUK was founded in 2010, sitting on the government's Financial Services Trade and Investment Board (FSTIB) and focusing on strategic issues relating to the financial industry. TheCityUK is closely working with the Investment Association.

and it would be complex and difficult to guarantee the accuracy of 'homemade' index. Therefore, this thesis considers UK-authorized equity unit trusts.

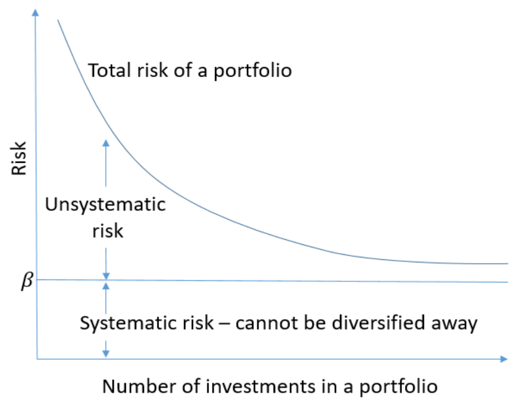
Performance is usually evaluated by risk-adjusted returns; that is, how much risk is involved in producing the return of investment. A portfolio's total risk consists of systematic market risk and unsystematic risk. As long as assets are invested in a stock market, assets have to suffer the risk from the market fluctuation. Thus, systematic risk cannot be eliminated.

The unsystematic risk captures firm-level shocks, which is most frequently referred to as idiosyncratic risk. It is possible to eliminate unsystematic risk virtually by diversification. For example, Steve Jobs passed away on the day of 5th October 2011, which is a firm shock. The share price of Apple was $54.04 on 5th October 2011, while closed at a split-adjusted price of $50.53 per share on 7th October. When the stock price of Apple fell by close to 10%, the S&P 500 went up by a little over 2%. If a well-diversified fund held Apple stock as well as many other stocks or market index, Apple's idiosyncratic risk would be eliminated. In other words, investors forming well-diversified portfolios face market risk only.

Portfolios suitably comprise two broad assets: risk-free assets such as money-market account or Treasury bills and risky assets such as shares of stock. To simplify the analysis, we consider a risky portfolio as a stock market index fund. The core task of constructing a portfolio is to determine the composition of the risky portion of the complete portfolio. Rational investors are eager for portfolios with maximum return and minimum risk. A nature question of what is the absolute maximum or minimum satisfying investors arise. Investors' attitude toward risk (i.e. risk aversion) assists in answering the nature question. To be specific, investors can use "utility function" which captures their risk aversion to rank portfolios with different expected returns and level of risk; then, they decide on the target risk level towards the risky portfolio. In the context of a single stock market index risky portfolio, the expected return of the optimal portfolio is equal to the sum returns of risk-free assets and risk-weight market index. The optimal portfolio theory and single-index model above are proposed by Markowitz (1952) and Jensen (1972).

For actively managed mutual funds, a prevalent risk-adjusted return method to assess fund's performance is the "abnormal return" of fund portfolio's return over the theoretical expected return (Jensen, 1968). The expected return is estimated by the single-index model in principle, which is also known as CAPM. More specifically, CAPM concentrates on the return that is rewarded by bearing risk and in particular, undiversifiable market risk. The risk-weight is represented by beta describing how much risk the investment will add to a portfolio regarding the equity market. The beta of a portfolio is the weighted average of the individual asset betas; thus, an investor can construct a portfolio with a remaining constant target beta if the betas of the underlying assets are known. Figure 1.1 gives a graphic description of the total risk of a portfolio.

Figure 1. 1:
Total risk of a portfolio



This figure draws the total risk components of an equity portfolio. The horizontal axis represents the number of stocks held in the portfolio. The vertical axis represents the risk level.
The total risk is measured by the standard deviation of portfolio returns, decomposing into systematic risk and unsystematic risk. That is, $Total\ risk = systematic\ risk + unsystematic\ risk$.
The systematic risk is relevant to equity market risk, indicated by beta β. The unsystematic risk is relevant to firm-level risk, displaying a dramatic reduction effect of diversification.

The classic performance evaluation approach implicitly assumes a constant beta for portfolios. Active fund managers, however, might switch the fund portfolio's risk according to the market situation, resulting in a time-varying beta. For example, when the market returns go up, in order to gain more profits, managers might tend to take a higher market risk indicated by a higher beta. By contrast, when the market returns go down, managers might shift to hold cash-equivalent equities to avoid loss indicated by a lower beta.

On the other hand, fund managers might consider market volatility. More specifically, when the market is more volatile, risk-averse managers might reduce beta to avoid market risk; whereas, if the market is relatively stable, managers might invest aggressively to raise beta, thus attempting to grab extra returns. The first beta-switching behavior is defined as market-return timing strategy; the second is defined as market-volatility timing behavior. This thesis investigates both timing strategies in our first two studies.

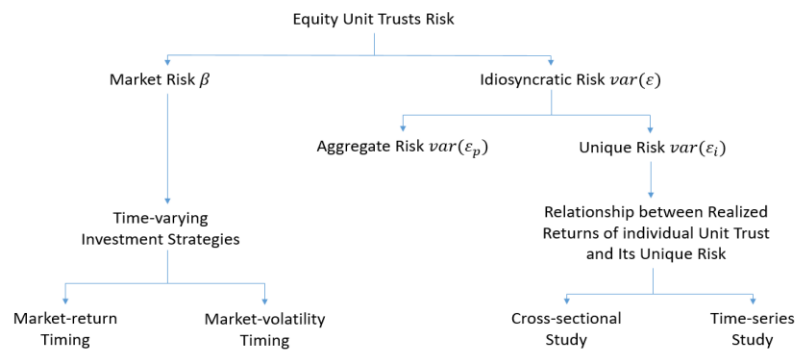
Regarding idiosyncratic risk, conventional studies advise investors to eliminate this risk by diversifying their asset portfolio effectively, which is aptly summed up by the phrase: "do not put all of your eggs in one basket.” Under the assumption of market efficiency, diversification can achieve the long-term financial goal of minimising risk. In particular, if the market is efficient, it is impossible to select under-priced stocks because there is no private information on the market and all public information is reflected in stock prices. Investors cannot be guaranteed against losses. The purpose of diversification is not to grab a short-term extra value by holding specific stocks but navigate the volatility of markets and eliminate unsystematic risk as investors have to take systematic market risks.

Nevertheless, the efficient market assumption cannot be held in real financial markets; the stock market is riddled with insider trading and market manipulation. Fund managers will pick up several specific successful stocks rather than diversifying their assets if they can obtain non-public firm information or receive the information in advance from their social network. Managers would like to play with their information and take the idiosyncratic risk, attempting to achieve much higher returns. As the management fees paid by investors are equivalent to the cost of sharing a manager’s private information (Henriksson and Merton, 1981), it is sensible for investors to inquire whether they can profit from the manager’s private information. Therefore, it is deemed worthwhile to explore undiversified risk regarding private information, and we define this risk as trust-specific unique risk for each UK equity unit trust in the third study.

1.2 Research Framework

This thesis investigates the risk of UK equity unit trusts from two aspects: time-varying market systematic risk and undiversified idiosyncratic risk. More specifically, the first two research projects explore market-return timing and market-volatility timing strategies. Trust managers can time the equity market based on the market movement of going up and down or based on market fluctuation both highly volatile and relatively stable. The last study examines whether undiversified risk contributes to real returns of UK equity unit trusts. Figure 1.2 draws the research framework of this thesis.

Figure 1. 2:
Research Framework



The first research is relevant to market-return timing performance.
The second research is relevant to market-volatility timing performance and joint market timing performance. Joint market timing suggests that trust managers might consider both circumstances of market return and market volatility at the same time when making an investment decision.
The third research is relevant to the idiosyncratic risk of equity unit trusts. More specifically, the study controlling for aggregate idiosyncratic risk explore the trust-specific unique risk at the individual level. The third study further to investigate the relationship between realized returns of individual unit trust and its trust-specific unique risk. The relationship study considers both cross-sectional and time-series regression methods.

This thesis employs trust portfolios rather than individual trusts in the first and second studies, primarily attributing to the research purpose of evaluating the selectivity and timing abilities of UK trust managers. Timing performance evaluation has been studied for decades, reporting the mixed empirical findings, which motivates us to investigate whether data frequency matters. To be specific, empirical findings based on monthly returns of UK unit trusts exhibit negative timing coefficients, failing to confirm the theoretical assumption (e.g., Fletcher, 1995; Blake et al., 2017). By contrast, we adopt daily data, attempting to find a different empirical result that is in line with theoretical assumption. As previous empirical studies use average monthly returns of trust portfolios (e.g., Fletcher, 1995; Blake et al., 2017), the average daily returns of trusts portfolios are employed in this thesis to minimise potential bias while doing the comparison.

The aggregate study gives a broad view of investment abilities of trust managers as a whole, examining the significant and widespread issue. In contrast, an individual study is great for diagnosing an issue or examining whether a particular trust manager is equipped with superior investment ability. We, therefore, move our attention to individual trust in the third research, and explore whether unit trust taking higher risk than peers can produce a higher realised return. Moreover, the individual study can give trust investors a piece of advice on selecting appropriate unit trusts conditional on the mean-variance theory to hold. We detail our three studies in the following sub-sections.

1.2.1 First Research: Stock-picking and Market Return-timing Abilities

The first research examines the investment ability of UK equity unit trusts managers. This study considers the investment skills of selectivity and market-return timing. The question of whether UK equity unit trusts can time the stock market returns and produce extra return is of significance. More specifically, as active equity funds employ dynamic investment strategies and have time-varying exposures on the financial market, extracting market timing ability from the skill of stock picking is a benefit for researchers and investors to track manager's investment behavior and ability accurately.

Moreover, skill assessment provides an alternative perspective to investigate an actively managed fund performance. To be specific, active funds are managed by professional managers; that is, the performance of active funds highly depends upon managers' investment skills. As a manager's investment ability is persistent, superior fund managers might be able to provide excess profits, regardless of market fluctuation. Therefore, it is worth to re-examine the investment abilities of fund managers in the context of UK fund market with updated research sample.

1.2.1.1 Motivations

Market-return timing performance has long been considered. We extend the literature in three important ways: first, this study employs daily returns to capture the high frequency of timing behavior. Previous studies use monthly returns and find negative or no timing skill (e.g., Fletcher, 1995; Cuthbertson, Nitzsche, and O'Sullivan, 2010; Blake et al., 2017). Goetzmann, Jonathan, and Ivković (2000), and Bollen and Busse (2001) document that a monthly test is weaker than a daily test when adopting standard timing models, because of the difference between horizons in manager's decision making and research data. Chance and Hemler (2001) use a unique data set, which is daily recommendations of allocating clients' capital reported by market timers voluntarily, and find significant timing ability when observations are daily, but insignificant timing skill when observations are monthly. Prior studies support that data frequency could seriously affect inferences regarding performance evaluation, and daily data might provide more reliable evidence than monthly data. To our knowledge, there is no paper assessing return-timing performance of UK unit trusts based on daily data. This thesis is motivated to seal this research gap.

Moreover, the econometric estimation problems of autoregression and heteroscedasticity generated due to high-frequent data motivate us to employ autoregression conditional heteroscedasticity (ARCH) type models. The autoregression issue could be attributed to nonsynchronous trading (Perry, 1985; Atochison, Butler, and Simonds, 1987). In particular, even though managers study the financial market and make decisions every day, they do not trade every day given high trading costs or market conditions. Infrequent trading would result in biased estimates of variance, serial correlation, and a contemporaneous correlation between assets (Scholes and Williams, 1977). ARCH-types are time-series models, accounting for past values when estimating parameters, which could overcome the autocorrelation problem.

Heteroscedasticity mainly results from the error term whose variance is not a constant but random variable. Standard estimation methods such as ordinary least square (OLS) assume that the variance of the error term is constant or equal to one under the assumption of standard normal distribution. In reality, the benchmark cannot capture all systematic risk; as a result, residuals might contain returns from unpriced systematic risk. The variance of residuals would be time-varying due to the variance of unpriced systematic risk. Ignoring heteroscedastic variances would result in unreliable statistical inference. ARCH-type models can overcome these statistics problems by using the time-series of joint equations: mean and conditional variance, accounting for autocorrelation and heteroscedastic variance when estimating parameters.

Additionally, this study focuses on equity unit trusts; trusts holdings of 80% are restricted to equity markets regardless of market conditions. That is, the unit trusts might not be well-diversified, and the idiosyncratic risk of unit trusts might not be fully eliminated. Consequently, the assumption that the variance of residual is constant cannot be held in our research sample. Therefore, we use GARCH-in-Mean model to account for the idiosyncratic risk of unit trusts by adding the conditional variance variable into the mean equation, in order to improve the model specification.

1.2.1.2 Findings

This study has four preliminary findings. Initially, we find over-performance and superior selectivity ability for UK equity unit trusts, challenging the hypothesis of an efficient market. Secondly, we find that investment behavior of timing the market returns reversely remains consistent with respect to daily data analysis. Although prior US fund studies obtain different results with daily and monthly returns (Goetzmann, Jonathan, and Ivković, 2000; Bollen and Busse, 2001), data frequency is not a significant factor in the analysis of market-return timing performance of UK equity unit trusts. Our finding of negative timing performance based on daily returns is consistent with prior findings based on monthly UK mutual fund returns (e.g., Fletcher, 1995; Cuthbertson, Nitzsche, and O'Sullivan, 2010; Blake et al., 2017). Thirdly, our result support that ARCH-type estimate methods perform better than the OLS method in analysing a high-frequent data set. More specifically, the ARCH family provides consistent and robust evidence on positive stock-picking ability across two different market-return timing models in comparison to the OLS approach. Finally, we find that the positive selectivity skill is robust in accounting for time-varying idiosyncratic risk of unit trusts in the aggregate.

1.2.2 Second Research: Market-volatility Timing and Joint Market Timing Performance

The first study fails to offer evidence of favourable market-return timing ability, motivating us to proceed to investigate timing strategy referring to market volatility because the volatility is more predictable and persistent than market return (Busse, 1999; Bollerslev, Chou, and Kroner, 1992). Moreover, literature documents that market-volatility timing strategy can produce substantial economic value in the common stock market (Fleming, Kirby, and Ostdiek, 2001; 2003; Johannes, Polson, and Stroud, 2002; Clements and Silvennoinen, 2013; Moreira and Muir, 2017), supporting managers to employ volatility-timing strategy while managing their portfolio. Thus, UK fund managers might time market volatility in order to add value and avoid loss.

1.2.2.1 Motivations

Prior empirical studies find mixed results on market-volatility timing performance. For example, Busse, (1999), Liao, Zhang, and Zhang (2017) and Yi et al. (2018) display successful counter-cyclically timing ability, whereas Giambona and Golec (2009) and Kim and In (2012) show almost equal percentage counter-cyclical and pro-cyclical volatility timing performance. For the UK equity mutual funds, Foran and O'Sullivan (2017) exhibit that only 6% of funds can significantly and counter-cyclically time market volatility. Foran and O'Sullivan (2017) adopt monthly returns. However, Busse (1999) and Fleming, Kirby and Ostdiek (2003) confirm that daily data allows for more efficient estimates of time variation in systematic risk than does monthly data. To our knowledge, there is rare study employ daily returns to investigate volatility-timing performance of UK equity unit trusts. Therefore, this thesis is motivated to fill this research gap; we also carry on monthly data analysis for comparison.

Furthermore, we take the joint timing strategy into account. To be specific, we argue that managers consider both market return and market volatility simultaneously rather than either factor alone. Consequently, fund managers might not take heavy/light positions in the market even if he successfully foresees an upswing/downswing of market return because he has to consider market volatility at the same time; managers might behave conservatively in lessening/increasing equity holdings if the anticipation of market volatility is high/low. Chen and Liang (2007) propose Sharpe-ratio expansion to demonstrate both timing behavior at the same time and find positive joint timing performance for US hedge funds. To our knowledge, the joint timing model has not been employed in mutual fund study, motivating us to extend the literature.

1.2.2.2 Findings

Similar to the first study, we use ARCH family to estimate parameters to address econometric problems of autocorrelation and heteroscedasticity. We also account for asymmetric characteristic of volatility while modelling daily conditional UK equity market volatility. We have three preliminary findings: first, we find significant successful volatility-timing ability by using daily data but reverse volatility-timing skill from monthly data, suggesting that data frequency is essential for volatility-timing performance evaluation.

Second, we demonstrate that daily data performs better than monthly data in volatility-timing performance evaluation because the findings in daily data analysis are consistent across unconditional and conditional volatility-timing models. To be specific, if the correlation between market returns and market volatility is high, it would be possible that the performance of market-return timing is incorrectly explained by the coefficients of market-volatility timing factor. We, therefore, investigate volatility-timing performance conditional on the return-timing term and find that counter-cyclical volatility-timing finding remains in daily data analysis; however, the significant pro-cyclical volatility-timing finding disappears in monthly data analysis. Besides, the correlation between volatility and returns is significant for monthly data while small for daily data. These results imply that pro-cyclical volatility-timing performance based on monthly data analysis might be biased and unreliable.

Last, we fail to find significant coefficient for the Sharpe-ratio term in the joint market timing model; whereas, we find significant coefficients for both volatility-timing factor and return-timing factor in conditional volatility timing model. We claim that managers adopt two timing strategies separately instead of simultaneously.

1.2.3 Third Research: Trust-specific Unique Risk and Volatility Investment Strategy

It is well accepted that a firm's shocks or news cannot be priced by the systematic market risk timely. The unpriced shocks are known as the idiosyncratic risk in the firm-level. In contrast, for each unit trust actively managed by professional investors, it is rational to question whether there is unpriced risk referring to the manager's private information in the trust-level. This question motivates us to concentrate on idiosyncratic risk of UK equity unit trusts.

1.2.3.1 Motivations

Many empirical studies have demonstrated that equity portfolios do not completely diversify the firm-level idiosyncratic risk (e.g., Campbell et al., 2001; Goetzmann, Jonathan, and Ivković, 2000; Ang et al., 2009). In the context of active mutual funds, the undiversified idiosyncratic risk is highly relative to the selectivity skill of managers in the aggregate. In the individual trust level, the idiosyncratic risk of an equity unit trust would be affected by two factors: firm's shocks and manager's private investment decision. Ferson and Schadt (1996) argue that a managed portfolio strategy using public information should not be judged as having superior performance, implying that public firm-level shocks should be priced. Therefore, we break down the total idiosyncratic risk of each equity trust into aggregate idiosyncratic risk and trust-specific unique risk. The aggregate idiosyncratic risk is relevant to the public firm-level shocks, capturing the typical response of managers at the aggregate level. This thesis emphasises the trust-specific unique risk.

Moreover, we further study whether fund managers take benefits from holding low volatility stocks, motivated by the existence of volatility anomaly. More specifically, volatility anomaly suggests that a low volatility portfolio outperforms the corresponding high volatility portfolio (Haugen and Heins, 1972; Haugen and Heins, 1975). Low/high volatility portfolios are constructed with stocks showing a low/high standard deviation of returns or market exposure beta. Volatility anomaly is remarkable, consistent, and comprehensive; the anomaly exists in the not only global stock markets but also bonds, credit, and futures markets across many different countries (Ang et al., 2009; Blitz and van Vliet, 2007; Chen et al., 2012; Baker and Haugen, 2012; Frazzini and Pedersen, 2014).

Baker, Bradley and Wurgler (2011) state that investor's preference for high volatility stocks could rationalize the presence of volatility anomaly in the stock market. In particular, retail investors might irrationally seek risk for chasing attractively high expected returns, whereas institutional investors do not offset the irrational demand partly because the agency mandates discourage investment in high alpha, low beta stocks. On the other hand, holding high-volatility stocks is a more natural way than selecting under-priced low volatility stocks to beat the market. Therefore, this study is motivated to test the volatility investment strategy of UK equity unit trusts in the context of volatility anomaly.

1.2.3.2 Findings

We have three preliminary findings. Firstly, the relationship between realized returns of equity trusts and their unique risk is positive in a short-term. To be specific, trusts sorted in high unique-risk group outperform the trusts grouped in low unique risk portfolio. Moreover, in the cross-sectional analysis, the coefficients of contemporary or 1-month lagged unique risk variable are significantly positive.

Secondly, a significant positive relationship is not consistent in the long term study. More specifically, the coefficient of the variable of 3-month lagged unique risk is zero, and coefficients of variables of 6-month and 12-month lagged unique risk change to negative, in the cross-sectional analysis. For each unique risk over the whole research period, the coefficient of unique risk factor is positive but statistically insignificant on average. In general, our relationship findings would give investors a piece of advice of selecting a relative high-risk trust based on their risk tolerance and capability, and timely change trust investment.

Last but not least, we demonstrate that almost all unit trusts tend to hold stocks having relatively high volatility and low beta, indicated by significant negative coefficients of volatility anomaly. This finding indirectly supports the hypothesis that the presence of volatility anomaly is partly due to institutional agency mandate restricting managers to offset volatility anomalous in the stock market.

1.2.3.3 Contributions

This thesis firstly proposes the concept of trust-specific unique risk for each equity unit trust. In particular, we construct a variable of aggregate idiosyncratic shocks. The augmented residuals conditional on the typical response of trust managers would be able to assess individual manager's risk decision concerning his/her private information and investment objective accurately. The standard deviation of this augmented residuals would be a random variable and different from peers; we, thus, name this standard deviation trust-specific unique risk.

Furthermore, this thesis shed light on the mixed findings on the relationship between risk and return from the perspective of UK equity unit trusts. We adopt three methods to investigate the relationship between trust-specific unique risk and realized returns of the unit trust: first, sorting unit trusts into five groups according to their unique risk level and rebalancing the groups at the beginning of each month; second, cross-sectional regression analysis; third, time-series model of GARCH-in-Mean model. These three approaches permit us to explore the relationship from the perspectives of short-term and long-term.

In addition, the study of volatility investment strategy contributes to explain the existence of volatility anomaly in the stock market. More specifically, our result demonstrates that, despite the presence of volatility anomaly in the UK stock market, UK domestic equity unit trusts do not take advantage from picking up under-priced low-volatility stocks, thereby failing to offset the volatility anomaly.

1.3 Organization of Thesis

Chapter 1 briefly introduces our studies of time-varying market risk and trust-specific unique risk for UK-authorized equity unit trusts. The remainder of the thesis proceeds as follows: Chapter 2 introduces the UK fund market, such as various types of funds. Regarding two particular types of open-ended mutual funds in the UK market, we draw a comparison between two types of funds and give particular attention to unit trusts.

Chapter 3 provides a literary review of timing performance and idiosyncratic risk. We detail the theoretical timing models development and recent empirical studies on time-varying beta analysis. We also state the measurement of idiosyncratic risk and the relationship between idiosyncratic risk and market returns at the firm level. Investment strategy concerning equity volatility (i.e., total volatility or idiosyncratic volatility) is contained in the chapter of literature review as well. Chapter 4 describes research sample construction and return data. Chapters 5, 6, and 7 present three studies separately, and Chapter 8 concludes this thesis.

Chapter 2: Research Background

This thesis studies UK-authorized equity unit trusts from July 1990 to June 2015. The UK fund market has recently exhibited a dramatic increase in market shares and global financial status. The reported official numbers support the vital position of the UK market. For example, the Investment Association's[3] (2017) annual survey of asset management in the UK 2016 – 2017 reports that global assets under Europe management are £18.3 trillion; within European countries, the UK's market share is 36%, outweighing the sum of market shares of the next three largest countries (i.e., 18% for France, 9% for Germany, and 7% for Switzerland).

Moreover, the UK asset management industry serves clients from both domestic and overseas. For example, £2.6 trillion is managed in the UK on behalf of overseas investors in Europe, US, Middle East and Asia. In the domestic UK market, the size of the asset management industry is up to 373% of GDP Investment Association (2017). Besides, the UK retail fund market exhibits a fast development pace. The value of funds held by UK investors was £1,045 billion at the end of 2016, increasing by 13% from 2015 (Investment Association, 2017). Overall, the UK fund market has been developed into an attractive and comprehensive investment market, which deserves to receive more academic attention.

This chapter describes the UK fund market. Section 2.1 briefily introduces open-ended funds, closed-end funds, exchange-traded funds (ETFs) and pension funds. There are two types of open-ended mutual funds in the UK: Unit Trusts and Open-ended investment companies (OEICs). Section 2.2 draws a comparison between unit trusts and OEICs. As this research focuses on unit trusts, section 2.3 presents more information relevant to unit trusts style.

2.1 Fund Types in the UK Fund Market

Several different fund products are available to retail investors in the UK market, including unit trusts, OEICs, investment trusts, exchange-traded funds (ETFs) and pension/life funds. More specifically, unit trusts and OEICs are open-ended funds, whereas investment trusts are closed-end funds. Typical characteristics of open-ended mutual funds include pooled

[3] The Investment Association is the trade body that represents UK investment managers, having over 200 members and managing over £6.9 trillion on behalf of clients in the UK and around the world. In 2015, the Investment Management Association (IMA) merged with the Investment Affairs Division of the Association of British Insurers, forming the Investment Association. The IMA was established by merging Association of Unit Trust and Investment Funds (AUTIF) and the Fund Managers Association in 2002. AUTIF was known as the Unit Trust Association, established in 1959.

investment, professional management and flexible exchange. Prices are usually calculated daily, generally reflecting the net asset value (NAV) of underlying properties held by the fund. Managers can create or redeem units according to the requirement of investors, leading to the change of asset under management (AUM). For example, if investors sell their units or shares back, and no other investors require buying them, the AUM will get smaller, and the fund managers will expect some cash outflow. In contrast, if investors buy new units or shares, and no other investors want to sell their holdings back, the AUM will get more substantial by generating cash inflow.

Closed-end funds do not need to rebalance the AUM by either redemption or creation from investors. To be specific, closed-end funds manage a fixed amount of capital raised through an initial public offering (IPO), then funds are listed and traded on a stock exchange similar to stocks. The price of closed-end funds fluctuates according to market demand and supply, as well as NAV of changing values of properties in the funds' holdings.

ETFs combine the characteristics of both open-ended and closed-end funds. More specifically, ETFs are listed and traded on the stock exchange, which is similar to closed-end funds or stocks. ETFs also allow for creation and redemption, resulting in the fluctuation of AUM, which is similar to open-ended funds. The price of ETFs is influenced by both demand/supply and the NAV of holdings.

All of the above investment vehicles (i.e., unit trusts, OEICs, investment trusts and ETFs) are investment products, implying that investors are exposed to the risk of incurring losses. In contrast to investment products whose investors have the potential risk of losing money, pension/life funds are guaranteed to pay a fixed payment at a pre-agreed time by the sponsor of the fund. Pension/life funds are only available for pension providers and insurers to purchase rather than opening to all investors freely.

2.2 Open-ended UK Mutual fund: Unit Trusts and OEICs

Unit trusts and OEICs represent a substantial proportion of the UK fund market, while unit trusts have a much longer history than OEICs. In 1931, the first unit trust (i.e., "First British Fixed Trust") was launched by Municipal & General, in order to simulate US mutual funds. The "First British Fixed Trust" was the first trust to invest in a solid portfolio of shares in blue-chip British companies. Four years later, Municipal & General launched a flexible unit trust, changing the composition of the portfolio flexibly instead of keeping a fixed set of shares. In 1996, about 65 years later, the first OEIC was launched.

Unit trusts and OEICs are quite similar in practical investment. The main difference is in their legal structure and pricing method (Investment Management Association[4], 2014). More specifically, the legal structure for collective investment schemes includes company, trust, contract and partnership. Unit trusts are established as trusts, while OEICs are incorporated as a company. Unit trusts can issue trust only without permission to issue shares, as unit trusts do not have their legal personality. In particular, the investors investing in trust are the legal owners of the units; the Trustee has a duty of oversight over the activities of the manager; the manager operates the investment pool. Benefits such as dividends gained from the unit trust are collected and distributed by the Trustee to the investors in the fund.

By contrast, OEICs have a corporate structure; similar to a company, OEICs can issue and redeem shares instead of units along with investors' coming in and going out. OEICs require at least one authorized corporate director whose responsibility is operating the OEIC. OEICs have no separate Trustee to monitor managers but are governed by company law.

Furthermore, unit trusts employ dual pricing, whereas OEICs adopt single pricing. To be specific, unit trusts have two pairs of prices: the buying (offer) price and the selling (bid) price. The difference between the bid and offer prices on unit trusts embraces the initial charge. The initial charge on a unit trust is made when the units are sold to the investor, which is a percentage of the bid price and covers the managers' start-up costs.

In contrast, OEICs' single price structure is much more straightforward, using a single mid-market price for buying and selling and paying initial charge separately. The initial charge of OEICs is paid to fund managers to cover their expenses such as commission, administration and dealing costs. Despite the existence of a few differences, some prior studies examine them jointly, namely UK mutual funds (e.g., Allen and Tan, 1999; Cuthbertson, Nitzsche, and O'Sullivan, 2010; 2012).

However, this thesis studies unit trusts rather than both, in order to minimise the estimation bias. Initially, components of returns for unit trusts and OEICs are different. To be specific, unit trust returns employed in this study contain the initial charge, whereas OEICs' single price

[4] Investment Management Association (IMA), estimated in 2002, was merged into Investment Association in 2015.

ignores initial charge referring to dealing costs. We cannot separate the initial charge from bid price because the DataStream employed to extract research data offers closing bid price only.

Moreover, Aragon and Ferson (2008) point out the different meaning of performance measures on a before-cost versus after-cost basis. The performance evaluated by the before-cost returns implies the investment ability of fund managers. By contrast, if we employ after-cost returns (i.e., offer price for unit trusts or single price for OEICs), the performance indicates the value added only. Considering that one of the aims of this thesis is to explore the investment ability of fund managers, we adopt before-cost returns calculated by closed bid price of UK unit trusts in empirical studies.

The performance of actively managed mutual funds can be defined at two broad levels: value-added and investment ability, according to the trading costs basis (Aragon and Ferson, 2008). More specifically, the basic idea of performance evaluation is to compare the return of the actively managed fund over some evaluation period to the return of a benchmark portfolio that represents a feasible investment alternative to the managed fund being evaluated. If the objective is to assess the investment ability of mutual fund manager, the benchmark should represent an equivalent investment alternative in all return-relevant aspects, except the reflection of fund manager's private investment ability.

In practice, some asset pricing models are employed to operationalize the concept of the equivalent benchmark portfolio. Early studies use the Capital Asset Pricing Model (CAPM) to construct a benchmark portfolio by combining safe assets and broadly diversified market portfolio; the weight of risky assets is based on the risk attitude of an investor. If the fund return is greater than the expected return of CAPM portfolio, the manager earns an abnormal return or Jensen alpha.

This Jensen alpha, however, is sometimes crude in their treatment of investment costs and fees, such as management fees paid to fund managers, fees paid to selling brokers, or transactions fees paid for buying and selling the underlying assets. As the trading costs of funds represent a drain from the net assets of the fund, a manager might generate higher returns than an equivalent benchmark before costs, but lower returns than the benchmark after costs. Aragon and Ferson (2008) clarify that, if a fund can beat the equivalent benchmark on an after-cost basis, the fund adds value for investors; if the fund outperforms the benchmark on a before-cost basis, the manager has investment ability.

2.3 Unit Trusts Styles

UK unit trusts are managed in two ways: passively and actively. Passively managed trusts, also known as index tracking trusts, aim to track the performance of a particular index, such as FTSE 100 or the FTSE All-Share in the UK. Actively managed trusts attempt to outperform their stated benchmark; the manager chooses the underlying holdings on the investors' behalf. The main difference between these two types of trusts is management fees. Passive trusts which require less day-to-day management, have lower ongoing charges than active trusts that involve extra works and analysis. Despite the strategy of tracking index for passive trusts, the manager still requires to make an investment decision of minimizing risk and maximizing returns. The performance of index trusts could be varied, in spite of tracking the same index. Although index trusts require investment strategy, the purpose of index trusts is not outperforming but tracking the benchmark.

A UK unit trust usually issues various share classes to satisfy different investors. Typically, "classes differ in terms of the fees and expenses that are paid out of the property of the fund due to the different costs involved in servicing the needs of the investors in the various classes" (Investment Management Association, 2014). More specifically, for dealing with dividends, trusts issue income share class and accumulated share class. Investors holding income share class will receive an income dividend at the end of the relevant accounting period, whereas investors holding an accumulated share class cannot get income dividend but automatically re-invest any accrued income back into the trust.

Moreover, share class of unit trusts are identified with alphabetic markers, such as 'class A' or 'class B', determined by how the sales charge is paid, for satisfying retail and institutional investors. The class A, for example, is the most common class; it is an upfront sales charge, implying that the cost of purchasing trust is at the beginning, and investors can avoid costly charge by long-term investment. The class B charges an annual fee for the life of the trust instead of upfront sales charge. Investors are forced to hold the trust of class B at least one year; otherwise, a contingent deferred sales charge might be triggered for early liquidation. Share classes of I, R, N, X and Y are issued particularly for institutional investors with a high net worth (e.g., more than $1 million). Institutional share classes usually charge the lowest fees and expenses per unit, as institutional investors usually purchase a large volume and pay higher fees than retail investors in the aggregate.

The UK funds industry has an extensive network. In order to assist investors in navigating around the vast universe of funds in the UK, Investment Association (IA) divides UK funds into over 30 sectors based on assets (e.g., equities, fixed income and mixed assets), geographic focus (e.g., UK, Europe ex UK, and North American, etc.), investment strategy (e.g., targeted absolute return and volatility managed) and investment focus (e.g., growth/small company, income and capital protection).

Chapter 3: Literature Review

This chapter aims at providing a comprehensive survey of mutual fund performance evaluation and the idiosyncratic risk of an equity portfolio. As the thesis investigates the risk of UK unit trusts, we mainly review studies related to time-varying market exposure of mutual funds (i.e., market timing behavior) and idiosyncratic risk.

We begin with the standard performance evaluation models because they are the foundation of timing performance evaluation. More specifically, in section 3.1, we introduce several benchmarks which are commonly employed to measure the performance of mutual funds, since the performance assessment of mutual funds is sensitive to the benchmark specification. We provide evidence to support how the benchmark embracing a timing factor can improve the accuracy of performance evaluation in the factor model. Section 3.2 presents various timing models such as market-return timing, market-volatility timing and joint market timing. This section primarily concentrates on the development of theoretical models. Empirical studies are described in section 3.3.

Our attention then moves from the systematic risk of fund portfolios to the idiosyncratic risk, particularly the measurement of idiosyncratic risk and the study of the relationship between idiosyncratic risk and returns in section 3.4. Section 3.5 gives volatility anomaly and volatility investment strategy a review. More specifically, volatility anomaly indicates that high/low volatile stocks tend to produce low/high returns. If investors, especially professional investors, are aware of this anomaly, they would benefit from investing in low-volatility stocks; then, the value of low-volatility stocks would increase to offset this anomaly. Empirically, many studies demonstrate the existence of volatility anomaly (e.g., Blitz and van Vliet, 2007; Chen *et al.*, 2012; Blitz, Pang and van Vliet, 2013). Section 3.5, therefore, reviews the literature of volatility anomaly and investment strategy of equities' volatility.

3.1 Performance Evaluation

Identifying an appropriate benchmark specification is the top priority in performance evaluation. In particular, the concept of performance evaluation is to measure the fund's abnormal return given the risk-taking of the fund portfolio. One obstacle preventing the implementation of this intuitive notion is quantifying the systematic risk while estimating a reasonable expected return. Systematic risk differing from unsystematic risk or idiosyncratic risk is incapable of being eliminated. The expected return of a well-diversified benchmark portfolio would be able to price all systematic risk accurately, ensuring an unbiased performance evaluation for active funds.

There are two main methods to construct benchmark portfolios: factor approach derived from the CAPM and holding-based approach. Although creating a set of benchmark portfolios corresponding to the characteristics of fund portfolio holdings is a straightforward way to build an appropriate benchmark for performance evaluation, holding data for mutual funds is not available for the UK market. This thesis employs factor benchmark and pays special attention to the time-varying market exposures indicated by the coefficient of timing factor.

3.1.1 Factor Benchmarks

Early investigators use the CAPM to estimate the expected return of passive benchmark portfolio, evaluating the performance of active mutual funds. A logical inconsistency, however, exists in the CAPM benchmark. To be specific, if CAPM assumes that all investors have common beliefs and information, then any measured abnormal performance can only occur when the market proxy is inefficient (Roll, 1978). On the other hand, researchers expect to obtain significant and positive abnormal return while evaluating the performance of active funds. The abnormal return is indicated by the constant alpha in the CAPM model. The value of alpha monitors stock-picking performance. Thus, it is unclear that the abnormal return or non-zero alpha reflect the mean-variance inefficiency of benchmark or the superior investment abilities.

Mean-variance inefficiency of the standard market proxies (i.e., the equal-weighted or value-weighted indices of equities listed in the stocks exchange market) encourages researchers to explore alternative asset pricing theories. Ross (1976), for example, develops arbitrage pricing theory (APT). Ross presumes that more than one factor of market proxy affects security returns, and other common sources of covariation might contribute to the construction of benchmark portfolios with normal performance. Lehmann and Modest (1987) employ CAPM and APT methods to construct benchmark portfolios, finding considerable difference relative performance in mutual funds. They conclude that identifying an appropriate factor model for risk and expected return is vital in the context of performance evaluation.

Fama and French (1993) and Carhart (1997) develops the CAPM model by identifying additional systematic risk pricing factors: size and value for characteristics of stocks and momentum for the investment strategy of mutual funds. More specifically, Fama and French (1992) find that small size and value stocks perform better than big size and growth stocks; and

Jegadeesh and Titman (1993) document the significant positive performance of momentum investment strategy, which is buying past winner stocks and selling past loser stocks. As it is possible to gain abnormal return by passively holding small, value, and past winner stocks in portfolio, size, value and momentum can be interpreted as undiversified passive benchmark returns. These three factors along with market index can capture patterns in mutual fund returns during the research period, allowing researchers to focus better on the effects of active management (stock picking), which should show up in the intercepts of three-factor or four-factor models (Fama and French, 2010). Four-factor model can be written as:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p\left(r_{mt} - r_{ft}\right) + \gamma_p SMB_t + \delta_p HML_t + \lambda_p MOM_t + \varepsilon_{pt}, \tag{3.1}$$

where r_{pt} is portfolio return at time t; r_{ft} is the risk-free return that is usually estimated by Treasury bill index at time t; r_{mt} is market index at time t; size SMB_t is measured by portfolio returns of small-cap stocks minus portfolio returns of large-cap stocks; value HML_t is measured by portfolio returns of high book-to-market ratio stocks minus portfolio returns of low book-to-market ratio stocks; and momentum MOM_t is measured by portfolio returns of past winner stocks minus portfolio returns of past loser stocks. The estimated alpha α_p is the abnormal return of portfolio p, and positive alpha indicates that portfolio returns outperform market returns by successfully holding under-priced stocks.

Fama and French (2015) add profitability and investment patterns to the conventional three-factor model (Fama and French, 1993) to further explain average stock returns. The updated five-factor model embraces factors of market excess return, size, value, profitability and investment. Fama and French (2015) suggest that the five-factor model performs better than the conventional three-factor model.

This thesis does not employ additional profitability and investment factors for three reasons: first, we extract benchmark factors from the website Xfi Centre for Finance and Investment. The website does not update the new risk-pricing factors proposed by Fama and French in 2015. Second, there is no explicit evidence to support the notion that fund managers employ investment strategy accounting for profitability and investment. On the other hand, investment strategy referring to a firm's size and value are well accepted by professional investors and documented by empirical studies (Carhart, 1997). Third, Fama and French (2015) argue that the average return described by the additional factors of profitability and investment can partly be explained by the book-to-market ratio. Fama and French (2015) also test the performance of a four-factor model that drops HML, finding that the four-factor model (i.e. factors of market excess return, size, profitability and investment) performs as well as the five-factor model. Therefore, we support the notion that despite the absence of risk-pricing factors of profitability and investment, the conventional four-factor model in Equation (3.1) can explain fund investment style well.

3.1.2 Importance of Timing Factor in Benchmarks

A fascinating feature of active funds is how their managers have professional investment knowledge to recognize noise information referring to economic situations, thus improving the possibility of making a successful investment decision. In comparison to passive funds whose portfolio mirrors a market index, it is reasonable to expect positive alpha and high extra returns generated by active elitists. After all, investors pay much higher management fees for active funds than passive. For example, the asset-weighted expense ratio[5] of US active funds in 2017 was 0.72%, whereas that ratio for passive funds was only 0.15% (Morningstar, 2018). Academic research that investigates active mutual fund performance, nevertheless, finds either zero or even negative alpha based on standard asset pricing models (e.g., Carhart, 1997; Chen, Jegadeesh, and Wermers, 2000; Fama and French, 2010).

Poor risk-adjusted performance of mutual funds might have been expected to disappoint investors and cause the fund industry to stagnate. Mutual funds, however, represent one of the fastest growing types of financial intermediary. For example, the US mutual funds held $18.7 trillion in total fund assets in 2017, which more than tripled their total fund assets in 2000. The total number of funds was 7,956 by the end of 2017, and a total of 464 mutual funds opened in 2017 (Investment Company Institute, 2018).

The enigma of fund industry growth motivates researchers to re-examine and interpret the manager's investment behavior in a new light. More specifically, by contrast with the standard capital asset pricing model assuming a constant target risk level for fund portfolio in one research period, some researchers claim that managers consider both individual stock value and common stock market's movement when they make investment decisions. Thus, managers might allocate assets to various risk classes and switch risk levels according to stock market movement, leading to non-stationary market exposure of the managed portfolio.

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[5] Corresponding to asset-weighted expense ratio which is calculated by multiplying the fund expense ratio by a weight, equal-weighted expense ratio might be also employed for measuring the average cost borne by fund investors. Asset-weighted expense ratio is better than equal-weighted average, as it provides a realistic view of the expenses for a fund in relation to fund size.

The basic notion of fund performance evaluation based on actual historical returns is that the returns on managed portfolios can be judged relative to those of passively selected portfolios with similar levels of risk. Carhart's four-factor model is useful to measure passive portfolio returns, as the prevalence of anomalies of stock performance on size, value, and past returns suggest a well-accepted passive investment strategy.

Asset pricing theory attributes the abnormal performance (i.e., significantly positive alpha) of an equity portfolio to successfully selecting under-priced stocks. Under the assumption of benchmark identifying all systematic market risk, the value of alpha would be generated by the fund manager's superior investment ability, that is, picking up successful stocks to construct his fund portfolio.

However, alpha in active fund portfolios might not accurately evaluate managers' selectivity skill. More specifically, as active managers could switch the risk level of the portfolio to avoid loss in a downward market or grab aggressive profits in an upward market, the risk-shifting leads to non-stationary relation between risk and return. As a result, estimated alpha under standard four-factor model could be positive even if the manager was an unsuccessful stock picker and irregular market timer; or the estimated alpha could be negative if the manager was both a successful stock picker and a successful market timer (Lehmann and Modest, 1987).

3.1.2.1 An Explanation for Negative Alpha: Risk Overestimation

Standard asset pricing approach could produce negative Jensen alpha due to risk overestimation for a market timer (Grinblatt and Titman, 1989). More specifically, the excess return of an investor's portfolio, which is consistent with Jensen measure, can be expressed as:

$$\tilde{r}_{pt} = \tilde{\beta}_{pt}\tilde{r}_{Et} + \tilde{\epsilon}_{pt}, \tag{3.2}$$

where $\tilde{r}_{Et}$ indicates mean-variance efficient benchmark returns. If the investor has timing information, the expected value of $\tilde{r}_{Et}$ conditioned on his timing information is not equal to $\bar{r}_{Et}$ for at least one period. The return of the mean-variance efficient portfolio can be expressed as:

$$\tilde{r}_E = \bar{r}_E + \widetilde{m} + \tilde{y}, \tag{3.3}$$

where $\widetilde{m}$ is a timing signal observed by the informed investor and $\tilde{y}$ is the realization of uncorrelated random noise. If an investor has selectivity information, in Equation (3.2), the expected value of $\tilde{\epsilon}_{pt}$ conditioned on selectivity information is nonzero for at least one asset in one period. It assumes that the beta response function is monotonically increasing in the timing signal and asymmetric about the long-run target beta $\hat{\beta}_p$ (Grinblatt and Titman, 1989). The beta function can be expressed as:

$$\tilde{\beta}_p = \hat{\beta}_p + f(\tilde{m}), \tag{3.4}$$

where $f(m) = -f(-m)$, $f(0) = 0$, and $f'(m) = \frac{\partial \beta_p}{\partial m} > 0$. Substituting Equation (3.4) and (3.3) into Equation (3.2) gets the model of beta adjustment:

$$\tilde{r}_p = \hat{\beta}_p \tilde{r}_E + f(\tilde{m})(\bar{r}_E + \tilde{m} + \tilde{y}) + \tilde{\epsilon}_{pt}. \tag{3.5}$$

The estimation of the Jensen measure is expressed as:

$$J = \hat{r}_p - b_p \hat{r}_E, \tag{3.6}$$

where $\hat{r}_p$ and $\hat{r}_E$ are the probability limit of the sample mean of portfolio excess returns and benchmark excess returns, respectively; b_p is the probability limit of the least squares slope coefficient from the time-series regression of excess returns of the evaluated portfolio against the excess returns of the efficient benchmark portfolio, which can be expressed as:

$$b_p = \frac{cov(\tilde{r}_p, \tilde{r}_E)}{\sigma_E^2} = \hat{\beta}_p + \frac{cov(\tilde{\beta}_p, \tilde{r}_E)}{\sigma_E^2} \bar{r}_E. \tag{3.7}$$

Jensen beta tends to overestimate the average risk of the portfolio by the factor proportional to the timing component $\frac{cov(\tilde{\beta}_p, \tilde{r}_E)}{\sigma_E^2}$. As a result, the Jensen alpha tends to be negative for positive timing $cov(\tilde{\beta}_p, \tilde{r}_E) > 0$ in Equation (3.6). Therefore, negative alpha estimated from lacking timing factor could be attributed to the overestimated average risk for a portfolio managed by a market timer.

Moreover, Ferson and Warther (1996) give another interpretation for negative alpha estimated from the constant beta of the fund. More specifically, based on economic conditions, the fund will lower its beta when the market is more volatile and raise it in less volatile markets' (Ferson and Warther, 1996). In other words, the beta of a fund is negatively related to the market return. If the benchmark return is estimated by the average beta of the fund multiplied by the average market premium, the systematic risk of the fund will be overestimated, and the average excess return of the fund will be less than the estimated benchmark return, leading to the estimation of negative alpha. Overall, the above analysis proves how a benchmark with constant beta, could misprice the market risk taken by the fund portfolio, thereby supporting the significance of timing factor compressed in the benchmark.

3.1.2.2 A Type of Investment Strategy: Market Timing

There could be many investors whose explicit strategy is to forecast market returns and adjust exposes to systematic risk. Prior studies confirm that it is reasonable to time the market by holding equities during bull markets and cash equivalents during bear markets; the incremental return is gained based on forecasting accuracy to some extent (e.g., Henriksson and Merton, 1981; Jiang, Yao, and Yu, 2007; Ferson and Mo, 2016). Sharpe (1975) points out that gains from a timing strategy highly depend upon the accurate prediction of whether the market will be good or bad each year. Even though the investor’s timing strategy is less-than-perfect, timing strategy has value for increasing the investor’s chance of avoiding the loss in a bear market. Chua, Woodward and To (1987) demonstrate that, once the investor’s bull market forecasting accuracy is at least 80%, the incremental return will be positive, even if the investor cannot forecast bear markets at all.

Jeffrey (1984) states that the stock market historically experienced more average and down years than spectacular years, and timing activities of investors usually miss a few rare spectacular years. However, deliberations about real fund portfolio emphasise how fund managers adopt a timing strategy and whether their timing strategy is successful and contributes to extra returns. Studies referring to the timing ability of fund managers do not concentrate market forecast on long-term bull and bear market conditions but short-term market increase and decrease movements.

Moreover, a thriving market timer could provide an investor with portfolio insurance, but the standard mean-variance optimization framework is inadequate in evaluating such market timers (Jagannathan and Korajczyk, 2017, Chap. 3). Therefore, it is essential to embrace timing factors in the factor benchmarks for assessing fund performance, and deconstruction of investment capability provides a better understanding of the nature of a manager’s skill set.

3.1.3 Holding-based Benchmarks

Apart from the return-based regression methodology, holding-based benchmark construction is an alternative approach of measuring fund performance. Grinblatt and Titman (1993; hereafter GT) use the past portfolio weights of a fund as a benchmark; that is, the benchmark is the current return generated by the portfolio held 12 months prior to the current month's holdings $\sum_{j=1}^{N} \widetilde{w}_{j,t-13}\tilde{R}_{j,t}$. The performance model can be written as:

$$GT_t = \sum_{j=1}^{N}\left(\widetilde{w}_{j,t-1} - \widetilde{w}_{j,t-13}\right)\tilde{R}_{j,t}, \tag{3.8}$$

where $\widetilde{w}_{j,t-1}$ and $\widetilde{w}_{j,t-13}$ indicate the fund portfolio weight on stock *j* at the end of month *t-1* and *t-13*, and $\tilde{R}_{j,t}$ indicates the month *t* return of stock *j*. The time-series average, across all the months in which a fund exists, gives the performance measurement for that fund. Comparing to the approach based on the conventional asset pricing model with the assumption of mean-variance efficiency, the GT holding-based model makes no assumptions about the relationship between risk and return.

GT's benchmark is the current value of the portfolio's last year holdings. The benchmark does not consider the performance of the common stock market. Daniel *et al.* (1997), by contrast, construct a benchmark portfolio using the return of stocks listed on the Stocks Exchange Markets (i.e., the NYSE, American Stock Exchange, and Nasdaq) concerning the fund portfolio's holdings style. In particular, Daniel *et al.* (1997) sort the universe of common stocks into three quintile groups based on the stock's size, book-to-market ratio, and prior-year return. Then, Daniel *et al.* (1997) sort 5´5´5 groups into portfolios, giving a total of 125 passive benchmark portfolios. The performance is assessed by subtracting the returns of a benchmark portfolio that matches the equity held in a particular fund from the fund's hypothetical returns. The fund hypothetical returns, generated from portfolio holdings, are calculated by the sum of holding's returns multiplied by its corresponding weight (Daniel et al., 1997).

Daniel *et al.* (1997) emphasise the difference of performance between fund portfolio and market portfolio during the same period, which is in line with the four-factor model. Moreover, holding-based benchmarks better capture the investment styles adopted by fund managers directly. In comparison to return-based factor models with the assumption of mean-variance efficiency, the characteristic-based approach getting rid of the assumption of risk and return relationship provides better estimates of expected returns than do factor sensitivities (Daniel and Titman, 1997). However, characteristic-based benchmarks cannot be constructed without fund holdings, and UK unit trusts do not report their holdings; thus, characteristic-based benchmarks cannot be adopted in this thesis. Therefore, this thesis follows the idea of the return-based factor method to estimate expected returns of the passive benchmark portfolio.

3.2 Timing Models

Market timing ability studies have been experienced for decades. Early studies focus on market return timing strategy where managers choose the risk level for their managed fund portfolios according to the predicted market return movements. However, empirical studies find that most fund managers have either no timing or negative timing skill from various fund markets such as the UK, China and Norway (e.g. Chen and Stockum, 1986; Pfleiderer and Bhattachary, 1983; Fletcher, 1995; Cuthbertson, Nitzsche, and O'Sullivan, 2010; Gallefoss et al., 2015; Yi et al., 2018).

Busse (1999) states that managers might behave like volatility timers; that is, managers switch the risk level of their portfolios according to the market volatility rather than the market return movement. In comparison to market return, market volatility might be easy to predict owing to volatility's characteristics of clustering, persistence and autocorrelation – high volatility is often followed by high volatility, and low by low (Bollerslev, Chou, and Kroner, 1992). In addition, Chen and Liang (2007) point out that a professional manager would consider market return and market volatility simultaneously while making investment decision, instead of solitary component of the market.

This section details theoretical timing models development. In particular, sub-section 3.2.1 concentrates on market-return timing models such as the quadratic model, piecewise-linear model and holding-based model. Market-volatility timing model and joint timing model are described in the sub-section 3.2.2 and 3.2.3, respectively.

3.2.1 Market-return Timing Models

Market return timing behavior is generally defined as the shifting of portfolio's market exposures according to the forecast of market returns. Fama (1972) first theoretically breaks down the overall performance of mutual fund into returns that are due to the skill of selecting the best securities of a given level of risk (i.e., selectivity or micro-ability) and returns that are due to predictions of general market price movements (i.e., timing or macro-ability). More specifically, Fama (1972) deconstructs a fund portfolio's total risk into target risk (which can be measured by systematic risk) and the manager's risk (which might partly result from a timing decision). Fund managers believe that risky portfolios would do abnormally well or poor in general during the period under consideration; thus, they might choose a portfolio with a level of risk higher or lower than the target risk level. The difference between returns from portfolio risk level and returns from target risk level are considered as returns from the manager's timing decision.

Studies on measuring manager's selectivity and return-timing abilities have long been recognized (e.g., Henriksson and Merton, 1981; Henriksson, 1984; Chen and Stockum, 1986; Ferson and Schadt, 1996; Cuthbertson, Nitzsche, and O'Sullivan, 2010). Treynor and Mazuy (1966; hereafter TM) first statistically test the nonstationary of systematic risk beta of US mutual funds, based on the quadratic characteristic line. Although Treynor and Mazuy fail to find strong evidence of varying beta presence, they still give an attractive standard method for exploiting selectivity and timing abilities of fund managers.

Henriksson and Merton (1981; hereafter HM) propose an alternative method to test return-timing ability, based upon the parallel investment performance between timing strategy and protective put options strategy. They prove that the characteristic line would be piecewise-linear. Recent studies contribute to developing these two standard return-timing models. We begin with a detailed description of the quadratic model and the piecewise-linear model.

3.2.1.1 Quadratic Models

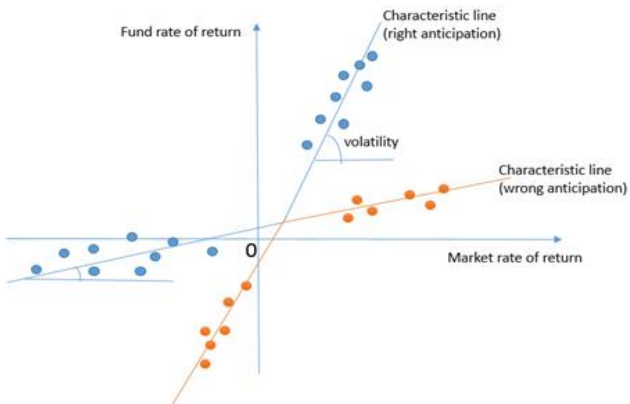
Treynor and Mazuy (1966) statistically test whether fund managers anticipate significant turns in the stock market and the response to that anticipation. The foundation of TM test is the characteristic line, plotting the rate of return for a managed fund against that of a suitable market average (see Figure 3.1). The slope of a fund's characteristic line indicates the fund portfolio's systematic risk (i.e., beta). If the fund manager does not shift portfolio's risk level, the characteristic line is straight, and the beta is constant. It is well known that common stocks and stock market is fluctuating, and some common stocks are more sensitive to market fluctuations than others; therefore, it is meaningful for fund managers to anticipate the general stock market movement and adjust the composition of their portfolios accordingly.

A successful market-return timing strategy would invest in high/low volatile stocks when the market goes up/down. As requiring perfect anticipation is rigorous for fund managers, the TM model can only assume that management has some, instead of perfect, prediction powers. That is, "the better the market performs, the more likely management is to have anticipated good performance and to have increased fund volatility appropriately; and the larger, on the average, the chosen volatility is likely to be" (Treynor and Mazuy, 1966, p.134). Therefore, the market exposure beta of fund portfolios is a gradual transition; from a flat slope at the extreme left to a steep slope at the extreme right, the slope varies more or less in between, producing a smoothly curved characteristic line pattern. The varying of risk exposure to fund portfolio could be captured by quadratic function, and TM model can be written as:

$$r_{p,t} = \alpha_p + \bar{\beta}_p r_{m,t} + \gamma_p r_{m,t}^2 + \varepsilon_{p,t}, \qquad (3.9)$$

where $r_{p,t}$ and $r_{m,t}$indicate the excess return of portfolio p and the equity market, respectively; $\bar{\beta}_p$ indicates the target risk exposure on the stock market; γ_p monitors time-varying risk level of portfolio p response to market movement. The error term ε_{pt} is assumed normally distributed with zero mean and constant variance. Treynor and Mazuy (1966) use 57 US mutual funds over ten years period, but only find one of the 57 funds has a significantly positive value of γ_p at the 5% significant level. They offer a little evidence to support the existence of timing ability in their sample study.

Figure 3.1:
Characteristic Line of the Fund



Source: Treynor and Mazny, 1966

Alexander, Benson and Eger (1982), however, argue that the beta of a fund portfolio could be nonstationary even if the fund manager is not engaged in timing decisions. More specifically, they use first-order Markov process to model the systematic risk of mutual fund and find a significant number of mutual funds showing nonstationary systematic risk beta. Alexander, Benson and Eger's (1982) results support the argument that the non-stationarity of beta is not a sufficient condition for identifying funds that actively engage in timing decisions. Ferson and Schadt (1996) also support the notion that the weights of a passive strategy (e.g., buy-and-hold investment strategy) could vary due to the change of relative values.

Chen and Stockum (1986) develop the TM model by employing random coefficient model. To be specific, if mutual fund betas are adjusted following fund managers' anticipation of stock market returns, and current market performance provides an unbiased estimate of future market performance, beta for mutual funds can be specified as (Hildreth and Houck, 1968; Singh et al., 1976):

$$\beta_{p,t} = \bar{\beta}'_P + \gamma'_p r_{m,t} + \epsilon_{p,t}, \tag{3.10}$$

where $\beta_{p,t}$ indicates the systematic risk for mutual fund p at time t, which is broken down into target beta (i.e., the beta level in the absence of market timing) $\bar{\beta}'_P$, changes due to market timing γ'_p, and random error (i.e., changes due to non-systematic factors) ϵ_{pt}. The random error ϵ_{pt} is essential in capturing non-stationary beta, as the beta of a fund portfolio $\beta_{p,t}$ may change over time even if the fund manager does not rebalance the fund's portfolio. When both γ'_p and $var(\epsilon_{pt})$ are statistically significant, the non-stationary beta could be caused by the market-timing strategy of managers and the market's random behavior together. Therefore, the quadratic timing function could be re-written as:

$$r_{p,t} = \alpha_p + \bar{\beta}'_p r_{m,t} + \gamma'_p r^2_{m,t} + \omega_{p,t}, \tag{3.11}$$

where $\omega_{pt} = \mu_{p,t} + \epsilon_{p,t} r_{m,t}$. Notably, the difference between Equation (3.11) and Equation (3.9) is the residual term demonstrating random behavior of the market that might result in non-stationary beta.

On the other hand, Pfleiderer and Bhattachary (1983) interpret how the residual term should contain information required for quantifying the manager's timing ability. Pfleiderer and Bhattachary (1983) express the error term as:

$$\widetilde{\omega}_{pt} = \theta\varphi\tilde{\epsilon}_t \tilde{r}_{m,t} + \tilde{\mu}_{p,t}, \tag{3.12}$$

where θ measures the manager's response to his information, φ is the correlation between the forecast and realized market excess returns, and $\tilde{\epsilon}_t$ is a mean-zero normal deviation which is independent of $\tilde{r}_{m,t}$. The exact measurement of a manager's timing ability is the estimated $\varphi = \sigma^2_m \big/ (\sigma^2_m + \sigma^2_\epsilon)$. Pfleiderer and Bhattachary (1983) separate manager's response from his forecast, and measure forecast ability based on the correlation between forecast and realized returns. Pfleiderer and Bhattachary's (1983) idea is consistent with the HM model of considering both response and forecast. By contrast, the HM model assumes that a successful fund manager should have a correct forecast and rationally react to his forecast, which will be revisited in the sub-section of piecewise-linear models.

The particular development of Pfleiderer and Bhattachary's (1983) model is presented here. Following Jensen's method, fund excess returns can be written as:

$$\tilde{r}_{p,t} = \alpha_p + \tilde{\beta}_{p,t}\tilde{r}_{m,t} + \tilde{\varepsilon}_{p,t}, \tag{3.13}$$

where $\tilde{r}_{p,t}$, $\tilde{\beta}_{p,t}$, $\tilde{r}_{m,t}$ and $\tilde{\varepsilon}_{p,t}$ are realized random variable of fund portfolio's excess returns, sensitivity of the fund's return to the market's return, market's excess returns and error term, in period t, respectively. The error term is assumed to be independent of market return. Let $\emptyset_t$ denote the information which the manager possesses at the beginning of the period t. The expected market excess return conditional on information can be expressed as:

$$r^*_{m,t} = E\left(\tilde{r}_{m,t}|\emptyset_t\right), \tag{3.14}$$

then random systematic risk beta can be specified as:

$$\tilde{\beta}_{p,t} = \beta_{T,t} + \theta\tilde{r}^*_{m,t}, \tag{3.15}$$

where $\beta_{T,t}$ is the target risk of the fund, and θ monitors the manager's response to his information. Assume that all random variables are jointly normally distributed. Following Jensen's theory, the realized market excess return can be expressed as:

$$\tilde{r}_{m,t} = d_0 + d_1\tilde{r}^*_{m,t} + \tilde{v}_t. \tag{3.16}$$

If $\tilde{r}^*_{m,t}$ is optical forecast conditional on timing information, then $d_0 = 0$, and $d_1 = 1$. The Equation (3.16) can be re-written as, in the optimal forecast condition:

$$\tilde{r}^*_{m,t} = d'_0 + d'_1\tilde{r}_{m,t} + \tilde{v}'_t = \tilde{r}_{m,t} + \tilde{v}'_t. \tag{3.17}$$

In a general situation, assuming that the manager observes a signal, $\tilde{r}_{m,t} + \tilde{\epsilon}_t$, at the beginning of period t, where $\tilde{\epsilon}_t$ is a mean-zero normal deviate which is independent of $\tilde{r}_{m,t}$, the optical forecast can be expressed as:

$$\tilde{r}^*_{m,t} = \varphi\left(\tilde{r}_{m,t} + \tilde{\epsilon}_t\right), \tag{3.18}$$

where $\varphi = {\sigma^2_m}\big/{\sigma^2_m + \sigma^2_\epsilon}$ is the correlation between forecast and realized market excess return. Combining Equation (3.13), (3.15) and (3.18), the fund portfolio excess returns can be re-written as:

$$\tilde{r}_{p,t} = \alpha_p + (\beta_{T,t} + \theta r^*_{m,t})\tilde{r}_{m,t} + \tilde{\varepsilon}_{p,t} \quad (3.19)$$

$$= \eta_0 + \eta_1 \tilde{r}_{m,t} + \eta_2 \tilde{r}^2_{m,,t} + \widetilde{\omega}_{p,t},$$

where $\eta_0 = \alpha_p$, $\eta_1 = \beta_{T,t}$, $\eta_2 = \theta\varphi$, and $\widetilde{\omega}_{p,t} = \theta\varphi\tilde{\epsilon}_t\tilde{r}_{m,t} + \tilde{\varepsilon}_{p,t}$. The quality of a manager's timing information is truly measured by φ, which is the correlation between manager's forecast and realized market excess return. That is, this method distinguishes the quality of forecast from manager's responses to his information. The forecast information can be extracted by regression $\widetilde{\omega}^2_{p,t}$ on $\tilde{r}^2_{m,,t}$:

$$\widetilde{\omega}^2_{p,t} = \theta^2\varphi^2\sigma^2_\epsilon\tilde{r}^2_{m,,t} + \tilde{\zeta}_t. \quad (3.20)$$

Substituting the consistent estimate of $\theta\varphi$ in Equation (3.12) into the estimation of $\theta^2\varphi^2\sigma^2_\epsilon$ in Equation (3.20), the σ^2_ϵ can be obtained which allows to estimate φ.

Pfleiderer and Bhattachary (1983), nevertheless, use the absolute parameter estimate, which might fail to recognize potential irregular timing behavior. Volkman (1999) goes further to adjust the quadratic coefficient by adding an indicator variable. In particular, the quality of timing information is expressed as $\rho = \vartheta\sqrt{\varphi}$, where ϑ is a positive unit scalar when estimated $\theta\varphi > 0$ and is a negative unit scalar when estimated $\theta\varphi < 0$. Volkman's (1999) idea is to use the sign of estimated coefficient of quadratic term to identify forecast is correct or wrong. However, the sign of $\theta\varphi$ might only indicate whether the manager's response and his forecast accord or not, which might be not appropriate for identifying the quality of timing information.

Additionally, Admati *et al.* (1986) agree that a measure of the quality of private information possessed by a fund manager is necessary for performance evaluation, as information received by a manager might be different from the manager's reaction to that information. Instead of using market portfolio, they suggest the construction of a timing portfolio, assuming that selectivity information is statistically independent of timing information that is restricted to be informed about the returns on a pre-specified set of timing portfolio. The selectivity information is indicated by the residuals in the regression of asset returns on the returns of the timing portfolio (i.e., uninformative information referring to timing portfolio).

Admati *et al.* (1986) give a theoretical proof that a simple quadratic regression is valid in measuring timing information under portfolio approach. More specifically, the regression equation can be expressed as:

$$\tilde{r}_{p,t} = \alpha_p + \beta r_{T,t} + \gamma r_{T,t}^2 + \widetilde{\omega}_{p,t} \tag{3.21}$$

where $\tilde{r}_{p,t}$ indicates returns realized on the managed portfolio in period t; $r_{T,t}$ indicates returns on the artificial timing portfolio. Based on the assumption that the response of manager to his information is linear, the quadratic term can measure the quality of the private information possessed by a fund manager.

Although Grinblatt and Titman (1989b) also support the notion that constructing a minimum-variance-efficient portfolio as benchmark could avoid bias generated by benchmark misspecification, benchmark construction is difficult for empirical studies. For example, minimum-variance-efficient portfolio construction requires correctly specified primitive assets that are available for managers, which is infeasible for empirical research (Ferson and Schadt, 1996).

Moreover, Admati *et al.'s* (1986) portfolio approach lacks an appealing economic story to tell about how the information originates in artificial timing portfolios (Verrecchis, R.E., discussion report of Admati et al.'s (1986) paper). Despite the unreliability of the portfolio approach, this approach still suggests a considerable simple estimation method, and the regression equation also indirectly supports the reasonableness of quadratic function in measuring timing performance.

Admati *et al.* (1986) propose a factor approach as well. In comparison to CAPM-based factor models, they postulate asset returns based on factors generating process. More specifically, assuming that different types or coordinates of selectivity information lie in different assets, selectivity information is the information related to idiosyncratic terms that precisely determine any individual asset returns. Factors affecting the realized returns of many assets account for timing information. However, Verrecchia, R.E. questions that Admati et al.'s factor approach raises serious econometric problems associated with designing tests to detect and distinguish timing and selectivity information (discussion report of Admati et al.'s (1986) paper).

3.2.1.2 Piecewise-linear Models

Henriksson and Merton (1981) provide an alternative insight on timing behavior by comparing to the protective put options investment. In particular, they create a test procedure where it is possible to separate the incremental returns from returns generated by selectivity and timing estimates without any restrictions on the distribution of forecasts. HM assume that there are two levels of risk and that successful market timer chooses high/low risk level when his forecast is market return above/below risk-free return. Merton (1981) demonstrates how timing ability in this setting is equivalent to the skill of creating free call options on the market index. Due to put-call parity, the timing ability is also equivalent to the skill of creating a free protective put options strategy. Therefore, the value of market timing ability could be regarded as the payoff of protective put options on the market portfolio. The HM regression specification can be written as:

$$r_{p,t} = \alpha + \beta_1 r_{m,t} + \beta_2 y_t + \varepsilon_t, \tag{3.22}$$

where $r_{p,t}$ and $r_{m,t}$ indicate the excess returns of portfolio p and market portfolio, respectively; $y_t \equiv max[0, R_{f,t} - R_{m,t}] = max[0, -r_{m,t}]$ assesses the value of the implicit protective put options; the coefficients α and β_2 indicate the selectivity and timing–forecast abilities, respectively. The value of put options would equal to zero when the market excess return is positive; the value would exactly offset losses when market return drops below risk-free return, that is, $-r_{m,t}$.

This review is given to understand how HM model develops and commenced with the equilibrium theory of value for market timing forecast (Merton,1981). Merton's (1981) equilibrium theory claims that the equilibrium management fees (i.e., the value of timing skills) are able to be determined in terms of market prices for options, given the isomorphic correspondence between successful timing strategy and options-bill strategy. To be specific, let A_t denote total dollars of fund assets, F_t denote total management fees paid by investors, and I_t denote the total dollars of investors invested in a fund. In one period between *t* and *t+1*, the end-of-period value of fund assets can be written as:

$$V_{t+1} = max[A_t R_{f,t}, A_t R_{m,t}] = A_t R_{m,t} + A_t max[0, R_{f,t} - R_{m,t}], \tag{3.23}$$

where V_{t+1} denotes the value of fund at the end of period of t, $R_{m,t}$ denotes the return from holding stocks, and $R_{f,t}$ denotes the return from holding bonds. Merton (1981) assumes that fund managers only predict the time that shocks will outperform and underperform bonds; they do not predict the magnitude of the superior performance. He further assumes that fund managers will hold stocks when they forecast $R_{m,t} > R_{f,t}$, and hold bonds when they forecast $R_{m,t} \leq R_{f,t}$.

From Equation (3.23), the return per dollar on the fund's assets can be written as:

$$X_t = max[R_{f,t}, R_{m,t}] = R_{m,t} + max[0, R_{f,t} - R_{m,t}], \tag{3.24}$$

and the return per dollar to the investor in the fund can be written as:

$$\frac{V_{t+1}}{I_t} = \frac{V_{t+1}/A_t}{(A_t+F_t)/A_t} = \frac{X_t}{1+m_t}, \tag{3.25}$$

where $m_t \equiv F_t/A_t$ is the management fee expressed as a fraction of assets held by the fund.

Merton (1981) subsequently compares the value of the successful timing portfolio to the value of options investment strategy without any timing information. He assumes that options could be purchased at a zero price. If investors follow protective put options investment strategy of holding A_t dollars in market portfolio and one-period put options on A_t shares of the market portfolio with exercise price per share of $R_{f,t}$, then end-of-period value of options portfolio will be identically equal to the value of timing portfolio in the absence of management fees, which can be presented as Equation (3.23) as well.

Let g_t denote the market price of a one-period put option on one share with an exercise price of $R_{f,t}$. The equilibrium management fee, m_t, represented in Equation (3.25), could be regarded as the economic benefit of extracting from market timer's differential timing information. If investors behave competitively, then the economic value of the market timer's forecast per dollar of investment assets should be equal to market price of options g_t, that is, $m_t = g_t$. Therefore, the value of timing skills is able to be determined in terms of market prices for options.

Henriksson and Merton's (1981) timing test is based on the equilibrium theory. The perfect pure market timer's investment strategy should correspond to a long position in the asset and a long position in a put options with a maturity of one period; the exercise price is equal to the asset price at the beginning of the period. As perfect timing strategy is an impossible achievement for managers in real financial market, HM test depends upon probabilities of a correct forecast. To be specific, let γ_t be the market timer's forecast variable, where $\gamma_t = 1$ if the forecast, made at time *t-1*, for time period *t* is that $R_{m,t} > R_{f,t}$ and $\gamma_t = 0$ if the forecast is that $R_{m,t} \leq R_{f,t}$. The probabilities for γ_t conditional on the realized return on the market can be defined as:

$$p_{1,t} \equiv prob[\gamma_t = 0 | R_{m,t} \leq R_{f,t}] \quad (3.26a)$$

$$1 - p_{1,t} = prob[\gamma_t = 1 | R_{m,t} \leq R_{f,t}],$$

and

$$p_{2,t} \equiv prob[\gamma_t = 1 | R_{m,t} > R_{f,t}] \quad (3.26b)$$

$$1 - p_{2,t} = prob[\gamma_t = 0 | R_{m,t} > R_{f,t}].$$

Therefore, $p_{1,t}$ is the conditional probability of a correct forecast given that $R_{m,t} \leq R_{f,t}$, and $p_{2,t}$ is the conditional probability of correct forecast given that $R_{m,t} > R_{f,t}$. $p_{1,t} + p_{2,t}$ is the sum of conditional probabilities of correct forecast, which is a sufficient statistic for the evaluation of forecasting ability. As the forecasts of fund managers are unobservable in most realized situation, HM borrowes the asset pricing theory to do a parametric test, represented in Equation (3.22).

Similar to Pfleiderer and Bhattachary (1983), HM considers a manager's choice and the possibility of a correct forecast. More specifically, it assumes that two target risk levels are available for managers to choose. Let η_1 denote the target beta of equity portfolio chosen by the manager whose forecast is that $R_{m,t} \leq R_{f,t}$ (i.e., $r_{m,t} \leq 0$) and η_2 denote the target beta when the manager's forecast is that $R_{m,t} > R_{f,t}$ (i.e., $r_{m,t} > 0$). If the manager is rational, then $\eta_2 > \eta_1$. Following the large sample least-squares estimates, β_1 and β_2 in Equation (3.22) can be written as:

$$plim\hat{\beta}_1 = E[\beta_t | r_{m,t} > 0] = p_2\eta_2 + (1 - p_2)\eta_1, \quad (3.27a)$$

and

$$plim\hat{\beta}_2 = E[\beta_t | r_{m,t} > 0] - E[\beta_t | r_{m,t} \leq 0] = (p_1 + p_2 - 1)(\eta_2 - \eta_1), \quad (3.27b)$$

where $plim\ \hat{\beta}_1$ is equal to the fraction invested in the market portfolio in the option strategy, and $plim\ \hat{\beta}_2$ is equal to the number of free put options on the market provided by the manager's market-timing ability. If β_2 equals to zero, it implies that either the manager has no timing ability (i.e., $p_1 + p_2 = 1$) or the manager does not act on his forecasts (i.e., $\eta_2 = \eta_1$). Unfortunately, a manager's choice and his forecast cannot be observed separately under the standard regression method. Empirically, Henriksson (1984) adopts HM model in Equation (3.22) to test timing ability of 116 open-ended mutual funds, finding that 62% of the funds in the sample have negative values of timing coefficient.

Goetzmann, Jonathan and Ivković (2000) point out that the HM parametric method using monthly returns is weak and biased downward, as market timers can make daily timing decisions. In the absence of mutual funds' daily returns, Goetzmann, Jonathan and Ivković (2000) mitigate the problem by collecting daily data on the risky asset alone. They use market index daily returns to construct an instrument correlated with the daily put options values. In particular, within each month, Goetzmann, Jonathan and Ivković (2000) use the daily market return and the risk free return to calculate the value of daily put options $max\{1 + R_{m,\tau}, 1 + R_{f,\tau}\}$, then they use the daily options value to estimate the monthly value of a daily timer's skill. The specification can be expressed as:

$$r_{p,t} = \alpha + \beta_1 r_{m,t} + \beta_2 P_{m,t} + \varepsilon_t$$
$$P_{m,t} = \left[\left(\prod_{\tau \in month(t)}^{t} max\{1 + R_{m,\tau}, 1 + R_{f,\tau}\}\right) - 1\right] - R_{m,t}, \tag{3.28}$$

where $P_{m,t}$ is the value added by perfect daily timing per dollar of fund assets. Although the adjusted HM model reveals few funds in a sample of 558 mutual funds exhibiting statistically significant timing skill, Goetzmann, Jonathan and Ivković (2000) demonstrate that the adjusted-FF-three test does mitigate biases in timing skill measurement. Goetzmann, Jonathan, and Ivković (2000) confirm the significance of data frequency in empirical studies of timing performance.

Additionally, Ferruz, Muñoz and Vargas (2010) correct the HM model by taking the put options price into account. The updated model is expressed as:

$$r_{p,t} = \alpha_{Put} + \beta_1 r_{m,t} + \beta_2 Put_t + \varepsilon_t$$
$$Put = max(0, r_f - r_m) - (1 - r_f)P \tag{3.29}$$

where P is the price of the European market put with a strike price equal to the risk-free rate. In comparison to the standard HM model, the updated alpha can explain the negative correlation between the alphas and the timing coefficients estimated using Equation (3.29), indicated by the function of $\alpha_{Put} = \alpha_{HM} - \beta_2(1 - r_f)P$.

3.2.1.3 Holding-based Models

Holding-based models can straightforwardly test the timing ability by measuring the change of weights assigned by the manager to the different sectors such as selectivity, timing and investment style. Although holding data is rarely available in the fund markets outside of the

US, we still give holding-based models a review due to the merit of the holding-based models. Moreover, the results from holding data might be roughly used to make a comparison to results from ex-post return data.

Daniel *et al.* (1997) break down fund returns into three components: characteristic selectivity (CS), characteristic Timing (CT), average style (AS). CS is measured by the excess return of holdings with respect to corresponding passive portfolios. More specifically, Daniel *et al.* (1997) firstly assign each stock to a passive portfolio according to its size, value, and momentum rank. Next, Daniel *et al.* (1997) calculate excess return of a particular stock, which is the difference between the stock returns and the matched passive portfolio returns. Lastly, for each fund, these differenced returns are multiplied by the portfolio weights of the particular fund to obtain the abnormal returns for each month. The CS measure can be written as:

$$CS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-1} \left(\tilde{R}_{j,t} + \tilde{R}_t^{b_{j,t-1}} \right), \tag{3.30}$$

where $\tilde{w}_{j,t-1}$ indicates the fund portfolio weight on stock j at the end of month *t-1*; $\tilde{R}_{j,t}$ indicates the month t return of stock j; $\tilde{R}_t^{b_{j,t-1}}$ is the month t return of the characteristic-based passive portfolio that matches the stock j during month *t-1*.

Furthermore, CT measures additional performance generated by changing the fund portfolio's weights to exploit time-varying expected returns of size, value and momentum portfolios. The CT measure can be written as:

$$CT_t = \sum_{j=1}^{N} \left(\tilde{w}_{j,t-1} \tilde{R}_t^{b_{j,t-1}} - \tilde{w}_{j,t-13} \tilde{R}_t^{b_{j,t-13}} \right), \tag{3.31}$$

where $\tilde{w}_{j,t-1} \tilde{R}_t^{b_{j,t-1}}$ indicates that the portfolio weight of stock j at month *t-1* (i.e., $\tilde{w}_{j,t-1}$) multiplies the month t return of benchmark portfolio that matches the stock j during month *t-1* (i.e., $\tilde{R}_t^{b_{j,t-1}}$) and $\tilde{w}_{j,t-13} \tilde{R}_t^{b_{j,t-13}}$ is measured in the same way.

Additionally, AS measures the fund return generated by the tendency of holding stocks with certain characteristics, which can be written as:

$$AS_t = \sum_{j=1}^{N} \tilde{w}_{j,t-13} \tilde{R}_t^{b_{j,t-13}}. \tag{3.32}$$

For each component, the time-series average, over all months in which a fund exists, gives the CS, CT and AS measures for that fund, respectively. The sum of CS, CT and AS components approximately equal the total fund return.

Holding-based approach provide evidence of significant positive selectivity ability (Daniel et al., 1997; Grinblatt and Titman, 1993), challenging many prior findings of negative or no stock-picking skill (Carhart, 1997; Blake and Timmermann, 1998; Busse, Goyal, and Wahal, 2010; Fama and French, 2010; Blake et al., 2017). Consistently with findings of return-based timing models, Daniel *et al.*, (1997) fail to offer evidence of positive timing ability. It is worth mentioning that, Daniel et al.'s method emphasises characteristic timing or investment style timing, rather than typical stock market timing. In other words, they test the shifting of the weight referring to simulating stock portfolios instead of total stock market portfolio.

Holding data of US mutual funds reports quarterly, displaying a demerit of failing to capture intermittently transactions within-quarter round-trip, and reducing the precise estimation of the timing of trades (Elton et al., 2010). Elton *et al.* (2010) empirically find that quarterly holdings may miss upwards of 20% of a typical fund's trades. Bollen and Busse (2001) determine that daily tests are more powerful than monthly tests, and Gallefoss et al. (2015) support that fund manager changes investment strategy dynamically. Therefore, the holding-based approach is worth considering later when more frequently data available in many other financial markets, such as monthly reports of UK mutual funds holdings.

3.2.2 Market-volatility Timing Model

As volatility is to some extent predictable (Bollerslev, Chou, and Kroner; 1992; Bollerslev, Engle, and Nelson, 1993), managers might time the volatility while managing a portfolio. More specifically, Andersen and Bollerslev (1998) argue that low explanatory power is an inevitable consequence of the noise inherent in the return-generating process. They prove that GARCH-type models can explain about 50% of the variation in the measure of ex-post volatility (i.e., cumulative squared intraday returns), supporting that standard volatility models deliver reasonably accurate forecasts.

This sub-section reviews literature on the market-volatility timing strategy. The review commences with the economic value of volatility-timing strategy. Previous studies have provided evidence that the investment strategy of timing the market volatility can produce economic value for managed portfolios. Moving to the volatility timing model, we detail the theoretical model proposed by Busse (1999).

3.2.2.1 Economic Value of Volatility Timing

Fleming, Kirby and Ostdiek (2001) systematically investigate the economic value of volatility-timing strategy and find substantial benefits generated by timing the market volatility. To be specific, Fleming, Kirby and Ostdiek (2001) construct a dynamic portfolio assumed to be managed by a short-horizon risk-averse investor. The risk-averse investor employs the mean-variance optimization rule (i.e., maximizing the expected return given target volatility or minimizing the portfolio's volatility given the expected return) to allocate fund assets across four asset classes: stocks, bonds, gold and cash. The investor rebalances portfolio holdings daily based on their current estimate of the conditional covariance matrix of returns. The dynamic trading strategy specifies the proportion of artificial portfolio invested in each asset class as a function of time. The value of volatility timing is measured by the estimated fee that the risk-averse investor would be willing to pay to switch from the ex-ante optimal static portfolio to the dynamic portfolio. Fleming, Kirby and Ostdiek (2001) demonstrate that the estimated fee (i.e., the profit of timing the market volatility) exceeds 1.7% per year on average, and the finding is robust in the estimation of risk regarding expected returns and transaction costs.

Apart from conditional volatility, realized volatility is an alternative method of measuring volatility by summing the squares of intra-daily returns sampled at very short intervals (Andersen, Bollerslev, et al., 2001; barndorff-Nielsen and Shephard, 2002). Merton (1980) maintains that, if the sample path of volatility is continuous, high frequent intra-daily data will improve the precision of estimates of volatility at any given point in time. This statement motives Fleming, Kirby and Ostdiek (2003) to proceed with their prior work of using the conditional volatility of the rolling estimator to assess the economic value of volatility-timing strategy (Fleming, Kirby, and Ostdiek, 2001). Fleming, Kirby and Ostdiek (2003) employ realized volatility and reveal that the performance fees are 1% to 2% per year for the minimum volatility strategy, and the fees are around 2.5% to 3.5% per year for the maximum volatility strategy. The updated findings from Fleming, Kirby and Ostdiek (2003) enhance the economic value of timing volatility.

Furthermore, Fleming, Kirby and Ostdiek (2003) proceed to investigate the value of daily volatility-timing strategy over longer investment horizons from one week to one year. Fleming, Kirby and Ostdiek (2003) suggest that the results for a daily horizon can provide a guide to the results for longer horizons. More specifically, the volatility-timing portfolio generates a higher Sharpe ratio than static portfolio at almost every horizon, although, for each strategy (i.e., efficient static and volatility-timing), the mean return tends to rise, and the volatility tends to fall as the measurement horizon gets longer, leading to an increase in the Sharpe ratios. The performance fee remains substantial value around 1% to 2% per year at each longer horizon, supporting the persistence of the economic value of volatility-timing strategy.

Moreira and Muir (2017), in addition, use monthly returns of simulated volatility-managed portfolios to investigate the value of volatility-timing strategy. If the previous month's realized variance is high, the volatility-managed portfolios will reduce the portfolios' risk exposure and vice versa; risk exposure is rebalanced for each month. Moreira and Muir (2017) display that these artificial portfolios produce significant alphas, increase Sharpe ratios and produce substantial utility gains for mean-variance investors. Moreira and Muir (2017) also document how the favourable performance is robust across multiple risk factors such as market, value, momentum, profitability, return on equity, investment and betting-against-beta as well as in the currency carry trade. The market-volatility portfolio, for instance, produces an overall 25% increase in the buy-and-hold Sharpe ratio, and a large lifetime utility of 65% for a mean-variance investor. Moreira and Muir (2017) attribute the profit of Sharpe ratio with respect to volatility-timing strategy to that the changes in a portfolio's volatility are not offset by proportional changes in the expected return.

Alternatively, Johannes, Polson and Stroud (2002) examine the economic benefits of predictability. They firstly form optional portfolios using five models considering the time-varying expected return and volatility. The five models are: the general model with stochastic expected return and volatility and correlated shocks (SMVC), the special case of SMVC with no correlation (SMV), the model with stochastic volatility but constant expected return (SV), the model with a stochastic expected return and constant volatility (SM) and the model with constant mean and variance (Constant). Subsequently, Johannes, Polson and Stroud (2002) compare the dynamic optimal portfolios' returns to the return of constant portfolio without predictability and the market return.

Johannes, Polson and Stroud (2002) show that the SV portfolio produces the best significant economic gains; the SM portfolio performs worse than SV portfolio, Constant portfolio and even the market index. To be specific, SV portfolio with risk aversion of 4 attains an annualized Sharpe ratio of 0.71, compared to the ratio of 0.49 for the market, 0.39 for the Constant portfolio and 0.31 for the SM portfolio. This finding suggests that volatility-timing strategy might be more attractive than the return-timing strategy due to superior performance.

Johannes, Polson and Stroud (2002) also confirm the substantial economic gains of SV portfolio with respect to the positive utility. The utility is measured by the certainty equivalent gain or loss; that is, a portfolio given a timing strategy generates returns over the returns of portfolios of no predictability strategy or buy-and-hold strategy. For example, the annualized certainty equivalent gain of SV portfolio with risk aversion of two and four over the constant portfolio is 4.92% and 3.26%, respectively.

Additionally, Clements and Silvennoinen (2013) use various volatility forecast approaches to form portfolios with time-varying assets weights. The portfolio's assets are allocated into three types: equities, bonds and gold. The time-varying weights are forecasted by short-term moving average, long-term moving average, exponentially weighted moving average (Fleming, Kirby, and Ostdiek, 2003), mixed interval data sampling (Ghysels, Santa-Clara, and Valkanov, 2006), as well as novel method on the basis of realized volatility. Clements and Silvennoinen (2013) evaluate the performance of volatility-timing portfolios based on Sharpe ratio and measure the economic value of methods for constructing volatility-timing portfolios based on incremental value. The incremental value measures the maximum return an investor would be willing to sacrifice to capture the gains of switching to another optimal portfolio. Clements and Silvennoinen (2013) demonstrate that portfolios are of similar economic benefits to several competing approaches and are quite stable across time, implicitly supporting that the investment strategy of timing the market volatility is undertaken in a portfolio allocation context.

3.2.2.2 Volatility-timing Model Development

Busse (1999) proposes an alternative market timing strategy, that is, the strategy of counter-cyclically timing the market volatility. Busse (1999) develops a volatility timing model and documents the existence of successful volatility-timing performance in the US mutual funds. More specifically, successful volatility-timing behavior suggests that the risk exposure of mutual funds would be reduced if the volatility of the corresponding risk factor increased. The systematic risk factor contains not only market risk but also anomalies such as the stocks' characteristics of size and value. It is possible for fund managers to time the volatility of anomalies. Busse (1999) proves that only market volatility is more important than the volatility of other conventional three pricing factors in the empirical analysis of US mutual funds timing performance. Most of following volatility-timing studies concentrate on market volatility only (Giambona and Golec, 2009; Liao, Zhang, and Zhang, 2017; Foran and O'Sullivan, 2017; Yi et al., 2018).

Busse (1999) assumes that the return-generating process of k pricing factor and factor sensitivity varies over time, a fund's return at time $t+1$ is given by:

$$r_{p,t+1} = \alpha_{p,t} + \sum_{j=1}^{k} \beta_{j,p,t} r_{j,t+1} + \varepsilon_{p,t+1}, \tag{3.33}$$

where $r_{p,t+1}$ is the excess return of fund p at time $t+1$; $\alpha_{p,t}$ is the abnormal return of fund p known at time t; $\beta_{j,p,t}$ is the sensitivity of fund p to factor j at time $t+1$; $\varepsilon_{p,t+1}$ is the error term of fund p at time $t+1$. Assume a conditionally normal distribution of the returns, the expected return of fund p at time $t+1$ can be expressed as:

$$E_t(r_{p,t+1}) = \alpha_{p,t} + \sum_{j=1}^{k} \beta_{j,p,t} E_t(r_{j,t+1}). \tag{3.34}$$

Assuming that the factors are orthogonal, the conditional variance at time t is given by:

$$\sigma_t^2(r_{p,t+1}) = \sum_{j=1}^{k} \beta_{j,p,t}^2 \sigma_{j,t+1}^2 + \sigma_t^2(\varepsilon_{p,t+1}). \tag{3.35}$$

From the standpoint of timing, the maximization problem is:

$$\max_{\beta_{1,p,t},\ldots,\beta_{k,p,t}} E_t[U_{t+1}(r_{p,t+1})]. \tag{3.36}$$

Differentiating $E_t[U_{t+1}(r_{p,t+1})]$ with respect to $\beta_{j,p,t}$ for $j=1$ to k and setting the result equal to zero gives:

$$\begin{aligned} &\frac{\partial}{\partial \beta_{j,p,t}} E_t[U_{t+1}(r_{p,t+1})] \\ &= E_t[U'_{t+1}(r_{p,t+1})]E_t[r_{j,t+1}] + \beta_{j,p,t} E_t[U''_{t+1}(r_{p,t+1})] var(r_{j,t+1}) \\ &= 0 \end{aligned} \tag{3.37}$$

$$j = 1, \ldots, k.$$

Solving Equation (3.37) for $\beta_{j,p,t}$ gives:

$$\beta_{j,p,t} = \frac{1}{a} \frac{E_t[r_{j,t+1}]}{\sigma_{j,t+1}^2} \quad j = 1, \ldots, k, \tag{3.38}$$

where $a = -{E_t[U''_{t+1}(r_{p,t+1})]} \big/ {E_t[U'_{t+1}(r_{p,t+1})]}$, which is the measure of risk aversion, assumed to be a fixed parameter. Taking the partial derivative of the optimal factor beta with respect to factor standard deviation gives:

$$\frac{\partial \beta_{j,p,t}}{\partial \sigma_{j,t+1}} = \frac{1}{a\sigma_{j,t+1}^2}\left[\frac{\partial E_t[r_{j,t+1}]}{\partial \sigma_{j,t+1}} - \frac{2E_t[r_{j,t+1}]}{\sigma_{j,t+1}}\right] \quad j = 1, \dots, k. \tag{3.39}$$

If $\frac{\partial E_t[r_{j,t+1}]}{\partial \sigma_{j,t+1}}$ is small or negative, we will expect a negative response of sensitivity to the volatility of the factor. In other words, when the volatility of a stock market increases, a rational investor would reduce the exposure of an equity fund to the market.

Moreover, Busse (1999) empirically documents how market volatility is more important than volatility on pricing factors of size, value and momentum. To be specific, Busse (1999) breaks down the total variance of the fund return into components associated with each of the four factors, and finds that the average contribution of S&P 500 is up to 90.6%, while the average contributions of the orthogonal size, value and momentum are only 8%, 1% and 0.3%, respectively. He concludes that there is no apparent reason for fund managers to time the volatilities of the four pricing factors.

Additionally, Busse (1999) extends Treynor and Mazuy's (1966) market return timing model, proposing a well-accepted empirical market-volatility timing model. To be specific, the time-series market systematic risk β_{mpt} is deconstructed into the target or mean beta $\bar{\beta}_{mp}$ and the time-varying beta β_{1mp} that changes depending on market volatility, that is:

$$\beta_{mpt} = \bar{\beta}_{mp} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) \tag{3.40}$$

If the fund manager engages in market volatility timing, the β_{1mp} would be significantly different from zero. The sign of the coefficient β_{mp1} should suggest how the unit trust responds to the changing market volatility and how such strategy affects the fund performance. The significant positive β_{1mp} suggests fund managers engage in pro-cyclical volatility timing strategy, whereas significant negative β_{1mp} suggests the countercyclical timing strategy.

Busse (1999) substitute Equation (3.40) into the conventional four-factor model and expresses the market-volatility timing model as:

$$r_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} r_{jt} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) r_{mt} + \varepsilon_{pt}. \tag{3.41}$$

Busse (1999) use Nelson's (1991) EGARCH method to model the dynamics of daily market volatility σ_{mt} and $\bar{\sigma}_m$ is the time-series mean of market volatility. As Busse (1999) use daily returns to assess volatility timing ability, an econometric problem of autocorrelation would arise due to nonsynchronous trading (Perry, 1985; Atochison, Butler, and Simonds, 1987).

Busse (1999) adopts autocorrelation model (AR) to address the autocorrelation problem by adding a lagged index term. The market-volatility timing model in Busse's (1999) empirical study is expressed as:

$$r_{pt} = \alpha_p + \sum_{j=1}^{4}\left[\beta_{0jp} r_{jt} + \beta_{ljp} r_{jt-1}\right] + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) r_{mt} + \varepsilon_{pt}. \tag{3.42}$$

3.2.2.3 Conditional Version of Volatility-timing Model

Busse (1999) questions that the estimated coefficient of the volatility-timing factor might explain part of the performance referring to the return-timing behavior, if the correlation between the market returns and market volatility is nonzero. As a result, the statistical inference with respect to timing ability will be inefficient. A straightforward solution is to add return-timing factor into the volatility timing model to account for return-timing performance.
The monthly market timing model is expressed as:

$$\beta_{mpt} = \beta_{mp0} + \gamma_{mp}(\sigma_{mt} + \bar{\sigma}_m) + \phi_p r_{mt} + \varepsilon_{mpt}, \tag{3.43}$$

and the daily market timing model is expressed as:

$$r_{pt} = \alpha_p + \beta_{mp0} r_{mt} + \gamma_{mp}(\sigma_{mt} + \bar{\sigma}_m) r_{mt} + \phi_p r_{mt}^2 + \beta_{lmp} r_{mt-1} + \varepsilon_{pt} \tag{3.44}$$

Busse (1999) empirically examines both timing strategies by two steps while playing with monthly data. The first step is to use daily returns to estimate portfolio’s market exposures β_{mpt} and monthly market volatility σ_{mt} within each month. Next, he employs Equation (3.43) to evaluate timing behavior. In terms of daily data, Busse (1999) adopts Equation (3.42) to assess both timing performance straightforwardly.

Busse (1999) reveals that the coefficient of volatility-timing factor in the conditional model remains the same as the corresponding coefficient in the single volatility-timing model. The result indicates that, despite the presence of high correlation between market return and market volatility, the performance of return-timing strategy does not affect the performance evaluation of volatility-timing behavior. On the other hand, the conditional models of Equation (3.43) and Equation (3.44) can assess the timing performance of funds for return-timing and volatility-timing separately.

3.2.3 Joint Market Timing Models

Chen and Liang (2007) state that fund managers can change the market exposure of their managed portfolios based on perceptions of both market return and market volatility simultaneously. The fund manager might not take heavy/light positions in the market even if he successfully previses an upswing/downswing of market return because he has to consider market volatility at the same time; managers might behave conservatively in lessening/increasing equity holdings if the anticipation of market volatility is high/low. Therefore, the time-varying market exposure beta for a utility-maximizing manager would be displayed as (Admati et al., 1986):

$$\beta_t = \frac{E\left(r_{m,t+1} \middle| S_t\right)}{\theta * Var\left(r_{m,t+1} \middle| S_t\right)} \tag{3.45}$$

where θ measures the constant risk aversion, and S_t denotes the manager's timing signal. Equation (3.45) describes how a market timer incorporates information into fund management: fund beta should increase with expected market return $E\left(r_{m,t+1} \middle| S_t\right)$ and decrease with the expected market variance $Var\left(r_{m,t+1} \middle| S_t\right)$. Thus, such an expression of beta justifies the examination of timing ability from two dimensions: market return and market volatility.

As only the return timing matters under the normality assumption for equity returns, Chen and Liang (2007) employ student t-distribution for equity returns in their study. More specifically, under the normality assumption, conditional market expected return and variance can be measured as:

$$\begin{gathered} E\left(r_{m,t+1} \middle| s_t\right) = \mu_{r_m} + \frac{Cov(r_{m,t+1}, s_t)}{Var(s_t)}(s_t - \mu_s) \\ Var\left(r_{m,t+1} \middle| s_t\right) = Var\left(r_{m,t+1}\right) - \frac{\left[Cov(r_{m,t+1}, s_t\right]^2}{Var(s_t)} \end{gathered} \tag{3.46}$$

where μ is the unconditional mean. The conditional market expected return is a linear function of the timing signal s_t, whereas the conditional variance is constant. However, the equity returns are not distributed normally and some studies debate that the assumption of normal distribution is not appropriate for the empirical analysis. Laplante (2003), for instance, assumes a joint t-distribution of asset returns and timing signal in his market timing model, which explicitly incorporates the signals about both the level and variance of the market portfolio. Kan and Zhou (2003) advocate the multivariate Student t-distribution as a better characterization of asset returns.

Chen and Liang (2007) present a joint market timing model with flexible distribution by relating fund returns to the squared Sharpe ratio of the market portfolio. Substituting the expression of beta in Equation (3.45) to the return generating factor model:

$$r_{p,t+1} = \alpha + \beta_t r_{m,t+1} + \varepsilon_{t+1}, t = 0, \dots, T-1, \tag{3.47}$$

the joint market timing model, under the multi-factor pricing framework, can be expressed as:

$$r_{p,t+1} = \alpha + \sum_{j=1}^{K} \beta_j r_{j,t+1} + \gamma \left(\frac{r_{m,t+1}}{\sigma_{m,t+1}|s_t} \right)^2 + \varepsilon_{t+1} \tag{3.48}$$

where γ measures the timing ability of a manager who can forecast both the level and volatility of the market portfolio. The timing signal of the market level $s_t = r_{m,t+1} + u_t$, and the signal of market variance $Var(r_{m,t+1}|s_t)$ is linearly related to $(s_t - \mu_s)^2$ under student t-distribution. The value of $(s_t - \mu_s)^2$ equals $(\sigma^2_{m,t+1} + \sigma^2_{u,t})$, containing the variance of forecasting errors in the timing signal and the market variance. For a fund employing buy-and-hold strategies, β_m alone captures the fund's market exposure and coefficient γ should be zero. However, a market-timing fund can enhance portfolio performance as long as the market's Sharpe ratio is nonzero. The timer should increase his market exposure with the expected Sharpe ratio of the market portfolio.

3.3 Empirical Studies

3.3.1 Market-return Timing Performance Evaluation

Regarding the absence of holding data for mutual funds outside the US market, return-based timing models prevail in the empirical analysis. Fletcher (1995), for example, investigates the stock picking and market-return timing performance of UK equity unit trusts. Fletcher (1995) forms a research sample containing 101 unit trusts authorized in the UK, extracting the monthly returns of trusts from January 1980 to December 1989. Fletcher (1995) tests various market indices (i.e., Financial Times All-Share Index, Financial Times 100 and an equally-weighted index) in the single factor model while evaluating selectivity and timing abilities based on quadratic and piecewise-linear models. Fletcher (1995) demonstrates that the average UK mutual funds exhibit positive selectivity ability but negative market-return timing skill.

Ferson and Schadt (1996) question the reliability of unconditional measures applied in early studies because unconditional models fail to control the beta change due to the change of market economic conditions. In particular, the time-varying value of the market exposure of an active fund would be attributed to either the manager's timing investment strategy or the market movements referring to news. The change driven by public information cannot be regarded as superior timing ability, thereby requiring to be controlled in the linear time-varying beta function. Ferson and Schadt (1996) add a set of lagged instruments of publicly available information into quadratic and piecewise-linear timing models. Ferson and Schadt (1996) examine the performance of 67 US mutual funds over a sample period from January 1968 to December 1990 by using both unconditional and conditional measures. Ferson and Schadt (1996) demonstrate that the power of assessing the return-timing ability of fund managers improves after taking conditional measures into account.

Cuthbertson, Nitzsche and O'Sullivan (2010) also employ conditional measure. In contrast to the majority of existing literature which employs the quadratic or piecewise-linear timing model, Cuthbertson, Nitzsche and O'Sullivan (2010) combine the nonparametric method advocated by Jiang (2003) with the conditional measure, displaying that a relatively about 1% of fund managers have the positive market timing ability, and around 19% of managers show negative timing ability. Cuthbertson, Nitzsche and O'Sullivan (2010) conclude that on average UK mutual funds miss-time the market.

As discussed in section 3.2 of theoretical timing models, one major obstacle in exploring the market timing skill of an active mutual fund is distinguishing the quality of the manager's forecast of the future market return from the aggressiveness of response in changing the fund beta. The quadratic and piecewise-linear regression model cannot separate these two elements. The nonparametric method, on the other hand, despite irrespective of how aggressively fund managers act on their forecast, can measure how often managers correctly forecast a market movement and act on it.

Recent empirical studies move their attention to econometric techniques in order to improve evaluation accuracy and gain reliable statistical inference. Empirical studies using OLS-type methods to estimate parameters of timing models would produce biased and unreliable results. In particular, OLS method requires fairly restrictions on data set such as no autocorrelation, normal distribution and homoscedasticity. Empirical data is hard to satisfy these rigorous assumptions, resulting in unreliable statistical inference.

The bootstrap method is increasingly popular in correcting the standard error and statistical significance. Kosowski *et al.* (2006) and Fama and French (2010) develop two different bootstrap methods and gain different results. The basic principle of bootstrapping is to randomly re-sample a dataset with replacement. Kosowski *et al.* (2006) implicitly assume that the residuals are independent across different funds and the impact of common risks stay unchanged during the sample period. Therefore, Kosowski *et al.* (2006) re-sample with replacement the residuals for all funds and find evidence of a small number of skilled managers. By contrast, Fama and French (2010) consider both systematic and unsystematic risk; they jointly re-sample with replacement the factor returns and the residuals for all funds, failing to find skilled managers.

The two empirical studies above examine selectivity skill only. Blake *et al.* (2017) adopt both bootstrap methods to evaluate the performance of selectivity and return-timing in the quadratic market-return timing model. Blake *et al.* (2017) use monthly returns of UK equity mutual funds from 1998 to 2008, drawing two primary conclusions: first, on average, managers cannot deliver outperformance from either stock selection or market timing once allowance is made for fund manager fees. Second, statistic inference is sensitive to the bootstrap methods adopted. Overall, literature suggests that the vast majority of UK fund managers are impoverished at timing the market returns.

3.3.2 Market-volatility Timing Performance Evaluation

Busse (1999) exhibits that 80% of managers in the research sample of 230 US domestic equity mutual funds can successfully time the market volatility from 1985 to 1995. In particular, fund managers decrease the fund's beta when the market volatility rises or increase the beta when the market volatility falls, that is, counter-cyclical volatility-timing strategy. Moreover, Busse (1999) documents that the volatility timing model produces higher risk-adjusted returns than standard CAPM-type models in the context of US mutual funds, potentially advocating that volatility-timing is an efficient strategy implemented by fund managers.

Likewise, Liao, Zhang and Zhang (2017) and Yi *et al.* (2018) also exhibit strong evidence to support that fund manager can counter-cyclically time market volatility in the Chinese stock market based on monthly returns of Chinese mutual funds. Foran and O'Sullivan (2017), nevertheless, show that only 6% of UK equity mutual funds significantly time the market volatility by reducing systematic risk in advance of higher conditional market volatility based on monthly returns analysis.

Giambona and Golec (2009) document how aggressive (high beta) funds prefer counter-cyclical volatility timing strategy because the beta and standard deviation of aggressive funds are high. To be specific, if a fund manager reduces market sensitivity when the market volatility increases, the total volatility of the fund would be lower although the average beta remains the same. Therefore, aggressive funds with high beta tend to employ counter-cyclical volatility timing strategy to reduce their total volatility and produce high risk-adjusted return without sacrificing beta.

By contrast, conservative (low beta) funds prefer to employ a pro-cyclical volatility strategy, that is, increasing market sensitivity beta when market volatility increases. The reason for absorbing higher volatility when market volatility is significant for risk-averse managers is related to management fees. More specifically, manager expects a relatively high payoff of expected return for bearing additional volatility. For example, Warren Buffet managing portfolio with an average low-risk level at Berkshire Hathaway buys stocks like Salomon Brothers during volatile markets, since he believes the payoffs are potentially more enormous (Giambona and Golec, 2009).

Giambona and Golec (2009) confirm that more considerable incentive fees are associated with less counter-cyclical or more pro-cyclical volatility-timing behavior. Kim and In (2012) also display equal percentages of counter-cyclical and pro-cyclical volatility timing performance for US mutual funds after accounting for the false discovery rate (FDR). Kim and In (2012) use FDR to avoid type 1 errors of misclassifying non-timers as volatility timers due to overestimating the number of counter-cyclical or pro-cyclical timing mutual funds. To be specific, Kim and In (2012) find that 40% of funds show non-timing performance; 29.6% of funds display counter-cyclical volatility timing performance; 30.4% of funds reveal pro-cyclical volatility timing performance. Kim and In's (2012) results advocate how the FDR is relatively small, implying that standard approach can provide entirely accurate results for volatility-timing performance evaluation. Moreover, small FDR potentially supports the notion that volatility is predictable, permitting managers to effectively implement the strategy of timing market volatility without having superior forecasting abilities.

Ferson and Mo (2016) states that volatility timing is relative to fund managers incentives. Busse (1999) presents that investors would prefer fund managers to reduce market exposure in anticipation of higher market volatility. However, fund managers face incentives to take actions that can depart from the interests of fund investors (Ferson and Mo, 2016). More specifically, Ferson and Mo (2016) investigate how volatility reaction and timing are related to incentives of flow-based and tournament. As volatility timing is negatively related to total performance and total performance is likely to be related to incentives, Ferson and Mo (2016) control for the ex-post total performance alphas and find that the proxy for adverse incentives has a negative relation to the volatility reaction and to the volatility timing behavior.

In other words, funds that are behind in the tournament tend to display more adverse volatility reaction and volatility timing behavior, raising their factor exposures when the factor second moments are higher. Furthermore, other things equal, when the convexity in incentives is greater, mutual funds are more likely to increase their factor exposures when volatility is high or is predicted to be high. Overall, Ferson and Mo (2016) provide evidence how adverse volatility-related behavior is more likely when fund incentives are more adverse.

3.3.3 Joint Market Timing Performance Evaluation

To our knowledge, Chen and Liang (2007) is the only empirical study accounting for market return and volatility timing performance simultaneously. Chen and Liang (2007) use a sample of 221 US hedge funds self-described market timing funds to study market timing ability from 1994 to 2005, and find that the joint timing coefficient is between 0.005 and 0.006 at a 1% significance level across the four specifications of single-, three-, and four-factor models and conditional regression models. These results suggest a positive relationship between fund returns and the squared Sharpe ratio of the market portfolio, potentially implying that Sharpe ratio or joint timing behavior impact on the adjustment of market exposure.

3.4 Idiosyncratic Risk

Idiosyncratic risk is the possibility that the price of an asset may decline due to an event that could specifically affect that asset but not the market as a whole. The idiosyncratic risk of an equity portfolio can be eliminated by diversification, allocating underlying assets into various types of equities. Conventional asset pricing theory assumes that portfolios are adequately diversified thus eliminating idiosyncratic risk, and the expected portfolio returns are a function of systematic market risk whereby market risk is measured by the standard deviation of market index returns.

However, Merton (1987) claims that rational investors who are unable to hold the market portfolio or fully-diversified portfolio would care about total or idiosyncratic risk rather than merely market risk. Merton (1987) theoretically documents the existence of idiosyncratic risk in equity portfolios, supported by many empirical studies (e.g., Campbell et al., 2001; Goetzmann, Jonathan, and Ivković, 2000; Ang et al., 2009). This section surveys the idiosyncratic risk measurement and the study about the relationship between idiosyncratic risk and market returns.

3.4.1 Idiosyncratic Risk Measurement

The primary method of measuring idiosyncratic risk for an equity portfolio is the standard deviation of regression residuals under the one-factor CAPM model or the Fama and French's (1993) three-factor model (Merton, 1987; Malkiel and Xu, 2002; Ang et al., 2006; 2009). More specifically, the linear model can be expressed as:

$$r_{i,t} = \alpha_i + \sum_{j=1}^{k} \beta_{i,j} r_{j,t} + \varepsilon_{i,t}\,;\ \varepsilon_{i,t} \sim iid\left(0, \sigma_{i,t}^2\right), \tag{3.49}$$

where $r_{i,t}$ denotes the excess return of asset i for month t; $\beta_{i,j}$ are the sensitivities of a firm i to the risk-pricing factors such as market excess return, mimicking portfolio returns of size, value and momentum. The idiosyncratic volatility for month t is defined as $\hat{\sigma}_{i,t}$ the sample standard deviation of the residuals in the month.

If the $\hat{\sigma}_{i,t}$ is simply assumed to follow a random walk, then:

$$\widehat{\sigma}_{i,t} \middle| \emptyset_t = \hat{\sigma}_{i,t}, \tag{3.50}$$

where $\emptyset_t$ is the information set, and a subscript indicates the inclusive most recent date available in the information set. In empirical studies, Ang et al. (2006; 2009) use daily returns to estimate monthly idiosyncratic volatility by calculating the standard deviation of daily estimated residuals within each month. Malkiel and Xu (2002) and Bali and Cakici (2008) estimate monthly idiosyncratic volatility by calculating standard deviation with a rolling window subsamples of monthly data. As the volatility exhibits the clustering characteristic, the lagged realized idiosyncratic volatility would be a proxy of the expected idiosyncratic volatility.

However, if the $\hat{\sigma}_{i,t}$ is not assumed to follow a random walk, the idiosyncratic volatility may be modelled by using an autoregressive process (AR). The estimated idiosyncratic risk can be expressed as:

$$\widehat{\sigma}_{i,t} = \alpha_0 + \textstyle\sum_{m=1}^{p} \alpha_m \widehat{\sigma}_{i,t-m} + \sum_{n=1}^{q} b_n \varepsilon_{i,t-n} + \varepsilon_{i,t}, \tag{3.51}$$

where $\varepsilon_{i,t}$ is the time series error for asset i in month t. Chua, Goh and Zhang (2010) adopt the auto-regression process to investigate expected idiosyncratic volatility by setting $p = 2$ and $q = 0$. Similarly, Huang et al. (2010) use best-fit autoregressive integrated moving average model (ARIMA) to predict a stock's idiosyncratic volatility next month based on the individual stock's realized idiosyncratic volatility over the previous twenty-four months, where the realized idiosyncratic volatility is estimated following Ang et al.'s (2006; 2009) method.

Alternatively, GARCH-type models are another straightforward way to estimate or forecast firm-level idiosyncratic volatility. Regarding the phenomenon of asymmetric volatility that is the observed tendency of equity market volatility to be higher in declining markets than in rising markets, many empirical studies use exponential GARCH model (Busse, 1999; Fu, 2009). To be specific, the exponential GARCH model can be written as:

$$\ln(\sigma_{i,t}^2) = \alpha_0 + \sum_{\mathrm{m}=1}^{p} \beta_{i,m} \ln\left(\sigma_{i,t-\mathrm{m}}^2\right) + \sum_{n=1}^{q} \gamma_{i,n} \left\{\theta\left(\frac{\varepsilon_{i,t-n}}{\sigma_{i,t-n}}\right) + \lambda\left[\left|\frac{\varepsilon_{i,t-n}}{\sigma_{i,t-n}}\right| - \left(\frac{2}{\pi}\right)^{\frac{1}{2}}\right]\right\}. \qquad (3.52)$$

The value $\left|\frac{\varepsilon_{i,t-n}}{\sigma_{i,t-n}}\right| - \left(\frac{2}{\pi}\right)^{\frac{1}{2}}$ is adopted to monitor the asymmetric volatility phenomenon. Under the exponential GARCH model, the expected idiosyncratic volatility would be estimated by the following specification:

$$\hat{\sigma}_{i,t}^2 | \emptyset = exp\left[\hat{\alpha}_i + \sum_{m=1}^{p} \hat{\beta}_{i,m} \ln\left(\hat{\sigma}_{i,t-m}^2\right) + \sum_{n=1}^{q} \hat{\gamma}_{i,n} \left\{\hat{\theta}\left(\frac{\hat{\varepsilon}_{i,t-n}}{\hat{\sigma}_{i,t-n}}\right) + \hat{\lambda}\left[\left|\frac{\hat{\varepsilon}_{i,t-n}}{\hat{\sigma}_{i,t-n}}\right| - \left(\frac{2}{\pi}\right)^{\frac{1}{2}}\right]\right\}\right]. \qquad (3.53)$$

Spiegel and Wang (2005), Fu (2009), Huang et al. (2010), Eiling (2013), and Peterson and Smedema (2011) forecast expected volatility by employing the exponentially-weighted method with varying information sets. In particular, Fu (2009) following the previous study of Spiegel and Wang (2005) use $\hat{\sigma}_{i,t}^2 | \emptyset_t$ to estimate the idiosyncratic volatility, whereas Eiling (2013) and Peterson and Smedema (2011) use $\hat{\sigma}_{i,t} | \emptyset_t$ for all $t \in \{1, 2, \ldots, T\}$ to estimate idiosyncratic volatility.

In general, the prevalent methods of estimating expected idiosyncratic volatility are the lagged realized volatility and the estimated volatility conditional on past information set. Realized volatility is measured by the standard deviation of daily regression residuals from multi-factor asset pricing model within each month. Estimated volatility is measured by the auto-regression or/and moving average methods such as rolling window, AR, ARIMA or exponential GARCH.

3.4.2 Relationship between Idiosyncratic Risk and Market Returns

Theoretically, as risk-averse investors would require high-expected returns to compensate for imperfect diversification, the relationship between systematic risk and expected return would be positive, and the relationship between idiosyncratic risk and expected return would be positive or zero (Merton, 1987). More specifically, Malkiel and Xu (2002) present two reasons to support the positive relationship between idiosyncratic risk and returns. Firstly, an idiosyncratic risk premium can be rationalized to compensate investors for the unbalanced supply of some assets. Merton (1987) demonstrates that less well-known stocks with smaller investors tend to have relatively larger expected returns than stocks in the comparable complete-information model. The less well-known stocks might be under-priced due to the high supply of the relative per capital. Secondly, imperfect diversification portfolio would take higher corresponding risk than actual market portfolio, requiring higher risk premium. The reason is that, if investors use less diversified portfolio to price individual securities, some of the systematic risks would be considered as idiosyncratic risk relative to the actual market portfolio (Malkiel and Xu, 2002).

Recent empirical studies, nevertheless, provide mixed evidence on the correlation between idiosyncratic risk and market returns. In particular, Boehme *et al.* (2009) empirically document the positive relationship between idiosyncratic risk and cross-section of stock returns by exploring stocks with low-volatility and limited short selling. Fu (2009) considers time-varying idiosyncratic volatility, finding a significantly positive relationship between the GARCH idiosyncratic volatilities and expected returns. Huang *et al.* (2010) also confirm a significantly positive relationship between the conditional idiosyncratic volatility estimated from monthly data and expected returns. Spiegel and Wang (2007) not only find positive relationship between idiosyncratic risk and stock returns in the US stock market but also explore how idiosyncratic volatility is much stronger and can eliminate the explanatory power of liquidity in determining stock returns. Indirectly, Goyal and Santa-Clara (2003) demonstrate a positive relationship between average stock variance and stock market returns, where average stock risk is mostly driven by idiosyncratic risk. Goyal and Santa-Clara (2003) state that average stock variance can predict stock market returns, whereas the variance of the market has no forecasting power for the market returns.

In contrast, other empirical studies present a different story in terms of idiosyncratic risk and returns. More specifically, Ang *et al.* (2006) use a straightforward method of ranking stocks into portfolios based on one-month lagged idiosyncratic volatility relative to the three-factor model (Fama and French, 1993), revealing how a portfolio with high idiosyncratic volatility produces abysmally low average returns. Ang *et al.* (2009) further confirm the presence of idiosyncratic volatility anomaly in over 23 developed markets. Fu (2009), nevertheless, argues that a risk-return relationship study should adopt variables of returns and expected idiosyncratic volatility during the same period, while one-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of this month due to the time-varying characteristic.

Bali and Cakici (2008) exhibit how the cross-sectional relationship between idiosyncratic volatility and expected stock returns is sensitive to the data frequency in idiosyncratic volatility estimation, the weighting schemes adopted to measure portfolio returns, the breakpoints employed to sort stocks into portfolios, and the employment of a screen for size, price and liquidity. Huang *et al.* (2010) find a negative relationship when the estimate is based on daily returns, but a significantly positive relationship when the conditional idiosyncratic volatility is estimated from monthly data. Overall, the relationship between idiosyncratic risk and returns is confused in empirical studies and sensitive to various variables.

3.5 Low-volatility Investment Strategy

3.5.1 Volatility Anomaly

Apart from idiosyncratic risk in the risk-return relationship study surveyed in the above sub-section 3.4.2, prior studies also emphasise the total risk measured by the standard deviation of portfolio returns and market risk beta estimated from the asset pricing models. Literature constructs low and high volatility portfolios by sorting stocks according to their standard deviation of total returns or market sensitivity beta, finding that low volatility portfolio outperforms high volatility portfolio. Haugen and Heins (1972, 1975) define this phenomenon as volatility anomaly. More specifically, Baker, Bradley and Wurgler (2011) display how $1 invested in the lowest-volatility portfolio in 1968 increases to $59.55 while in the highest-volatility portfolio is only $0.58 in 2008. Given the inflation eroded the real value of a dollar to about 17 cents over the research period, the low-risk portfolio earns $10.12, but the high-risk portfolio loses $0.93 in real terms.

Furthermore, volatility anomaly is not only in the US market but also in the global stock markets. In particular, Blitz and van Vliet (2007) rank stocks on their historical volatility into decile portfolios and uncover an apparent volatility anomaly in the US, European and Japanese equity markets over the period from 1986 to 2006. Baker and Haugen (2012) provide proof that stock portfolios bearing relative high volatility of portfolio total returns yield a negative reward in the 21 developed and 12 emerging equity markets from 1990 to 2011. Blitz, Pang and van Vliet (2013) also advocate a sizable presence of volatility effect in emerging markets.

Additionally, volatility anomaly is not only in the stock market but extends to bonds, credit, futures and mutual funds markets. More specifically, Frazzini and Pedersen (2014) display volatility anomaly in the bonds, credit and futures markets across many different countries. Jordan and Riley (2015) confirm the presence of volatility anomaly in the US mutual funds market by comparing the performance of fund portfolios constructed by sorting the funds on their volatility of historical fund returns.

If there is a substantial overlap between low-volatility and value investment strategies, the low-volatility effect would be a manifestation of the value effect. A typical example of supporting the overlap is that, during the tech bubble, both strategies of low-volatility and value investment avoided risky and over-priced tech stocks. Blitz (2016) maintains that low-volatility effect is stronger than the value effect, and cannot be dismissed as the value effect. Moreover, low-volatility effect is robust accounting for the standard size, value and momentum effects (Blitz and van Vliet, 2007; Blitz, Pang, and van Vliet, 2013), and in large-cap stocks with long-holding periods (Blitz, Pang, and van Vliet, 2013). To be specific, Blitz and van Vliet (2007) present evidence that the annual spread of low versus high volatility decile portfolios is 12% from 1986 to 2006. Blitz, Pang and van Vliet (2013) show that the optimal strategic allocation of low volatility investments is sizable even when using highly conservative assumptions regarding their future expected returns. In general, the risk anomaly is one of the strongest and longest-standing anomalies of equity markets, which has posed significant challenge to classic finance theory.

We draw particular attention to the idiosyncratic volatility anomaly. A possible explanation is return reversal (Fu, 2009; Huang et al., 2010). Huang *et al.* (2010) control past stock return in the study of risk-return relationship and the finding of negative relationship between idiosyncratic volatility and portfolio returns disappears in the cross-sectional regression. Fu (2009) also explains that stocks with high idiosyncratic volatilities should have high contemporaneous returns, but the positive abnormal returns tend to reverse leading to negative abnormal returns in the following month.

By contrast, Chen *et al.* (2012) argue that idiosyncratic volatility anomaly cannot be explained by short-term return reversal if stock portfolios have a significant idiosyncratic volatility anomaly effect. To be specific, for the subsample of big and small stocks and the subsample of stocks with price above $5[6], the coefficient of idiosyncratic volatility in the Fama-MacBeth regression remains significantly negative after accounting for last month stock returns.

3.5.2 Investment Strategy Regarding the Volatility of Equity Returns

Literature attempts to rationalize the anomalous relationship between the stocks' returns and their volatility from the perspective of trading strategy. Theoretically, if investors identify the volatility anomaly, rational investors would take benefits from purchasing low-volatility stocks, thereby offsetting the anomaly. However, the consistent existence of volatility anomaly in the stock market suggests that investors might not take rational volatility investment strategy.

On the one hand, the irregular volatility strategy can be attributed to the restriction on borrowing and short-selling. To be specific, borrowing restriction, applicable for both individual and some institutional investors, leads to the under-pricing of low volatility stocks and overpricing of high volatility stocks (Blitz and van Vliet, 2007; Baker, Bradley, and Wurgler, 2011). Frazzini and Pedersen (2014) uncover that many constrained investors tend to hold riskier assets, leading to bidding up high-beta assets.

Short-selling constraints, nevertheless, do not permit arbitrageurs to correct the inflated prices of high volatility stocks immediately by going long on ignored low-risk stocks and shorting high-risk stocks, which in turn, leads to underperformance of high volatility stocks (Hong and Sraer, 2016). Besides, if anomalous excess returns reverse quickly, arbitrage would be costly due to frequently rebalancing portfolios, thereby losing the appeal (Li, Sullivan, and Garcia-Feijóo, 2014).

On the other hand, behavioral finance provides proof of irrational trading behavior. More specifically, as some market participants are irrational, a preference for lotteries or the well-established biases of representativeness and overconfidence leads to a demand for higher-volatility stocks. The "smart money", however, does not offset the irrational demand for risk partly owing to the typical institutional investor's mandate of beating a fixed benchmark. The mandate discourages investments in low-volatility stocks, since holding high-volatility stocks is a more natural way to beat the benchmark than searching for stocks (Baker, Bradley, and Wurgler, 2011). Moreover, Karceski (2002) points out that mutual fund managers care most about outperforming peers during bull markets because fund buyers tend to chase returns

[6] Chen *et al.* (2012) define the stock whose price below $5 as penny stock.

through time and across funds. As high-beta stocks tend to show outperformance in up markets, the demand of fund managers for high-beta stocks has increased.

In addition, Blitz, Pang and van Vliet (2013) uncover that the phenomenon of volatility anomaly appears to have strengthened over time in emerging markets, and one reason might be the combination of the increased institutionalization of emerging markets and hindered arbitrage activity by agency mandate. In other words, the increase of institutional investors restricted on arbitrage investment strategy would potentially intensify volatility anomaly.

Jordan and Riley (2015), nevertheless, empirically reveal how US mutual fund managers take advantage of volatility anomaly; that is, managers pick up under-priced low-volatility stocks. To be specific, Jordan and Riley (2015) construct volatility anomaly factor LVH, similar to Fama-French's size and value volatility factor, by using returns of low volatility stock portfolio to minus returns of high volatility stock portfolio. They add LVH to multi-factor asset pricing model, in order to explain abnormal returns alpha of US mutual funds' portfolios grouped by funds' total volatility; LVH factor provides a home game explanation of fund performance. Jordan and Riley (2015) display significant positive coefficients of volatility anomaly factors across various volatility portfolios of US mutual funds and insignificant abnormal returns alpha, supporting the notion that US fund managers do select stocks by considering the stock's volatility and tend to pick up low-volatility stocks.

3.6 Summary

In conclusion, the study referring to time-varying market exposure of mutual funds has attracted researchers' attention for a long time. Timing models such as quadratic return-timing model, piecewise-linear return-timing model and quadratic volatility-timing model are employed widely in empirical studies. However, the majority of empirical studies use monthly returns to examine timing performance, resulting in biased and unreliable statistical inference due to the inconsistency between the research horizon and the horizon of real timing decisions (Pfleiderer and Bhattachary, 1983; Goetzmann, Jonathan, and Ivković, 2000; Chance and Hemler, 2001; Bollen and Busse, 2001). Some studies demonstrate that analysis of using daily returns give contradictory evidence for timing performance evaluation to the analysis of employing monthly returns (Goetzmann, Jonathan, and Ivković, 2000; Bollen and Busse, 2001; Gallefoss et al., 2015). Rare empirical studies conduct an examination of timing performance evaluation by employing high-frequent dataset such as daily returns in the context of UK market. Moreover, it is reasonable for a rational risk-averse investor to deal with market return and volatility at the same time while making investment decisions. There is only one paper Chen and Liang (2007), to our knowledge, concentrating on the joint market timing strategy.

In addition, the literature of idiosyncratic risk focuses on the equity market based on the simulated equity portfolios, exploring the firm-level idiosyncratic risk. Prior studies advocate the presence of idiosyncratic risk and volatility anomaly. Moving to the context of real equity portfolio such as equity unit trust, a set of questions deserves more attention: first, whether an idiosyncratic risk exists. Second, is there a trust-level idiosyncratic risk representing the private information and decisions of the trust manager? Third, whether trust managers can produce relatively high returns for trust investors if they bear the additional trust-level idiosyncratic risk.

Chapter 4: Research Sample Construction and Data

4.1 Research Sample Construction

We combine information on UK-authorized equity unit trusts from three data sources: DataStream, Bloomberg, and Trustnet. DataStream and Bloomberg are global financial and macroeconomic data sources covering equities, market indices and unit trusts, *etc*.. Trustnet is a commercial data source offering updated information of unit trusts operating in the present UK market. We extract the information for each trust, including name, company, SEDOL code (i.e., Stock Exchange Daily Official List), base date and status (e.g., survival or dead), *etc*. from DataStream and Bloomberg. As DataStream does not provide a target equity market in which each trust invests, we use Bloomberg to fill in missing information. Trustnet is adopted to confirm that all independent and active UK equity unit trusts are embraced in this research sample. Regarding name change or different abbreviation of the name for the same trust in different databases, we manually merge datasets according to the unique SEDOL code rather than fund name.

This thesis encompasses the primary share class for each trust only, as other classes fail to represent separate independent portfolios. In particular, the same unit trust is usually issued with several share classes for different potential clients, such as retail investors and institutional investors. For example, retail investors could not share the same investment class with life assurance companies. The agent would be most likely to reduce charges or fees as an incentive to attract a substantial size of investment of life assurance. We use the base date which is the first date on which DataStream has data for the unit trust to identify the share class of trusts.

The research sample incorporates both survival and dead trusts in order to avoid survivorship bias. The vast majority of funds disappear due to poor performance and small market value (Elton, Gruber, and Blake, 1996). Blake and Timmermann (1998) examine the UK equity fund's performance in the periods preceding their death, finding that a fund's average underperformance is around –3.3% per year, during the final year of its life, compared with the universe of funds in existence at the same time. Thus, if the research sample for assessing fund performance excludes funds that are shut down or merged into another one within the same period, the average performance of funds would be overestimated (e.g., Grinblatt and Titman, 1989; Malkiel, 1995; Elton, Gruber, and Blake, 1996; Rohleder, Scholz, and Wilkens, 2011).

Previous studies use different methodology to estimate survivorship bias and find consistent results of existing positive and statistically significant survivorship bias. Rohleder, Scholz and Wilkens (2011) systematically document that there is bias when ignoring non-survivors, regardless of the methods applied. Carhart *et al.* (2002) also confirm that the bias in average performance typically increases with the sample length. Blake and Timmermann (1998) exhibit around 0.8% survivor bias per year on average in the UK fund market. Therefore, it is essential to encompass both survivor and non-survivor in this research sample.

This research sample removes funds surviving less than 3-years for two reasons, consistent with prior studies. Since the statistic regression method requires at least 36 observations, prior studies usually select funds with 60-month minimum length ensuring they have enough observations and reducing the estimation error. Kosowski *et al.* (2006) uncover that there is a 0.2% difference for estimated returns from restricted and non-restricted survivorship-free research sample.

Overall, this study deals with 478 unit trusts with completed data information in DataStream and Bloomberg, covering 220 UK equity unit trusts that are available for trading in Trustnet by the end of June 2016. Unit trusts are treated as a survivor if their returns display on data sources by the end of June 2015 and non-survivor otherwise. As a result, the sample includes 282 surviving equity unit trusts and 196 non-surviving trusts authorized in the UK fund market. We sort trusts into sub-groups based on the investment objective of geographic location, namely Asia excluding Japan, Asia including Japan, Japan, Europe excluding the UK, Europe including the UK, the UK, North America and Global.

4.2 Data Frequency

The thesis extracts both daily and monthly returns of UK equity unit trusts. We adopt daily returns in the study of timing investment behavior because data frequency might seriously affect statistical inferences regarding performance evaluation. Most timing performance studies adopt monthly returns, finding contrary evidence on successful timing strategy (Fletcher, 1995; Cuthbertson, Nitzsche, and O’Sullivan, 2010; Blake et al., 2017). However, monthly returns might neither able to fully capture high frequent trading activities of fund managers, nor to track activities as accurately as possible. Therefore, this study employs daily returns to examine timing performance in the context of UK unit trusts.

Chance and Hemler (2001) survey 30 market timers' performance using specific recommendations executed in customer accounts. These 30 market timers allocate clients' capital only to equity and cash and voluntarily disclose their recommendations every day. Chance and Hemler (2001) find significant ability when recommendations are observed daily, and that ability generally cannot be detected when recommendations of successful timers are observed monthly. Considering that money managers generally do not report daily data in a form readily accessible to researchers and analysts, this research sample is unique and small. Although the sample of Chance and Hemler's (2001) study has 30 observations, the result advocates that fund managers might switch their portfolio's risk level frequently. Moreover, Mamaysky, Spiegel and Zhang (2008) and Gallefoss *et al.* (2015) document that factor loadings vary significantly over time, implying that fund managers change strategy dynamically.

In addition, Goetzmann, Jonathan, and Ivković (2000), and Bollen and Busse (2001) construct daily timing portfolio by simulating market timer. Bollen and Busse (2001) first construct a synthetic portfolio that matches fund characteristics but has no timing ability. They investigate the power of tests by generating simulated returns for each fund under models of Treynor and Mazuy (1966) and Henriksson and Merton (1981). Under TM model, they set timing coefficient equals to 5, 7.5, 10, 15 and 20. Under HM model, they consider both perfect timer and imperfect timer. They set $p = 1$ when generate simulated returns for the perfect timer, and $0.6 < p < 0.9$ when generate simulated returns for the imperfect timer; p denotes the fraction of observations for which the timing decision is made correctly. Subsequently, they use simulated returns to run TM and HM models, finding that daily tests are more powerful as daily tests result in significant timing coefficients much more often than the monthly tests.

A simulation study of Goetzmann, Jonathan, and Ivković (2000) concentrates on HM-style parametric test only and employs the standard HM test on both daily returns and monthly returns. They also consider both perfect timing and imperfect timing skills by constructing a set of artificial portfolios concerning two types of timers. Goetzmann, Jonathan, and Ivković's (2000) finding suggests that the standard HM parametric test has low power to detect timing skill when the frequency with which the market timer reaches timing decisions is higher than the frequency with which fund returns are measured. Pfleiderer and Bhattachary (1983) also debate a measurement problem generated by the difference between the decision horizon and the evaluation horizon. Therefore, this study employs daily returns when we adopt TM- and HM-type models to assess timing performance of UK unit trusts.

4.3 Unit Trust Returns

Unit trusts historical returns are extracted from the DataStream. The formulation of the total return index (RI) in the DataStream is expressed as:

$$RI_t = RI_{t-1} \times \frac{PI_t}{PI_{t-1}} \times (1 + DY_t), \tag{4.1}$$

where RI_t and RI_{t-1} is return index on day t and previous day respectively; PI_t and PI_{t-1} is bid price index on day t and previous day respectively; DY_t is a gross dividend yield of the price index. We ignore tax and reinvestment charges, as the research purpose is measuring investment abilities of fund managers instead of net returns received by trust buyers. More specifically, tax and other charges are not related to the investment abilities of fund managers but the policies, company regulation and real gains of investors, thereby being skipped. Additionally, the total return is the sum of the capital gains and any dividends paid during the holding period (Brooks, 2014), thereby adding back the dividends in the formulation is reasonable.

Chapter 5: Stock-picking and Market Return-timing Abilities: Evidence from Daily Returns of UK Unit Trusts

5.1 Introduction

The UK unit trusts industry exhibits fast growth but is rarely receiving academic attention. This thesis attempts to enrich UK fund performance literature by investigating investment abilities of fund managers. We quantify investment abilities into selectivity (identifying specific securities which are undervalued or will be better than others) and market-return timing (identifying the market movement and turning point). In the multi-factor regression analysis, selectivity skill is represented by alpha (i.e., intercept) and timing skill is represented by time-varying beta (i.e., the function of the market exposure of active funds). If fund managers use timing investment strategy altering their portfolios' risk level either higher or lower than target levels from their anticipation of market conditions, the beta will be time-varying, which can be demonstrated by a quadratic function (Treynor and Mazuy, 1966; Chen and Stockum, 1986) or piecewise-linear function (Merton, 1981; Henriksson and Merton, 1981; Henriksson, 1984).

Analysis of investment ability has two considerable merits: improving the benchmark specification for assessing the performance of active mutual funds and providing a better understanding of the nature of a manager's skill set. Standard asset pricing models calculate beta according to the covariance between fund returns and market returns divided by the market variance. Studies of using this standard model to evaluate mutual fund performance have an implicit assumption that managers employ buy-and-hold investment strategies to passively build fund portfolios.

However, in the context of actively managed mutual funds, employing this standard simulated portfolio as benchmark would mislead the market risk taken by a fund portfolio, resulting in an unreliable finding on performance assessment. On the other hand, an active fund manager considers market movements and individual stocks every day, making investment decisions to add extra value for fund investors. Therefore, the macro-ability of timing market situations would be of equal importance as micro-ability in picking up successful stocks, and should not be omitted.

This study adopts daily returns to evaluate investment abilities of fund managers, since active managers examine equity markets every day and make investment decision intermittently, rather than regularly such as once a month. A research horizon of monthly observation might differ from real decision horizon, resulting in estimation bias (Pfleiderer and Bhattachary, 1983; Goetzmann, Jonathan, and Ivković, 2000). More specifically, Bollen and Busse (2001) theoretically demonstrate that tests using daily data are more potent than the monthly tests. Chance and Hemler (2001) use unique data of daily recommendations of allocating clients' capital, advocating the idea that managers are a daily market timer. Chance and Hemler (2001) provide proof of significant timing ability while observations are daily, but the ability is no longer able to be detected when using monthly data.

Previous studies substantiate the notion that data frequency could seriously affect inferences regarding performance evaluation in the US fund market. To our knowledge, no prior studies use daily returns to investigate UK mutual fund performance, which motivates us to fill this research gap. However, daily data generates econometric problems while estimating parameters. More specifically, daily returns exhibit autocorrelation characteristics owing to nonsynchronous trading (Perry, 1985; Atochison, Butler, and Simonds, 1987). As the OLS estimation method assumes no autocorrelation in the dataset, previous studies add lagged values of factors as independent variables to address this econometric problem (Dimson, 1979; Busse, 1999).

Moreover, the error term might have heteroscedasticity due to containing terms of random behavior (Pfleiderer and Bhattachary, 1983; Chen and Stockum, 1986; Ferson and Schadt, 1996), which cannot satisfy another underlying assumption under the OLS method, that is, homoscedastic errors. Previous studies either combine procedures of Newey-West or White with OLS approach or adopt bootstrap methods to mitigate the heteroscedastic effect.

In this study, we employ the autoregressive conditional heteroscedasticity (ARCH) model to overcome both econometric problems together. The ARCH model has developed into a big family with various types of specification. The core of ARCH-type models are joint equations: mean equation and conditional variance equation. The research model is expressed in the mean equation. The conditional variance equation accounts for time variation, reiterating a set of lagged residuals and the variances of residuals, which can solve the problems of nonsynchronous trading and heteroscedasticity effect and improve the accuracy of parameter estimates and confidence interval of timing models in the mean equation.

ARCH-type models provide three additional benefits on performance evaluation. Firstly, ARCH family permits us to assess fund performance conditional on past daily shocks. More specifically, Ferson and Schadt (1996) argure that beta change due to public information cannot be considered as timing performance. They use a set of one-month lagged instrumental variables to account for public information. Nevertheless, one-month lagged information might not monitor the timely market information or breaking news. As the error term of research model would contain these unpriced shocks, the conditional variance equation in ARCH joint equations can control a time-series of past daily shocks by a function of the magnitude of the previous periods' error terms. Besides, the latest shock takes the highest weight in the volatility equation, improving the timeliness of the market information.

Secondly, one of ARCH-type models, ARCH-in-Mean, takes time-varying idiosyncratic risk of fund portfolios into account while assessing portfolio performance. To be specific, adding the conditional variance of residuals into mean equation improves the estimate accuracy of alpha (i.e., abnormal return), as the change of alpha is highly related to the change of fund volatility in the previous year. Jordan and Riley (2015) demonstrate that a one standard deviation increase in fund volatility in the previous year predicts a decrease in the four-factor alpha of around 1% in the following year.

Lastly, the ARCH-in-Mean model offers us an alternative way to shed light on the study of the relationship between the idiosyncratic risk of mutual funds and their fund returns. Many prior studies examine the relationship between idiosyncratic risk and returns using simulated portfolios or market portfolios (e.g., Ang et al., 2006; Ang et al., 2009; Fu, 2009). Rare studies investigate the relationship based on real managed portfolios, especially UK equity unit trusts. One similar study conducted by Bangassa, Su, and Joseph (2012) uses GARCH-in-Mean model to investigate the UK investment trusts which are closed-end mutual funds. Our research enriches literature on risk-return relationship study by examining real portfolios actively managed by professional investors. In general, it has considerable merits that employ the ARCH family estimate coefficients and t-statistics in the performance evaluation model.

This study uses a comprehensive research sample, including all equity unit trusts authorized and traded in the UK market. We construct this sample for three reasons. Initially, the international investment strategy is beneficial to achieve diversification and reduce portfolio's risk, as holdings of equity unit trusts are free to allocate in any equity market worldwide (Dimson, Marsh, and Staunton, 2002; Reilly and Brown, 2002, p.201). If a portfolio diversified globally, it is possible to reduce the undiversified market systematic risk by consisting all types of assets in all equity markets.

Secondly, UK foreign unit trusts exhibit a high market requirement recently, indicated by the rapid growth in the market size from £48.1 trillion to £108.5 trillion over the period 2004 – 2014 (TheCityUK, 2015). The possible reason would be that international unit trusts offer UK retail investors who cannot construct a well-diversified global market portfolio due to the high cost of purchasing sufficient numbers of stocks an option to market international investment. Our research would give UK retail investors more information about the UK foreign unit trusts performance.

Finally, we classify trusts by investment objectives of geography. Previous studies on UK foreign unit trusts concentrate on a specific market objective, such as international (Blake and Timmermann, 1998; Fletcher and Marshall, 2005) or emerging markets (Abel and Fletcher, 2004). This study attempts to detail target markets with regions and specific countries. We follow the advice of Fama and French (2012) to choose four regions (i.e., Asian, Europe, North America and Global) ensuring the sample size big enough in regression analysis. We separate Japan from Asian for two reasons: first, the Japanese financial market is close to the Western developed market; second, in the stock market study, Fama and French (2012) reveal many common findings in all regions except Japan. Thus, we give UK unit trusts investing in Japanese equity market particular attention. Besides, we examine UK domestic unit trusts separately due to the large market share.

Overall, this study uses daily returns and ARCH-type models to assess the investment abilities of UK-authorized equity unit trusts. Three main contributions are high-frequent data, time-series estimation method and comprehensive research sample. The remainder of this chapter is organized as follows. Section 5.2 develops our research hypotheses. Section 5.3 introduces descriptive statistics daily returns of unit trusts and benchmark variables. Section 5.4 presents methodologies, including specific timing models and estimation methods, followed by empirical results in section 5.5. The finding of irregular timing behavior is discussed in section 5.6, and section 5.7 concludes.

5.2 Research Hypotheses Development

Fama and French (2010) propose an alternative perspective of equilibrium accounting to investigating mutual fund performance. To be specific, when returns are measured before costs such as fees and other expenses, passive investors obtain almost zero abnormal expected return relative to passive benchmarks. The active investment must also be a zero in the aggregate before costs due to equilibrium model. In particular, an equilibrium model ensures that for every investor who outperforms the market, there is someone who underperforms. In other words, if some active investors produce positive abnormal returns, they will win at the expense of other active investors by correspondence before costs. Therefore, on average, the abnormal return of portfolio of UK equity unit trusts estimated by pre-expense returns of unit trusts would be zero; then, the abnormal return estimated by post-expense returns would be negative by about the amount of fund expenses.

This study uses pre-expense returns calculated from bid-to-bid prices with dividends reinvested because the research purpose is whether managers have skill producing expected returns more substantial than the comparable passive benchmark. The regressions based on raw returns of unit trusts could focus on managers' investment skill, especially the selectivity skill. If we found positive abnormal return, it would imply that trust managers can outperform passive portfolio by picking up successful stocks. This result would challenge the market efficient hypothesis and indicate that the equity market is informationally inefficient. Although the abnormal return in our research is zero or negative, we cannot claim that there is no selectivity skill at the individual trust level. It potentially suggests that, for the UK-authorized equity unit trusts, the number of managers with superior stock-picking skill is not greater than the number of managers with weak selecting ability. Therefore, we draw our first hypothesis as:

Hypothesis 1: *On average, actively managed UK-authorized equity unit trusts do not produce significant outperformance above a passive benchmark portfolio of the UK stock market.*

The assumption of return timing strategy is that investors move in the market when the market excess return is positive and move out the market when the market excess return is negative. If trust managers did not consider market movement and shift their portfolios' risk level, the coefficient of timing factor would be insignificant in the regression model. If we found significant coefficient for timing factor, we would suggest that trust managers do consider the macro-situation of the equity market and do make response towards their anticipation of market forces.

More specifically, a significant positive coefficient would maintain that trust managers in our research sample successfully follow the assumed timing strategy. However, if we found significant negative coefficients of timing factors, we would claim that managers either give an opposite response to their correct market forecast or make an assumed response to the incorrect market forecast. We discuss this issue in detail later based on our empirical results. The second hypothesis in this thesis is:

Hypothesis 2: *On average, managers actively managing UK equity unit trusts use market return timing investment strategy.*

The OLS method is widely adopted to estimate the parameter of a linear regression model due to feasible computation and easy use. However, several underlying assumptions of OLS approach deserve particular attention while doing any econometrics test. The result possibly is unreliable or incorrect if some assumptions are broken.

There are three assumptions related to our data. The first one is homoscedasticity, which means the error terms in the regression should all have the same variance. If the variance is not constant, then the linear regression model has heteroscedastic errors and likely to give either too narrow or too wide confidence intervals, leading to incorrect statistical inference.

The second assumption is no autocorrelation, which means that the error terms of different observations should not be correlated with each other. In our research of using time-series daily returns, for example, the regression is likely to suffer from autocorrelation because a unit trust's return today will certainly be dependent on the return of yesterday. Hence, error terms in different observations will surely be correlated with each other. The OLS estimates will not be best linear unbiased estimate if autocorrelation does not be corrected, then the estimates will not be reliable enough.

The third assumption relevant to our data is that the errors are normally distributed, conditional upon the independent variables. However, non-normal distribution is not a surprise in empirical studies. Although our data is not normally distributed, the validity of the OLS method is not affected.

When we do OLS regression, we combine Newey-West procedure with OLS to relieve effect of heteroskedasticity and autocorrelation. White is one popular procedure to produce consistent standard errors for OLS regression coefficient estimates in the presence of heteroskedasticity. In contrast, the Newey-West variance estimator is a robust extension variance estimator when there is autocorrelation in addition to possible heteroskedasticity. The Newey-West procedure fixes the estimated standard errors by estimating only the most critical covariance matrix of parameters instead of all covariance, partly accounting for heteroscedastic residuals. However, the Newey-West variance estimator handles autocorrelation up to a specified lag which is stipulated by researchers and then any autocorrelation at lags greater than the specified lag, will be ignored. Thus, power of Newey-West procedure might be weak.

For the time-series ARCH family, the conditional variance equation can capture past squared error terms with flexible lag structure by allowing lagged conditional variances to enter, reducing the weights of error terms over time but never going down to absolute zero. Moreover, the error distribution is flexible under ARCH-type models, seeing details in the section of methodologies. Thus, we propose a hypothesis that ARCH family can solve econometric problems better for our data set, that is:

Hypothesis 3: *Estimation method of the ARCH family performs better than the method of OLS with Newey-West procedure for daily data analysis.*

Financial theory supposes that rational investors should expect a higher return by taking additional risk. A possible way to empirically test this concept is to let the return of a security be partly determined by its risk (Brooks, 2014). In the study of equity unit trusts actively managed by professional investors who charge high management fees, a question arises as to whether managers intend to pursue additional returns to attract investors by taking extra risk.

As target beta is set up in advance and reported to the investors, the extra risk might come from the idiosyncratic risk of trust portfolios. In particular, high transaction cost would less motivate managers to establish a compeletly well-diversifed portfolio. On the other hand, if managers seek to beat passive managed portfolio, drawing more investors and increasing their compensation, they would invest in several particular stocks to grab abnormal return, thereby taking additional idiosyncratic risk.

We, therefore, create a hypothesis that the idiosyncratic risk exists in trust portfolios and positively contributes to trust returns on average. We add the conditional variance term into the performance evaluation model, following the ARCH-in-Mean specification proposed by Engle, Lilien, and Robins (1987). If the coefficient of conditiona variance is positive and statistically significant, then increased idiosyncratic risk, given by an rise in the conditional variance, results in an growth in the trust returns. We would support that trusts can generate positive risk premium with respect to their idiosyncratic risk. The fourth hypothesis is presented as:

Hypothesis 4: *On average, managers of UK-authorized equity unit trusts can be rewarded for taking additional idiosyncratic risk for their portfolios by obtaining higher trusts returns.*

All UK-authorized unit trusts are sold to UK investors. A straightforward way for managers to sell their trusts is offering investors a considerable profit; otherwise, their trusts will not survive if no one buys them. In other words, all unit trusts in our reseach sample should perform similarly. Theorically, UK international equity unit trusts might enjoy relatively low systematic risk in comparison with UK domestic trusts due to imperfect correlation between systematic risk factors across different countries. Nevertheless, managers investing in foreign markets might not receive timely news and have to face other risks such as exchange rate fluctuations. The relative merits of low systematic risk would be weakened.

By contrast, although trust managers with domestic focus fail to diversify market systematic risk, they are beneficial to pick up under-valued stocks to increase abnormal returns. More specifically, they feast on informational advantages in local markets and have no need to deal with exchange rate risk, asymmetric information and time lags. Therefore, we anticipate that, on average, unit trusts with foreign markets investment objective in our sample perform as well as trusts with local focus under the efficient market hypothesis. We describe our fifth hypothesis as:

Hypothesis 5: *On average, there is no significant difference in investment abilities of managers between UK domestic and foreign equity unit trusts.*

Kacperczyk, Van Nieuwerburgh and Veldkamp (2014) state that fund managers concentrating on different skills in different financial conditions, as managers are not born with investment talents but possessing consummate skills by hard working and studying. Kacperczyk, Van Nieuwerburgh and Veldkamp (2014) prove that managers pick stocks well during expansions and by timing the market in recessions. Moreover, Kosowski (2011) investigates the average performance of US mutual funds, revealing that funds perform better in recession than in boom periods.

Although prior studies document that investment strategy of fund managers and performance of mutual funds vary in difference financial conditions, we propose our hypothesis of no significant difference in the investment abilities assessment. The reason is that we emphasise the length of research period, instead of bull or bear financial periods. More specifically, if the research period is quiet long such as 25 years in a time-series analysis of UK unit trusts, many trusts would have changed their managers and gone through several financial cycles. However, each unit trust is supervised by his fund company which would name a new manager with equal or better investment ability, in order to retain the clients.

Furthermore, despite a short research period such as 5 years, the stock market fluctuates from day to day, suffering several cycles of up and down within 5 years. In other words, the circumstances of recession and expansion would not significantly impact our time-series findings. Therefore, on average, we predict that findings on the aggregate investment ability evaluation of UK unit trusts are not varying with respect to the research period. The last hypothesis of this thesis is drawn as:

Hypothesis 6: *On average, there is no significant difference in the performance of investment abilities of UK-authorized unit trust managers for any given of length of the research period.*

5.3 Descriptive Statistics

Our research sample and return data are reported in chapter 4. Generally, we have daily returns of UK-authorized equity unit trusts from July 1990 to June 2015. The research sample has 478 unit trusts, including 282 survivors and 196 non-survivor; thus, the data is free of survivorship bias. The restriction that at least 80% assets of equity unit trusts must be allocated in equity market potentially impact on timing evaluation. More specifically, in the context of timing behavior, investors move in and out of market when the market excess returns are positive and negative, respectively. However, for managers of equity trusts, although they successfully forecast that the market will fall, they cannot completely leave the equity market. We, therefore, slightly relax timing assumption as timing the market by switching between high- and low-beta equities.

Table 5.1 displays the summary statistics of the excess daily returns of 478 UK-authorized equity unit trusts. We sort trusts into eight geographic groups based on their target investment region. Excess return is measured by the difference between trust's daily returns and returns on the UK three-month Treasury bill. The trust returns slightly exceed risk-free returns, indicated by positive mean excess returns in most geographical groups and aggregate portfolio of unit trusts.

Furthermore, Table 5.1 exhibits strong evidence of non-normality in our research data. In particular, excess daily returns exhibit high excess kurtosis and small negative skewness relative to a normal distribution, suggesting that tail event occurs often. Jarque-Bera (J-B) test rejects the null hypothesis of normality at the 1% level, indicated by extensive statistics in the column of J-B. These results should come as no surprise since the non-normality of stock returns is well established and has spurred the study of alternative distributional assumptions (Bollen and Busse, 2001).

In addition, the stationary test of Augmented Dickey-Fuller (ADF) shows significantly large negative statistics reported in the last column of Table 5.1, rejecting the null hypothesis that a unit root is present in our time series sample. In other words, our time-series returns are stationary, implying that the OLS method is appropriate for estimating the slope coefficients in our study.

Table 5. 1:
Descriptive Statistics of the Excess Daily Returns for the Geographical-groups and Aggregate Portfolio

	N	*N (surviving)*	*Mean*	*Min*	*Max*	*Std. Dev.*	*Skew.*	*Kurt.*	*J-B*	*ADF*
Asia excluding Japan	17	14	0.02	–8.15	7.80	0.01	–0.45	7.73	5976***	–63.41***
Asia including Japan	7	6	0.01	–8.89	7.34	0.01	–0.39	7.20	4697***	–66.96***
Japan	15	10	–0.01	–7.92	6.58	0.01	–0.18	6.16	2607***	–53.23***
Europe excluding UK	27	23	0.02	–7.22	7.52	0.01	–0.48	7.53	5530***	–54.73***
Europe including UK[7]	15	7	0.02	–75.63	77.63	0.02	0.98	981.7	2.47E+08***	–41.69***
UK	262	128	0.02	–7.05	5.84	0.01	–0.73	10.15	13707***	–68.71***
North America	24	20	0.02	–7.06	5.81	0.01	–0.25	6.74	3659***	–70.34***
Global	111	74	0.01	–10.21	12.08	0.01	–0.24	28.13	162724***	–63.50***
All	478	282	0.02	–5.97	5.44	0.01	–0.64	8.93	9490***	–64.38***

These excess returns are for a total of 478 UK equity unit trusts according to the aggregate portfolio and various geographical focuses, over the period July 1990 to June 2015. The unit trusts groupings are derived from the holding shares of each unit trust allocated in various countries' stock markets. The geographical focus information is primarily from the DataStream, with missing information filled in with data from Bloomberg. The N denotes the number of unit trusts that exist for no less than three years within the entire data period for various groups and aggregate portfolio, and the N (surviving) denotes the number of unit trusts with free returns for trading by the end of 30 June 2015. The base year is the date of the first unit trust issue year in each group and the entire research sample. The numbers on the right side of the table represent the summary statistics as well as skewness and kurtosis of excess daily returns in the group and aggregate level. J-B is the normality test. ADF is the stationary test.
The values of *Mean, Min, and Max* are multiplied by 100 to express them in percentage terms.
The symbols ***, ** and * represent the statistical significance at the 1%, 5%, and 10% level, respectively.

Table 5.2 reveals substantial evidence of autocorrelation in daily returns. The column AC reports the degree of similarity between a given time series and a lagged version of itself over successive time intervals. The correlation measures the number of autocorrelation. The number of the first-order autocorrelation is positive, whereas the number of sixth-order is negative, implying that the direction of correlation between current return and past return changes depends on the time intervals. Across the orders from one to six reported in Table 5.2, Q-statistics of autocorrelation test is large exceeding 300, and p-values of the test are zero, implying that autocorrelation strongly exists at 1% significant level.

[7] The odd descriptive statistics of daily returns of the Europe including UK portfolio show extremely large minimum and maximum portfolio's excess returns. However, given that manual-recording mistakes were ruled out and the sub-sample of Europe including UK contains a small number of observations, the efficiency of our main results can be maintained. To be specific, our research sample embraces 478 UK equity unit trusts, divided into 8 groups based on the geographical investment focuses. Although the result of group of Europe including UK might be slightly biased, the main results referring to UK domestic unit trusts, UK international unit trusts and aggregate trusts portfolio are reliable as the sub-sample of Europe including UK contains only 15 trusts.

Table 5. 2:
Autocorrelations of Excess Daily Returns for the Geographic-groups and Aggregate Portfolio

	Auto(1)			*Auto(2)*			*Auto(3)*		
	AC	*Q-Stat*	*Prob*	*AC*	*Q-Stat*	*Prob*	*AC*	*Q-Stat*	*Prob*
Asia excluding Japan	0.222	310.95	0.000	0.036	319.36	0.000	0.019	321.58	0.000
Asia including Japan	0.159	156.48	0.000	0.031	162.37	0.000	0.030	168.09	0.000
Japan	0.220	305.91	0.000	–0.018	308.05	0.000	–0.016	309.74	0.000
Europe excluding UK	0.126	100.04	0.000	–0.025	103.95	0.000	–0.017	105.88	0.000
Europe including UK	–0.082	42.822	0.000	–0.007	43.160	0.000	–0.263	481.82	0.000
UK	0.144	131.52	0.000	0.011	132.30	0.000	0.023	135.53	0.000
North America	0.121	92.574	0.000	0.006	92.804	0.000	0.012	93.785	0.000
Global	0.220	306.82	0.000	0.046	320.16	0.000	0.015	321.50	0.000
All	0.207	271.63	0.000	0.020	274.22	0.000	0.027	278.86	0.000
	Auto(4)			*Auto(5)*			*Auto(6)*		
	AC	*Q-Stat*	*Prob*	*AC*	*Q-Stat*	*Prob*	*AC*	*Q-Stat*	*Prob*
Asia excluding Japan	–0.003	321.65	0.000	0.006	321.85	0.000	–0.018	323.79	0.000
Asia including Japan	–0.001	168.09	0.000	0.026	172.19	0.000	0.009	172.70	0.000
Japan	0.011	310.48	0.000	-0.010	311.10	0.000	–0.021	313.83	0.000
Europe excluding UK	0.014	107.06	0.000	0.015	108.51	0.000	–0.041	119.39	0.000
Europe including UK	0.008	482.18	0.000	0.008	482.62	0.000	–0.014	483.87	0.000
UK	0.044	147.71	0.000	0.034	154.96	0.000	–0.031	161.12	0.000
North America	0.004	93.900	0.000	-0.031	99.813	0.000	–0.020	102.30	0.000
Global	0.044	333.51	0.000	0.014	334.78	0.000	–0.011	335.48	0.000
All	0.044	291.28	0.000	0.025	295.14	0.000	–0.029	300.59	0.000

These excess returns are for a total of 478 UK equity unit trusts according to the aggregate portfolio and various geographical focuses, over the period July 1990 to June 2015. The fund groupings are derived from the holding shares of each unit trust listed in various countries' stock markets. The geographical focus information is primarily from the DataStream, with missing information filled in with data from Bloomberg. Auto(n) denotes the autocorrelation at n lags. AC denotes the number of autocorrelation, which is the degree of similarity between a given time series and a lagged version of itself over successive time intervals. Q-statistic is autocorrelation test. Prob denotes the test p-values.

Table 5.3 reports descriptive statistics of excess returns of explanatory variables, comprising the market excess return, size, value and momentum. Variables are extracted from the website of the Xfi Centre for Finance and Investment[8]. $r_m - r_f$ represents the excess daily return on the market portfolio. We use the FTSE All-Share Index to estimate the return on the market portfolio and use three-month UK Treasury bill index to estimate the return on the riskless asset. SMB represents size factor, which is the daily return on three small portfolios minus the daily return on three big portfolios. HML represents the book-to-market factor, which is the daily return on two value portfolios minus the daily return on two growth portfolios. MOM represents a momentum factor, which is the daily return on the two high prior return portfolios minus the daily return on the two low prior return portfolios. Factors of size, value and momentum are formed equally weighted, following the methodology presented on Ken French's website[9].

Daily returns of explanatory variables exhibit similar characteristics to trusts daily returns. More specifically, variables' returns are non-normally distributed, indicated by negative skewness, high excess kurtosis, and significant statistics of J-B test. Time series returns of

[8] Xfi Centre: http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/files
[9] Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

variables in Table 5.3 are stationary, indicated by significant negative statistics of ADF test. Moreover, columns of $Auto(n)$ provide strong evidence of the presence of autocorrelation, indicated by significant statistics of autocorrelation test. Autocorrelation of daily returns would produce autocorrelation residuals in regression analysis, violating the OLS assumption that the error terms are uncorrelated. If the autocorrelations of the errors at low lags are positive/negative, the standard errors will tend to be underestimated/overestimated. Although error term might not bias the coefficient estimates, t-statistics might be biased resulting in invalid inference. Therefore, GARCH method is more appropriate for our data analysis than OLS.

Table 5. 3:
Descriptive Statistics of Explanatory Variables in the Benchmark

	Mean	*Min*	*Max*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J-B*
$r_m - r_f$	0.020	–8.358	9.202	0.01045	–0.04373	9.67527	11730***
SMB	–2.13E-05	–6.301	3.561	0.00709	–0.51064	8.26494	7570.57***
HML	0.007	–4.187	5.784	0.00619	0.32862	9.96364	12877.27***
MOM	–0.038	–8.134	5.994	0.00780	–0.58155	12.3375	23305.09***
	Auto(1)	***Auto(2)***	***Auto(3)***	***Auto(4)***	***Auto(5)***	***Auto(6)***	***ADF***
$r_m - r_f$	0.03	6.79**	22.65***	37.21***	48.42***	59.15***	–35.15***
SMB	4.63**	6.68**	12.56***	37.90***	37.94***	38.66***	–38.80***
HML	147.63***	156.54***	161.61***	184.46***	199.40***	200.02***	–68.12***
MOM	113.17***	116.22***	134.52***	135.11***	135.48***	136.23***	–47.03***

These explanatory variables are utilised in equations of performance evaluation of UK unit trusts, over the period July 1990 to June 2015. Daily data is extracted from the website of the Xfi Centre for Finance and Investment. $r_m - r_f$ denotes the market excess returns of FTSE All-Share index returns minus 3-month Treasury bill rate of returns. SMB denotes the risk-pricing factor size of small-cap stocks returns minus large-cap stocks returns. HML denotes the risk-pricing factor value of high book-to-market stocks returns minus low book-to-market stocks returns. MOM denotes the risk-pricing factor momentum of past winner stocks returns minus past loser stocks returns.
This table reports summary statistics of mean, minimum returns Min, maximum returns Max, standard deviation $Std.Dev.$, skewness and kurtosis. J-B is the normality test. Auto(n) denotes the Q-statistic for autocorrelation at n lags. ADF is the stationary test.
The values of *Mean, Min, and Max* are multiplied by 100 to express them in percentage terms.
The symbols ***, ** and * represent the statistical significance at the 1%, 5%, and 10% level, respectively.

5.4 Methodologies

5.4.1 Market-return Timing Models

The purpose of assessing a portfolio's performance is to determine whether the managed portfolio performs better than some comparison benchmarks. If benchmark returns could measure returns of the passively managed portfolio, the difference between returns of active unit trusts and returns of the passive benchmark (i.e., Jensen alpha or abnormal return) would imply the ability of successfully selecting under-valued stocks (Jensen, 1968). This thesis uses Carhart's (1997) four-factor model to measure benchmark returns. Performance evaluation model can be expressed as:

$$r_{pt} - r_{ft} = \alpha_p + \beta_p\left(r_{mt} - r_{ft}\right) + \gamma_p SMB_t + \delta_p HML_t + \lambda_p MOM_t + \varepsilon_{pt}, \qquad (5.1)$$

where $r_{pt} - r_{ft}$ is the excess daily return on unit trusts; $r_{mt} - r_{ft}$ is the excess daily return on the market portfolio; SMB_t, HML_t, and MOM_t are factor mimicking portfolios for size, book-to-market value, and momentum effects, respectively; and α_p represents abnormal return.

Four-factor model assumes a stationary systematic risk level, that is, a constant β_p in Equation (5.1). However, if fund managers adopt timing strategy of switching market exposure based on their forecast of equity market movement, the coefficient of market returns will be time-varying instead of constant. Thus, the standard four-factor model would be misspecified as the model fails to monitor the timing behavior of active managers.

Timing studies propose that quadratic factor of market returns (Treynor and Mazuy, 1966; Chen and Stockum, 1986) and a dummy variable of market returns (Henriksson and Merton, 1981) can capture timing performance. This study generalises standard timing models to multifactor framework expressed as:

$$\begin{gathered} r_{pt} - r_{ft} = \alpha_p + \bar{\beta}_p(r_{mt} - r_{ft}) + \beta_{p1}(r_{mt} - r_{ft})^2 + \gamma_p SMB_t + \delta_p HML_t + \lambda_p MOM_t + \varepsilon_{pt} \\ \varepsilon_{pt} = u_{pt}(r_{mt} - r_{ft}) + \omega_{pt}, \end{gathered} \tag{5.2}$$

and

$$\begin{gathered} r_{pt} - r_{ft} = \alpha_p + \bar{\beta}_p(r_{mt} - r_{ft}) + \beta_{p1} y(t) + \gamma_p SMB_t + \delta_p HML_t + \lambda_p MOM_t + \varepsilon_{pt} \\ y(t) \equiv max[0, r_{ft} - r_{mt}]. \end{gathered} \tag{5.3}$$

The quadratic model in Equation (5.2) breaks down the systematic risk for unit trust p at time t into target beta $\bar{\beta}_p$ (i.e., the beta level in the absence of market timing), changes due to market timing β_{p1}, and random error u_{pt} (i.e., changes due to non-systematic factors). The random error is essential in capturing non-stationary beta, as the beta of a fund portfolio may change over time if the fund manager does not rebalance the fund's portfolio (Alexander, Benson, and Eger, 1982; Ferson and Schadt, 1996). The error term in Equation (5.2) exhibits the presence of heteroscedasticity as error term is confounded with market excess returns.

Piecewise-linear model in Equation (5.3) explores the successful timing strategy from the perspective of options-like strategy. As market timing strategy is equivalent to the strategy of protective put options created by the investors, the value of market timing ability could be regarded as the payoff of protective put options on the market portfolio (Merton, 1981). To be specific, investors long put options to hedge the risk of stock's price going down with exercise price of risk-free return r_{ft}. If the stock price fell, investors would have a right to sell the stock at a predetermined price r_{ft}, and the value of put options would be $r_{ft} - r_{mt}$; if the stock price rose, investors would sell the stock at market price, and the value of put options would be zero. Thus, $y(t) \equiv max[0, r_{ft} - r_{mt}]$ captures the value of protective put options, and β_{p1} assesses timing skill. Unit trusts remain at target risk level $\bar{\beta}_p$ when $r_{mt} > r_{ft}$, and change to low-risk level $(\bar{\beta}_p - \beta_{p1})$ when $r_{mt} < r_{ft}$.

If fund managers were engaged in market timing strategy, β_{p1} would be significantly different from zero. If fund managers could exhibit assumed strong timing ability (i.e., market exposure of unit trust increases when the market goes up, and the exposure decreases when the market falls), the sign of β_{p1} would be positive.

5.4.2 Estimation Methods

Prior studies estimate coefficients under OLS-type methods. By contrast, this study employs GARCH-type estimation methods in order to overcome econometric problems of autocorrelation and heteroscedasticity. The standard GARCH (p, q) model can be written as (Bollerslev, 1986):

Mean Equation:

$$y_t = \mu + \varepsilon_t, \varepsilon_t \sim (0, \sigma_t^2), \tag{5.4}$$

Conditional Variance Equation:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{5.5}$$

where σ_t^2 and σ_{t-j}^2 are the current and the j^{th} lagged level of conditional variance, ε_{t-i} is the i^{th} lagged level of residual. The conditional variance equation can model volatility with a weighted average of past squared residuals. GARCH allows flexible lag structure by allowing lagged conditional variances to enter, declining weights that never entirely reach zero. Moreover, the additional parameter of lagged conditional variance responds to the correlation between the current level of volatility and its level during the immediately preceding period.

The determination of order p and q is a significant practical problem, as we have a long research period of 25 years. GARCH (1, 1) is the most straightforward and most frequently applied parameters in prior studies Hansen and Lunde (2005). For a long span of data, however, first-order might not fully capture both fast and slow decay of information, thereby requiring additional lag terms (Engle, 2001). Bangassa, Su and Joseph (2012) confirm that single order is only available to reduce the ARCH effect, but cannot eliminate them. Engle and Lee (1999) maintain GARCH (2, 2) can identify both a short-run (transitory) component as well as a long-run (trend) component. Tsay (2014), nevertheless, debates that some higher-order GARCH models allow for more complex autocorrelation structure, thereby being implemented more often. Zivot (2009) advocates that higher-order GARCH (p, q) process, such as $p, q > 2$, often has many local maxima and minima; typically selected orders are $p, q \leq 2$.

Bollerslev (1988) proposes that the research purpose would be considered while determining p, q orders of GARCH. The primary purpose of adopting GARCH in this study is to overcome econometric problems, and then order identification is based upon two criteria – modelling ARCH effect better and fitting data better. In particular, diagnostic tests of modified Q-statistic and LM are employed to test the presence of autocorrelation and heteroscedasticity. Traditional model selection criteria, such as the Akaike information criterion (AIC) and the Bayesian information criterion (BIC), are adopted to discover the most appropriate order combination for our dataset. AIC and BIC attempt to balance good fit with parsimony, which can be used for comparing non-nested models, whereas conventional statistical tests such as R-square cannot do this. Lower AIC and BIC means that a model is considered to be more likely to be the actual model. Empirically, we test several order combinations within $1 \leq p, q \leq 2$ for two reasons: first, order 2 is the most commonly used higher-order GARCH model. Second, the algebra becomes tedious if the study goes beyond the second-order case (He and Terasvirta, 1999).

The distribution of error terms is flexible under GARCH methods, such as conditionally normal distribution, t-distribution (Bollerslev, 1987), and generalised error distribution (Nelson, 1991). We employ t-distributed errors for two reasons: first, conditionally t-distributed errors can account for leptokurtosis and fat tail described in our data, which is better than normal-distributed and generalised-distributed errors. Second, conditionally t-distributed error permits a distinction between conditional heteroscedasticity and conditional leptokurtic distribution, either of which could account for the observed unconditional kurtosis in the data (Bollerslev, 1987). To be specific, if the unconditional distribution corresponding to GARCH (p, q) with conditionally standard errors is leptokurtic, it will be not clear whether the model sufficiently accounts for the marked leptokurtosis in financial time-series data.

In order to further improve the model specification, we adopt the GARCH-in-Mean model, permitting the conditional variance to influence the mean return. In this way, changing lagged conditional variances directly affect the expected return on a portfolio, resolving some of the empirical paradoxes in the term structure Engle, Lilien, and Robins (1987). The mean equation is modified as:

$$y_t = \mu + \delta\sigma_t + \varepsilon_t, \varepsilon_t \sim (0, \sigma_t^2), \tag{5.6}$$

where conditional variance, σ_t^2, interprets the risk premium of the portfolio; δ can be interpreted as the time-varying sensitivity of portfolio returns to its risk premium. An additional merit of GARCH-in-Mean model is examining the relationship between trusts' returns and their idiosyncratic risk in the aggregate. In other words, the coefficient δ is significantly positive, implying that, on average, managers of UK-authorized equity unit trusts can be rewarded for taking additional idiosyncratic risk for their portfolios by obtaining a higher trusts returns.

Economic theory has little advice on options of adding variance or standard deviation of regression residuals into the mean equation. We follow Engle, Lilien, and Robins's (1987) suggestion of using statistics of log-likelihood to identify the most appropriate term for our dataset. Larger values of log-likelihood are preferred. Similar to the GARCH model in empirical analysis, we use the quadric and piecewise-linear function to replace the mean value, and the conditional variance equation is the same as GARCH.

We do several model fit tests such as likelihood ratio test, AIC, and modified Q-statistics. The likelihood ratio test compares the maximum likelihood estimator to the real value of the parameters. More specifically, researchers estimate the unconstrained model and achieve a given maximized value of the log-likelihood function, denoted L_u. Next, they estimate the model imposing the constraints based on assumptions and get a new value of the log-likelihood function, denoted L_r. They compare the value of L_u and L_r, and the test statistic is given by $LR = -2(L_r - L_u) \sim \chi^2(m)$, where m is the number of restrictions. Likelihood ratio test computes Chi-Square χ^2. If the calculated χ^2 is larger than a significant percentile, the test will reject the null hypothesis because the model does not fit research data. Therefore, we prefer a large test statistic. Besides, we adopt AIC to test goodness-of-fit and modified Q-statistics to test autoregression, which is similar to tests in the GARCH model.

Table 5. 4:
Tests for ARCH Effects in Estimated Residuals of Four-factor Return-timing Models under OLS

	MQ(q)						*LM*					
	Auto(2)	***Prob***	***Auto(4)***	***Prob***	***Auto(6)***	***Prob***	***Arch(1)***	***Prob***	***Arch(2)***	***Prob***	***Arch(3)***	***Prob***
Panel A: Quadratic model												
Asia excluding Japan	342.97	0.00	675.36	0.00	877.50	0.00	187.63	0.00	292.55	0.00	399.14	0.00
Asia including Japan	209.43	0.00	391.04	0.00	483.26	0.00	134.87	0.00	183.70	0.00	245.24	0.00
Japan	348.19	0.00	511.37	0.00	658.18	0.00	245.54	0.00	296.91	0.00	333.94	0.00
Europe excluding UK	692.21	0.00	930.53	0.00	1215.7	0.00	561.22	0.00	581.98	0.00	609.70	0.00
Europe including UK	42.725	0.00	1138.8	0.00	1138.9	0.00	42.695	0.00	43.040	0.00	1148.8	0.00
UK	872.48	0.00	1390.9	0.00	1825.9	0.00	589.98	0.00	686.62	0.00	740.64	0.00
North America	710.34	0.00	1266.5	0.00	1975.0	0.00	363.44	0.00	572.47	0.00	718.87	0.00
Global	7.0434	0.03	1309.3	0.00	1313.2	0.00	3.6932	0.06	6.8711	0.03	1300.7	0.00
All	674.50	0.00	1209.8	0.00	1591.2	0.00	380.27	0.00	542.58	0.00	662.07	0.00
Panel B: Piecewise-linear model												
Asia excluding Japan	348.82	0.00	677.51	0.00	884.00	0.00	188.19	0.00	297.39	0.00	398.41	0.00
Asia including Japan	213.11	0.00	390.82	0.00	486.23	0.00	135.93	0.00	186.71	0.00	243.89	0.00
Japan	346.81	0.00	512.09	0.00	658.87	0.00	243.27	0.00	295.69	0.00	333.73	0.00
Europe excluding UK	709.61	0.00	947.87	0.00	1230.9	0.00	566.16	0.00	591.69	0.00	618.34	0.00
Europe including UK	42.825	0.00	1138.5	0.00	1138.5	0.00	42.795	0.00	43.141	0.00	1148.5	0.00
UK	1016.1	0.00	1559.9	0.00	2016.8	0.00	639.92	0.00	782.50	0.00	826.67	0.00
North America	720.52	0.00	1280.3	0.00	1994.1	0.00	372.31	0.00	579.37	0.00	725.45	0.00
Global	7.4591	0.02	1312.9	0.00	1316.9	0.00	3.7956	0.05	7.2741	0.03	1304.0	0.00
All	739.40	0.00	1286.9	0.00	1687.1	0.00	387.95	0.00	592.27	0.00	704.31	0.00

This table reports the test statistics of modified Q-statistic *MQ(q)* and Lagrange multiplier test $\boldsymbol{LM}$. Modified Q-statistic and Lagrange multiplier test whether estimated residuals under OLS with New-West accounts for the econometric problem of autoregression and heteroscedasticity. Auto(n) denotes the Q-statistic for n-lag autocorrelation of the squared residuals. Arch(n) denotes n-lag residuals in squared residual regression. Prob denotes the test p-values.
Panel A reports test results under Quadratic return-timing model. Panel B reports test results under Piecewise-linear return-timing model.

5.5 Empirical Results

We begin by using OLS estimation approach to estimate coefficients and t-statistics of two timing models for two reasons. The first one is to confirm that the GARCH family is appropriate for our research data. In particular, we employ modified Q-statistic and Lagrange multiplier (LM) to test whether estimated residuals under OLS display autoregressive and heteroscedasticity characteristics. The result is reported in Table 5.4.

Modified Q-statistic is an autocorrelation test. Strong values of $MQ(q)$ suggest the existing of autoregressive of squared residuals and support the clustering characteristic of volatility. LM is an ARCH effect test, measuring *n*-lag residuals in squared residual regression. The large value of LM indicates the presence of conditional heteroscedasticity. Almost all *p-values* of $MQ(q)$ and LM are zero, strongly rejecting the null hypothesis of no volatility clustering and ARCH effect, respectively. $MQ(q)$ and LM tests document that the Newey-West process can partly account for ARCH effect, but cannot fully capture the ARCH effect. Thus, it is necessary to employ a more appropriate and efficient estimation method than OLS-type models, that is, GARCH family.

The second reason for employing OLS is for comparison. In principle, despite the existence of autocorrelation and heteroscedasticity, the estimated coefficients would be unbiased but for t-statistics. As a result, the statistical inference would be unreliable. Thus, we use both estimation methods to test whether GARCH would offer more efficient and reliable estimates than OLS with Newey-West procedure. The results under OLS-Newey-West will be discussed in the sub-section 5.2.2, in addition to the analysis of the results under the GARCH estimate approach. As GARCH has a big family, it is necessary to identify the best GARCH type for our research data. We mainly concentrate on order combination of GARCH in the sub-section 5.5.1.

5.5.1 Order Combination Identification for GARCH (p, q)

Table 5.5 reports estimation results under the GARCH method with four different order combinations ($1 \leq p, q \leq 2$). AIC and BIC are traditional selection indicators for GARCH-types models, which are reported in the last two columns of Table 5.5 under each timing model. The lowest values of AIC and BIC are preferred. We find negative AIC and BIC, implying that GARCH fits our data set well. The difference between AIC and BIC values of the same trust portfolio in different GARCH's order combination is incredibly minute. For example, the value of AIC for the aggregate portfolio of unit trusts is –8.0889 under GARCH (1, 1) while the value is –8.0890 under GARCH (1, 2). The small difference suggests that the evidence against high AIC and BIC is not worth more than a bare mention. In other words, the traditional model selection indicators support that perform well in our research, but they fail to provide strong evidence on the best GARCH type.

Table 5. 5:
Selectivity and Return-timing Skill Evaluated under GARCH (p, q) Methods across Quadratic and Piecewise-linear Models

	Quadratic							*Piecewise-linear*						
	α_p	*z-statistics*	β_{p1}	*z-statistics*	R^2	*AIC*	*BIC*	α_p	*z-statistics*	β_{p1}	*z-statistics*	R^2	*AIC*	*BIC*
Panel A: GARCH (1, 1)														
Asia ex- Japan	2.72	2.75***	–2.11	–5.57***	0.22	–6.74	–6.73	4.85	3.71***	–0.12	–4.39***	0.22	–6.74	–6.73
Asia in- Japan	2.45	2.27**	–1.54	–3.71***	0.17	–6.58	–6.57	3.79	2.65***	–0.08	–2.11**	0.17	–6.58	–6.57
Japan	–0.77	–0.66	–0.96	–2.03**	0.05	–6.44	–6.43	1.00	0.65	–0.08	–2.52**	0.05	–6.44	–6.43
Europe ex- UK	2.94	3.58***	–2.92	–7.63***	0.38	–7.07	–7.06	5.26	4.78***	–0.14	–5.82***	0.38	–7.07	–7.06
Europe in- UK	3.06	4.04***	–2.87	–8.23***	0.10	–7.16	–7.15	5.24	5.12***	–0.14	–6.24***	0.10	–7.16	–7.15
UK	1.93	4.44***	–1.74	–8.16***	0.54	–8.26	–8.25	3.32	5.64***	–0.09	–6.45***	0.54	–8.26	–8.25
North America	3.33	3.28***	–1.66	–3.69***	0.13	–6.70	–6.69	6.05	4.43***	–0.13	–4.30***	0.13	–6.71	–6.69
Global	2.44	4.17***	–1.79	–6.51***	0.32	–7.83	–7.82	4.52	5.80***	–0.11	–6.51***	0.32	–7.83	–7.82
All	1.82	3.73***	–1.63	–6.50***	0.47	–8.09	–8.08	3.48	5.29***	–0.09	–6.27***	0.47	–8.09	–8.08
Panel B: GARCH (1, 2)														
Asia ex- Japan	2.69	2.72***	–2.06	–5.38***	0.22	–6.74	–6.73	4.72	3.60***	–0.12	–4.22***	0.22	–6.74	–6.73
Asia in- Japan	2.32	2.14**	–1.50	–3.54***	0.17	–6.58	–6.57	3.61	2.51**	–0.08	–2.53**	0.17	–6.58	–6.57
Japan	–0.83	–0.70	–0.97	–2.06**	0.05	–6.44	–6.43	0.81	0.52	–0.08	–2.40**	0.05	–6.44	–6.43
Europe ex- UK	2.90	3.55***	–2.95	–7.85***	0.38	–7.07	–7.06	5.21	4.76***	–0.14	–5.89***	0.38	–7.07	–7.06
Europe in- UK	2.96	3.91***	–2.66	–7.60***	0.10	–7.16	–7.15	5.18	5.07***	–0.13	–6.10***	0.10	–7.16	–7.15
UK	1.87	4.37***	–1.85	–9.28***	0.54	–8.27	–8.26	3.40	5.86***	–0.09	–7.22***	0.54	–8.27	–8.26
North America	3.43	3.37***	–1.96	–4.28***	0.12	–6.71	–6.69	6.25	4.57***	–0.14	–4.62***	0.13	–6.71	–6.69
Global	2.44	4.16***	–1.76	–6.41***	0.32	–7.83	–7.82	4.51	5.79***	–0.11	–6.46***	0.32	–7.83	–7.82
All	1.83	3.74***	–1.70	–6.81***	0.47	–8.09	–8.08	3.51	5.33***	–0.10	–6.43***	0.47	–8.09	–8.08
Panel C: GARCH (2, 1)														
Asia ex- Japan	2.70	2.73***	–2.11	–5.12***	0.22	–6.74	–6.73	4.81	3.67***	–0.12	–4.35***	0.22	–6.74	–6.73
Asia in- Japan	2.41	2.23**	–1.54	–3.68***	0.17	–6.58	–6.57	3.74	2.60***	–0.08	–2.62***	0.17	–6.58	–6.57
Japan	–0.74	–0.63	–0.98	–2.06**	0.05	–6.44	–6.43	0.98	0.63	–0.09	–2.49**	0.05	–6.44	–6.43
Europe ex- UK	2.93	3.57***	–2.92	–7.66***	0.38	–7.07	–7.06	5.25	4.77***	–0.14	–5.84***	0.38	–7.07	–7.06
Europe in- UK	3.02	3.99***	–2.63	–7.37***	0.10	–7.17	–7.15	5.24	5.13***	–0.13	–6.01***	0.10	–7.17	–7.15
UK	1.90	4.40***	–1.80	–8.58***	0.54	–8.27	–8.25	3.38	5.76***	–0.09	–6.85***	0.54	–8.27	–8.25
North America	3.37	3.31***	–1.82	–3.40***	0.12	–6.70	–6.69	6.16	4.50***	–0.14	–4.49***	0.13	–6.71	–6.69
Global	2.44	4.17***	–1.77	–6.42***	0.32	–7.83	–7.82	4.51	5.79***	–0.11	–6.47***	0.32	–7.83	–7.82
All	1.83	3.75***	–1.69	–6.74***	0.47	–8.09	–8.08	3.51	5.34***	–0.10	–6.41***	0.47	–8.09	–8.08
Panel D: GARCH (2, 2)														
Asia ex- Japan	2.70	2.74***	–1.95	–5.11***	0.22	–6.75	–6.73	4.71	3.62***	–0.11	–4.12***	0.22	–6.75	-6.73
Asia in- Japan	2.41	2.24**	–1.42	–3.37***	0.17	–6.59	–6.57	3.66	2.56**	–0.07	–2.44**	0.17	–6.59	-6.57
Japan	–0.98	–0.84	–0.98	–2.10**	0.05	–6.45	–6.43	0.75	0.48	–0.08	–2.50**	0.05	–6.45	-6.43
Europe ex- UK	2.94	3.63***	–2.81	–7.41***	0.38	–7.07	–7.06	5.12	4.71***	–0.14	–-5.59***	0.10	–7.07	-7.06
Europe in- UK	2.80	3.65***	–2.25	–7.45***	0.10	–7.15	–7.13	5.24	5.13***	–0.13	–6.04***	0.38	–7.17	-7.15
UK	1.96	4.60***	–1.76	–8.78***	0.54	–8.27	–8.26	3.37	5.84***	–0.09	–6.70***	0.54	–8.27	-8.26
North America	3.51	3.84***	–1.83	–4.04***	0.12	–6.71	–6.70	6.29	4.65***	–0.14	–4.51***	0.13	–6.71	-6.70
Global	2.43	4.16***	–1.76	–6.41***	0.32	–7.83	–7.81	4.51	5.79***	–0.11	–6.45***	0.32	–7.83	-7.81
All	1.83	3.37***	–1.65	–6.56***	0.47	–8.09	–8.08	3.56	5.47***	–0.09	–6.28***	0.47	–8.10	-8.08

This table reports the estimated coefficients of $\boldsymbol{\alpha_p}$ and $\boldsymbol{\beta_{p1}}$ in the mean equation measuring the abilities of selectivity and market timing, respectively. The z-statistics are reported followed by coefficients. The parameters are estimated under GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2) with t-distributed errors, across quadratic and piecewise-linear return-timing models augmented Carhart's four risk-pricing factors, over the period from July 1990 to June 2015. The coefficients R2, AIC, and BIC are the goodness-of-fit test. The ex- in the first row indicates the excluding, and the in- in the first row indicates including.
The value of estimated constants, αp, are multiplied by 104 to express them.
The symbols ***, ** and * represent the statistical significance at the 1%, 5%, and 10% level, respectively.

Regarding that the purpose of implementing the GARCH model is to deal with ARCH effect, we further to use modified Q-statistic and the LM test to identify the most appropriate order combination empirically. Table 5.6 reports the statistics of the modified Q test (MQ) and LM test. Columns under MQ(q) exhibit Q-statistics of the autocorrelation test for two timing models across four types of order combination of GARCH. Results suggest that GARCH (1, 2) is able to account for autocorrelation in residuals perfectly, indicated by p-values of over 0.1 for Auto(6) (see Panel C and D of Table 5.6). In the rest panels of Table 5.6, the Q-statistics are statistically significant at 1% level up to 6-lag of autocorrelation for the geographic groups of Europe excluding UK and UK, implying that the corresponding order combinations cannot fully account for the impact of autocorrelation in regression residuals.

In terms of the ARCH effect test, reported in the columns under LM. The results are quite mixed. In general, GARCH (1, 2) performs the best among all combinations, indicated by large p-values in comparison to other GARCH types, despite failing to address the ARCH effect adequately on the portfolio of Europe excluding UK and aggregate research portfolio. More specifically, in panel C of Table 5.6, p-values of LM test for regional portfolio of Europe excluding UK are 0.019, 0.036 and 0.084 with respect to one-lag, two-lag and three-lag residuals in squared residual regression, respectively. These results imply the existence of heteroscedasticity, as autocorrelation are completely addressed indicated by Q-statistics. Panel D of Table 5.6 demonstrates consistent results under the piecewise-linear model with the results under quadratic model.

For the rest order combinations reported in other panels, only three out of eight regional portfolios accept a null hypothesis of no ARCH effect in the first lag residuals under GARCH (1, 1), seeing Panel A and B. Higher-order GARCH types perform better than GARCH (1, 1). In particular, three out of eight geographic groups fail to account for ARCH effect under GARCH (2, 1) and two out of eight groups still have ARCH effect in residuals under GARCH (2, 2), reported in Panels from E to H separately.

We highlight the results of ARCH effect test for UK domestic unit trusts and aggregate UK-authorized unit trusts. More specifically, GARCH (1, 2) cannot fully address the ARCH effect until the third lagged residuals, whereas the rest of GARCH types fail to capture the ARCH effect across all lags. Moving to aggregate UK unit trust, the significant statistic of the LM test appears at the third lagged residuals which cannot be found at the first and second lagged residuals, seeing the last row of Panel C and D for GARCH (1, 2). By contrast, GARCH (1, 1) again fails to reject a null hypothesis of no ARCH effect across three lags under two timing models. The other two GARCH types reveal different LM test results for two timing models.

We propose a possible reason for confused LM test results, which is the misspecification of timing models, since the only problem of heteroscedasticity remains in residuals. To be specific, the heteroscedasticity arises mainly due to the variance of residuals and is not constant but varying. In other words, there might be an unpriced risk in the error term. For example, Ferson and Schadt (1996) state that macroeconomic instruments might passively influence the change of market exposure. Our study, nevertheless, does not adopt Ferson and Schadt's (1996) conditional model but uses the GARCH's conditional variance equation. The conditional variance can monitor the impact of public economic news timely. The unexplained residual risk suggests that the benchmarks in both timing models fail to price entirely financial information.

Moreover, our study so far emphasises on market systematic risk factors, implicitly assuming that trust portfolios diversify idiosyncratic risk. Active managers, however, might intensely or by chance bear idiosyncratic risk. The unpriced idiosyncratic risk would impact the variance of residuals, leading to heteroscedasticity. Thus, it is reasonable to use GARCH-in-Mean to improve model specification and investigate selectivity ability conditional on idiosyncratic risk.

Table 5. 6:

Tests for ARCH Effects in Estimated Residuals of Four-factor Return-timing Models under GARCH (p, q)

	MQ(q)						*LM*					
	Auto(2)	*Prob*	*Auto(4)*	*Prob*	*Auto(6)*	*Prob*	*Arch(1)*	*Prob*	*Arch(2)*	*Prob*	*Arch(3)*	*Prob*
Panel A: Quadratic model GARCH (1, 1)												
Asia ex- Japan	1.4363	0.488	1.4367	0.838	2.5947	0.858	1.4192	0.234	1.4320	0.489	1.4338	0.698
Asia in- Japan	5.1260	0.077	7.4481	0.114	7.4553	0.281	4.2168	0.040	5.0218	0.081	6.0021	0.112
Japan	14.114	0.001	14.406	0.006	14.883	0.021	13.757	0.000	13.935	0.001	13.954	0.003
Europe ex- UK	30.434	0.000	31.648	0.000	33.705	0.000	30.386	0.000	30.426	0.000	31.011	0.000
Europe in- UK	0.0009	1.000	0.0016	1.000	0.0029	1.000	0.0005	0.982	0.0009	1.000	0.0009	1.000
UK	36.022	0.000	36.669	0.000	38.983	0.000	34.988	0.000	37.078	0.000	37.424	0.000
North America	6.0092	0.050	6.2194	0.101	6.2355	0.397	5.3227	0.021	5.8965	0.052	6.0858	0.108
Global	0.1462	0.930	1.0686	0.899	0.1710	0.978	0.1086	0.742	0.1467	0.929	1.0706	0.784
All	5.2655	0.072	8.7613	0.067	10.642	0.100	5.1102	0.024	5.3248	0.070	8.7743	0.032
Panel B: Piecewise-linear model GARCH (1, 1)												
Asia ex- Japan	1.2408	0.538	1.2430	0.871	2.4352	0.876	1.2096	0.271	1.2358	0.539	1.2390	0.744
Asia in- Japan	5.0302	0.081	7.2654	0.123	7.2763	0.296	4.0217	0.045	4.9253	0.085	5.8092	0.121
Japan	13.919	0.001	14.185	0.007	14.618	0.023	13.557	0.000	13.741	0.001	13.747	0.003
Europe ex- UK	33.226	0.000	34.013	0.000	36.142	0.000	33.145	0.000	33.1733	0.000	33.542	0.000
Europe in- UK	0.0009	1.000	0.0016	1.000	0.0029	1.000	0.0005	0.982	0.0009	1.000	0.0009	1.000
UK	32.258	0.000	32.831	0.000	35.311	0.000	31.356	0.000	33.131	0.000	33.382	0.000
North America	5.5785	0.061	5.8854	0.208	5.8923	0.435	4.9269	0.026	5.4768	0.065	5.7503	0.124
Global	0.1702	0.918	1.1119	0.892	1.2119	0.976	0.1353	0.713	0.1708	0.918	1.1148	0.774
All	5.1432	0.076	9.2538	0.055	11.140	0.084	4.9819	0.026	5.2033	0.074	9.2304	0.026
Panel C: Quadratic model GARCH (1, 2)												
Asia ex- Japan	0.2745	0.872	0.7206	0.949	1.4229	0.964	0.0769	0.782	0.2731	0.872	0.4682	0.926
Asia in- Japan	1.6604	0.436	6.6991	0.153	7.0233	0.319	0.0375	0.847	1.6576	0.437	4.3917	0.222
Japan	2.2717	0.321	2.4466	0.654	2.7895	0.835	1.3760	0.241	2.2396	0.326	2.3575	0.502
Europe ex- UK	6.7935	0.033	9.3215	0.054	9.9212	0.128	5.5078	0.019	6.6387	0.036	6.6490	0.084
Europe in- UK	0.0008	1.000	0.0016	1.000	0.0029	1.000	0.0005	0.982	0.0008	1.000	0.0008	1.000
UK	5.2598	0.072	7.6199	0.107	8.4296	0.208	4.3985	0.036	5.1546	0.076	5.2692	0.153
North America	2.2990	0.317	3.7597	0.439	4.2057	0.649	0.0698	0.792	2.2955	0.317	3.4442	0.328
Global	0.1543	0.926	0.9414	0.919	1.0391	0.984	0.1131	0.737	0.1548	0.926	0.9434	0.815
All	2.1966	0.333	7.3461	0.119	8.8060	0.185	2.1866	0.139	2.1969	0.333	7.3198	0.062
Panel D: Piecewise-linear model GARCH (1, 2)												
Asia ex- Japan	2.0545	0.358	7.9953	0.092	9.3889	0.153	0.1059	0.745	0.3373	0.845	0.4987	0.919
Asia in- Japan	1.7504	0.417	6.6816	0.154	7.0377	0.317	0.0182	0.893	1.7482	0.417	4.3202	0.229
Japan	2.3045	0.316	2.5112	0.643	2.8263	0.830	1.4092	0.235	2.2717	0.321	2.4214	0.490
Europe ex- UK	8.3605	0.015	10.450	0.033	10.945	0.090	6.8082	0.009	8.1529	0.017	8.1549	0.043
Europe in- UK	0.0009	1.000	0.0016	1.000	0.0029	1.000	0.0005	0.983	0.0009	1.000	0.0008	1.000
UK	4.4458	0.108	6.2779	0.179	6.9793	0.323	3.3223	0.068	4.3541	0.113	4.5480	0.208
North America	2.2308	0.328	3.8601	0.425	4.2987	0.636	0.0505	0.822	2.2281	0.328	3.6034	0.308
Global	0.1791	0.914	0.9579	0.916	1.0529	0.984	0.1399	0.708	0.1797	0.914	0.9609	0.811
All	0.3392	0.844	0.7657	0.943	1.4619	0.962	2.0442	0.153	2.0557	0.358	7.9517	0.047
Panel E: Quadratic model GARCH (2, 1)												
Asia ex- Japan	0.5196	0.771	0.5787	0.965	1.6283	0.951	0.2876	0.592	0.5162	0.773	0.5161	0.915
Asia in- Japan	3.3453	0.188	6.2714	0.180	6.3132	0.389	1.8433	0.175	3.2852	0.194	4.5119	0.211
Japan	6.5803	0.037	6.7360	0.151	7.0785	0.314	5.0574	0.025	6.4269	0.040	6.4674	0.091
Europe ex- UK	16.015	0.000	17.786	0.001	19.472	0.003	14.936	0.000	15.652	0.000	16.387	0.001
Europe in- UK	0.0007	1.000	0.0013	1.000	0.0026	1.000	0.0004	0.984	0.0007	1.000	0.0007	1.000
UK	15.711	0.000	17.001	0.002	18.457	0.005	15.079	0.000	15.432	0.000	16.745	0.001
North America	4.3542	0.113	4.5759	0.334	4.6082	0.595	1.3266	0.249	4.2933	0.117	4.4034	0.221
Global	0.1525	0.927	0.9452	0.918	1.0439	0.984	0.1127	0.737	0.1530	0.926	0.9472	0.814
All	2.8228	0.244	6.8458	0.144	8.4883	0.204	2.8058	0.094	2.8200	0.244	6.7722	0.080

(To be continued)

Table 5.6: *(Continue)*

	MQ(q)						*LM*					
	Auto(2)	*Prob*	*Auto(4)*	*Prob*	*Auto(6)*	*Prob*	*Arch(1)*	*Prob*	*Arch(2)*	*Prob*	*Arch(3)*	*Prob*
Panel F: Piecewise-linear model GARCH (2, 1)												
Asia ex- Japan	0.4799	0.787	0.5381	0.970	1.6061	0.952	0.2292	0.632	0.4770	0.788	0.4773	0.924
Asia in- Japan	3.3478	0.188	6.1714	0.187	6.2200	0.399	1.7669	0.184	3.2885	0.193	4.4109	0.220
Japan	6.5204	0.038	6.6544	0.155	6.9614	0.324	5.0088	0.025	6.3691	0.041	6.3906	0.094
Europe ex- UK	18.020	0.000	19.273	0.001	20.965	0.002	16.707	0.000	17.577	0.000	18.064	0.000
Europe in- UK	0.0007	1.000	0.0013	1.000	0.0025	1.000	0.0004	0.984	0.0007	1.000	0.0007	1.000
UK	13.545	0.001	14.605	0.006	16.081	0.013	12.597	0.000	13.249	0.001	14.439	0.002
North America	4.1586	0.125	4.4325	0.351	4.4621	0.614	1.1442	0.285	4.1061	0.128	4.2810	0.233
Global	0.1769	0.915	0.9659	0.915	1.0621	0.983	0.1394	0.709	0.1775	0.915	0.9688	0.809
All	2.6124	0.271	7.2841	0.122	8.8747	0.181	2.5840	0.108	2.6084	0.271	7.1736	0.067
Panel G: Quadratic model GARCH (2, 2)												
Asia ex- Japan	0.3921	0.822	0.4735	0.976	1.5062	0.959	0.0066	0.935	0.3919	0.822	0.4606	0.927
Asia in- Japan	0.1858	0.911	0.4292	0.980	0.6276	0.996	0.0327	0.857	0.1861	0.911	0.3314	0.954
Japan	2.2794	0.320	2.8469	0.584	3.0319	0.805	2.2198	0.136	2.2946	0.318	2.4958	0.476
Europe ex- UK	14.980	0.001	16.959	0.002	18.699	0.005	14.680	0.000	15.210	0.001	16.702	0.001
Europe in- UK	0.0013	0.999	0.0025	1.000	0.0045	1.000	0.0007	0.980	0.0007	1.000	0.0007	1.000
UK	24.843	0.000	25.911	0.000	26.085	0.000	22.081	0.000	25.830	0.000	26.487	0.000
North America	0.8246	0.662	1.1365	0.888	1.1435	0.980	0.8248	0.364	0.8222	0.663	0.9174	0.821
Global	0.1573	0.924	0.9847	0.912	1.0817	0.982	0.1136	0.736	0.1578	0.924	0.9868	0.804
All	4.1600	0.125	6.2184	0.183	7.4496	0.281	4.1188	0.042	4.1477	0.126	6.1849	0.103
Panel H: Piecewise-linear model GARCH (2, 2)												
Asia ex- Japan	0.3239	0.850	0.4283	0.980	1.4630	0.962	0.0007	0.979	0.3237	0.851	0.4192	0.936
Asia in- Japan	0.1624	0.922	0.3794	0.984	0.5549	0.997	0.0449	0.832	0.1628	0.922	0.2662	0.966
Japan	2.2444	0.326	2.7661	0.598	2.9266	0.818	2.1857	0.139	2.2592	0.323	2.4218	0.490
Europe ex- UK	16.724	0.000	18.161	0.001	19.772	0.003	16.525	0.000	16.945	0.000	18.053	0.000
Europe in- UK	0.0008	1.000	0.0014	1.000	0.0026	1.000	0.0004	0.984	0.0008	1.000	0.0008	1.000
UK	20.216	0.000	21.088	0.000	21.221	0.002	17.835	0.000	20.945	0.000	21.446	0.000
North America	0.6879	0.709	0.9931	0.911	0.9981	0.986	0.6881	0.407	0.6863	0.710	0.7382	0.864
Global	0.1822	0.913	1.0031	0.909	1.0972	0.982	0.1403	0.708	0.1828	0.913	1.0062	0.800
All	3.7263	0.155	8.8603	0.065	9.8477	0.131	3.3527	0.067	3.7880	0.151	8.7048	0.034

This table reports the test statistics of modified Q-statistic *MQ(q)* and Lagrange multiplier test ***LM***. Modified Q-statistic and Lagrange multiplier test whether estimated residuals under GARCH-type estimation methods can address ARCH effect. Auto(n) denotes the Q-statistic for n-lag autocorrelation of the squared residuals. Arch(n) denotes n-lag residuals in squared residual regression. Prob denotes the test p-values.

This table exhibits test results under various order-combanition of GARCH in different panels.

Panel A, C, E and G reports test results using Quadratic return-timing model under GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2), respecitively. Panel B, D, F and H reports test results using Piecewise-linear return-timing mode under GARCH (1, 1), GARCH (1, 2), GARCH (2, 1) and GARCH (2, 2), respecitively.

The ex- in the first row indicates the excluding, and the in- in the first row indicates including.

Table 5. 7:
OLS Methods with Newey-West Procedure for the Selectivity and Timing Performance for the Four-factor Quadratic and Piecewise-linear Models

	Quadratic					*Piecewis-linear*				
	α_p	*t-statistic*	β_{p1}	*t-statistic*	R^2	α_p	*t-statistic*	β_{p1}	*t-statistic*	R^2
Asia excluding Japan	1.48	1.07	–1.67	–2.65***	0.22	5.07	2.73***	–0.15	–3.29***	0.22
Asia including Japan	1.92	1.28	–1.74	–2.66***	0.17	5.24	2.58**	–0.14	–2.93***	0.17
Japan	–1.22	–0.81	–0.64	–1.22	0.05	1.03	0.51	–0.08	–1.69**	0.05
Europe excluding UK	1.88	1.95*	–1.93	–3.78***	0.38	5.47	3.60***	–0.16	–4.07***	0.38
Europe including UK	2.09	1.56	–2.04	–4.37***	0.10	5.68	2.75***	–0.16	–3.74***	0.10
UK	1.80	3.22***	–1.56	–3.96***	0.55	3.84	3.71***	–0.10	–3.59***	0.54
North America	1.24	0.91	–0.44	–0.53	0.13	4.15	2.15**	–0.09	–1.91*	0.13
Global	1.35	1.85*	–1.23	–3.40***	0.32	4.13	3.83***	–0.11	–4.15***	0.33
All	1.45	2.41**	–1.39	–4.06***	0.48	3.89	3.95***	–0.11	–4.16***	0.48

The estimations of excess daily returns represent the abilities of selectivity and market timing, under the OLS approach with Newey-West standard errors, across both quadratic and piecewise-linear return-timing models with four-factor benchmark, over the period from July 1990 to June 2015. The total of 478 UK equity unit trusts is divided into eight geographic-groups according to the geographic location of focused equity markets. The t-statistics reported in parentheses are adjusted with the Newey-West procedure. The t-statistics are reported followed by coefficients. R^2 is the goodness-of-fit test.
The value of estimated constants, α_p, are multiplied by 10^4 to express them.
The symbols ***, ** and * represent the statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.2 Investment Abilities Evaluation under OLS-Newey-West and GARCH

This sub-section presents findings on selectivity and market-return timing abilities and the comparison of estimate methods between OLS-Newey-West and GARCH (1, 2). Table 5.7 presents the stock-picking, and market-timing performance of UK-authorized unit trusts for both timing models under OLS-Newey-West. We display the estimated coefficient indicating the performance of selectivity and market-return timing and the t-statistics which test whether the average selectivity and timing performance is significantly different from zero. Columns under terms of quadratic and piecewise-linear report estimate for quadratic timing model and piecewise-linear timing model, respectively.

We find positive alpha, excepting Japan under the quadratic timing model, implying that UK equity unit trusts can produce abnormal returns by picking up stocks in the aggregate. The t-statistics require to be considered cautiously because of the inconsistent estimates in both timing models. In particular, the coefficients of alpha in the piecewise-linear timing model are statistically significant except the alpha in one geographic group of Japan. By contrast, the significant coefficients of alpha are exhibited in two geographic portfolios (i.e., Europe excluding UK and UK) and the aggregate portfolio of UK-authorized equity unit trusts in the quadratic timing model.

Under the method of GARCH (1, 2), the estimated coefficients for evaluating skills of stock-picking and market-timing are displayed in Panel B of Table 5.5. The coefficients of alpha and beta are in line with the corresponding estimates under OLS-Newey-West; that is, positive alpha except Japan in the quadratic timing model and negative beta, implying superior selectivity skill and reverse timing behavior.

GARCH uses z-statistics to test the statistical significance level of coefficients. Results of z-statistics are entirely consistent in both timing models. To be specific, the coefficients of alpha are statistically significant for all geographic groups except Japan and the aggregate UK equity unit trusts in both timing models. The estimates beta are significant at the 1% level in both timing models across all regional portfolios and the aggregate portfolio. Therefore, our results state that GARCH provides reliable and entirely consistent evidence on favourable selectivity and irregular timing performance.

In general, we reject our first research hypothesis that actively managed UK-authorized equity unit trusts do not produce significant outperformance above a passive benchmark portfolio of UK stock market on average. The finding of significantly positive abnormal return is distinct from findings in previous studies of underperformance or neutral performance of UK mutual funds (Black, Fraser, and Power, 1992; Fletcher, 1999; Blake and Timmermann, 1998; Quigley and Sinquefield, 2000; Abel and Fletcher, 2004). Positive alphas further support that performance evaluation models without a timing factor would lead to downward bias and negative Jensen alpha.

We do not claim that we reject our second research hypothesis that active managers adopt an investment strategy of market-return timing because our significant beta support that the market exposure of active trusts is time-varying. The paper closest to ours is Fletcher (1995) who uses monthly returns of 101 UK unit trusts over 1980 – 1989 to investigate selectivity and timing abilities by employing quadratic and piecewise-linear models with three single index benchmarks and estimating parameters under OLS-Newey-West. Fletcher (1995) also uncovers significantly negative timing performance in aggregate and groups with three different investment objectives (growth, general and income). We fail to find evidence on favourable timing performance for UK unit trusts, which is in line with prior studies of using monthly returns of UK mutual funds (Fletcher, 1995; Byrne, Fletcher, and Ntozi, 2006; Cuthbertson, Nitzsche, and O'Sullivan, 2010b; Cuthbertson, Nitzsche, and O'Sullivan, 2012; Blake et al., 2017). We conclude that data frequency is not a disturbance in timing performance evaluation in the context of UK market, although Bollen and Busse (2001) find different results for daily and monthly returns under both market-return timing models in the US fund market.

Our results empirically support the third hypothesis that GARCH provides more reliable evidence than OLS. The OLS estimation is inefficient albeit unbiased. To be specific, the OLS method is easy to reject the alternative hypothesis of having selectivity and market timing skills which might have a chance to occur, as estimated t-statistics are small, and the confidence interval is narrow. In Table 5.7, for instance, t-statistics of alphas under OLS are smaller than corresponding statistics under GARCH (1, 2) in Panel B of Table 5.5.

Moreover, the t-statistics of alphas in the quadratic timing model differ from statistics in the piecewise-linear timing model for the same unit trusts portfolio, leading to inconsistent inference for selectivity skill. Under the OLS-Newey-West estimation method, Fletcher (1995) also reveals statistically insignificant alpha against the Financial Times All-Share proxy in the quadratic timing model but the alpha changes to significant in the piecewise-linear model in the aggregate. In contrast, we adopt GARCH (1, 2) to estimate parameters and find entirely consistent z-statistics for alphas in both timing models across all regional groups and aggregate portfolio. Thus, our results suggest that the GARCH estimation method is appropriate for a daily returns investigation, providing more efficient and valid inference than OLS.

5.5.3 Investment Abilities Evaluation under GARCH-in-Mean

This study considers GARCH (1, 2)-in-Mean in order to improve the accuracy of estimates. More specifically, GARCH (1, 2) cannot account entirely for the heteroscedasticity effect in regression residuals (see Table 5.6), implying that the idiosyncratic risk of unit trusts is not eliminated. The idiosyncratic risk might impact on the selectivity assessment for actively managed equity trusts, thereby adopting GARCH (1, 2)-in-Mean to account for conditional residual risk while evaluating investment abilities in both timing models. We employ two GARCH specifications, conditional variance and conditional standard deviation, to track residual risk.

Results are reported in Table 5.8. Panel A and B preset coefficients and z-statistics estimated when the GARCH specification is conditional variance in both timing models, and Panel C and D display estimates when the GARCH specification is conditional standard deviation in both timing models. We cannot identify a superior specification between variance and standard deviation owing to almost similar statistics of model fit tests, in line with findings in previous studies (e.g., Baillie and DeGennaro, 1990; Poon and Taylor, 1992). As French, Schwert and

Stambaugh (1987) argue that, when considering the power of conditional variance in the mean equation to be a parameter, the best estimates of the power are close to ½ rather than 1, we focus on standard deviation specification in the following analysis.

In Panel C and D, the columns of δ_p exhibit positive coefficients across all geographic portfolios and aggregate portfolio of UK equity unit trusts. These coefficients are statistically significant, indicated by large z-statistics of over 1.96. Regarded by positive $\delta_p(Std. Dev.)$ and large z-statistics, we have three findings. Firstly, superior stock-picking skill trust managers are considerably enhanced as managers can remain the risk premium of trusts conditional on time-varying idiosyncratic risk at 5% statistical significance level. Group of Europe including the UK is an exception with insignificant risk premium conditional on time-varying non-systematic risk. The possible reason might be relatively stable conditional volatility of residuals, indicated by p-values of ARCH effect tests which are equal to one in Table 5.6.

Secondly, we demonstrate that returns of unit trusts are positively related to their idiosyncratic risk. This positive relationship supports the fourth hypothesis that, on average, UK trust managers can be rewarded for taking additional idiosyncratic risk for their portfolios by achieving a positive risk premium.

Finally, significant positive risk premium supports a financial hypothesis of risk-averse investment behavior. More specifically, trust's investors require high compensation while taking additional risk, and managers can satisfy investors' requirement by producing positivity risk premium conditional on the time-varying risk of unit trusts.

We take notice on the column of α_p in Panel C and D of Table 5.8. Comparing the constant α_p under the GARCH-in-Mean to the alpha under GARCH reported in Table 5.5, the value of α_p in the Table 5.8 reduces to negative and statistical significance of the α_p disappears, implying that the risk premium of unit trusts is time-varying to the trusts' residual risk rather than constant. The disappearance of the value of α_p suggests that the abnormal return indicated by α_p in the GARCH model is explained by the coefficient δ_p in the GARCH-in-Mean model.

The right-hand four columns in Table 5.8 report statistics of model fitness tests, including the likelihood ratio test (L), AIC and modified Q-statistic test up to lag 6 ($MQ(6)$). Substantially large statistics of likelihood ratio test and negative statistics of AIC indicate that GARCH-in-Mean fits our data well. P-values of Q-statistics test recorded in the last column exceed 0.1, implying that modified Q-statistics test rejects the null hypothesis of existing autoregression in regression residuals. We do not report results of the LM test as the test statistics are the same to statistics under GARCH (1, 2) in Table 5.6.

In general, we find positive stock-picking skill but reverse return-timing performance for UK equity unit trusts on average in both timing models considering three estimation methods. More specifically, significant negative betas document a reverse timing behavior of trust managers, echoing findings in GARCH (1, 2) model. Regarded by geographic groups of UK foreign equity unit trusts, UK Japan trusts reveal different selectivity performance, either insignificant positive alpha in GARCH (1, 2) model or significant negative alpha in GARCH (1, 2)-in-Mean model across both timing models. This finding partly rejects our fifth hypothesis that on average, there is no significant difference in investment abilities of managers between UK domestic and foreign equity unit trusts.

One possible reason might be the benchmark adopted in our research. This thesis examines UK domestic and international unit trusts; whereas, we build a benchmark portfolio whose investment strategy is passively holding UK stocks with characteristics of small size, value and past winner. Initially, we do not construct global benchmark while evaluating the performance of UK international unit trusts because Fama and French (2012) document that the global models cannot perform well in explaining average returns on regional size-value or size-momentum portfolios, especially for Japanese data.

Moreover, we do not consider corresponding local benchmarks to the regional groups (i.e., Asia, Europe and North America) for two reasons. On the one hand, one of the research purposes in our study is to serve UK trust investors. It is of primary concern to the UK trust investors whether UK foreign trusts outperform UK domestic passive portfolio while making a trusts-investment decision. The finding of significant positive abnormal return of UK foreign trusts referring to our passive benchmark would suggest that international investment strategy is successful. On the other hand, if foreign market indices are adopted straightforwardly to evaluate UK trusts performance, there is the potential for additional bias in the evaluation of trust/manager performance due to the fluctuation of the exchange-traded rates.

In order to give further investigation on the performance of UK international unit trusts, we group trusts into six portfolios based on the geography of the target investment market: Asia (including/excluding Japan), Europe (including/excluding UK), North America and Global. Results are reported in panel B of Table 5.5. We find a significant positive alpha across portfolios of Asia excluding Japan, Europe excluding the UK, North America and Global, implying that UK fund managers can produce additional value for trust investors by investing in foreign equity markets.

More specifically, under the quadratic model estimation, the annualised abnormal returns of trust portfolios investing in markets of Asia, Europe, North America and Global are about 9.68%, 10.44%, 12.34% and 8.78%, respectively. By contrast, the annualised abnormal return of UK domestic unit trusts is 6.73%. Our results suggest that UK equity unit trusts with foreign regional markets investment objective in our sample perform better than local country-specific focus.

The potential reason could be explained from two perspectives. On the one hand, international investment objective is beneficial for constructing a portfolio with low systematic risk owing to the low correlation between equities in different countries' markets. On the other hand, in comparison to trusts investing in the local market, a disadvantage of investing in foreign financial markets might be the information cost. Nevertheless, in the age of Big Data, trust managers can obtain and deal with international information by social media or computer system quickly, efficiently, and in real-time, thereby reducing the information cost. Therefore, better performance of UK foreign unit trusts can be attributed to the low level of investment risk and information cost.

Table 5. 8:
Selectivity and Return-Timing Evaluation under GARCH (1, 2)-in-Mean Methods

	α_p	*z-statistic*	β_{p1}	*z-statistic*	δ_p	*z-statistic*	*L*	*AIC*	*MQ(6)*	*Prob*
Panel A: Quadratic Model: δ_p *(variance)*										
Asia excluding Japan	–0.04	–0.03	–2.3688	–5.95***	4.7608	2.06**	21315	–6.7446	1.3199	0.971
Asia including Japan	–1.15	–0.63	–1.8864	–4.29***	5.2269	2.32**	20360	–6.5820	6.8677	0.333
Japan	–5.42	–2.60***	–1.2345	–2.58***	5.6041	2.55**	20367	–6.4445	3.0333	0.805
Europe excluding UK	0.80	0.66	–3.4045	–8.42***	5.8235	2.38**	22347	–7.0712	9.9370	0.127
Europe including UK	3.05	3.42***	–2.6417	–7.45***	–0.2656	–0.20	22627	–7.1600	0.0030	1.000
UK	0.90	1.59	–2.1328	–9.77***	9.8817	2.90***	26128	–8.2686	9.2368	0.161
North America	–0.59	–0.39	–2.6205	–5.34***	7.2702	3.40***	21195	–6.7067	2.8362	0.829
Global	1.76	1.95*	–1.8706	–6.47***	3.5197	0.94	24733	–7.8269	1.2366	0.975
All	0.56	0.83	–2.0045	–7.71***	9.8882	2.74***	25562	–8.0894	9.7658	0.135
Panel B: Piecewise-linear Model: δ_p *(variance)*										
Asia excluding Japan	2.35	1.36	–0.1325	–4.69***	4.6788	2.02**	21314	–6.7444	1.3636	0.968
Asia including Japan	0.64	0.33	–0.1028	–3.21***	5.1784	2.29**	20359	–6.5817	6.9290	0.327
Japan	–3.56	–1.60	–0.0977	–3.01***	5.8843	2.66***	20368	–6.4448	3.0946	0.797
Europe excluding UK	3.75	2.84***	–0.1642	–6.40***	5.0248	2.05**	22342	–7.0698	10.854	0.093
Europe including UK	5.27	4.79***	–0.1332	–5.99***	–0.2734	–0.21	22625	–7.1594	0.0029	1.000
UK	2.67	4.17***	–0.1054	–7.70***	9.1644	2.75***	26128	–8.2686	7.5826	0.270
North America	2.66	1.58	–0.1749	–5.53***	7.5468	3.56***	21199	–6.7078	3.0058	0.808
Global	3.94	4.04***	–0.1151	–6.48***	3.4645	0.94	24736	–7.8277	1.2445	0.975
All	2.50	3.35***	–0.1104	–6.98***	9.6141	2.71***	25564	–8.0898	10.416	0.108
Panel C: Quadratic Model: δ_p *(Standard Deviation)*										
Asia excluding Japan	–3.95	–1.16	–2.3558	–5.92***	0.0905	2.01**	21315	–6.7445	1.3429	0.969
Asia including Japan	–4.98	–1.35	–1.8317	–4.17***	0.0929	2.06**	20360	–6.5818	7.0440	0.317
Japan	–11.49	–2.67**	–1.2280	–2.56**	0.1219	2.53**	20367	–6.4444	2.7604	0.838
Europe excluding UK	–2.09	–0.83	–3.3225	–8.27***	0.0859	2.10**	22346	–7.0710	9.7100	0.137
Europe including UK	–0.81	–0.32	–2.8924	–7.98***	0.0657	1.60	22628	–7.1604	0.0029	1.000
UK	–1.31	–1.06	–2.1503	–9.78***	0.1042	2.86***	26129	–8.2687	9.0345	0.172
North America	–7.50	–2.24**	–2.5860	–5.33***	0.1508	3.39***	21195	–6.7067	2.9052	0.821
Global	–1.70	–0.82	–1.9932	–6.86***	0.0970	2.03**	24735	–7.8274	1.1966	0.977
All	–2.27	–1.55	–2.0349	–7.82***	0.1183	2.98***	25563	–8.0896	9.6127	0.142
Panel D: Piecewise-linear Model: δ_p *(Standard Deviation)*										
Asia excluding Japan	–1.61	–0.48	–0.1329	–4.69***	0.0908	2.00**	21314	–6.7443	1.3811	0.967
Asia including Japan	–3.28	–0.90	–0.1006	–3.13***	0.0933	2.05**	20359	–6.5815	7.0599	0.315
Japan	–10.05	–2.33**	–0.0983	–3.01***	0.1294	2.66***	20368	–6.4447	2.4924	0.646
Europe excluding UK	0.96	0.38	–0.1631	–6.34***	0.0792	1.92*	22342	–7.0697	10.610	0.101
Europe including UK	1.84	0.74	–0.1450	–6.31***	0.0615	1.50	22626	–7.1598	0.0029	1.000
UK	0.50	0.42	–0.1083	–7.80***	0.1029	2.82***	26129	–8.2688	7.4828	0.278
North America	–4.78	–1.45	–0.1768	–5.59***	0.1614	3.65***	21199	–6.7079	3.0031	0.808
Global	0.39	0.19	–0.1232	–6.86***	0.1023	2.15**	24738	–7.8282	1.2186	0.976
All	–0.44	–0.30	–0.1146	–7.17***	0.1229	3.09***	25565	–8.0902	10.375	0.110

This table reports the results of selectivity and return-timing performance under the GARCH (1, 2)-in-Mean estimation method with generalized error distribution across two timing models from July 1990 to June 2015. The total of 478 UK equity unit trusts is divided into eight geographic-groups according to geographical of underlying holdings. $\boldsymbol{\alpha_p}$ denotes the constant alpha of the regression return-timing models. $\boldsymbol{\beta_{p1}}$ denotes the coefficients of the timing factors in quadratic and piecewise-linear return-timing models, respectively. The coefficients of $\boldsymbol{\delta_p}$ in the mean equation denote the risk premium conditional on the residual risk of unit trusts portfolio. $\boldsymbol{\delta_p}$ captures the selectivity ability of trust managers under the GARCH-in-Mean model. The z-statistics are reported followed by coefficients.
L denotes the value of maximum log-likelihood. AIC is the goodness-of-fit test. MQ(6) denotes the modified Q-statistic for autocorrelation test for the squared process at six-lag. Prob denotes the test p-values.
The value of estimated constants $\boldsymbol{\alpha_p}$ are multiplied by 10^4 to express them.
The symbols ***, ** and * represent the statistical significance at the 1%, 5%, and 10% level, respectively.

5.5.4 Performance Evaluation over Sub-periods

Our research period is considerably longer with 25 years, covering several economic cycles. The findings of timing performance over the whole research period might be unreliable because the probability of changes in individual share's risk would increase. We, therefore, divide the research period into five equal sub-periods to further conduct timing tests.

Table 5.9 reports the results of re-estimated coefficients of selectivity and timing performance using GARCH (1, 2) with t-distribution across both dramatic and piecewise-linear timing models. In general, our previous findings of significantly positive selectivity and negative timing can only be found during the recent decade from 2005 to 2015. By contrast, findings referring to stock-picking and market-timing abilities are mixed. To be specific, under the quadratic timing model, we find an insignificant positive performance of stock-picking and market-timing on average over 1990 to 1995. In the next five years, the stock-picking ability is positive at a 5% significance level, whereas market-timing performance changes from positive to significant negative. During 2000 to 2005, both stock-picking and market-timing skills change to negative but are statistically insignificant. Piecewise-linear model displays consistent results except for insignificant negative timing performance over 1990 to 1995.

Results in Table 5.9 fail to support our last hypothesis of no significant difference in the performance of investment abilities of UK-authorized unit trust managers for any given of length of research period. It is worth to mention that we consider random short research period instead of particular recessions or expansions. Our finding points out that the macro-economic environment plays an essential role in the trust performance on average. The macro-economic contributes to the general financial market development, producing opportunities and risks for trust managers. For example, trust managers show positive market-return timing performance for UK domestic and aggregate UK equity unit trusts over 1990–1995 when the UK market was not an open market. On 7th February 1992, the UK and other members of the European Communities signed The Maastricht Treaty in Netherlands to further European integration. The positive return-timing performance might due to the slight fluctuation of the market during that period.

On the other hand, UK managers might not be attracted by economic globalization in 1990s, as the assets of the international fund management industry are only $48.1 trillion in 2004 (TheCityUK, 2015). One possible reason would be a dramatically high cost for obtaining international information timely and efficiently decades ago. The dramatic development of

Table 5. 9:
Selectivity and Return-timing Evaluation under GARCH (1, 2) Methods over Sub-period

	Quadratic					Piecewise-linear				
	α_p	z-statistic	β_{p1}	z-statistic	AIC	α_p	z-statistic	β_{p1}	z-statistic	AIC
Panel A: July 1990 to June 1995										
Asia excluding Japan	2.97	1.33	–4.40	–3.20	–6.85	5.33	1.77	–0.16	–2.22	–6.85
Asia including Japan	3.67	1.44	–2.81	–1.78	–6.61	2.96	0.82	–0.02	–0.21	–6.61
Japan	–7.87	–2.75	3.50	1.64	–6.27	–10.1	–2.48	0.14	1.28	–6.26
Europe excluding UK	2.14	1.47	–3.32	–3.45	–7.63	3.43	1.73	–0.10	–2.04	–7.63
Europe including UK	1.02	0.01	–0.82	–0.03	–4.56	5.36	0.05	–0.17	–0.10	–4.57
UK	–0.45	–0.55	0.80	2.14	–8.78	–0.77	–0.69	0.03	1.00	–8.79
North America	4.71	2.21	–0.77	–0.62	–6.91	5.48	1.90	–0.04	–0.61	–6.91
Global	1.54	1.20	–0.96	–1.17	–7.92	2.21	1.24	–0.04	–0.92	–7.92
All	0.30	0.32	0.15	0.23	–8.57	0.48	0.37	–0.01	–0.13	–8.57
Panel B: July 1995 to June 2000										
Asia excluding Japan	–3.06	–1.32	0.52	0.34	–6.64	–3.06	–1.01	0.01	0.13	–6.64
Asia including Japan	–5.49	–2.51	2.90	1.71	–6.67	–7.19	–2.48	0.12	1.51	–6.67
Japan	–3.55	–1.32	–1.07	–0.56	–6.52	–4.06	–1.14	–0.00	–0.04	–6.52
Europe excluding UK	3.52	1.91	–6.00	–4.41	–7.27	6.07	2.47	–0.21	–3.50	–7.27
Europe including UK	4.99	2.95	–6.16	–4.80	–7.38	7.59	3.36	–0.22	–3.82	–7.38
UK	2.60	3.09	–2.73	–4.03	–8.72	4.11	3.55	–0.11	–3.67	–8.72
North America	6.44	3.00	–5.93	–3.76	–7.00	9.83	3.49	–0.24	–3.47	–7.00
Global	3.20	2.76	–3.65	–4.62	–8.21	5.24	3.44	–0.15	–3.92	–8.21
All	1.91	2.03	–2.69	–3.92	–8.54	3.41	2.68	–0.11	–3.31	–8.54
Panel C: July 2000 to June 2005										
Asia excluding Japan	0.05	0.02	–0.43	–0.57	–6.79	1.66	0.55	–0.06	–1.08	–6.79
Asia including Japan	1.02	0.38	–0.74	–0.81	–6.49	3.15	0.89	–0.08	–1.26	–6.49
Japan	–7.51	–2.54	0.97	0.99	–6.38	–7.43	–1.97	0.03	0.39	–6.38
Europe excluding UK	–2.77	–1.48	0.30	0.40	–7.08	–1.83	–0.75	–0.02	–0.44	–7.08
Europe including UK	–2.08	–1.11	–0.31	–0.41	–7.10	–0.44	–0.18	–0.06	–1.13	–7.11
UK	–0.28	–0.29	–0.79	–0.97	–8.34	1.42	1.11	–0.08	–2.74	–8.34
North America	–5.48	–2.04	0.80	0.83	–6.44	–4.83	–1.37	–0.00	–0.02	–6.44
Global	–2.54	–1.97	0.10	0.20	–7.91	–1.55	–0.90	–0.03	–0.77	–7.91
All	–1.87	–1.59	–0.10	–0.21	–8.10	–0.58	–0.37	–0.04	–1.34	–8.10
Panel D: July 2005 to June 2010										
Asia excluding Japan	8.93	3.45	–2.32	–3.57	–6.34	12.54	3.74	-0.17	–3.03	–6.34
Asia including Japan	10.68	3.81	–2.07	–3.20	–6.22	14.42	3.99	-0.17	–2.82	–6.22
Japan	1.85	0.65	–1.66	–2.88	–6.27	6.86	1.88	-0.19	–3.23	–6.27
Europe excluding UK	5.67	2.85	–1.81	–3.08	–6.80	7.79	3.02	-0.11	–2.30	–6.80
Europe including UK	5.96	2.87	–1.88	–2.57	–6.75	8.22	2.97	-0.12	–2.19	–6.75
UK	4.66	3.84	–2.27	–5.33	–7.62	6.74	4.16	-0.12	–3.83	–7.62
North America	2.89	1.18	–0.36	–0.53	–6.43	3.99	1.24	-0.04	–0.70	–6.43
Global	5.49	3.99	–1.14	–2.84	-7.53	7.01	3.89	-0.08	–2.14	–7.53
All	5.02	3.72	–1.47	–3.34	-7.53	6.57	3.66	-0.09	–2.35	–7.53
Panel E: July 2010 to June 2015										
Asia excluding Japan	4.21	2.12	–3.28	–3.03	–7.23	5.95	2.28	–0.13	–2.32	–7.23
Asia including Japan	3.79	1.70	–3.68	–3.46	–7.02	6.29	2.14	–0.16	–2.82	–7.02
Japan	5.36	2.35	–3.07	–2.65	–6.90	7.57	2.53	–0.14	–2.22	–6.90
Europe excluding UK	2.68	1.18	–4.04	–2.69	–6.86	4.87	1.60	–0.16	–2.30	–6.86
Europe including UK	0.65	0.02	–1.84	–0.19	–5.39	0.66	0.02	–0.05	–0.09	–5.49
UK	3.48	2.91	–3.20	–4.44	–8.04	5.87	3.63	–0.15	–4.26	–8.05
North America	5.80	2.56	–3.19	–2.33	–6.89	8.57	2.87	–0.16	–2.39	–6.89
Global	3.39	2.39	–2.90	–3.77	–7.80	5.47	2.89	–0.13	–3.21	–7.80
All	3.37	2.60	–3.19	–4.38	–7.93	5.52	3.16	–0.14	–3.72	–7.93

This table reports the selectivity and return-timing coefficients and z-statistics under GARCH (1, 2) estimation method across two return-timing models over five equal sub-period over the research period. AIC is the goodness-of-fit test. $\boldsymbol{\alpha_p}$ captures the selectivity skill and $\boldsymbol{\beta_{p1}}$ captures the return-timing ability. 478 UK equity unit trusts are sorted based on geographical investment objective into eight geographic-groups. The value of estimated constants α_p is multiplied by 10^4 to express them.

information and communication technology, recently, improves the information transfer efficiency, motiving trust managers looking to invest in international markets.

5.6 Discussion on Negative Timing Performance

Findings of significantly negative timing performance are not new phenomena in the UK mutual funds study. More specifically, Byrne, Fletcher and Ntozi (2006) employ Becker et al.'s (1999) conditional approach, failing to find evidence of superior conditional market timing performance either on average or by individual UK unit trusts. Worse, they find significantly negative stock-picking skill. Moreover, Cuthbertson, Nitzsche and O'Sullivan (2010) investigate UK equity mutual funds timing ability from a conditional version as well. They adopt a nonparametric approach to separate timing ability from information response. Timing ability assesses the quality of timing information processed by fund managers, and the response indicates an aggressiveness of reaction to timing information. Their finding suggests that UK mutual funds miss-time the market on average.

Other studies emphasise separating the manager's skill from luck by using false discount rate methods or bootstrapping. Findings of previous studies generally suggest that the majority of poorly performing funds can be attributed to bad skills of the manager rather than bad luck. To be specific, Cuthbertson, Nitzsche and O'Sullivan (2012) employ a false discount rate method developed by Barras et al. (2010) to study timing skill on the individual fund level. Cuthbertson, Nitzsche, and O'Sullivan (2008) follow Kosowski et al.'s (2006) approach to investigate skill and luck. They re-sample regression residuals to correct t-statistics estimation. Fama and French (2010) Propose an alternative bootstrap simulation. Kosowski et al.'s (2006) sample simulations independently for each fund, while Fama and French (2010) jointly sample fund returns and explanatory returns. Independent simulation might miss the effects of correlated movement in the volatilities of four-factor explanatory returns and residuals. Blake *et al.* (2017) make a comparison between these two bootstrapping methods and find that fund managers of UK equity mutual funds are unable to deliver outperformance from either selectivity or timing skills net of fees under either bootstrapping method.

Overall, previous studies conclude that fund managers do time the market returns but using an opposite strategy in the UK mutual fund market. That is, managers take a lower/higher level of risk exposure to the stock market when the market goes up/down. The negative coefficient of the timing factor means no timing ability or always making the wrong decision. In this sub-section, we give two explanations referring to irregular reverse timing behavior in our research: financial environment and timing strategy.

5.6.1 Financial Environment

The financial environment might be a reason for irregular timing performances. Matallín-Sáez, Moreno and Rodríguez (2015) document that there is an asymmetric correlation between market phenomenon and the anomaly of market timing. More specifically, stocks move more closely together when the market goes down than when the market goes up, indicated by the weaker correlation between stocks in the upward market than that correlation in the reduced market. Matallín-Sáez, Moreno and Rodríguez (2015) empirically find a higher increase in the mean covariance between stocks when the market upswings than that increase when the market declines. Therefore, it is easy to overestimate the beta in the down market and resulting in a negative measure of timing ability.

Moreover, as mentioned above, managers do not handle both skills at the same time but switching their focus according to the market situation. In particular, Kacperczyk et al. (2014) document that successful managers pick stocks well in booms and time the market well in recessions, and skilled managers vary the use of their skills over the business cycle.

In addition, our results of sub-period analysis potentially support that market information might influence the evaluation of managers' investment abilities. In panel B of Table 5.9, from 1995 to 2000, unit trusts holding Asian stocks exhibit negative selectivity and positive timing skills, while unit trusts holding stocks in other financial market display opposite investment abilities. In the meantime, Asia suffered a financial crisis that gripped much of its East and Southeast regions beginning in July 1997. Our finding empirically supports how managers time the market well in recessions as well.

5.6.2 Timing Strategy

On the other hand, fund managers might adopt other investment strategies to time the dynamic market such as market volatility. Busse (1999) uncover favorable timing performance based on market volatility changes; he argues that it is reasonable for managers to timing market volatility because volatility is predictable and persistent. Moreover, managers might shift the fund portfolio's risk level by switching investment style. Chen, Adams, and Taffler (2013) find that growth-oriented US fund managers switch stocks along the value/growth continuum (style-timing skill), explaining at least 45% of the abnormal returns reported.

Additionally, negative coefficients of timing factor might suggest that fund managers do not follow an assumed, perfect timing strategy instead of no timing ability. More specifically, Wei, Wermers, and Yao (2014) empirically study the performance of contrary mutual funds and find that contrary funds generate superior performance both when they trade against and with the herd, indicating that they possess superior private information. Menkhoff and Schmidt (2005), through a questionnaire survey, find that most fund managers rely on the strategies of buy-and-hold, momentum and contrary trading. The choice of strategy is different for each fund manager, highly related to the manager's confidence and risk-averse level. Contrary traders, in specific, prefer showing overconfidence and peculiar risk aversion.

5.7 Conclusions

This study employs the GARCH family to assess the performance of UK equity unit trusts based on daily returns. Daily data can capture high frequent timing activity, but suffering significant econometric problems of autocorrelation and heteroscedasticity; thus, we use the GARCH family to estimate parameters in order to produce reliable and efficient results. We find significantly positive stock-picking and negative market-timing skills, reconciling to prior findings.

Moreover, we use the GARCH-in-Mean model to further study selectivity ability by controlling for the time-varying residual risk of unit trusts. We find positive conditional risk premium, enhancing the evidence of superior selectivity ability. The positive conditional risk premium also supports the notion that managers can be rewarded when they choose additional risk.

In addition, we divide our whole research period into five equal sub-periods. We use the same timing models and the GARCH estimation method, but find different results among sub-periods. We argue that financial environment might affect managers selecting investment strategy.

Adverse timing findings might suggest that managers adopt different timing strategies in different financial situations, rather than market-return timing alone. Managers could time market volatility or time the investment style of their fund portfolio. They also might use a buy-and-hold investment strategy. Thus, we will investigate market-volatility timing and joint timing performance in our second research.

Chapter 6: Market Volatility-timing and Joint Market Timing Performance: Evidence from Daily and Monthly Returns

6.1 Introduction

Return-timing performance models argue that active fund managers would alter the risk level of the managed portfolio according to their forecast of market movement. More specifically, in order to grasp the additional value and avoid loss, a successful manager would increase market exposure when the market upswings and decrease market exposure when the market downturns. Empirical studies, nevertheless, find irregular market-return timing performance by employing two prevalent timing models: the quadratic model and the piecewise-linear model (e.g., Henriksson, 1984; Fletcher, 1995; Cuthbertson, Nitzsche, and O'Sullivan, 2010; Blake et al., 2017), concluding that fund managers have no superior timing ability.

Busse (1999) proposes that fund managers might shift the market sensitivity of mutual funds based on market volatility rather than the market return, as volatility is more predictable and persistent than the return. Accurate prediction referring to market is of significance for grabbing potential gains from timing strategy (Sharpe, 1975). To be specific, Bollerslev, Chou, and Kroner (1992) document how volatility exhibits clustering characteristics; that is, high volatility is often followed by high volatility and low by low. Johannes, Polson and Stroud (2002) state how forecasting volatility is not substantially affected by estimation risk or parameter uncertainty. Johannes, Polson and Stroud (2002) provide empirical proof that simulated market-volatility portfolio outperforms both simulated market-return portfolio and constant portfolio. Therefore, the predictability of volatility encourages fund managers to implement volatility-timing strategy without being equipped with superior forecasting skills.

Furthermore, market-volatility timing strategy can produce substantial economic value in the common stock market (Fleming, Kirby, and Ostdiek, 2001; 2003; Johannes, Polson, and Stroud, 2002; Clements and Silvennoinen, 2013; Moreira and Muir, 2017). More specifically, Fleming, Kirby, and Ostdiek (2001; 2003) construct a dynamic portfolio using mean-variance optimization rule and rebalance portfolio holdings daily based on estimated or realized equities' volatility. They use the estimated fee that the risk-averse investor would be willing to pay to switch from the ex-ante optimal static portfolio to the dynamic portfolio to assess the value of volatility-timing strategy. They find a quite high estimated fees; that is, when employing conditional volatility, the estimated fee exceeds 1.7% per year on average; when employing realized volatility, the estimated fee is around 2.5% per year.

Moreira and Muir (2017) form volatility-managed portfolios and rebalance portfolios' risk exposure monthly based on the last month's realized volatility. Their market-volatility portfolio produces an alpha of 4.9% and an overall 25% increase in the buy-and-hold Sharpe ratio. Johannes, Polson and Stroud (2002) exhibit that the portfolio with stochastic volatility and constant expected returns produces significant certainty equivalent gain of 4.92% where the risk aversion is assumed to equal to two, exceeding the gain of constant portfolio without predictability. Therefore, favourable economic benefits encourage managers to employ volatility-timing strategy while managing their portfolio.

Empirical studies, however, find mixed results on market-volatility timing ability of mutual fund managers. In particular, Busse (1999) uncovers that 80% of sample funds counter-cyclically time the market volatility by reducing market exposure of funds if the market volatility increases and vice versa. Liao, Zhang, and Zhang (2017) and Yi et al. (2018) also provide substantial proof of supporting the notion that the fund manager can counter-cyclically time the Chinese stock market volatility. Chen and Liang (2007) study US hedge funds and display significant counter-cyclically volatility timing performance.

In contrast, other studies exhibit pro-cyclical volatility timing performance of increasing/reducing the market exposure of funds when the market volatility is high/low. For example, Giambona and Golec (2009) separate funds into aggressive (i.e., high beta) and conservative (i.e., low beta), and reveal that aggressive/conservative style funds time the volatility counter-cyclically/pro-cyclically on average. Kim and In (2012) maintain about equal percentages of counter-cyclical and pro-cyclical volatility timing performance for US mutual funds after taking the false discovery rate (FDR) into account. Foran and O'Sullivan (2017) adopt Busse's (1999) model to study volatility timing performance of UK equity mutual funds. They use monthly returns and show that only 6% of funds can significantly and counter-cyclically time market volatility.

Busse (1999) argues that monthly returns cannot fully monitor the timing behavior; daily data allows for more efficient estimates of time variation in systematic risk than does monthly data. Fleming, Kirby and Ostdiek (2003) propose that daily standard deviation of intraday returns increases the value of volatility timing strategy relative to monthly volatility, suggesting that high-frequent data improves the evaluation of timing ability. Previous studies rarely use daily returns to assess volatility timing ability of UK unit trusts, to our knowledge, motivating us to enrich the literature.

If the correlation between market index daily returns and conditional volatility is nonzero, the performance of a successful market return timer might be explained by the coefficients of market volatility timing factor (Busse, 1999). Ferson and Mo's (2016) study of employing holdings-based dataset also supports the notion that both market returns and volatility timing are substantial fractions of funds' total performance averagely. In order to control the influence of market-return timing behavior, Busse (1999) further expresses the time-varying market exposure conditional on the market-return term. Recent empirical studies employ this linear function from Taylor-series expansion to investigate timing behavior from both aspects: market return and market volatility (Yi et al., 2018; Liao, Zhang, and Zhang, 2017).

In addition, Chen and Liang (2007) maintain that a fund manager might make an investment decision based on perceptions of both market return and market volatility simultaneously. To be specific, fund managers might not take heavy/light positions in the market even if he successfully previses an upswing/downswing of market return because he has to consider market volatility at the same time; managers might behave conservatively in lessening/increasing equity holdings if anticipation of market volatility is high/low. Therefore, joint timing behavior deserves more research attention.

Chen and Liang (2007) present a joint timing model with flexible distribution by relating fund returns to the squared Sharpe ratios of the market portfolio. More specifically, the time-varying market exposure of an optimal portfolio managed by a utility-maximizing manager with fixed risk aversion could be measured by the Sharpe ratio conditional on manager's timing signal (Admati et al., 1986). Chen and Liang (2007) substitute this time-varying market exposure for the constant beta in the return generating factor model of the fund's portfolio, proposing a multi-factor joint timing model. The estimated coefficient of squared Sharpe ratio term in this joint timing model justifies the examination of timing ability from two dimensions: market return and market volatility simultaneously.

Chen and Liang (2007) develop this joint timing model to examine the performance of US hedge funds and find that the joint timing coefficient is between 0.005 and 0.006 at a 1% significance level across various benchmark specifications, implying that market return and volatility impact on the adjustment of market exposure at the same time. To our knowledge, no mutual fund studies investigate both market return and volatility timing behavior jointly; this study seals this research gap.

This study shares the same research data with the first research of market-return timing evaluation. The daily volatility of market returns is tracked by GARCH-type models. We consider two types of asymmetric GARCH model to monitor the asymmetric characteristic of volatility. Monthly data is adopted as well for comparison. Similar to the first study, daily data suffers significant econometric problems of autocorrelation and heteroscedasticity which cannot be entirely corrected by Newey-West procedure. We employ GARCH to estimate parameters of timing models in our research.

Overall, the main contribution of this empirical study is to document how data frequency has a significant impact on volatility-timing performance evaluation. The remainder of this chapter is organized as follows. Section 6.2 presents descriptive statistics of unit trusts returns and explanatory variables in the benchmark. Section 6.3 exhibits methods of measuring market volatility and the descriptive statistics of estimated market volatility. Section 6.4 presents market-volatility timing and joint timing models, followed by empirical results in section 6.5. Section 6.6 concludes.

6.2 Descriptive Statistics

The dataset of this research is the same as the first one, that is, UK-authorized equity unit trusts. Table 6.1 exhibits the descriptive statistics of excess daily and monthly returns of UK unit trusts and explanatory variables from July 1990 to June 2015. The summary statistics of daily data in Panel A and C are borrowed from Table 5.1 in Chapter 5 for comparison. Panel A and B of Table 6.1 display summary statistics of daily and monthly returns of unit trust portfolios grouped by geographic investment focus and average returns of all trusts in the research sample. Daily and monthly returns of the UK unit trust exhibit consistent descriptive statistics such as positive excess returns relative to the three-month UK Treasury bill index, negative skewness and high excess kurtosis. Geographic group of Japanese is an exception, displaying a slightly negative mean of the excess return of –0.008% per day or –0.17% per month.

Moreover, negative skewness and high kurtosis indicate that the distribution of returns is not normal but close to student-t distribution. The significant statistics of the Jarque-Bera normality test also advocate the non-normal distribution of unit trusts returns. The distribution of monthly returns is relatively close to being normally distributed, indicated by relatively small kurtosis and statistics of the Jarque-Bera normality test. The geographic group, Japan, is also an exception. In particular, the statistic of the Jarque-Bera normality test is only 0.07 and insignificant, thus failing to reject the hypothesis of a normal distribution.

Besides, the last column of Table 6.1 records the statistics of the stationary test of Augmented Dickey-Fuller (ADF). These statistics are significantly negative, rejecting the null hypothesis that a unit root is present in our time series sample. In other words, our time-series excess returns of UK unit trusts are stationary, implying that the OLS method is appropriate for estimating the slope coefficients.

Panel C and D of Table 6.1 show descriptive statistics of explanatory variables in the benchmark. Daily and monthly market excess returns and factor returns of book-to-market are consistent and positive, implying that market returns exceed risk-free returns during our research period. By contrast, mean returns of size and momentum factors are inconsistent, that is, negative in daily data and positive in monthly data.

Furthermore, the distribution of four benchmark factors fails to follow a normal distribution, indicated by non-zero skewness and excess kurtosis, and significant statistics of the Jarque-Bera test. The OLS estimation method is still appropriate in our research, since the time-series factor returns are stationary, in line with unit trusts returns. The estimate of coefficients would be valid while the estimate of t-statistics for significance inference would be biased under OLS estimation.

Table 6. 1:
Descriptive Statistics of the Excess Returns for the Unit Trusts Portfolios and Explanatory Variables in Benchmark

	Mean	*Min*	*Max*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J-B*	*ADF*
Panel A: Daily Excess Returns of Unit Trusts Portfolios								
Asia excluding Japan	0.015	–8.148	7.797	0.01062	–0.45151	7.73076	5976***	-63.41***
Asia including Japan	0.014	–8.885	7.340	0.01108	–0.38870	7.19851	4697***	-66.96***
Japan	–0.008	–7.923	6.583	0.01060	–0.17915	6.16074	2607***	-53.23***
Europe excluding UK	0.020	–7.222	7.523	0.01047	–0.47532	7.53456	5530***	-54.73***
Europe including UK	0.019	–75.633	77.627	0.01922	0.98390	981.695	2.47E+08***	-41.69***
UK	0.017	–7.053	5.838	0.00722	–0.73134	10.1460	13707***	-68.71***
North America	0.022	–7.060	5.805	0.01030	–0.24551	6.73638	3659***	-70.34***
Global	0.014	–10.209	12.075	0.00702	–0.23907	28.1277	162724***	-63.50***
All	0.016	–5.970	5.436	0.00703	–0.64207	8.93195	9490***	-64.38***
Panel B: Monthly Excess Returns of Unit Trusts Portfolios								
Asia excluding Japan	0.320	–29.775	18.992	0.06153	–0.38492	5.08361	60.24***	–15.57***
Asia including Japan	0.328	–28.941	21.165	0.06443	–0.30144	4.52985	33.01***	–14.58***
Japan	–0.170	–14.918	14.810	0.05455	–0.00909	3.07450	0.07	–14.96***
Europe excluding UK	0.415	–18.367	14.590	0.05078	–0.64240	4.58788	50.93***	–16.13***
Europe including UK	0.414	–71.263	72.281	0.07720	–0.17243	52.2370	29598***	–22.26***
UK	0.374	–16.983	11.056	0.03981	–0.91632	5.10747	95.22***	–14.70***
North America	0.441	–13.728	15.590	0.04764	–0.25437	3.54598	6.80**	–15.66***
Global	0.304	–15.374	10.333	0.04206	–0.67790	4.22836	40.86***	–15.32***
All	0.330	–15.645	9.784	0.04026	–0.85473	4.61407	67.48***	–14.91***
Panel C: Daily Returns of Explanatory Variables in Benchmark								
$r_m - r_f$	0.020	–8.358	9.202	0.01045	–0.04373	9.67527	11730***	–35.15***
SMB	–2.13E-05	–6.301	3.561	0.00709	–0.51064	8.26494	7570.57***	–38.80***
HML	0.007	–4.187	5.784	0.00619	0.32862	9.96364	12877.27***	–68.12***
MOM	–0.038	–8.134	5.994	0.00780	–0.58155	12.3375	23305.09***	–47.03***
Panel D: Monthly Returns of Explanatory Variables in Benchmark								
$r_m - r_f$	0.392	–13.606	10.485	0.04101	–0.54919	3.64676	20.31***	–16.01***
SMB	0.181	–11.476	15.607	0.03303	0.07771	4.95337	48.00***	–14.62***
HML	0.147	–18.608	12.287	0.03394	–0.49501	9.66793	568.02***	–11.80***
MOM	0.999	–25.028	16.044	0.04766	–1.00500	7.74722	332.20***	–12.48***

This table reports the summary statistics of daily and monthly returns of UK-authorized equity unit trusts and explanatory variables in benchmark over the period July 1990 to June 2015. There are 478 unit trusts in this research sample. Unit trusts authorized and traded in the UK fund market are available to invest in various countries' financial market. Those unit trusts are sorted in various groups based on the geographical focuses such as Asia excluding Japan, Asia including Japan, Japan, Europe excluding UK, Europe including UK, UK, North America and Global. The explanatory variables comprise the market excess return $r_m - r_f$, pricing factors of size SMB, value HML and momentum MOM. This table presents means, minimum return Min, maximum return Max, standard deviation $Std.Dev.$, skewness and kurtosis for variables. J-B is the Jarque-Bera normality test. ADF is the stationary test.
Panel A presents the summary statistics of daily returns of geographical portfolios and aggregate portfolio of the UK equity unit trusts, and Panel B presents the summary statistics of monthly returns regarding the various trust portfolios. Panel C and D display the descriptive statistics of explanatory variables for daily and monthly data, respectively.
The values of *Mean, Min and Max*, are multiplied by 100 to express them in percentage terms.
The symbols ***, ** and * represent the statistical significance at the 1%, 5% and 10% levels, respectively.
Panel A and Panel C in Table 6.1 are from Table 5.1

6.3 Market Volatility

Two types of market volatility proxy are prevalent in literature: realized volatility and implied volatility. Realized volatility is measured by historical returns, tracking past market fluctuation and actual changes. By contrast, implied volatility is an estimate of future prices of a security or the market based on probability. As the purpose of this study is to assess fund manager's ability to time market volatility rather than the ability to forecast future market volatility tendency, we employ realized volatility calculated from the daily historical returns of the common stock market.

Moreover, the correlation between implied volatility and historical volatility is high. Busse (1999) demonstrates that the correlation between implied and conditional volatility is up to

0.92. Implied volatility denotes Chicago Board Options Exchange (CBOE) implied volatility series; conditional volatility is estimated under the EGARCH model by using S&P 500 daily returns. Busse (1999) further adopts both volatilities and find similar results in the timing performance study. Thus, even though the implied volatility[10] is not available for the duration of our research period, it is not expected to detract from our study.

We use historical daily returns of the FTSE All-Share Index to calculate monthly and daily market volatility. Monthly volatility is measured by standard deviation, whereas daily volatility is measured by the GARCH-type models conditional on past returns. As our databases (i.e., DataStream and Bloomberg) do not offer intraday returns, we employ conditional version to monitor daily volatility rather than standard deviation of intraday returns. We maintain that GARCH daily volatility is also appropriate for our research because McMillan, Speight and Apgwilym (2000) document that GARCH model provides a superior forecast for the daily volatility of UK FTSE All-Share and FTSE 100 stock indexes returns.

6.3.1 Market Volatility Estimation Methods

Monthly volatility is measured by the standard deviation of daily market returns within each month, which is given by:

$$\sigma_{mt} = \left[\frac{\sum_{i=1}^{n_t}(R_{mti} - \bar{R}_{mt})^2}{n}\right]^{1/2}, \tag{6.1}$$

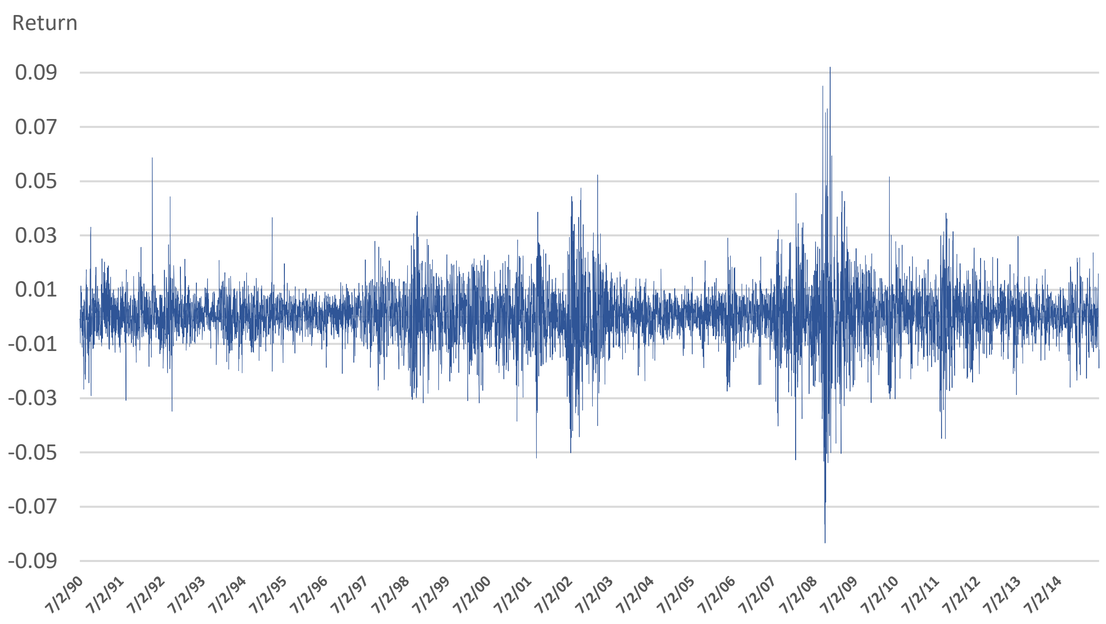
where n_t is the number of observations in month t; R_{mti} denotes excess daily returns of FTSE All-Share Index in month t; $\bar{R}_{mt}$ denotes average excess daily market returns in month t. This equation cannot be implemented to measure daily volatility as the inter-day returns are not available.

We model daily volatility conditional on past daily returns given that volatility is autocorrelated (i.e., volatility clustering or volatility pooling). To be specific, volatility clustering describes the tendency of large changes in asset prices (of either sign) to follow large changes and small changes (of either sign) to follow small changes' (Mandelbrot, 1963). Figure 6.1 plots the daily return of the FTSE All-share index from 1990 to 2015, describing the phenomenon of volatility

[10] Price index of FTSE 100 volatility index start from 2000/01/04 in DataStream. Previous literature studying the UK implied volatility use FTSE 100 Index options call and put strike prices and Black-Scholes option pricing model. The database is the Financial Times and the London Stock Exchange Daily Official List (Gemmill, 1996).

clustering. More specifically, volatility occurs in bursts of returns. During 1993 to 1994, the positive and negative returns are relatively small, indicating a relative tranquillity in the market; in contrast, over the mid-2007 to late 2008, the market is far more volatile, evidenced by many large positive and large negative returns during the short space of time. If the current level of volatility tends to have a positive correlation with volatility level during the immediately preceding periods, the ARCH model, developed by Engle (1982), would parameterise this volatility clustering phenomenon elegantly by setting conditional variance equal to a constant plus a weighted average (with positive weights) of past squared residuals.

Figure 6. 1:
Daily FTSE All-Share Returns for July 1990 – June 2015



This figure describes the phenomenon of volatility clustering that high volatility of returns is followed by high volatility and low by low.

The basic concept of ARCH is that the variance of residuals is dependent on the past values of the residuals of the mean regression. The mean equation of the market returns is expressed as:

$$r_{m,t} - r_{f,t} = \mu + \varepsilon_{m,t}, \tag{6.2}$$

where $r_{m,t}$ and $r_{f,t}$ denotes the daily returns of FTSE All-Share Index and 3-month Treasury bill index, respectively; μ denotes the mean of market excess returns; $\varepsilon_{m,t}$ denotes the time-series error terms or market shocks. The residual $\varepsilon_{m,t}$ is assumed to be serially uncorrelated and have zero mean, expressed as $z_t\sigma_t$ where $\{z_t\}$ is a sequence of independent and identically distributed (i.i.d.) random variables with a zero mean and unit variance and σ_t represents the standard deviation of the return at time t. The series $\{z_t\}$ is collectively known as the standardised residuals. The variance σ_t^2 can be expressed as $\left(\varepsilon_{m,t}/z_t\right)^2$. The conditional variance equation of the ARCH model is written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2, \tag{6.3}$$

where q is the number of lagged returns used. The empirical study requires a quite high value of q, leading to the problem of estimating a high number of parameters, which decreases the overall accuracy of the model. Bollerslev (1986) generalizes the ARCH model by allowing the conditional variance to be dependent upon own previous lags, which is expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{6.4}$$

where σ_t^2 and σ_{t-j}^2 are the current and the j^{th} lagged level of conditional variance, respectively, and ε_{t-i} is the i^{th} lagged level of residual. For p=0, the process reduces to the ARCH (q) process, so q is regarded as ARCH order, and p is regarded as GARCH order.

We adopt the standard GARCH to model daily volatility of the stock market, in which large shocks in the return series imply a high value of ε_{t-i}^2, thereby implying a high value of volatility. Squared value considers the magnitude without the sign of the unanticipated excess returns. However, aggregate market volatility responds asymmetrically to negative and positive shocks. In particular, negative shock results in more risk potentially than positive shock, supported by the empirical findings of a negative relationship between realized market returns and volatility (e.g., Chirstie, 1982; Schwert, 1989; Bekaert and Wu, 2000; Hibbert, Daigler, and Dupoyet, 2008).

Based on the fundamental factors of the firm, Black (1976) first claims that negative return of a firm's stock results in the increase of debt to equity ratio of the firm; then, shareholders who bear the residual risk of the firm to perceive their future cash flow stream as being relatively more risky. Thus, the relation between stock current returns and its future volatility is negative. On the other hand, Campbell and Hentschel (1992) theoretically advocate how that due to the time-varying risk premium, the expected future stock returns rise along with the increase of volatility; then, current stock prices will fall to adjust to this change in the future expectations. Therefore, an increase in future volatility causes current negative returns.

As the vanilla GARCH with the assumption of symmetric distribution fails to distinguish the different degree of impact from good news and bad news, we further to adopt two famous asymmetric GARCH models –GJR-GARCH and Exponential GARCH (EGARCH)– while measuring daily market volatility. Glosten, Jagannathan and Runkle (1993) develop a GJR-GARCH model by the addition of an identification term to the standard GARCH model. The mean equation is the same with standard GARCH expressed in Equation (6.2), and the conditional variance equation is expressed as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q}[\alpha_i + \gamma_i I_{(\varepsilon_{t-i}<0)}]\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p}\beta_j \sigma_{t-j}^2, \tag{6.5}$$

where, $I_{(\varepsilon_{t-i}<0)}$ is a dummy variable setting to 1 if ε_{t-i} is negative, and 0 otherwise, and γ monitors the asymmetric effect. For a negative shock to the returns, the coefficient of the lagged error terms will be $\sum_{i=1}^{q}(\alpha_i + \gamma_i)$, whereas, for a positive shock of the same magnitude, the coefficient will be $\sum_{i=1}^{q}\alpha_i$.

The conditional variance of shocks given information at time t must remain nonnegative with a probability of one. Standard GARCH and GJR-GARCH models ensure the nonnegative variance by making σ_t^2 a linear combination (with positive weights) of positive random variables. Nelson (1991), alternatively, presents EGARCH by using a logarithmic function to ensure nonnegative variance, which is expressed as:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q}\alpha_i g(z_{t-i}) + \sum_{\mathrm{j}=1}^{p}\beta_j \ln\left(\sigma_{t-\mathrm{j}}^2\right) \tag{6.6}$$

$$g(z_t) \equiv \theta z_t + \gamma[|z_t| - E|z_t|],$$

where $\varepsilon_t = z_t\sigma_t$ ($z_t \sim i.i.d. with\, E(z_t) = 0, Var(z_t) = 1$). The two components of $g(z_t)$ are θz_t and $\gamma[|z_t| - E|z_t|]$ with zero means for each component. If the z_t is positive, $g(z_t)$ is linear in z_t with slope $\theta + \gamma$, whereas if the z_t is negative, $g(z_t)$ is linear with slope $\theta - \gamma$, thereby permitting the conditional variance process $\{\sigma_t^2\}$ to respond asymmetrically to increases and decreases in stock price.

Overall, daily market volatility is modelled by GARCH, GJR-GARCH and EGARCH in this thesis. Since the distribution of factor returns shows fat tails, we adopt both normal and student's t distribution while estimating parameters. Moreover, as the second-order is the most commonly used within higher-order GARCH-types models (Zivot, 2009), we restrict order within $1 \leq p, q \leq 2$ in our empirical study. We use traditional goodness-of-fit tests such as Log-likelihood ratio, Akaike Information Criterion (AIC) and Schwarz Criterion (BIC), as well as the statistical significance of estimated coefficients of conditional variance equation to identify the best appropriate GARCH type for our data set.

Panel A of Table 6.2 reports the statistics of Log-likelihood, AIC, and BIC tests for the selected GARCH-type models with two sets of order combinations. In the first column, the GARCH types and orders are found. The next three columns show statistics of three goodness-of-fit tests estimated under the normality distributed assumption, whereas the last three columns display the statistics estimated under the student-t distributed assumption. Large Log-likelihood and small AIC and BIC are preferred. Results suggest that *t*-distributed conditional shocks perform better than normal distribution across all GARCH-types models. Further, the higher-order combination produces higher statistics of log-likelihood, as well as lower statistics of AIC and BIC, indicating that the second-order case is preferred over the first-order.

Panel B of Table 6.2 exhibits the estimated market mean returns μ and coefficients in the conditional variance equation. The value of returns is assumed to be distributed according to student's t distribution. The coefficient γ monitors the asymmetric effect in both EGARCH and GJR-GARCH models. The statistically significant γ advocates the existence of asymmetric phenomena in the market volatility, and the asymmetric effect can be adjusted by the linear function of ARCH factor in the EGARCH model or dummy variable in the GJR-GARCH model. Our results reveal a statistically significant coefficients γ at 1% level across four types of asymmetric GARCH models, suggesting that asymmetric models perform better than vanilla GARCH while modelling volatility of UK stock market daily excess returns.

GJR-GARCH (2, 2) display the largest Log-likelihood statistic and the smallest AIC and BIC statistics, recorded in Panel A of Table 6.2, implying that GJR-GARCH (2, 2) is the best model to track market's daily volatility. However, the coefficients of the first and the second lagged squared error term are insignificant, recorded in the last row under the columns α_1 and α_2 in Panel B of Table 6.2. The insignificant coefficients potentially demonstrate that the first-order might be sufficient to monitor the autocorrelation of market shocks for GJR-GARCH. In other words, the second-order might tedious for modelling the autocorrelation of market shocks.

We select EGARCH (2, 2) to track UK stock market volatility in our research for two reasons. On the one hand, EGARCH (2, 2) specification better demonstrates lagged error terms, indicated by large absolute z-statistics in Panel B of Table 6.2. On the other hand, EGARCH (2, 2) suffer a minimal loss of goodness of fit in comparison to GJR-GARCH (2, 2), indicated by the statistics of *Log-likelihood* under t-distribution in Panel A of Table 6.2. Therefore, we employ EGARCH (2, 2) to model daily conditional market return volatility, and employ standard deviation of daily returns within each month to model monthly realized market volatility.

Table 6. 2:
GARCH Family Models Comparison on Modelling Market Returns Volatility

Panel A: Model Selection Criteria

	Normal distribution			*t-distribution*		
	Log likelihood	*AIC*	*BIC*	*Log likelihood*	*AIC*	*BIC*
GARCH(1,1)	21027.81	–6.656265	–6.651990	21091.65	–6.676159	–6.670815
EGARCH(1,1)	21113.61	–6.683113	–6.677770	21170.38	–6.700769	–6.694357
GJR-GARCH(1,1)	21100.83	–6.679067	–6.673724	21162.51	–6.698278	–6.696057
GARCH(2,2)	21029.22	–6.656077	–6.649665	21093.59	–6.676141	–6.668660
EGARCH(2,2)	21123.97	–6.685444	–6.676894	21184.45	–6.704275	–6.694656
GJR-GARCH(2,2)	21101.06	–6.678189	–6.669639	21186.12	–6.704804	–6.695186

Panel B: Estimated Coefficients (t-distribution)

	μ	**α_0**	**α_1**	**α_2**	**γ_1**	**γ_2**	**β_1**	**β_2**
GARCH(1,1)	0.048	1.12e-06	0.09	–	–	–	0.90	–
	(5.10)	(5.17)	(11.64)				(109.48)	
EGARCH(1,1)	0.029	–0.23	0.13	–	–0.09	–	0.99	–
	(3.18)	(–10.01)	(11.03)		(–13.01)		(488.81)	
GJR-GARCH(1,1)	0.028	1.19e-06	0.01	–	0.12	–	0.91	–
	(3.00)	(6.71)	(2.06)		(11.18)		(133.61)	
GARCH(2,2)	0.05	1.55e-06	0.06	0.06	–	–	0.67	0.19
	(5.02)	(2.39)	(4.27)	(1.20)			(1.33)	(0.43)
EGARCH(2,2)	0.031	–0.02	0.13	–0.11	–0.14	0.13	1.85	–0.85
	(3.38)	(–3.01)	(6.97)	(–6.14)	(–10.17)	(10.63)	(47.72)	(–22.12)
GJR-GARCH(2,2)	0.030	2.71e-08	0.002	–0.001	0.17	–0.16	1.84	–0.84
	(3.22)	(2.64)	(0.37)	(–0.24)	(9.86)	(–9.98)	(85.95)	(–40.53)

This table reports the test statistics regarding various GARCH-type models. Panel A shows the statistics of goodness-of-fit test such as Log-likelihood, Akaike Information Criterion (AIC) and Schwarz Criterion (BIC). Panel B shows the estimated coefficients for various GARCH-type models. z-statistics are presented in the bracket.
The mean value μ is multiplied by 100 to express them in percentage terms.
The mean Equation of all GARCH-types models are

$$r_{mt} - r_{ft} = \mu + \varepsilon_t$$

The conditional variance Equation of GARCH (p, q) are

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where σ_t^2 and σ_{t-j}^2 are the current and the i^{th} lagged level of conditional variance, ε_{t-i} is the i^{th} lagged level of residual. For p=0, the process reduces to the ARCH (q) process, so q is regarded as ARCH order and p is regarded as GARCH order.
The conditional variance Equation of EGARCH(p, q) are

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \frac{\gamma_i \varepsilon_{mt-i} + \alpha_i |\varepsilon_{mt-i}|}{\sigma_{mt-i}} + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2)$$

where if the ε_{t-i} is positive, the ARCH factor is linear with slope $\alpha + \gamma$; and if the ε_{t-i} is negative, the ARCH factor is linear with slope $\alpha - \gamma$, thereby allowing the conditional variance process $\{\sigma_t^2\}$ to respond asymmetrically to increases and decreases in stock price.
The conditional variance Equation of GJR-GARCH(p, q) are

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} [\alpha_i + \gamma_i I_{(\varepsilon_{t-i}<0)}]\, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where, $I_{(\varepsilon_{t-i}<0)}$ is a dummy variable setting to 1 if ε_{t-i} is negative, and 0 otherwise. γ captures the asymmetric effect in both EGARCH and GJR-GARCH models.

6.3.2 Descriptive Statistics of Estimated Market Volatility

Table 6.3 displays the summary statistics of UK stock market volatility. To be specific, the row of σ_{mmt} represents the monthly market volatility measured by the market excess daily returns within each month. The row of σ_{mdt}^2 represents the conditional variance of market excess daily returns measured by the EGARCH (2, 2) under the t-distributed assumption, and σ_{mdt} represents market daily volatility measured by the square root of conditional variance. The statistics of mean, standard deviation, skewness and kurtosis are quite close for monthly and daily volatility of UK market returns, seeing the first and last rows in Table 6.3. Figure 6.2 displays the volatility behavior of both monthly and daily data, explicitly describe the similarity between monthly and daily volatility. Besides, Figure 6.2 advocates the presence of volatility clustering with high volatility followed by high volatility and low by low. The issue of volatility clustering is more severe in daily data than in monthly.

Table 6. 3:
Descriptive Statistics of the Estimated Market Volatility

	Mean	*Min*	*Max*	*Std. Dev.*	*Skewness*	*Kurtosis*	*J-B*	*ADF*
$\boldsymbol{\sigma_{mmt}}$	0.009	0.003	0.044	0.005	2.521	13.383	1665.4***	–7.27***
$\boldsymbol{\sigma_{mdt}^2}$	0.0001	1.19e-05	0.002	0.00013	5.4740	50.5617	626956***	–7.08***
$\boldsymbol{\sigma_{mdt}}$	0.009	0.003	0.045	0.004	2.182	11.166	22564***	–6.28***

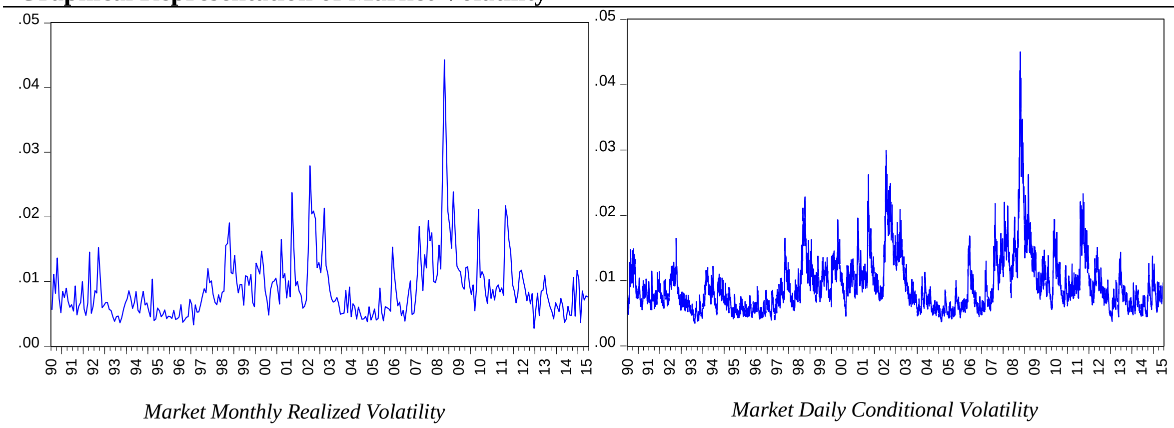
This table reports the summary statistics of UK stock market volatility from 1991 to 2015. $\boldsymbol{\sigma_{mtm}}$ represents the monthly volatility calculated by the standard deviation of daily market excess returns within each month. $\boldsymbol{\sigma_{mdt}^2}$ is the daily conditional variance estimated by EGARCH(2, 2); $\boldsymbol{\sigma_{mdt}}$ is the square root of conditional variance $\boldsymbol{\sigma_{mdt}^2}$.

The FTSE All-Share Index returns represent the market returns, and the three-month UK Treasury bill index represents the risk-free rate of returns.

This table represents means, minimum returns $\boldsymbol{Min}$, maximum returns $\boldsymbol{Max}$, standard deviation $\boldsymbol{Std.Dev.}$, skewness and kurtosis. The last two columns report test statistics. J-B is the normality test. ADF is the stationary test.

The symbols ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Figure 6. 2:
Graphical Representation of Market Volatility



The left graph shows the graph of the monthly standard deviation of daily market excess returns $\boldsymbol{\sigma_{mmt}}$.
The right graph shows the graph of daily conditional standard deviation measured by EGARCH (2, 2) $\boldsymbol{\sigma_{mdt}}$.

6.4 Methodologies

6.4.1 Market-volatility Timing Model

As multifactor models do a better job of demonstrating the return-generating process of mutual funds (Elton et al., 1993), we employ the prevailing four-factor model as a benchmark to control returns of equity unit trusts from investment style, which is given by:

$$R_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} R_{jt} + \varepsilon_{pt}, \qquad (6.7)$$

where R_{pt} is the excess return of unit trust p at time *t*, R_{jt} indicates risk-adjusted factors at time *t*, including market excess return factor R_{mt}, size factor SMB_t, value factor HML_t, and the momentum factor MOM_t. ε_{pt} is the idiosyncratic return of unit trusts portfolio at time *t*.

The volatility-timing model is similar in some respects to the pioneering timing literature of Treynor and Mazuy (1966). Busse (1999) employs a simplified Taylor series expansion to express market beta as a linear function of the difference between market volatility and its time-series mean, which is expressed as:

$$\beta_{mpt} = \bar{\beta}_{mp} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m). \qquad (6.8)$$

Equation (6.8) deconstructs the systematic risk for unit trust p at time t into mean or target beta $\bar{\beta}_{mp}$ and changes depending on market volatility β_{1mp}. If the fund manager engages in market volatility timing, the β_{1mp} would be significantly different from zero. The sign of the coefficient β_{mp1} would suggest how the unit trust responds to changing market volatility and how such a strategy affects fund performance. Substituting Equation (6.8) into Equation (6.7) gives the market-volatility timing model:

$$R_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} R_{jt} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) R_{mt} + \varepsilon_{pt}, \qquad (6.9)$$

where abnormal return α_p indicates the selectivity ability of fund managers, β_{1mp} indicates the volatility timing ability. The significant positive β_{1mp} suggests that fund managers engage in pro-cyclical volatility timing strategy, whereas significant negative β_{1mp} supports a countercyclical timing strategy.

In addition, Busse (1999) questions that if the correlation between market return and volatility is large, the successful ability to time market returns might be manifested in the volatility-timing coefficients. Thus, it is essential to assess market-volatility timing performance conditional on market-return timing behavior. On the other hand, if the correlation is too small to offer evidence of presence, the return-timing performance will not be explained by the volatility-timing coefficients, even though unit trusts can successfully time market returns. By extending Taylor series expansion, Busse (1999) expresses the time-varying beta as:

$$\beta_{mpt} = \bar{\beta}_{mp} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) + \beta_{2mp}(r_{mt} - r_{ft}). \tag{6.10}$$

Therefore, market-return and market-volatility timing abilities can be evaluated separately in the market timing model:

$$R_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} R_{jt} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m)R_{mt} + \beta_{2mp}R_{mt}^2 + \varepsilon_{pt}, \tag{6.11}$$

where β_{1mp} denotes the market volatility timing ability and β_{2mp} denotes the market return timing ability. If fund managers adopt market-volatility timing strategy solely, the volatility-timing coefficient β_{1mp} will be a statistically significant and return-timing coefficient β_{2mp} will be insignificant. Likewise, if managers only employ market-return timing strategy, β_{1mp} will be insignificant and β_{2mp} will be statistically significant. It is worth noting that if both timing coefficients β_{1mp} and β_{2mp} are statistically significant, it suggests that managers use both timing strategies, but it does not constrain fund managers to have to consider the market return and market volatility at the same time while managing market exposures of mutual funds.

6.4.2 Joint Timing Model

The joint timing model assumes that fund managers change market exposure based on perceptions of both market return and market volatility simultaneously. For example, in a highly volatile market condition, even if the fund manager forecasts a high level of market return, he may not take higher exposure to the market, as the majority of fund buyers are risk-averse. Admati *et al.* (1986) express the time-varying beta of the equity portfolio managed by a utility-maximising manager as:

$$\beta_t = \frac{E(r_{m,t+1}|s_t)}{\theta * Var(r_{m,t+1}|s_t)}, \tag{6.12}$$

where θ is the risk aversion assumed to be constant, s_t denotes the manager's timing signal. Equation (6.12) describes how a market timer incorporates information into fund management: fund beta should increase with expected market return $E(r_{m,t+1}|s_t)$ and decrease with the expected market variance $Var(r_{m,t+1}|s_t)$, thereby justifying the examination of timing ability from both market return and volatility dimensions. Consistent with Equation (6.12), Chen and Liang (2007) develop a joint timing model, expressed as:

$$r_{p,t} = \alpha + \sum_{j=1}^{4} \beta_j r_{j,t} + \gamma \left(\frac{r_{m,t}}{\sigma_{m,t|s_{t-1}}}\right)^2 + \varepsilon_t, \tag{6.13}$$

where γ measures the joint timing ability of a fund manager who shifts the risk level of unit trusts based on the contemporaneous market return and volatility, and β_m measure the fund's market exposure if the $r_{j,t}$ represents the market excess returns. The joint timing term is similar to the squared Sharpe ratio of the market portfolio – the ration of expected excess return to the (conditional) standard deviation. Although the joint timing coefficient is not a straightforward approach of describing joint timing behavior, the coefficient γ still can illustrate the impact of joint timing ability on the adjustment of market exposure according to the relation between fund returns and the squared Sharpe ratio. In Equation (6.13), if fund managers implement a buy-and-hold strategy, β_m alone can capture the fund's market exposure and γ should be zero.

6.5 Empirical Results

Prior studies estimate coefficients under the OLS-types method. However, as daily data might suffer econometric problems of autocorrelation and heteroscedasticity, we employ a GARCH method to solve the problems. In this section, we firstly report test results of the autocorrelation of excess returns of equity unit trusts portfolios, as well as heteroscedasticity of regression residuals in the sub-section 6.5.1.

Moreover, we provide evidence on the importance of market volatility in comparison to other volatility of investment style factors. In particular, it is possible for managers to time the volatility of other risk factors such as size, value and momentum. We empirically document that trust managers in our research sample concentrate on market volatility intently in the aggregate, seeing the sub-section 6.5.2.

In addition, we present results of volatility-timing performance evaluation based on daily data analysis in the sub-section 6.5.3, and the data frequency effect on volatility-timing performance evaluation is reported in the sub-section 6.5.4. The sub-section 6.5.5 states findings referring to joint timing performance.

6.5.1 Autocorrelation and Heteroscedasticity Tests

We use the autocorrelation function and the Ljung-Box Q-statistics to test high-order serial correlation, reported in Table 6.4. If there is no serial correlation in the UK unit trusts returns, the autocorrelations statistics would be nearly zero across various lags, and Q-statistics would be insignificant with large p-values. We report test statistics at the lags of first, fifth and tenth separately, denoted by $Auto(n)$. The column of AC exhibits the number of the autocorrelation of the aggregate portfolio of unit trusts and eight geographical groups. The next two columns show the Q-statistics and p-value of Q-statistics test for the three autocorrelation lags. Panel A of Table 6.4 displays tests results of monthly data and Panel B exhibits corresponding test results of daily data.

The numbers of autocorrelation for monthly data are smaller than the numbers for daily data, and the number of autocorrelation decreases over the lags. To be specific, the numbers of autocorrelation for monthly data at the first, fifth and tenth lags are 0.14, –0.02 and –0.02, respectively; whereas, the corresponding numbers for daily data are 0.21, 0.03 and 0.02, respectively. Moreover, all the reported p-values of Q-statistics in Panel B are zero, implying that the autocorrelation of excess daily returns of unit trusts is statistically significant. By contrast, Q-statistics for monthly data are insignificant, indicated by large p-values. Autocorrelation tests document how the autocorrelation is more prevalent in the daily data set than in the monthly data set.

Moreover, one assumption of the OLS method is homoscedasticity, that is, the stable variance of residuals. Many empirical studies, nevertheless, argue that residuals under market-return and market-volatility timing models tend to be heteroscedasticity due to the misspecification of the benchmark (Pfleiderer and Bhattachary, 1983; Chen and Stockum, 1986; Ferson and Schadt, 1996). Prior studies use Newey-West procedure to account for heteroscedastic residuals by estimating only the most critical covariance matrix of parameters instead of all covariance. We adopt OLS-Newey-West as well. Then, we use Lagrange multiplier (LM) to test whether Newey-West can fully account for heteroscedasticity. Heteroscedasticity would bias the estimate of t-statistics, resulting in unreliable inference.

Table 6. 4:
Autocorrelations of Excess Returns for Portfolios of UK Equity Unit Trusts

	Auto(1)			Auto(5)			Auto(10)		
	AC	Q-Stat	Prob	AC	Q-Stat	Prob	AC	Q-Stat	Prob
Panel A: Autocorrelations of Monthly Excess Unit Trusts Returns									
Asia excluding Japan	0.099	2.96	0.085	–0.001	4.89	0.429	–0.006	11.26	0.337
Asia including Japan	0.159	7.44	0.006	–0.001	8.31	0.081	–0.070	17.58	0.062
Japan	0.141	5.99	0.014	0.034	10.61	0.060	–0.055	14.39	0.156
Europe excluding UK	0.064	1.24	0.265	–0.004	4.45	0.487	–0.024	6.10	0.807
Europe including UK	–0.251	19.11	0.000	0.011	19.85	0.001	0.017	20.121	0.036
UK	0.155	7.31	0.007	–0.025	12.50	0.029	–0.034	15.37	0.119
North America	0.098	2.92	0.087	–0.028	3.47	0.627	0.003	11.70	0.305
Global	0.115	3.98	0.046	–0.014	4.87	0.432	0.004	8.24	0.605
All	0.141	6.06	0.014	–0.018	10.24	0.069	–0.021	13.49	0.198
Panel B: Autocorrelations of Daily Excess Unit Trusts Returns									
Asia excluding Japan	0.222	310.95	0.000	0.006	321.85	0.000	0.018	334.35	0.000
Asia including Japan	0.159	156.48	0.000	0.026	172.19	0.000	0.009	184.70	0.000
Japan	0.220	305.91	0.000	–0.010	311.10	0.000	–0.001	328.20	0.000
Europe excluding UK	0.126	100.04	0.000	0.015	108.51	0.000	0.010	127.25	0.000
Europe including UK	–0.082	42.82	0.000	0.008	482.62	0.000	0.006	484.64	0.000
UK	0.144	131.52	0.000	0.034	154.96	0.000	0.009	183.93	0.000
North America	0.121	92.57	0.000	–0.031	99.81	0.000	0.022	110.19	0.000
Global	0.220	306.82	0.000	0.014	334.78	0.000	0.029	362.86	0.000
All	0.207	271.63	0.000	0.025	295.14	0.000	0.020	322.96	0.000

This table reports the autocorrelation statistics of excess returns for 478 UK-authorized equity unit trusts over the period July 1990 to June 2015. The unit trusts are grouped based on geographic investment focus into eight portfolios. The last row represents the autocorrelation statistics of unit trusts returns at the aggregate level.
Auto(n) denotes the autocorrelation at n lags. AC denotes the number of autocorrelation. Q-statistic is the autocorrelation test. Prob denotes the test p-value.

Table 6.5 presents statistics of R-square and LM test for volatility-timing, market-timing, and joint-timing models. Panel A reports test results for monthly data and Panel B uncover the corresponding test statistics for daily data. Statistics of R-square are larger for monthly data than that for daily data, suggesting that monthly data fits the models under OLS estimation approach better than daily data. Furthermore, in Panel B of Table 6.5, LM statistics for daily data are highly significant with a substantial value of z-statistics, implying that large heteroscedasticity cannot be corrected by the Newey-West procedure. For monthly data, although the statistics of LM test in some trust portfolios are still significant, the value of z-statistics is much smaller than that in daily data. Therefore, the effects of autocorrelation and heteroscedasticity cannot be ignored while estimating parameters, especially in the daily data study.

Table 6. 5:
ARCH Effect Test of Regression Residuals

	Volatility Timing Model		Market Timing Model		Joint Timing Model	
	R^2	LM test	R^2	LM test	R^2	LM test
Panel A: monthly returns						
Asia excluding Japan	0.5263	1.25	0.5280	1.20	0.5252	1.36
Asia including Japan	0.4716	15.57***	0.4732	15.53***	0.4730	14.87***
Japan	0.2574	3.95**	0.2749	2.71	0.2607	1.96
Europe excluding UK	0.7551	3.34*	0.7581	4.22**	0.7455	5.25**
Europe including UK	0.3095	94.75***	0.3126	94.50***	0.2998	94.77***
UK	0.9661	15.71***	0.9684	25.70***	0.9650	29.76***
North America	0.6103	0.01	0.6151	0.11	0.6108	0.01
Global	0.8032	19.27***	0.8096	24.63***	0.8025	20.51***
All	0.9207	0.19	0.9251	0.33	0.9199	0.22
Panel B: daily returns						
Asia excluding Japan	0.2197	199.97***	0.2223	199.07***	0.2203	194.16***
Asia including Japan	0.1715	136.13***	0.1742	141.04***	0.1719	135.60***
Japan	0.0516	244.24***	0.0518	250.25***	0.0498	249.59
Europe excluding UK	0.3816	648.20***	0.3854	630.97***	0.3837	641.51***
Europe including UK	0.0953	43.03***	0.0966	43.08***	0.0953	43.02***
UK	0.5416	801.00***	0.5465	671.87***	0.5416	791.72***
North America	0.1282	368.09***	0.1285	392.90***	0.1270	365.42***
Global	0.3219	3.66*	0.3252	3.93**	0.3218	3.56*
All	0.4720	445.84***	0.4762	425.29***	0.4721	430.99***

This table presents the test statistics of model goodness-of-fit and ARCH effect regarding the monthly and daily data reported in Panel A and Panel B, respectively. This table exhibits the test statistics across three timing models.
Volatility timing model: $R_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} R_{jt} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m)R_{mt} + \varepsilon_{pt};$
Market timing model: $R_{pt} = \alpha_p + \sum_{j=1}^{4} \beta_{jp} R_{jt} + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m)R_{mt} + \beta_{2mp}R_{mt}^2 + \varepsilon_{pt};$
Joint timing model $r_{p,t} = \alpha + \sum_{j=1}^{4} \beta_j r_{j,t} + \gamma \left(\frac{r_{m,t}}{\sigma_{m,t|s_{t-1}}}\right)^2 + \varepsilon_t.$
R^2 denots the goodness of fit test. LM test denotes the Lagrange multiplier test reporting the significance of heteroscedasticity in the regression residual terms.
The monthly market volatility, adopted in the monthly data analysis, is calculated by the standard deviation of the market excess daily returns. The daily market volatility, employed in the daily data analysis, is calculated by the EGARCH(2, 2) model.
The symbols ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

The significance of LM test statistics is not surprising because literature has agreed with the presence of autoregressive conditional heteroscedasticity (ARCH) effect in high-frequent data, thereby proposing ARCH-type models to deal with ARCH effect (Nelson, 1991). The core idea of ARCH-type model is the additional parameter of conditional variance responding to the correlation between the current level of volatility and its level during the immediately preceding period. ARCH is a dynamic model, allowing volatility shocks to persist over time then accounting for volatility clustering and time variation. By this construction, the ARCH family can better correct the ARCH effect and produce efficient and reliable inference. As we use ARCH-type model to solve econometric problems in parameter estimation, the phenomenon of asymmetric volatility is not a significant problem. Thus, we select the standard GARCH (1, 1) with t-distribution to estimate parameters; the t-distribution accounts for the high excess kurtosis of returns of unit trusts and explanatory variables.

6.5.2 Factor Importance: Market volatility v.s. Style volatility

This study concentrates on market volatility rather than considering the volatility of style factor returns because the average contribution of other three factors (i.e., size, value, and momentum) are so small that we do not expect managers timing volatilities of investment styles. We provide evidence that the contribution of market volatility is significantly larger than contributions of style factors below following Busse's (1999) approach.

The conditional variance of unit trusts portfolio returns is broken down into components associated with each of the four factors. We assume that the four factors are orthogonal. The variance of a trust portfolio can be expressed as:

$$\sigma_t^2(R_{pt+1}) = \sum_{j=1}^{4} \beta_{jpt}^2 \, \sigma_{jt+1}^2 + \sigma_t^2(\varepsilon_{pt+1}). \quad (6.14)$$

The deconstruction reveals how the amount of information of each orthogonal variable contributes to the dependent variable. The contribution of each factor’s variance to the total variance of unit trusts portfolio can be measured based on Equation (6.14). More specifically, we only include the variance of market excess return in the variance breakdown model initially, estimating the coefficient for the market variance. Next, we fix the coefficient of market variance to control the contribution from the information of market variance and add the factor of size’s variance to the breakdown model to estimate the coefficient for size factor’s variance. The remaining coefficient for each factor’s variance can be estimated in the same manner. Last, we use Equation (6.15) to measure each factor’s contribution:

$$C_j = \frac{\beta_{jp} * \bar{\sigma}_j^2}{\bar{\sigma}_p^2}, \quad (6.15)$$

where C_j is the contribution of factor j; β_{jp} is the estimated coefficient in the regression for factor j; $\bar{\sigma}_j^2$ and $\bar{\sigma}_p^2$ are the average variance of factor j and UK unit trusts portfolio.

In the context of UK equity unit trusts, the average of daily conditional variance of the excess return on the FTSE All-Share Index, the orthogonal SMB, the orthogonal HML, and the orthogonal MMC indices are 0.0107%, 0.0050%, 0.0038%, and 0.0063%, respectively. Factor of market index contributes of 89.88% of the variance explained by the four-factor model at an aggregate level, while the rest of factors only contributes of 3% (size), 0.15% (value), and 6.3% (momentum) of the variance averagely, in line with Busse’s (1999, p. 1019) finding in the US mutual fund market.

These contributions depend on the order in which we orthogonalize the factors. More specifically, if we take the size index as the first index instead of the market index, the size index can explain the portfolio variance up to 86%. Likewise, if we take the momentum or value index first, the explanation power of those two indices is up to 63% and 35.72%, respectively. Busse (1999) advocates the notion that index taken first usually dominates that of the other indices. However, if Fama-French model or Carhart model cannot accurately capture fund investment style Ferson and Harvey (1999), Ferson, Sarkissian, and Simin (1999), why fund managers would time the volatility of size, value, and momentum (Busse, 1999). Therefore, we maintain that fund manager rarely time the volatility of size, value and momentum. It is valid and reasonable to implement the volatility-timing model of Equation (6.9) in our empirical study.

6.5.3 Market-volatility Timing Performance: Daily Data Analysis

Panel A of Table 6.6 exhibits the empirical results of market-volatility timing performance on daily data under the GARCH (1, 1) estimate method. On average, we reveal successful volatility timing performance at the 1% significance level for the aggregate UK-authorized equity unit trusts by using daily returns, indicated by significant negative volatility-timing coefficient β_{1m} and large t-statistics in the last row of Panel A. Negative coefficient β_{1m} implies that fund managers counter-cyclically time the market volatility, that is, reducing portfolio's market exposure when the market risk increase and vice versa. Finding of counter-cyclical timing ability is consistent with Busse's (1999) finding of using daily data as well, suggesting that fund managers have the favourable volatility-timing ability. Equity unit trusts timing the market volatility counter-cyclically produce positive abnormal return at 5% significance level, indicated by the statistics of alpha in the second column α of Table 6.6.

Moreover, UK equity unit trusts employ different investment strategies with respect to different geographic investment objectives. In particular, equity trusts concentrating on specific countries' stock market tend to adopt counter-cyclical volatility-timing strategy, indicated by the significant negative volatility-timing coefficients in the geographic-groups of Japan and the UK, recorded in the column of β_{1m} in Panel A of Table 6.6. By contrast, UK unit trusts whose holdings located in a region containing several countries' markets either fail to exhibit significant volatility-timing skill (e.g., Asia, North America, and global) or adopt pro-cyclical volatility-timing ability (e.g., Europe). The potential reason might be the market daily volatility indices in different countries within an object of investment area are various.

6.5.4 Market-volatility Timing Performance: Daily Data v.s. Monthly Data

Panel B of Table 6.6 demonstrates volatility-timing performance on monthly data. The findings on monthly data are different from the findings on daily data. We find unfavourable volatility timing performance for UK equity unit trusts in the aggregate, indicated by the positive coefficient β_{1m} in Panel B, implying pro-cyclical volatility timing behaviour. The finding based on monthly data analysis is in line with Foran and O'Sullivan's (2017) finding of large percentage of UK equity mutual funds timing market volatility pro-cyclically. Foran and O'Sullivan (2017) adopt monthly returns of UK mutual funds.

Moreover, aggregate UK-authorized equity unit trusts show pro-cyclical volatility timing performance at the 10% significance level, reported in the last row of Panel B in Table 6.6. UK domestic and UK Europe equity unit trusts display pro-cyclical volatility timing strategy at 1% significance level. UK equity trusts whose investment objective focus on Asia, North America and global fails to uncover significant ability of timing market volatility. In addition, we find the statistics of alpha in the second column α of Panel B are negative, implying a negative abnormal returns for UK equity unit trusts on average. In particular, UK domestic and UK Japan equity unit trusts provide negative abnormal return at the 1% significance level.

The different findings from daily and monthly data might be attributed to the correlation between monthly market return and volatility. To be specific, the correlation between FTSE All-Share index monthly excess returns and the monthly volatility of index returns is –0.33 over our research period, whereas the corresponding correlation between excess daily returns and daily volatility is only 0.02. As discussed in the above (see Sub-section 6.4.1), it would be possible that the timing manifests of market returns timing are reported in the volatility coefficients under the pure volatility-timing model. Thus, we further to use Equation (6.11) to re-evaluate market-volatility timing performance conditional on market-return timing behavior.

Table 6. 6:
Market-volatility Timing Performance Estimated by GARCH (1, 1) with t-distribution

	α	β_m	β_{smb}	β_{hml}	β_{mom}	β_{1m}	R^2	LM test
Panel A: Daily Data								
Asia excluding Japan	0.00014	0.5305	0.4381	–0.0364	–0.0047	0.1774	0.2173	1.43
	(1.47)	(42.47)	(24.82)	(–2.08)	(–0.33)	(0.11)		
Asia including Japan	0.00014	0.5019	0.4509	–0.0205	–0.0080	0.2759	0.1699	4.00*
	(1.42)	(35.89)	(23.59)	(–1.06)	(–0.51)	(0.15)		
Japan	–0.00016	0.2793	0.2474	–0.0721	–0.0214	–7.77	0.0503	12.43***
	(–1.43)	(18.71)	(12.48)	(–3.72)	(–1.30)	(–4.19)		
Europe excluding UK	0.00013	0.6974	0.4689	–0.0727	–0.0052	4.8905	0.3805	40.64***
	(1.75)	(64.91)	(30.97)	(–4.94)	(–0.42)	(3.21)		
Europe including UK	0.00015	0.6408	0.4574	–0.0691	–0.0038	5.5376	0.0951	0.00
	(2.15)	(66.69)	(33.90)	(–5.37)	(–0.34)	(3.88)		
UK	0.00010	0.6341	0.4290	–0.0073	–0.0131	–4.6801	0.5379	24.20***
	(2.50)	(111.22)	(53.31)	(–0.98)	(–2.00)	(–4.66)		
North America	0.00023	0.4146	0.3324	–0.1496	–0.0073	–2.6834	0.1240	3.75**
	(2.40)	(32.23)	(18.14)	(–8.44)	(–0.47)	(–1.39)		
Global	0.00014	0.4774	0.3673	–0.0557	–0.0017	–1.9324	0.3199	0.08
	(2.52)	(65.12)	(35.67)	(–5.81)	(–0.20)	(–1.64)		
All	0.00009	0.5849	0.4191	–0.0401	–0.0076	–3.1801	0.4694	2.92*
	(2.05)	(92.43)	(46.30)	(–4.75)	(–1.05)	(–2.93)		
Panel B: Monthly Data								
Asia excluding Japan	–0.00124	1.0085	0.2240	–0.1119	0.0302	8.7166	0.5235	0.25
	(–0.55)	(16.68)	(3.15)	(–1.31)	(0.58)	(1.03)		
Asia including Japan	–0.00185	0.9777	0.3082	–0.0486	0.0625	6.9438	0.4695	1.14
	(–0.76)	(14.88)	(3.80)	(–0.49)	(0.96)	(0.69)		
Japan	–0.00740	0.7195	0.2032	–0.0263	0.0900	–10.6761	0.2549	0.39
	(–2.74)	(202.37)	(2.22)	(–0.20)	(1.32)	(–0.90)		
Europe excluding UK	–0.00025	1.0571	0.1756	–0.0953	0.0028	12.0138	0.7503	0.67
	(–0.18)	(29.69)	(4.22)	(–1.78)	(0.08)	(3.24)		
Europe including UK	–0.00067	1.0119	0.2005	–0.0806	–0.0154	13.6187	0.2939	0.00
	(–0.54)	(31.42)	(5.74)	(–2.02)	(–0.55)	(3.28)		
UK	–0.00104	0.9163	0.2823	–0.0186	0.0107	2.7953	0.9654	0.98
	(–2.61)	(88.41)	(25.86)	(–1.38)	(1.08)	(2.95)		
North America	0.00046	0.9180	0.0021	–0.2407	–0.0393	1.4500	0.6097	0.00
	(0.26)	(33.97)	(0.04)	(–3.13)	(–0.90)	(0.21)		
Global	–0.00102	0.8838	0.1476	–0.1313	0.0212	6.5334	0.8027	0.91
	(–1.06)	(34.98)	(5.08)	(–4.01)	(1.01)	(1.53)		
All	–0.00118	0.9113	0.2230	–0.0565	0.0165	4.9058	0.9206	0.50
	(–1.73)	(49.87)	(11.44)	(–2.47)	(1.06)	(1.78)		

This table reports the estimated coefficients for the volatility-timing model under GARCH (1, 1) with t-distribution estimation method,

$$R_{pt} = \alpha_p + \beta_m R_{mt} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{mom} MOM_t + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m) R_{mt} + \varepsilon_{pt}$$

Z-statistics are reported in the bracket. R^2 is the goodness of fit test for the mean equation of GARCH (1, 1). LM denotes the Lagrange multiplier test that is heteroscedasticity test.
Panel A shows sample coefficients of using daily data where the daily market volatility is measured by the EGARCH (2, 2) conditional on the past market daily returns. Panel B shows sample coefficients of employing monthly data where the monthly market volatility is calculated by the standard deviation of daily returns within each month.
The symbols ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

Table 6.7 reports the estimated coefficients for the market timing model Equation (6.11). In Panel B of Table 6.7, the significance of market-volatility timing coefficient disappears, and the coefficient of market-return timing factor is significantly negative at the 1% level. In contrast, evaluation of volatility-timing ability does not change after adding market-return timing term, which is supported by the previous discussion that the return-timing performance will not be explained by the volatility-timing coefficients if the correlation is too small. Furthermore, the finding of reverse return-timing performance is in line with the first study finding in this thesis (see Chapter 5). The dramatic decline of LM statistics indicates that GARCH method successfully addresses the econometric problem of the ARCH effect. LM test confirms that the results in our research are efficient and reliable.

Table 6. 7:
Market Return and Volatility Timing Performance Estimated by GARCH (1, 1) with t-distribution

	α	β_m	β_{smb}	β_{hml}	β_{mom}	β_{1m}	β_{2m}	LM test
Panel A: Daily Data								
Asia excluding Japan	0.00024	0.5225	0.4292	–0.0343	–0.0035	0.6962	–1.9527	0.99
	(2.36)	(41.82)	(24.28)	(–1.97)	(–0.24)	(0.41)	(–5.11)	
Asia including Japan	0.00019	0.4925	0.4416	–0.0195	–0.0054	0.9661	–1.3554	2.22
	(1.76)	(35.09)	(23.02)	(–1.02)	(–0.35)	(0.52)	(–3.20)	
Japan	–0.00017	0.2728	0.2402	–0.0695	–0.0197	–7.7239	–0.6048	8.32***
	(–1.41)	(18.25)	(12.09)	(–3.61)	(–1.20)	(–4.17)	(–1.28)	
Europe excluding UK	0.00026	0.6883	0.4584	–0.0721	–0.0048	5.8452	–2.9440	30.02***
	(3.11)	(63.38)	(30.14)	(–4.96)	(–0.38)	(3.42)	(–7.96)	
Europe including UK	0.00031	0.6364	0.4500	–0.0665	–0.0050	6.9614	–3.0318	0.00
	(3.96)	(65.76)	(33.18)	(–5.18)	(–0.46)	(4.42)	(–8.42)	
UK	0.00015	0.6297	0.4248	–0.0064	–0.0125	–3.8925	–1.4564	33.83***
	(3.39)	(108.70)	(52.35)	(–0.85)	(–1.88)	(–3.71)	(–6.42)	
North America	0.00019	0.3992	0.3199	–0.1480	–0.0042	–3.1982	–1.0454	0.02
	(1.87)	(30.86)	(17.57)	(–8.38)	(–0.28)	(–1.57)	(–2.19)	
Global	0.00019	0.4709	0.3615	–0.0547	–0.0002	–1.3405	–1.4859	0.06
	(3.20)	(63.36)	(35.18)	(–5.77)	(–0.02)	(–1.15)	(–5.29)	
All	0.00013	0.5804	0.4144	–0.0380	–0.0070	–2.7028	–1.3770	3.52*
	(2.64)	(90.31)	(45.78)	(–4.54)	(–0.97)	(–2.43)	(–5.26)	
Panel B: Monthly Data								
Asia excluding Japan	0.00017	1.0102	0.2283	–0.1090	0.0258	4.0314	–1.1542	0.43
	(0.06)	(16.87)	(3.18)	(–1.25)	(0.49)	(0.44)	(–1.29)	
Asia including Japan	–0.00017	0.9807	0.3028	–0.0431	0.0559	1.8078	–1.3495	0.74
	(–0.06)	(15.18)	(3.17)	(–0.42)	(0.84)	(0.18)	(–1.29)	
Japan	–0.00248	0.7357	0.2395	0.0105	0.0817	–24.8372	–3.1162	0.00
	(–0.76)	(9.56)	(2.45)	(0.09)	(1.17)	(–1.92)	(–2.38)	
Europe excluding UK	0.00036	1.0611	0.1733	–0.0918	0.0012	9.5208	–0.5764	0.68
	(0.22)	(29.59)	(4.15)	(–1.72)	(0.03)	(2.11)	(–0.98)	
Europe including UK	0.00167	1.0312	0.1940	–0.0608	–0.0247	3.9116	–2.0160	0.00
	(1.21)	(33.63)	(5.52)	(–1.58)	(–0.86)	(1.17)	(–4.36)	
UK	–0.00012	0.9170	0.2840	–0.0170	0.0100	0.2319	–0.7437	1.63
	(–0.26)	(95.39)	(25.55)	(–1.29)	(0.98)	(0.24)	(–4.94)	
North America	0.00202	0.9182	0.0057	–0.2336	–0.0438	–3.2722	–1.1334	0.03
	(0.93)	(31.16)	(0.10)	(–3.07)	(–0.97)	(–0.42)	(–1.37)	
Global	0.00036	0.8817	0.1440	–0.1241	0.0184	3.0781	–0.9452	1.89
	(0.31)	(35.50)	(4.89)	(–3.81)	(0.85)	(0.79)	(–2.31)	
All	0.00017	0.9126	0.2194	–0.0530	0.0075	1.1428	–1.2215	3.10*
	(0.20)	(53.03)	(12.78)	(–2.46)	(0.47)	(0.42)	(–5.01)	

This table reports the estimated coefficients for the market timing model under GARCH (1, 1) with t-distribution estimation method,

$$R_{pt} = \alpha_p + \beta_m R_{mt} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{mom} MOM_t + \beta_{1mp}(\sigma_{mt} - \bar{\sigma}_m)R_{mt} + \beta_{2mp}R_{mt}^2 + \varepsilon_{pt}$$

Z-statistics are reported in the bracket. LM denotes the Lagrange multiplier test that is heteroscedasticity test.
Panel A shows sample coefficients of using daily data where the daily market volatility is measured by the EGARCH (2, 2) conditional on the past market daily returns. Panel B shows sample coefficients of employing monthly data where the monthly market volatility is calculated by the standard deviation of daily returns within each month.
The symbols ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

We maintain that high-frequent dataset provides better and more reliable evidence on volatility-timing performance evaluation than monthly data set. On the one hand, fund managers do analysis every day and trading intermittently. The daily data can monitor high frequent investment behavior better than monthly data, which is vital for timing behavior analysis because inference would be biased due to inconsistent horizon between research and real decision. On the other hand, in comparison to market return, market volatility is fairly dynamic and shorter-lived volatility dynamics can be typically observed with high-frequent dataset, see Figure 6.2.

Overall, the empirical results advocate that daily returns reveal significant counter-cyclical volatility-timing strategy for the UK equity unit trusts in the aggregate. Our finding also confirms Busse's (1999) analysis that fund managers, on average, would tend to adopt market-volatility timing strategies rather than market-return timing strategies due to the persistence of forecastable volatility. Moreover, the comparison between daily and monthly data analysis provide proof that daily data performs better than monthly data in volatility-timing performance evaluation.

6.5.5 Joint Timing Performance

Table 6.8 exhibits the results of joint timing performance demonstrated by the squared market Sharpe-ratio term in the Equation (6.13) under the GARCH (1, 1) with the t-distribution estimation method. The coefficients in Panel A are estimated by using daily data, and the estimated coefficients in Panel B are for monthly data. We expect to obtain a significant positive coefficient for market Sharpe-ratio. More specifically, the Sharpe ratio rises when the expected market excess return increases given a target standard deviation, or the standard deviation of market returns decreases given the expected market excess return. When the Sharpe ratio increases, fund managers would increase the market exposures of trust portfolios, in order to obtain extra value given the market risk.

However, on average, we cannot find significant joint timing coefficients for both daily and monthly data, indicated by the value of γ in the last row of each Panel. For geographic-groups of unit trusts, the evidence of joint timing performance is scarce to be observed across both dataset analysis, indicated by the insignificant coefficient γ. There are three exceptions: regional groups of Asia excluding Japan, Europe including and excluding UK, reported in panel A of Table 6.8. Trusts sorted into these three regional groups show joint timing behavior at 1% significant level, suggesting that managers might consider market returns and risk together when making an investment decision. The sign of the coefficient, however, is negative, which is opposite to the results from Chen and Liang (2007) who find a significant positive relation between U.S. hedge fund returns and squared Sharpe ratio of the U.S. market portfolio. The hedge funds in their research sample declare to adopt a market timing strategy, whereas we cannot find information about timing strategy for UK equity unit trusts in our database.

By contrast, Table 6.7 displays significant coefficients of market-volatility and market-return timing terms, suggesting that fund managers do switch the portfolio’s risk level according to the market conditions change. Furthermore, positive volatility-timing ability and negative return-timing skill might be a reason for the negative sign of Sharpe-ratio term. We, therefore, conclude that managers of UK equity unit trusts can successfully time the market volatility, but time market returns inefficiently, and they do not combine these two timing strategies but adopt them separately.

Table 6. 8:
Joint Timing Performance Estimated by GARCH (1, 1) with t-distribution

	α	β_m	β_{smb}	β_{hml}	β_{mom}	γ	R^2	LM test
Panel A: Daily Data								
Asia excluding Japan	0.00021	0.5253	0.4326	–0.0353	–0.0024	–0.0001	0.2177	0.99
	(2.05)	(44.06)	(24.58)	(–2.02)	(–0.17)	(–2.98)		
Asia including Japan	0.00015	0.4960	0.4448	–0.0201	–0.0050	–4.99e-05	0.1700	2.17
	(1.28)	(37.30)	(23.24)	(–1.05)	(–0.33)	(–1.07)		
Japan	–0.00017	0.2548	0.2445	–0.0732	–0.0094	–4.21e-05	0.0494	9.41***
	(–1.34)	(18.33)	(12.36)	(–3.79)	(–0.58)	(–0.77)		
Europe excluding UK	0.00028	0.6919	0.4604	–0.0714	–0.0073	–0.0002	0.3818	22.28***
	(3.30)	(65.11)	(30.34)	(–4.91)	(–0.60)	(–7.29)		
Europe including UK	0.00028	0.6408	0.4545	–0.0654	–0.0071	–0.0002	0.0950	0.00
	(3.51)	(69.11)	(33.58)	(–5.10)	(–0.65)	(–5.58)		
UK	0.00009	0.6293	0.4270	–0.0079	–0.0094	–2.59e-05	0.5394	31.82***
	(2.06)	(110.30)	(52.71)	(–1.06)	(–1.44)	(–1.58)		
North America	0.00010	0.4170	0.3292	–0.1425	–0.0257	–2.40e-05	0.1270	53.96***
	(0.25)	(12.11)	(6.61)	(–2.89)	(–0.67)	(–0.15)		
Global	0.00012	0.4703	0.3640	–0.0564	0.0022	–1.87e-05	0.3213	0.04
	(1.88)	(66.19)	(35.45)	(–5.95)	(0.27)	(–0.73)		
All	0.00009	0.5794	0.4160	–0.0397	–0.0040	–3.21e-05	0.4707	2.96*
	(1.65)	(91.57)	(46.02)	(–4.74)	(–0.57)	(–1.53)		
Panel B: Monthly Data								
Asia excluding Japan	–0.00142	1.0554	0.2606	–0.0954	0.0358	–4.18e-05	0.5222	0.35
	(–0.54)	(20.18)	(3.72)	(–1.15)	(0.69)	(–0.56)		
Asia including Japan	–0.00068	1.0273	0.3223	–0.0378	0.0696	–9.35e-05	0.4710	0.63
	(–0.24)	(16.34)	(3.99)	(–0.38)	(1.07)	(–1.39)		
Japan	–0.00401	0.6954	0.1867	–0.0372	0.1066	–0.0001	0.2572	0.30
	(–1.23)	(10.22)	(2.07)	(–0.29)	(1.49)	(–1.18)		
Europe excluding UK	–0.00199	1.1050	0.2094	–0.0902	–0.0109	2.35e-05	0.7393	0.37
	(–1.23)	(34.34)	(5.41)	(–1.77)[c]	(–0.30)	(0.59)		
Europe including UK	–0.00075	1.0878	0.2292	–0.0962	–0.0161	–6.07e-05	0.2877	0.00
	(–0.53)	(37.91)	(6.54)	(–2.49)	(–0.57)	(–1.78)		
UK	–0.00095	0.9240	0.2891	–0.0167	0.0087	–1.01e-05	0.9643	0.81
	(–2.14)	(101.95)	(25.71)	(–1.24)	(0.89)	(–0.95)		
North America	0.00088	0.9310	0.0055	–0.2355	0.0377	–2.42e-05	0.6100	0.00
	(0.41)	(20.65)	(0.10)	(–3.11)	(–0.84)	(–0.39)		
Global	–0.00161	0.9275	0.1849	–0.1280	0.0140	–2.15e-05	0.8019	4.03**
	(–1.35)	(38.84)	(6.80)	(–3.73)	(0.60)	(–0.60)		
All	–0.00120	0.9524	0.2140	–0.0306	0.0251	–2.89e-05	0.9191	2.46
	(–1.40)	(60.73)	(11.20)	(–1.36)	(1.55)	(–1.28)		

This table reports the estimated coefficients for the market timing model under GARCH (1, 1) with t-distribution estimation method,

$$R_{pt} = \alpha_p + \beta_m R_{mt} + \beta_{smb} SMB_t + \beta_{hml} HML_t + \beta_{mom} MOM_t + \gamma \left(\frac{r_{m,t}}{\sigma_{m,t|s_{t-1}}}\right)^2 + \varepsilon_{pt}$$

Z-statistics are reported in the bracket. R^2 is the goodness of fit test for the mean equation of GARCH (1, 1). LM denotes the Lagrange multiplier test that is heteroscedasticity test.

Panel A shows sample coefficients of using daily data where the daily market volatility is measured by the EGARCH (2, 2) conditional on the past market daily returns. Panel B shows sample coefficients of employing monthly data where the monthly market volatility is calculated by the standard deviation of daily returns within each month.

The symbols ***, ** and * represent significance at the 1%, 5% and 10% level, respectively.

6.6 Conclusions

This study examines market timing performance from two dimensions: market volatility and market return. We use daily data since it performs better than monthly data by demonstrating high frequent timing activity. We use GARCH to estimate parameters because daily data suffer a significant ARCH effect. We first study volatility timing ability alone. We find significant successful volatility-timing ability by using daily data but reverse volatility-timing skill from monthly data, suggesting that data frequency is essential for volatility-timing performance evaluation.

Moreover, as the correlation between volatility and returns is large for monthly data and small for daily data, the evaluation of volatility-timing performance might be biased due to the correlation. We study volatility-timing performance conditional on the market-return term and find that counter-cyclical volatility-timing finding remains in the daily data analysis, while the significant volatility-timing finding disappears in the monthly data study. These results imply that the return-timing performance is manifested in the volatility-timing coefficients in the monthly data analysis due to the large correlation. Besides, we find significant adverse return-timing skill in the conditional volatility-timing model. The consistent reverse return-timing performance in empirical studies suggests that managers tend to increase market exposure when the market returns decline and vice versa. The irregular return-timing behavior deserves more academic attention in future study.

In addition, we examine joint timing performance, failing to find significant coefficients for Sharpe-ratio term. Thus, we point out that trust managers can counter-cyclically time market volatility and reversely time market returns separately, but do not employ these two timing strategies jointly. We also suggest that trust managers, on average, would tend to adopt market-volatility timing strategy rather than market-return timing strategy due to the characteristics of volatility: persistent and forecastable.

Chapter 7: Relationship between Realized Returns of UK Unit Trust and Trust-specific Unique Risk and Volatility Investment Strategy

7.1 Introduction

Modern asset pricing theory assumes that expected returns are a function of risk, whereby risk is measured by the variance or standard deviation of returns. Not all risk is priced in the conventional pricing model, as idiosyncratic risk can be eliminated in a well-diversified portfolio. Idiosyncratic risk is the possibility that the price of an asset may decline due to an event which could specifically affect the asset but not the market as a whole; that is, idiosyncratic risk is a firm-level unsystematic risk. Relatively, systematic risk refers to market risk. However, empirical studies document that investors usually hold a small fraction of thousands of traded securities available when constructing their actual portfolios (e.g., Merton, 1987; Campbell et al., 2001; Goetzmann and Kumar, 2008; Polkovnichenko, 2005; Duxbury et al., 2013); idiosyncratic risk, thus, would not be eliminated in the real investment portfolio.

The idiosyncratic risk referring to the shocks for a particular firm is significantly related to the selectivity ability evaluation for an active fund manager. However, if a firm publicly reports a piece of news resulting in the share price volatile, all fund managers would give a response to this news while making their investment decision. As a managed portfolio strategy using public information should not be judged as having superior performance (Ferson and Schadt, 1996), the part of idiosyncratic risk regarding the public news should be priced. The unpriced idiosyncratic risk for each active mutual fund would be relative to the private information of the individual fund manager. Therefore, it is essential to account for public firm-level shocks when assessing the selectivity skill of a fund manager relative to peers.

The breakdown of total idiosyncratic risk of active mutual funds is significant for two reasons: First, investors would pay equal or more attention to idiosyncratic risk than market risk, as firm-level idiosyncratic volatility is increasingly volatile. Campbell *et al.* (2001) display a significant positive tendency in firm-level idiosyncratic volatility, indicated by the decline of correlations in stock performance in previous decades. Second, investors who would like to grab additional value have to pick up mis-specified individual stocks. As the pricing errors are possibly larger when idiosyncratic volatility is high (Shleifer and Vishny, 1997), fund managers would mainly deal with idiosyncratic shocks volatility rather than aggregate market volatility.

We deconstruct the total firm-level idiosyncratic shocks into aggregate shocks and trust-specific residuals. The aggregate idiosyncratic shocks capture the typical response of managers to the public news, which is not reflected in the market immediately. The news might be macro-information such as Brexit and Trade War, or might be specific firm news such as Steve Jobs' death. The research department of each fund company would gather and analyse these pieces of news, providing a report and sharing with colleagues. Further, managers might share information through a social network such as Facebook or Twitter. This public firm-level information should be priced by aggregate idiosyncratic shocks (AIS).

This study investigates the trust-specific unique risk for each UK equity unit trusts measured by the volatility of residuals controlling the AIS. The unit trust is a type of open-ended mutual funds in the UK fund market. The trust-specific unique risk would accurately capture individual fund manager's selectivity skill and risk-taking behavior which is different from peers. We assume that the trust-specific residuals mainly rely on the manager's private information and their investment objective.

We examine the relationship between realized returns of unit trusts and their trust-specific unique risk, exploring whether trust managers can produce higher returns for trust investors when they take a higher unique risk. This study focuses on realized returns because Karceski (2002) demonstrates that mutual fund investors exhibit return-chasing behavior, and realized returns are the profits received by investors. Pástor and Stambaugh (2002) support the notion that investing in equity mutual funds involves a combination of historical fund data and managerial skill judgements. The relationship study would offer fund investors a way of selecting between unit trusts with the same standard deviation of total returns. To be specific, if we find a significant positive relationship between realized returns and unique risk, we would suggest investors select the unit trust with high unique risk and less exposure to the market based on their risk tolerance and capability, as there is a high possibility for that trust to achieve relatively high future returns.

In addition, this thesis studies whether fund managers take benefits from low volatility stocks in the context of volatility anomaly. Volatility anomaly suggests that low volatility portfolio constructed by stocks with a low standard deviation of returns or beta coefficients outperforms corresponding high volatility portfolio (Haugen and Heins, 1972; 1975). The volatility anomaly is remarkable, persistent and comprehensive (Baker and Haugen, 2012); exists in the global stock markets (Ang et al., 2009; Blitz and van Vliet, 2007; Chen et al., 2012; Frazzini and Pedersen, 2014); and extends to bonds, credit, and futures markets across many different countries (Frazzini and Pedersen, 2014).

Some studies claim that the presence of volatility anomaly partly due to risk-seeking behavior of investors. Market participants are irrational and have a higher demand for high-volatility stocks, but the "smart money" fails to offset this irrational demand due to institutional investors holding high-volatility stocks as well (Baker, Bradley, and Wurgler, 2011). Moreover, high volatility investment is an easy way to beat the market. Fund investors tend to chase returns through time; high-risk stocks easily outperform the market during bull markets (Karceski, 2002). On the other hand, Jordan and Riley (2015) empirically document that US mutual fund managers take advantage of volatility anomaly by picking up under-priced low-volatility stocks. The contradiction between theory and practice motivates us to shed lights on the volatility investment strategy of UK equity unit trusts in the context of volatility anomaly.

This research has the following contributions. Initially, we use actively managed real portfolio (i.e., UK equity unit trusts) to deeply investigate idiosyncratic risk relative to firm-level shocks and the manager's investment decision. By contrast, prior studies simulate stock portfolios to examine idiosyncratic risk relying solely upon firm-level shocks. Secondly, this study proposes an easy way to measure a manager's unique risk decision relative to peers, requiring historical returns of unit trusts that fund investors are interested in and the stock market index returns. We then use this trust-level unique risk to predict the tendency of UK unit trust's future returns. The previous study, Cremers and Petajisto (2009), creates "Active Share" to predict US mutual fund performance. The Active Share is the part of portfolio holdings that is different from the benchmark index holdings. Although Active Share accurately measures idiosyncratic returns of the fund portfolio, it cannot be implemented in other fund markets without holding data. Thirdly, we study the relationship between realized returns and trust-specific unique risk from various perspective: short-term and long-term, as well as cross-sectional within each month and time-series for each unit trust.

This study uses daily and monthly returns of UK domestic equity unit trust from June 1990 to July 2015. We break down the total returns of individual unit trust into market returns, aggregate idiosyncratic shocks, and trust-specific unique returns. We follow Hunter et al.'s (2014) idea to construct aggregate idiosyncratic risk factor, which is the sum of estimated alpha and residuals of regressing trusts aggregate returns on the market index factor (i.e., AIS). As we price market risk only, the residuals would contain all unpriced systematic risk relative to common investment strategies on market anomalies such as size, value, or momentum as well as a typical response to public firm shocks. We add the estimated AIS to the conventional single-index asset pricing model and measure the trust-specific unique risk as to the standard deviation of regressed residuals for each unit trust.

We find three preliminary findings. The first finding is a positive relationship between realized returns of unit trusts and their trust-specific unique risk in the short term across all trusts and a positive but insignificant relationship in the long term for individual trusts. Our advice on unit trust strategy could be selecting relative higher risk trusts given the risk tolerance and capability and avoiding to hold the same trust for a very long term.

Moreover, the short lagged unique risk could be an efficient predictor of future performance of UK unit trust, producing consistent positive relation with contemporise conditional unique risk. However, long lagged unique risks, such as 3-month, 6-month, or 12-month lagged unique risk, cannot be an appropriate predictor for expected risk since the relationship between realized returns and long lagged risk is either approximate to zero or negative. This finding also implies that a positive relation is not consistent.

Additionally, we find that unit trusts with high unique risk still prefer to hold relatively high volatility and low beta stocks, producing better returns than unit trusts with low unique risk. This finding indirectly supports the hypothesis that the presence of volatility anomaly could partly attribute to the risk-chasing behavior of market participant.

The remainder of this chapter is organized as follows. Section 7.2 describes the trust-specific unique risk estimation. Section 7.3 states the data and descriptive statistics. Section 7.4 explains the methodologies of the relationship study and volatility investment strategy evaluation, followed by the empirical results and discussion in Section 7.5. Section 7.6 concludes.

7.2 Trust-specific Unique Risk Estimation

The unique risk of individual unit trusts mainly relies on the trust manager's unique investment decision manifested in the stock holdings differing from peers. We cannot directly measure unique risk by calculating the variance of different holdings for each trust due to the absence of holding data for UK unit trusts. We, therefore, propose an indirectly return-based method to measure trust-specific unique risk.

We assume that trust managers' decision-making relies on public and private information. The conventional asset pricing model suggests that market excess returns can capture public information at the market level. However, if a piece of firm news does not disclose the market return but is reported publicly, the risk regarding this news, referred to as the firm-level idiosyncratic risk should also be priced when measuring unique risk for each unit trust. The residuals of controlling for returns generated by processing public market-level and firm-level information would represent the trust-specific unique returns produced by processing private information. This study proposes to use aggregate idiosyncratic shocks to represent firm-level public information, and the trust-specific unique risk would be measured as the standard deviation of augmented residuals.

7.2.1 Trust-specific Unique Risk Identification

We explain the trust-specific unique risk from the return generating process. More specifically, we assume that there are n stocks available in the market. Let $\tilde{R}_i$ denote the actual reported returns of stock i, and w_i denote the fraction of underlying assets of equity unit trust p allocated to security i, where $i = 1, 2, \ldots, n$. We assume there are N unit trusts available in the market. Returns of trust portfolio p, $\tilde{R}_p, i = 1, 2, \ldots, N$, can be written as:

$$\begin{aligned}\tilde{R}_p &= (1 - \textstyle\sum_1^n w_i)\tilde{R}_f + \sum_1^n w_i \tilde{R}_i \\ &= \tilde{R}_f + \textstyle\sum_1^n w_i(\tilde{R}_i - \tilde{R}_f),\end{aligned} \tag{7.1}$$

where $\tilde{R}_f$ denotes the risk-free return from three-month UK Treasury bill. We assume that the equity unit trusts hold only Treasury bills and common stocks for simplicity. In the following research, we denote, by $r_i = \tilde{R}_i - \tilde{R}_f$ and $r_p = \tilde{R}_p - \tilde{R}_f$, the excess returns of common stock i, and excess returns of unit trust p, respectively. The variance of excess returns of unit trust p can be written as:

$$var(r_p) = \textstyle\sum_1^n w_i^2 var(r_i) + 2\sum_1^n w_i \sum_1^{n-1} w_j\, cov(r_i, r_j); j \in n\ but\ j \neq i, \tag{7.2}$$

where $\mathrm{var}(r_i)$ denotes the variance of excess returns of stock i, and $cov(r_i, r_j)$ denotes the covariance of excess returns between two different stocks i and j. The variance of individual unit trust mainly depends on the weights of stock i in the trust portfolio. If the stock i is not selected in the trust portfolio p, the weight of this stock i will be zero in the function of trust portfolio return and variance.

We further assume that managers holding the same stock i have unbiased information about a particular stock, which is known as conditional-homogeneous-beliefs (Grossman and Stiglitz, 1976). This assumption could assist us in constructing commonality variables to capture all shared information among managers. If the covariance between stocks i and j is high, we would assume the firms i and j in the same industry. The unique risk for a unit trust p is the variance of the trust's total return subtracting variance of average returns with peers.

7.2.2 Aggregate Idiosyncratic Shocks Construction

If the exact holdings are available for each unit trust, the variance of commonality can be directly calculated by the variance of stocks embraced in all unit trusts. However, data on stock allocation in UK unit trusts are not available as is the case for US mutual funds. We indirectly solve the problem by constructing a commonality variable. This commonality represents common responses of unit trusts managers in our research sample to the public firm-level news.

We borrow Hunter et al.'s (2014) methods of constructing an active peer benchmark in which the benchmark represents an equal investment in all same-category funds. To be specific, we assume that the returns and errors of unit trust p have the following structure:

$$r_p = \alpha_p + \beta r_m + \varepsilon_p;\ \varepsilon_p = \rho_p L_p + \omega_p, \tag{7.3}$$

and aggregate portfolio returns of unit trusts and the portfolio's error term can be expressed as:

$$r_a = \alpha_{ais} + \beta r_m + \varepsilon_{ais};\ \varepsilon_{ais} = \rho_{ais} L_a + \omega_{ais}, \tag{7.4}$$

where L is a zero-mean random variable (i.e., an unpriced risk factor); ω is an independent and identically distributed (across funds) error term. r_p denotes excess returns of unit trust p; r_a denotes aggregate excess returns of all unit trusts in our research sample; r_m denotes the excess returns of the stock market. From Equation (7.4), we can get:

$$L_a = \frac{\varepsilon_{ais}}{\rho_{ais}} - \frac{\omega_{ais}}{\rho_{ais}}. \tag{7.5}$$

If there is a commonality in investment strategies, the asset pricing model errors are correlated across unit trusts. The unpriced risk factor L_a from unit trust aggregate returns would be able to explain part of the unpriced risk factor L_p for each unit trust p (Hunter et al., 2014).

Substituting Equation (7.5) into Equation (7.3), the returns of unit trust p can be re-written as:

$$
\begin{aligned}
r_p &= \alpha_p + \beta r_m + \rho_p \left(\frac{\varepsilon_{ais}}{\rho_{ais}} - \frac{\omega_{ais}}{\rho_{ais}} \right) + \omega_p \\
&= \alpha_p + \beta r_m + \frac{\rho_p}{\rho_{ais}} \varepsilon_{ais} + (\omega_p - \frac{\rho_p}{\rho_{ais}} \omega_{ais}).
\end{aligned}
\tag{7.6}
$$

Therefore, if a unit trust p adopts the same investment strategies to peers at the aggregate level, the residual of the unit trust ε_p would be sufficiently correlated with residual of trust aggregate portfolio ε_{ais}. It would lower the variance of residual by adding ε_{ais} to the standard CAPM model (Hunter et al., 2014). The reduced variance could be attributed to equal investment or similar holdings. Consequently, aggregate residuals ε_{ais} represent commonality generated by employing a similar investment strategy.

As α_{ais} measures abnormal returns due to stock-picking skill at the aggregate level, we include alpha value to adjust the abnormal return of individual unit trust p. Moreover, the correlation between $(\alpha_{ais} + \varepsilon_{ais})$ and r_m is significant zero, suggesting that $(\alpha_{ais} + \varepsilon_{ais})$ could capture commonality among fund industries independently. Therefore, we name $(\alpha_{ais} + \varepsilon_{ais})$ aggregate idiosyncratic shocks (AIS), considering as the second standard variable.

7.2.3 Trust-specific Unique Risk Estimation

In this study, we assume that public information mainly contains stock market returns, and unit trust managers shared information. As equity unit trusts in our research sample must hold equities over 80%, stock market returns would be one significant standard variable contributing to the total returns of an individual unit trust. In addition, fund managers share information that has not been disclosed on the stock market through their network. The shared information could be good or bad news for a specific firm; there is a high possibility of employing a similar investment strategy for trust managers by processing this shared firm-level news. We, therefore, add the constructed variable of aggregate idiosyncratic shocks (AIS) to asset pricing model to account for investment strategy commonality.

We then break down the individual trust return p into three components: returns from common stock market represented by the FTSE All-Share index returns, returns from common investment strategy represented by the AIS and returns from unique holdings α_p. The excess returns of unit trust p can be re-written as:

$$
r_p = \alpha_p + \beta r_m + \gamma AIS + \epsilon_p;\ \epsilon_p = \delta_p Uni_p + \tau_p, \tag{7.7}
$$

where Uni_p is a zero-mean random variable (i.e., an unpriced risk factor for individual unit trust p), and ϵ_p is an independent and identically distributed error term. The variance of excess returns of equity unit trust p also can be written as:

$$var(r_p) = \beta_p^2 var(r_m) + \gamma_p^2 var(\varepsilon_{ais}) + \delta_p^2 var(Uni_p), \tag{7.8}$$

where $\mathrm{var}(r_p)$ denotes the variance of excess returns of individual unit trust p; $\mathrm{var}(r_m)$ denotes the variance of excess market returns; $\mathrm{var}(\varepsilon_{ais})$ denotes the variance of idiosyncratic shocks at an aggregate trust level; and $\mathrm{var}(Uni_p)$ denotes the variance of additional returns for each unit trust p after controlling for commonalities at the stock market level and unit trust market level. We, therefore, define $\sigma(Uni_p)$ as a trust-specific unique risk for each unit trust p.

7.3 Data and Descriptive Statistics

7.3.1 Data

This study uses monthly returns of UK domestic equity unit trusts from January 1990 to June 2015. Our research sample focuses on equity unit trusts whose assets are at least 80% allocated on equities based on the definition of Investment Association. Moreover, our sample restricts the trusts' holdings to UK domestic equity markets, ensuring the market information and expected returns of the market are equal across all equity unit trusts. Besides, this sample is free of survivorship bias by collecting all domestic equity trusts that were in existence in our research period. We remove unit trusts whose time length of existing is less than three years to ensure sufficient observations for each unit trust.

This research sample embraces 262 UK domestic equity unit trusts. We extract the daily and monthly total return index of each unit trust from DataStream and calculate returns by log function, which is log-normality and time-additive. Market index return (i.e., FTSE All-Share Index return) and risk-free rate of return (i.e., three-month UK Treasury bill index return), other anomaly variables (size, value and momentum), as well as equal-weighted and value-weighted volatility portfolio returns are extracted from the website of Xfi Centre for Finance and Investment.

7.3.2 Descriptive Statistics

Table 7.1 displays the descriptive statistics of monthly returns for 262 UK domestic equity unit trusts and risk variables from July 1990 to June 2015. The first three variables are excess returns of aggregate unit trusts, market excess returns, and aggregate idiosyncratic returns, respectively. The AIS is estimated by the single-factor asset pricing model. Regarding these three variables, monthly returns have slightly negative skewness and excess kurtosis. To be specific, the skewness of r_a, r_m, and AIS is -0.89, -0.50, and -0.62, respectively; and excess kurtosis of them is 1.87, 0.59, 2.56, respectively.

Although variables are non-normal distribution indicated by the statistical significance of the difference either of skewness or kurtosis values from zero, monthly returns still fit the OLS regression because ADF test suggests stationarity of data at a 99% significance level. Besides, the last two columns of Panel A display the result of Cumby-Huizinga autocorrelation test. Only aggregate portfolio returns of unit trusts have significant autocorrelation at the first lag, and the autocorrelation disappears at the second lag.

The last two variables are volatility anomaly factors, similar to conventional anomaly factors of size (smb), value (hml) and momentum (mom) reported in the middle three of rows, respectively. At the end of each month, UK stocks are assigned to five volatility groups using the standard deviation of daily stock returns as the breakpoints. The volatility anomaly factor lvh is the average return on the portfolio of last quintile stocks minus the average return on the portfolio of first quintile stocks. We account for the weighting schemes of portfolio construction. lvh_ew indicates that the volatility portfolio return is measured by the equal-weighted average, while lvh_vw indicates that the volatility portfolio return is measured by the value-weighted average.

The positive mean of lvh_vw reported in the last row of Table 7.1 supports the existence of volatility anomaly that the low-volatility stocks outperform high-volatility stocks; whereas, the negative mean of lvh_ew provides evidence to the opposite. These results suggest that volatility anomaly is sensitive to weighting schemes of portfolio construction in the UK stock market. More specifically, the value-weighted average return lowers the small capital company weighting; the average return of the high-volatility portfolio is larger than the return of the low-volatility portfolio. On the other hand, equal-weighted average return over-weights the small companies; the average return of the high-volatility portfolio is smaller than the return of the low-volatility portfolio. Consequently, we propose that the volatility of stocks relate considerably to the capital size of firms, and the high-volatility group tends to comprise small companies. The high correlation between factors of size and volatility reported in Panel B of Table 7.2 supports the proposal. The contrary statistic between two types of volatility portfolio returns is in line with prior study of Bali and Cakici (2008) who demonstrate that the relationship between returns of stock portfolio and idiosyncratic risk is sensitive to the weighting schemes adopted to measure portfolio returns.

We use the value-weighted volatility anomaly factor to examine the trust manager's volatility investment behavior. Initially, the value-weighted volatility factor accounts for the impact of size anomaly when evaluating unit trusts performance and investment style of equity unit trusts. Secondly, the value-weighted approach prevails as a measurement of the stock market concerning the economy. FTSE All-Share index, for instance, is constructed by the value-weighted method. By contrast, the equal-weighted method has no clear distinction of stock size to the economy. Last but not least, value-weighted factor returns are more appropriate for regression analysis than equal-weighted factors. In particular, in the last row of Table 7.1, although the significant $SK\ test$ statistics reject the null hypothesis of normal-distributed returns for volatility portfolios, the data of the value-weighted average returns of the volatility portfolio is stationarity indicated by the significant ADF statistics; thus, the return data of volatility variables can fit the OLS regression analysis. More importantly, lvh_vw does not have autocorrelation, as the statistics of Cumby-Huizinga test $Auto(x)$ is insignificantly reported in the bottom of the last two columns. By contrast, average returns calculated by the equal-weight method show a significant autocorrelation problem at the 1% level. Therefore, the study of volatility investment strategy employs the value-weighted volatility anomaly factor.

Table 7. 1:
Descriptive Statistics

	Mean	*Std. Dev.*	*Max*	*Min*	*Skew*	*Kurt*	*SK test*	*ADF*	*Auto(1)*	*Auto(2)*
r_a	0.26	0.0405	11.06	–16.83	–0.89	4.87	37.94***	–14.97***	6.68***	0.48
r_m	0.38	0.0414	10.48	–13.61	–0.50	3.59	13.58***	–16.35***	1.07	1.47
AIS	–0.09	0.0119	3.45	–5.57	–0.62	5.56	30.05***	–18.27***	0.79	0.32
smb	0.15	0.0330	15.61	–11.48	0.08	4.95	14.91***	–14.79***	7.49***	0.41
hml	0.14	0.0337	12.29	–18.61	–0.49	9.80	48.64***	–11.89***	40.34***	3.65
mom	0.99	0.0473	16.04	–25.03	–1.01	7.85	60.19***	–12.58***	30.00***	0.02
lvh_ew	–0.44	0.0451	11.72	–24.24	–1.15	6.62	–	–15.79***	29.72***	4.18**
lvh_vw	0.12	0.0654	19.51	–30.96	–0.49	5.32	25.79***	–13.03***	24.23	1.65

This table reports the descriptive statistics of monthly returns for 262 UK domestic equity unit trusts and risk variables from July 1990 to June 2015. r_a is the aggregate monthly returns of all unit trusts minus the 3-month UK Treasury bill rate. r_m is the FTSE All-Share Index monthly returns minus the 3-month UK Treasury bill rate. AIS is the sum of the estimated risk factor: $r_a = \alpha_{ais} + \beta r_m + \varepsilon_{ais}$; $AIS = \alpha_{ais} + \varepsilon_{ais}$. smb, hml, mom indicate Fama-French and Chart's risk factors of size, book-to-market ratio, and momentum, respectively. lvh_vw indicates volatility anomaly factor that is value-weighted low volatility stock portfolio returns minus high volatility stock portfolio returns. lvh_ew indicates volatility anomaly factor that is equal-weighted low volatility stock portfolio returns minis high volatility stock portfolio returns.

This table presents means, standard deviation (*Std. Dev.*), maximum returns (*Max*), minimum returns (*Min*), skewness (*Skew*), and kurtosis (*Kurt*) for variables. The right columns represent test statistics. *SK test* normality of skewness and kurtosis, indicated by chi-squared statistics. *ADF* indicates a unit-root stationary test of Dickey-Fuller. *Auto(x)* indicates Cumby-Huizinga autocorrelation test with x lagged order.

The values of *Mean, Min, and Max* are multiplied by 100 to express them in percentage terms.

The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7.2 shows correlations among return variables. Panel A represents the correlation between two variables adopted in the model of estimating trust-specific unique risk, whereby the two variables are market excess returns r_m and aggregate idiosyncratic shocks AIS. The correlation between these two variables is zero with t-statistics of one, implying that these two variables are independent of each other and supporting the notion that aggregate idiosyncratic returns could be an additional risk factor to capture unpriced firm-level public information.

Panel B of Table 7.2 reports correlations among risk factors employed in the study of the investment strategy of UK equity unit trusts. The correlations between size and volatility factors are large and significant. More specifically, the coefficient between size and equal-weighted volatility anomalies is –0.534 with zero t-statistics and the coefficient between size and value-weighted anomalies is –0.573 with zero t-statistics. The sizable absolute value suggests that the capital size of a firm and the volatility of stock returns are strongly associated with each other. The negative value indicates that the small capital companies tend to show high volatility in share returns and vice versa.

Table 7. 2:
Cross Correlations

Panel A: Aggregate Unit Trusts Returns and Common Variables

	$\boldsymbol{r_a}$	$\boldsymbol{r_m}$	$\boldsymbol{AIS}$
$\boldsymbol{r_a}$	1		
$\boldsymbol{r_m}$	0.9557 (0.00)	1	
$\boldsymbol{AIS}$	0.2943 (0.00)	0.0000 (1.00)	1

Panel B: Risk Pricing Factors

	$\boldsymbol{R_m}$	$\boldsymbol{smb}$	$\boldsymbol{hml}$	$\boldsymbol{mom}$	$\boldsymbol{lvh\_ew}$	$\boldsymbol{lvh\_vw}$
$\boldsymbol{R_m}$	1					
$\boldsymbol{smb}$	0.0735 (0.2004)	1				
$\boldsymbol{hml}$	0.1423 (0.0129)	–0.0985 (0.0861)	1			
$\boldsymbol{mom}$	–0.2281 (0.0001)	–0.1064 (0.0636)	–0.5333 (0.0000)	1		
$\boldsymbol{lvh\_ew}$	–0.3763 (0.0000)	–0.5342 (0.0000)	0.1496 (0.0089)	0.0931 (0.1046)	1	
$\boldsymbol{lvh\_vw}$	–0.3763 (0.0000)	–0.5728 (0.0000)	0.2226 (0.0001)	0.0583 (0.3103)	0.7991 (0.0000)	1

This table displays the statistics and t-statistics of cross-correlation coefficients between every two variables. The t-statistics are reported in the bracket. The variables in Panel A are aggregate unit trusts excess returns $\boldsymbol{r_a}$, market excess returns $\boldsymbol{r_m}$, and aggregate idiosyncratic shocks $\boldsymbol{AIS}$. Variables in Panel B are market returns $\boldsymbol{R_m}$, Fama-French's pricing factors of size $\boldsymbol{smb}$ and value $\boldsymbol{hml}$, Carhart's pricing factor of momentum $\boldsymbol{mom}$, and volatility anomaly factors constructed from equity-weight volatility stock portfolios $\boldsymbol{lvh\_ew}$ and value-weighted volatility stock portfolios $\boldsymbol{lvh\_vw}$.

7.4 Methodologies

7.4.1 Relationship between Realized Returns and Trust-specific Unique risk

We use methods of ranking-groups, cross-section regression and time-series regression to investigate the relationship between realized returns of individual unit trusts and trust-specific unique risk. To be specific, we sort each unit trust into five groups based on the standard deviation of prior 12 month residuals; the residuals are estimated by the Equation (7.7). We rebalance the groups at the beginning of each month and then compare the performance of five sorted groups. On the one hand, we graph the value of £1 investment in five unique-risk groups and the market index, respectively. On the other hand, we measure mean and geometric mean returns, as well as risk-adjusted returns such as Shape ratio, Treynor ratio, and Jensen alpha for each unique-risk group.

The cross-sectional regression analysis follows Fama and Macbeth's (1973) model. More specifically, the original Fama-Macbeth method estimates parameters in two steps. The first step regresses each asset against the proposed risk factors to determine that asset's beta for that risk factor. The next step regresses all asset returns for a fixed period against the estimated betas to determine the risk premium for each factor. In our research, we use trust-specific unique risk to replace the estimated beta in the first step and employ the second step. We regress all unit trust returns against their one-month lagged unique risk for each month, obtaining a time series of risk premia for each trust-specific unique risk. The empirical model can be written as:

$$R_{p,t} = \gamma_{p,t}\sigma^{j}_{p,t-1} + \varepsilon_t, j = 1, \dots, N, t = 1, \dots, T, \tag{7.9}$$

where $R_{p,t}$ is the realized returns of unit trust p in month t, $\sigma_{\mathrm{p},t-1}$ is the estimated trust-specific unique risk of unit trust p in month $t-1$. We do the regression in each month across all unit trusts in our research sample. The coefficient $\gamma_{p,t}$ captures the relation between realized returns of unit trusts and their 1-month lagged unique risk in month t.

Assuming disturbance terms are independent and identically distributed, the risk premium γ_a for trusts' additional returns is calculated by averaging γ_{at} over the research period. To be specific, the final risk premium is $\gamma_a = \frac{1}{T}\sum_1^T \gamma_{at}$, and t-statistics for the risk premium is $\frac{\gamma_a}{\sigma_{\gamma_a}/\sqrt{T}}$.

The maximum month T equals 284 in this study.

The time-series analysis for relationship study is using the GARCH-in-Mean model to explore the long-term relationship between realized returns and trust-specific unique risk for each unit trust. Different from the above relationship studies, we use daily returns instead of monthly returns because the observations of monthly data might not be enough for GARCH regression if the surviving period of a unit trust is too short. Furthermore, we adopt contemporary unique risk instead of 1-month lagged unique risk in the time-series analysis because the theory perspective suggests that the risk and return trade-off should be contemporaneous, as investors earn returns for bearing the risk in the same period. If volatility is highly persistent as following a random walk process, merely using the lagged value as an estimate of the expected value is reasonable.

Fu (2009) argues that 1-month lagged idiosyncratic volatility may not be an appropriate proxy for the expected idiosyncratic volatility of this month due to the time-varying characteristic of volatility. Fu (2009) states three reasons to support time-varying idiosyncratic risk: switching investment strategy is infrequent given the high trading cost; consumption of a particular fund is subject to manager's characteristics and the agency's marketing strategy; peer funds' performance may also impact the fund's cash flow.

Although volatility is time-varying, volatility exhibits characteristics of cluster and persistence: high/low volatility is often followed by high/low volatility (Bollerslev, Chou, and Kroner, 1992). Thus, it is still reasonable and valid to use 1-month lagged volatility to predict current volatility. Ang et al. (2006; 2009), for example, employ 1-month lagged idiosyncratic volatility to study the cross-sectional relationship between stock returns and idiosyncratic risk. For comparison, we also use contemporary trust-specific unique risk estimated by the GARCH approach to repeat the above cross-sectional analysis.

Therefore, we follow Ang *et al.*, (2006) using lagged trust-specific unique risk to do cross-sectional analysis, and use the GARCH-in-Mean model by adding the contemporary forecast unique risk to the mean equation which is represented by the augmented asset pricing model of Equation (7.7) to do time-series analysis. The time-series empirical model can be written as:

Mean Equation:

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \gamma_p AIS_t + \delta_p \sigma_{p,t} + \varepsilon_{p,t}, \varepsilon_{p,t} \sim (0, \sigma_t^2) \qquad (7.10)$$

Conditional Variance Equation:

$$\sigma_{p,t}^2 = \alpha'_0 + \lambda_1 \varepsilon_{p,t-1}^2 + \lambda_2 \sigma_{p,t-1}^2 \tag{7.11}$$

where conditional variance $\sigma_{p,t}^2$ represents the contemporary trust-specific unique risk for each unit trust p; and δ_p represents the time-varying sensitivity of portfolio returns to its conditional unique risk for each unit trust p (Bollerslev, Chou, and Kroner, 1992).

The ARCH model proposes an impressive concept on modelling time-varying volatility, having been used popularly and developed to a big family since 1982. The ARCH model is represented by bundling joint mean and conditional variance equations (Engle, 1982). The conditional variance equation can model volatility with a weighted average of past squared residuals. Generalized ARCH (GARCH) model develops the conditional variance equation by allowing lagged conditional variances to enter with declining weights that never go completely zero. Moreover, the additional parameter of lagged conditional variance responds to the correlation between the current level of volatility and its level during the immediately preceding period (Bollerslev, 1986).

This study uses the GARCH-in-Mean model to develop the mean equation by adding the conditional variance to the mean equation (Engle, Lilien, and Robins, 1987). The GARCH-in-Mean model provides an essential tool for estimation of the linear relationship between realized returns and unique risk in a time series context.

Cross-sectional regression investigates the relationship within each month across all UK domestic equity unit trusts, while time-series regression explores the relationship for each unit trust over the whole research period, offering additional information of relationship from the long-term version. Combining short-term and long-term versions could give fund consumers advice about not only how to choose the fund, given the risk tolerance but also how long to hold the particular fund given the long term performance.

7.4.2 Volatility Investment Strategy

We borrow Carhart's (1997) idea of studying momentum investment strategy to explore UK unit trust's volatility investment strategy. We construct the volatility anomaly factor LVH by using the average returns of the lowest volatility stock portfolio to minus the average returns of the highest volatility stock portfolio, following anomaly studies of Fama and French (2015), Jordan and Riley (2015). We consider two types of weighted portfolio: value-weighted and equal-weighted, indicated by lvh_vw and lvh_ew, respectively. We use lvh_vw due to the discussion in the sub-section 7.3.2.

Positive lvh_vw supports the existence of volatility anomaly. One potential reason is risk-seeking investors tend to hold high-volatility stocks resulting in over-pricing; institutional investors do not offset the anomaly by picking up under-priced low-volatility stocks but prefer holding high-volatility stocks easily outperforming the market during the bull period (Baker, Bradley, and Wurgler, 2011; Karceski, 2002). We, therefore, test whether UK fund managers take benefits from volatility anomaly by selecting low volatility stocks.

We use the sorted five unique-risk groups to do analysis, in order to further explore whether UK unit trusts with low unique-risk select low volatility stocks. The regression model for testing volatility investment strategy can be written as:

$$r_p = \alpha + \beta r_m + \gamma LVH + \varepsilon_p, \quad (7.12)$$

where r_p denotes excess returns of unique-risk portfolios; LVH denotes the volatility anomaly factor lvh_vw; the coefficient γ interprets volatility strategy implemented in the unit trusts with various unique risk levels. The positive/negative γ suggests that managers tend to hold low/high volatile stocks.

7.5 Empirical Results

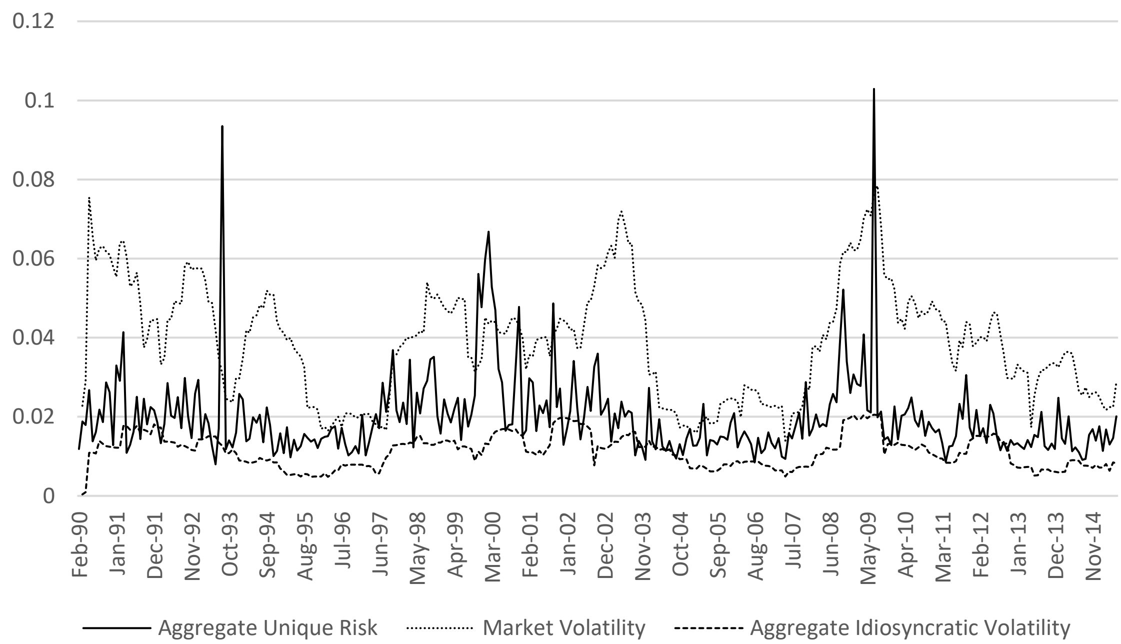
7.5.1 Existence of Trust-specific Unique Risk

Figure 7.1 supports the existence of unique risk for UK domestic equity unit trusts. The market volatility is measured by the standard deviation of FTSE All-Share index returns on prior 12 months, and the aggregate idiosyncratic volatility is measured by the standard deviation of estimated AIS returns in the prior 12 months. The aggregate unique risk graphed in Figure 7.1 is measured as follows. We use Equation (7.7) to regress individual unit trust returns on market excess returns, and AIS returns across all unit trusts, extracting the time-series residuals. The standard deviation of the extracted residuals on the prior 12 months is the proxy of aggregate unique risk relevant to private information processed by each unit trust at the aggregate level.

The volatilities of three return components are not consistent. Aggregate idiosyncratic volatility displays a similar trend to market volatility but flatter than market volatility, partly attributed to the diversification of the aggregate portfolio. More specifically, the aggregate idiosyncratic shocks are residuals of regressing one portfolio returns of UK unit trusts on market excess returns; there is a high possibility for the portfolio embracing all unit trusts in our research sample to reach diversification, thereby eliminating the residual risk of the aggregate portfolio. Thus, the aggregate idiosyncratic volatility is flatter than the other two types of volatility.

In addition, the aggregate unique risk generally fluctuates between 1% and 5% but goes extremely high in three research periods. In particular, the aggregate unique volatility surge to 9.5% around 1993; to 7% from 1999 to 2001; and even over 10% around 2009. The unique risk is highly volatile, supporting that the idiosyncratic risk exists; that unit trust portfolios are not sufficiently diversified; that managers do take additional risk while selecting individual stocks. The significance of the standard deviation of regression residuals is manifest in the large fluctuation of unique risk.

Figure 7. 1:
Aggregate Unique Risk



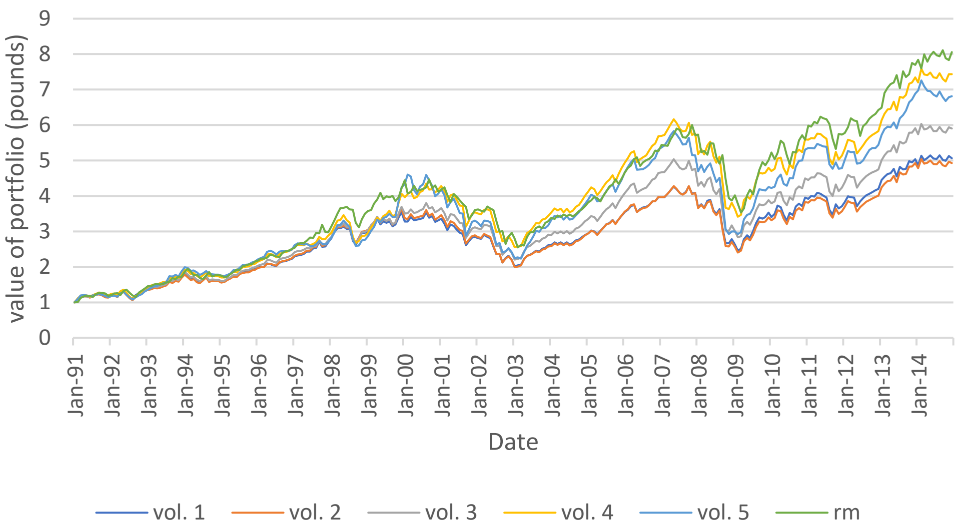
Aggregate unique risk is measured by the standard deviation of aggregate augmented residuals on prior 12 months, and the augmented residuals are obtained by regressing augmented market index model across unit trusts within each month. Market volatility is measured by the standard deviation of prior 12 months monthly returns of FTSE All-Share Index monthly returns. Aggregate idiosyncratic volatility is measured by the standard deviation of active peer benchmark factor returns on prior 12 month.

7.5.2 Relationship Study

7.5.2.1 Ranking into Groups Based on 1-month Lagged Unique Risk

We find the positive relationship between realized returns of unit trusts and their trust-specific unique risk. Figure 7.2 exhibits the time-series value of the £1 invested in the five formed unique-risk groups as well as the FTSE All-Share Index from January 1991 to June 2015. The risk portfolios are sorted on one-month lagged estimated trust-specific unique risk. The bottom two unique-risk groups (vol.1 and vol.2) are worth about £5.25 and £5.15, respectively, while the top two risk groups (vol.4 and vol.5) are worth up to £7.83 and £7.40, respectively. The middle-risk group performed at the intermediate level with the value of £6.18 in June 2015. However, all risk groups generally cannot outperform the market index whose value is up to about £8 in 2015. The top two risk groups perform close to the market movement, especially when the market goes down (e.g., 2000 to 2003, and 2008 to 2009), implying that fund managers can cut their losses and keep assets safe.

Figure 7. 2:
The Return on £1 Invested in Unit Trusts Sorted on 1-month Lagged Trust-specific Unique Risk



This figure shows the changing value of £1 invested in January 1991 through December 2014 in five equal-weighted portfolios of active UK domestic equity unit trusts. Unit trusts are sorted into deciles based on the 1-month lagged trust-specific unique risk, and each portfolio is re-sorted at the beginning of each month. Portfolios are equal weighted. The first decile represents the group comprising unit trusts with the lowest trust-specific unique risk, and the rest deciles represent risk groups in turn. The low unique-risk group (vol. 1) buys the 20% of unit trusts in the sample with the lowest standard deviation of augmented residuals in the prior calendar month, and the same with the other unique-risk groups. The market portfolio (rm) represents the value of £1 invested in the FTSE All-Share Index.

Table 7.3 exhibits the performance evaluation of the five unique-risk portfolio returns, corresponding to Figure 7.2. We assess the annual average returns and risk-adjusted performance measures. The arithmetic average returns for the fourth and fifth risk groups are the largest with 9.49% and 9.36% per year, respectively. By contrast, the average returns for the first and second risk groups are small, only 7.76% and 7.71% per year, respectively. Mean return of the highest risk portfolio is 1.60% per year is higher than that of the lowest risk portfolio. Distinguishing compounding returns between the top and bottom groups is positive as well, with 1.42% per year in geometric returns. Given no short selling for UK unit trusts, fund consumers cannot directly capture that difference in performance. The difference represents the opportunity cost of investing in trusts with low unique risk instead of high unique risk.

Moreover, volatilities of risk portfolio's average returns are close to each other. Total volatility of the high unique risk portfolio is slightly higher than that of the low unique risk portfolio, which is 0.04 per year. Risk-adjusted returns are similar as well between high and low unique risk portfolios, indicated by the Sharpe ratio of 0.0057 and Treynor ratio of 0.0015 in the portfolio of longing high unique risk trusts and shorting low unique risk trusts. The Treynor ratio's betas of risk portfolios, which is measured by dividing covariance of portfolio return and market return by variance of market return, display a declining trend with portfolio's unique risk increase. Treynor beta of the low-risk portfolio is 1.01, while the beta of high-risk portfolio declines to 0.79, implying that low unique risk portfolio is more sensitive to the market movement than high unique risk portfolio. The fourth risk portfolio performs the best among all groups, exhibiting the highest mean returns and risk-adjusted ratios averagely. The fourth portfolio, however, still cannot outperform the market in our whole research period.

Table 7. 3:
Performance of Returns on Portfolios of Unit Trusts Sorted on 1-month Lagged Unique Risk

	Low	*2*	*3*	*4*	*High*	*High-Low*	*rm*
Average Return	7.76	7.71	8.43	9.48	9.36	1.60	9.60
Geometric Return	6.81	6.73	7.48	8.46	8.23	1.42	8.60
Total Risk	0.4749	0.4794	0.4743	0.4900	0.5157	0.0408	0.4874
Sharpe Ratio	0.0764	0.0851	0.0918	0.1046	0.0821	0.0057	0.1121
Systematic Risk	1.0117	0.9923	0.9891	0.9172	0.7892	–0.2225	–
Treynor Ratio	0.0030	0.0034	0.0037	0.0047	0.0045	0.0015	–
Jensen Alpha	–0.14	–0.14	–0.07	0.02	0.03	0.17	–
	(–3.44)	(–2.72)	(–1.08)	(0.25)	(0.23)	(1.33)	

This table reports returns and risk-adjusted performance measurement on five equal-weighted unique-risk portfolios of UK domestic equity unit trusts throughout the research period (Jan. 1991 – Dec. 2014). The low/high portfolio holds the 20% of unit trusts with the lowest/highest 1-month lagged unique risk in the sample. Unique risk is measured by the standard deviation of residuals ϵ_p from the model $r_p = \alpha_p + \beta r_m + \gamma AIS + \epsilon_p$.

The average return is the mean monthly return for the portfolio multiplied by 12. Geometric return is the monthly compound return multiplied by 12. Total risk is measured by the standard deviation of monthly portfolio returns. We report annualized standard deviation by multiplying 12. Sharpe ratio is the average monthly return earned over the risk-free rate per unit of total risk. the risk-free rate is the returns of three-month UK Treasury bill index. Systematic risk is the beta calculated by the function $\beta = \frac{cov(R_p,R_m)}{\sigma_m^2}$. Treynor ratio is the average portfolio's monthly excess returns divided by the portfolio's systematic risk taken. Jensen alpha is the difference between a portfolio's monthly excess returns and the expected market excess returns. The t-statistics of alpha are reported in the bracket.

The values of average return, geometric return, and Jensen alpha are multiplied by 100 to express them in percentage terms.

7.5.2.2 Regression Analysis

This study adopts the regression analysis method to carry on the relationship study. The results are reported in Table 7.4. We conduct regression analysis at the aggregate level and individual level, reported in Panel A and Panel B of Table 7.4, respectively. This cross-sectional study considers both 1-month lagged trust-specific unique risk estimated by the standard deviation of augmented daily residuals in the last month and contemporary unique risk estimated by the GARCH model, reported in the first and second row of Panel A and B, respectively.

We uncover a significant positive relation at the aggregate level, indicated by the coefficients of 0.02 and 0.03 and t-statistics of 4.69 and 5.89 for lagged and conditional cross-sectional regression, respectively. At the individual level, over 293 months, 134 months show positive coefficients for the relationship study where 33 months exhibits the significant positive coefficients at the 90% level. Contemporary unique risk displays similar results. In addition, we consider the long lagged trust-specific unique risk by employing 3-month, 6-month and 12-month lagged unique risk in the Fama-MacBeth's method, reported in Panel C of Table 7.4. We find that the positive relation is not robust when adopting long lagged unique risk. In particular, the coefficient of cross-sectional regression on 3-month is approximate to zero, while coefficients on 6-month and 12-month are significantly negative.

The results of the time-series GARCH-in-Mean model are reported in the last row of Panel A and B of Table 7.4, corresponding to the aggregate level and individual level. The long-term time-series regression shows a positive relationship between realized returns of unit trusts and their trust-specific unique risk, indicated by 0.07 of coefficient statistics of conditional standard deviation in aggregate. This positive relation, nevertheless, might not be robust, indicated by the t-statistics of 0.74. At the individual level, 66% of trusts show positive coefficients, whereas only 55% of positive coefficients are significant over the whole research period.

Our findings are consistent with prior studies of a positive relation between idiosyncratic risk and expected returns of simulated stock portfolios (Goyal and Santa-Clara, 2003; Spiegel and Wang, 2007; Boehme et al., 2009; Fu, 2009; Huang et al., 2010). More specifically, Boehme *et al.* (2009) empirically advocate the positive relationship between idiosyncratic risk and cross-section of stock returns by exploring stocks with low-visibility and limited short selling. Fu (2009) considers time-varying idiosyncratic volatility, exhibiting a significantly positive relationship between the EGARCH idiosyncratic volatilities and expected returns. Huang *et al.* (2010) also reveal a significantly positive relationship between the conditional idiosyncratic volatility estimated from monthly data and expected returns. Spiegel and Wang (2007) display a positive relationship in the US data as well; further exploring that idiosyncratic volatility is much stronger and can swamp the explanatory power of liquidity that is negatively related to returns. Goyal and Santa-Clara (2003) implicitly suggest a positive relationship between average stock variance[11] and stock market returns. In particular, given this positive relation, they use average stock variance to predict stock market returns.

7.5.2.3 Discussion

Fu (2009) maintains that, due to the characteristic of time-varying of volatility, lagged idiosyncratic volatility might not be an appropriate proxy for expected idiosyncratic volatility. Fu (2009) also exhibits contrary results by adopting lagged and contemporise volatility. In our research of examining UK domestic equity unit trusts, we state that 1-month lagged unique risk could be an appropriate risk proxy, producing consistent positive relation with contemporise conditional unique risk. On the other hand, as the persistence of volatility is not very long, we conclude that the short lagged unique risk such as 1-month lagged could be an efficient predictor of future performance of UK unit trusts.

Moreover, this positive relation could advise fund investors to select relatively high-risk unit trust within their risk tolerance and capability since the majority trust managers can produce relatively high realized return for investors when they take increased risk relative to peers. We advocate the notion that most UK trust managers can pick up under-priced stocks, as the high unique-risk group produces positive alpha with lower market exposure beta, whereas the low-risk group produces negative alpha with high market exposure beta (i.e., systematic risk), reported in Table 7.3. To be specific, the performance of the low-risk group highly relies on the performance of the stock market, whereas the performance of the high-risk group mainly depends on the active fund managers picking up specific successful stocks.

In addition, Jacobs and Levy (1996) examine the optimal portfolios for the assumed risk tolerances, finding that the manager with higher information ratio exhibits both higher residual risks and higher expected excess returns than those of the manager with a lower information ratio. As such, real managers would be able to grab higher returns than in virtual optimal portfolios by taking a higher residual risk. As the residual value in this study is relevant to the optimal portfolio managed by a rational investor with public information only, the relevant residual will be generated owing to the advantage of holding private information mainly. It is worthy of note that the standard deviation of individual fund residuals relative to the virtual portfolio is unique, affected by not only managers information but also investment objectives.

[11] If individual stocks could be proxy for the idiosyncratic income of investors, average stock risk could be a measure of the income stocks of cross-sectional variance among investors.

Table 7. 4:
Relationship between Realized Returns and Trust-specific Unique Risk

Panel A: aggregate level	*coefficient*	*t-statistics*
Cross-sectional (lagged volatility)	0.02	4.69
Cross-sectional (GARCH volatility)	0.03	5.89
Time-series (GARCH-in-mean)	0.07	0.74

Panel B: individual level	*loop*	$t \leq -1.645$	$-1.645 < t < 0$	$0 \leq t < 1.645$	$t \geq 1.645$
Each month (lagged volatility)	293 months	101 (34%)	33 (11%)	45 (16%)	114 (39%)
Each month (GARCH volatility)	305 months	117 (38%)	27 (9%)	40 (13%)	121 (40%)
Individual fund	262 unit trusts	42 (20%)	31 (14%)	62 (30%)	76 (36%)

Panel C: cross-sectional long lagged volatility test	*coefficient*	*t-statistics*
3-month lagged unique risk	0.00	0.79
6-month lagged unique risk	–0.03	–6.40
12-month lagged unique risk	–0.02	–4.84

This table exhibits results of regression analysis on the relationship between realized returns of UK equity unit trusts and their trust-specific unique risk. Panel A reports regression coefficients and t-statistics at the aggregate level. The t-statistics are reported in the bracket.

The first row shows results from cross-sectional regression of adopting 1-month lagged standard deviation of augmented residuals. The second row shows results from cross-sectional regression of adopting contemporises GARCH (1, 1) conditional volatility. We follow Fama-MacBeth's method to estimate aggregate coefficients and t-statistics, that is, $\gamma_a = \frac{1}{T}\sum_1^T \gamma_{at}$ and $\frac{\gamma_a}{\sigma_{\gamma_a}/\sqrt{T}}$.

Time-series study uses GARCH (1, 1)-in-mean model of adding conditional standard deviation to the mean equation. Aggregate coefficient of conditional volatility in the mean equation and t-statistics for risk premium is measured by regressing estimated coefficients across unit trusts.

Panel B reports regression results at the individual level. We conduct cross-sectional regression at each month, and then summarize the number and percentage of the month showing the estimated coefficients corresponding to the four range of t-statistics. Research period of cross-sectional regression of lagged volatility is 293 months, less 12 months than that of GARCH volatility, because the conditional standard deviation is measured by augmented residuals on prior 12 months.

The last row of Panel B reports the results of using the GARCH-in-Mean method to study the relationship for each unit trusts. The research sample has 262 UK equity unit trusts, whereas there are only 211 unit trusts exhibits estimated coefficients. GARCH fails to offer estimated coefficients for 51 unit trusts in our research sample. The possible reason could be that the observations of these unit trusts are not enough. In order to avoid survivorship bias, this research includes all UK domestic equity unit trusts that were in existence in our research period, resulting in the observations might be not enough for some trusts with a short surviving period. The last four columns report the amount and percentage of unit trusts whose estimated coefficients and t-statistics in the corresponding significant range.

In order to ensure observations as many as possible, we adopt daily returns in GARCH-in-Mean regression. However, we use monthly returns in GARCH (1, 1) model to estimate conditional variance for the cross-sectional study for comparing to monthly lagged unique risk study. Moreover, even the conditional variance missing for some unit trusts, the relationship study across all unit trusts can be conducted.

Panel C reports coefficients and t-statistics of the cross-sectional relationship study using the volatility of long lagged augmented residuals as a risk proxy. This study adopts 3-month, 6-month, and 12-month lagged trust-specific unique risk, respectively, in the Fama-MacBeth's cross-sectional regression method.

However, this positive relationship is not consistent, indicated by the insignificant coefficient of GARCH-in-Mean model, as well as zero coefficient of using 3-month lagged unique risk and even significant negative coefficients of using 6-month and 12-month lagged unique risk in cross-sectional analysis. We propose a possible reason would be the changing of trust managers, or how trust managers employ various investment strategies in different financial contexts. On the other hand, being a human, trust managers might cannot always be rational. For example, they could become over-confident after an extremely excellent performance; or they could have noise trading for a specific time. In general, our advice on unit trusts strategy for investors could be picking up a relatively higher risk trust but not holding the same trust in the long term.

7.5.3 Volatility Investment Strategy

Regression results of adding a market volatility factor to the asset pricing model are reported in Panel A of Table 7.5. We reveal a significant coefficient of volatility anomaly factor γ, implying that trust managers consider the stock volatility when building their trust portfolio. The coefficient γ is negative, implying that, although the volatility anomaly exists in the UK common stock market indicated by the positive mean of lvh_vw in Table 7.1, trust managers do not take the benefits by selecting the under-priced low volatility stocks. Consequently, the volatility anomaly cannot be counterpoised. The absolute value of γ is much more abundant in the high unique-risk group than that in the small risk group, suggesting that UK equity unit trusts tend to select specific high volatile stocks, increasing the trust-specific unique risk.

Furthermore, the high unique-risk group in the last row of Panel A of Table 7.5 displays lower beta and higher alpha than low unique-risk group, suggesting that unit trusts with high unique risk are less exposed to the market return but prefer to chase specific high volatility stocks to grasp positive abnormal return. In particular, the beta coefficient and alpha of low-risk portfolio are 0.95 and -0.13, while beta and alpha in the high-risk portfolio are 0.74 and 0.11, respectively.

Additionally, in comparison to Panel B reporting risk coefficients under standard CAPM model, beta in Panel A of Table 7.5 drops primarily after adding the volatility anomaly factor lvh_vw, attributing to the high correlation between market returns and volatility anomaly returns. To be specific, the volatility investment strategy might be manifested in market exposure, as the correlation between R_m and lvh_vw is –0.38 reported in Panel B of Table 7.2. Moreover, the increment on the adjusted R-square statistics suggests that the volatility factor could explain high-risk portfolio better. More specifically, R-square statistics have a substantial increase from 0.6970 of the single-index model to 0.8094 of the volatility anomaly model. This finding implies that the volatility factor adequately explains the investment style of unit trusts with high unique risk.

As the volatility factor potentially offers a home game explanation, we further employ the conventional four-factor model to explain risk portfolio's performance, reported in Panel C of Table 7.5. The home game means explaining the performance of portfolios formed by sorting on a character using a factor formed on that same characteristic (Fama and French, 2016). In our research, although we are not constructing risk portfolios based on the volatility of underlying stocks of the fund, using LVH still potentially create a home game situation if the volatility factor drives the performance of funds (Jordan and Riley, 2015). We find that high unique-risk group creates exposure profoundly to small capital, growth, and past winner stocks, indicated by the factors' estimated coefficients of 0.59, 0.07, and 0.05, respectively, at 95% significance level. This result is not surprising because the absolute value of the correlation between anomaly factors of volatility and size is substantial, that is, 0.57 at 99% significance level (see Panel B of Table 7.2).

In addition, across three asset-pricing-type models, we find that unit trust groups with high beta produce low abnormal return alpha. More specifically, the lowest three risk portfolios with beta coefficients over 0.90 all produce negative abnormal returns. This finding is consistent with Frazzini and Pedersen's (2014) finding that high beta is associated with low alpha. Frazzini and Pedersen (2014) construct the betting against beta factor by longing leveraged low-beta assets and shorting high-beta assets produces significant positive risk-adjusted returns. Frazzini and Pedersen (2014) advocate that leverage constrained investors (e.g., mutual fund managers) overweight risky assets (e.g., overweight stocks instead of bonds), causing those assets to offer lower returns. Our results also support their proposal. Over half of unit trusts in our research sample overweight high-beta stocks producing lower returns. Our research further proposes that, if professional investors took a higher risk by selecting more risky/volatile stocks, they would then create the opportunity to obtain higher returns.

Table 7. 5:
Volatility Investment Strategy

Panel A: volatility effect model

	α	β	γ	*Adj-R²*
Low	–0.13***	0.95***	–0.02***	0.9721
2	–0.13**	0.94***	–0.03***	0.9544
3	–0.05	0.90***	–0.05***	0.9333
4	0.06	0.85***	–0.12***	0.8807
High	0.11	0.74***	–0.24***	0.8094

Panel B: market index model

	α	β	*Adj-R²*
Low	–0.14***	0.96***	0.9715
2	–0.14***	0.96***	0.9524
3	–0.07	0.94***	0.9263
4	0.02	0.93***	0.8498
High	0.03	0.89***	0.6970

Panel C: four-factor model

	α	β	β_1	β_2	β_3	*Adj-R²*
Low	–0.17***	0.96***	0.01***	0.02*	0.01	0.9752
2	–0.18***	0.95***	0.13***	0.03**	0.01	0.9625
3	–0.15***	0.93***	0.21***	0.03*	0.03**	0.9552
4	–0.10*	0.91***	0.39***	0.03	0.04*	0.9426
High	–0.14*	0.86***	0.59***	–0.07**	0.05**	0.9074

This table reports test results of volatility investment strategy in five risk groups. We study the UK equity unit trusts from 1991 February to 2015 June. Risk groups are sorted by the 1-month lagged standard deviation of prior 12-month augmented residuals for market index model. Panel A reports results of volatility investment strategy test. The volatility strategy model is $r_p = \alpha + \beta r_m + \gamma LVH + \varepsilon_p$.

Panel B and C report results of using a conventional asset pricing factor model to study the investment style of UK equity unit trusts for comparing. Results in Panel B are estimated from the market index model $r_p = \alpha + \beta r_m + \varepsilon_p$. Results in Panel C are estimated from Carhart's four-factor model: $r_p = \alpha + \beta r_m + \beta_1 smb + \beta_2 hml + \beta_3 mom + \varepsilon_p$.

The last column reports the adjusted R-square statistics.

The values of alpha are multiplied by 100 to express them in percentage terms.

***, **, and * represent significance level of 1%, 5%, and 10%, respectively.

7.6 Conclusions

This study proposes a trust-specific unique risk to capture active risk taken by trust managers relative to peers. We use ranking-group and regression methods to examine whether trust managers can produce additional returns for trust investors when managers actively pick up high-risk stocks. We find a positive relationship between realized returns of unit trusts and their trust-specific unique risk. We further to explore this positive relationship from short-term and long-term perspectives, and find that the positive relationship changes to insignificant in the time-series long-term study.

Moreover, on the one hand, prior studies argue that the risk and return trade-off should be contemporaneous. On the other hand, other studies document that the volatility exhibits the characteristic of volatility clustering, suggesting that lagged volatility could be a predictor for future volatility. We, therefore, consider various volatility proxies in the cross-sectional analysis, maintaining that 1-month lagged trust-specific unique risk can predict current unique risk, but the long-legged unique risk is not an appropriate risk proxy. Thus, we give trust investors the advice to pick up UK equity unit trust with relatively high risk within their risk tolerance and capability but not to hold the same unit trust for an extended period.

In addition, this study investigates the volatility investment strategy of UK equity unit trusts. We find that trusts with high trust-specific unique risk outperforming low unique risk trusts, tend to invest in specific high volatile stocks and reduce market exposure. This finding supports the hypothesis that the existence of volatility anomaly in the stocks markets might partly be due to risk-chasing investment behavior. The volatility anomaly factor provides a strong home game explanation of unit trusts performance, and the explanatory power is almost equally effective to conventional pricing factors of size, value and momentum.

Chapter 8: Conclusions

This thesis investigates the risk of UK equity unit trusts, considering time-varying market risk and trust-specific unique risk. The first research focuses on market-return timing, examining the investment abilities to pick up under-priced stocks and time the market return. We find that trust managers exhibit significant positive selectivity ability while showing the significant negative market-return timing ability. The negative return-timing performance is unfavourable but consistent with prior studies.

The reverse return-timing finding motivates us to question the strategy adopted by managers to time the equity market. Considering that market volatility is more accessible to be predicted than market return due to the characteristics of volatility clustering, managers might time the market volatility rather than the market return. We, therefore, examine volatility timing performance and find a favourable result that trust managers can successfully time the market volatility and provide a positive abnormal return on average.

As market returns and the volatility of market returns are highly correlated, it is natural to question the reliability of successful volatility timing findings. In particular, market return-timing behavior might be incorrectly explained by the coefficient of market volatility, thereby adding the return-timing factor into the volatility-timing model to control the correlation effect. The finding of significant superior volatility-timing performance and reverse return-timing performance is robust. In addition, taking trust managers' perspective on investment into account, it is rational to consider both returns and volatility simultaneously. We use a joint-timing model to do the test but fail to find significant evidence.

As ingredients of systematic market risk and unsystematic idiosyncratic risk together describe the risk of active equity unit trusts fairly, we then move our attention from time-varying market risk to the trust-specific idiosyncratic risk. More specifically, we construct a variable aggregate idiosyncratic shock to capture trust managers response to firm-level shocks at the aggregate level. We concentrate on the idiosyncratic risk referring to each trust manager's private information and investment objective at the individual trust level by controlling aggregate idiosyncratic risk, that is, trust-specific unique risk.

The research question of the third study is whether trust managers can produce high realized returns for investors regarding high trust-specific unique risk. We find a significant positive relationship between realized returns of unit trusts and their unique risk in the short-term, while a positive but insignificant relationship in the long-term. We advise trust investors to select a relative high-risk unit trust within their risk tolerance and capability and shift the trust holdings in the long-term investment. Moreover, we explore the volatility investment strategy of UK equity unit trusts and find that unit trusts with high trust-specific unique risk tend to hold high volatile stocks and vice versa. This finding indirectly supports the hypothesis that volatility anomaly existence might partly be attributed to risk-chasing behavior of institutional investors.

The remainder of this chapter proceeds as follow. We first overview the contributions of this thesis in section 8.1, followed by limitation in section 8.2. Section 8.3 discusses the implications of this thesis and future research.

8.1 Contributions

The first contribution of this thesis is to use daily data to do timing behavior analysis. In particular, daily data can monitor trust manager's timing behavior timely, since managers make investment decisions randomly instead of regularly such as once a month. Prior studies confirm that managers are daily timer (Chance and Hemler, 2001), and that daily data has more power than monthly data in the return-timing performance analysis (Bollen and Busse, 2001; Goetzmann, Jonathan, and Ivković, 2000). For volatility-timing strategy test, Busse (1999) uses daily returns of US mutual funds and find favourable volatility-timing performance. This thesis contributes to enrich the literature on timing performance evaluation by employing daily data set to examine timing behavior of UK equity unit trusts.

Our finding of reverse return-timing performance is in line with prior findings based on monthly returns of UK mutual funds, whereas the finding of successful volatility-timing ability in the aggregate contradict the finding from the monthly data analysis. In particular, using monthly returns of UK equity mutual funds, Fletcher (1995) reveal significant negative return-timing performance and Foran and O'Sullivan (2017) fail to find evidence on favourable volatility-timing performance. Therefore, our study empirically suggests that data frequency is significant for assessing volatility-timing behavior but insignificant for return-timing performance evaluation in the context of the UK fund industry.

The second contribution of this thesis is to employ the ARCH family models to estimate parameters, displaying five merits: first, as daily returns exhibit more obvious autocorrelation features than monthly returns, time-series conditional variance equation in the ARCH-type models can address the autocorrelation problem by using the iteration process. Second, ARCH-type models can control heteroscedasticity in the residual term. Prior studies have documented that empirical data that cannot satisfy strict statistics estimation assumptions such as no serial correlation and homoscedasticity results in parameter estimation and significant level suffering bias. Prior studies employ bootstrapping technology to deal with non-normal distribution issue (Kosowski et al., 2006; Fama and French, 2010). The basic idea of the bootstrap method is re-sampling residuals hundreds of times to refine the true alpha and alpha's t-statistics. By contrast, ARCH-types models use joint equations of mean and conditional variance to control auto-correlation and heteroscedasticity in time, thereby correcting estimation bias.

The third merit is that the time-series ARCH family can track the behavior of the dynamic market better. Ferson and Warther (1996) argue that as the change of systematic risk could attribute to either timing behavior or market dynamics, it is critical to account for public economic information that leads to market movement while measuring manager's timing performance. Ferson and Warther, (1996) propose several macro-economic indices to demonstrate dynamic market movement. However, macro-economic indices usually lag and indirectly capture the market reaction to current news. ARCH-type models can overcome this problem by estimating the parameters of the mean equation and conditional variance equation simultaneously, thereby monitoring the news effect on the market in time.

The fourth merit of using ARCH family is the accuracy improvement of modelling market volatility. More specifically, as the stock returns negatively correlated with the volatility of the next period due to leverage effect or volatility feedback hypothesis (Black, 1976; Schwert, 1989; Bekaert and Wu, 2000), a professional manager would consider the asymmetric volatility effect when forecasting market volatility and making a volatility-timing investment decision. Therefore, it would improve the volatility-timing model specification and accuracy, if we account for the asymmetric characteristic of volatility while monitoring market volatility and assessing the volatility-timing behavior.

Last but not least, the ARCH-in-Mean model can provide reliable evidence on evaluating the selectivity skill of trust managers and examining the risk-return relationship. To be specific, although well-diversified portfolios get rid of idiosyncratic risk, this type of portfolios is not attractive to active fund managers because managers are eager to produce higher returns for investors by picking up particular under-diversified stocks and taking additional idiosyncratic risk than the market and/or peers. The ARCH-in-Mean model takes the conditional idiosyncratic risk into account while estimating timing models, providing more reliable evidence on selectivity ability evaluation than standard performance evaluation models. Moreover, the ARCH-in-Mean offers a straightforward approach to test the long-term relationship between realized returns of trust and its trust-specific unique idiosyncratic risk at the individual trust level. Therefore, it is a vital contribution to employ the ARCH family to investigate the performance of time-varying market risk and trust-specific idiosyncratic risk in the context of UK equity unit trusts, enriching the literature on the timing performance evaluation of mutual funds and idiosyncratic risk study.

The third contribution of this thesis is to propose the concept of trust-specific unique risk. We extend the study of idiosyncratic risk in the equity market to the fund market. We break down the idiosyncratic returns of unit trusts into aggregate idiosyncratic shocks of demonstrating the typical responses of managers to the public firm news and trust-specific unique returns of evaluating the value of manager's own investment decisions for each unit trust. The trust-specific unique risk mainly relies on individual trust managers investment ability by processing their private information. We also explore the relationship between realized returns of unit trusts and their trust-specific unique risk, investigating whether trust managers can produce high returns when taking the high unique risk.

8.2 Limitations

The main limitation for the study of UK unit trusts is the scarcity of holding data for each unit trust. Holding-based data would accurately reveal the trading behavior for each unit trust, allowing us to directly capture the change of holdings in different market conditions for each unit trusts, and to propose a straightforward approach to measure the unique risk comparing to peers by calculating the standard deviation of the sum of weight returns of stock holdings different from peers. This thesis overcomes the limitation of lack of holding data by concentrating on data frequency and estimation accuracy in the analysis of return-based models.

Another limitation is that the market intraday returns are not available in our research database. Although we cannot measure realized daily volatility by calculating the standard deviation of market intraday returns, we do not maintain that our findings of superior volatility-timing performance are biased. The main reason is that trust managers are not prophets but professional and knowledgable investors; that is, they use volatility models and their private information to forecast market volatility rather than know how the market fluctuates in advance. Therefore, we state that the well-accepted ARCH-type volatility models are an appropriate and reasonable method for assessing the volatility-timing ability of trust managers.

8.3 Implications and Future Research

This thesis has implications for trust investors, trust agents and trust managers. From the perspective of investors of UK unit trusts, since equity unit trusts exhibit significant time-varying market risk and idiosyncratic risk, trust investors might consider the trusts' risk carefully. To be specific, reverse return-timing and superior volatility-timing performance support that the systematic risk of equity unit trusts is time-varying instead of the constant value of reported beta. Buy-and-hold trust investment strategy, according to the reported annual value of beta might not achieve the expected return on average for investors. Moreover, we find that trusts bearing higher idiosyncratic risk than peers can generate higher realized returns for investors, suggesting investors to invest in relatively high-risk trusts based on their risk tolerance and capability. The positive relationship between risk and return, nevertheless, is not consistent, indicating that buy-and-hold strategy for UK equity unit trusts is not the best option. Therefore, we give advice to trust investors with strategy of timing unit trusts returns based on the risk level of trusts.

It is hard for retail investors to switch unit trusts timely and successfully due to lack of time and information to do analysis. Trust agents might be able to see the benefit of providing a more detailed risk assessment of trusts in the advertisement and marketing in order to attract more retail investors. For example, agents could display the graph of historical beta fluctuation instead of simple number of annual beta. Agents could also report the average risk level of trust industry or the index of volatility of average returns of UK equity unit trusts.

For fund managers, as the performance of timing investment strategy is confusing, managers should concentrate on to improve stock-picking skill rather than skill of timing the stock market. On the other hand, the unclear findings of timing strategy may be attributed to the analysis bias. The analysis of timing behavior of trust managers can be further improved by proposing an alternative timing hypothesis. More specifically, the irregular return-timing empirical finding motivates us to argue the hypothesis of return-timing behavior: managers increase the market exposure when the market excess return is positive and decrease the market exposure when the market excess return is negative.

We challenge this hypothesis from two perspectives: first, prior studies adopt realized contemporary market excess return to assess the return-timing ability, implicitly assume that managers correctly forecast market returns; then, the coefficient of timing factor demonstrate the responses of managers to their forecast. To our knowledge, there is no literature empirically documents the economic value of assumed return-timing strategy. It would contribute to shed lights on the return-timing behavior by simulating assumed return-timing portfolios and reverse return-timing portfolios in the context of the UK stock market and then evaluating the performance of both types of portfolios.

Furthermore, from the perspective of prospect theory, investors are loss-averse rather than risk-averse. In particular, Tversky and Kahneman (1992) state that investors make decisions based on the potential value of losses and gains rather than the final outcomes. Tversky and Kahneman (1992) observe consistent risk-seeking choices when people must choose between a sure loss and a substantial probability of a larger loss. In other words, when managers make a decision with respect to anticipation of negative market excess return (i.e., potential loss), managers might choose risk-seeking behavior to increase market exposure of trusts rather than risk-averse of reduce market exposure. Therefore, it is reasonable to assume that trust managers time the market gains and losses, rather than positive and negative market excess returns.

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