Drawdown Measure and Market Timing Skills: An International Empirical Study

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Statement of Authentication

The work presented in this thesis is, to the best of my knowledge and belief, original except as acknowledged in the text. I hereby declare that I have not submitted this material, either in full or in part, for a degree at this or any other institution.

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List of abbreviations

AD	Average Drawdown
ADF	Augmented Dickey-Fuller
BP	Benchmark Portfolio
CAPM	Capital Asset Pricing Model
CDA	Classical Data Analysis
DF	Dickey and Fuller’s (1979) Test
EDA	Explanatory Data Analysis
EMH	Efficient Market Hypothesis
HM	Henriksson and Merton
HML	High Minus Low
IP	Investment Performance
JB	Jarque-Bera Test
MA	Moving Average
MKT	Market Excess Return
MOM	Momentum
MSCI	Morgan Stanley Capital International
NHM	New Henriksson and Merton

NTM	New Treynor and Mazuy
RI	Return Index
S&P 500	Standard and Poor's 500 Stock Index
SMB	Small Minus Big
SML	Security Market Line
THM	Traditional Henriksson and Merton
TM	Treynor and Mazuy
TTM	Traditional Treynor and Mazuy

Abstract

Despite the fact that classical timing measures have unique and effective features for the evaluation of a portfolio manager's timing skill, they suffer some limitations. These limitations versus the potential features of other risk measures, e.g., dynamic risk measures, provide the possibility to propose alternative timing measures. A set of potential reasons such as the unique features of technical timing measures, the superiority of average drawdown measure compared to variance (or standard deviation), the lack of sufficient positive timing evidence resulting from the existing timing measures, the ignoring of the effects of worst market losses occurring over the holding period of an investment, the low forecasting power of the existing timing measures stimulate us to propose the average drawdown market timing measures. Subsequently, this study adds the average drawdown market timing measures to the Carhart (1997) standard model for estimating selection and market timing skills of a portfolio manager. This study collects data of 3087 stocks from 23 developed countries and constructs the 23 country-level portfolios. The purpose is to compare performance of the average drawdown timing approach and the traditional timing approach. The timing measures are constructed using two most-common timing measures of Treynor and Mazuy (1966) and Henriksson and Merton (1981). Another purpose is to compare the daily performance and the monthly performance of average drawdown timing models. The results show that portfolio managers have significant timing and selection skills using the average drawdown timing measures. The predictive power of these timing measures is better than the power of traditional timing measures based on higher statistical and economic significance. The daily performance of the average drawdown timing measures is better than the monthly performance. These results are robust to different checks, e.g., different lag lengths, simulation tests, and alternative monthly returns.

Chapter 1 : Introduction

1.1 Research Case

The portfolios in various security classes are the most important economic and financial intermediaries in lending financial sources to the world economies (Huhmann, 2005). These portfolios help rational investors to follow proper investment strategies and obtain positive risk-adjusted returns in financial markets. Such a role of the portfolios in the markets stimulates market practitioners to respond a key question on whether a portfolio manager has sufficient managerial abilities to predict market movements and to select an efficient portfolio. A large number of the empirical studies document these two portfolio managers' abilities, market timing skill and selection skill, in the literature. These two abilities are important for three reasons. First, good performance of a portfolio causes some biases in the Efficient Market Hypothesis. This responds to a key question on whether any market participant (e.g., portfolio manager) possesses monopolistic access to any relevant information about asset price. Second, a rational investor tends to obtain potential benefits by professional fund-management skills. Third, a portfolio manager's performance evaluation is an essential function for investment companies to provide compensation schemes for employing and keeping high quality managers (Prather and Middleton, 2006).

According to definition, a portfolio manager's market timing skill is the manager's ability to predict market movements. A review of the literature exhibits that most of the empirical studies in this area follow two approaches. The first approach is based on the classical analysis using the classical measures that assess portfolio managers' selection and timing abilities (e.g., Grinblatt and Keloharju, 2000). This analysis develops the performance persistence concepts (e.g., Goetzmann and Ibbotson, 1994) and employs various timing models to generate abnormal returns, as indicator of a portfolio manager's selection skill, and to consider the upward returns of the squared market risk premium (Treynor and Mazuy, 1966) and the market risk premium (Henriksson and Merton, 1981), as indicators of a portfolio manager's timing skills (Fama and French, 1993; Carhart, 1997; Du et al., 2009). The second approach is based on dynamic models in general and technical analyses in particular that adds technical timing measures to asset pricing models for simultaneously estimating a portfolio manager's selection and market timing skills (e.g., Glabadanidis, 2014, 2015, 2017).

To address the aforementioned discussions, this study proposes new market timing measures grounded on the average drawdown (AD) measure to assess a portfolio manager's timing abilities. This study firstly uses the Bollen and Busse (2001) methodology and extracts the daily and monthly data of the stock prices of 3087 firms from 23 developed countries over the period 4 January 1988 till 30 June 2016. Then, this study constructs 23 portfolios based on the stocks active in each country, and compares the proposed market timing measures with the classical measures. In next step, this study compares the daily and monthly performance of portfolio managers based on the proposed measures as in Bollen and Busse (2001). Finally, it compares the performance of each portfolio based on the proposed market timing measures to find the best portfolio manager.

1.2 Intellectual Context

Theoretical perspective of a portfolio manager's performance evaluation is appealing because it causes debates on the Efficient Market Hypothesis (Prather and Middleton, 2006). Accurate predictions are very important in the economic and financial analyses (Chou et al., 2011). The predictive skill of an occurrence, e.g., whether returns on a portfolio in a time period will go up relative to Treasury bill rates in next period, would be a crucial issue in the asset allocation of a portfolio manager. This skill (referred to as a portfolio manager's predictability) assesses a portfolio manager's performance with respect to his skill in forecasting market movements.

To quantity this skill, the literature has documented numerous measures (referred to as market timing measures) during the recent decades. Each of the measures assesses a dimension of a portfolio manager's timing skills by considering their unique features. However, despite the measures have unique and effective features for the evaluation of a portfolio manager's timing skill, they suffer some limitations (Chen et al., 2010). These limitations in the existing classical timing measures along with the potential features of other risk measures in the risk management literature, e.g., dynamic risk measures, provide the possibility to propose alternative timing measures. The reasons are obviously presented as follow:

The first reason in selecting an alternative timing measure stems from the lack of dynamic timing measures in the existing literature and the unique features of these measures, especially technical timing measures, in comparison with the classical timing measures. More specifically, the technical analysis grounded on dynamic analysis uses the past and current market price, the trading volume, and also other publicly information available on market to forecast future market prices. This analysis is very popular in practice with abundant financial trading advice that is largely based on technical measures. From the standpoint of a dynamic analysis, the technical analysis has substantial role and power in predicting the returns on stock portfolios as well as individual stocks. Several logical reasons stimulate us to justify the use of technical analyses relative to the existing classical analyses to examine the performance of a portfolio manager. First, a logical investor's heterogeneity as well as asymmetric information available in stock market may generate the persistent behavioral biases in market prices. Previous studies that support this implication are consisting of Treynor and Ferguson (1985), Brown and Jennings (1989), and Hong and Stein (1999), among others. Moreover, the Wang (1993) theoretical model exhibits explicitly how an economic agent inhabits a traditional selection model under uncertainty, and information available in market provides useful and informative signals on average past prices as well as other agents' private information. Thus, technical analyses allow us to assess more accurately the above biases, and to consider average past prices. Second, an active investor often follows stock price trends in practice that may provide the continued persistence of both upside trends and downside trends. Empirical studies in this area contain Fung and Hsieh (2001) who construct trend measures based on the returns on look-back straddle options. Third, the Brock et al (1992) study documents the moving average (MA) performance, as a very common measure of technical analysis, and exhibits that it is a good strategy in technical analysis. Other studies such as Brock et al (1992) find considerable evidence that technical measures have high significant forecasting ability. Fourth, Blume et al (1994) suggest a theoretical framework grounded on technical analysis using price data and trading volume, and conclude that it is the part of an investor's learning process. Lo et al. (2000) find the high predictive ability of MA. Zhu and Zhou (2009) find a strong theoretical reason why a technical measure can be a potentially beneficial state variable in a market where an investor tends to learn over time the key value of the risky security he invests in. Neely et al (2010, 2011) also exhibit much forecasting power of technical analysis on stock excess returns as information generated from economic fundamentals. Such a literature includes Faber (2007) and Kilgallen (2012) who document risk-adjusted returns on the MA strategy using different portfolios constructed from commodities and currencies. Moreover, Huang and Zhou (2013) use the MA measure to forecast returns on the U.S. stock market, whereas Goh et al (2012) use the same methodology on government bond risk premiums and yields. Motivated by the forecasting power of the MA measure, Jiang (2013) and Han et al (2013) construct a trend variable with substantial cross-sectional explanatory power and considerable historical performance. Similarly, Glabadanidis (2014, 2015, 2017) documents the performance of a simple MA timing strategy using international and U.S. portfolios as well as U.S. individual stocks. Overall, the above evidence highlights the predictive ability of a MA timing measure for assessing the performance of stock portfolios and consequently their relevant managers.

The second reason in selecting an alternative timing measure is related to the Christopherson et al (1999) approach. They believe that the prior studies documented on the existing performance measures ignore information regarding the varying nature of the economy. Therefore, the measures cannot correctly assess expected returns when a portfolio manager reflects market information or uses dynamic trading strategies. These biases cause some problems in the existing performance evaluation models to estimate alpha and beta. This thus provides intuition behind the conditional performance evaluation approach of Ferson and Walther (1996) and Ferson and Schadt (1996) who believe that conditional performance evaluation can generate more precious estimates about risk and return. This approach assumes that a portfolio's alpha and beta varies dynamically with varying market conditions, and a portfolio manager is able to reflect information available on market by modifying his portfolio's alpha and beta (Christopherson et al., 1999). Ferson and Schadt (1996) run a dynamic performance evaluation model for the estimation of dynamic alphas. Similarly, Christopherson et al (1998) estimate a dynamic alpha using the Ferson and Schadt (1996) dynamic model and find that the model allows an investor to consider various market information by varying his portfolio's alpha and beta, and incorporating the dynamic nature of his alpha and beta. Christopherson et al (1999) assumes that dynamic changes in a portfolio's beta reflect all information available on market price. These reasons thus motive us to propose dynamic market timing measures and their relevant evaluation models to benefit from the features of dynamic measures and models.

Another motivation is directly related to superiority of the AD measure extracted from the mean-AD approach relative to variance and standard deviation extracted from the mean-variance approach. For example, Tavakoli Baghdadabad et al (2013) and Tavakoli Baghdadabad and Glabadanidis (2013) examine the mean-AD approach against the classical mean-variance approach, and propose two risk measures of AD and maximum drawdown. They report the superiority of the betas estimated from AD and its relevant performance evaluation models relative to the classical betas and capital asset pricing model (CAPM). The same results can be also found in Tavakoli Baghdadabad and Glabadanidis (2013), who report the superiority of nine risk-adjusted performance indicators constructed from maximum drawdown risk measure relative to their corresponding classical indicators.

Another implication that stimulates us to propose a new timing measure stems from empirical evidence that the classical market timing measures, such as those proposed by Henriksson and Merton (1981) and Henriksson (1984), obtain the mostly negative timing performance on managed portfolios. These results are also reported in Becker et al (1999), Jiang (2003), and Jiang et al (2007). These findings thus provide more motivation to construct new market timing measures, and to seek whether these new measures can help us to find more positive evidence of market timing. These new measures allow a market stockholder to distinguish among a good, average, and bad market timer. The construction of such measures, e.g., drawdown, considers more assumptions when assessing the performance of a portfolio manager (Shukla and Inwegen, 1995). Despite the literature exhibits a great number of the studies to assess a portfolio manager's skill in forecasting market movements, it has ignored the aspect from market timing measures that incorporate extreme (loss) volatility drags (or drawdowns).

More technically, the existing classical timing measures ignore the effect of the worst market losses occurred over the holding period of an investment. Specifically, economic and financial recessions cause great turmoils in stock market and subsequently a negative impact on stock portfolios. These turmoils generate extreme volatilities along with extreme losses (drawdowns), and generate bad signals on market prices. Thus, a portfolio manager often should take into account the market prediction of these drawdowns as a useful indicator for quantifying the market variability. These drawdowns impose bad effects on the performance of a portfolio and subsequently its manager. From a rational investor's perspective, a market timer should monitor extreme losses (drawdowns) because their realized relatively great returns may stimulate an investor to suffer larger volatilities during market volatilities. Graham and Harvey (1996) exhibit that changes in extreme volatilities and their relevant losses improve the performance of an investment. Therefore, prediction of the drawdowns is required to evaluate the performance of an investment. The portfolio market as well as other financial markets is often faced with these losses. They are the reflection of market natural shocks that can generate potentially great financial losses. These drawdowns are also referred to as extreme volatility drag or loss volatility drag. From the theoretical perspective, they are the worst losses occurred on an investment. The classical timing measures neglect these drags in predicting market movements. Cooper (2010) believes that a portfolio manager with higher extreme volatility experiences a greater decrease in his managed capital during market drawdown. This implies that ignoring the drags may make some biases in the classical market timing measures. However, the existing classical timing measures ignore these drags.

Another limitation of the classical timing measures is that their forecasting power may decrease when stock market is faced with extreme volatilities. Cooper (2010) explains that higher volatilities (or extreme volatility drags) can increase the predictability of stock returns, implying that the existence of a timing model or a timing measure that incorporates these drags may reinforce the forecasting power of the measure and its relevant model. Busse (1999) demonstrates that timing in the market volatility improves the performance of a portfolio. In a series of the studies, Fleming et al (2001, 2003), Johannes et al (2002), and Marquering and Verbeek (2004) find that timing in the extreme volatility adds value to the performance of a portfolio. Ferson et al (2003) demonstrate that the prediction of stock market returns in an efficient market is problematic, whereas market extreme volatility (as a case of drawdown) is obviously predictable. Bali and Weinbaum (2007) believe that volatility forecast on extreme returns generate proper information content. In a series of interesting studies, Longin (2000), Bali (2003), and Patton and Sheppard (2011) find that the classical volatility measures cannot generate proper estimates of market risk during high market volatility. They believe that the reason stems from the fact that negative jumps possess different impacts upon future volatilities relative to positive jumps, and that extreme negative jumps possess different impacts on future volatilities relative to negative jumps. Thus, these jumps can improve the predictability of future volatilities using volatility trading strategies. Moreover, Audrino and Hu (2016) exhibit that volatility jumps are a proper factor for forecasting the extremely jumpy periods. Kim and In (2012) find that if market volatilities are high, a portfolio manager expects to stay elevated during next period and adjusts their exposures so that he can easily predict volatilities. Cao et al (2013) explain that, despite market returns do not possess sufficient persistence for reliably prediction, market extreme volatilities possess more persistent so that it is easier for a portfolio manager who predicts extreme losses. Despite Hsieh et al (2012) examine their proposed market timing strategies using drawdown and suggest two drawdown and draw-up strategies over the crisis period, their idea fails to model the strategies and their relevant timing measures. Generally, the classical timing measures take into account only the returns higher than the target return as an indicator of superior performance. These measures do not consider intermittent and consecutive losses realized from extreme volatilities (or extreme losses) over the holding period of a portfolio. This exercise is very important because it allows investors to separate a portfolio manager who controls these losses in his investment choice from one who does not.

Another limiting feature of the classical timing measures stems from their focusing on point gains (their positive spreads between market excess returns and free risk returns or their squared spreads). These classical measures do not allow to evaluate the worst losses occurred over the investment period of a portfolio. Such classical measures thus do not allow distinguishing between a manager who obtains extreme losses during his investment period from one who obtains only insignificant losses. If a portfolio manager, who is often faced with the worst (extreme) losses in market, could forecast these losses, he would manage his portfolios in a better way. The existing classical measures actually ignore these extreme losses in their current calculation method. One reason may be the ignoring of the time series features of stock returns over the investment period of a portfolio (Schuhmacher and Eling, 2011).

Another limiting feature of the existing literature is related to the lack of adequate power of standard performance evaluation models to exhibit the evidence of abnormal performance. These models are also flawed in empirical tests, and hence fail to present a reliable guide for portfolio performance. These limitations cause that a portfolio manager fails to exhibit consistently the evidence of achieving his superior performance (Cumby and Modest, 1987).

Given the limitations of the existing classical timing measures, the unique and superior features of dynamic timing measures, and the superiority of mean-AD approach relative to the mean-variance approach, this study proposes two AD-based market timing measures grounded on the mean-AD approach, and incorporates them with the moving average dynamic approach in order to assess the performance of a portfolio manager. These new timing measures consider simultaneously point timing and extreme (loss) volatility drags (or drawdowns).

1.3 Research Gap

Generally, the existing literature follows two common approaches for the prediction of market movements. The first approach is based on the classical analysis using the classical measures that assess portfolio managers' selection and timing abilities (e.g., Henriksson and Merton, 1981, Treynor and Mazuy, 1966, Grinblatt and Keloharju, 2000). The second approach is based on dynamic models in general and technical analyses in particular that adds technical timing measures to asset pricing models for simultaneously estimating a portfolio manager's selection skill and market timing skill (e.g., Glabadanidis, 2014, 2015, 2017). However, the existence studies (i) ignore the worst losses occurred over the holding period of a portfolio, (ii) ignore the extreme (loss) volatility drags (or drawdowns), and (iii) concentrate only on point losses (gains). Additionally, the market timing literature actually neglect, (i) the high predictability of technical analyses, especially the MA timing measures, and (ii) the superiority of AD against variance and standard deviation, to construct new timing measures.

1.4 Research Contribution

To address the above research gaps, this study proposes two market timing measures based on AD. The extant timing measures in the mean-variance framework apply conditional or squared risk premium to predict market movements. The dynamic timing measures also use technical analyses, e.g., moving average (MA) timing measures. This study incorporates two measures of AD and MA to construct new two timing measures in the AD form. The AD calculates the loss average occurred over the holding period of a portfolio (Tavakoli Baghdadabad et al., 2013). The AD is a natural measure of risk that allows an investor to reconcile optimal allocations with securities and actual assets, and provides effective allocations for an institutional investor (Hamelink and Hoesli, 2004). This feature of AD in allocating money on assets can strongly reinforce timing strategies since success in allocating money can improve the performance of an investment (Sorensen and Amott, 1988). Another feature of AD is to incorporate the time-dependence of returns on a portfolio and to formulate loss volatility drags and extreme volatility drags in assessing the risk levels of a portfolio. According to the above features, this study proposes the AD market timing measure to improve predictability of the classical timing measures.

More specifically, this study fills its research gaps by organising several analyses. First, this study proposes two AD-based market timing measures to evaluate portfolio managers' timing ability. Second, to address the first contribution, it applies the Bollen and Busse (2001) approach and adds the AD timing measure to the Carhart (1997) four-factor model to evaluate both portfolio managers' market timing and selection ability. Third, this study examines its proposed timing methodology on daily data, and compares its result with monthly data to find out whether the performance of daily data has substantial superiority relative to monthly data. Finally, this study proposes a decision pattern for a rational investor to select superior portfolios and their controlling managers.

1.5 Thesis Outlines

A summarily review of the existence literature exhibits that most of the empirical studies in the area of portfolios' performance evaluation follow two approaches. The first approach is based on the classical analysis using the measures that assess portfolio managers' selection and timing abilities (e.g., Grinblatt and Keloharju, 2000). The second approach is based on dynamic models in general and technical analyses in particular that adds technical timing measures to asset pricing models for simultaneously estimating a portfolio manager's selection and market timing skills (e.g., Glabadanidis, 2014, 2015, 2017). However, the existence studies (i) ignore the worst losses occurred over the holding period of a portfolio, (ii) ignore the extreme (loss) volatility drags (or drawdowns), and (iii) concentrate only on point losses (gains). Additionally, the market timing literature actually neglect, (i) the high predictability of technical analyses, especially the MA timing measures, and (ii) the superiority of AD against variance and standard deviation, to construct new timing measures. To address these research gaps, this study proposes two AD market timing measures to provide a better estimation and prediction on market movements by considering a combination from both the loss average occurred over the holding period of a portfolio and market risk premium. Next chapters document this idea in details, and conduct empirical analyses to support it as:

Chapter 2 review the existing literature, consisting of the supporting theories of the performance evaluation, the market timing measures and their relevant timing models, the dynamic timing measures, the moving average timing measures, and the AD risk measures and their relevant performance evaluation models.

Chapter 3 presents an overview of statistical and econometric analyses. It presents the traditional market timing strategies, the dynamic timing measures, the AD timing measures, the proposed AD timing models, the research objectives, the research hypotheses, the research questions, the research conceptual design, the research method, the research population and sampling, the sampling method and survivorship bias, the data collection, the construction of country-level portfolios, and the descriptive statistics consisting of the normality test, the unit root test, the Wald test, the redundant test, and the research hypotheses test. Finally, it presents some robustness checks to control for the basic results of this study.

Chapter 4 presents basis analyses using statistical and econometric methods to cover research objectives. First, it conducts normality tests for both daily data and monthly data to understand about the dispersion features of the data used in this study. Second, it reports the results of unit root tests to know whether the data follow a stationary trend across time. Third, it uses two tests of Wald and redundant to know whether the timing measures added to the standard Carhart (1997) four-factor model provide a significant value for the model and its relevant dependent variable. Fourth, it presents the results of portfolio managers' market timing and selection abilities for 23 countries under study. To conduct this step, market timing models are firstly run by daily portfolio returns and then the models are estimated by monthly portfolio returns extracted from daily returns. Fifth, it performs several robustness checks to understand whether the baseline findings of this study remind unchanged if the analysis assumptions and some research variables change. Sixth, it tests research hypotheses using the results obtained from the basic analyses. Finally, it provides supplementary explanations, and relates empirical evidence with the existing performance evaluation studies.

And finally, chapter 5 contains a summary of this study, and presents summarily its main results. It then represents main implications and recommendation policies, research limitations, and some suggestions for future studies.

Chapter 2 : Literature Review

This chapter presents a review of the portfolio theory and the efficient market theory as supportive theories of this study. It then presents the definitions of the performance evaluation, the portfolio management strategies, the traditional portfolio performance measures, the portfolio performance models, the performance measure of selection ability, the performance measure of market timing, the dynamic market timing measures and their relevant performance models. Finally, an overall conclusion is presented at the end of this chapter.

Generally, the investment performance of a portfolio has a long history in the finance literature. Findings about the performance of such portfolios are simultaneously extracted from two theories. The first theory is the portfolio theory that provides an understanding of the relation between risk and return because literature uses a risk-return benchmark to evaluate the portfolio performance (e.g., Jensen, 1968, 1969, Black et al., 1972, and Blume and Friend, 1973). The second theory is the efficient market hypothesis (EMH) that provides an understanding of asset price determination due to the existence of differential investment information in the market (Chang and Lewellen, 1984).

2.1 The Portfolio Theory

Markowitz (1952, 1959) proposes the modern portfolio theory. He formulates the portfolio problem by selecting mean and variance of a portfolio. He constructs his mean-variance portfolio based on two scenarios by holding constant variance and maximizing expected return, or by holding constant expected return and minimizing variance. These two scenarios contribute literature to construct an efficient frontier on which investor can select his preferred portfolio based on individual risk-return preferences.

The theory provides implication that the choice of assets for a portfolio is not only dependence on asset characteristics. Rather, an investor should know how each asset co-moves with other assets. These co-movements provide the possibility to construct an asset portfolio with higher expected returns and lower levels of risk than an asset portfolio constructed by ignoring the interactions between assets.

Consequently, the mean-variance portfolio theory provides the possibility to estimate inputs by estimating correlation coefficients (or alternatively co-variances). An applicable principal tool for estimating co-variances is the index models that have provided wide uses beyond of estimating covariance structures. Generally, the portfolio theory guides us to use both risk and return for the performance evaluation of as assess.

2.2 Efficient Market Theory

The rudimentary role of a capital market is to allocate the ownership for economy's capital stock. The ideal here is a market where price provides precise signals for money allocation: that is, a market where a firm can make precise investment decisions and an investor can select an asset among other assets. This process in the choice of an asset is based on the assumption that the asset prices at any time reflect all information available in the market. A market where price always fully reflects available information is referred to as "efficient".

The investment performance of a portfolio is also related to the efficient market hypothesis and perhaps to an understanding of the asset price determination process due to the existence of potential implications about the differential investment information in the market (Chang and Lewellen, 1984). Identical to the portfolio theory, performance evaluation based on this theory is stated by examining a portfolio manager's selection ability (Jensen, 1968, 1969, Black et al., 1972, Blume and Friend, 1973), since the risk levels of the examined portfolio is assumed to be stationary across time.

The main purpose of this theory in studying the performance of a portfolio is to determine (i) whether a portfolio manager has access to special information that allows him to generate abnormal expected returns, and (ii) whether the portfolio is better at uncovering such information than other portfolios. Since the selection measure is the ability of a portfolio to generate larger returns than some norms without attempting to identify what is responsible to the large returns, the special information that provides high performance can be either interesting insight on the potential implications of publicly information available on the market, which is implicit in market prices, or monopolistically provide specific information.

Before reviewing the various performance evaluation measures and models documented in the literature, this section defines some of the basic concepts of performance evaluation to allow readers to acquire a better understanding of the matter. It begins by defining performance evaluation in finance and portfolio management, and consequently illustrating portfolio management strategies. Accurate understanding about the intuition behind these definitions is a primary step towards grasping the performance evaluation measures and models of a portfolio.

2.3 Investment Performance

Investment performance (IP) is defined as the return on a single asset. The IP can be also extended to multiple assets for defining the performance of a portfolio. It is often assessed in a specific currency and over a specific time period (Feibel, 2003). According to the IP, an investor often considers three different types of return.

The first type is based on the total return, which considers income (e.g., interest and dividends), and the price return, which considers capital appreciation. The second type uses the net return, which considers the return of all expenses, fees, and taxes, and the gross return, which considers the return before all expenses, fees, and taxes. The third type is based on the money-weighted return, which focuses on whether a manager can specify the timing of cash outflows and inflows in his portfolio, and the time-weighted return, which represents that a manager is not responsible to the timing of cash outflows and inflows of his portfolio (Feibel, 2003).

However, the IP is theoretically defined as the amount of returns obtained from an investment over a specific time period. Therefore, the returns on investment and the strategies of an investment manager to earn the returns play a key role in the IP. To address the role, the next subsection presents further information on managing the investment returns in the portfolio management.

2.4 Portfolio Management Strategy

In the portfolio management, there are two different strategies to manage investment returns on a portfolio, passive and active portfolio management strategy. The passive portfolio management strategy is commonly called as a buy-and-hold strategy, where the weights on the portfolio assets are determined at the beginning of each investment period and nearly held constant till the end of the period. The theoretically supportive assumptions of the passive portfolio management strategy are based on the efficient market hypothesis and the homogeneity of expectations. Hence, if a market is efficient, a portfolio manager is not able to capitalize on mispricing of assets to earn returns from his actively trading strategy. Furthermore, if an investor has homogeneous expectations, a portfolio manager is not able to take advantage of any spread in the assets' market expectations about risk and return to produce abnormal performance for active trades (e.g., Blake, 1994).

Unlike the passive portfolio management strategy, the theoretically supportive assumptions of the active portfolio management strategy are based on (i) the markets where they are not continuously efficient, and (ii) the investors who have strongly heterogeneous expectations about risk and return. Therefore, an active manager believes that he has both the skill to get more precious estimates of assets' return and risk, and the skill to appear any mispricing of assets. Overall, a portfolio manager frequently adjusts his portfolio weights to use various strategies and employs any opportunity to beat the market (Blake, 1994).

An active portfolio manager, therefore, requires the mastering of various abilities to optimally conduct his activities such as asset allocation, asset selection and market timing. Hence, a portfolio manager must decide firstly on the allocation of his asset portfolio across a series of wide asset classes such as share, bond, cash or other money market assets. This is commonly called as asset allocation and exhibits one of the key and most substantial decisions in the portfolio management because it focuses not only on the potential performance of most portfolios (e.g., Blake, 1994), but it considers the variability of their returns (e.g., Sharpe, 1992).

To conduct these two strategies, the literature presents tools (or measures) to assess the performance of portfolio managers. We here present these performance measures. Before presenting the traditional performance measures and models based on the above strategies, it seems to be logical to summarily review the risk-adjusted performance measures based on the portfolio theory.

2.5 The Risk-Adjusted Performance Measures

Up to this point we had a summarily review on the portfolio theory and the portfolio management strategies. Now, it would be appropriate to have a briefly review on portfolio evaluation, which relies on the portfolio theory. The first interesting work on performance evaluation is related to Cowles (1933) who compares the performance of managed portfolios and passive portfolios. He concludes that these managed portfolios underperform the passive portfolios. However, although he examines returns on a portfolio, he ignores the levels of portfolio risk in his calculations.

As mentioned in above, the portfolio theory suggests us to consider both risk and return to assess performance. Using this idea, early studies use a variety of evaluation techniques based on risk and return. These techniques include the Sharpe measure (Sharpe, 1966), the Treynor measure (Treynor, 1965), the Jensen's alpha (1968,1969), the Treynor and Black (1973) measure, and the Modigliani and Modigliani (1997) measure. Each of these studies evaluates risk-adjusted performance based on a measure of risk. Some studies use total risk (e.g., Sharpe, 1966) and others use beta as an appropriate measure of risk (e.g., Treynor, 1965, Jensen, 1968, 1969). The joint characteristic of these measures is that the combination of returns on each portfolio and returns on free-risk asset lie along a straight line to evaluate performance.

2.5.1 The Sharpe Measure

Sharpe (1964) introduces a Capital Asset Pricing Model (CAPM) based on an idea that all investors should choose a broadly diversified market portfolio combined with free-risk assets according to investors' attitude toward risk. He proposes a performance measure based on the model, namely, Sharpe measure, to evaluate the performance of a portfolio as:

$$SR_p = \frac{R_p - R_f}{\sigma_p} \tag{2-1}$$

where R_p is the return on portfolio p, R_f is the return on free-risk asset, and σ_p is the standard deviation of the excess return of the portfolio p.

This measure evaluates the degree on which portfolio can earn a return in excess of the risk-free return at each unit of risk. As a performance indicator, the Sharpe ratio of a portfolio is compared to the Sharpe measure of market portfolio. The portfolio performs better than the market portfolio, if it has a Sharpe measure higher than the market portfolio. However, this ratio may be inappropriate when portfolio returns are not normal, and also this measure ignores a manager's responsibility to the timing of the cash outflows and inflows of a portfolio. In other word, it only evaluates the selection skill of a portfolio manager and neglects other his skills, e.g., the market timing skill.

2.5.2 The Jensen Alpha

The Jensen alpha is perhaps one of the most well-known traditional measures of investment performance. Jensen (1968) introduces this measure using the CAPM concepts by running the portfolio excess returns into the market portfolio returns. This alpha is defined as intercept of the following regression model.

$$r_{p,t} = \alpha_p + \beta_p r_{m,t} + \varepsilon_{p,t} \tag{2-2}$$

where $r_{p,t}$ is the return on portfolio p in excess of the free-risk return at time t, $r_{m,t}$ is the return on market portfolio m in excess of the free-risk return at time t, α_p is the intercept of the model, β_p is the systematic risk (the sensitivity of return on portfolio p to return on market portfolio m), and $\varepsilon_{p,t}$ is the random error term. Supposing that the expected value of $\varepsilon_{p,t}$ is zero, the Jensen alpha thus represents the spread between the portfolio expected return and the market portfolio expected return. However, this measure ignores a manager's responsibility to the timing of the cash outflows and inflows of a portfolio. Additionally, this ratio only evaluates the selection skill of a portfolio manager and neglects other his skills, e.g., the market timing skill. More specifically, it evaluates the deviation of a portfolio from the security market line (SML) and picks up a manager's skill to predict future price of the portfolio.

The benchmark portfolio used to estimate this measure is supposed to be a mean-variant efficient portfolio from an uninformed investor's perspective. A passive investment portfolio thus expects to obtain a zero intercept, whereas an active investment portfolio, which has a manager with superior skills (or information), expects to obtain a positive alpha (intercept).

2.5.3 The Treynor Measure

One potential problem for the Jensen alpha is realized when $\beta_p > 1$. The market portfolio strategy in this measure uses a high negative weight on the free-risk asset. Practically, short-term Treasury bill rates are often used to reflect the free-risk returns. Thus, a few number of investors may borrow very cheap Treasury bill rates, which actually make an infeasible market portfolio strategy.

Under this limitation, Treynor (1965) introduces a measure that compensates the portfolio into the amount of leverage used as:

$$T_p = \frac{R_p - R_f}{\beta_p} \tag{2-3}$$

Identical to the Sharpe measure, a higher Treynor measure reflects better performance. Contrary to the Sharpe measure, the excess returns are normalized by the systematic risk (β), not the total risk (σ). However, this ratio ignores a manager's responsibility to the timing of the cash outflows and inflows of a portfolio. In addition, it only evaluates the selection skill of a portfolio manager (α) and neglects other his skills, e.g., the market timing skill.

2.5.4 The Treynor-Black Measure

Treynor and Black (1973) examine a situation where asset selection skill reflects expectations of nonzero Jensen alpha for individual assets, or equivalently, the market portfolio return. They use the mean-variance optimal portfolio and exhibit that the optimal deviations from holding the market portfolio for each asset depend on the assessment measure as:

$$AR_p = \left[\frac{\alpha_p}{\sigma(\varepsilon_p)}\right]^2 \tag{2-4}$$

where $\sigma(\varepsilon_p)$ is defined as the standard deviation of the portfolio p residual in Eq. (2-2). They define an active portfolio by ignoring the deviations from the market portfolio and exhibit that the active portfolio measure depends on the proportion of the individual stocks. They believe that market timing skill may make changes in leverage and market risk. Identical to the aforementioned measures, this measure also ignores a manager's responsibility to the timing of the cash outflows and inflows of a portfolio. It also evaluates the selection skill of a portfolio manager and neglects other his skills, e.g., the market timing skill.

2.5.5 The Modigliani-Modigliani Measure

Modigliani and Modigliani (1997) introduce a measure of the risk-adjusted returns that evaluate the returns adjusted by the portfolio risk relative to the market portfolio returns. This ratio is also referred to as the M-square measure (M_p^2) as:

$$M_p^2 = \frac{R_p - R_f}{\sigma_p} . \sigma_m + R_f \tag{2-5}$$

where σ_m is the standard deviation of the market portfolio returns.

2.5.6 The Leverage Ratio

Modigliani and Modigliani (1997) also propose the leverage ratio (L_p) of a portfolio by dividing the standard deviation of returns on market portfolio by the standard deviation of returns on a given portfolio as:

$$L_p = \frac{\sigma_m}{\sigma_p} \tag{2-6}$$

A leverage ratio higher than one exhibits that the standard deviation of returns on the portfolio is less than the standard deviation of returns on market portfolio, and that an investor tends to take into account levering the portfolio by borrowing money at the risk-free rate and then investing in the portfolio. In contrast, a leverage ratio less than one exhibits that the portfolio risk is higher than the market portfolio risk, and that an investor tends to take into account un-levering the portfolio by selling off part of the holding in the portfolio and then investing the proceeds in the risk-free asset.

However, there are other risk-adjusted performance measures in the performance evaluation literature such as Sortino measure suggested by Sortino and Price (1994), portfolio performance index suggested by Pedersen and Rudholm (2003), upside potential ratio suggested by Sortino and Price (1994), and optimized risk-adjusted measures suggested by Tavakoli Baghdadabad (2013, 2015), which investigate the performance of a portfolio based on different risks. These measures are comprehensively discussed in most of the investment and finance books, and are less related to this study. We thus confine only to review the above six measures.

2.6 Portfolio Manager’s Selection Ability

A portfolio manager’s selection ability is based on the forecasting ability of firm-specific events and consequently the price of an individual asset (Kon, 1983). According to the active portfolio management strategy, when the proportions are determined in a portfolio, a portfolio manager should decide which of assets should be held in the portfolio. This is commonly called as asset selection. To pursuit this skill, a portfolio manager uses his information and assumptions regarding the market to take the privilege of any mispricing[1] happened. Hence, the portfolio manager believes that most shares are being fairly priced but a few numbers are either being over-priced or under-priced (Blake, 1994) and thus uses his existing information about the mispricing to earn abnormal returns. If a portfolio manager has superior skill to identify the under- and/or over-priced assets then he uses his skill to earn excess returns.

2.7 Portfolio Manager's Market Timing Ability

Kon (1983) defines market timing as the forecasts on future realization of the market portfolio. If a portfolio manager believes he is able to do better than average forecasts of returns on the market portfolio, he will adjust the levels of his portfolio risk to predict market movements. If he can adjust the levels of risk, he will obtain abnormal returns with respect to a proper benchmark. Baker and Wurgler (2002) present a general definition for market timing in the corporate finance framework in which market timing is to issue stocks at high price and to repurchase them at low price. According to the active portfolio management strategy, Jensen (1968) believes that a portfolio manager's forecasting skill may include a skill to predict the price movements of individual asses relative to market portfolio and/or a skill to predict the overall behaviour of asset prices in future. This skill in the performance evaluation literature is referred to as the portfolio manager's skill to time the market.

[1] The mispricing of an asset occurs when an informed investor's expected return is different from the market belief. When an asset is being overpriced (underpriced), it is expected to fall (rise) in price.

An active portfolio manager performs market timing by varying the beta of his portfolio across time based on his expectations regarding the market. For example, if a portfolio manager obtains negative (positive) information regarding the market, he will decrease (increase) his portfolio's beta by capitalizing on his expectations. When the portfolio manager possesses superior forecasting skills, he will be able to provide abnormal excess returns for his investors.

Overall, selection and timing skills have general definitions. The selectivity ability reflects the skill to select investments relative to the market portfolio, while the timing ability reflects the skill to predict returns on the market portfolio (Grinblatt and Titman, 1989).

Note that timing skills can also be employed if a portfolio manager has expectations about shares with specific characteristics. Hence, if the portfolio manager believes that shares with certain characteristics (size[2], book to market ratio[3], momentum[4], and etc.) are earning high returns, he will propel his portfolio weights towards them in order to time different share characteristics. Considering this important point, the literature presents several performance evaluation measures that assess these two portfolio managers' abilities in the framework of standard asset pricing models.

[2] Size is a risk measure, which is defined as the return of the smallest one-third of portfolio stocks minus the return on the stocks in the top third ranked by market capitalization.

[3] Book to market ratio is a risk measure, which is defined as the return of the smallest one-third of portfolio stocks minus the return on the stocks in the top third ranked by book-to-market ratio.

[4] Momentum is a risk measures, which is defined as the average return on the two high prior return portfolio stocks minus the average return on the two low prior return portfolio stocks.

2.8 The Single-Factor Selection Ability Models

The first model that provides wide attention in the literature is the single-factor model, and especially a variant of the model, which is called as the market model. This model is firstly introduced by Markowitz based on the portfolio theory and then developed by Sharpe (1966) as:

$$R_{it} = \alpha_i + \beta_i R_{mt} + e_{it} \qquad (2\text{-}7)$$

where R_{it} is the return on stock i at time t, α_i is the unique expected return on stock i, β_i is the sensitivity of stock i to the movements of market portfolio, R_{mt} is the return on the market portfolio m at time t, and e_{it} is the unique risky return of stock i at time t that has a zero mean and variance σ_{ei}^2.

Consequently, Jensen (1968) presents the Jensen's alpha as the intercept estimated from the following regression:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + e_{pt} \qquad (2\text{-}8)$$

where R_{pt} is the return on portfolio p at time t, R_{ft} is the return on free-risk asset at time t. R_{mt} is the return on the market portfolio m at time t. β_p is the sensitivity of profile p to the market portfolio, and e_{pt} is the random error with zero mean.

The intercept (α_p) of this regression is referred to as a portfolio manager's selection ability. It is defined as the abnormal return higher than the return that a manager expects to earn in the CAPM, meaning that a portfolio manager earns a non-equilibrium return. More specifically, alpha shows the return earned by a portfolio manager over a combination of the market portfolio and the free-risk asset. Since a rational investor is free to invest a part of his funds in the market portfolio and their remaining in free-risk assets, this would be an appealing approach to justify this model. The intercept (alpha) evaluates the excess return that is not able to be described by the portfolio beta. An alpha higher than zero indicates superior performance. The Jensen's alpha is extracted from the CAPM and thus relies on the assumption of normal distributed returns. As explained in the CAPM, the asset portfolios with the same beta in equilibrium condition earn the same expected return. Thus, any positive deviation exhibits superior performance. Alpha also evaluates portfolio performance by considering the correlation features of the portfolio with the market portfolio using the portfolio beta (Gaurav and Kat, 2002).

Using the above model, the literature presents two important studies, among others. Jensen (1969) uses the above CAPM model to assess the performance of mutual funds over the period of 1945 to 1964. He does not find any evidence that funds are able to produce superior returns. Ippolito (1989) also finds a positive alpha for mutual funds using the Jensen model over the period of 1965-1984. However, these studies and their developed performance models only evaluate the selection skill of a portfolio manager and neglect other his skills, e.g., the market timing skill.

2.9 The Single-Factor Market Timing Models

The prior studies in literature have investigated some alternative performance evaluation measures, but we now face an important issue. A key purpose in examining the past performance is to obtain insight into the future. When the past performance is irrelevant to future performance, thus performance evaluation will not help us to predict market timing and to determine the time of choosing a portfolio (Elton and Gruber, 1997). On a theoretical basis, market timing is defined as the portfolio manager's ability to predict the future direction of the market and hence adjusting the market exposure of the portfolio.

Merton (1981) develops a single factor model for evaluating a portfolio manager's market timing skill. The model does not consider any distribution of market returns or any particular model of asset valuation, but it considers a simple form of the predictive model for an investment manager by taking positive market risk premiums relative to negative premiums.

Henriksson and Merton (1981) use the Merton (1981) market timing model based on the CAPM model for examining the timing skill of an investment manager. This timing model allows a market timer to predict market movements when equities outperform free-risk securities and when free-risk securities outperform equities. They propose a different estimation of market timing and believe that a portfolio manager allocates money between stock and cash in terms of the forecast of future market return. They estimate the following model with respect to two target betas as:

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \gamma_p R^*_{m,t} + \varepsilon_{p,t} \qquad (2\text{-}9)$$

where $R^*_{m,t} = I[R_{m,t} > 0]R_{m,t}$ and $I[R_{m,t} > 0]$ are an indicator equal to one if $R_{m,t}$ is positive and zero otherwise. γ_p in Eq. (2-9) evaluates the difference between target betas, and is positive for a portfolio manager who successfully times market.

Henriksson (1984) assesses the market timing performance of 116 mutual funds by examining the Henriksson and Merton (1981) model, Eq. (2-9). He believes that the empirical findings found on the Henriksson and Merton (1981) model are not able to support the hypothesis that portfolio managers can successfully time market movements. He finds that only three funds out of 116 funds exhibit significantly positive estimates of a portfolio manager's market timing skill.

Chang and Lewellen (1984) use a single-factor timing model and examine the performance of 67 mutual funds over the period of January 1971 to December 1979. They find little evidence of fund managers' market timing ability. They also evaluate fund managers' selection skill and find a positive estimate but not significant for 41 out of the 67 portfolios.

Jagannathan and Korajczyk (1985) estimate both selection ability and market timing ability on options and leveraged securities using the Henriksson and Merton (1981) model.

Cumby and Modest (1987) use the Henriksson and Merton (1981) measure on single-factor models in order to evaluate the timing performance of currency portfolios. They conduct two separated empirical tests on sub-samples and whole sample, and find strong evidence of market timing ability in the whole sample and weaker evidence in the subsamples.

Kao et al (1998) examine international mutual fund managers' selection and market timing abilities using the two-beta model proposed by Merton (1981) and Henriksson and Merton (1981) over the period of 1989 to 1993. They document several interesting findings. First, the performance of international mutual fund managers exhibits good selection skills. Second, the managers are poor market-timers. Third, a negative relation exists between a manager's market timing skills and his selection skills.

Fung et al (2002) investigate the performance of 115 equity-based hedge funds using a simple Henriksson and Merton (1981) timing model over the period of 1994-2000. They find that hedge fund managers do not demonstrate evidence of a positive market timing skill but do exhibit superior selection skill, implying a negative relation between these two skills.

However, the problems appeared in the use of single-factor performance evaluation models lead to the development of multi-factor models and their relevant performance measures. The first reason for the use of multi-factor models is related to the studies of Ross (1978) and Grinblatt and Titman (1987) who believe that if returns are produced by N factors, then N diversified portfolios are appropriate to explain relative returns, and hence a linear combination of these N diversified portfolios would be efficient. The second reason for the use of the multi-factor models is related to arbitrage pricing theory, which assumes that expected returns would be explained as a linear function of sensitivities to more than one factor. Therefore, deviations estimated from this linear function would be the indicator of a portfolio manager's selection skill. These reasons thus develop the multi-factor performance evaluation models in the literature.

2.10 The Multi-Factor Selection Ability Models

Despite the wide use of single-index market model, a number of researchers respond to a key question whether multi-index models can explain the relation between risk and return. The multi-index models are also applied by portfolio managers to find out the sensitivity of a portfolio to different economic effects and to allow a portfolio manager to make active betas on how the market index changes in the next period. Thus, multi-index models are considered as the basic tool for evaluating the performance of portfolio managers.

The different types of these models have been developing for various uses, and this may also continue in the future. A portfolio manager interests in finding out the sensitivity of a portfolio to basic economic effects, and hence a multi-index model is able to consider these effects. However, multi-index models are actually beneficial in understanding the portfolio choice. These models not only simplify the inputs to the portfolio choice problem, but they can provide better forecasts and make an easier choice process.

Elton, Gruber, and Blake (1996) develop a four-factor model by responding to this question whether past information can predict future information. They use four factors of the S&P market index, the size index, the bond index, and the value/growth index, and find persistence in portfolio managers' superior abilities.

The multi-factor models of the Jensen measure are theoretically and practically more appropriate than single-factor models. However, this still remains us with the drawback of which multi-factor models should be used in practice. In this sense, several authors have used multi-factor models to evaluate portfolio performance (e.g., Lehmann and Modest, 1987, Connor and Korajzcyk, 1991).

A second idea to develop multiple models is to find asset portfolios which evaluate investments held by a portfolio. This idea has been developed by Sharpe (1992), Elton et al (1996), and Blake et al (1993). For instance, Elton et al (1996) use a four-factor model, consisting of the S&P 500 Index, the size index, the bond index, and the growth value index, to describe the returns on a portfolio. Sharpe (1992) uses a 12-factor model to describe the returns on a great number of portfolios, consisting of domestic and international stock and bond funds. Another advantage of the multi-factor models is that the estimated betas show the type of assets that each portfolio is holding. The challenges for the use of a proper set of indexes to evaluate portfolio performance have still remained among researchers. However, Elton et al (1996) show that a performance model based on five factors is sufficient to describe the returns on a portfolio.

Overall, the multi-factor selection ability models only assess a portfolio manager's selection skill and ignore his market timing skill.

2.11 The Multi-Factor Market Timing Models

The use of the single- and multi-factor performance models assumes that betas are reasonably constant and a manager does not vary them to obtain excess returns using market timing (e.g., Treynor and Mazuy, 1966, Henriksson, 1984, Lehmann and Modest, 1987). The overall result is that timing does not raise risk-adjusted returns and may even reduce them (Elton and Gruber, 1997).

Chen and Liang (2007) propose a new measure that times stock return volatility and uses the multi-factor timing models, which jointly include the Fama and French (1993) factors with the Henriksson and Merton (1981) (referred to as HM) and Treynor and Mazuy (1966) (referred to as TM) timing measures, to examine whether hedge funds' managers have sufficient skill to time the U.S. stock market in a sample of 221 hedge funds over the period of 1994 to 2005. They find positive timing abilities in their sample.

Lee and Rahman (1990) estimate empirically market timing skill and selectivity ability of 93 mutual funds. They use the Bhattacharya and Pfleiderer

(1983) performance evaluation technique at the individual stock level and find evidence of superior predictive ability on fund managers. Specifically, they show that funds without any forecasting skill may use a passive management strategy and present diversification services for shareholders.

Kon (1983) proposes a methodology for evaluating the mutual fund mangers' market timing performance. Despite he finds significant evidence of superior timing ability at the individual fund levels, the multivariate estimates exhibit consistent evidence with the efficient market hypothesis. This implies that a fund manager do not have special information about the formation of expectations on the market portfolio returns.

Becker et al (1999) examine a multi-factor market timing model based on the Treynor and Mazuy (1966) timing measure on a sample of 400 U.S. mutual funds over the period of 1976 to 1994. Their model allows mutual fund manager's payoff to depend on fund returns in excess of a benchmark index. The model distinguishes timing between publicly available information and finer information. They do not find evidence of significant market timing ability.

However, most of the above studies do not report positive evidence of market timing using the existing market timing measures.

2.12 Dynamic Approaches to Performance Evaluation

Performance evaluation usually responds to a key question whether an investment manager is able to produce a superior risk/return trade-off for his potential investors, e.g., whether a portfolio manager adds a value to his investors' wealth. A portfolio manager may be an expert in his field, but the existence of certain special abilities does not provide high performance. The opportunity costs of a poor diversification across time as well as across assets, e.g., the transaction costs and the management fees, all must be suffered by an investor. The question thus is not whether a portfolio manager has special abilities, but the question is the fact whether he has enough ability to compensate all the costs, which can certainly be so substantial. In responding to these statements, we only can tell about truly superior ability and performance. Responding to the above question is not easy because it needs to construct a performance benchmark for finding out what classifications are normal and what are not. Therefore, a number of authors have been working on this problem since the 1960s. Using the portfolio theory and the asset pricing model, they suggest benchmarks such as Sharpe ratio, Jensen's alpha, and etc. Consequently, other works focus on the question whether an investment manager is a good timer for the prediction of the upside and downside movements of the market. Using only a few set of historical returns, this is a hard question to respond, even using the extant large econometrical toolkit. However, these developed benchmarks suffer from the same problem: they need to explicit assumptions regarding the return construction process. They usually require that portfolio and index returns follow a normal distribution. Despite an investment manager follows traditional non-mechanical and non-leveraged strategies using the traditional performance evaluation measures, the use of these measures cannot be an unrealistic assumption. However, this has changed over the past 20 years. Nowadays, more and more portfolio managers are using options and/or following some specific dynamic trading strategies, e.g., portfolio insurance and moving average strategies. We thus present a summarily review of these trading strategies, especially moving average, based on return generating process.

Following a new approach, Christopherson et al (1999) believe that the prior studies documented on unconditional performance measures ignore information regarding the varying nature of the economy. Therefore, unconditional measures cannot correctly assess expected return when a portfolio manager reflects market information or uses dynamic trading strategies. These biases cause some problems in the existing performance evaluation models to estimate alpha and beta. This thus provides intuition behind the conditional performance evaluation, consistent with Ferson and Walther (1996) and Ferson and Schadt (1996), who state an approach that the conditional performance evaluation can generate more precious estimates about risk and return. This approach assumes that a portfolio's alpha and beta varies dynamically with varying market conditions, and a portfolio manager is able to reflect information available on market by modifying his portfolio's alpha and beta (Christopherson et al., 1999).

Ferson and Schadt (1996) run a dynamic performance evaluation model for the estimation of dynamic alphas. Similarly, Christopherson et al (1998) estimate a dynamic alpha using the Ferson and Schadt (1996) dynamic model, and find that a dynamic model allows an investor to consider various market information by varying his portfolio's alpha and beta, and incorporating the dynamic nature of alpha and beta. Christopherson et al (1999) assumes that dynamic changes in a portfolio's beta reflect all information available on market price.

2.12.1. Moving Average Market Timing Measure

This measure relies on technical analysis. This analysis uses past and current market prices, trading volume, and other potential information to forecast future market prices. Brock et al (1992) define the moving average (MA) based on its various implementations as a technical analysis. They find implications that some technical measures have high significant forecasting ability. Blume et al (1994) suggest a theoretical framework using price data and trading volume to conduct technical analyses. Lo et al (2000) use a series of technical measures and find some forecasting abilities in MAs. Zhu and Zhou (2009) present a theoretical reason why a technical measure can be a potentially useful factor in an environment where a rational investor needs to learn over time the value of the risky security he invests in. Neely et al (2010, 2011) believe that technical analyses have high predictive power on stock risk premium as well as the potential information generated by economic fundamentals. In addition, the literature documents the studies of Faber (2007) and Kilgallen (2012) whose use the risk-adjusted returns of the MA strategies using the commodity and currency portfolios. More recently, Goh et al (2012) use the MA measure to predict the returns on government bond risk premiums and yields, while Huang and Zhou (2013) use the same idea on the U.S. stock market. Jiang (2013) and Han and Zhou (2013) examine the forecasting power of the MA measure by constructing a trend factor with considerable historical performance and substantial cross-sectional explanatory power.

Glabadanidis (2015) suggests a MA market timing measure using past market price to forecast future market price. He introduces his MA dynamic timing measure by firstly computing the following MA measure:

$$A_{it,L} = \frac{P_{it-L+1} + P_{it-L+2} + \cdots + P_{it-1} + P_{it}}{L} \tag{2-10}$$

where $A_{it,L}$ is the MA of portfolio i at the end of month t, P_{it} is the price on portfolio i at the end of month t, and L is the period length. To compute the MA, he uses a 24-

month length for his baseline analysis, and the lengths of 6, 12, 36, 48, and 60 months for his controlling checks.

His MA switching strategy considers the following form:

$$\tilde{R}_{it,L} = \begin{cases} R_{it} & \text{if } P_{it-1} > A_{it-1,L} \\ R_{ft} & \text{Otherwise} \end{cases} \qquad (2\text{-}11)$$

where R_{it} denotes the return on portfolio i at the end of month t and R_{ft} is the return on free-risk asset at the end of month t. If the price is higher than the MA, this stimulates an investor to invest in the portfolio at the month t + 1. If the price is lower than the MA, this stimulates an investor to leave the risky portfolio (or invest on free-risk portfolio) at the month t + 1.

He finds several main results. First, the returns on a MA switching strategy are better than the returns on a standard buy-and-hold strategy of a portfolio. Second, the MA switching strategy has perfect timing ability on individual stocks or a single portfolio due to the existence of cross-sectional spreads between the abnormal returns of various portfolios. These spreads remain unchanged when controlling for the past price returns of the four-factor Carhart (1997) model. Third, the conditional models demonstrate a specific degree of the MA abnormal returns, but do not perfectly omit them. Fourth, there is the robustness of the MA strategy performance of 18,000 individual stocks available on the Center for Research in Security Prices. Fifth, there is the robustness of the MA strategy performance for several international stock markets, and Sixth, the lagged returns about the switching into the stocks and their relevant portfolios have higher considerable predictive abilities than the predictability of standard instrumental factors, such as the investor's sentiment, the default spread, the liquidity risk, and the recession dummy variable.

Glabadanidis (2017) examines the MA timing measure constructed by Eq. (2-11) with a combination of the portfolios sorted into the MV measure, and find its superior performance relative to the classical buy and hold timing measures.

Following the above empirical works, this study uses the logic behind the use of last prices (lagged data) in the MA timing measure for constructing new timing measures in the form of average drawdown. Specifically, this study follows the Gladanidis studies by considering a 24-observation lag length as its baseline analysis, and the lag lengths of 6, 12, 36, 48, and 60 observations as its controlling checks.

2.13 Drawdown Measure

This measure is an alternative risk measure relative to the existing risk measures that has been recently used in finance and economy. Most of the studies on drawdowns can be found in journals outside of finance (Dacorogna et al., 2001), and only a few studies have been published in the journals related to finance and economy (Chekhlov et al., 2005, Alexander and Baptista, 2006, Eling and Schuhmacher, 2007). The drawdown is the loss happened over the holding period of an investment. It is the loss resulted from an investment when an asset is sold at the local minimum and bought at a next local maximum. It is decomposed into two main types of maximum drawdown (MD) and average drawdown (AD) (Gilli and Schumann, 2009). The MD is the loss resulted from an investment when an asset is sold at the local minimum and bought at a next local maximum or the worst loss resulted from an investment (here a portfolio) over its holding period (Alexander and Baptista, 2006). It is the worst returns that an investor earns when he sells an asset at the lowest price and buys it at the highest price. In the portfolio management, most of institutional investors use drawdown risk measure to select an efficient portfolio. In this sense, Hamelink and Hoesli (2004) examine a mixed-asset portfolio with MD and find that MD is one of the most natural risk factors. Their findings help an institutional investor to reconcile the optimal allocations to actual securities. However, since MD considers the maximum of the loss happed over the holding period of an investment, it is a strict risk measure relative to AD. Eling and Schuhmacher (2007) and Schuhmacher and Eling (2011) compare MD with the Sharpe ratio and find some distinguished features for MD. They find that the drawdown measures are as well as the Sharpe ratio, and that the scale and location condition are sufficient for an investor's expected utility to justify the rankings of drawdown measures. Tavakoli Baghdadabad and Glabadanidis (2013) construct nine performance evaluation measures by the MD based on the portfolio theory and examine the risk-adjusted performance of eleven management styles of a comprehensive sample of 400 Malaysian mutual funds. Specially, they construct nine risk-adjusted measures of Treynor, Sortino, M-squared, information ratio, Jensen's alpha, modified Sharpe ratio, upside partial ratio, fund performance index, and leverage factor. They consider two sub-periods of 2000-2005 and 2006-2011 for their analysis. Their findings obviously indicate that the replacement framework based on mean-MD behaviour, the MD beta, and the MD-based CAPM can be replaced with the standard framework based on mean-variance behaviour, beta, and CAPM, respectively. Similarly, the framework can be replaced with mean-semi-variance behaviour, downside beta, and downside CAPM to modify the aforementioned risk-adjusted measures. Tavakoli Baghdadabad et al (2013) also construct seven risk-adjusted performance measures of Sharpe, M-squared, Treynor, Jensen's alpha, information ratio, modified Sharpe ratio, and fund performance index by optimizing MD in a linear programming framework. They evaluate these optimized measures on 70 Malaysian mutual funds over the period of 2000 to 2011. They report two important implications. First, the optimized MD would be an alternative risk measure to select mutual funds. Second, the optimized measures help fund managers to optimally evaluate the funds' performance. Subsequently, Tavakoli Baghdadabad (2015) proposes the risk measure of n-degree MD, which is a developed version of n-degree lower partial moment, to examine the reduction impacts of the n-degree MD on risk tolerances derived from the management styles of U.S. equity-based mutual funds. They find that effect of the MD risk tolerances in the n-degree MD model is a remarkable decrease in fund returns.

In contrast, the AD is the average loss happened over the holding period of an investment (Gilli and Schumann, 2009). It is the loss average resulted from an investment when an asset is sold at the local minimum and bought at a next local maximum or the loss average resulted from an investment over its holding period (Tavakoli Baghdadabad et al., 2013). It is the loss average that an investor earns when he sells an asset at the lowest price and buys it at the highest price. Grossman and Zhou (1993) and Dacorogna et al (2001) primarily introduce the AD as a risk measure to examine risk-averse investors' attitude toward the risk.

Tavakoli Baghdadabad et al (2013) compare the mean-AD behavior against the mean-variance behavior. They develop an asset pricing model based on AD to estimate the AD beta. They use 11,000 U.S. equity-based mutual funds over the period of 2000 to 2011 and find the superiority evidence of AD, the AD beta, and its relevant pricing model (the AD-based CAPM) relative to standard deviation, beta and CAPM, respectively. They propose an AD measure in the mean-AD behaviour framework, where the risk of an asset is assessed by the downside standard deviation of the asset on the loss happened from a local minimum to the next local maximum plus the risk premium as:

$$\mathrm{AD_{it}(X_{it})} = \min[\left(\mathrm{A}_{\rho-1} + (\mathrm{R_{it}} - \mathrm{R_{ft}})\right), 0] \quad (2\text{-}12)$$

Given the observations for $\mathrm{X_{it}} = 0,1, \dots, \mathrm{T}$, the A_{ρ} simply denotes the loss (extreme loss or worst loss) average that an investor suffers from 0 to ρ. $\mathrm{R_{it}}$ denotes the returns on asset i at time t, and $\mathrm{R_{ft}}$ denotes the returns on free-risk asset f at time t. It uses the average of losses or extreme volatilities happened in the holding period of an asset from 0 to ρ.

Similarly, Tavakoli Baghdadabad and Glabadanidis (2013) use the AD measure to examine the mean-AD approach versus the mean-variance approach using a sample of 700 Malaysia mutual funds over the period of 2000 to 2011. They compute the AD beta and run a CAPM version based on AD, and consequently compare them with standard beta and CAPM, respectively. Their findings obviously support the AD beta and its relevant pricing model versus standard beta and CAPM.

Tavakoli Baghdadabad (2013) uses the monthly returns of 1720 US hedge funds over the period of 2000 to 2011 to examine investors' attitude toward drawdown risk. To address this purpose, they run linear programming models to optimise drawdown risk measures of MD and AD. They find interesting findings in the favour of drawdown risk.

Tavakoli Baghdadabad (2014) examines effect of the AD risk reduction on US mutual funds. He proposes the n-degree AD measure, which is a developed version of n-degree lower partial moment, to empirically examine effect of the n-degree AD reduction on the risk tolerances derived from the funds. He finds that the effect of changes in the AD tolerances derived from the n-degree AD model is a decrease in the fund returns. Moreover, the n-degree AD optimization model reduces an investor's risk more than the existing mean-variance models, implying that AD is fitted with a risk-averse investor's approach. The findings of his study thus show that, in the choice of a portfolio, the AD constructs the efficient investment opportunity set in a lower level of risk than the mean-variance approach.

2.14 Chapter Summary

This chapter presents a comprehensive review of performance evaluation literature. It firstly reviews the portfolio theory and the efficient market theory as supportive theories of this study. It then presents the definitions of performance evaluation, the portfolio management strategies, the traditional portfolio performance measures, and the portfolio performance models. It explains two common skills of a portfolio manager, consisting of selection skill and market timing skill, and demonstrate mathematically and conceptually how we quantity these skills to evaluate performance of the manager. Consequently, it presents some innovations on market timing measures and their relevant timing models, especially the dynamic market timing measures and models. It presents moving average market timing measure as one of the most popular dynamic measures, and provides some superior features of the moving average market timing measures relative to the standard buy and hold market timing strategy. Finally, it reviews drawdown risk measures, especially the AD measure, and provides empirical evidence for the superiority of these measures, especially the AD measure, versus the existing mean-variance approach (Note that the existing timing measures are grounded on the mean-variance approach).

Overall, a review of the existing empirical studies on the AD measure provides key findings in the favour of this measure. Compared to the mean-variance approach that theoretically allows us to construct the existing market timing measures, AD, the AD beta, and the AD-based CAPM constructed by the mean-AD approach highlight higher potential ability to examine the dispersion of portfolio returns. These findings thus stimulate us to construct dynamic timing measures based on AD. More specifically, we merge potential features of the moving average market timing measure and those of AD to construct new market timing measures. Next chapter allows us to know how we can construct these new measures.

Chapter 3 : Research Methodology

3.1 Introduction

This chapter presents an overview of statistical and econometric analyses. It presents the traditional market timing strategies, the dynamic timing measures, the average drawdown (AD) timing measures, the proposed AD timing models, the research objectives, the research hypotheses, the research questions, the research conceptual design, the research method, the research population and sampling, the sampling method and survivorship bias, the data collection, the construction of country-level portfolios, and the descriptive statistics consisting of the normality test, the unit root test, the Wald test, the redundant test, and the test of proofing research hypotheses. Finally, it presents some robustness checks to control for the basic results of this study.

The general idea in majority of the traditional measures of investment performance is simple. The measures compare the returns of a portfolio over a specific time period with the returns of a benchmark portfolio (BP). The BP is potentially an investment alternative for the evaluating portfolio. If the purpose is to assess the investment skill of a portfolio manager, the BP should represent a potential investment alternative for the evaluating portfolio, except that it should not represent the investment skill of the manager. The BP also exhibits that all the portfolio characteristics are the same for the evaluating portfolio and the benchmark. These problems impose limitations in practice. More importantly, majority of the existence measures of portfolio performance evaluation are constructed from their distinguished definitions from BP.

To further illustrate the BP concepts, it is important to know some basic models for what properties of a portfolio help to earn higher (or lower) expected returns. This matter stimulates researchers to use asset pricing models, e.g., CAPM, because these models allow them to estimate the expected returns. A set of the empirical studies in literature developed portfolio performance measures and formulated these measures into the asset pricing models to evaluate the performance of a portfolio manager. Another set of the studies used the risk-adjusted performance measures. Obviously, Chapter 2 reviewed innovations developed by different researchers to propose the Sharpe measure (Sharpe, 1964), the Jensen alpha (Jensen, 1968), the Treynor measure (Treynor, 1965), the Treynor-Black measure (Treynor and Black, 1973), the Modigliani-Modigliani measure (Modigliani and Modigliani, 1997), the leverage ratio (Modigliani and Modigliani, 1997), the Sortino measure (Sortino and Price, 1994), the portfolio performance index (Pedersen and Rudholm, 2003), the upside potential ratio (Sortino and Price, 1994), and the optimized risk-adjusted measures (Tavakoli Baghdadabad, 2013, 2015). In addition, these measures have been comprehensively discussed in most of the investment and finance books, and are basic performance evaluation measures for this study. However, these measures may be inappropriate when portfolio returns are not normal, and also they ignore a manager's responsibility to the timing of the cash outflows and inflows of a portfolio. In other word, they only evaluate the selection skill of a portfolio manager and neglect other his skills, e.g., the market timing skill. These shortages thus stimulate us to focus on new market timing measures and their relevant timing models.

3.2 Market Timing Strategies

Timing as a part of portfolio managers' performance is referred to as the skill of employing superior information about the future realization of common factors that influence returns on market portfolio (Kon, 1983). Selectivity skill is called as the use of asset-specific information (Kon, 1983). If the common factors illustrate a significant component of the variance of returns on market portfolio, so a significant fraction of the performance of portfolio will be called as timing.

To conduct the market timing strategies, there are two known timing strategies. The first strategy is the timing strategy suggested by Treynor and Mazuy (1966) who state that a successful timer would decrease exposure to the market when returns are low and raise exposure to the market when returns are high. These changes in exposure result in a convex relation between market risk premium and portfolio, which leads to a regression with a quadratic term of the market return. Specifically, Treynor and Mazuy (1966) introduce the following regression to estimate market timing.

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \gamma_p R_{m,t}^2 + \varepsilon_{p,t} \qquad (3\text{-}1)$$

where $R_{p,t}$ is the excess return on portfolio p at time t, $R_{m,t}$ is the excess return on the market portfolio m at time t, γ_p evaluates the market timing skill, α_p is an indicator of selection skill for portfolio p, β_p is the sensitivity of returns on portfolio p to returns on market portfolio m. If a portfolio manager increases (decreases) portfolio market exposure prior to a market increase (decrease), portfolio return will be a convex function of market return, and so γ_p will be positive. The coefficient β_p

can change in different statuses of the market portfolio. Eq. (3-1) is graphically defined as

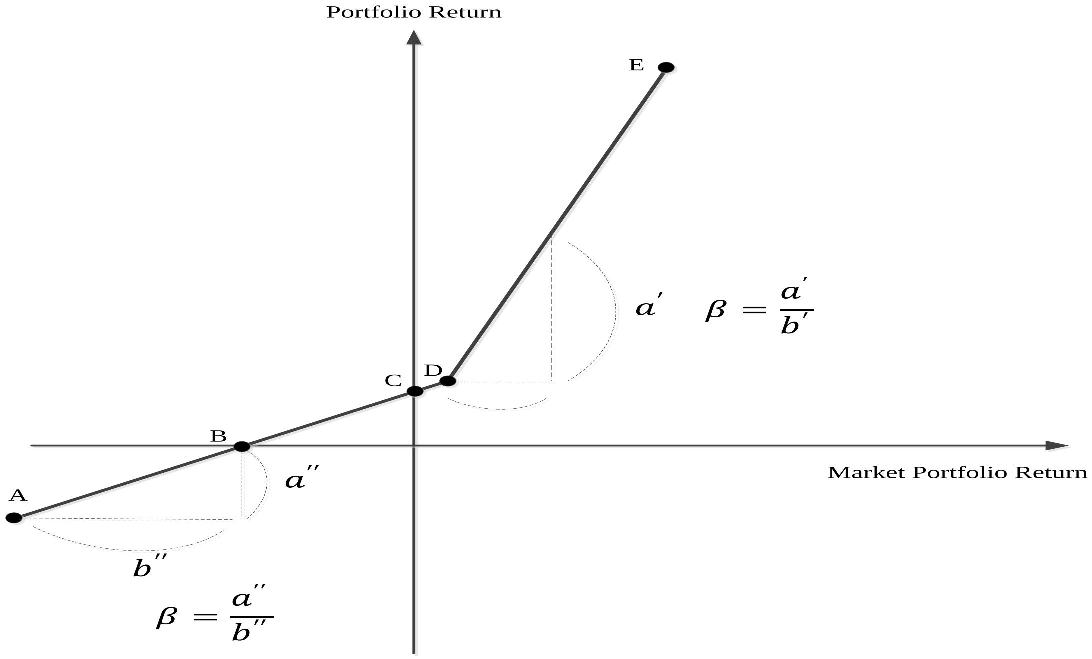

Figure 3-1: The Characteristic Line of Stock Portfolio

Figure (3-1) exhibits the characteristic line of stock portfolio which outwits the market portfolio. It chooses an asset composition with high beta (the DE characteristic line) when the market portfolio is increasing, and when there is a fall on the market portfolio, a low beta composition is in place (the AC characteristic line). In addition, when the market portfolio is increasing, the returns on the stock portfolio will be higher than the market portfolio returns. Therefore, the slope of the DE characteristic line is higher than one. In contrast, when the market portfolio is decreasing, the structure of portfolio's equity is shaped in a manner that the realized losses will be less than the losses realized on the market portfolio. Note that the slope of the AC characteristic line is less than one, indicating that β_p can take both negative and positive magnitudes. The characteristic line of this model is broken, as opposed to the standard CAPM model. Generally, β_p takes positive magnitudes according to the AB and CE characteristic lines and negative magnitudes according to the BC characteristic line.

The second strategy is the timing strategy suggested by Henriksson and Merton (1981). They propose a different estimation of market timing, and believe that a portfolio manager allocates money between stock and cash in terms of the forecast of future market returns. They estimate the following model with respect to two target betas as

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \gamma_p R^*_{m,t} + \varepsilon_{p,t} \tag{3-2}$$

where $R^*_{m,t} = I[R_{m,t} > 0]R_{m,t}$ and $I[R_{m,t} > 0]$ are indicators equal to one if $R_{m,t}$ is positive and zero otherwise. γ_p in Eq. (3-2) evaluates the difference between target betas, and is positive for a portfolio manager who successfully times returns on the market portfolio.

These two timing strategies contribute to the existing literature for developing the multi-factor timing models of performance evaluation. In this sense, Grinblatt and Titman (1994) believe that performance evaluation estimates are fully sensitive to the benchmark portfolios. They add the two timing measures suggested in Eq. (3-1) and (3-2) to the Carhart (1997) four-factor pricing model, and introduce two timing models that involve three Fama and French's (1993) factors of market excess return, book-to-market ratio and size, and a momentum factor introduced by Carhart (1997). Their models are defined as:

$$\mathrm{R_{p,t}} = \mathrm{\alpha_p} + \mathrm{\beta_p R_{m,t}} + \gamma_p \mathrm{R^2_{m,t}} + \mathrm{\beta_p SMB_{p,t}} + \mathrm{\beta_p HML_{p,t}} + \mathrm{\beta_p MOM_{p,t}} + \mathrm{\varepsilon_{p,t}} \qquad (3\text{-}3)$$

and

$$\mathrm{R_{p,t}} = \mathrm{\alpha_p} + \mathrm{\beta_p R_{m,t}} + \gamma_p \mathrm{R^*_{m,t}} + \mathrm{\beta_p SMB_{p,t}} + \mathrm{\beta_p HML_{p,t}} + \mathrm{\beta_p MOM_{p,t}} + \mathrm{\varepsilon_{p,t}} \qquad (3\text{-}4)$$

where $\mathrm{SMB_{p,t}}$ is the return of the smallest one-third of portfolio stocks minus the return on the stocks in the top third ranked by market capitalization, which is mathematically defined as $\mathrm{SMB} = \frac{1}{3}(\text{small value} + \text{small neutral} + \text{small growth}) - \frac{1}{3}(\text{big value} + \text{big neutral} + \text{big growth})$. $\mathrm{HML_{p,t}}$ is the return of the smallest one-second of portfolio stocks minus the return on the stocks in the top second ranked by book-to-market ratio, which is mathematically defined as $\mathrm{HML} = \frac{1}{2}(\text{small value} + \text{big value}) - \frac{1}{2}(\text{small growth} + \text{big growth})$. $\mathrm{MOM_{p,t}}$ is the average return on the two high prior return portfolio stocks minus the average return on the two low prior return portfolio stocks, which is mathematically defined as $\mathrm{MOM} = \frac{1}{2}(\text{Small high} + \text{Big high}) - \frac{1}{2}(\text{Small low} + \text{Big low})$.

The main insight of different versions of the Carhart (1997) timing models is that market excess return, SMB, HML, MOM, and timing measure matter in pricing. However, as explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. For example, Laurent, Laurent, and Danielle (2013) report a positive sign for SMB, HML, and MOM on the mutual fund returns. Yong and Liang (2007) and Borja and Francisco

(2013) estimate a negative sign for SMB and positive signs for HML and MOM. Geoffrey and Sapp (2007) report positive signs for SMB and HML, and a negative sign for MOM. Comer, Larry, and Rodriguez (2009) exhibit a positive sign for HML and negative signs for SMB and MOM. Glabadanidis (2017) find negative signs for SMB and HML and a positive sign for MOM. This evidence, among others, imply that the SMB, HML, and MOM coefficients in the timing models can take positive values as well as negative values, indicating that determining their signs is merely an empirical exercise.

Consequently, Bollen and Busse (2001) propose another version of the market timing measures according to Treynor and Mazuy (1966) and Henriksson and Merton (1981). They propose the following equations:

$$\mathrm{R_{p,t}} = \alpha_p + \beta_p \mathrm{R_{m,t}} + \gamma_p \mathrm{R_{m,t}^{TM}} + \beta_p \mathrm{SMB_{p,t}} + \beta_p \mathrm{HML_{p,t}} + \beta_p \mathrm{MOM_{p,t}} + \varepsilon_{p,t} \tag{3-5}$$

$$\mathrm{R_{p,t}} = \alpha_p + \beta_p \mathrm{R_{m,t}} + \gamma_p \mathrm{R_{m,t}^{HM}} + \beta_p \mathrm{SMB_{p,t}} + \beta_p \mathrm{HML_{p,t}} + \beta_p \mathrm{MOM_{p,t}} + \varepsilon_{p,t} \tag{3-6}$$

where $\mathrm{R_{m,t}^{TM}} = (\mathrm{r_{m,t}} - \mathrm{r_{f,t}})^2$ and $\mathrm{R_{m,t}^{HM}} = (\mathrm{r_{m,t}} - \mathrm{r_{f,t}}) \geq 0$ are consistent with Treynor and Mazuy (1966) and Henriksson and Merton (1981) measures, respectively, and denote an indicator of market timing γ_p.

However, two of the most common market timing measures are those introduced by Treynor and Mazuy (1966) and Henriksson and Merton (1981) who add

$$\mathrm{TM} = (\mathrm{r_m} - \mathrm{r_f})^2 \quad (3\text{-}7)$$

and

$$\mathrm{HM} = \max[(\mathrm{r_m} - \mathrm{r_f}),0] \quad (3\text{-}8)$$

to the asset pricing models for evaluating portfolio managers' market timing ability, where R_m and R_f are the returns on market portfolio and the returns on free-risk asset, respectively. More specifically, a combination of timing measures and alphas rather than the risk-adjusted performance measures can better enhance the power of performance evaluation models. This study thus employs both timing models and alphas to evaluate portfolio managers' performance. To construct the timing measures, this study uses Bollen and Busse (2001) measures because they provide a simple understanding for readers.

3.3 Dynamic Timing Measures

These measures have been recently used to involve the use of past market price, and, potentially, other market available information to forecast future market prices. Among the existence dynamic timing measures, Glabadanidis (2015, 2017) introduce a dynamic timing measure based on moving average (MA). They firstly compute MA using the following equation:

$$\mathrm{A_{it,L}} = \frac{\mathrm{P_{it-L+1}} + \mathrm{P_{it-L+2}} + \cdots + \mathrm{P_{it-1}} + \mathrm{P_{it}}}{\mathrm{L}} \quad (3\text{-}9)$$

where $A_{it,L}$ is the MA of portfolio i at the end of month t, P_{it} is the price on portfolio i at the end of month t, and L is the period length. To compute MA, he uses a 24-month lag length as his baseline analysis, and the lag lengths of 6, 12, 36, 48, and 60 months as his controlling checks. Their MA switching strategy considers the following form:

$$\widetilde{R}_{it,L} = \begin{cases} R_{it} & \text{if } P_{it-1} > A_{it-1,L} \\ R_{ft} & \text{Otherwise} \end{cases} \tag{3-10}$$

where R_{it} denotes the return on portfolio i at the end of month t and R_{ft} is the return on free-risk asset at the end of month t. If the price is higher than MA, this stimulates an investor to invest in the portfolio in month t + 1. If the price is lower than MA, this stimulates an investor to leave the risky portfolio (or invest on free-risk portfolio) in month t + 1.

To construct the proposed timing measures, this study uses the idea of the use of past market price to build the dynamic AD timing measures using the lag lengths proposed in MA. This innovation contributes to consider the information content available on the AD measure and also those available on MA. However, one of the research objectives of this study is to compare results of the AD timing measures at daily frequency with those at monthly frequency. To make a fair comparison, this study considers the lag lengths of past 24 days for constructing the daily AD measures and the lag lengths of two months for constructing the monthly AD measures. The first note is that the AD timing measure will formulate $\rho - 1$ (as will be defined in next subsections of this chapter), where ρ is the market price. A lag length of two months give us information content of the first month $\rho = 2 - 1$, so when considering the lag length of two months, it means that we consider information content of the first month. On the other hand, 24 days is almost equal to one month. Thus, considering the 24-day lag length for constructing the daily AD measures and the 2-month lag length for constructing the monthly AD measures provide a consistency for our fair comparisons. The second note is that the lag lengths of 6, 12, 36, 48, and 60 days are considered as controlling checks for reconstructing the daily AD measures and the lag lengths of 3, 4, 5, 6, and 7 months are considered as controlling checks for reconstructing the monthly AD measures.

3.4 The Average Drawdown (AD) Timing Measures

The AD is the loss (extreme loss or worst loss) average happen when a stock is bought under loss status. In the mean-AD behavior framework, an investor's utility is $U = U(\mu_P, \sum_2^P)$, where $\sum_2^P$ denotes the AD of returns on a portfolio. In this sense, risk of a portfolio i is individually assessed by the standard deviation of a combination of loss (extreme loss or worst loss) average from a loss to the next loss plus risk premium (Tavakoli et al., 2013, Tavakoli and Glabadanidis, 2013, Tavakoli, 2014) as:

$$AD_i = \sqrt{E\{\min[(A_{\rho-1} + (R_{it} - \mu_{it}), 0]^2\}} \tag{3-11}$$

where $A_{\rho-1}$ denotes the loss (extreme loss or worst loss) average that an investor suffers from 0 to $\rho - 1$. R_{it} is the returns on portfolio i at time t and μ_{it} is the average of the returns on portfolio i at time t. Eq. (3-11) is an alternative case of semi-deviation that can be rewritten with respect to return on benchmark portfolio (BP) as:

$$AD_{BP,i} = \sqrt{E\{\min[(A_{\rho-1} + (R_{it} - BP_t), 0]^2\}} \tag{3-12}$$

where BP_t is the market index at time t.

The AD is also formulated by replacing free-risk returns with BP and μ as:

$$AD_{it}(X_{it}) = \min[\left(A_{\rho-1} + (R_{it} - R_{ft})\right), 0] \tag{3-13}$$

Given the observations for $X_{it} = 0,1, \ldots, T$, the $A_{\rho-1}$ simply denotes the loss (extreme loss or worst loss) average that an investor suffers from 0 to $\rho - 1$. It uses the average of loss or extreme volatilities in its own calculation. Other variables are defined as above.

Eq. (3-13) considers downside returns. Following Henriksson and Merton (1981), this study converts Eq. (3-13) to a timing measure so that it can take into account upside returns of Eq. (3-13) in order to provide the possibility for formulating upside movements of market portfolio returns as:

$$AD_{mt} = \mathrm{Max}[\left(A_{\rho-1} + (R_{mt} - R_{ft})\right), 0] \quad \text{or} \quad AD_{mt} = \left(A_{\rho-1} + (R_{mt} - R_{ft})\right) \geq 0 \tag{3-14}$$

where R_{mt} and R_{ft} are the returns on market portfolio and the returns on free-risk asset, respectively. Following Glabadanidis (2015, 2017), the period length of ρ is extracted from the MA timing measure that considers a basic lag length of 24 for the daily AD measures. This means that the past 24 days are technically applied to construct the daily AD timing measures. To make a fair comparison between the daily AD timing measures and the monthly AD timing measures, we consider $\rho = 2$ as our basic analysis for constructing the monthly AD measure, and ρs of 3, 4, 5, 6, and 7 as our controlling checks.

Following Treynor and Mazuy (1966), this study converts Eq. (3-13) to a timing measure so that it can take into account upside returns of Eq. (3-13) in order to provide the possibility for formulating upside movements of market portfolio returns as:

$$\mathrm{AD_{mt}} = \left(\mathrm{A}_{\rho-1} + (\mathrm{R_{mt}} - \mathrm{R_{ft}})\right)^2 \qquad (3\text{-}15)$$

where $\mathrm{AD_{mt}}$ is the AD timing measure of the market portfolio m. The period length of ρ is extracted from the Glabadanidis (2015, 2017) MA timing measure that considers a basic lag length of 24. This means that the last 24 observations are technically applied to construct the daily and monthly AD timing measures.

3.5 Proposed Average Drawdown (AD) Timing Models

This section presents the AD-based timing models we propose to estimate market timing skill. We firstly add the AD timing measures to a simple Capital Asset Pricing Model (CAPM) to formulate simple AD timing models for better understanding, but not for our empirical exercises. We then propose the multi-factor AD timing models and apply them in our empirical exercises.

We add the AD timing measure in the Treynor and Mazuy (1966) form to the single-factor CAPM for formulating an AD timing model as:

$$\mathrm{R_{p,t}} = \alpha_\mathrm{p} + \beta_\mathrm{p}\mathrm{R_{m,t}} + \gamma_\mathrm{p}(AD_{\mathrm{m,t}})^2 + \varepsilon_{\mathrm{p,t}} \qquad (3\text{-}16)$$

where $\mathrm{AD_{m,t}} = \mathrm{A}_{\rho-1} + (\mathrm{R_{mt}} - \mathrm{R_{ft}})$ and $\mathrm{A}_{\rho-1}$ denotes the loss average that an investor suffers from 0 to $\rho - 1$. γ_p evaluates timing skill in the AD form. If a portfolio manager increases (decreases) market portfolio exposure prior to a market increase (decrease), then portfolio return will be a convex function of market return and γ_p will be positive.

We then add the AD timing measure in the Henriksson and Merton (1981) form to the single-factor CAPM for formulating an AD timing model as:

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \gamma_p AD^{*}_{m,t} + \varepsilon_{p,t} \tag{3-17}$$

Where $AD^{*}_{m,t} = \mathrm{Max}[\left(A_{\rho-1} + (R_{mt} - R_{ft})\right), 0]$. γ_p assesses the difference between target betas, and is positive for a manager who successfully times market portfolio.

Consequently, this study develops the multi-factor timing models, as in Grinblatt and Titman (1994) and Bollen and Busse (2001), by adding the AD timing measures to the Carhart (1997) four-factor model as:

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} +$$

$$\gamma_p AD^{2}_{m,t} + \varepsilon_{p,t} \tag{3-18}$$

and

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} +$$

$$\gamma_p AD^{*}_{m,t} + \varepsilon_{p,t} \tag{3-19}$$

where $R_{p,t}$ is the excess return on portfolio p at time t, $SMB_{p,t}$ is the return of the smallest one-third of portfolio stocks minus the return on the stocks in the top third ranked by market capitalization at time t. $HML_{p,t}$ is the return of the smallest one-third of portfolio stocks minus the return on the stocks in the top third ranked by book-to-market ratio at time t. $MOM_{p,t}$ is the average return on the two high prior return portfolio stocks minus the average return on the two low prior return portfolio stocks at time t, γ_p denotes the market timing indicator, α_p is the indicator of selection ability, and $\varepsilon_{p,t}$ is the error term component.

Using Eq. (3-18) and (3-19), this study conducts its empirical exercises and estimates parameters of all the models at the daily and monthly frequency data. Next, it compares the results of these exercises with the results derived from the traditional timing models of Eq. (3-3) and (3-4). Note that, despite Glabadanidis (2015) explains that it is perhaps unfair to compare a dynamic market timing measure with traditional timing measure, we conduct this comparison analysis throughout most of the thesis.

3.6 Research Objectives

The main objective of this study is to propose a decision pattern based on the AD timing measure beyond the traditional timing measures to evaluate the performance of portfolio managers. Specifically, the following research objectives are presented:

Main Objective 1: To examine portfolio managers' timing and selection abilities based on the AD timing approach and to compare its performance with the traditional approach.

Sub-Objective 1: To compare the prediction power of the AD timing measure in the Treynor and Mazuy (1966) form with those of the traditional Treynor and Mazuy (1966) timing measure.

Sub-Objective 2: To compare the prediction power of the AD timing measure in the Henriksson and Merton (1981) form with those of the traditional Henriksson and Merton (1981) timing measure.

Sub-Objective 3: To compare the portfolio managers' selection ability of the AD-based timing models with those of the traditional timing models.

Main Objective 2: To compare the daily and monthly performance of timing measures.

Sub-Objective 4: To compare the daily and monthly performance of the AD timing measures in the Treynor and Mazuy (1966) form.

Sub-Objective 5: To compare the daily and monthly performance of the AD timing measures in the Henriksson and Merton (1981) form.

3.7 The Development of Research Hypotheses

This study aims to assert several research hypotheses based on the existing literature. It provides supportive empirical evidence to construct these hypotheses as follows:

The existence of statistically significant positive evidence in the proposed market timing measures:

Henriksson and Merton (1981) and Treynor and Mazuy (1966), among others, exhibit that if the market timing coefficients of a timing model for a portfolio are statistically positive and significant, manager of the portfolio is correctly predicting market movements. Thus, he can adjust his portfolio weights to use various strategies, and employs any opportunity to beat the market (Blake, 1994). However, the existing literature shows that the traditional market timing measures and their relevant timing models exhibit either negative timing evidence or poorly positive timing evidence in most of the markets. A great number of the studies such as Merton (1981), Henriksson and Merton (1981), Henriksson (1984), Becker et al (1999), and Jiang (2003), among others, find poor timing evidence of managed portfolios' managers using the traditional timing measures and their relevant timing models. More findings can be also found in Kryzanowski et al (1996) and Ferson and Schadt (1996). This poor evidence stimulates researchers to propose new timing measures for assessing the movements of market portfolio returns. As a result, the significant and positive market timing coefficients estimated from the timing models can be an appropriate screening indicator to distinguish the predictability of a market timing measure from other measures. Therefore, this study applies this idea to develop four research hypotheses as:

Hypothesis 1: The portfolio managers have significant timing skills using the daily AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements.

Hypothesis 2: The portfolio managers have significant timing skills using the daily AD timing measures in the Henriksson and Merton (1981) form to predict the market movements.

Hypothesis 3: The portfolio managers have significant timing skills using the monthly AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements.

Hypothesis 4: The portfolio managers have significant timing skills using the monthly AD timing measures in the Henriksson and Merton (1981) form to predict the market movements.

The existence of statistically significant positive evidence in the intercepts estimated from the proposed market timing models:

Henriksson and Merton (1981) and Treynor and Mazuy (1966), among others, also exhibit that the intercept of a timing model is the proper indicator of a portfolio manager's selection ability. They demonstrate that if the intercept of a timing model for a portfolio is statistically positive and significant, manager of the portfolio is selecting an efficient portfolio. A great number of the studies such as Merton (1981), Henriksson and Merton (1981), Henriksson (1984), Becker et al. (1999), and Jiang (2003), among others, exhibit that the estimation and interpretation of both market timing skill and selection skill for a portfolio manager can provide more implications for assessing the performance of the manager. More studies can be also found in Kryzanowski et al (1996), Ferson and Schadt (1996), Grinblatt and Titman (1994) and Bollen and Busse (2001), reporting that statistically positive and significant intercept of a timing model can be an appropriate indicator for a portfolio manager's selection ability. As a result, this study applies the above idea to develop four research hypotheses as:

Hypothesis 5: The portfolio managers have significant selection skills using the daily AD timing models in the Treynor and Mazuy (1966) form to select proper portfolios over the research period.

Hypothesis 6: The portfolio managers have significant selection skills using the daily AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period.

Hypothesis 7: The portfolio managers have significant selection skills using the monthly AD timing models in the Treynor and Mazuy (1966) form to select proper portfolios over the research period.

Hypothesis 8: The portfolio managers have significant selection skills using the monthly AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period.

Higher market timing coefficients estimated from the timing models exhibit a more successful market timer:

Generally, a manager tends to buy a portfolio when cash inflow happens and to sell it when cash outflow happens, indicating timing ability of the manager. The manager might be also engaged in timing by buying a portfolio when he has sufficient cash to invest and selling the portfolio when he needs to make cash. However, a portfolio manager's skill in predicting these market trends is a key determinant that is often taken into account using higher timing magnitudes (higher timing coefficients) estimated from the timing models (e.g., Merton, 1981, Henriksson and Merton, 1981). More specifically, Shukla and Inwegen (1995) compare the performance of U.S. and U.K. managed portfolio managers using the traditional timing measures and show that U.S. managers have higher timing abilities than U.K. fund managers based on higher statistically significant timing magnitudes (higher statistically significant timing coefficients). Bollen and Busse (2001) show that higher positive timing coefficient estimated from a timing model for a portfolio manager can imply that the manager is a more successful market timer than another one. A great set of the studies such as Gallagher and Jarnecic (2004) and Jiang et al (2007), among others, support this matter. However, the above studies among a great number of the existing timing studies show that a portfolio manager possesses better timing skill than others if he can obtain a higher magnitude of timing coefficients, implying that he has higher skill in predicting market movements. As a result, this study applies the above idea to develop two research hypotheses as:

Hypothesis 9: The prediction power of the AD timing measure in the Treynor and Mazuy (1966) form is better than those of the traditional Treynor and Mazuy (1966) timing measure.

Hypothesis 10: The prediction power of the AD timing measure in the Henriksson and Merton (1981) form is better than those of the traditional Henriksson and Merton (1981) timing measure.

The effect of different frequency data on the proposed market timing measures:

Bollen and Bassu (2001) show that the market timing measures at the daily frequency data have better timing performance than the measures at the monthly frequency data, indicating poor market timing estimated from the monthly frequency data relative to the daily frequency data. This result can be also found in Goetzmann et al (2000) and Jiang et al (2007) who show that timing measures are biased downward when using monthly returns, and the timing measures at the monthly frequency data underestimate a portfolio manager’s timing skill. The above analyses stimulate us to develop two research hypotheses to examine whether the proposed timing measures and their relevant timing models have higher timing power at the daily frequency data than those at the monthly frequency data. As a result, this study develops two research hypotheses as:

Hypothesis 11: The daily performance of the AD timing measures in the Treynor and Mazuy (1966) form is better than their monthly performance.

Hypothesis 12: The daily performance of the AD timing measures in the Henriksson and Merton (1981) form is better than their monthly performance.

3.8 Research Questions

This study aims to respond several research questions based on the development of research hypotheses. It thus presents twelve research questions based on the above hypotheses as:

Question 1: Do the portfolio managers have significant timing skills using the daily AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements?

Question 2: Do the portfolio managers have significant timing skills using the daily AD timing measures in the Henriksson and Merton (1981) form to predict the market movements?

Question 3: Do the portfolio managers have significant timing skills using the monthly AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements?

Question 4: Do the portfolio managers have significant timing skills using the monthly AD timing measures in the Henriksson and Merton (1981) form to predict the market movements?

Question 5: Do the portfolio managers have significant selection skills using the daily AD timing models in the Treynor and Mazuy (1966) form to select proper portfolios over the research period?

Question 6: Do the portfolio managers have significant selection skills using the daily AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period?

Question 7: Do the portfolio managers have significant selection skills using the monthly AD timing models in the Treynor and Mazuy (1966) form to select proper portfolios over the research period?

Question 8: Do the portfolio managers have significant selection skills using the monthly AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period?

Question 9: Does the prediction power of the AD timing measure in the Treynor and Mazuy (1966) form is better than those of the traditional Treynor and Mazuy (1966) timing measure?

Question 10: Does the prediction power of the AD timing measure in the Henriksson and Merton (1981) form is better than those of the traditional Henriksson and Merton (1981) timing measure?

Question 11: Does the daily performance of the AD timing measures in the Treynor and Mazuy (1966) form is better than their monthly performance?

Question 12: Does the daily performance of the AD timing measures in the Henriksson and Merton (1981) form is better than their monthly performance?

3.9 Research Design

The conceptual model of this study contains two main objectives and five subsidiary objectives. It also includes twelve research hypotheses and their corresponding twelve research questions. The following diagram depicts logically the interrelations among research objectives, research hypotheses, and research questions. The research sub-objectives of 1, 2, and 3 cover the first main research objective, and the research sub-objectives of 4 and 5 cover the second main research objective. The research hypotheses 1 to 4 cover directly the first main research objective. The research hypotheses 5 to 8 cover the third research sub-objective. The research hypothesis 9 covers the first research sub-objective. The research hypothesis 10 covers the second research sub-objective. The research hypothesis 11 covers the fourth research sub-objective, and the research hypothesis 12 covers the fifth research sub-objective. The research questions 1 to 12 cover their corresponding research hypotheses 1 to 12, respectively.

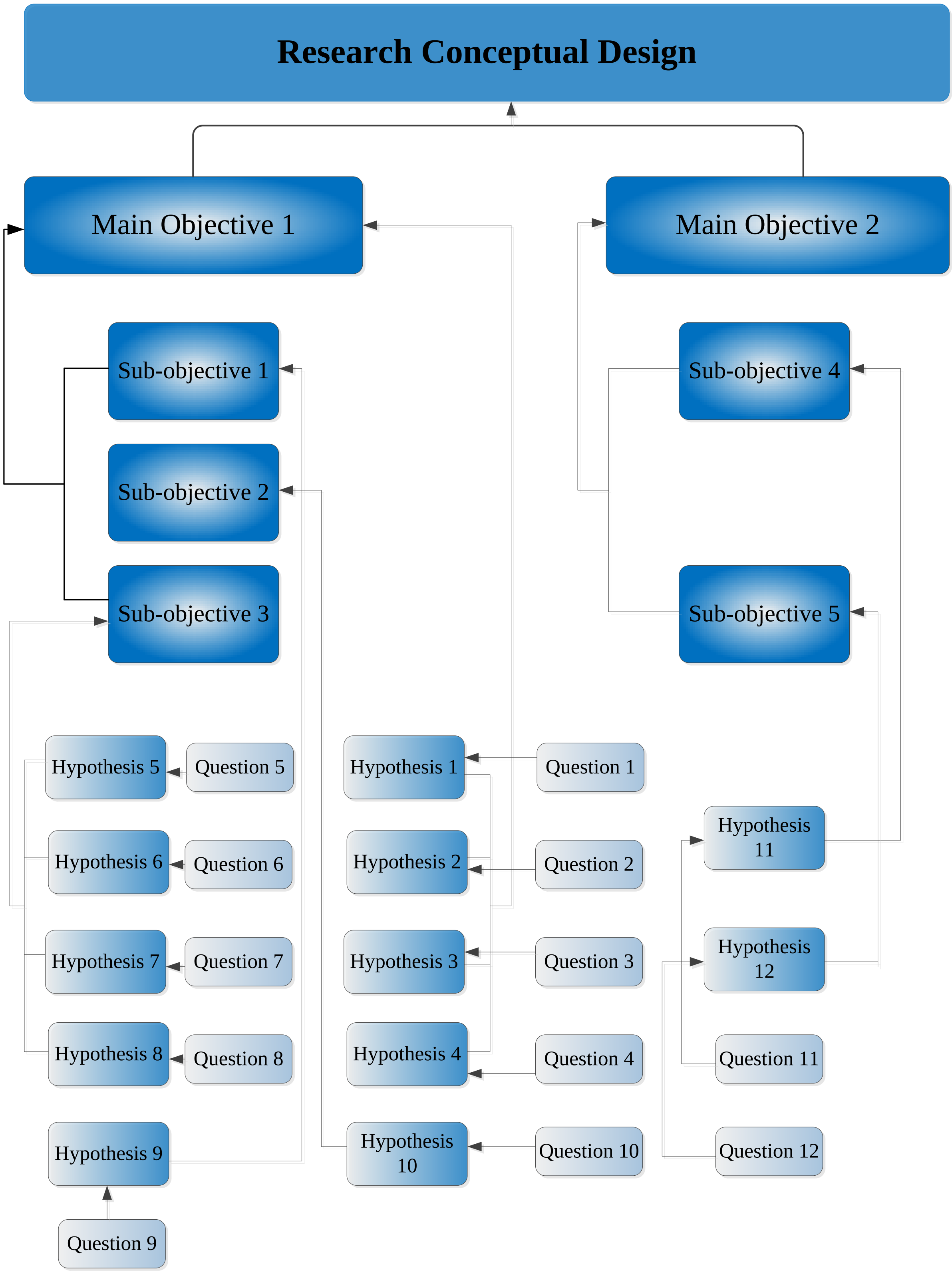

Figure 3-2: The Research Conceptual Design

3.10 Research Method

This study is based on quantitative methodology. This method focuses on objective assessments by applying the statistical and mathematical analyses of data generated from questionnaires, surveys, and polls, or by manipulating pre-extant statistical data using computational techniques. A quantitative research also concentrates on collecting numerical data to describe a specific phenomenon (Babbie, 2010).

3.11 Population and Sample

The research population contains all stocks available on the DataStream database. The research sample only contains all stocks active on 23 developed countries from 4 January 1988 till 30 June 2016. A long period allows us to consider economic cycles, latterly financial crisis and alternative risk regimes. The choice of the research sample and its relevant time period is according to Ang et al (2009) and Tavakoli Baghdadabad and Mallik (2017). These countries contain Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, UK, and US.

3.12 Sampling Method and Survivorship Bias

This study is almost free of survivorship bias since the sample contains a big number of stock data. The contribution of the 23 developed countries, among other countries, available on the database is also very big and their significance is obviously presented in Ang et al (2009). Regardless of these reasons, this study uses the MSCI World all country gross index as market index for distinguishing between upside and downside market movements. As presented in Atanasov and Nitschka (2014) and Tavakoli Baghdadabad and Mallik (2017, 2018), these selective 23 countries are key determinants for constructing the MSCI World all country gross index. These reasons thus reduce survivorship biases across the research sample.

3.13 Data Structure

This study collects all required data from the DataStream. For the daily returns, this study uses return index (RI)[5] and dividend yields distributed into shareholders at the daily frequency to construct portfolio excess returns as:

$$\mathrm{R_{j,d}} = \frac{\mathrm{RI_{j,d}} - \mathrm{RI_{j,d-1}} + \mathrm{D_{j,d}}}{\mathrm{RI_{j,d-1}}} \quad (3\text{-}20)$$

where $\mathrm{RI_{j,d}}$ is the RI of stock j at day d, $\mathrm{RI_{j,d-1}}$ is the RI of stock j at day d-1, and $\mathrm{D_{j,d}}$ is the dividend yield distributed into daily basis for stock j at day d.

For the monthly returns, this study uses return index (RI) and dividend yields distributed into shareholders at the monthly frequency to construct portfolio excess returns as:

$$\mathrm{R_{j,t}} = \frac{\mathrm{RI_{j,t}} - \mathrm{RI_{j,t-1}} + \mathrm{D_{j,t}}}{\mathrm{RI_{j,t-1}}} \quad (3\text{-}21)$$

where $\mathrm{RI_{j,t}}$ is the RI of stock j at month t, $\mathrm{RI_{j,t-1}}$ is the RI of stock j at month t-1, and $\mathrm{D_{j,t}}$ is the dividend yield distributed into monthly basis for stock j at month t.

[5] Note that most of the studies use RI instead of considering stock price to calculate stock returns.

We also use the MSCI World all country gross index as market index because our sample (23 countries under study) has the highest contribution for constructing the index. We use 90-day Treasury bill as free-risk return. The Carhart (1997) momentum factor and the Fama and French (1993) book-to-market ratio and size risk factors are all collected from the Kenneth French website[6] (e.g., Du et al., 2009).

3.14 Stock Portfolio Construction

To conduct the empirical exercises for the proposed market timing measures, this study requires managed portfolios that are professionally handled by a manager. However, since there is not access to these types of the portfolios, e.g., mutual funds, hedge funds, funds of funds, and etc., due to the research limitations, this study constructs its portfolio in the county level. For each county, this study thus collects all stocks active in the country over the sample period, 4 January 1988 till 30 June 2016. There are not any restricting indicators for screening the stocks active in each country in order to generate portfolios with more stocks in the sample and also possess a larger sample with less survivorship biases. Only one indicator, the research sample period, is applied to screen the stocks of each county. According to this indicator, Table (3-1) exhibits the number of shares within each country-level portfolio, the proportion of each country-level portfolio within our sample, and the daily and monthly returns of each portfolio. Thus, the whole sample takes into account 3087 stocks from the 23 developed countries. For the daily and monthly portfolio returns, this study firstly uses Eq. (3-20) and (3-21) for the calculation of

[6] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

the daily and monthly stock returns. This study then calculates the equal-weighted average returns of the stocks in each country to obtain portfolio returns.

Table 3-1: The features of the research sample

Countries	Number of Shares	Percentage of each portfolio in the whole sample (in %)	Daily returns	Monthly returns
Australia	61	1.98	1.70	0.34
Austria	18	0.58	0.35	0.19
Belgium	38	1.23	-0.51	-0.08
Canada	136	4.41	0.04	0.06
Denmark	17	0.55	-0.84	-0.14
Finland	8	0.26	3.00	0.56
France	58	1.88	-0.47	-0.02
Germany	72	2.33	-0.22	-0.006
Greece	18	0.58	-0.38	-0.03
Hong Kong	84	2.72	0.54	0.19
Ireland	10	0.32	-1.00	-0.19
Italy	42	1.36	0.01	-0.002
Japan	746	24.17	-0.45	-0.05
Netherlands	48	1.55	0.63	0.26
New Zealand	16	0.52	3.40	1.43
Norway	20	0.65	1.90	1.29
Portugal	15	0.49	7.10	5.31
Singapore	65	2.11	0.67	0.43
Spain	21	0.68	0.77	0.50
Sweden	21	0.68	-0.71	-0.11
Switzerland	70	2.27	1.10	0.57
U.K.	252	8.16	-0.07	0.03
U.S.	1251	40.52	3.80	2.38

Note: This table reports the features of 3087 shares from 23 country-level portfolios, consisting of the number of shares within each portfolio, the proportion of each portfolio within the whole sample, and the daily and monthly returns of each portfolio. For the daily and monthly portfolio returns, this study firstly uses Eq. (3-20) and (3-21) for the calculation of the returns on each share and then calculates the equal-weighted average returns of the shares within each country to obtain portfolio returns.

3.15 Descriptive Statistics

This section illustrates descriptive statistics used in this study that are often applied to most of the studies. These statistics are consisting of the normality test, the unit root test, the Wald test, and the redundant test.

3.15.1 Normality Test

Suppose a random variable μ_i with the numeric observations of $x_1, x_2, x_3, \ldots, x_n$. This random variable has a variety of normality tests that have been developed by different statisticians. These descriptive statistics can help us to find out various aspects of the data characteristics. The first statistic is the sample mean as given by

$$E(\mu_i) = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{3-22}$$

where x_i denotes the observations i, …, n.

The second statistic is the sample variance (s^2) as given by

$$s^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2 \tag{3-23}$$

where $\bar{x}$ denotes the mean of observations.

The third statistic is the sample skewness as given by

$$S = \frac{1}{n} \times \frac{\sum_{i=1}^{n}(x_i - \bar{x})^3}{(\sigma^2)^{3/2}} \tag{3-24}$$

Skewness presents a measure of the symmetric of the data around the mean. Skewness is zero for a normal distribution. A right-skewed distribution has positive skewness and a left-skewed distribution has negative skewness.

The fourth statistic is the sample kurtosis as given by

$$K = \frac{1}{n} \times \frac{\sum_{i=1}^{n}(x_i - \bar{x})^4}{(\sigma^2)^2} \tag{3-25}$$

Kurtosis presents a measure of the thickness of the tails in a probability density function. Kurtosis is 3 for a normal distribution, and excess kurtosis is $K - 3$. A thick-tailed or fat-tailed distribution has a kurtosis exceeds 3. There are three types of excess kurtosis in statistic including mesokurtic, leptokurtic, and platykurtic. A distribution is mesokurtic when excess kurtosis is zero. A distribution is leptokurtic when excess kurtosis has a large positive value, and a distribution is platykurtic when its excess kurtosis has a negative value.

Using the aforementioned statistics, the normality test provides the possibility to understand whether data follow a normal distribution with respect to the following assumptions

$$\text{Mean:} \qquad E(\mu_i) = 0 \tag{3-26}$$

$$\text{Variance:} \qquad E[\mu_i - E(\mu_i)]^2 = E({\mu_i}^2) = \sigma^2 \tag{3-27}$$

The above assumptions can be more defined as:

$$\mu_i \sim N(0, \sigma^2) \tag{3-28}$$

where N denotes the normal distribution, μ_i is a random variable with the numeric observations of $x_1, x_2, x_3, \ldots, x_n$, and the terms in the parentheses denote two parameters of the normal distribution, mean and variance.

Finally, these assumptions support presenting the Jarque-Bera (JB) test to examine normality and not-normality of the data. The JB is an asymptotic (large sample) test which is computed by skewness and kurtosis of a random variable as given by

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{3-29}$$

where n denotes sample size, S is skewness, and K is kurtosis. S and K are respectively equal to 0 and 3 for a normally distributed variable. Under the null hypothesis that the random variable is normally distributed, the JB statistic given in Eq. (3-28) follows the chi-square distribution with two freedom degrees. The test defines the null hypothesis where the variable is normally distributed, against its alternative hypothesis is defined where the variable is not normally distributed. The null hypothesis is rejected when the p-value is less than or equal to 0.05.

3.15.2 Unit Root Test

In the time-series regressions, it is necessary to know whether or not a time series variable possesses a unit root and is non-stationary. A time series is stationary if its statistical properties, e.g., mean, variance, and autocorrelation, become constant over time.

This test is also defined using the following random walk model:

$$Y_t = \rho Y_{t-1} + u_t \qquad -1 \leq \rho \leq 1 \tag{3-30}$$

where u_t is a white noise error term. If $\rho = 1$, Eq. (3-30) becomes a random walk model without drift, and faces the unit root problem (a situation of nonstationary). If $|\rho| \leq 1$, then the time series Y_t becomes stationary. More specifically, Y_t is run into its lagged value Y_{t-1} and examines if the estimated ρ is statistically equal to 1. If so, then Y_t is nonstationary. This test can be theoretically extended to more advanced concepts. By subtracting Y_{t-1} from both sides of Eq. (3-30), it is modified by

$$Y_t - Y_{t-1} = \rho Y_{t-1} - Y_{t-1} + u_t = (\rho - 1)Y_{t-1} + u_t \qquad (3\text{-}31)$$

Eq. (3-31) can be also rewritten as

$$\Delta Y_t = \delta Y_{t-1} + u_t \qquad (3\text{-}32)$$

where $\delta = (\rho - 1)$ and Δ are the first-difference statistics.

Alternatively, Eq. (3-32) is replaced to Eq. (3-30) to test the null hypothesis of $\delta = 0$. If $\delta = 0$, then $\rho = 1$ indicates a unit root and a nonstationary time series. If $\delta = 0$, Eq. (3-30) is written as

$$\Delta Y_t = (Y_t - Y_{t-1}) = u_t \qquad (3\text{-}33)$$

Again, Eq. (3-33) exhibits that the first differences of a random walk time series are stationary.

However, Eq. (3-30) is a simple model that allows us to take the first differences of Y_t and run them into Y_{t-1} in order to find out whether or not the estimated slope coefficient δ is zero. A coefficient δ equal to zero shows that Y_t is nonstationary, whereas a negative coefficient δ shows a stationary time series for Y_t. Despite the potential attributes of these tests to find out whether a time series is stationary (or nonstationary), there is a shortage in these tests. Specifically, under the null hypothesis that $\delta = 0$ (or $\rho = 1$), the t-value of the estimated coefficient of Y_{t-1} does not follow t-distribution; that is, it does not possess an asymptotic normal distribution.

To resolve this shortage, Dickey and Fuller (1979) suggest that, under the null hypothesis of $\delta = 0$, the estimated t-value of Y_{t-1} in Eq. (3-30) follows the τ statistic. They compute the critical values of the τ statistic on the three 1%, 5%, and 10% significance levels. The results of their test are referred to as the Dickey-Fuller (DF) test in the econometrics literature. The DF test contains several decisions. The aforementioned specifications appear that a random walk model may have drift, or it may not have drift or it may possess both stochastic and deterministic trends. The DF test is thus estimated in three different forms based on three different null hypotheses as:

$$\Delta Y_t = \delta Y_{t-1} + u_t \tag{3-34}$$

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + u_t \tag{3-35}$$

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + u_t \tag{3-36}$$

where t is the trend or time variable. For each model, the null hypothesis is defined as $\delta = 0$, meaning that there is a unit root (or a nonstationary time series). The alternative hypothesis is defined as $\delta < 0$, meaning that the time series is stationary. The rejection of the null hypothesis means that Y_t is stationary with zero mean in Eq. (3-34), that Y_t has a stationary time series with a nonzero mean in Eq. (3-35), and that Y_t is stationary based on a deterministic trend in Eq. (3-36).

Note that the critical values of the τ statistic to test the null hypothesis of $\delta = 0$ are different for each of the three above specifications of the DF test. These tests follow the following procedure to obtain proper decisions. If the absolute value of the τ statistic ($|\tau|$) exceeds the DF critical value, then the null hypothesis of $\delta = 0$ is rejected, meaning that the time series is stationary. If the $|\tau|$ does not exceed the critical value, the null hypothesis is not rejected, meaning that the time series is nonstationary. These critical values are computed in the three 1%, 5%, and 10% significance levels.

3.15.2.1 The Augmented Dickey-Fuller (ADF) Test

To conduct the DF test as presented in Eq. (3-34), (3-35), and (3-36), it is assumed that the error term u_t is not correlated. However, in the case that u_t is correlated, Dickey and Fuller (1979) suggest the augmented Dickey–Fuller (ADF) test to satisfy this new assumption. This assumption is conducted by adding the lagged values to the dependent variable Y_t as

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \tag{3-37}$$

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \tag{3-38}$$

$$\Delta Y_t = \beta_1 + \beta_2 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \tag{3-39}$$

where ε_t is defined as a pure white noise error term, and $Y_{t-1} = (Y_{t-1} - Y_{t-2})$, $Y_{t-2} = (Y_{t-2} - Y_{t-3})$, and etc. The choice of the number of lagged terms is often an empirical exercise so that increase in lags as long as the error terms in the above specifications are not correlated. Other procedures in the ADF statistic for proofing the hypotheses are fully identical to those in the DF statistic.

3.15.2.2 The Phillips–Perron (PP) Test

The DF test presents an important assumption that the error term ε_t is identically and independently distributed. The ADF test also adjusts the DF test to consider possible serial correlation of the error term ε_t by adding the difference lagged terms to the model. Phillips and Perron (1988) apply a nonparametric statistical method to consider the serial correlation in the error term without adding the difference lagged terms to the model. The procedures in the PP statistic for proofing the hypotheses are fully identical to those in the DF and ADF statistics.

3.15.2.3 The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test

The ADF and PP tests use a null hypothesis that the time series Y_t are $I(0)$, referred to as stationarity tests. One of the most commonly-used stationarity tests is the KPSS test introduced by Kwiatkowski, Phillips, Schmidt and Shin (1992). They introduce the following equation.

$$Y_t = \beta' D_t + \mu_t + u_t \qquad (3\text{-}40)$$

$$\mu_t = \mu_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim WN(0, \sigma_\varepsilon^2) \qquad (3\text{-}41)$$

where D_t denotes deterministic components (e.g., constant or constant plus time trend), u_t denotes $I(0)$ and can be heteroskedastic. u_t exhibits a pure random walk with variance σ_ε^2. The null hypothesis of this test shows that Y_t is $I(0)$ and is defined as $H_0: \sigma_\varepsilon^2 = 0$, implying that u_t is a constant. This null hypothesis explains a unit moving average root in the autoregressive-moving-average representation of ΔY_t. In contrast, the alternative hypothesis of the KPSS test is $\sigma_\varepsilon^2 > 0$. The KPSS test statistic is given by

$$\text{KPSS} = \frac{(T^{-2}\sum_{t=1}^{T}\hat{S}_t^2)}{\hat{\lambda}^2} \tag{3-42}$$

where $\hat{S}_t^2 = \sum_{j=1}^{t}\hat{u}_j$, $\hat{u}_t$ denotes the regression residual of Y_t on D_t and $\hat{\lambda}^2$ denotes a long-run variance estimate of u_t using $\hat{u}_t$. Under the null hypothesis that Y_t is $I(0)$, KPSS converges to the standard Brownian motion function that depends on the deterministic term D_t form but not its coefficient value, β. Specifically, if $D_t = 1$ then

$$\text{KPSS} \xrightarrow{d} \int_0^1 V_1(r)dr \tag{3-43}$$

where $V_1(r) = W(r) - rW(1)$, $W(r)$ denotes a standard Brownian motion of $r\epsilon[0,1]$. If $D_t = (1,t)'$, then

$$\text{KPSS} \xrightarrow{d} \int_0^1 V_2(r)dr \tag{3-44}$$

where $V_2(r) = W(r) + r(2-3r)W(1) + 6r(r^2-1)\int_0^1 W(s)ds$.

Specifically, if the KPSS test statistic (LM) is higher than the critical values at the 1%, 5%, and 10% significant levels, the null hypothesis is rejected, implying that the data does not follow a stationary trend.

3.15.3 The Wald Test

The Wald test (also referred to as the Wald Chi-Squared Test) allows us to find out whether an explanatory variable in a regression model is significant and adds a significant value to the regression model; variable that does not add anything in any meaningful way to the model must be deleted. Since, we tend to add timing measures to the multi-factor CAPM as a standard performance evaluation model, thus we seek to find out whether these measures add a significant value to the model.

To conduct this test, consider the following general nonlinear regression model:

$$y = f(\beta) + \varepsilon \tag{3-45}$$

where y and ε denote T-vectors and β denotes a k-vector of parameters. The restriction on the parameters is defined as:

$$H_0: g(\beta) = 0 \tag{3-46}$$

where g denotes a smooth function, $g: R^k \rightarrow R^q$, imposing q restrictions on β. The statistic of this test is computed as:

$$W = g(\beta)' \left[\frac{\partial g(\beta)}{\partial \beta} V(b) \frac{\partial g(\beta)}{\partial \beta'}\right] g(\beta)|_{\beta=b} \tag{3-47}$$

where T denotes the number of observations and b denotes the vector of unrestricted parameter estimates, and V denotes an estimate of the b covariance. V in the standard regression case is given by

$$V(b) = s^2 \left(\sum_i \frac{\partial f_i(\beta)}{\partial \beta} \frac{\partial f_i(\beta)}{\partial \beta'}\right)^{-1} |_{\beta=b} \tag{3-48}$$

where μ denotes the vector of unrestricted residuals, s^2 denotes the usual estimator of the unrestricted residual variance, $s^2 = (u'u)/(N-k)$, but the estimator of V may differ.

Under the null hypothesis, the Wald statistic possesses an asymptotic $\chi^2(q)$ distribution, where q denotes the number of restrictions under the hypothesis.

For the following linear regression model

$$y = X\beta + \varepsilon \tag{3-49}$$

The linear restrictions are defined as:

$$H_0 = R\beta - r = 0 \tag{3-50}$$

where R denotes a known $q \times k$ matrix, and r denotes a q-vector. The Wald statistic in Eq. (3-50) is thus rewritten as:

$$W = (Rb - r)'(Rs^2(X'X)^{-1}R')^{-1}(Rb - r) \tag{3-51}$$

Eq. (3-51) is asymptotically distributed as $\chi^2(q)$ under the null hypothesis.

F-statistic can be rewritten by considering the assumption that the errors εs have identical and independent normal distribution as:

$$F = \frac{W}{q} = \frac{(\tilde{u}'\tilde{u} - u'u)/q}{(u'u)/(T-k)} \tag{3-52}$$

where ũ denotes the vector of residuals for the restricted regression. F-statistic in Eq. (3-52) compares the residual sum of squares with and without the restrictions imposed. The null hypothesis of the Wald test states that a set of parameters is equal to some values. Specially, the null hypothesis states that the market timing coefficient equals to zero. The null hypothesis will be rejected, If F-statistic is larger than F-critical, suggesting that removing the timing variable from the model will harm the fit of regression model (Fox, 1997).

3.15.4 The Redundant Variables Test

This test allows us to estimate the statistical significance of either one group or several groups of the included variables. It answers to a key question whether a variable (or a sum of variables) added to a regression model have zero coefficients so that we must delete it (or them) from the model. This test is extendable to the models estimated by OLS, ARCH, and etc. It is applicable for the condition that the model is specified using regressors, not using a formula. It is also applicable for the condition that we tend to add a new regressor (or several regressors) to a predefined model. Since, we tend to add timing measures to the multi-factor CAPM as a predefined performance evaluation model, thus we seek to find out whether these measures add a significant value to dependent variables, portfolio excess returns. The test statistics are the F-statistic and the Log likelihood ratio. Under the null hypothesis, the F-statistic statistic has a finite F-distribution when the errors are identically and independently distributed under the normal random data. The null hypothesis of this test states that the coefficients of timing measures are equal to zero. The null hypothesis will be rejected, If F-statistic is larger than F-critical. The freedom degree of this test is determined by the number of excluded variables and the number of observations under the null hypothesis (Wooldridge, 2002).

3.16 Quantitative Techniques

There are two common approaches to conduct the data analyses. These two approaches are consisting of the explanatory data analysis (EDA) and the classical data analysis (CDA).

The EDA is defined as an approach (or philosophy) of data analysis that allows us to use a variety of techniques to (i) maximize insight for a data set, (ii) uncover the underlying structure, (iii) extract the key variables, (iv) reveal the outliers and anomalies, (v) test different assumptions, (vi) develop the parsimonious models, and (vii) identify the optimal factor settings. The EDA is an attitude (or philosophy) about how data is analysed (See, for more information Tukey, 1977, Mosteller and Tukey, 1977, Velleman and Hoaglin, 1981).

While EDA focuses on graphical techniques, CDA focuses on quantitative techniques. Most of the CDAs are decomposed into two groups of (i) interval estimation and (ii) hypothesis tests.

The interval estimation is common in statistics to test a parameter for a sample of data. The parameter value of all the possible data (not only the sample data) is referred to as the population parameter. An estimate of the correct parameter value is resulted from the sample data, which is referred to as point estimate (or sample estimate). The interval estimates develop on point estimates by combining the uncertainty of point estimates. The interval estimates thus quantify the uncertainty in the sample estimates by calculating lower and upper magnitudes of an interval, which contains the population parameter at a given confident level.

In contrast, the hypothesis tests consider the uncertainty of sample estimates. While the interval estimates consider an interval, the hypothesis tests attempt to reject a claim about a population parameter of the sample data. This test has five components. The first component is called as the null hypothesis, a typically accepted fact that a researcher tries to nullify. The second component is contrary to the null hypothesis. The rejection of a hypothesis means that it is false. The acceptance of a hypothesis does not imply that it is true, but it concludes that we do not have reliable evidence to believe otherwise. The third component is defined as the test statistic, which is based on a specific hypothesis test. The fourth component is defined as the significance level (or the test sensitivity). For Example, a significance level of 0.05 implies that the null hypothesis is inadvertently rejected in 5% of the time when it is true, indicating the type I error as well. Despite in practice the levels of 0.1, 0.05, and 0.01 are employed by different researchers, the choice of the significance levels is arbitrary. The probability of the rejection of the null hypothesis, when it is false, is referred to as the power of the hypothesis test. The probability of the acceptance of the null hypothesis, when the alternative hypothesis is true (type II error), can only be tested using a specific alternative hypothesis. The fifth component is the critical region, which contains the values of the test statistic, causing a rejection in the null hypothesis. A cut-off value is calculated for the test statistic based on the distribution of the significance levels and the test statistics. These cut-off values define the critical region by considering values either below or above or both based on the direction of the hypothesis test.

3.17 Paired Two-Tailed Sample T-test Statistic

The paired sample mean t-test allows us to determine if the means of two groups under study are equal (Snedecor and Cochran, 1989). The two-tailed term means that the rejection region of the statistical hypothesis places on both sides of the sampling distribution. There are three assumptions on this test.

First, the data of two groups are either paired or not paired. The paired data means that a one by one relation exists between the values of the two groups. For example, if $\mathrm{E}_1, \mathrm{E}_2, \dots, \mathrm{E}_\mathrm{n}$ and $\mathrm{F}_1, \mathrm{F}_2, \dots, \mathrm{F}_\mathrm{n}$ are the components of the two groups, then $\mathrm{E_i}$ corresponds to $\mathrm{F_i}$. For the paired samples, the spread $\mathrm{E_i} - \mathrm{F_i}$ is typically computed. For the unpaired samples, the sample size for the two groups may or may not be equal. The calculations of paired data are simpler than the calculations of unpaired data. Since there is a one by one relation between the group of daily data and the group of monthly data and also the group of traditional market timing measures and the group of new market timing measures, the data of this study is based on the paired data feature.

Second, the variances of the two groups may or may not be known. The feature of my thesis exhibits the known variances for the groups under study.

Third, the type of alternative hypotheses allows us to define whether a test is two-tailed or one-tailed. A two-tailed test is related to an alternative hypothesis for which the means of two groups are not equal, while a one-tailed test is related to alternative hypotheses for which the mean of a group is higher (or lower) than the mean of another one. Since this study tends to test whether the group of monthly data is less than the group of daily data, and also the group of traditional market timing measures is less than the group of new market timing measures, so the alternative hypothesis of the one-tailed test is applicable in this study.

Thus, the above assumptions allow us to define the paired one-tailed sample mean t-test as:

$$\begin{cases} \mathrm{H_0}: & \mu_1 = \mu_2 \\ \mathrm{H_1}: & \mu_1 < \mu_2 \end{cases} \tag{3-53}$$

Since the variances of two groups are not assumed to be equal, then test statistic is defined as:

$$T = \frac{\bar{Y}_1 - \bar{Y}_2}{\sqrt{\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2}}} \quad (3\text{-}54)$$

where N_1 and N_2 denote the sample sizes, $\bar{Y}_1$ and $\bar{Y}_2$ denote the sample means, and s_1^2 and s_2^2 denote the sample variances.

The null hypothesis is rejected under $|T| < t_{\alpha,v}$, where $t_{\alpha,v}$ is the critical value of t-distribution with the freedom degree of v, which is calculated as:

$$v = \frac{\left(\frac{s_1^2}{N_1 + \frac{s_2^2}{N_2}}\right)^2}{\frac{\left(\frac{s_1^2}{N_1}\right)^2}{(N_1 - 1)} + \frac{\left(\frac{s_2^2}{N_2}\right)^2}{(N_2 - 1)}} \quad (3\text{-}55)$$

For the proof of research hypotheses in Chapter 4, μ_1 is defined as the group of monthly data and the group of traditional market timing measures, and μ_2 is defined as the group of daily data and the group of new market timing measures.

3.18 One Sample T-test Statistic

This statistic states that the rejection region of the statistical hypothesis places on one side of the sampling distribution. Since this study is seeking positive evidence of portfolio managers' selection and market timing abilities in the research sample, the one sample mean t-tests are used to determine if the means of these two abilities in the research sample are greater than zero. If so, there are positive coefficients of portfolio managers' selection and market timing skills in the sample. The null hypothesis and its relevant alternative hypothesis are defined as:

$$\begin{cases} H_0: & \mu_2 \leq 0 \\ H_1: & \mu_2 > 0 \end{cases} \quad (3\text{-}56)$$

where μ_2 is defined in separated hypothesis tests as the mean of selection skills estimated from the proposed timing models and the mean of market timing skills estimated from the models. Subsequently, the test statistic is defined as:

$$T = \frac{\overline{Y}_2 - \mu}{\frac{s_2}{\sqrt{n_2}}} \tag{3-57}$$

where $\overline{Y}_2$ is the sample mean, μ is the hypothesized population mean, s_2 is the sample standard deviation, and n is the number of observations. The null hypothesis is rejected under $|T| > t_{\alpha,v}$, where $t_{\alpha,v}$ is the critical value of t-distribution with the freedom degree of $n - 1$.

3.19 Research Hypotheses Test

This study uses the following steps to test the research hypotheses.

To test the research hypotheses 1 to 8, this study firstly constructs the proposed market timing measures using Eq. (3-14) and (3-15) at the daily and monthly frequencies. Then, it uses Eq. (3-18) and (3-19) to estimate the daily and monthly market timing and selection abilities of portfolio managers based on the proposed market timing measures. Finally, it uses the one sample t-test statistic defined in Eq. (3-56) and (3-57) to prove statistically the research hypotheses.

To test the research hypotheses 9 and 10, this study firstly constructs the traditional and proposed market timing measures using Eq. (3-7), (3-8), (3-14) and (3-15). It then uses Eq. (3-3), (3-4), (3-18) and (3-19) to estimate the portfolio managers' market timing and selection abilities based on the traditional and proposed market timing measures. Consequently, it uses the paired sample t-test statistic defined in Eq. (3-53), (3-54), and (3-55) to understand which of measure provides higher (necessarily positive) market timing evidence.

To test the research hypotheses 11 and 12, this study firstly constructs the proposed market timing measures using Eq. (3-14) and (3-15) at the daily and monthly frequencies. Then, it uses Eq. (3-18) and (3-19) to estimate the daily and monthly market timing abilities of portfolio managers based on the proposed market timing measures. Consequently, it uses the paired sample t-test statistic defined in Eq. (3-53), (3-54), and (3-55) to understand which of frequency provides higher (necessarily positive) market timing evidence.

3.20 Robustness checks

To conduct a double controlling check on the baseline results, this study uses alternative procedure to estimate the monthly market timing ability. The first check is to construct the monthly data using the daily data as

$$\mathrm{R^M} = \prod_{\mathrm{t=T}}^{\mathrm{T+N-1}} (1 + \mathrm{R_t^D}) - 1 \qquad (3\text{-}58)$$

where $\mathrm{R^M}$ is the monthly return based on the daily return $\mathrm{R^D}$, N denotes the trading days in a given month, and T is the first day of each month.

Next, in order to compare the daily estimates and the monthly estimates, this study reconstructs a monthly market timing measure based on Bollen and Bassu (2001) and makes a proxy for monthly payoffs of a successful market timer. The magnitude of monthly variable is calculated each month as

$$\mathrm{P_{m,\tau}^T} = \left(\prod_{\mathrm{t=1}}^{\mathrm{N}} \max[1 + \mathrm{R_{m,t}^T}, 1 + \mathrm{R_{f,t}}\right) - 1 - \mathrm{R_{m,t}^T} \qquad (3\text{-}59)$$

$$P^{AD}_{m,\tau} = \left(\prod_{t=1}^{N} \max[1 + R^{AD}_{m,t}, 1 + R_{f,t}\right) - 1 - R^{AD}_{m,t} \tag{3-60}$$

where $P^{T}_{m,\tau}$ and $P^{AD}_{m,\tau}$ are the monthly traditional and AD market timing measures, respectively, N is the number of days at month τ, $R^{T}_{m,t}$ is the market return m at day t in the standard form for constructing the monthly traditional market timing measure, $R^{AD}_{m,t}$ is the market return m at day t in the AD form, $A_{\rho-1} + (R_{mt})$, for constructing the monthly AD market timing measure, and $R_{f,t}$ is the free-risk return. Then, these two factors are used in the following regression based on monthly returns to consider the correlation between the monthly portfolio return and the monthly magnitude of daily timing as

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} + \gamma_p P^{T}_{m,\tau} + \varepsilon_{p,t} \tag{3-61}$$

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} + \gamma_p P^{AD}_{m,\tau} + \varepsilon_{p,t} \tag{3-62}$$

where γ_p evaluates the timing skill of a portfolio manager. As theoretically expected, a positive sign of γ_p exhibits a portfolio manager's skill in predicting market movements. The α_p and β_p, SMB, HML, and MOM coefficients can take positive signs as well negative signs, indicating that determining their signs is merely an empirical exercise.

The second robustness check is to examine the power of the proposed timing tests by generating portfolio returns under two alternative hypotheses of either Treynor and Mazuy (1966) (TM) or Henriksson and Merton (1981) (HM) for market timing abilities. The purpose is to demonstrate whether the return frequency can increase the power of market timing for the proposed market timing measures. To generate returns under the TM alternative, we construct a time series of portfolio betas as

$$\beta_{P,t:t+T} = \beta_P + \gamma \bar{r}_{m,t:t+T} \tag{3-63}$$

where $\bar{r}_{m,t:t+T}$ is the daily mean market excess return in the AD form, $(A_{\rho-1} + (R_{mt} - R_{ft}))$, from day t until day $t: t + T$, and $t: t + T$ represents a portfolio manager's timing interval (one day, two days, one week, two weeks, or one month). The market beta β_{MKT} is the portfolio beta from the following non-timing model.

$$R_{p,t} = \alpha_p + \beta_{MKT} R_{m,t} + \beta_{SMB} SMB_{p,t} + \beta_{HML} HML_{p,t} +$$

$$\beta_{MOM} MOM_{p,t} + \varepsilon_{p,t} \tag{3-64}$$

This study substitutes the beta from Eq. (3-64) into the non-timing model and adds a randomly sampled residual from the non-timing model regression to generate a portfolio return under the TM alternative. This study generates returns by setting γ equal to 5, 7.5, 10, 15, and 20. These values result in mild to aggressive trading behavior. Consistent with Bollen and Busse (2001), we consider the monthly timing interval for T.

In the HM timing simulations, we take the market beta of a perfect timer as

$$\beta_{P,t:t+T} = I[\bar{r}_{m,t:t+T} > 0]\beta_{MKT} \tag{3-65}$$

where $\bar{r}_{m,t:t+T}$ is $A_{\rho-1} + (R_{mt} - R_{ft})$. This study substitutes the beta from Eq. (3-65) into the non-timing model and adds a randomly sampled residual from the non-timing model regression of Eq. (3-64) to generate a portfolio return under the HM alternative. We also consider a range of $0.6 < \mathrm{I} < 1$ for the timing decisions.

Finally, this study uses Eq. (3-18) and (3-19) on the daily and monthly frequency data constructed under the TM and HM alternatives, and examines portfolio timing significance at the confidence level of 95% using standard t-statistics.

3.21 Chapter Summary

This chapter presents an overview of statistical and econometric analyses. It presents the traditional market timing strategies, the dynamic timing measures, the average drawdown (AD) timing measures, the proposed AD timing models, the research objectives, the research hypotheses, the research questions, the research conceptual design, the research method, the research population and sampling, the sampling method and survivorship bias, the data collection, the construction of country-level portfolios, and the descriptive statistics consisting of the normality test, the unit root test, the Wald test, the redundant test, and the test of proofing research hypotheses. Finally, it presents some robustness checks to control for the basic results of this study.

These tests are empirically used in next chapter to examine statistically and economically the research objectives.

Chapter 4 : Analysis

4.1 Introduction

This chapter presents basis analyses using statistical and econometric methods to cover the research objectives. First, it conducts the normality tests for both daily data and monthly data to understand about the dispersion features of the data used in this study. These data are returns on the country-level portfolios, the MSCI index, the SMB, HML, MOM risk factors, the traditional and suggested market timing measures. None of these data, especially returns on the country-level portfolios, is normally distributed at the confidence level of 95%. The choice of such a non-normality sample can exhibit much more drags and volatilities, and thus stimulate us to use the timing measures for the assessment of market asymmetries. Second, it reports the results of unit root tests to know whether the data follow a stationary trend across time. Third, it uses the mostly-common two econometric tests of Wald and Redundant to find out whether the market timing measures added to the predefined standard four-factor models make significant values on dependent variable of the models, portfolio excess returns. Fourth, it presents the results of portfolio managers' market timing and selection abilities for 23 countries under study. To conduct this step, market timing models are firstly run by daily portfolio returns, and then the models are estimated by monthly portfolio returns extracted from daily returns. Fifth, it performs several robustness checks to understand whether the basic findings of this study remind unchanged if the analysis assumptions and some research variables change. Sixth, it tests the research hypotheses by the results obtained from the basic analyses. Seventh, it provides supplementary explanations and relates empirical evidence with the existing performance evaluation studies. Finally, a separated conclusion section is presented at the end of this chapter.

4.2 Normality Test

This subsection uses the theoretical explanations of the subsection (3.15.1) in chapter 3 for conducting the normality tests. Table 4-1 reports summarily descriptive statistics of daily data for all research variables. The second column contains the mean of portfolio excess returns constructed from the equal-weighted average of all stocks active in each of the countries under study. It also presents other explanatory variables along with the traditional and suggested market timing measures. The column reports that portfolio excess returns constructed from stocks active in Portugal have the highest mean (7.1%) among other country-level excess returns, and portfolio excess returns constructed from stocks active in Ireland have the lowest mean (-1%) across the countries. Among the standard known risk factors, the momentum (MOM) has the highest return (2.7%) and market excess return (MKT) has the lowest return (-1.20%). The proposed HM and TM market timing measures have magnitudes of 0.17% and 0.05%, respectively, while the traditional HM and TM market timing measures have lower magnitudes of 0.12% and 0.03%, respectively.

The third column presents the median of the variables where the results are almost identical to those reported for the mean of the variables. Again, portfolio excess returns constructed from stocks active in Portugal have the highest median (2%) among other country-level excess returns, and portfolio excess returns constructed from stocks active in Ireland have the lowest median (-1.3%) across the countries. Among the standard known risk factors, the momentum (MOM) has the highest return (6%) and market excess return (MKT) has the lowest return (-1.3%). The proposed HM and TM market timing measures have magnitudes of 0.06% and 0.03%, respectively, while the traditional HM and TM market timing measures have lower magnitudes of 0.01% and 0.02%, respectively.

The fourth column reports standard deviation of the variables where the highest standard deviation is for U.S. with a value of 26% and the lowest standard deviation is for Belgium with a value of 1.2% across the countries. Among the standard known risk factors, momentum (MOM) and market excess return (MKT) have the highest and the lowest standard deviations with the values of 83% and 1.3%, respectively. The proposed HM and TM market timing measures have the standard deviations of 0.39% and 0.06%, respectively, while the traditional HM and TM market timing measures have higher standard deviations of 0.42% and 0.07%, respectively. This implicates lower standard deviations for the proposed timing measures than for the traditional timing measures.

The fifth column represents skewness of the variables where U.S. and Japan have the highest and the lowest skewness of portfolio excess returns with the values of 60.08% and 0.24%, respectively. The HML and MOM risk factors have the highest and the lowest skewness of the standard known risk factors with the values of 0.43% and -0.93%, respectively. The proposed HM and TM market timing measures have the skewness of 6.5% and 3.77%, respectively, while the traditional HM and TM market timing measures have the skewness of 7.53% and 4.40%, respectively. The results exhibit that the proposed timing measures have less skewed dispersions than the traditional timing measures.

For the sixth column, it shows kurtosis of the variables where all portfolio excess returns exhibit a leptokurtic distribution with relatively large positive kurtosis. The highest kurtosis is for U.S. and the lowest one is for Japan across the 23 countries under study. Among the standard known risk factors, MOM and MKT have the highest and the lowest kurtosis with the values of 15.09% and 4.29%, respectively. The proposed HM and TM market timing measures have the kurtosis of 72.77% and 33.14%, respectively, while the traditional HM and TM market timing measures have the kurtosis of 87.37% and 45.25%, respectively. Again, the results exhibit less kurtosis dispersions for the proposed timing measures than for the traditional timing measures.

The seventh column also exhibits the Sharpe ratio for the variables. This ratio is defined by dividing mean by standard deviation. The results of this ratio exhibit that the portfolios of two countries, Portugal and New Zealand, have the highest ratio with the values of 59% and 56%, respectively. Two countries of Denmark and Ireland also have the lowest Sharpe ratio with negative values of -60% and -56%, respectively. The MOM and MKT risk factors have the highest and the lowest Sharpe ratios with the quantitative magnitudes of 3.25% and -92.31%, respectively. The proposed HM and TM market timing measures have the Sharpe ratios of 43.59% and 83.33%, respectively, while the traditional HM and TM market timing measures have the Sharpe ratios of 28.57% and 42.86%, respectively. This implicates higher Sharpe ratios for the proposed timing measures than for the traditional timing measures.

Table 4-1 gives us several interesting and important findings. First, the daily average returns of the AD-based market timing measures are greater than those from the traditional market timing measures. Second, these spreads in daily average returns come with a less return standard deviation for the AD-based market timing measures, and thus the AD-based market timing measures appear to dominate the traditional market timing measures in a mean-variance sense. Third, the traditional market timing measures have a higher return skewness than the AD-based market timing measures. This feature makes the AD-based market timing measures very attractive to investors who possess a preference for high return skewness. Fourth, the same results can be observed for returns' kurtosis. Fifth, the trade-off between risk and return is tremendously improved as observed by the much greater Sharpe ratios for the AD-based market timing measure returns relative to the Sharpe ratios of the traditional market timing measure returns. These results, especially superiority of the Sharp ratios of the AD-based market timing measures relative to the Sharp ratios of the traditional market timing measures, implicate higher profitability of the AD-based market timing measures relative to their traditional corresponding measures. This result is consistent with Glabadanid (2014) who found profitability of the moving average market timing strategies relative to the existing traditional timing measures using the above analysis.

The last two columns report the results for the Jarque-Bera (JB) normality test where the null hypothesis is rejected to all the variables under study at the confidence level of 95% because their p-values are less than 5%. This means that none of the variables are normally distributed at the confidence level of 95%. The choice of such a non-normality sample can exhibit much more drags and volatilities in portfolio returns, and thus can stimulate us to use such measures for the assessment of market asymmetries.

Table 4-1: Daily descriptive statistics of normality test

Countries	Mean	Median	Std. Dev.	Skewness	Kurtosis	Sharpe ratio	Jarque-Bera	P-Value
Australia	1.70	0.46	4.40	2.20	7.64	39%	12694.84	0.00
Austria	0.35	0.24	1.80	3.03	23.26	19%	138621.5	0.00
Belgium	-0.51	-0.61	1.20	1.67	27.22	-43%	185264.6	0.00
Canada	0.04	-0.24	3.30	51.57	3716.11	1%	4.23E+09	0.00
Denmark	-0.84	-0.94	1.40	0.31	5.04	-60%	1425.25	0.00
Finland	3.00	1.00	17.00	9.83	101.32	18%	3114912	0.00
France	-0.47	-0.76	3.00	11.33	193.95	-16%	11455933	0.00
Germany	-0.22	-0.50	2.40	29.42	1622.78	-9%	8.14E+08	0.00
Greece	-0.38	-0.46	2.10	0.25	5.57	-18%	2133.22	0.00
Hong Kong	0.54	0.39	1.90	0.62	9.99	28%	15649.74	0.00
Ireland	-1.00	-1.30	1.80	1.55	19.29	-56%	85238.5	0.00
Italy	0.01	-0.38	2.70	4.63	37.76	0%	400982.6	0.00
Japan	-0.45	-0.59	1.80	0.24	4.99	-25%	1307.79	0.00
Netherlands	0.63	0.37	2.00	2.72	26.17	32%	175514.2	0.00
New Zealand	3.40	0.54	6.10	1.59	5.54	56%	5166.2	0.00
Norway	1.90	-0.38	7.60	2.53	8.44	25%	17160.87	0.00
Portugal	7.10	2.00	12.00	4.87	79.91	59%	1862352	0.00
Singapore	0.67	0.5	2.40	3.37	23.41	28%	143236.6	0.00
Spain	0.77	0.48	2.60	3.16	22.96	30%	135914.8	0.00
Sweden	-0.71	-0.81	1.70	0.98	7.64	-42%	7899.329	0.00
Switzerland	1.10	0.55	2.70	1.53	6.07	41%	5860.48	0.00
U.K.	-0.07	-0.32	1.50	1.72	12.11	-5%	29402.81	0.00
U.S.	3.80	-0.34	26.00	60.08	4495.99	15%	6.26E+09	0.00
MKT	-1.20	-1.30	1.30	0.15	4.29	-92.31%	547.38	0.00
SMB	0.54	2.00	58.00	-0.25	7.28	0.93%	5766.735	0.00
HML	1.20	0.00	58.00	0.43	12.62	2.07%	28927.11	0.00
MOM	2.70	6.00	83.00	-0.93	15.09	3.25%	46366.85	0.00
NHM	0.17	0.06	0.39	6.50	72.77	43.59%	2276012	0.00
NTM	0.05	0.03	0.06	3.77	33.14	83.33%	577093.1	0.00
THM	0.12	0.01	0.42	7.53	87.37	28.57%	1560797	0.00
TTM	0.03	0.02	0.07	4.40	45.25	42.86%	299216.5	0.00

Note: This table reports descriptive statistics of daily data for all research variables. The second column contains portfolio excess returns constructed from the equal-weighted average of all stocks active in each of the countries under study, and also returns on the four standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). It also contains the traditional Treynor and Mazuy (1966) (TTM) and Henriksson and Merton (1981) (THM) market timing measures and the proposed Treynor and Mazuy (1966) (NTM) and Henriksson and Merton (1981) (NHM) market timing measures. Columns 3, 4, 5, 6, and 7 report median, standard deviation, skewness, kurtosis, and Sharpe ratio, respectively. Columns 8 and 9 report the results of Jarque-Bera tests and their P-values, respectively. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-2 reports summarily descriptive statistics of monthly data for all research variables. The second column contains the mean of portfolio excess returns constructed from the equal-weighted average of all stocks active in each of the countries under study. It also presents other explanatory variables along with the traditional and suggested market timing measures. Similar to the daily data, the column reports that portfolio excess returns constructed from stocks active in Portugal have the highest mean (5.31%) among other country-level excess returns, and portfolio excess returns constructed from stocks active in Ireland have the lowest mean (-0.19%) across the countries. Among the standard known risk factors, MOM has the highest return (0.57%) and MKT has the lowest return (0.0025%). The proposed NHM and NTM market timing measures have magnitudes of 0.018% and 0.004%, respectively, while the traditional THM and TTM market timing measures have the values of 0.014% and 0.002%, respectively.

The third column presents the median of the variables where the results are almost identical to those reported for the mean of the variables. Again, portfolio excess returns constructed from stocks active in Portugal have the highest median (0.3%) among other country-level excess returns, and portfolio excess returns constructed from stocks active in Ireland have the lowest median (-0.21%) across the countries. Among the standard known risk factors, MOM has the highest return (0.66%) and HML has the lowest return (-0.03%). The proposed NHM and NTM market timing measures have magnitudes of 0.011% and 0.003%, respectively, while the traditional THM and TTM market timing measures have the values of 0.007% and 0.001%, respectively.

The fourth column reports standard deviation of the monthly variables where the highest standard deviation is for U.S. with a value of 11.22% and the lowest standard deviation is for Denmark and Ireland with the same value of 0.19%. Among the standard known risk factors, MOM and MKT have the highest and the lowest standard deviations with the values of 4.76% and 0.045%, respectively. The proposed NHM and NTM market timing measures have the standard deviations of 0.022% and 0.0047%, respectively, while the traditional THM and TTM market timing measures have the standard deviations of 0.025% and 0.005%, respectively. Similar to the daily data, there are lower standard deviations for the proposed timing measures than for the traditional timing measures. In addition, the magnitude of the daily data dispersion is higher than the monthly data dispersion.

The fifth column represents skewness of the monthly variables where Austria and Denmark have the highest and the lowest skewness of portfolio excess returns with the values of 12.02% and 0.32%, respectively. The SMB and MOM risk factors have the highest and the lowest skewness of the standard known risk factors with the values of 0.79% and -1.58%, respectively. The proposed NHM and NTM market timing measures have the skewness of 1.98% and 4.19%, respectively, while the traditional THM and TTM market timing measures have the skewness of 2.16% and 5.18%, respectively. Similar to the daily data, new timing measures have less skewed dispersions than the traditional timing measures. In addition, magnitude of the daily data dispersion is higher than the monthly data dispersion.

For the sixth column, it shows kurtosis of the monthly variables where all portfolio excess returns exhibit a leptokurtic distribution with relatively large positive kurtosis. The highest kurtosis is for Austria and the lowest one is for Japan across the 23 countries. Among the standard known risk factors, MOM and MKT have the highest and the lowest kurtosis with the values of 14.41% and 4.62%, respectively. The proposed NHM and NTM market timing measures have the kurtosis of 7.78% and 28.27%, respectively, while the traditional THM and TTM market timing measures have the kurtosis of 8.56% and 38.65%, respectively. Identical to the daily data, the results exhibit less kurtosis dispersions for the proposed timing measures than for the traditional timing measures. In addition, magnitude of the daily data dispersion is higher than the monthly data dispersion.

The seventh column also exhibits the Sharpe ratio for the monthly variables. This ratio is defined by dividing mean by standard deviation. The results of this ratio exhibit that Finland and Portugal have the highest Sharpe ratios with the values of 54% and 49%, respectively. Ireland also has the lowest ratio with a negative value of -100%. The MOM and SMB risk factors have the highest and the lowest Share ratios with the quantitative magnitudes of 11.97% and 3.45%, respectively. The proposed NHM and NTM market timing measures have the Sharpe ratios of 81.82% and 85.11%, respectively, while the traditional THM and TTM market timing measures have lower Sharpe ratios of 56% and 40%, respectively.

Identical to the daily data results in Table 4-1, Table 4-2 gives us interesting and important findings. First, the monthly average returns of the AD-based market timing measures are greater than those from the traditional market timing measures. Second, these spreads in monthly average returns come with a less return standard deviation for the AD-based market timing measures, and thus the AD-based market timing measures appear to dominate the traditional market timing measures in a mean-variance sense. Third, the traditional market timing measures have a higher return skewness than the AD-based market timing measures, indicating that the AD-based market timing measures are very attractive to investors who possess a preference for high return skewness. Fourth, the same results are obtained for returns' kurtosis. Fifth, the trade-off between risk and return is tremendously improved as observed by the much greater Sharpe ratios for the AD-based market timing measure returns relative to the Sharpe ratios of the traditional market timing measure returns. These results, especially superiority of the Sharp ratios of the AD-based market timing measures relative to the Sharp ratios of the traditional market timing measures, implicate higher profitability of the AD-based market timing measures relative to their traditional corresponding measures.

The last two columns report the results for the Jarque-Bera (JB) normality test where the null hypothesis is rejected to all the variables under study at the confidence level of 95% because their p-values are less than 5%. This means that none of the monthly variables are normally distributed at the confidence level of 95%. Similar to the daily data, the choice of such a non-normality sample can exhibit much more drags and volatilities in monthly returns, and thus can stimulate us to use such measures for the assessment of market asymmetries.

Table 4-2: Monthly descriptive statistics of normality test

Countries	Mean	Median	Std. Dev.	Skewness	Kurtosis	Sharpe ratio	Jarque-Bera	P-Value
Australia	0.34	0.10	0.80	2.80	13.90	43%	2142.59	0.00
Austria	0.19	0.08	1.22	12.02	170.89	16%	409954.8	0.00
Belgium	-0.08	-0.11	0.22	1.23	7.08	-36%	325.50	0.00
Canada	0.06	-0.02	0.50	3.04	14.58	12%	2440.53	0.00

Denmark	-0.14	-0.19	0.19	0.32	2.30	-74%	12.97	0.00
Finland	0.56	0.19	1.04	3.01	15.68	54%	2811.74	0.00
France	-0.02	-0.14	0.86	7.89	72.70	-2%	72785.95	0.00
Germany	-0.006	-0.11	0.33	1.95	12.88	-2%	1610.17	0.00
Greece	-0.03	-0.09	0.39	3.72	27.89	-8%	9623.34	0.00
Hong Kong	0.19	0.09	0.49	2.87	15.33	39%	2639.47	0.00
Ireland	-0.19	-0.21	0.19	0.67	4.03	-100%	40.84	0.00
Italy	-0.002	-0.061	0.32	1.43	6.02	-1%	247.59	0.00
Japan	-0.05	-0.14	0.29	0.43	2.26	-17%	18.26	0.00
Netherlands	0.26	0.07	0.89	5.51	39.14	29%	20353.83	0.00
New Zealand	1.43	0.09	2.93	3.66	23.36	49%	6675.68	0.00
Norway	1.29	-0.07	5.25	5.20	33.83	25%	15087.19	0.00
Portugal	5.31	0.30	10.94	3.25	16.49	49%	3208.72	0.00
Singapore	0.43	0.16	2.49	9.86	112.00	17%	174879.7	0.00
Spain	0.50	0.10	3.12	10.42	115.82	16%	187607.1	0.00
Sweden	-0.11	-0.15	0.34	7.23	84.69	-32%	98092.74	0.00
Switzerland	0.57	0.14	1.41	3.11	12.87	40%	1944.01	0.00
U.K.	0.03	-0.06	0.42	4.42	34.21	7%	14999.01	0.00
U.S.	2.38	-0.06	11.22	7.42	61.63	21%	52130.32	0.00
MKT	0.0025	0.0073	0.045	-0.44	4.62	5.56%	48.62	0.00
SMB	0.11	0.05	3.19	0.79	11.75	3.45%	1127.16	0.00
HML	0.21	-0.03	2.92	0.13	5.83	7.19%	115.38	0.00
MOM	0.57	0.66	4.76	-1.58	14.41	11.97%	1999.17	0.00
NHM	0.018	0.011	0.022	1.98	7.78	81.82%	708.07	0.00
NTM	0.004	0.003	0.0047	4.19	28.27	85.11%	19644.99	0.00
THM	0.014	0.007	0.025	2.16	8.56	56%	550.74	0.00
TTM	0.002	0.001	0.005	5.18	38.65	40%	10104.67	0.00

Note: This table reports descriptive statistics of monthly data for all research variables. The second column contains portfolio excess returns constructed from the equal-weighted average of all stocks active in each of the countries under study, and also returns on the four standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). It also contains the traditional Treynor and Mazuy (1966) (TTM) and Henriksson and Merton (1981) (THM) market timing measures and the proposed Treynor and Mazuy (1966) (NTM) and Henriksson and Merton (1981) (NHM) market timing measures. Columns 3, 4, 5, 6, and 7 report median, standard deviation, skewness, kurtosis, and Sharpe ratio, respectively. Columns 8 and 9 report the results of Jarque-Bera tests and their P-values, respectively. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.3 Unit Root Test

This subsection uses the theoretical explanations of the subsection (3.15.2) in chapter 3 for conducting three unit root tests.

The second column of Table 4-3 reports the results of unit root test for daily variables using the Augmented Dickey-Fuller Test. The critical values for this test are -3.98, -3.42, and -3.13 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the τ statistic in all variables reported in Table 4-3 are greater than the critical values at the 1% and 5% significance levels. This means that the null hypothesis is rejected to all the variables constructed from the daily data, indicating that the time series variables are all stationary.

The third column of Table 4-3 reports the results of unit root test for daily variables using the Phillips-Perron Test. The critical values for this test are -3.95, -3.41, and -3.12 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the τ statistic in all variables reported in Table 4-3 are greater than the critical values at the 1% significance level. This means that the null hypothesis is rejected to all the variables constructed from the daily data, indicating that the time series variables are all stationary.

The fourth column of Table 4-3 reports the results of unit root test for daily variables using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test. The critical values for this test are 0.216, 0.146, and 0.119 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the LM-STAT statistic in all variables reported in Table 4-3 are greater than the critical values at the 1%, 5%, and 10% significance levels. This means that the null hypothesis is rejected to all the variables constructed from the daily data, indicating that the time series variables are all stationary.

Table 4-3: The results of unit root test for the daily variables

Countries	τ Statistic		LM-STAT
	Augmented Dickey-Fuller Test	Phillips-Perron Test	Kwiatkowski-Phillips-Schmidt-Shin Test
Australia	-43.73*	-18.64*	1.22*
Austria	-6.74*	-46.58*	0.20**
Belgium	-6.22*	-100.84*	0.37*
Canada	-7.68*	-129.36*	0.53*
Denmark	-7.24*	-117.14*	0.22*
Finland	-9.04*	-9.32*	0.12***
France	-11.27*	-26.41*	0.13***
Germany	-6.67*	125.13*	0.37*
Greece	-6.60*	-111.08*	0.40*
Hong Kong	-7.02*	93.43*	0.37*
Ireland	-7.23*	-125.24*	0.24*
Italy	-32.78*	-52.96*	0.53*
Japan	-7.60*	-119.84*	0.19**
Netherlands	-4.47*	-67.83*	0.40*
New Zealand	-3.63**	-21.55*	0.77*
Norway	-3.75**	-7.65*	0.69*
Portugal	-5.97*	-41.58*	0.62*
Singapore	-5.62*	-54.32*	0.14**
Spain	-6.54*	-57.40*	0.15**
Sweden	-6.75*	-117.16*	0.33*
Switzerland	-4.22*	-18.30*	0.27*
U.K.	-7.84*	-47.20*	0.30*
U.S.	-12.14*	-101.22*	0.71*

MKT	-7.91*	-113.68*	0.26*
SMB	-81.38*	-82.35*	0.12***
HML	-79.88*	-81.35*	0.13***
MOM	-70.60*	-71.69*	0.11***
NHM	-7.79*	-99.97*	0.67*
NTM	-7.28*	-115.29*	0.23*
THM	-6.57*	-108.73*	0.44*
TTM	-9.56*	-122.99*	0.27*

Note: This table reports results of three unit root tests for daily variables used in this study, as defined in the subsection (3.15.2) of chapter 3. The first column represents the countries under study, and explanatory variables so that MKT, SMB, HML, and MOM are respectively returns on the four standard known risk factors of market excess return, small minus big, high minus low, and momentum. The column also contains the traditional Treynor and Mazuy (1966) (TTM) and Henriksson and Merton (1981) (THM) market timing measures and the proposed Treynor and Mazuy (1966) (NTM) and Henriksson and Merton (1981) (NHM) market timing measures. Columns 2 reports the critical values of the Augmented Dickey-Fuller test. These critical values for all variables are -3.98, -3.42, and -3.13 for the 1%, 5%, and 10% significant levels, respectively. Columns 3 reports the critical values of the Phillips-Perron test. These critical values for all variables are -3.95, -3.41, and -3.12 for the 1%, 5%, and 10% significant levels, respectively. Columns 4 reports the critical values of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These critical values for all variables are 0.216, 0.146, and 0.119 for the 1%, 5%, and 10% significant levels, respectively. The null hypothesis states that time series is nonstationary, while the alternative hypothesis states that time series is stationary. * shows significance at the level of 1%. ** shows significance at the level of 5%. *** shows significance at the level of 10%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 Jun 2016.

Table 4-4 also reports results of three unit root tests for monthly variables. The second column of Table 4-4 reports the results of unit root test for monthly variables using the Augmented Dickey-Fuller Test. The critical values for this test are -3.98, -3.42, and -3.13 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the τ statistic in all variables reported in Table 4-4 are greater than the critical values at the 1% and 5% significance levels. This means that the null hypothesis is rejected to all the variables constructed from the monthly data, indicating that the time series variables are all stationary.

The third column of Table 4-4 reports the results of unit root test for monthly variables using the Phillips-Perron Test. The critical values for this test are -3.98, -3.42, and -3.13 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the τ statistic in all variables reported in Table 4-4 are greater than the critical values at the 1% and 5% significance levels. This means that the null hypothesis is rejected to all the variables constructed from the monthly data, indicating that the time series variables are all stationary.

The fourth column of Table 4-4 reports the results of unit root test for monthly variables using the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) Test. The critical values for this test are 0.216, 0.146, and 0.119 at the 1%, 5%, and 10% significance levels, respectively. According to the theoretical basis presented in the subsection (3.15.2) of Chapter 3, the null hypothesis states that time series is nonstationary and the alternative hypothesis states that time series is stationary. The absolute values of the LM-STAT statistic in all variables reported in Table 4-4 are greater than the critical values at the 1%, 5%, and 10% significance levels. This means that the null hypothesis is rejected to all the variables constructed from the monthly data, indicating that the time series variables are all stationary.

Table 4-4: The results of unit root test for the monthly variables

Countries	τ Statistic		LM-STAT
	Augmented Dickey-Fuller Test	Phillips-Perron Test	Kwiatkowski-Phillips-Schmidt-Shin Test
Australia	-4.05*	-5.57*	0.20**
Austria	-9.93*	-9.97*	0.25*
Belgium	-4.32*	-4.98*	0.14**
Canada	-6.03*	-5.95*	0.15**
Denmark	-18.21*	-4.74*	0.12***
Finland	-6.28*	-5.62*	0.13***
France	-7.03*	-8.88*	0.12***
Germany	-4.14*	-8.26*	0.16**
Greece	-5.77*	-5.65*	0.14**
Hong Kong	-6.22*	-4.95*	0.14***
Ireland	-4.12*	-8.54*	0.13***
Italy	-4.39*	-4.09*	0.17**
Japan	-17.91*	-5.15*	0.12***
Netherlands	-4.96*	-4.25*	0.13***
New Zealand	-7.76*	-7.57*	0.27*
Norway	-4.09*	-6.86*	0.15**
Portugal	-5.08*	-9.45*	0.18**
Singapore	-6.13*	-5.31*	0.12***
Spain	-6.00*	-5.67*	0.12***
Sweden	-19.06*	-11.47*	0.13***
Switzerland	-3.86**	-3.87**	0.13***
U.K.	-6.37*	-6.87*	0.14**
U.S.	-5.73*	-6.44*	0.15**
MKT	-17.33*	-17.32*	0.12***
SMB	-19.41*	-19.50*	0.13***
HML	-15.77*	-15.88*	0.12***
MOM	-17.19*	-17.19*	0.13***
NHM	-19.55*	-18.70*	0.12***
NTM	-5.23*	-12.42*	0.13***
THM	-18.71*	-18.71*	0.54*
TTM	-5.49*	-13.40*	0.13***

Note: This table reports results of three unit root tests for monthly variables used in this study, as defined in the subsection (3.15.2) of chapter 3. The first column represents the countries under study, and explanatory variables so that MKT, SMB, HML, and MOM are respectively returns on the four standard known risk factors of market excess return, small minus big, high minus low, and momentum. The column also contains the traditional Treynor and Mazuy (1966) (TTM) and Henriksson and Merton (1981) (THM) market timing measures and the proposed Treynor and Mazuy (1966) (NTM) and Henriksson and Merton (1981) (NHM) market timing measures. Columns 2 reports the critical values of the Augmented Dickey-Fuller test. These critical values for all variables are -3.98, -3.42, and -3.13 for the 1%, 5%, and 10%

significant levels, respectively. Columns 3 reports the critical values of the Phillips-Perron test. These critical values for all variables are -3.98, -3.42, and -3.13 for the 1%, 5%, and 10% significant levels, respectively. Columns 4 reports the critical values of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. These critical values for all variables are 0.216, 0.146, and 0.119 for the 1%, 5%, and 10% significant levels, respectively. The null hypothesis states that time series is nonstationary, while the alternative hypothesis states that time series is stationary. * shows significance at the level of 1%. ** shows significance at the level of 5%. *** shows significance at the level of 10%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 Jun 2016.

4.4 The Wald Test

The Wald test (also referred to as the Wald Chi-Squared Test) allows us to find out whether an explanatory variable in a regression model is significant and adds a significant value to the regression model; variable that does not add anything in any meaningful way to the model must be deleted. Since, we tend to add timing measures to the multi-factor CAPM, as a predefined standard performance evaluation model, thus we seek to find out whether these measures add a significant value to the model. F-statistic in Eq. (3-52) compares the residual sum of squares with and without the restrictions imposed. The null hypothesis of the Wald test states that a set of parameters is equal to some values. Specially, the null hypothesis states that the market timing coefficient equals to zero. The null hypothesis will be rejected, If F-statistic is larger than F-critical, suggesting that removing the timing variable from the model will harm the fit of regression model.

Table 4-5 shows that all P-values of the Wald test Chi-squares for the traditional and suggested timing measures are less than 0.05, implying that market timing variables in our timing models are significant and add significant values to the models. Spread between F-statistic and F-critical in the daily timing measures is much larger than spread in the monthly timing measures, indicating that the daily timing measures add more significant values to the regression models relative to the monthly timing measures.

Table 4-5: The results of Wald test on the timing variables

	Timing Models							
	Daily THM	Daily TTM	Daily NHM	Daily NTM	Monthly THM	Monthly TTM	Monthly NHM	Monthly NTM
Australia	184.71 (0.00)	972.65 (0.00)	642.5 (0.00)	3802.7 (0.00)	18.01 (0.00)	33.58 (0.00)	52.07 (0.00)	50.92 (0.00)
Austria	509.47 (0.00)	713.5 (0.00)	508.29 (0.00)	823.36 (0.00)	8.68 (0.12)	8.95 (0.11)	9.50 (0.09)	10.47 (0.06)
Belgium	3806.1 (0.00)	8690.8 (0.00)	4500.6 (0.00)	6085.6 (0.00)	96.41 (0.00)	114.93 (0.00)	75.79 (0.00)	113.02 (0.00)
Canada	16.12 (0.00)	21.35 (0.00)	26.25 (0.00)	41.39 (0.00)	7.40 (0.19)	4.85 (0.00)	9.33 (0.09)	6.25 (0.28)
Denmark	11610.1 (0.00)	11044.3 (0.00)	12353.5 (0.00)	9896.7 (0.00)	203.11 (0.00)	222.33 (0.00)	197.7 (0.00)	226.61 (0.00)
Finland	37.31 (0.00)	72.63 (0.00)	41.78 (0.00)	47.22 (0.00)	92.24 (0.00)	67.00 (0.00)	111.44 (0.00)	101.99 (0.00)
France	3238.4 (0.00)	10376.8 (0.00)	4678.9 (0.00)	1262.8 (0.00)	37.83 (0.00)	21.27 (0.00)	20.69 (0.00)	18.07 (0.00)
Germany	764.53 (0.00)	695.6 (0.00)	828.3 (0.00)	872.9 (0.00)	21.66 (0.00)	16.68 (0.00)	18.21 (0.00)	17.04 (0.00)
Greece	422.41 (0.00)	585.39 (0.00)	448.33 (0.00)	452.7 (0.00)	10.96 (0.05)	11.06 (0.05)	10.73 (0.05)	10.22 (0.06)
Hong Kong	824.63 (0.00)	1528.07 (0.00)	1464.7 (0.00)	853.17 (0.00)	68.09 (0.00)	27.77 (0.00)	62.75 (0.00)	38.06 (0.00)
Ireland	6669.8 (0.00)	2501.6 (0.00)	6656.3 (0.00)	2080.8 (0.00)	363.21 (0.00)	43.73 (0.00)	356.17 (0.00)	408.78 (0.00)
Italy	2112.5 (0.00)	5028.2 (0.00)	2949.4 (0.00)	1987.1 (0.00)	17.00 (0.00)	17.42 (0.00)	16.69 (0.00)	10.94 (0.05)
Japan	7632.8 (0.00)	2124.7 (0.00)	3449.07 (0.00)	1125.7 (0.00)	12.93 (0.00)	41.91 (0.00)	31.47 (0.00)	39.19 (0.00)
Netherlands	1001.2 (0.00)	1935.8 (0.00)	1203.8 (0.00)	1431.7 (0.00)	29.39 (0.00)	33.58 (0.00)	29.65 (0.00)	34.70 (0.00)
New Zealand	37.85 (0.00)	13.55 (0.00)	26.83 (0.00)	48.16 (0.00)	38.93 (0.00)	53.76 (0.00)	51.15 (0.00)	73.45 (0.00)
Norway	998.8 (0.00)	1612.48 (0.00)	1202.7 (0.00)	1022.3 (0.00)	20.45 (0.00)	22.91 (0.00)	19.53 (0.00)	22.53 (0.00)
Portugal	14.81 (0.01)	17.13 (0.00)	14.82 (0.01)	42.33 (0.00)	55.82 (0.00)	72.35 (0.00)	59.30 (0.00)	79.84 (0.00)
Singapore	1151.1 (0.00)	2097.6 (0.00)	1193.4 (0.00)	892.7 (0.00)	83.98 (0.00)	16.91 (0.00)	46.07 (0.00)	18.60 (0.00)

Spain	2962.4 (0.00)	6083.3 (0.00)	3790.6 (0.00)	4416.1 (0.00)	7.07 (0.21)	9.62 (0.00)	6.59 (0.25)	10.24 (0.06)
Sweden	3566.7 (0.00)	3489.4 (0.00)	5138.2 (0.00)	6466.4 (0.00)	29.83 (0.00)	36.03 (0.00)	29.73 (0.00)	38.82 (0.00)
Switzerland	3470.1 (0.00)	8981.4 (0.00)	4239.5 (0.00)	6286.1 (0.00)	38.80 (0.00)	61.08 (0.00)	35.87 (0.00)	66.95 (0.00)
U.K.	3646.1 (0.00)	7821.6 (0.00)	4833.2 (0.00)	5160.6 (0.00)	30.69 (0.00)	18.60 (0.00)	23.01 (0.00)	21.39 (0.00)
U.S.	19.75 (0.00)	36.85 (0.00)	15.64 (0.00)	38.11 (0.00)	12.31 (0.00)	15.05 (0.01)	14.68 (0.01)	15.94 (0.00)

Note: This table reports results of the Wald test Chi-squares to find out whether a timing variable in a regression model is significant and adds a significant value to the timing model; variable that does not add anything in any meaningful way to the model must be deleted. F-statistic in Eq. (3-52) compares the residual sum of squares with and without the restrictions imposed. The null hypothesis of the Wald test states that the market timing coefficient equals to zero. The null hypothesis will be rejected, If F-statistic is larger than F-critical (or P-value is less than 0.05), suggesting that removing the timing variable from the model will harm the fit of regression model. P-values of the Wald test Chi-squares place in parentheses. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 Jun 2016.

4.5 The Redundant Variables Test

This study uses another supplementary test in supporting the Wald test. Since this study adds new variables (market timing measures) to the Carhart (1997) model, so it firstly should find out whether the timing measures have statistical significant for determining dependent variables, portfolio excess returns. To address this matter, we use a sum of redundant variable tests. Specifically, the test allows us to know whether the timing measures as well as other explanatory variables add significant values to dependent variables, portfolio excess returns. The null hypothesis states that the coefficient of market timing measure is equal to zero. The hypothesis will be rejected, if F-statistic is larger than F-critical.

Table 4-6 reports the results of this test for our timing measures. Since F-statistic is larger than F-critical, the null hypothesis is rejected for all the timing measures at the significant levels of 5% and 10%. These results indicate that the coefficients of timing measures do not take a zero value, implying that they are not redundant and add significant values to dependent variables, portfolio excess returns. Similar to the Wald test results, spread between F-statistic and F-critical in the daily timing measures is much larger than spread in the monthly timing measures, indicating that the daily timing measures add more significant values to dependent variables, portfolio excess returns, relative to the monthly timing measures.

Table 4-6: The results of redundant test on the timing measures

	F-statistic							
Countries	Daily THM	Daily TTM	Daily NHM	Daily NTM	Monthly THM	Monthly TTM	Monthly NHM	Monthly NTM
Australia	42.89^{*}	5.92^{*}	36.45^{*}	43.38^{*}	6.82^{*}	12.04^{*}	3.81^{**}	14.42^{*}
Austria	13.52^{*}	42.91^{*}	9.01^{*}	38.19^{*}	3.06^{**}	3.001^{**}	3.05^{**}	3.10^{**}
Belgium	8.07^{*}	70.76^{*}	4.33^{*}	147.08^{*}	18.56^{*}	36.14^{*}	4.08^{*}	39.42^{*}
Canada	4.71^{*}	8.53^{*}	6.75^{*}	9.65^{*}	3.17^{**}	2.91^{**}	3.28^{**}	8.17^{*}
Denmark	2.93^{**}	2.85^{**}	2.71^{**}	2.95^{**}	5.90^{*}	7.69^{*}	2.89^{**}	5.03^{*}
Finland	11.95^{*}	6.54^{*}	8.63^{*}	12.57^{*}	11.42^{*}	28.50^{*}	0.005	27.15^{*}
France	76.48^{*}	90.44^{*}	28.96^{*}	145.01^{*}	15.68^{*}	26.62^{*}	2.90^{**}	55.87^{*}
Germany	0.48	14.97^{*}	4.56^{*}	43.08^{*}	5.22^{*}	8.24^{*}	3.08^{**}	8.74^{*}
Greece	5.67^{*}	11.27^{*}	2.42	18.01^{*}	3.14^{**}	3.19^{**}	3.00^{**}	4.69^{*}
Hong Kong	73.92^{*}	85.71^{*}	23.01^{*}	130.03^{*}	19.50^{*}	31.20^{*}	2.96^{**}	29.35^{*}
Ireland	14.85^{*}	2.81^{**}	8.60^{*}	3.34^{**}	7.82^{*}	14.33^{*}	2.79^{**}	7.53^{*}
Italy	3.05^{**}	7.52^{*}	2.88^{**}	16.18^{*}	3.04^{**}	3.73^{**}	3.00^{**}	4.28^{*}
Japan	44.16^{*}	3.04^{**}	82.68^{*}	44.97^{*}	14.75^{*}	23.79^{*}	5.23^{*}	23.19^{*}
Netherlands	25.78^{*}	67.13^{*}	11.98^{*}	95.76^{*}	2.88^{**}	2.92^{**}	2.79^{**}	2.73^{**}
New Zealand	48.19^{*}	234.95^{*}	6.63^{*}	561.64^{*}	3.38^{**}	4.48^{*}	2.83^{**}	2.94^{**}
Norway	132.92^{*}	5.02^{*}	78.33^{*}	3.04^{**}	3.79^{**}	2.78^{**}	2.78^{**}	2.85^{**}
Portugal	41.90^{*}	83.70^{*}	18.10^{*}	121.48^{*}	2.77^{**}	2.80^{**}	2.89^{**}	2.88^{**}
Singapore	98.04^{*}	176.04^{*}	8.71^{*}	452.24^{*}	42.89^{*}	73.57^{*}	3.49	211.99^{*}
Spain	3.84^{*}	2.75^{**}	4.42^{*}	4.77^{*}	2.86^{**}	2.82^{**}	2.86^{**}	2.82^{**}
Sweden	8.60^{*}	2.90^{**}	9.24^{*}	3.10^{**}	2.85^{**}	2.79^{**}	2.82^{**}	2.93^{**}
Switzerland	128.63^{*}	60.51^{*}	86.79^{*}	43.88^{*}	2.77^{**}	2.88^{**}	3.01^{**}	2.87^{**}
U.K.	3.12^{**}	22.21^{*}	2.91^{**}	97.75^{*}	13.72^{*}	22.03^{*}	0.43	18.15^{*}
U.S.	8.23^{*}	3.002^{**}	5.34^{*}	2.93^{**}	2.89^{**}	2.90^{**}	2.86^{**}	2.84^{**}

Note: This table reports the results of redundant tests on all timing measures. It reports the values of F-statistic for each test. * indicates significant at the confidence level of 5%. ** indicates significant at the confidence level of 10%. If F-statistic is larger than F-critical, the null hypothesis will be rejected, implying that the timing measure is not redundant and adds a significant value to dependent variables, portfolio excess returns. The columns contain the traditional Treynor and Mazuy (1966) (TTM) and Henriksson and Merton (1981) (THM) market timing measures and the proposed Treynor and Mazuy (1966) (NTM) and Henriksson and Merton (1981) (NHM) market timing measures at the daily and monthly frequencies. For the daily timing measures with the freedom degree of 1 and the number of observations of 7429, F-critical is equal to 3.84 and 2.70 for the significance levels of 5% and 10%, respectively. For the monthly timing measures with the freedom degree of 1 and the number of observations of 336, F-critical is equal to 3.86 and 2.72 for the significant levels of 5% and 10%, respectively.

4.6 Daily Traditional Timing Models

To provide an exact and fair judgment basis between the AD-based timing models and the traditional timing models and to examine their selection and market timing measures, this subsection firstly reports the estimates of performance evaluation timing models using Eq. (3-4) presented in the subsection (3.2) of Chapter 3, and then estimates the AD-based performance evaluation timing models.

Table 4-7 reports the daily estimates of traditional Henriksson and Merton (1981) (THM) timing models, where the portfolios of nine counties show significant positive evidence of market timing at the confidence level of 95%. These countries are consisting of Austria, Belgium, France, Greece, Italy, Spain, Sweden, Switzerland, and UK. Seven countries of Australia, Denmark, Finland, Hong Kong, Netherlands, Norway, and Portugal exhibit positive evidence of market timing, but not statistically significant. Among the portfolios of these 23 countries, seven countries of Canada, Germany, Ireland, Japan, New Zealand, Singapore, and U.S. indicate statistically significant and insignificant negative evidence of market timing. According the THM timing model, it is obvious that less than half of the countries used in the research sample exhibits positive and significant market timing skills for managers active in stock market of the countries. The highest market timing skill (THM) is related to Sweden with a positive and significant value of 0.31, whereas the lowest market timing skill (THM) is related to Singapore with a negative and significant value of -0.83.

As explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in all estimates, implying that determining their signs is merely an empirical exercise. However, significantly positive signs found in SMB, HML, and MOM can be consistent with Laurent et al (2013), among others. There are significant positive MKTs for the majority of our timing estimates.

The second column of Table 4-7 also reports the results of alphas estimated from the THM timing models. These alphas are an indicator of portfolio managers' selection ability. The estimated alphas show that portfolio managers of Australia, Austria, Belgium, Canada, Denmark, Germany, Greece, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, U.K., and U.S. have positive and significant selection skills in the stock market of their countries. The portfolio managers of other countries possess either statistically significant negative skills or statistically insignificant positive selection skills in their stock markets. The highest portfolio selection skill (α) is related to Portugal with a positive and significant value of 0.07, whereas the lowest portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.0007.

Table 4-7: The daily results of market timing models on THM

Countries	α	MKT	SMB	HML	MOM	R_m^*	R^2
Australia	0.019 **(4.96)**	0.11 **(10.02)**	0.0007 **(5.74)**	3.14E-05 (0.22)	0.0005 **(4.69)**	0.011 (0.49)	0.92
Austria	0.0062 **(3.22)**	0.22 **(22.23)**	0.00072 **(5.22)**	0.0049 **(3.68)**	0.00029 **(2.65)**	0.049 **(2.01)**	0.79
Belgium	0.0012 **(5.10)**	0.53 **(53.15)**	0.00056 **(5.86)**	0.0015 **(13.54)**	0.00069 **(7.52)**	0.096 **(5.25)**	0.64
Canada	0.007 **(2.10)**	0.53 **(3.90)**	0.0014 (0.78)	0.0014 (0.89)	0.00015 (0.11)	-0.13 (-0.47)	0.16
Denmark	0.0006 **(3.20)**	0.74 **(78.73)**	0.0016 **(13.42)**	0.0016 **(12.44)**	0.00044 **(4.20)**	0.034 (1.81)	0.59
Finland	0.033 (1.14)	0.30 **(4.77)**	0.0016 **(2.43)**	0.0011 (1.93)	0.0018 **(4.13)**	0.22 (1.58)	0.94
France	0.0031 (1.42)	0.67 **(56.91)**	0.0012 **(9.37)**	0.0015 **(10.42)**	0.00041 **(3.50)**	0.22 **(8.43)**	0.88
Germany	0.0095 **(13.96)**	0.95 **(25.25)**	0.0021 **(3.40)**	0.00093 **(2.17)**	0.00021 (0.79)	-0.084 (-0.80)	0.28
Greece	0.0014 **(2.04)**	0.44 **(18.51)**	0.00089 **(3.43)**	0.0011 **(4.17)**	0.0006 **(3.17)**	0.11 **(1.97)**	0.38
Hong Kong	0.010 **(20.18)**	0.38 **(25.87)**	0.0016 **(8.55)**	0.00042 (1.92)	0.0008 **(4.71)**	0.016 (0.50)	0.47
Ireland	-0.0007 **(-2.25)**	0.81 **(46.75)**	0.0019 **(5.96)**	0.0028 **(8.32)**	0.00024 (1.04)	-0.21 **(-3.85)**	0.30
Italy	0.009 **(2.05)**	0.62 **(42.99)**	0.0017 **(10.60)**	0.0014 **(8.25)**	8.66E-05 (0.63)	0.20 **(7.00)**	0.84
Japan	0.008 **(30.29)**	1.00 **(78.53)**	0.0011 **(6.04)**	0.0014 **(8.25)**	0.0016 **(10.30)**	-0.43 **(-13.62)**	0.52
Netherlands	0.011 **(13.02)**	0.45 **(28.59)**	0.0014 **(8.79)**	0.0016 **(9.61)**	0.0002 (1.81)	0.047 (1.43)	0.66
New Zealand	0.034 **(5.38)**	-0.041 (-1.84)	0.00047 (1.94)	-0.00033 (-1.11)	-0.0003 (-1.15)	-0.078 (-1.78)	0.91
Norway	0.025 **(2.79)**	0.45 **(30.17)**	0.0013 **(8.26)**	0.0016 **(8.66)**	0.0008 **(5.36)**	0.055 (1.72)	0.96
Portugal	0.07 **(2.08)**	0.091 (0.54)	-4.15E-05 (-0.018)	0.0009 (0.44)	0.001 (0.55)	0.35 (0.89)	0.82
Singapore	0.0011 **(4.78)**	0.0085 (0.66)	0.00037 (1.60)	0.002 **(8.08)**	8.31E-05 (0.47)	-0.83 **(-19.82)**	0.74
Spain	0.017 **(4.32)**	0.78 **(53.72)**	0.0013 **(7.58)**	0.0016 **(8.02)**	0.0005 **(3.20)**	0.11 **(3.71)**	0.80
Sweden	0.0022 **(2.01)**	0.80 **(56.62)**	0.0022 **(14.72)**	0.0013 **(8.11)**	-6.11E-05	0.31 **(10.54)**	0.64

					(-0.51)		
Switzerland	0.017 **(2.84)**	0.45 **(57.50)**	0.001 **(12.15)**	0.00088 **(8.81)**	4.63E-05 (0.56)	0.086 **(5.87)**	0.93
U.K.	0.004 **(2.13)**	0.38 **(57.71)**	0.00089 **(12.76)**	0.0013 **(15.78)**	0.00015 **(2.32)**	0.070 **(4.62)**	0.87
U.S.	0.067 **(4.82)**	2.93 **(3.23)**	0.0092 (0.70)	-0.0047 (-0.30)	0.0034 (0.35)	-2.48 (-0.73)	0.039

Note: This table reports the daily results of market timing models using the traditional Henriksson and Merton (1981) (THM) market timing measure, R^*. It uses Eq. (3-4) presented in the subsection (3.2) of Chapter 3 for estimating traditional timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-8 reports the daily estimates of the traditional Treynor and Mazuy (1966) (TTM) timing models using Eq. (3-3) defined in the subsection (3.2) of chapter 3, where portfolio managers of the eleven counties of Australia, Belgium, Denmark, France, Germany, Italy, Singapore, Spain, Sweden, Switzerland, and U.K. show significant positive evidence of market timing at the confidence level of 95%. Compared to the THM results, portfolio managers of further countries show significant and positive timing skills using the TTM. Six countries of Finland, Greece, Netherlands, Norway, Portugal, and U.S. show positive evidence of market timing, but not statistically significant. Among the portfolios of these 23 countries, six countries of Austria, Canada, Hong Kong, Ireland, Japan, and New Zealand indicate statistically significant and insignificant negative evidence of market timing. According the TTM timing model, it is obvious that more than the half of countries used in the research sample shows positive and significant market timing skills of managers active in stock market of the countries. Singapore has the highest market timing skill (TTM) with a positive and significant value of 10.96, while Japan has the lowest market timing skill (TTM) with a negative and significant value of -2.94.

As explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in all estimates, implying that determining their signs is merely an empirical exercise. However, significantly positive signs found in SMB, HML, and MOM can be consistent with Laurent et al (2013), among others. The existence of significant positive MKTs for the majority of our timing estimates indicates that dispersion of stock and market returns places around the CE characteristic line in Figure (3-1).

The second column of Table 4-8 also reports the results of alphas estimated from the TTM timing model. These alphas are an indicator of portfolio managers' selection ability in the models. The estimated alphas show that portfolio managers of Australia, Austria, Belgium, Canada, France, Germany, Greece, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, U.K., and U.S. have positive and significant selection skills in the stock market of their countries. The portfolio managers of other countries possess either statistically significant negative skills or statistically insignificant positive selection skills in their stock markets. Similar to the THM results, the highest portfolio selection skill (α) is related to Portugal with a positive and significant value of 0.072, while the lowest portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.0014.

Table 4-8: The daily results of market timing models on TTM

Countries	α	MKT	SMB	HML	MOM	R_m^2	R^2
Australia	0.023 **(1.97)**	0.25 **(29.41)**	0.0008 **(6.75)**	0.0006 **(4.63)**	0.0004 **(3.73)**	0.64 **(3.82)**	0.95
Austria	0.006 **(2.28)**	0.23 **(25.86)**	0.0007 **(5.40)**	0.0005 **(3.66)**	0.0002 **(2.34)**	-0.23 (-1.27)	0.80
Belgium	0.0014 **(7.18)**	0.59 **(85.58)**	0.00052 **(5.55)**	0.0015 **(12.82)**	0.0007 **(7.85)**	2.01 **(11.84)**	0.64
Canada	0.0067 **(1.98)**	0.45 **(3.85)**	0.0013 (0.74)	0.0014 (0.88)	7.87E-05 (0.05)	-1.87 (-0.71)	0.17
Denmark	0.0001 (0.51)	0.72 **(93.49)**	0.0012 **(11.25)**	0.0015 **(12.03)**	0.0003 **(3.15)**	1.02 **(5.76)**	0.61
Finland	0.034 (1.17)	0.40 **(8.14)**	0.0017 **(2.44)**	0.0012 **(2.16)**	0.0018 **(4.10)**	1.91 (1.57)	0.94
France	0.003 **(2.17)**	0.75 **(88.20)**	0.0014 **(12.56)**	0.0016 **(12.38)**	0.0006 **(5.46)**	2.39 **(13.63)**	0.86
Germany	0.0086 **(13.54)**	0.95 **(23.72)**	0.0019 **(3.24)**	0.0006 (1.45)	0.0002 (1.01)	2.15 **(2.37)**	0.29
Greece	0.0016 **(2.05)**	0.46 **(22.97)**	0.0007 **(2.70)**	0.0012 **(4.57)**	0.0003 (1.96)	0.65 (1.20)	0.40
Hong Kong	0.011 **(6.05)**	0.42 **(36.77)**	0.0016 **(8.75)**	0.0005 **(2.67)**	0.0005 **(3.12)**	-1.24 **(-4.71)**	0.62
Ireland	-0.0014 **(-6.16)**	0.77 **(57.48)**	0.0018 **(7.18)**	0.0027 **(11.29)**	0.00034 **(1.97)**	-0.06 (-0.10)	0.30
Italy	0.0086 **(4.41)**	0.70 **(63.45)**	0.0018 **(11.21)**	0.0014 **(8.14)**	0.00012 (0.87)	2.05 **(7.70)**	0.81
Japan	0.0033 **(2.12)**	0.56 **(42.27)**	0.0009 **(4.85)**	0.0011 **(6.32)**	0.0008 **(5.59)**	-2.94 **(- 10.10)**	0.61
Netherlands	0.011 **(13.47)**	0.47 **(40.16)**	0.0014 **(8.81)**	0.0016 **(9.70)**	0.0002 (1.77)	0.35 (1.31)	0.66
New Zealand	0.036 **(2.50)**	0.03 **(2.27)**	7.41E- 05 (0.28)	2.14E- 05 (0.07)	-3.34E- 05 (-0.14)	-0.85 **(-2.18)**	0.94
Norway	0.025 **(2.82)**	0.46 **(38.26)**	0.0013 **(8.40)**	0.0016 **(8.89)**	0.0008 **(5.27)**	0.072 (0.28)	0.96
Portugal	0.072 **(1.97)**	0.23 (1.62)	7.55E- 05 (0.033)	0.0011 (0.51)	0.0009 (0.53)	2.42 (0.61)	0.82
Singapore	0.014 **(40.79)**	0.95 **(34.55)**	0.0011 **(2.55)**	-0.0013 **(-2.83)**	0.00036 (1.07)	10.96 **(13.26)**	0.76
Spain	0.018 **(4.43)**	0.82 **(73.74)**	0.0013 **(7.65)**	0.0017 **(8.20)**	0.0004 **(3.11)**	0.87 **(3.30)**	0.80
Sweden	0.00012 (0.71)	0.043 **(3.17)**	- 0.00015 (-0.66)	-0.0002 (-0.85)	0.00014 (0.87)	1.21 **(2.98)**	0.25
Switzerland	0.017 **(9.12)**	0.46 **(81.35)**	0.0012 **(15.73)**	0.0008 **(9.81)**	0.0002 **(2.98)**	1.26 **(12.55)**	0.91
U.K.	0.0041	0.41	0.0008	0.0013	0.0001	0.70	0.85

	(4.32)	**(79.80)**	**(13.13)**	**(17.27)**	**(2.89)**	**(6.04)**	
U.S.	0.062 **(3.32)**	2.00 **(2.16)**	0.009 (0.67)	-0.007 (-0.48)	0.002 (0.19)	0.42 (0.01)	0.06

Note: This table reports the daily results of market timing models using the traditional Treynor and Mazuy (1966) (TTM) market timing measure. It uses Eq. (3-3) presented in the subsection (3.2) of Chapter 3 for estimating traditional timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.7 Daily New HM (NHM) Timing Models

This subsection reports the results of the AD-based timing model estimates. It begins by running Eq. (3-19) and uses the proposed Henriksson and Merton (1981) (NHM) timing models to estimate portfolio managers' market timing and selection skills.

Table 4-9 reports the daily estimates of the NHM timing models where portfolio managers of twelve counties of Australia, Austria, Belgium, Denmark, France, Greece, Italy, Netherlands, Spain, Sweden, Switzerland, and U.K. show significant positive evidence of market timing at the confidence level of 95%. Compared to the THM results, portfolio managers of further countries show significant and positive timing skills using the NHM. Six countries of Finland, New Zealand, Norway, Portugal, Singapore, and US exhibit positive evidence of market timing, but not statistically significant. Among the portfolios of these 23 countries, the remaining five countries indicate either statistically significant negative evidence or statistically insignificant negative evidence of market timing. According the NHM timing model, it is obvious that the half of countries used in the research sample shows positive and significant market timing skills of managers active in stock market of the countries. The highest market timing skill for NHM is related to Sweden with a positive and significant value of 0.32, but point estimate (magnitude of estimated coefficient) in NHM is greater than THM. The lowest market timing skill for NHM is related to Ireland with a negative and significant value of -0.22 as well.

As explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in all estimates, implying that determining their signs is merely an empirical exercise. However, significantly positive signs found in SMB, HML, and MOM can be consistent with Laurent et al (2013), among others. There are significant positive MKTs for the majority of our timing estimates.

The second column of Table 4-9 also represents the results of alphas estimated from the NHM timing model. These alphas are an indicator of portfolio managers' selection ability in the models. The estimated alphas show that portfolio managers of the nineteen countries of Australia, Austria, Belgium, Canada, Denmark, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, U.K., and U.S. have significant and positive selection skills in the stock market of their countries. The portfolio managers of other countries possess either statistically significant negative selection skills or statistically insignificant positive selection skills in their stock markets.

Similar to the THM results, the highest portfolio selection skill (α) is related to Portugal with a positive and significant value of 0.071 and the lowest portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.001.

Table 4-9: The daily results of market timing models on NHM

Countries	α	MKT	SMB	HML	MOM	AD_m^*	R^2
Australia	0.023 **(1.96)**	0.23 **(23.45)**	0.00088 **(6.81)**	0.00067 **(4.70)**	0.00045 **(3.67)**	0.063 **(2.43)**	0.95
Austria	0.0061 **(3.90)**	0.21 **(22.20)**	0.0006 **(4.87)**	0.0004 **(3.15)**	0.0003 **(2.72)**	0.096 **(3.16)**	0.78
Belgium	0.0013 **(5.89)**	0.53 **(59.90)**	0.00056 **(5.90)**	0.0015 **(13.54)**	0.00068 **(7.34)**	0.11 **(5.06)**	0.64
Canada	0.0073 **(3.01)**	0.54 **(4.92)**	0.0016 (1.01)	0.0016 (1.10)	0.0003 (0.29)	-0.22 (-0.72)	0.14
Denmark	0.0006 **(3.58)**	0.74 **(86.91)**	0.0016 **(13.33)**	0.0016 **(12.42)**	0.00043 **(4.20)**	0.051 **(2.10)**	0.59
Finland	0.034 (1.15)	0.31 **(5.45)**	0.0017 **(2.43)**	0.0011 **(2.04)**	0.0018 **(4.08)**	0.28 (1.52)	0.94
France	0.003 (1.80)	0.66 **(65.88)**	0.0014 **(12.56)**	0.0016 **(12.22)**	0.0005 **(5.22)**	0.27 **(11.34)**	0.86
Germany	0.0097 **(14.40)**	0.96 **(26.39)**	0.0021 **(3.43)**	0.0009 **(2.34)**	0.0001 (0.64)	-0.09 (-1.38)	0.28
Greece	0.0013 (1.83)	0.43 **(20.00)**	0.0007 **(2.97)**	0.0012 **(4.25)**	0.0004 **(2.19)**	0.14 **(2.15)**	0.38
Hong Kong	0.011 **(6.21)**	0.47 **(36.87)**	0.0016 **(8.68)**	0.0005 **(2.61)**	0.0005 **(3.23)**	-0.13 **(-3.25)**	0.62
Ireland	-0.001 **(-3.52)**	0.79 **(49.04)**	0.0018 **(5.92)**	0.0027 **(8.20)**	0.0003 (1.27)	-0.22 **(-2.93)**	0.30
Italy	0.010 **(2.11)**	0.63 **(50.08)**	0.0017 **(10.76)**	0.0014 **(8.49)**	5.78E-05 (0.42)	0.23 **(6.65)**	0.84
Japan	0.0043 **(2.89)**	0.69 **(57.05)**	0.0009 **(4.88)**	0.0012 **(6.60)**	0.0008 **(5.70)**	-0.14 **(-4.15)**	0.61
Netherlands	0.011 **(13.15)**	0.45 **(31.75)**	0.0014 **(8.77)**	0.0016 **(9.54)**	0.0002 (1.81)	0.075 **(1.96)**	0.66
New Zealand	0.036 **(2.52)**	0.073 **(4.08)**	7.56E-05 (0.29)	3.32E-05 (0.11)	-2.27E-05 (-0.12)	0.015 (1.33)	0.94
Norway	0.025 **(2.80)**	0.45 **(33.50)**	0.0013 **(8.31)**	0.0016 **(8.76)**	0.0008 **(5.34)**	0.052 (1.36)	0.96
Portugal	0.071 **(2.08)**	0.107 (0.68)	-1.94E-05 (-0.008)	0.001 (0.45)	0.0009 (0.53)	0.45 (0.95)	0.82
Singapore	0.011 **(2.87)**	0.40 **(34.97)**	0.0015 **(10.55)**	0.0006 **(4.00)**	9.55E-05 (0.68)	0.02 (1.12)	0.79

Spain	0.017 **(4.34)**	0.78 **(58.56)**	0.0013 **(7.63)**	0.0016 **(8.00)**	0.0004 **(3.10)**	0.15 **(4.33)**	0.80
Sweden	0.0027 **(2.39)**	0.82 **(67.29)**	0.0022 **(14.95)**	0.0013 **(8.48)**	-0.0001 (-1.04)	0.32 **(8.49)**	0.64
Switzerland	0.016 **(8.96)**	0.42 **(61.59)**	0.0012 **(15.76)**	0.0008 **(9.88)**	0.0002 **(2.75)**	0.12 **(7.72)**	0.93
UK	0.004 **(2.28)**	0.39 **(63.30)**	0.0009 **(13.22)**	0.0013 **(16.12)**	0.00013 **(2.07)**	0.086 **(4.88)**	0.87
US	0.067 **(3.29)**	2.25 **(2.16)**	0.010 (0.69)	-0.0066 (-0.38)	0.0014 (0.13)	0.04 (0.39)	0.062

Note: This table reports the daily results of market timing models using the proposed Henriksson and Merton (1981) (NHM) market timing measure. It uses Eq. (3-19) defined in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). The lag length of ρ in Eq. (3-14) is 24 according to Glabadanidis (2015). R^2s place in the last column of the table. T-statistics also place in parentheses and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.8 Daily New TM (NTM) Timing Models

Table 4-10 reports the daily estimates of the proposed Treynor and Mazuy (1966) (NTM) timing models using Eq. (3-18), where portfolio managers of the fifteen counties of Australia, Austria, Belgium, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Singapore, Spain, Sweden, Switzerland, and U.K. show significant positive evidence of market timing at the confidence level of 95%. Compared to the TTM results, portfolio managers of further countries show significant and positive timing skills using the NTM. Four countries of Finland, Greece, Portugal, and U.S. show positive evidence of market timing, but not statistically significant. Among the portfolios of these 23 countries, four countries indicate either statistically significant negative evidence or statistically insignificant negative evidence of market timing. According the NTM timing model, it is obvious that more than half of the countries used in the research sample exhibits positive and significant market timing skills of managers active in stock market of the countries. Similar to the previous results, the highest market timing skill (NTM) is related to Singapore with a positive and significant value of 15.86, while the lowest market timing skill (NTM) is related to New Zealand with a negative and significant value of -0.96.

As explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in all estimates, implying that determining their signs is merely an empirical exercise. However, significantly positive signs found in SMB, HML, and MOM can be consistent with Laurent et al (2013), among others. Austria exhibits negative signs for SMB and HML and a positive sign for MOM consistent with Glabadanidis (2017). The existence of significant positive MKTs for the majority of our timing estimates indicates that dispersion of stock and market returns places around the CE characteristic line in Figure (3-1).

The second column of Table 4-10 also represents the results of alphas estimated from the NTM timing model, Eq. (3-18). These alphas are an indicator of portfolio managers' selection ability in the model. The estimated alphas show that portfolio managers of Australia, Belgium, Canada, Denmark, France, Germany, Greece, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Switzerland, U.K., and U.S. have positive and significant selection skills in the stock market of their countries. The portfolio managers of other countries possess either statistically negative selection skills or statistically insignificant positive selection skills in their stock markets. Similar to the TTM results, the highest portfolio selection skill (α) is related to Portugal with a positive and significant value of 0.072, while the lowest portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.0014.

Table 4-10: The daily results of market timing models on NTM

Countries	α	MKT	SMB	HML	MOM	AD_m^2	R^2
Australia	0.036 **(60.30)**	1.86 **(36.03)**	0.00049 (0.63)	0.0014 (1.72)	0.0036 **(6.25)**	8.29 **(6.68)**	0.73
Austria	-0.0003 **(-2.19)**	0.024 (1.80)	-0.0004 **(-2.20)**	-0.0005 **(-2.41)**	-7.08E-05 (-0.46)	1.62 **(4.80)**	0.68
Belgium	0.0016 **(8.14)**	0.64 **(73.18)**	0.00048 **(5.07)**	0.0015 **(12.64)**	0.0007 **(7.47)**	2.51 **(12.95)**	0.64
Canada	0.0076 **(4.98)**	0.48 **(4.68)**	0.0018 (1.22)	0.0014 (1.17)	9.66E-05 (0.089)	-3.04 (-1.61)	0.10
Denmark	0.0007 **(4.66)**	0.77 **(92.30)**	0.0016 **(13.42)**	0.0016 **(12.30)**	0.00043 **(4.16)**	0.69 **(4.64)**	0.59
Finland	0.035 (1.18)	0.42 **(5.78)**	0.0016 **(2.41)**	0.0012 **(2.25)**	0.0017 **(4.02)**	1.65 (1.15)	0.94
France	0.0063 **(14.78)**	1.26 **(34.62)**	0.0013 **(2.39)**	0.00016 (0.28)	-0.00049 (-1.23)	10.81 **(12.04)**	0.69
Germany	0.0091 **(16.06)**	1.07 **(25.69)**	0.0019 **(3.23)**	0.00065 (1.49)	0.00034 (1.28)	4.17 **(4.86)**	0.28
Greece	0.0017 **(2.12)**	0.46 **(19.15)**	0.0007 **(2.73)**	0.0013 **(4.70)**	0.0003 (1.87)	0.38 (0.74)	0.40
Hong Kong	0.012 **(44.12)**	0.79 **(32.83)**	0.00093 **(2.59)**	-0.0005 (-1.38)	0.00022 (0.92)	6.74 **(11.40)**	0.77
Ireland	-0.0014 **(-6.45)**	0.81 **(54.36)**	0.0018 **(7.15)**	0.0026 **(11.00)**	0.00036 **(2.12)**	0.87 **(3.40)**	0.30
Italy	0.0083 **(7.17)**	0.74 **(56.02)**	0.0018 **(11.82)**	0.0013 **(7.56)**	0.00018 (1.20)	2.62 **(10.03)**	0.77
Japan	0.0068 **(31.72)**	0.99 **(87.33)**	0.001 **(5.24)**	0.001 **(6.17)**	0.0019 **(12.13)**	1.63 **(7.62)**	0.51
Netherlands	0.012 **(6.38)**	0.48 **(33.78)**	0.0011 **(6.71)**	0.0013 **(7.42)**	0.0001 (1.30)	-0.36 (-1.16)	0.76
New Zealand	0.036 **(2.49)**	0.021 (1.11)	9.02E-05 (0.34)	1.97E-05 (0.07)	-2.04E-05 (-0.09)	-0.96 **(-2.23)**	0.94
Norway	0.025 **(2.82)**	0.44 **(29.67)**	0.0013 **(8.64)**	0.0016 **(9.10)**	0.0008 **(5.19)**	-0.67 **(-2.37)**	0.96
Portugal	0.072 **(1.99)**	0.25 (1.54)	5.95E-05	0.0011 (0.52)	0.0009 (0.50)	2.22 (0.58)	0.82

			(0.026)				
Singapore	0.014 **(41.87)**	1.19 **(39.29)**	0.001 **(2.23)**	-0.0015 **(-3.26)**	0.00014 (0.44)	15.86 **(21.26)**	0.78
Spain	0.018 **(4.44)**	0.84 **(57.09)**	0.0013 **(7.58)**	0.0017 **(8.08)**	0.00047 **(3.03)**	1.04 **(3.62)**	0.80
Sweden	0.00014 (0.85)	0.064 **(4.55)**	-0.0002 (-1.12)	-0.0002 (-1.00)	0.00015 (1.02)	1.57 **(4.53)**	0.35
Switzerland	0.017 **(9.19)**	0.46 **(69.04)**	0.0012 **(15.97)**	0.0009 **(10.30)**	0.0002 **(2.54)**	0.61 **(5.33)**	0.91
U.K.	0.0038 **(6.49)**	0.41 **(71.45)**	0.0008 **(14.06)**	0.0011 **(14.61)**	0.0003 **(5.05)**	1.05 **(9.62)**	0.82
U.S.	0.062 **(3.32)**	2.16 **(2.04)**	0.009 (0.66)	-0.008 (-0.50)	0.002 (0.20)	5.50 (0.12)	0.06

Note: This table reports the daily results of market timing models using the proposed Treynor and Mazuy (1966) (NTM) market timing measure. It uses Eq. (3-18) defined in the subsection (3.5) of Chapter 3 for estimating new timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). The lag length of ρ in Eq. (3-15) is 24 according to Glabadanidis (2015). R^2s place in the last column of the table. T-statistics also place in parentheses and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.9 Monthly Traditional Timing Models

To estimate portfolio managers' selection and market timing abilities at the monthly frequency data, this subsection uses the THM timing model defined in Eq. (3-4) of Chapter 3.

Table 4-11 reports the monthly estimates of traditional Henriksson and Merton (1981) (THM) timing models, where the portfolio returns of only two countries of Belgium and Ireland exhibit significant positive evidence of market timing at the confidence level of 95%. This number is much less than the timing evidence reported in the daily THM, which reports positive and significant timing evidence for nine counties. The portfolio managers of thirteen countries exhibit positive evidence of market timing, but not statistically significant. Among the portfolios of these 23 countries, eight countries indicate statistically significant and insignificant negative evidence of market timing. According the monthly THM timing model, it is obvious that only 8% of countries used in the research sample shows positive and significant market timing skills of managers active in stock market of the countries. Contrary to the daily THM results, the highest market timing skill is related to Ireland with a positive and significant value of 1.07, which shows a less point estimate (magnitude of timing coefficient) than the daily THM. Unlike the daily THM results, the lowest monthly market timing skill is related to Finland with a negative and significant value of -4.89.

As explained in the literature, theory does not present specific guidance about expected signs of SMB, HML, and MOM in the timing models. There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in all estimates, implying that determining their signs is merely an empirical exercise. However, significantly positive and negative signs found in SMB, HML, and MOM can be consistent with Geoffrey and Sapp (2007), Geoffrey and Sapp (2007), and Glabadanidis (2017), among others.

The second column of Table 4-11 also represents the results of monthly alphas estimated from the monthly THM timing model. The estimated monthly alphas show that portfolio managers of only one country, Japan, have positive and significant selection skills in stock market. It means that only 4% of countries used in the research sample shows positive and significant selection skill of managers active in stock market of the countries. The portfolio managers of other countries possess either statistically insignificant positive selection skills or statistically insignificant and significant negative selection skills in their stock markets. The highest monthly portfolio selection skill (α) is related to Japan with a positive and significant value of 0.03, whereas the lowest monthly portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.20.

Overall, a simple comparison between the daily THM timing models and the monthly THM timing models exhibits better performance of the daily models relative to the monthly models for at least two reasons. First, there is more positive evidence of market timing in the daily models relative to the monthly models. Second, the daily models have higher economic and statistical significance than the monthly models.

Table 4-11: The monthly results of market timing models on THM

Countries	α	MKT	SMB	HML	MOM	R_m^*	R^2
Australia	0.38 (0.87)	-0.88 (-1.14)	0.0083 (1.20)	0.013 (1.37)	-0.0034 (-0.73)	-0.17 (-0.11)	0.79
Austria	0.17 (0.51)	-1.45 (-0.29)	-0.036 (-0.86)	-0.037 (-0.77)	0.014 (0.57)	1.51 (0.17)	0.34
Belgium	-0.07 (-0.7)	-0.50 **(-3.59)**	0.003 **(2.38)**	0.0047 **(3.99)**	-0.0024 **(-3.42)**	0.51 **(2.01)**	0.86
Canada	0.002 (0.09)	-0.29 (-0.47)	-0.008 (-1.57)	-0.003 (-0.62)	0.005 (1.64)	-0.06 (-0.05)	0.63
Denmark	0.008 (1.34)	-0.021 (-0.13)	-0.006 **(-4.76)**	-0.002 (-1.73)	0.002 **(3.18)**	-0.41 (-1.49)	0.84
Finland	0.06 (1.37)	1.90 (1.53)	-0.014 (-1.30)	0.0051 (0.43)	0.028 **(3.93)**	-4.89 **(-2.22)**	0.63
France	-0.05 (-0.1)	-2.33 (-1.22)	0.005 (0.33)	-0.0003 (-0.01)	-0.0031 (-0.22)	2.03 (0.53)	0.51
Germany	0.011 (0.83)	0.08 (0.24)	-0.007 **(-2.56)**	0.002 (0.71)	0.006 **(3.48)**	-0.81 (-1.31)	0.74
Greece	-0.04 (-0.35)	-0.25 (-0.42)	0.0015 (0.43)	0.01 **(2.44)**	-0.004 **(-2.11)**	0.17 (0.17)	0.70
Hong Kong	0.19 (1.71)	-1.08 **(-3.36)**	0.0014 (0.44)	0.0056 (1.58)	-0.0014 (-0.66)	0.34 (0.56)	0.80
Ireland	-0.20 **(-2.48)**	-0.39 **(-2.70)**	0.0047 **(3.60)**	0.005 **(3.97)**	-0.004 **(-6.96)**	1.07 **(3.57)**	0.81
Italy	0.005	-0.33	-0.009	-0.003	0.006	-0.25	0.84

	(0.54)	(-1.26)	**(-4.05)**	(-1.20)	**(4.37)**	(-0.53)	
Japan	0.03	0.74	-0.005	0.0026	0.007	-1.88	0.87
	(3.57)	**(3.58)**	**(-2.90)**	(1.31)	**(5.85)**	**(-5.04)**	
Netherlands	0.0016	-1.86	-0.019	-0.025	-0.0038	0.68	0.82
	(0.05)	**(-2.40)**	**(-2.94)**	**(-3.38)**	(-0.87)	(0.49)	
New Zealand	-0.02	-1.33	-0.029	-0.002	0.03	0.66	0.60
	(-0.13)	(-0.35)	(-0.89)	(-0.06)	(1.49)	(0.09)	
Norway	-0.25	-8.11	-0.05	-0.03	0.04	13.94	0.61
	(-0.91)	(-1.19)	(-0.91)	(-0.50)	(1.22)	(1.16)	
Portugal	5.15	-7.29	-0.09	-0.09	0.025	6.70	0.45
	(1.40)	(-0.24)	(-0.49)	(-0.54)	(0.20)	(0.14)	
Singapore	0.44	-2.59	0.036	0.035	-0.013	-0.61	0.66
	(0.30)	(-0.68)	(0.68)	(0.74)	(-0.38)	(-0.06)	
Spain	0.41	-3.30	0.011	0.04	-0.0001	4.91	0.70
	(0.26)	(-0.37)	(0.20)	(0.72)	(-0.006)	(0.32)	
Sweden	-0.016	-0.62	-0.006	-0.0037	0.0016	1.06	0.48
	(-0.78)	(-1.21)	(-1.45)	(-0.75)	(0.57)	(1.15)	
Switzerland	-0.015	-2.21	-0.050	-0.03	0.01	1.57	0.80
	(-0.29)	(-1.73)	**(-4.49)**	**(-3.13)**	(1.49)	(0.69)	
U.K.	0.026	-0.59	0.011	0.013	-0.0057	0.54	0.68
	(0.19)	(-1.14)	**(2.63)**	**(2.63)**	(-1.58)	(0.48)	
U.S.	2.15	-8.83	-0.12	-0.21	-0.05	17.73	0.62
	(0.39)	(-0.18)	(-0.40)	(-1.15)	(-0.64)	(0.22)	

Note: This table reports the monthly results of market timing models using the traditional Henriksson and Merton (1981) (THM) market timing measure. It uses Eq. (3-4) defined in the subsection (3.2) of Chapter 3 for estimating traditional market timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-12 reports the monthly estimates of traditional Treynor and Mazuy (1966) (TTM) timing models as defined in Eq. (3-3), where portfolio managers of only four countries of Belgium, Denmark, Ireland, and Japan exhibit significant positive evidence of market timing at the confidence level of 95%. Compared to the daily TTM estimates, only 17% of countries used in the research sample exhibits positive and significant monthly market timing skill of managers active in stock market of the countries. This ratio for the daily TTM models is approximately 47%, indicating higher estimates for the daily data than for the monthly data. Nine countries show positive evidence of market timing, but not statistically significant. Moreover, ten countries indicate either statistically significant negative evidence or statistically insignificant negative evidence of market timing. The highest monthly market timing skill is related to Japan with a positive and significant value of 3.68. The lowest monthly market timing skill is related to Finland with a negative and significant value of -2.27.

There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in most estimates. The MKTs are statistically insignificant in most tests.

The second column of Table 4-12 also reports the results of monthly alphas estimated from the TTM timing model, Eq. (3-3). These alphas are an indicator of portfolio managers' selection ability in the models. The estimated alphas show that portfolio managers of only one country, Finland, have positive and significant selection skills in stock market. A comparison between the daily TTM results and the monthly TTM results shows that the daily TTM models exhibit a ratio of 4% in the research sample for portfolio managers' selection ability, whereas the monthly TTM models exhibit a higher ratio of 82% in the research sample for the ability, indicating better performance for the daily TTM models. The highest monthly portfolio selection skill (α) is related to Finland with a positive and significant value of 0.56, while the lowest monthly portfolio selection skill (α) is related to Ireland with a negative and significant value of -0.19.

Table 4-12: The monthly results of market timing models on TTM

Countries	α	MKT	SMB	HML	MOM	R_m^2	R^2
Australia	0.38 (0.86)	-0.96 **(-2.17)**	0.008 (1.16)	0.013 (1.35)	-0.0035 (-0.74)	-0.55 (-0.12)	0.79
Austria	0.20 (0.51)	-0.73 (-0.23)	-0.035 (-0.83)	-0.037 (-0.75)	0.015 (0.55)	-0.23 (-0.005)	0.32
Belgium	-0.06 (-0.64)	-0.20 (-1.91)	0.002 (1.82)	0.003 **(2.92)**	-0.002 **(-3.06)**	3.65 **(4.99)**	0.86
Canada	0.08 (0.42)	-0.25 (-0.56)	0.002 (0.46)	0.005 (0.64)	-0.002 (-0.53)	-1.57 (-0.39)	0.64
Denmark	-0.13 (-1.49)	0.22 **(3.47)**	0.0018 (1.70)	-0.0006 (-0.65)	-0.002 **(-4.21)**	2.69 **(2.89)**	0.86
Finland	0.56 **(1.99)**	-0.14 (-0.20)	0.01 (1.22)	0.019 **(2.09)**	-0.016 **(-3.80)**	-2.27 **(-2.44)**	0.73
France	-0.046 (-0.12)	-1.04 (-0.56)	0.011 (0.57)	0.011 (0.29)	-0.005 (-0.24)	12.92 (1.36)	0.43
Germany	-0.0016 (-0.007)	-0.41 (-1.70)	0.0048 (1.49)	-0.0016 (-0.32)	-0.0046 (-1.91)	-0.030 (-0.011)	0.76
Greece	-0.042 (-0.37)	-0.16 (-0.52)	0.0014 (0.43)	0.01 **(2.45)**	-0.0048 **(-2.08)**	2.29 (0.59)	0.70
Hong Kong	0.19 (1.74)	-0.91 **(-5.39)**	0.0014 (0.45)	0.0057 (1.60)	-0.0013 (-0.62)	1.97 (1.03)	0.80
Ireland	-0.19 **(-2.44)**	0.18 **(2.49)**	0.0047 **(3.44)**	0.005 **(3.67)**	-0.004 **(-6.76)**	2.44 **(2.29)**	0.81
Italy	0.031 (0.22)	-0.35 **(-2.55)**	0.0038 (1.87)	0.00043 (0.21)	-0.0024 **(-2.17)**	2.72 (1.94)	0.85
Japan	-0.043 (-0.24)	-0.10 (-1.19)	0.002 **(2.14)**	5.35E-05 (0.03)	-0.0011 (-1.79)	3.68 **(4.14)**	0.91
Netherlands	0.26 (0.56)	-0.30 (-0.46)	0.0031 (0.29)	0.0016 (0.14)	0.0007 (0.11)	-2.08 (-0.20)	0.83
New Zealand	1.44 (1.28)	2.52 (1.02)	-0.007 (-0.14)	0.024 (0.46)	0.0027 (0.10)	-4.13 (-0.14)	0.61
Norway	1.30 (0.42)	-0.36 (-0.06)	0.015 (0.16)	0.062 (0.62)	-0.0039 (-0.06)	-33.77 (-0.31)	0.64
Portugal	5.33 (1.55)	-4.07 (-0.32)	-0.09 (-0.49)	-0.09 (-0.55)	0.024 (0.19)	-30.96 (-0.17)	0.45
Singapore	0.48 (0.24)	-2.23 (-0.72)	0.026 (0.43)	0.001 (0.018)	-0.0087 (-0.18)	-21.04 (-1.14)	0.63
Spain	0.47 (0.29)	-0.76 (-0.14)	0.012 (0.21)	0.04 (0.69)	0.0013 (0.04)	11.52 (0.15)	0.69
Sweden	-0.11 (-0.45)	-0.105 (-0.16)	0.0035 (0.42)	-0.0035 (-0.35)	-0.004 (-0.71)	1.36 (0.13)	0.49
Switzerland	0.55 (0.67)	-0.24 (-0.19)	0.003 (0.34)	-0.007 (-0.51)	-0.009 (-1.20)	3.74 (0.26)	0.85
U.K.	0.027 (0.19)	-0.28 (-0.99)	0.011 **(2.67)**	0.013 **(2.60)**	-0.005 (-1.55)	4.14 (1.29)	0.68
U.S.	2.36 (0.43)	0.23 (0.013)	-0.11 (-0.40)	-0.21 (-1.15)	-0.05 (-0.62)	39.19 (0.12)	0.62

Note: This table reports the monthly results of market timing models using the traditional Treynor and Mazuy (1966) (TTM) market timing measure. It uses Eq. (3-3) defined in the subsection (3.2) of Chapter 3 for estimating traditional timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.10 Monthly New HM (NHM) Timing Models

This subsection reports the results of the monthly AD-based timing model estimates. It begins by running Eq. (3-19) and uses the proposed Henriksson and Merton (1981) (NHM) timing models to estimate portfolio managers' market timing and selection skills.

Table 4-13 reports the monthly estimates of the NHM timing models, where portfolio managers of five countries of Denmark, Ireland, Italy, Sweden, and Switzerland exhibit significant positive evidence of market timing at the confidence level of 95%. This number contains a ratio of 21% in the research sample compared to the daily estimates of the NHM timing models, which possess a ratio of 52% in the sample, indicating a weaker timing performance for the monthly NHM timing models. Compared to the monthly THM timing models that have a ratio of 8% for market timing ability, the monthly NHM timing models have a higher ratio of 21%. Thirteen countries exhibit positive evidence of market timing, but not statistically significant. The remaining five countries indicate either statistically significant negative evidence or statistically insignificant negative evidence of market timing.

The highest monthly NHM market timing skill is related to Switzerland with a positive and significant value of 8.76, while the lowest NHM market timing skill is related to Finland with a statistically insignificant negative value of -4.77.

There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in most estimates. The MKTs are statistically insignificant in most tests.

The second column of Table 4-13 also represents the results of monthly alphas estimated from the monthly NHM timing model. The estimated alphas highlight that none of the portfolio managers exhibit positive and significant selection skills in their stock markets.

Table 4-13: The monthly results of market timing models on NHM

Countries	α	MKT	SMB	HML	MOM	AD_m^*	R^2
Australia	0.40 (0.88)	-0.94 (-1.45)	0.0086 (1.11)	0.015 (1.68)	-0.0024 (-0.48)	-0.48 (-0.28)	0.78
Austria	0.18 (0.55)	-1.10 (-0.29)	-0.036 (-0.94)	-0.037 (-0.77)	0.014 (0.56)	1.15 (0.12)	0.34
Belgium	-0.06 (-0.73)	-0.40 **(-3.05)**	0.003 **(2.37)**	0.0047 **(4.05)**	-0.0023 **(-3.32)**	0.44 (1.43)	0.86
Canada	-0.0076 (-0.35)	-0.55 (-1.01)	-0.0087 (-1.59)	-0.0026 (-0.43)	0.0067 (1.88)	0.78 (0.61)	0.63
Denmark	-0.0097 (-1.84)	-0.49 **(-3.74)**	-0.0065 **(-4.94)**	-0.0008 (-0.55)	0.0043 **(4.91)**	0.92 **(2.99)**	0.85
Finland	0.033 (0.77)	1.31 (1.22)	-0.016 (-1.58)	0.0074 (0.63)	0.031 **(4.48)**	-4.77 (-1.91)	0.64
France	-0.043 (-0.08)	-2.10 (-1.22)	0.005 (0.33)	-0.0002 (-0.01)	-0.002 (-0.18)	2.32 (0.50)	0.51
Germany	-0.005 (-0.03)	-0.71 (-1.80)	0.0048 (1.58)	0.0018 (0.37)	-0.0043 (-1.68)	0.15 (0.15)	0.73
Greece	-0.03 (-0.32)	-0.11 (-0.23)	0.001 (0.45)	0.01 **(2.43)**	-0.004 **(-2.13)**	-0.13 (-0.11)	0.70
Hong Kong	0.20 (1.76)	-0.95 **(-3.25)**	0.0014 (0.45)	0.0056 (1.57)	-0.0013 (-0.63)	0.14 (0.19)	0.80
Ireland	-0.19 **(-2.34)**	-0.22 (-1.91)	0.0048 **(3.62)**	0.005 **(4.15)**	-0.0047 **(-7.01)**	1.02 **(3.13)**	0.81

Italy	-0.011 (-1.21)	-0.76 **(-3.31)**	-0.009 **(-4.13)**	-0.0011 (-0.43)	0.007 **(5.30)**	1.05 **(1.98)**	0.84
Japan	-0.003 (-0.44)	-0.032 (-0.19)	-0.0052 **(-3.05)**	0.006 **(3.27)**	0.0099 **(8.65)**	-0.17 (-0.42)	0.88
Netherlands	-0.008 (-0.32)	-2.17 **(-3.18)**	-0.019 **(-2.80)**	-0.023 **(-3.10)**	-0.0033 (-0.74)	2.02 (1.28)	0.82
New Zealand	-0.13 (-1.01)	-3.93 (-1.19)	-0.033 (-1.03)	0.012 (0.35)	0.044 **(2.08)**	10.36 (1.36)	0.61
Norway	-0.24 (-1.05)	-8.84 (-1.48)	-0.046 (-0.78)	-0.026 (-0.40)	0.045 (1.17)	21.95 (1.59)	0.60
Portugal	5.10 (1.43)	-9.24 (-0.44)	-0.094 (-0.50)	-0.089 (-0.52)	0.026 (0.20)	15.07 (0.40)	0.45
Singapore	0.45 (0.32)	-2.45 (-0.73)	0.036 (0.68)	0.035 (0.77)	-0.013 (-0.39)	-1.24 (-0.11)	0.66
Spain	0.42 (0.28)	-3.06 (-0.43)	0.011 (0.19)	0.044 (0.72)	0.0009 (0.03)	6.36 (0.43)	0.70
Sweden	-0.021 (-1.21)	-0.80 (-1.77)	-0.006 (-1.37)	-0.002 (-0.52)	0.002 (0.82)	2.12 **(2.12)**	0.48
Switzerland	-0.088 (-1.95)	-4.03 **(-3.50)**	-0.05 **(-4.34)**	-0.02 **(-2.14)**	0.017 **(2.34)**	8.76 **(3.29)**	0.78
U.K.	0.027 (0.19)	-0.60 (-1.38)	0.011 **(2.69)**	0.013 **(2.62)**	-0.0057 (-1.53)	0.81 (0.58)	0.68
U.S.	2.23 (0.41)	-7.35 (-0.19)	-0.12 (-0.41)	-0.20 (-1.11)	-0.053 (-0.61)	21.07 (0.25)	0.62

Note: This table reports the monthly results of market timing models using the proposed Henriksson and Merton (1981) (NHM) market timing measure. It uses Eq. (3-19) defined in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.11 Monthly New TM (NTM) Timing Models

Table 4-14 reports the monthly estimates of the proposed Treynor and Mazuy (1966) (NTM) timing models, Eq. (3-18), where portfolio managers of thirteen countries exhibit significant positive evidence of market timing at the confidence level of 95%. This provides a lower ratio of 56% for the monthly NTM timing models compared to the ratio of 65% for the daily NTM timing models. In contrast, this ratio is higher than the ratio of the monthly TTM timing models, which have a ratio of 17%. This provides two key results. First, the daily NTM timing models have a better performance than the monthly NTM timing models. Second, there is more positive evidence of market timing in the NTM timing models in comparison with their corresponding traditional models (TTMs). Table 4-14 also reports that eight countries exhibit positive evidence of market timing, but not statistically significant. Portfolio managers of the remaining countries show statistically insignificant negative evidence of market timing. According to the monthly NTM timing models, Singapore has the highest market timing skill with a positive and significant value of 44.51, while Denmark has the lowest monthly market timing skill with a negative and significant value of 0.93.

There are both positive signs and negative signs in the SMB, HML, and MOM coefficients, but not significant in most tests. MKTs are not significant in most timing tests. The existence of a combination of positive and negative MKTs in our timing tests from one side and the existence of positive timing evidence from another side implies that dispersion of stock and market returns places around the BE characteristic line in Figure (3-1).

The second column of Table 4-14 also reports the results of monthly alphas estimated from the monthly NTM timing model, Eq. (3-18). The estimated monthly alphas show that portfolio managers of only one country, Finland, have positive and significant selection skills in stock market. The portfolio managers of other countries possess either statistically significant negative selection skills or statistically insignificant positive selection skills in the markets. Finland has the highest monthly portfolio selection skill (α) with a positive and significant value of 0.53, while Ireland has the lowest portfolio selection skill (α) with a negative and significant value of -0.20.

Table 4-14: The monthly results of market timing models on NTM

Countries	α	MKT	SMB	HML	MOM	AD_m^2	R^2
Australia	0.37 (0.85)	-0.24 (-0.50)	0.005 (0.84)	0.011 (1.36)	-0.001 (-0.25)	10.84 **(6.65)**	0.80
Austria	0.20 (0.48)	-0.72 (-0.18)	-0.035 (-0.82)	-0.037 (-0.73)	0.015 (0.58)	0.14 (0.007)	0.32
Belgium	-0.07 (-0.79)	0.07 (0.76)	0.002 (1.90)	0.003 **(3.43)**	-0.002 **(-3.08)**	4.05 **(14.60)**	0.88
Canada	0.059 (0.31)	0.16 (0.29)	0.001 (0.23)	0.003 (0.39)	-0.001 (-0.36)	5.43 **(2.47)**	0.65
Denmark	-0.13 (-1.42)	0.28 **(3.03)**	0.002 (1.57)	-0.001 (-0.90)	-0.002 **(-4.36)**	0.93 **(2.75)**	0.86
Finland	0.53 **(1.98)**	0.42 (0.50)	0.008 (1.01)	0.01 (1.60)	-0.015 **(-3.88)**	8.36 **(2.55)**	0.73
France	-0.08 (-0.24)	-0.16 (-0.14)	0.003 (0.21)	-0.003 (-0.16)	-0.002 (-0.18)	20.24 **(5.11)**	0.54
Germany	-0.007 (-0.02)	-0.28 (-1.19)	0.004 (1.47)	-0.001 (-0.36)	-0.004 (-1.72)	2.06 **(2.15)**	0.77
Greece	-0.04 (-0.37)	-0.07 (-0.20)	0.001 (0.35)	0.01 **(2.34)**	-0.004 **(-2.05)**	1.33 (0.83)	0.70
Hong Kong	0.18 (1.71)	-0.54 **(-2.86)**	0.0003 (0.09)	0.003 (1.11)	-0.0009 (-0.40)	5.33 **(5.40)**	0.81
Ireland	-0.19 **(-2.32)**	0.23 **(2.31)**	0.004 **(3.39)**	0.004 **(3.36)**	-0.004 **(-6.91)**	1.25 **(3.13)**	0.81
Italy	0.028 (0.20)	-0.14 (-0.92)	0.003 (1.59)	-0.0006 (-0.27)	-0.002 (-1.91)	2.91 **(4.23)**	0.85
Japan	-0.04 (-0.30)	0.14 (1.69)	0.002 **(1.99)**	-0.0003 (-0.25)	-0.0008 (-1.33)	3.27 **(8.65)**	0.91
Netherlands	0.25 (0.55)	-0.26 (-0.39)	0.003 (0.27)	0.001 (0.13)	0.0008 (0.12)	0.57 (0.09)	0.83
New Zealand	1.42 (1.29)	2.69 (1.03)	-0.007 (-0.16)	0.02 (0.45)	0.003 (0.11)	2.43 (0.15)	0.61
Norway	1.27 (0.40)	-1.30 (-0.22)	0.016 (0.17)	0.06 (0.68)	-0.004 (-0.07)	-11.05 (-0.11)	0.64
Portugal	5.36 (1.56)	-6.28 (-0.57)	-0.08 (-0.46)	-0.08 (-0.50)	0.02 (0.16)	-29.55 (-0.17)	0.45
Singapore	0.29 (0.28)	0.11 (0.04)	0.02 (0.40)	0.01 (0.41)	-0.009 (-0.31)	44.51 **(5.82)**	0.68
Spain	0.48 (0.31)	-0.44 (-0.06)	0.012 (0.19)	0.042 (0.57)	0.001 (0.05)	3.13 (0.08)	0.69
Sweden	-0.10 (-0.45)	-0.06 (-0.09)	0.003 (0.42)	-0.003 (-0.37)	-0.004 (-0.76)	0.57 (0.16)	0.49

Switzerland	0.55 (0.66)	-0.07 (-0.07)	0.003 (0.28)	-0.008 (-0.57)	-0.009 (-1.15)	2.06 (0.18)	0.85
U.K.	0.02 (0.16)	0.024 (0.06)	0.01 **(2.34)**	0.011 **(2.01)**	-0.005 (-1.43)	3.97 **(3.03)**	0.69
U.S.	2.32 (0.43)	3.14 (0.18)	-0.12 (-0.44)	-0.23 (-1.11)	-0.04 (-0.47)	37.51 (0.35)	0.62

Note: This table reports the monthly results of market timing models using the proposed Treynor and Mazuy (1966) (NTM) market timing measure. It uses Eq. (3-18) defined in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.12 Robustness Checks

This subsection reports a series of controlling checks to know whether the basic results of this study remain unchanged if the analysis assumptions and some research variables change. These checks are reported as follows:

4.12.1 Reconstructing Monthly Returns

Eq. (3-58) in Chapter 3 presented an alternative way to construct the monthly returns from the daily returns. This construction method helps us to make a comparison between the traditional market timing models and the AD-based market timing models at the monthly frequency in a different fashion. To conduct this check, the monthly returns are constructed by Eq. (3-59) and (3-60) as proxies for monthly payoffs of a successful market timer. Then, Eq. (3-61) and (3-62) are run by these two proxies to estimate the traditional and AD-based market timing measures. Table 4-15 reports the results of these estimates.

Panel A of Table 4-15 exhibits the results of alternative monthly traditional market timing models, Eq. (3-61), where portfolio managers of fifteen countries exhibit statistically significant positive evidence of market timing at the confidence level of 95%. This number contains a ratio of 65% in the research sample. Eight countries show positive evidence of market timing, but not statistically significant. The highest monthly market timing skill is related to Norway with a positive and significant value of 0.86. The lowest market timing skill is related to Greece with a statistically significant positive value of 0.069.

The second column of Panel A in Table 4-15 represents the results of monthly alphas estimated from the alternative monthly traditional market timing models. The estimated alphas highlight that none of the portfolio managers exhibits statistically significant positive selection skills in their stock markets. Only Austria reports a positive alpha coefficient, but not statistically significant. The rest of the countries exhibit negative alpha coefficients.

Panel B of Table 4-15 reports the monthly estimates of the alternative AD-based market timing models, Eq. (3-62), where portfolio managers of seventeen countries show significant positive evidence of market timing at the confidence level of 95%. This number contains a ratio of 74% in the research sample compared to the alternative monthly traditional market timing models in Panel A, which possess a ratio of 65% in the sample. This implicates a stronger timing performance for the alternative monthly AD-based timing models. Three countries exhibit positive evidence of market timing, but not statistically significant. The remaining three countries indicate statistically insignificant negative evidence of market timing. Economic significance for the estimated AD-based market timing measures, which is defined as the magnitude of the estimated AD-based timing coefficients in the regressions, are higher than the estimated traditional market timing measures. The highest monthly AD-based market timing skill is related to U.S. with a positive and significant value of 2.20, whereas the lowest market timing skill is related to Hong Kong with a statistically significant negative magnitude of -0.084 as well.

The second column of Panel B in Table 4-15 also represents the results of monthly alphas estimated from the alternative monthly AD-based market timing models. The estimated alphas show that portfolio managers of only three countries have positive selection skills, but not statistically significant, in their stock markets. Despite the AD-based market timing models has better timing performance than the traditional market timing models due to either more positive market timing coefficients or higher magnitudes of market timing coefficients, none of the models is able to show portfolio managers' selection ability.

Table 4-15: The monthly estimate results of market timing models using alternative monthly timing measures

Countries	Panel A: the traditional timing estimates							Panel B: the AD-based timing estimates						
	α	MKT	SMB	HML	MOM	P^T	R^2	α	MKT	SMB	HML	MOM	P^{AD}	R^2
Australia	-0.08	-0.27	0.011	0.015	0.02	0.20	0.74	-0.17	1.53	0.014	0.018	0.023	0.25	0.75
	(-3.30)	(-0.56)	(1.58)	**(2.02)**	**(4.35)**	**(6.03)**		**(-4.50)**	**(2.98)**	**(2.14)**	**(2.48)**	**(5.18)**	**(4.95)**	
Austria	0.0015	-0.41	-0.03	-0.02	-0.001	0.024	0.32	0.037	0.019	-0.033	-0.023	-0.0004	-0.046	0.32
	(0.02)	(-0.33)	(-1.73)	(-1.22)	(-0.16)	(0.28)		(0.37)	(0.01)	(-1.80)	(-1.16)	(-0.03)	(-0.34)	
Belgium	-0.037	-0.038	-0.004	0.0031	0.008	0.092	0.77	-0.08	0.73	-0.0022	0.005	0.0093	0.11	0.82
	(-6.11)	(-0.32)	**(-2.26)**	(1.64)	**(6.95)**	**(10.72)**		**(-9.77)**	**(5.90)**	(-1.53)	**(3.12)**	**(9.47)**	**(10.66)**	
Canada	-0.012	-0.095	-0.007	-0.0028	0.005	0.033	0.63	-0.06	1.09	-0.005	-0.0014	0.0056	0.097	0.62
	(-0.62)	(-0.25)	(-1.35)	(-0.47)	(1.56)	(1.30)		**(-2.14)**	**(2.80)**	(-0.91)	(-0.24)	(1.57)	**(2.43)**	
Denmark	-0.034	0.025	-0.005	-0.0016	0.0027	0.092	0.77	-0.07	0.77	-0.0033	-7.37E-05	0.003	0.10	0.81
	(-6.41)	(0.25)	**(-3.36)**	(-1.01)	**(2.76)**	**(12.27)**		**(-9.82)**	**(6.90)**	**(-2.61)**	(-0.05)	**(4.69)**	**(11.15)**	
Finland	-0.033	0.25	-0.016	0.016	0.037	0.026	0.66	0.021	-0.42	-0.019	0.015	0.038	-0.069	0.66
	(-0.91)	(0.35)	(-1.56)	(1.41)	**(5.29)**	(0.53)		(0.36)	(-0.57)	(-1.81)	(1.35)	**(5.46)**	(-0.89)	
France	-0.041	0.58	-0.007	0.016	0.021	0.067	0.39	-0.022	0.35	-0.009	0.016	0.022	0.009	0.41
	(-0.99)	(0.72)	(-0.66)	(1.22)	**(2.55)**	(1.18)		(-0.33)	(0.41)	(-0.78)	(1.23)	**(2.78)**	(0.10)	
Germany	-0.056	0.089	-0.005	0.0049	0.0068	0.13	0.67	-0.12	1.23	-0.0021	0.0072	0.0079	0.19	0.68
	(-5.01)	(0.41)	(-1.60)	(1.42)	**(3.31)**	**(8.78)**		**(-7.55)**	**(5.18)**	(-0.71)	**(2.20)**	**(4.02)**	**(8.30)**	
Greece	-0.028	-0.24	0.003	0.0062	0.001	0.069	0.65	-0.091	1.13	0.0061	0.007	0.0008	0.13	0.64
	(-1.96)	(-0.90)	(0.93)	(1.38)	(0.40)	**(3.58)**		**(-4.06)**	**(3.96)**	(1.52)	(1.75)	(0.33)	**(4.52)**	
Hong Kong	-0.040	0.26	0.011	0.020	0.013	0.073	0.72	-0.048	0.57	0.011	0.020	0.014	0.084	0.72
	(-2.50)	(0.86)	**(2.60)**	**(3.99)**	**(4.51)**	**(3.36)**		(-1.90)	(1.80)	**(2.55)**	**(4.05)**	**(4.76)**	**(3.42)**	
Ireland	-0.033	-0.14	-0.0015	0.0018	0.0038	0.086	0.70	-0.076	0.52	0.0004	0.0035	0.005	0.11	0.68
	(-5.70)	(-1.26)	(-0.92)	(1.02)	**(3.56)**	**(10.38)**		**(-8.51)**	**(3.93)**	(0.26)	**(2.11)**	**(4.89)**	**(9.42)**	

Italy	-0.042 **(-4.51)**	0.048 (0.26)	-0.0061 **(-2.28)**	-0.0011 (-0.38)	0.0052 **(2.99)**	0.11 **(8.76)**	0.76	-0.12 **(-8.70)**	1.75 **(8.99)**	-0.0038 (-1.56)	0.0005 (0.20)	0.0064 **(3.98)**	0.18 **(9.81)**	0.77
Japan	-0.058 **(-8.60)**	0.25 (1.93)	-0.0034 (-1.83)	0.0058 **(2.75)**	0.0087 **(6.95)**	0.14 **(15.05)**	0.84	-0.11 **(-12.16)**	1.28 **(9.26)**	-0.0007 (-0.48)	0.0085 **(4.81)**	0.01 **(9.61)**	0.16 **(13.23)**	0.88
Netherlands	-0.011 (-0.47)	-1.26 **(-2.75)**	-0.016 **(-2.48)**	-0.027 **(-3.67)**	-0.007 (-1.77)	0.07 **(2.20)**	0.82	-0.11 **(-2.97)**	0.97 **(1.98)**	-0.012 (-1.76)	-0.024 **(-3.22)**	-0.008 (-1.90)	0.19 **(3.82)**	0.80
New Zealand	-0.27 **(-2.26)**	2.91 (1.25)	-0.014 (-0.42)	0.014 (0.38)	0.028 (1.27)	0.66 **(4.03)**	0.56	-0.66 **(-3.53)**	10.27 **(4.24)**	-0.0035 (-0.10)	0.019 (0.53)	0.03 (1.35)	0.98 **(3.91)**	0.57
Norway	-0.32 (-1.56)	1.32 (0.32)	-0.018 (-0.32)	-0.028 (-0.43)	0.001 (0.02)	0.86 **(3.07)**	0.60	-1.12 **(-3.34)**	17.18 **(3.92)**	0.013 (0.21)	-0.0088 (-0.13)	-0.0052 (-0.13)	1.70 **(3.81)**	0.58
Portugal	-0.15 (-0.29)	-10.11 (-1.01)	-0.015 (-0.10)	-0.13 (-0.80)	-0.055 (-0.57)	0.61 (0.88)	0.44	-1.13 (-1.38)	10.69 (1.01)	0.026 (0.17)	-0.10 (-0.62)	-0.055 (-0.56)	1.81 (1.66)	0.42
Singapore	-0.092 (-0.87)	4.66 **(2.29)**	0.023 (0.77)	0.13 **(4.13)**	0.042 **(2.14)**	0.06 (0.42)	0.52	0.11 (0.67)	-0.22 (-0.10)	0.015 (0.51)	0.13 **(3.90)**	0.035 (1.78)	-0.25 (-1.17)	0.52
Spain	-0.02 (-0.20)	-1.73 (-0.80)	0.015 (0.48)	0.014 (0.40)	0.020 (0.97)	0.029 (0.19)	0.68	-0.08 (-0.45)	0.35 (0.15)	0.018 (0.57)	0.017 (0.51)	0.018 (0.87)	0.10 (0.43)	0.68
Sweden	-0.025 (-1.60)	0.033 (0.10)	-0.0045 (-1.00)	-0.0038 (-0.76)	9.01E-05 (0.03)	0.073 **(3.33)**	0.45	-0.07 **(-2.89)**	0.60 (1.87)	-0.0025 (-0.55)	-0.0023 (-0.47)	0.0004 (0.13)	0.11 **(3.40)**	0.43
Switzerland	-0.095 **(-2.33)**	-0.18 (-0.23)	-0.042 **(-3.59)**	-0.037 **(-2.91)**	0.0037 (0.49)	0.28 **(5.11)**	0.77	-0.28 **(-4.47)**	4.28 **(5.34)**	-0.035 **(-3.11)**	-0.033 **(-2.67)**	0.0042 (0.57)	0.44 **(5.28)**	0.78
UK	-0.041 **(-2.54)**	0.63 **(2.01)**	-0.0025 (-0.55)	0.0014 (0.27)	0.012 **(4.15)**	0.088 **(3.98)**	0.60	-0.09 **(-3.89)**	1.44 **(4.49)**	-0.0023 (-0.53)	0.0012 (0.26)	0.013 **(4.77)**	0.13 **(4.10)**	0.65
US	-0.51 (-1.15)	4.76 (0.55)	-0.022 (-0.17)	0.11 (0.78)	0.043 (0.51)	1.20 (1.91)	0.60	-1.51 **(-2.12)**	25.02 **(2.75)**	0.014 (0.11)	0.13 (0.92)	0.039 (0.47)	2.20 **(2.33)**	0.59

Note: This table reports the monthly results of the alternative traditional and AD-based market timing models using the proxies constructed in the subsection (3.20) of chapter 3. These proxies are referred to as the monthly payoffs of a successful market timer. To conduct this controlling check, this study uses an alternative procedure to estimate the monthly market timing ability. This study thus constructs the monthly returns using the daily returns as:

$$R^{M} = \prod_{t=T}^{T+N-1}(1 + R_t^D) - 1$$

where R^M is the monthly return based on the daily return R^D, N denotes the trading days in a given month, and T is the first day of each month. Following Eq. (3-59) and (3-60), we then reconstruct monthly market timing measures based on Bollen and Bassu (2001). The magnitudes of monthly variable for the traditional and AD-based timing measures are monthly calculated as:

$$P_{m,\tau}^{T} = \left(\prod_{t=1}^{N} \max[1 + R_{m,t}^{T}, 1 + R_{f,t}\right) - 1 - R_{m,t}^{T}$$

$$P_{m,\tau}^{AD} = \left(\prod_{t=1}^{N} \max[1 + R_{m,t}^{AD}, 1 + R_{f,t}\right) - 1 - R_{m,t}^{AD}$$

where $P_{m,\tau}^{T}$ and $P_{m,\tau}^{AD}$ are the monthly traditional and AD market timing measures, respectively, N is the number of days at month τ, $R_{m,t}^{T}$ is the market return m at day t in the standard form for constructing the monthly traditional market timing measure, $R_{m,t}^{AD}$ is the return on market portfolio m at day t, that is calculated by $A_{\rho-1} + (R_{mt})$ for constructing the monthly AD market timing measure where ρ includes a lag equal to 2, and $R_{f,t}$ is the free-risk return. Then, these two factors are used in the following regression based on monthly returns to consider the correlation between the monthly return of a portfolio and the monthly magnitude of daily timing as:

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} + \gamma_p P_{m,\tau}^{T} + \varepsilon_{p,t}$$

$$R_{p,t} = \alpha_p + \beta_p R_{m,t} + \beta_p SMB_{p,t} + \beta_p HML_{p,t} + \beta_p MOM_{p,t} + \gamma_p P_{m,\tau}^{AD} + \varepsilon_{p,t}$$

α_p is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM). R^2s place in the last column of the table. T-statistics also place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

4.12.2 Simulation Check

This subsection conducts another controlling check based on simulation to examine the power of our proposed timing tests by generating portfolio returns under two alternative hypotheses of the Treynor and Mazuy (1966) (TM) and Henriksson and Merton (1981) (HM) timing abilities. The purpose is to demonstrate whether the frequency of returns (e.g., daily returns or monthly returns) can increase the power of market timing. This analysis helps us to know about portfolio managers' aggressive trading behavior.

To generate returns under the HM alternative, this study firstly constructs a time series of portfolio betas as in Eq. (3-65), where the market beta is estimated by the non-timing model of Eq. (3-64). Then, the non-timing beta and the residual of the non-timing model estimated from previous step are subtracted to generate portfolio returns under the HM alternative. Next, the returns are constructed from setting I equal to 0.6, 0.7, 0.8, 0.9, and 1. Finally, this study runs the HM timing models using Eq. (3-19) on the daily and monthly data constructed under the HM alternatives, and examines portfolio timing significance at the confidence level of 95%.

Panels A and B of Table 4-16 report the results of power tests for the daily and monthly data constructed from the AD timing measure under the HM alternative. Panel A shows that the daily timing tests have positive coefficients in all countries, except US. In contrast, most of the monthly timing tests exhibit negative timing coefficients across countries. Thus, the daily timing coefficients demonstrate significantly positive magnitudes much more often than the monthly timing coefficients. For instance, with a $\gamma = 0.6$, the daily estimates in the research sample (23 countries under study) obtain significantly positive coefficients about 87% of the time using the HM model, whereas the monthly estimates obtain significantly positive coefficients about 4% of the time using the model. The superiority evidence of the daily data is much more than the monthly data even when alternative monthly data, as in Table 4-16, is applied to estimate the AD-based timing measures. Panel B of Table 4-16 exhibits this analysis with the alternative monthly data, where the monthly estimates demonstrate lower statistical significance than the daily data, and their timing coefficients are negative in most timing tests, implying again that the daily tests result in much more significant timing coefficients than the monthly tests. A reason for more negative timing coefficients in Panel B is that βs estimated from non-timing model at the monthly frequency, Eq. (3-64), are negative and these values lead to negative values in Eq. (3-65) and so estimated negative magnitudes for the timing coefficients.

Table 4-16 also shows a positive relation between increase in γs and the power of timing activities. As γs (the timing frequencies) increase from 0.6 to 1, the relative power (the AD timing coefficient) of the daily tests increases. For example, when γs (the timing frequencies) for Australia increase from 0.6 to 1 the relative power (the AD timing coefficient) of the daily tests increases from 1.01 to 1.65, and their statistical significance tend to increase from 38.34 to 62.68. The same relation can be seen for the monthly AD timing coefficients, but their significant coefficients are much less than those reported for the daily data. These results are consistent with Bollen and Bassu (2001).

Table 4-16: Size and power analysis for the daily and monthly data constructed under the HM alternative

Countries	Panel A: the daily AD timing measure					Panel B: the monthly AD timing measure				
	0.6	0.7	0.8	0.9	1	0.6	0.7	0.8	0.9	1
Australia	1.01	1.17	1.33	1.49	1.65	-0.49	-0.56	-0.64	-0.71	-0.78
	(38.34)	**(44.42)**	**(50.51)**	**(56.60)**	**(62.68)**	(-0.26)	(-0.30)	(-0.34)	(-0.38)	(-0.41)
Austria	0.31	0.35	0.39	0.42	0.46	-1.29	-1.31	-1.33	-1.35	-1.37
	(10.10)	**(11.26)**	**(12.42)**	**(13.58)**	**(14.73)**	(-0.11)	(-0.11)	(-0.11)	(-0.11)	(-0.12)
Belgium	0.56	0.63	0.71	0.78	0.86	0.30	0.28	0.26	0.24	0.22
	(25.26)	**(28.57)**	**(31.88)**	**(35.18)**	**(38.49)**	(0.95)	(0.89)	(0.83)	(0.77)	(0.71)
Canada	0.17	0.23	0.30	0.36	0.42	-0.58	-0.61	-0.65	-0.69	-0.73
	(0.59)	(0.80)	(1.01)	(1.22)	(1.43)	(-0.37)	(-0.40)	(-0.42)	(-0.45)	(-0.47)
Denmark	0.74	0.82	0.90	0.98	1.06	0.33	0.35	0.37	0.39	0.41
	(28.66)	**(31.78)**	**(34.89)**	**(38.00)**	**(41.12)**	(0.21)	(1.31)	(1.39)	(1.46)	(1.54)
Finland	0.55	0.58	0.62	0.66	0.70	-2.34	-2.50	-2.66	-2.82	-2.98
	(2.50)	**(2.67)**	**(2.84)**	**(3.01)**	**(3.18)**	(-0.84)	(-0.90)	(-0.96)	(-1.02)	(-1.08)
France	0.79	0.88	0.97	1.07	1.16	0.34	0.023	-0.29	-0.61	-0.92
	(25.48)	**(28.48)**	**(31.49)**	**(34.49)**	**(37.49)**	(0.06)	(0.004)	(-0.06)	(-0.12)	(-0.19)
Germany	0.54	0.61	0.71	0.80	0.90	-0.47	-0.51	-0.55	-0.59	-0.62
	(3.53)	**(4.00)**	**(4.62)**	**(5.25)**	**(5.88)**	(-0.54)	(-0.58)	(-0.62)	(-0.67)	(-0.71)
Greece	0.58	0.65	0.71	0.78	0.84	-0.11	-0.07	-0.036	0.005	0.047
	(8.75)	**(9.74)**	**(10.73)**	**(11.72)**	**(12.71)**	(-0.11)	(-0.07)	(-0.03)	(0.005)	(0.04)
Hong Kong	0.23	0.29	0.35	0.40	0.46	-0.39	-0.51	-0.64	-0.76	-0.88
	(5.47)	**(6.82)**	**(8.18)**	**(9.54)**	**(10.89)**	(-0.52)	(-0.68)	(-0.84)	(-1.01)	(-1.17)
Ireland	0.27	0.35	0.42	0.50	0.58	0.91	0.94	0.98	1.01	1.04
	(3.59)	**(4.61)**	**(5.62)**	**(6.63)**	**(7.65)**	**(2.86)**	**(2.96)**	**(3.06)**	**(3.15)**	**(3.25)**
Italy	0.88	0.99	1.10	1.21	1.32	0.33	0.31	0.29	0.27	0.26
	(24.24)	**(27.20)**	**(30.16)**	**(33.12)**	**(36.08)**	(0.68)	(0.64)	(0.61)	(0.57)	(0.53)
Japan	0.16	0.26	0.36	0.47	0.57	0.21	0.18	0.16	0.14	0.11

	(3.85)	**(6.22)**	**(8.59)**	**(10.97)**	**(13.34)**	(0.71)	(0.63)	(0.55)	(0.47)	(0.39)
Netherlands	0.31	0.36	0.40	0.45	0.50	-0.84	-0.81	-0.78	-0.75	-0.72
	(8.34)	**(9.55)**	**(10.77)**	**(11.99)**	**(13.20)**	(-0.35)	(-0.34)	(-0.33)	(-0.31)	(-0.30)
New Zealand	1.14	1.35	1.55	1.75	1.95	3.25	3.64	4.03	4.42	4.81
	(17.68)	**(20.91)**	**(24.14)**	**(27.37)**	**(30.61)**	(0.34)	(0.38)	(0.42)	(0.47)	(0.51)
Norway	1.48	1.72	1.96	2.21	2.45	-6.71	-6.25	-5.80	-5.34	-4.89
	(38.72)	**(45.06)**	**(51.40)**	**(57.73)**	**(64.07)**	(-0.29)	(-0.27)	(-0.25)	(-0.23)	(-0.21)
Portugal	0.51	0.52	0.52	0.52	0.53	25.15	26.04	26.93	27.82	28.71
	(1.04)	(1.10)	(1.11)	(1.12)	(1.13)	(0.64)	(0.66)	(0.68)	(0.71)	(0.73)
Singapore	0.39	0.46	0.53	0.60	0.67	-5.87	-6.96	-8.06	-9.15	-10.24
	(13.74)	**(16.20)**	**(18.67)**	**(21.13)**	**(23.59)**	(-0.55)	(-0.65)	(-0.76)	(-0.86)	(-0.96)
Spain	0.53	0.60	0.67	0.73	0.80	7.31	7.53	7.74	7.96	8.18
	(13.65)	**(15.31)**	**(16.96)**	**(18.62)**	**(20.28)**	(0.50)	(0.51)	(0.53)	(0.54)	(0.56)
Sweden	0.86	0.94	1.03	1.11	1.19	0.003	-0.021	-0.045	-0.07	-0.09
	(23.09)	**(25.37)**	**(27.64)**	**(29.91)**	**(32.19)**	(0.001)	(-0.008)	(-0.01)	(-0.02)	(-0.03)
Switzerland	0.68	0.77	0.87	0.96	1.05	1.08	1.29	1.51	1.72	1.93
	(40.46)	**(45.97)**	**(51.48)**	**(56.99)**	**(62.50)**	(0.36)	(0.43)	(0.50)	(0.57)	(0.64)
U.K.	0.54	0.61	0.69	0.77	0.85	0.70	0.64	0.57	0.51	0.45
	(28.83)	**(32.97)**	**(37.11)**	**(41.26)**	**(45.40)**	(0.55)	(0.50)	(0.45)	(0.40)	(0.36)
U.S.	-1.01	-0.74	-0.47	-0.20	0.06	22.17	22.41	22.66	22.91	23.15
	(-0.23)	(-0.17)	(-0.11)	(-0.04)	(0.01)	(0.25)	(0.25)	(0.25)	(0.26)	(0.26)

Note: Panels A and B of this table report results of the AD timing coefficients at the daily and monthly frequencies, respectively. Panel A reports the power of the proposed timing tests by generating portfolio returns under alternative hypothesis of Henriksson and Merton (1981) (HM) timing ability. To generate the daily returns under the HM alternative, this study first runs the following non-timing model for each country as:

$$R_{p,t} = \alpha_p + \beta_{MKT}R_{m,t} + \beta_{SMB}SMB_{p,t} + \beta_{HML}HML_{p,t} + \beta_{MOM}MOM_{p,t} + \varepsilon_{p,t}$$

where $R_{p,t}$ is the return on portfolio p for each county at day t, α_p is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM) for portfolio p at day t.

Then, the beta and residual estimated from the non-timing model are subtracted to generate portfolio returns of each country under the HM alternative. Next, a time series of portfolio betas is constructed to each country as:

$\beta_{P,t:t+T} = I[\bar{r}_{m,t:t+T} > 0]\beta_{MKT}$

where $\bar{r}_{m,t:t+T}$ is the mean daily market excess return in the AD form, $(A_{\rho-1} + (R_{mt} - R_{ft}))$, from day t until day $t: t+T$. R_{mt} is the return on market portfolio m at day t and $A_{\rho-1}$ denotes the loss average suffered from 0 to $\rho - 1$, where $\rho = 24$. It generates returns by setting I equal to 0.6, 0.7, 0.8, 0.9, and 1. Finally, these alternative portfolio returns are used in the basic timing tests, Eq. (3-19), to estimate alternative daily AD timing coefficients. Panel B also reports the results of monthly data, where this study follows the above steps, except that it considers $\rho = 2$. These values result in mild to aggressive trading behavior. T-statistics place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Subsequently, this subsection conducts the same controlling check to examine the power of the proposed timing tests by generating portfolio returns under alternative hypothesis of the TM timing abilities. The purpose is to demonstrate whether the return frequency can increase the power of AD market timing based on the TM approach. This analysis also helps us to find out portfolio managers' aggressive trading behaviour based on the AD market timing measure in the TM form.

To generate returns under the TM alternative, this study firstly constructs a time series of portfolio betas as in Eq. (3-63), where the market beta is estimated by the non-timing model of Eq. (3-64). Then, the non-timing beta and the residual of the non-timing model estimated from previous step are subtracted to generate portfolio returns under the TM alternative. Next, the returns are constructed from setting γ equal to 5, 7.5, 10, 15, and 20. Finally, this study runs the TM timing models using Eq. (3-19) on the daily and monthly data constructed under the TM alternatives, and examines portfolio timing significance at the confidence level of 95%.

Panels A and B of Table 4-17 report the results of power tests for the daily and monthly data constructed from the AD timing measure under the TM alternative. Panel A shows that the daily timing tests result in positive and significant coefficients in most countries, except the timing coefficients of US. In contrast, the monthly timing tests obtain either statistically significant negative timing coefficients or statistically insignificant positive timing coefficients in most countries. Thus, the daily timing coefficients result in significantly positive timing coefficients much more often than the monthly timing coefficients for portfolio managers. For instance, with a $\gamma = 5$ (worst scenario), the daily estimates in the research sample (23 countries under study) obtain significantly positive coefficients about 65% of the time using the TM model, whereas the monthly estimates obtain significantly positive coefficients about 34% of the time. This ratio for other γs in the daily frequencies is higher than $\gamma = 5$, where the $\gamma = 7.5, 10, 15,$ and 20 obtain the ratios of 73%, 78%, 91%, and 91%, respectively. For the monthly frequencies, $\gamma = 7.5, 10, 15,$ and 20 obtain the same ratio of 34% that is much less than the daily data. The superiority of the daily data is much more than the monthly data even when alternative monthly data, as in Table 4-17, is applied to estimate the AD timing measures. Panel B of Table 4-17 shows this analysis with the alternative monthly data, where the estimates demonstrate higher statistical significance than the typical monthly data, but timing coefficients are still negative in most timing tests, implying again that the daily tests obtain much more significant timing coefficients relative to the monthly tests.

Table 4-17 also shows a positive relation between increase in γs and the power of timing activities. As γs (the timing frequencies) increase from 5 to 20, the relative power (the AD timing coefficient) of the daily tests increases. For example, when γs (the timing frequencies) for Australia increase from 5 to 20, the relative power (the AD timing coefficient) of the daily tests increases from 0.64 to 2.61 and their statistical significance increases from 3.89 to 12.23. In contrast, a combination of negative and positive relations can be seen for the monthly AD timing coefficients with respect to the fact that their statistical significant are much less than those reported for the daily data. A negative timing coefficient in Panel B can be due to negative estimate of β in the non-timing model of Eq. (3-64) that leads to a negative value in Eq. (3-63) and so a negative estimate in Eq. (3-19).

Table 4-17: Size and power analysis for the daily and monthly data constructed under the TM alternative

Countries	Panel A: the daily AD timing measure					Panel B: the monthly AD timing measure				
	γ=5	γ=7.5	γ=10	γ=15	γ=20	γ=5	γ=7.5	γ=10	γ=15	γ=20
Australia	0.64	0.97	1.29	1.95	2.61	11.90	11.98	12.05	12.15	12.19
	(3.89)	**(5.75)**	**(7.44)**	**(10.19)**	**(12.23)**	**(2.40)**	**(2.44)**	**(2.48)**	**(2.55)**	**(2.63)**
Austria	-1.05	0.66	1.05	1.19	2.27	-8.33	-9.02	-9.71	-11.05	-12.30
	(-5.04)	**(3.86)**	**(6.16)**	**(6.20)**	**(11.19)**	(-0.20)	(-0.21)	(-0.23)	(-0.27)	(-0.31)
Belgium	1.61	2.25	2.71	2.98	4.12	5.90	5.85	5.79	5.82	5.82
	(14.21)	**(19.09)**	**(21.65)**	**(19.38)**	**(23.69)**	**(7.70)**	**(7.27)**	**(6.68)**	**(5.74)**	**(5.74)**
Canada	-8.46	-8.63	-8.55	-7.63	-6.45	2.14	2.12	2.10	2.06	2.08
	(-4.99)	**(-6.09)**	**(-6.83)**	**(-7.03)**	**(-6.38)**	(0.47)	(0.45)	(0.43)	(0.39)	(0.37)
Denmark	8.65	13.96	19.25	29.68	40.08	1.04	0.80	0.91	1.17	1.46
	(5.10)	**(9.43)**	**(14.05)**	**(22.08)**	**(31.50)**	(1.28)	(0.87)	(0.96)	(1.19)	(1.45)
Finland	2.27	2.60	2.71	2.89	3.47	0.84	0.98	1.11	1.34	1.54
	(1.77)	**(2.14)**	**(2.12)**	**(2.53)**	**(3.40)**	(0.14)	(0.16)	(0.18)	(0.22)	(0.25)
France	5.40	10.12	14.94	24.72	34.71	23.55	23.40	23.10	22.10	20.64
	(4.28)	**(7.98)**	**(9.91)**	**(15.38)**	**(22.54)**	**(2.53)**	**(2.52)**	**(2.49)**	**(2.37)**	**(2.20)**
Germany	4.65	9.14	14.12	24.57	35.26	1.25	1.04	0.80	0.27	-0.19
	(6.56)	**(11.89)**	**(16.90)**	**(24.97)**	**(30.58)**	(0.44)	(0.35)	(0.27)	(0.09)	(-0.07)
Greece	-2.57	-1.09	0.17	1.82	2.89	1.37	1.45	1.55	1.78	2.06
	(-6.80)	**(-3.14)**	(0.52)	**(5.28)**	**(8.22)**	(0.36)	(0.36)	(0.36)	(0.39)	(0.45)
Hong Kong	5.55	10.25	15.23	25.35	35.66	5.04	5.23	5.40	5.75	6.10
	(5.54)	**(8.34)**	**(11.28)**	**(17.60)**	**(22.60)**	**(2.76)**	**(2.81)**	**(2.86)**	**(2.95)**	**(3.04)**
Ireland	6.92	12.14	17.43	28.04	38.68	3.09	2.88	2.73	2.67	2.89
	(4.37)	**(7.93)**	**(10.21)**	**(15.64)**	**(20.29)**	**(2.91)**	**(2.78)**	**(2.72)**	**(2.77)**	**(3.02)**
Italy	1.43	1.16	1.70	2.81	3.91	3.74	3.81	3.88	4.01	4.18
	(5.66)	**(4.60)**	**(6.89)**	**(11.73)**	**(15.88)**	**(2.33)**	**(2.23)**	**(2.14)**	**(2.02)**	**(2.04)**
Japan	4.46	9.15	14.15	24.48	34.76	4.59	4.41	4.23	4.33	4.03

	(9.50)	**(16.92)**	**(22.81)**	**(30.71)**	**(35.21)**	**(4.56)**	**(4.14)**	**(3.81)**	**(4.00)**		**(3.62)**
Netherlands	-1.96	-1.34	-0.74	0.50	1.54	-1.87	-1.72	-1.57	-1.27		-0.96
	(-8.03)	**(-5.57)**	**(-3.12)**	**(2.19)**	**(6.40)**	(-0.19)	(-0.17)	(-0.16)	(-0.13)		(-0.11)
New Zealand	-2.31	-1.65	0.84	1.46	2.09	-20.71	-20.66	-20.62	-20.53		-20.46
	(-5.32)	**(-4.32)**	**(2.54)**	**(4.59)**	**(6.58)**	(-0.49)	(-0.49)	(-0.49)	(-0.49)		(-0.49)
Norway	-1.60	-1.41	-1.10	1.63	1.72	-29.71	-29.65	-29.58	-29.45		-29.31
	(-4.87)	**(-4.56)**	**(-3.69)**	**(4.08)**	**(6.48)**	(-0.27)	(-0.27)	(-0.27)	(-0.27)		(-0.27)
Portugal	34.27	38.99	43.74	53.33	63.16	-45.06	-45.28	-45.51	-45.95		-46.38
	(20.50)	**(22.89)**	**(25.11)**	**(29.03)**	**(32.33)**	(-0.23)	(-0.23)	(-0.23)	(-0.24)		(-0.24)
Singapore	1.74	6.42	11.14	20.90	30.98	-7.58	-7.30	-7.04	-6.53		-6.08
	(3.25)	**(6.07)**	**(10.31)**	**(16.21)**	**(22.96)**	(-0.52)	(-0.50)	(-0.48)	(-0.45)		(-0.42)
Spain	0.53	0.63	0.86	1.85	2.93	12.57	12.68	12.80	13.05		13.31
	(2.00)	**(2.50)**	**(3.45)**	**(7.62)**	**(11.92)**	(0.20)	(0.20)	(0.20)	(0.21)		(0.22)
Sweden	0.93	1.48	2.13	3.39	4.57	3.43	4.32	5.23	7.12		9.15
	(3.80)	**(6.31)**	**(9.39)**	**(14.96)**	**(19.31)**	(1.06)	(1.33)	(1.60)	**(2.11)**		**(2.60)**
Switzerland	0.97	1.30	1.63	2.30	2.97	3.24	3.40	3.55	3.87		4.18
	(8.69)	**(11.29)**	**(13.41)**	**(16.30)**	**(17.92)**	(0.20)	(0.21)	(0.22)	(0.25)		(0.28)
U.K.	0.53	1.07	1.63	2.70	3.73	7.90	7.84	7.77	7.36		7.33
	(4.62)	**(9.59)**	**(14.20)**	**(21.06)**	**(25.37)**	**(2.24)**	**(2.11)**	**(2.00)**	(1.75)		(1.66)
U.S.	-5.16	-9.31	-13.34	-20.85	-27.64	43.56	43.52	43.48	43.41		43.34
	(-0.08)	(-0.17)	(-0.28)	(-0.56)	(-0.91)	(0.15)	(0.15)	(0.15)	(0.15)		(0.15)

Note: Panels A and B of this table report results of the AD timing coefficients at the daily and monthly frequencies, respectively. Panel A reports the power of the proposed timing tests by generating portfolio returns under alternative hypothesis of Treynor and Mazuy (1966) (TM) timing ability. To generate the daily returns under the TM alternative, this study firstly runs the following non-timing model for each county as:

$$R_{p,t} = \alpha_p + \beta_{MKT}R_{m,t} + \beta_{SMB}SMB_{p,t} + \beta_{HML}HML_{p,t} + \beta_{MOM}MOM_{p,t} + \varepsilon_{p,t}$$

where $R_{p,t}$ is the return on portfolio p for each county at day t, α_p is an indicator of selection ability for a portfolio manager. Other explanatory variables contain returns on the standard known risk factors of market excess return (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM) for portfolio p at day t.

Then, the beta and residual estimated from the non-timing model are subtracted to generate portfolio returns of each country under the TM alternative. Next, a time series of portfolio betas is constructed to each country as:

$\beta_{P,t:t+T} = \beta_P + \gamma \bar{r}_{m,t:t+T}$

where $\bar{r}_{m,t:t+T}$ is the mean daily market excess return in the AD form, $(A_{\rho-1} + (R_{mt} - R_{ft}))$, from day t until day $t: t + T$, and $t: t + T$ represents a portfolio manager's timing interval (one day, two days, one week, two weeks, or one month). R_{mt} is the return on market portfolio m at day t and $A_{\rho-1}$ denotes the loss average suffered from 0 to $\rho - 1$, where $\rho = 24$. It generates returns by setting γ equal to 5, 7.5, 10, 15, and 20. Finally, these alternative portfolio returns are used in the basic timing tests, Eq. (3-19), to estimate the alternative daily AD timing coefficients. Panel B also reports the results of monthly data, where this study follows the above steps for monthly data, except that it considers $\rho = 2$. These values result in mild to aggressive trading behavior. T-statistics place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Overall, these analyses highlight that the daily return frequency of the AD-based timing measures can increase the power of market timing in comparison with the monthly return frequency. These analyses also exhibit that portfolio managers may reflect more aggressive trading behaviour at the daily frequency rather than at the monthly frequency.

4.12.3 Controlling Checks for Different Lags

Eq. (3-14) and (3-15) of chapter 3 defined the ρ for the AD market timing measures with the lag length of 24 for the daily data, as in Glabadanidis (2014, 2017), and the lag length of 2 for monthly data. In this subsection, this study proceeds to change the ρs of the daily AD market timing measures consistent with Glabadanidis (2014, 2017) who used different lags of 6, 12, 36, 48, and 60 to control for his MA timing measures. For the AD measures at the monthly frequency, this study considers the ρs of 3, 4, 5, 6, and 7 for constructing the measures. To conduct this check, this study firstly constructs the AD-based measures using Eq. (3-14) and (3-15), which contain separately the lag lengths of 6, 12, 36, 48, and 60 for the daily frequency and the lag lengths of 3, 4, 5, 6, and 7 for the monthly frequency. Then, it runs Eq. (3-18) and (3-19) using these measures.

Table 4-18 reports the daily estimates of Eq. (3-19) for the proposed Henriksson and Merton (1981) (NHM) timing models, where ρ is calculated using different lags. The results are very close to our basic results in Table 4-9, where portfolio managers of twelve counties of Australia, Austria, Belgium, Denmark, France, Greece, Italy, Netherlands, Spain, Sweden, Switzerland, and U.K. exhibit significant positive evidence of market timing at the confidence level of 95%. Compared to the THM results, portfolio managers of most countries exhibit significant and positive timing skills using the NHM. There is a positive relation between the length of lags and the magnitude (economic significance) of the AD-based market timing measures in most countries, indicating an increasing trend from lag 6 to lag 60. It is obvious that more than the half of countries in the research sample exhibits positive and significant market timing skills of managers active in stock market of the countries. Similar to the basic results, the highest market timing skill for NHM is related to Sweden, while the lowest market timing skill is related to Ireland.

Table 4-18 also shows that the results of portfolio managers' selection abilities (alphas) are very close to the basic results in Table 4-9, where portfolio managers of the nineteen countries of Australia, Austria, Belgium, Canada, Denmark, Germany, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, U.K., and U.S. have positive and significant selection skills in the stock market of their countries. The portfolio managers of other countries possess either negative selection skills or statistically insignificant selection skills in their stock markets. The highest portfolio selection skill (α) is related to Portgual and the lowest portfolio selection skill (α) is related to Ireland.

Table 4-18: The daily results of NHM market timing models with different lags

Countries	Lag 6		Lag 12		Lag 36		Lag 48		Lag 60	
	α	NHM	α	NHM	A	NHM	α	NHM	α	NHM
Australia	0.022	0.061	0.023	0.062	0.023	0.078	0.021	0.097	0.021	0.098
	(2.40)	**(2.16)**	**(1.97)**	**(2.27)**	**(1.96)**	**(3.07)**	**(2.37)**	**(4.01)**	**(2.37)**	**(4.09)**
Austria	0.0062	0.074	0.0062	0.078	0.0062	0.082	0.0062	0.087	0.0061	0.096
	(3.95)	**(2.31)**	**(3.94)**	**(2.49)**	**(3.22)**	**(2.78)**	**(5.03)**	**(2.83)**	**(3.89)**	**(3.29)**
Belgium	0.0012	0.12	0.0012	0.12	0.0013	0.11	0.0013	0.10	0.0013	0.096
	(5.85)	**(5.73)**	**(5.85)**	**(5.43)**	**(5.86)**	**(5.06)**	**(5.91)**	**(4.75)**	**(5.97)**	**(4.55)**
Canada	0.007	-0.19	0.007	-0.21	0.007	-0.22	0.007	-0.22	0.007	-0.22
	(3.01)	(-0.64)	**(3.04)**	(-0.73)	**(3.01)**	(-0.73)	**(2.99)**	(-0.77)	**(2.55)**	(-0.67)
Denmark	0.0006	0.067	0.0006	0.064	0.0006	0.048	0.0006	0.052	0.0006	0.048
	(3.43)	**(2.63)**	**(3.44)**	**(2.53)**	**(3.58)**	**(2.04)**	**(3.52)**	**(2.26)**	**(3.55)**	**(2.14)**
Finland	0.034	0.30	0.034	0.29	0.034	0.25	0.034	0.24	0.034	0.22
	(1.15)	(1.53)	(1.15)	(1.55)	(1.15)	(1.43)	(1.15)	(1.39)	(1.15)	(1.31)
France	0.003	0.25	0.003	0.26	0.003	0.27	0.003	0.27	0.003	0.26
	(1.87)	**(10.35)**	(1.83)	**(11.01)**	(1.79)	**(11.48)**	(1.79)	**(11.15)**	(1.80)	**(10.92)**
Germany	0.0086	-0.02	0.0083	-0.07	0.0083	-0.011	0.0083	-0.18	0.0083	-0.18
	(10.95)	(-0.87)	**(9.53)**	(-1.20)	**(9.61)**	(-1.28)	**(9.57)**	(-1.31)	**(9.56)**	(-1.33)
Greece	0.0015	0.13	0.0015	0.14	0.0013	0.14	0.0013	0.14	0.0013	0.14
	(2.38)	**(1.98)**	**(2.30)**	**(2.12)**	(1.84)	**(2.08)**	(1.82)	**(2.11)**	(1.81)	**(2.17)**
Hong Kong	0.011	-0.091	0.011	-0.13	0.011	-0.11	0.011	-0.11	0.011	-0.10
	(6.15)	**(-2.09)**	**(6.18)**	**(-3.25)**	**(6.19)**	**(-2.85)**	**(6.19)**	**(-2.93)**	**(6.18)**	**(-2.83)**
Ireland	-0.0011	-0.15	-0.0011	-0.19	-0.001	-0.21	-0.009	-0.23	-0.0009	-0.25
	(-3.92)	**(-2.08)**	**(-3.74)**	**(-2.49)**	**(-3.54)**	**(-2.92)**	**(-3.36)**	**(-3.28)**	**(-3.24)**	**(-3.54)**
Italy	0.010	0.19	0.010	0.23	0.010	0.24	0.010	0.24	0.010	0.24
	(2.14)	**(5.09)**	**(2.11)**	**(6.28)**	**(2.10)**	**(7.07)**	**(2.10)**	**(7.21)**	**(2.10)**	**(7.30)**
Japan	0.0041	-0.12	0.0043	-0.14	0.0042	-0.12	0.0042	-0.16	0.0041	-0.17

	(2.75)	**(-4.10)**	**(2.87)**	**(-4.15)**	**(2.84)**	**(-4.12)**	**(2.80)**	**(-4.17)**	**(2.77)**	**(-4.18)**
Netherlands	0.011	0.051	0.011	0.051	0.011	0.082	0.011	0.083	0.011	0.084
	(13.29)	(1.30)	**(13.27)**	(1.32)	**(13.11)**	**(2.17)**	**(13.09)**	**(2.21)**	**(13.07)**	**(2.23)**
New Zealand	0.036	0.010	0.036	0.012	0.036	0.014	0.036	0.015	0.036	0.017
	(2.51)	(1.30)	**(2.52)**	(1.32)	**(2.52)**	(1.35)	**(2.52)**	(1.35)	**(2.52)**	(1.37)
Norway	0.025	0.04	0.025	0.026	0.025	0.054	0.025	0.056	0.025	0.052
	(2.81)	(1.04)	**(2.81)**	(0.68)	**(2.80)**	(1.45)	**(2.80)**	(1.53)	**(2.80)**	(1.42)
Portugal	0.071	0.42	0.071	0.46	0.071	0.45	0.071	0.44	0.071	0.44
	(2.10)	(0.87)	**(2.08)**	(0.99)	**(2.08)**	(0.96)	**(2.08)**	(0.93)	**(2.08)**	(0.94)
Singapore	0.011	0.01	0.011	0.012	0.011	0.03	0.011	0.04	0.011	0.05
	(2.84)	(1.09)	**(2.87)**	(1.10)	**(2.87)**	(1.14)	**(2.87)**	(1.14)	**(2.86)**	(1.15)
Spain	0.017	0.12	0.017	0.14	0.017	0.15	0.017	0.16	0.017	0.15
	(4.38)	**(3.15)**	**(4.36)**	**(3.70)**	**(4.35)**	**(4.17)**	**(4.34)**	**(4.35)**	**(4.34)**	**(4.33)**
Sweden	0.0029	0.28	0.0027	0.32	0.0027	0.33	0.0027	0.33	0.0027	0.33
	(2.52)	**(7.54)**	**(2.39)**	**(8.79)**	**(2.35)**	**(8.96)**	**(2.32)**	**(9.37)**	**(2.32)**	**(9.41)**
Switzerland	0.016	0.10	0.016	0.12	0.016	0.12	0.016	0.12	0.016	0.13
	(9.00)	**(6.08)**	**(8.97)**	**(7.41)**	**(8.95)**	**(8.09)**	**(8.94)**	**(8.33)**	**(8.94)**	**(8.45)**
U.K.	0.0041	0.072	0.0041	0.074	0.004	0.087	0.004	0.088	0.004	0.086
	(2.31)	**(3.93)**	**(2.31)**	**(4.03)**	**(2.28)**	**(4.85)**	**(2.28)**	**(4.93)**	**(2.28)**	**(4.88)**
U.S.	0.066	0.02	0.066	0.03	0.067	0.05	0.067	0.07	0.067	0.42
	(3.31)	(0.36)	**(3.25)**	(0.37)	**(3.28)**	(0.40)	**(3.28)**	(0.41)	**(3.31)**	(0.44)

Note: This table reports the daily results of market timing models using the proposed Henriksson and Merton (1981) (NHM) market timing measure constructed from the lag lengths (ρs) of 6, 12, 36, 48, and 60. It uses Eq. (3-19) presented in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. NHM is the Henriksson and Merton (1981) (NHM) market timing measure. T-statistics place in parentheses and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-19 reports daily estimates of the proposed Treynor and Mazuy (1966) (NTM) timing models using different lags. It shows that these results are very close to the basic results in Table 4-10, where portfolio managers of the fifteen countries exhibit significant positive evidence of market timing at the confidence level of 95%. Portfolio managers of most countries exhibit significant and positive timing skills using the NTM. Among the portfolios of these 23 countries, four countries of Finland, Greece, Portugal, and U.S. exhibit positive evidence of market timing, but not statistically significant. One country indicates statistically insignificant negative evidence of market timing. It is obvious that more than half of the countries in the research sample exhibits positive and significant market timing skills of managers active in stock market. The highest market timing skill is related to Singapore, while the lowest market timing skill is related to New Zealand.

Table 4-19 also represents the results of alphas estimated from the NTM timing models with different lags. Again, the results are similar to the results of portfolio managers' selection ability (alphas) in Table 4-10. For example, the estimated alphas show that all countries, except Austria, Finland, Ireland, and Sweden, exhibit positive and significant selection skills. The highest portfolio selection skill (α) is related to Portugal and the lowest portfolio selection skill (α) is related to Ireland.

Table 4-19: The daily results of NTM market timing models with different lags

Countries	Lag 6		Lag 12		Lag 36		Lag 48		Lag 60	
	α	NTM	α	NTM	A	NTM	α	NTM	α	NTM
Australia	0.036	7.92	0.036	8.29	0.036	8.28	0.036	8.11	0.036	8.00
	(6.28)	**(6.45)**	**(6.30)**	**(6.68)**	**(6.12)**	**(6.35)**	**(6.05)**	**(6.11)**	**(5.98)**	**(5.94)**
Austria	-0.0003	1.12	-0.0003	1.36	-0.0003	1.73	-0.0003	1.85	-0.0003	1.91
	(-0.60)	**(3.49)**	**(-2.17)**	**(4.18)**	**(-2.20)**	**(5.08)**	**(-2.23)**	**(5.31)**	**(-2.25)**	**(5.41)**
Belgium	0.0016	1.97	0.0016	2.21	0.0016	2.61	0.0016	2.66	0.0015	2.67
	(8.16)	**(11.46)**	**(8.26)**	**(12.95)**	**(8.08)**	**(14.26)**	**(7.99)**	**(14.47)**	**(7.92)**	**(14.57)**
Canada	0.0076	-3.08	0.0075	-3.04	0.0076	-2.90	0.0076	-2.91	0.0076	-2.92
	(5.01)	(-1.69)	**(4.99)**	(-1.78)	**(4.98)**	(-1.52)	**(4.99)**	(-1.47)	**(4.99)**	(-1.44)
Denmark	0.0007	0.12	0.0007	0.46	0.0007	0.86	0.0007	1.01	0.0007	1.09
	(4.81)	(0.86)	**(4.75)**	**(3.17)**	**(4.60)**	**(5.72)**	**(4.53)**	**(6.71)**	**(4.48)**	**(7.21)**
Finland	0.035	2.21	0.035	1.61	0.035	1.50	0.034	1.43	0.034	1.50
	(1.18)	(1.51)	(1.18)	(1.15)	(1.18)	(1.09)	(1.18)	(1.06)	(1.18)	(1.12)
France	0.0063	9.63	0.0063	9.99	0.0062	11.29	0.0062	11.48	0.0061	11.69
	(14.91)	**(11.22)**	**(14.92)**	**(11.53)**	**(14.66)**	**(12.43)**	**(14.56)**	**(12.43)**	**(14.47)**	**(14.45)**
Germany	0.0091	3.63	0.0091	3.92	0.0091	4.25	0.0091	4.30	0.0090	4.34
	(16.11)	**(4.37)**	**(16.13)**	**(4.63)**	**(16.04)**	**(5.19)**	**(15.99)**	**(5.39)**	**(15.95)**	**(5.52)**
Greece	0.0017	-0.27	0.0017	0.13	0.0016	0.53	0.0016	0.65	0.0016	0.73
	(2.14)	(-0.51)	**(2.13)**	(0.26)	**(2.11)**	(1.03)	**(2.09)**	(1.24)	**(2.09)**	(1.36)
Hong Kong	0.012	5.37	0.012	6.01	0.012	6.97	0.012	7.03	0.012	7.12
	(14.22)	**(9.50)**	**(14.25)**	**(10.55)**	**(14.01)**	**(11.66)**	**(14.90)**	**(11.56)**	**(14.80)**	**(11.53)**
Ireland	-0.0013	0.26	-0.0014	0.79	-0.0014	1.05	-0.0014	1.10	-0.0014	1.04
	(-6.41)	(1.26)	**(-6.47)**	**(3.34)**	**(-6.47)**	**(4.00)**	**(-6.47)**	**(4.09)**	**(-6.44)**	**(3.76)**
Italy	0.0083	1.90	0.0083	2.23	0.0083	2.75	0.0083	2.85	0.0083	2.85
	(7.19)	**(6.86)**	**(7.20)**	**(8.50)**	**(7.15)**	**(10.77)**	**(7.13)**	**(11.21)**	**(7.12)**	**(11.30)**
Japan	0.0068	1.42	0.0068	1.76	0.0068	1.62	0.0068	1.58	0.0068	1.53

	(3.74)	**(6.30)**	**(3.97)**	**(8.11)**	**(3.64)**	**(7.80)**	**(3.51)**	**(7.69)**	**(3.40)**	**(7.47)**
Netherlands	0.012	-1.11	0.012	-0.61	0.012	-0.13	0.012	-0.018	0.012	0.035
	(6.40)	**(-3.35)**	**(6.39)**	(-1.91)	**(6.38)**	(-0.44)	**(6.38)**	(-0.06)	**(6.37)**	(0.11)
New Zealand	0.036	-1.49	0.036	-1.05	0.036	-0.84	0.036	-0.81	0.036	-0.79
	(2.48)	**(-3.38)**	**(2.49)**	**(-2.47)**	**(2.49)**	**(-1.99)**	**(2.49)**	(-1.92)	**(2.49)**	(-1.88)
Norway	0.025	-1.16	0.025	-0.93	0.024	-0.82	0.025	-0.72	0.025	-0.68
	(2.82)	**(-3.86)**	**(2.82)**	**(-3.23)**	(1.71)	**(-2.58)**	(1.71)	**(-2.26)**	(1.71)	**(-2.15)**
Portugal	0.072	1.52	0.072	1.96	0.072	2.58	0.072	2.62	0.072	2.78
	(1.97)	(0.40)	**(1.98)**	(0.53)	**(1.97)**	(0.70)	**(1.97)**	(0.70)	**(1.97)**	(0.73)
Singapore	0.014	13.73	0.014	14.64	0.014	16.10	0.014	16.27	0.014	16.40
	(4.96)	**(4.19)**	**(4.06)**	**(4.32)**	**(4.70)**	**(4.34)**	**(4.51)**	**(4.19)**	**(4.34)**	**(4.01)**
Spain	0.018	0.50	0.018	0.94	0.018	1.18	0.018	1.27	0.018	1.31
	(4.44)	(1.76)	**(4.44)**	**(3.24)**	**(4.44)**	**(4.16)**	**(4.44)**	**(4.51)**	**(4.43)**	**(4.65)**
Sweden	0.00014	1.36	0.00014	1.47	0.00013	1.65	0.00013	1.71	0.00012	1.75
	(0.85)	**(4.12)**	(0.88)	**(4.39)**	(0.82)	**(4.69)**	(0.79)	**(4.78)**	(0.75)	**(4.82)**
Switzerland	0.017	-0.09	0.017	0.33	0.017	0.78	0.017	0.90	0.017	0.97
	(9.20)	(-0.68)	**(9.20)**	**(2.82)**	**(9.18)**	**(7.16)**	**(9.18)**	**(8.38)**	**(9.17)**	**(9.13)**
U.K.	0.0039	0.69	0.0039	0.83	0.0038	1.10	0.0038	1.13	0.0038	1.13
	(6.50)	**(6.13)**	**(6.51)**	**(7.65)**	**(6.48)**	**(10.12)**	**(6.46)**	**(10.43)**	**(6.45)**	**(10.52)**
U.S.	0.064	5.87	0.064	5.48	0.062	4.96	0.062	4.75	0.062	4.77
	(4.13)	(0.13)	**(4.12)**	(0.13)	**(3.32)**	(0.12)	**(3.31)**	(0.12)	**(3.30)**	(0.12)

Note: This table reports the daily results of market timing models using the proposed Treynor and Mazuy (1966) (NTM) market timing measure constructed from the lag lengths (ρs) of 6, 12, 36, 48, and 60. It uses Eq. (3-18) presented in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. NTM is the Treynor and Mazuy (1966) (NTM) market timing measure. T-statistics place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-20 exhibits the monthly estimates of the proposed Henriksson and Merton (1981) (NHM) timing models using the lag lengths of 3, 4, 5, 6, and 7. It shows that portfolio managers of a few countries, such as Denmark, Ireland, Italy, Switzerland and Sweden, exhibit significant positive evidence of market timing, but the timing coefficients are not significant at all lags. When moving from lag 3 to lag 7, the point estimates and statistical significant of timing coefficients increase in most countries, implying a positive relation between the number of lags and the economic and statistical significance of the NHM timing coefficients. Compared to the daily results of timing coefficients estimated using different lags in Table 4-18, there are weaker timing coefficients in the monthly estimates than in the daily estimates.

Table 4-20 also represents the results of alphas estimated from the NHM timing models with different lags. The estimated alphas show that none of portfolio managers has significant and positive selection skills in stock market. These findings are identical to the basic results reported in Table 4-13.

Table 4-20: The monthly results of NHM market timing models with different lags

Countries	Lag 3		Lag 4		Lag 5		Lag 6		Lag 7	
	α	NHM	α	NHM	A	NHM	α	NHM	α	NHM
Australia	0.39	0.89	0.40	-0.12	0.40	-0.69	0.40	-0.87	0.40	-0.86
	(0.85)	(0.47)	(0.87)	(-0.06)	(0.89)	(-0.43)	(0.89)	(-0.55)	(0.89)	(-0.56)
Austria	0.21	-0.83	0.20	-0.69	0.19	1.02	0.19	1.11	0.18	1.16
	(0.62)	(-0.08)	(0.61)	(-0.06)	(0.56)	(0.11)	(0.55)	(0.12)	(0.55)	(0.13)
Belgium	-0.067	0.41	-0.067	0.41	-0.068	0.47	-0.067	0.43	-0.067	0.39
	(-0.72)	(1.33)	(-0.72)	(1.30)	(-0.73)	(1.56)	(-0.73)	(1.45)	(-0.72)	(1.37)
Canada	-0.023	2.24	-0.012	1.24	-0.005	0.60	-0.007	0.80	-0.004	0.46
	(-1.07)	(1.73)	(-0.58)	(0.95)	(-0.27)	(0.49)	(-0.37)	(0.67)	(-0.19)	(0.40)
Denmark	-0.0023	0.25	-0.0063	0.61	-0.010	1.02	-0.0094	0.91	-0.0068	0.68
	(-0.44)	(0.80)	(-1.19)	(1.93)	**(-2.09)**	**(3.46)**	(-1.85)	**(3.17)**	(-1.35)	**(2.43)**
Finland	-0.094	6.45	-0.019	-0.18	0.047	-6.02	0.046	-5.89	0.040	-5.45
	(-2.28)	**(2.60)**	(-0.47)	(-0.07)	(1.13)	**(-2.49)**	(1.11)	**(-2.51)**	(0.99)	**(-2.37)**
France	-0.05	3.12	-0.042	2.24	-0.039	2.01	-0.038	1.90	-0.037	1.79
	(-0.11)	(0.75)	(-0.08)	(0.45)	(-0.07)	(0.44)	(-0.07)	(0.43)	(-0.07)	(0.41)
Germany	0.001	-0.46	0.006	-1.00	-0.002	-0.07	0.0001	-0.36	0.0018	-0.54
	(0.008)	(-0.55)	(0.05)	(-1.28)	(-0.02)	(-0.08)	(0.00)	(-0.41)	(0.014)	(-0.64)
Greece	-0.03	-0.03	-0.03	-0.27	-0.03	0.06	-0.03	0.18	-0.03	0.16
	(-0.33)	(-0.03)	(-0.30)	(-0.25)	(-0.33)	(0.06)	(-0.34)	(0.16)	(-0.34)	(0.15)
Hong Kong	0.19	0.42	0.19	0.35	0.20	0.18	0.20	0.23	0.20	0.18
	(1.73)	(0.59)	(1.74)	(0.46)	(1.75)	(0.25)	(1.75)	(0.33)	(1.75)	(0.27)
Ireland	-0.19	0.26	-0.19	0.72	-0.20	1.12	-0.20	1.14	-0.19	1.15
	(-2.29)	(0.99)	**(-2.33)**	**(2.26)**	**(-2.35)**	**(3.48)**	**(-2.36)**	**(3.53)**	**(-2.37)**	**(3.57)**
Italy	-0.006	0.65	-0.009	0.88	-0.011	1.13	-0.015	1.47	-0.014	1.40
	(-0.69)	(1.20)	(-1.00)	(1.62)	(-1.33)	**(2.21)**	(-1.77)	**(2.94)**	(-1.68)	**(2.86)**
Japan	-0.0017	-0.31	-0.0014	-0.32	-0.0041	-0.066	-0.0036	-0.10	-0.0015	-0.28

	(-0.26)	(-0.77)	(-0.21)	(-0.77)	(-0.61)	(-0.17)	(-0.55)	(-0.27)	(-0.23)	(-0.76)
Netherlands	-0.0052	1.82	-0.013	2.46	-0.014	2.54	-0.01	2.13	-0.003	1.55
	(-0.19)	(1.12)	(-0.49)	(1.52)	(-0.56)	(1.67)	(-0.38)	(1.43)	(-0.12)	(1.07)
New Zealand	-0.031	1.60	-0.11	8.98	-0.11	8.82	-0.098	7.39	-0.08	6.23
	(-0.24)	(0.20)	(-0.89)	(1.15)	(-0.89)	(1.20)	(-0.77)	(1.03)	(-0.66)	(0.88)
Norway	-0.08	8.32	-0.18	16.88	-0.25	22.12	-0.26	22.81	-0.32	28.64
	(-0.37)	(0.59)	(-0.79)	(1.19)	(-1.08)	(1.67)	(-1.13)	(1.75)	(-1.41)	**(2.22)**
Portugal	5.20	6.15	5.05	19.82	5.10	15.56	5.09	16.23	5.11	14.40
	(1.49)	(0.16)	(1.42)	(0.50)	(1.42)	(0.40)	(1.42)	(0.43)	(1.43)	(0.38)
Singapore	0.39	4.14	0.43	0.68	0.45	-1.95	0.46	-2.25	0.46	-2.27
	(0.33)	(0.42)	(0.32)	(0.06)	(0.32)	(-0.18)	(0.32)	(-0.21)	(0.32)	(-0.22)
Spain	0.44	5.26	0.43	6.01	0.43	5.47	0.43	5.50	0.44	4.81
	(0.29)	(0.34)	(0.29)	(0.41)	(0.28)	(0.35)	(0.28)	(0.36)	(0.28)	(0.30)
Sweden	-0.015	1.59	-0.018	1.83	-0.022	2.22	-0.02	2.05	-0.017	1.77
	(-0.85)	(1.48)	(-1.01)	(1.69)	(-1.29)	**(2.19)**	(-1.19)	**(2.07)**	(-1.01)	(1.83)
Switzerland	0.061	-4.34	-0.02	3.25	-0.10	9.99	-0.089	8.77	-0.07	7.41
	(1.38)	(-1.63)	(0.56)	(1.22)	**(-2.28)**	**(3.83)**	**(-2.00)**	**(3.48)**	(-1.67)	**(3.02)**
UK	0.023	1.20	0.024	1.07	0.027	0.83	0.028	0.73	0.028	0.71
	(0.17)	(0.99)	(0.17)	(0.84)	(0.19)	(0.61)	(0.20)	(0.54)	(0.20)	(0.53)
US	2.21	22.73	2.23	20.68	2.23	20.88	2.20	23.68	2.21	23.37
	(0.41)	(0.27)	(0.41)	(0.23)	(0.41)	(0.25)	(0.41)	(0.29)	(0.41)	(0.30)

Note: This table reports the monthly results of market timing models using the proposed Henriksson and Merton (1981) (NHM) market timing measure constructed from the lag lengths (ρs) of 3, 4, 5, 6, and 7. It uses Eq. (3-19) presented in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. NHM is the Henriksson and Merton (1981) (NHM) market timing measure. T-statistics place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Table 4-21 presents the monthly estimates of the proposed Treynor and Mazuy (1966) (NTM) timing models using the lag lengths of 3, 4, 5, 6, and 7. It shows that portfolio managers of Australia, Belgium, France, Hong Kong, Ireland, Italy, Japan, Singapore, and U.K. exhibit significant positive evidence of market timing. Compared to the monthly estimates of the NHM timing coefficients in Table 4-20, there are more evidence of market timing in the NTM timing coefficients. When moving from lag 3 to lag 7, there is almost a significant positive relation between the number of lags and the economic and statistical significance of timing coefficients. Compared to the daily results of the NTM timing coefficients estimated using different lags in Table 4-19, there are weaker timing coefficients in the monthly estimates than in the daily estimates.

Table 4-21 also represents the results of alphas estimated from the NTM timing models with different lags. None of the portfolio managers exhibits significant and positive selection skills in stock market.

Table 4-21: The monthly results of NTM market timing models with different lags

Countries	Lag 3		Lag 4		Lag 5		Lag 6		Lag 7	
	α	NTM	α	NTM	A	NTM	α	NTM	α	NTM
Australia	0.38	8.67	0.37	10.24	0.37	14.58	0.37	17.81	0.37	17.06
	(0.81)	**(2.70)**	(0.80)	**(2.41)**	(0.82)	**(4.13)**	(0.81)	**(5.73)**	(0.82)	**(4.58)**
Austria	0.21	-3.52	0.22	-7.57	0.22	-8.17	0.21	-6.17	0.21	-6.70
	(0.51)	(-0.12)	(0.53)	(-0.20)	(0.54)	(-0.25)	(0.53)	(-0.20)	(0.53)	(-0.20)
Belgium	-0.07	4.56	-0.07	5.54	-0.07	6.00	-0.07	6.53	-0.07	6.52
	(-0.75)	**(12.29)**	(-0.77)	**(10.55)**	(-0.79)	**(11.61)**	(-0.82)	**(11.97)**	(-0.82)	**(10.98)**
Canada	0.06	6.09	0.06	4.66	0.06	4.97	0.06	5.01	0.06	4.28
	(0.32)	**(2.45)**	(0.34)	(1.31)	(0.34)	(1.36)	(0.34)	(1.31)	(0.35)	(1.06)
Denmark	-0.13	0.91	-0.13	0.96	-0.13	1.03	-0.13	0.81	-0.13	1.01
	(-1.42)	**(1.97)**	(-1.43)	(1.62)	(-1.43)	(1.80)	(-1.43)	(1.38)	(-1.43)	(1.57)
Finland	0.55	1.19	0.56	-1.49	0.56	0.52	0.55	2.10	0.55	1.81
	(1.95)	(0.26)	(1.93)	(-0.23)	**(1.97)**	(0.10)	(1.96)	(0.42)	(1.96)	(0.33)
France	-0.08	24.79	-0.08	25.38	-0.07	21.31	-0.08	24.28	-0.07	21.36
	(-0.26)	**(4.73)**	(-0.25)	**(3.33)**	(-0.19)	**(1.99)**	(-0.23)	**(2.36)**	(-0.19)	(1.95)
Germany	-0.009	3.42	-0.01	4.87	-0.01	3.78	-0.009	3.51	-0.008	3.12
	(-0.03)	**(2.63)**	(-0.05)	**(2.48)**	(-0.04)	(1.63)	(-0.03)	(1.62)	(-0.03)	(1.31)
Greece	-0.04	1.39	-0.03	0.73	-0.04	1.02	-0.04	1.10	-0.04	1.25
	(-0.36)	(0.61)	(-0.35)	(0.25)	(-0.35)	(0.37)	(-0.35)	(0.37)	(-0.36)	(0.39)
Hong Kong	0.19	4.35	0.19	6.08	0.19	6.89	0.19	7.52	0.19	7.62
	(1.67)	**(2.92)**	(1.26)	**(3.62)**	(1.24)	**(4.56)**	(1.23)	**(4.76)**	(1.23)	**(4.67)**
Ireland	-0.19	0.75	-0.19	1.73	-0.19	2.66	-0.19	2.76	-0.19	3.05
	(-2.31)	(1.44)	**(-2.34)**	**(2.44)**	**(-2.36)**	**(3.54)**	**(-2.36)**	**(3.53)**	**(-2.36)**	**(3.56)**
Italy	0.029	3.04	0.029	2.74	0.029	3.12	0.028	3.73	0.029	3.84
	(0.21)	**(3.02)**	(0.21)	**(2.19)**	(0.21)	**(2.70)**	(0.20)	**(3.06)**	(0.20)	**(2.93)**
Japan	-0.04	3.73	-0.04	4.82	-0.04	4.73	-0.04	4.90	-0.04	5.13

	(-0.25)	**(7.40)**	(-0.26)	**(7.18)**	(-0.25)	**(6.24)**	(-0.26)	**(6.42)**	(-0.26)	**(6.18)**
Netherlands	0.26 (0.56)	0.08 (0.01)	0.26 (0.57)	-0.98 (-0.11)	0.26 (0.57)	-1.17 (-0.13)	0.26 (0.56)	-1.03 (-0.12)	0.26 (0.57)	-1.59 (-0.17)
New Zealand	1.40 (1.23)	12.34 (0.60)	1.39 (1.23)	16.68 (0.60)	1.39 (1.26)	15.93 (0.55)	1.37 (1.23)	23.09 (0.82)	1.38 (1.24)	21.96 (0.70)
Norway	1.26 (0.39)	-10.77 (-0.08)	1.27 (0.40)	-16.82 (-0.13)	1.28 (0.41)	-21.31 (-0.18)	1.29 (0.41)	-24.47 (-0.21)	1.30 (0.41)	-26.58 (-0.23)
Portugal	5.37 (1.57)	-40.41 (-0.17)	5.42 (1.58)	-58.90 (-0.23)	5.38 (1.57)	-46.06 (-0.19)	5.39 (1.57)	-49.34 (-0.21)	5.34 (1.56)	-33.09 (-0.15)
Singapore	0.16 (0.27)	102.54 **(7.77)**	0.21 (0.28)	84.62 **(6.42)**	0.36 (0.31)	26.63 **(2.22)**	0.36 (0.21)	30.50 **(2.03)**	0.38 (0.21)	23.34 (1.50)
Spain	0.48 (0.31)	4.54 (0.09)	0.47 (0.30)	7.33 (0.16)	0.47 (0.30)	7.69 (0.15)	0.47 (0.30)	6.73 (0.12)	0.47 (0.30)	9.07 (0.15)
Sweden	-0.11 (-0.44)	0.79 (0.16)	-0.11 (-0.45)	1.53 (0.22)	-0.11 (-0.44)	1.32 (0.19)	-0.11 (-0.44)	1.00 (0.14)	-0.10 (-0.44)	0.75 (0.10)
Switzerland	0.55 (0.66)	3.09 (0.27)	0.55 (0.66)	3.00 (0.26)	0.55 (0.66)	3.06 (0.24)	0.55 (0.66)	3.51 (0.30)	0.55 (0.66)	3.46 (0.28)
U.K.	0.02 (0.16)	5.01 **(2.70)**	0.02 (0.14)	6.12 **(2.16)**	0.02 (0.15)	5.86 **(2.16)**	0.017 (0.13)	7.08 **(2.43)**	0.018 (0.13)	7.12 **(2.27)**
U.S.	2.29 (0.42)	50.45 (0.20)	2.33 (0.43)	43.27 (0.17)	2.33 (0.43)	43.60 (0.20)	2.34 (0.43)	41.83 (0.17)	2.32 (0.43)	50.45 (0.20)

Note: This table reports the monthly results of market timing models using the proposed Treynor and Mazuy (1966) (NTM) market timing measure constructed from the lag lengths (ρs) of 3, 4, 5, 6, and 7. It uses Eq. (3-18) presented in the subsection (3.5) of Chapter 3 for estimating the AD-based timing measure. α is an indicator of selection ability for a portfolio manager. NTM is the Treynor and Mazuy (1966) (NTM) market timing measure. T-statistics place in parentheses, and the bolded values denote significance at the confidence level of 95%. The sample contains the data of 3100 firms from 1 Jan 1988 through 31 June 2016.

Overall, the basic results remain unchanged when using the length of different lags in the AD-based timing measures.

4.13 The Test of Research Hypotheses

This section reports the results of research hypothesis tests based on the results of portfolio managers' selection and market timing estimates. Using the above estimates, this study tests the research hypotheses by one sample t-test statistic and two-tailed sample t-test statistic. Table 4-22 reports the results of these tests. The first column represents the number of research hypotheses as defined in chapter 3. The second column represents the number of test statistic equations as defined in chapter 3. The third and fourth columns represent the test statistics and the critical values of those tests, respectively. The last two columns present a decision and its relevant interpretation.

The one sample t-test statistic helps us to understand whether there is statistically positive evidence of portfolio managers' market timing and selection abilities in the research sample. If so, the null hypothesis of the test should be rejected to prove a mean of market timing and selection abilities larger than zero for portfolio managers in the sample. If the absolute value of the test statistic is larger than the critical value, then the null hypothesis of the one sample t-test statistic can be rejected. The rejection of the null hypothesis thus proves the existence of positive market timing and selection evidence for portfolio managers. Using this statistic, this study tests the research hypotheses 1 to 8.

For the research hypothesis 1, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (3.206) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the one sample t-test statistic can be rejected. This result proves the first research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency is larger than zero. The existence of positive evidence of portfolio managers' market timing skills answers to the first research question, and covers the first main research objective.

For the research hypothesis 2, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the HM form at the daily frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' AD-based timing skills in the HM form at the daily frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (2.201) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the second research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the HM form at the daily frequency is larger than zero. The existence of positive evidence of portfolio managers' market timing skills answers to the second research question, and covers the first main research objective.

For the research hypothesis 3, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (2.48) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the third research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is larger than zero. The existence of positive evidence of portfolio managers' market timing skills answers to the third research question, and covers the first main research objective.

For the research hypothesis 4, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (2.72) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the fourth research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is larger than zero. The existence of positive evidence of portfolio managers' market timing skills answers to the fourth research question, and covers the first main research objective.

For the research hypothesis 5, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' selection skills estimated from the

AD-based timing models in the TM form at the daily frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the TM form at the daily frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (4.068) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the fifth research hypothesis, indicating that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the TM form at the daily frequency is larger than zero. The existence of positive evidence of portfolio managers' selection skills also answers to the fifth research question. Thus, the results of the fifth research hypothesis and question cover the third research sub-objective and the first main research objective.

For the research hypothesis 6, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the daily frequency is smaller or equal to zero. The alternative research hypothesis is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the daily frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (3.965) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the one sample t-test statistic can be rejected. This result proves the sixth research hypothesis, indicating that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the daily frequency is larger than zero. The existence of positive evidence of portfolio managers' selection skills also answers to the sixth research question. Thus, the results of the sixth research hypothesis and question cover the third research sub-objective and the first main research objective.

For the research hypothesis 7, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the TM form at the monthly frequency is smaller or equal to zero. The alternative hypothesis is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the TM form at the monthly frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (2.27) is larger than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the seventh research hypothesis, indicating that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the TM form at the monthly frequency is larger than zero. The existence of positive evidence of portfolio managers' selection skills also answers to the seventh research question. Thus, the results of the seventh research hypothesis and question cover the third research sub-objective and the first main research objective.

For the research hypothesis 8, the null hypothesis of the one sample t-test statistic is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the monthly frequency is smaller or equal to zero. The alternative hypothesis is that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the monthly frequency is larger than zero. Table 4-22 shows that the absolute value of the test statistic (1.532) is less than the critical value (1.717), where the free degree is 22 (23-1), then the null hypothesis of the one sample t-test statistic cannot be rejected. This result does not prove the eighth research hypothesis, indicating that the mean of portfolio managers' selection skills estimated from the AD-based timing models in the HM form at the monthly frequency is less than zero. This analysis also answers to the eighth research question. Thus, the results of the eighth research hypothesis and question cover the third research sub-objective and the first main research objective.

The two-tailed sample t-test statistic helps us to compare the mean of two samples. In the research hypotheses 9 and 10, this test helps us to compare the AD-based timing measures with the traditional timing measures. In the research hypotheses 11 and 12, this test helps us to compare the AD-based timing measures at the daily frequency with the AD-based timing measures at the monthly frequency. If the absolute value of the test statistic is larger than the critical value, then the null hypothesis of the two-tailed sample t-test statistic can be rejected. Using this statistic, this study tests the research hypotheses 9 to 12.

For the research hypothesis 9, the null hypothesis of the two-tailed sample t-test statistic is that the mean of portfolio managers' traditional TM timing skills is equal to the mean of portfolio managers' AD-based timing skills in the TM form. The alternative hypothesis is that the mean of portfolio managers' traditional TM timing skills is less than the mean of portfolio managers' AD-based timing skills in the TM form. Table 4-22 shows that the absolute value of the test statistic (-3.420) is greater than the critical value (2.074), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the ninth research hypothesis, indicating that the mean of portfolio managers' traditional TM timing skills is less than the mean of portfolio managers' AD-based timing skills in the TM form. This implies that there is more positive timing evidence in the AD-based timing measures in the TM form relative to the traditional timing measures, indicating better prediction power of the AD timing measure in the TM form than those of the traditional TM timing measure. This analysis also answers to the ninth research question in which the mean of portfolio managers' AD-based timing skills in the TM form is larger than the mean of portfolio managers' traditional TM timing skills. Thus, the results of the ninth research hypothesis and question cover the first research sub-objective and the first main research objective.

For the research hypothesis 10, the null hypothesis of the two-tailed sample t-test statistic is that the mean of portfolio managers' traditional HM timing skills is equal to the mean of portfolio managers' AD-based timing skills in the HM form. The alternative hypothesis is that the mean of portfolio managers' traditional HM timing skills is less than the mean of portfolio managers' AD-based timing skills in the HM form. Table 4-22 shows that the absolute value of the test statistic (-3.120) is greater than the critical value (2.074), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the tenth research hypothesis, indicating that the mean of portfolio managers' traditional HM timing skills is less than the mean of portfolio managers' AD-based timing skills in the HM form. This implies that there is more positive timing evidence in the AD-based timing measures in the HM form relative to the traditional timing measures, indicating better prediction power of the AD timing measure in the HM form than those of the traditional HM timing measure. This analysis also answers to the tenth research question. Thus, the results of the tenth research hypothesis and question cover the second research sub-objective and the first main research objective.

For the research hypothesis 11, the null hypothesis of the two-tailed sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is equal to the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency. The alternative hypothesis is that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is less than the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency. Table 4-22 shows that the absolute value of the test statistic (-2.20) is greater than the critical value (2.074), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the eleventh research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the TM form at the monthly frequency is less than the mean of portfolio managers' AD-based timing skills in the TM form at the daily frequency. This implies that there is more positive timing evidence in the daily AD-based timing measures in the TM form relative to the monthly AD-based timing measures in the TM form, indicating better prediction power of the daily AD-based timing measure in the TM form than those of the monthly AD-based timing measure in the TM form. This analysis also answers to the eleventh research question. Thus, the results of the eleventh research hypothesis and question cover the fourth research sub-objective and the second main research objective.

For the research hypothesis 12, the null hypothesis of the two-tailed sample t-test statistic is that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is equal to the mean of portfolio managers' AD-based timing skills in the HM form at the daily frequency. The alternative research hypothesis is that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is less than the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency. Table 4-22 shows that the absolute value of the test statistic (2.684) is greater than the critical value (2.074), where the free degree is 22 (23-1), then the null hypothesis of the statistic can be rejected. This result proves the twelfth research hypothesis, indicating that the mean of portfolio managers' AD-based timing skills in the HM form at the monthly frequency is less than the mean of portfolio managers' AD-based timing skills in the HM form at the daily frequency. This implies that there is more positive timing evidence in the daily AD-based timing measures in the HM form rather than the monthly AD-based timing measures in the HM form, indicating better prediction power of the daily AD-based timing measure in the HM form than those of the monthly AD-based timing measure in the HM form. This analysis also answers to the twelfth research question. Thus, the results of the twelfth research hypothesis and question cover the fifth research sub-objective and the second main research objective.

Table 4-22: The results of research hypothesis tests

Hypothesis	Equation number	Test statistic	Critical value	Decision	Interpretation
1	3-56	3.206	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant timing skills using the daily AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements.
2	3-56	2.201	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant timing skills using the daily AD timing measures in the Henriksson and Merton (1981) form to predict the market movements.
3	3-56	2.480	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant timing skills using the monthly AD timing measures in the Treynor and Mazuy (1966) form to predict the market movements.
4	3-56	2.720	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant timing skills using the monthly AD timing measures in the Henriksson and Merton (1981) form to predict the market movements.
5	3-56	4.068	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant selection skills using the daily AD timing models in the Treynor and Mazuy (1966) form to select proper portfolios over the research period.
6	3-56	3.965	1.717	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that portfolio managers have significant selection skills using the daily AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period.
7	3-56	2.27	1.717	The rejection	The alternative hypothesis is accepted, proving that portfolio managers have significant selection skills using the monthly AD timing models in

				of null hypothesis.	the Treynor and Mazuy (1966) form to select proper portfolios over the research period.
8	3-56	1.532	1.717	The null hypothesis is not rejected.	The alternative hypothesis is not accepted, proving that portfolio managers do not have significant selection skills using the monthly AD timing models in the Henriksson and Merton (1981) form to select proper portfolios over the research period.
9	3-53	-3.420	2.074	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that the prediction power of the AD timing measure in the Treynor and Mazuy (1966) form is better than those of the traditional Treynor and Mazuy (1966) timing measure.
10	3-53	-3.120	2.074	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that the prediction power of the AD timing measure in the Henriksson and Merton (1981) form is better than those of the traditional Henriksson and Merton (1981) timing measure.
11	3-53	-2.22	2.074	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that the daily performance of the AD timing measures in the Treynor and Mazuy (1966) form is better than the monthly performance.
12	3-53	2.684	2.074	The rejection of null hypothesis.	The alternative hypothesis is accepted, proving that the daily performance of the AD timing measures in the Henriksson and Merton (1981) form is better than the monthly performance.

Note: This table reports the results of research hypothesis tests. The first column presents the research hypotheses as defined in Chapter 3. The second column presents the type of test statistics, where Eq. (3-53) denotes a two-tailed sample t-test statistic and Eq. (3-56) denotes a one sample t-test statistic. The third column represents test statistic, where this statistic for hypotheses 1 to 8 is Eq. (3-56) and for hypotheses 9 to 12 is Eq. (3-53). The fourth column is the critical value of t-distribution with the freedom degree of $n - 1$, where $n = 23$ (number of the countries under study). For the hypotheses 1 and 2, μ_2 defined in Eq. (3-56) is the mean of timing skills of the daily AD-based timing measures. For the hypotheses 3 and 4, μ_2 defined in Eq. (3-56) is the mean of timing skills of the monthly AD-based timing measures. For the hypotheses 5 and 6, μ_2 defined in Eq. (3-56) is the mean of selection skills of the daily AD-based timing models. For the hypotheses 7 and 8, μ_2 defined in Eq. (3-56) is the mean of selection skills of the monthly AD-based timing models. For the hypothesis 9, μ_1 defined in Eq. (3-53) is the mean of traditional Treynor and Mazuy (1966) timing skill and μ_2 defined in Eq. (3-53) is the mean of the AD-based timing skill in the Treynor and Mazuy (1966) form. For the hypothesis 10, μ_1 defined in Eq. (3-53) is the mean of traditional Henriksson and Merton (1981) timing skill and μ_2 defined in Eq. (3-53) is the mean of the AD-based timing skill in the Henriksson and Merton (1981) form. For the hypothesis 11, μ_1 defined in Eq. (3-53) is the mean of the monthly AD timing measures in the Henriksson and Merton (1981) form, and μ_2 defined in Eq. (3-53) is the mean of the daily AD timing measures in the Henriksson and Merton (1981) form. For the hypothesis 12, μ_1 defined in Eq. (3-53) is the mean of the monthly AD timing measures in the Treynor and Mazuy (1966) form, and μ_2 defined in Eq. (3-53) is the mean of the daily AD timing measures in the Treynor and Mazuy (1966) form.

4.14 Discussion

Theoretical perspective of a portfolio manager's performance evaluation is appealing because it causes debates on the Efficient Market Hypothesis (Prather and Middleton, 2006). Accurate predictions are very important in the economic and financial analyses (Chou et al., 2011). The predictive skill of an occurrence, e.g., whether returns on a portfolio in a time period will go up relative to Treasury bill rates in the next period, would be a crucial issue in the asset allocation of a portfolio manager. This skill (referred to as a portfolio manager's predictability) assesses a portfolio manager's performance with respect to his skill in forecasting the market movements.

More specifically, if a portfolio manager has a skill to select an efficient portfolio, the intercepts of the timing models will be positive. Thus, the passive strategies, which is also defined as random buy and hold switching strategies, are expected to obtain a zero intercept. In contrast, if the manager is not forecasting asset prices, the passive strategies (random buy and hold switching strategies) will be negative. Such a result may cause a remarkable increase in expenses due to unsuccessful forecasting exercises. On the other hand, the market timing is defined as the forecast of future realization of the market portfolio. A market timer attempts to capitalize on expectation that he may possess about the behavior of the market returns in the next period. If the portfolio manager believes that he has skill to forecast market portfolio returns, he will adjust the risk levels of his portfolio in the prediction of market movements. If the manager has a successful forecast, he will obtain abnormal returns relative to a proper benchmark. For instance, if a manager correctly perceives a high probability of the rise of the market returns in the next period, he will increase his portfolio return by increasing its risk. In contrast, if return on the market portfolio is expected to reduce in next period, he will decrease the portfolio losses by decreasing the risk levels of his portfolio. Thus, a portfolio manager can actually adjust the risk levels of his portfolio by varying the mixture of the composing stocks of his portfolio, e.g., the stocks versus money market securities, and/or changing the proportion of defensive versus aggressive stocks. In fact, a manager adjusts the mixture of the composing stocks of his portfolio to reflect his perception from future market movements. In addition, regardless of changing the mixture of the composing stocks in portfolio, the manager still can change the risk levels of his portfolio by altering the proportion of defensive versus aggressive stocks. In both cases, the manager should alter the systematic risk of his portfolio. Hence, a market timer often switches from less risky to more risky securities (or vice versa) to get rid of the market movements (Chen et al., 1992).

Despite the classical market timing measures have unique and effective features for the evaluation of a portfolio manager's timing skill, they suffer some limitations (Chen et al., 2010). Thus, this study constructs two market timing measures based on the average drawdown risk measure and adds these measures to the mostly-used performance evaluation model, the Carhart (1997) four-factor model, to estimate two skills for a portfolio manager. The first skill is the selection ability of an efficient portfolio and the second one is the timing ability of the market movements.

Before conducting econometric analyses, all the daily and monthly portfolio returns exhibit a stationary trend, and more importantly, they are not normally distributed at the confidence level of 95%. The choice of a non-normality sample helps us to have much more drags and volatilities among the returns. This condition is very interesting for dynamic measures, such as AD, because the features of these measures allow us to assess the condition (Tavakoli Baghdadabad and Glabadanidis, 2013, Tavakoli Baghdadabad et al., 2013, Tavakoli Baghdadabad, 2014). More specifically, the existing performance measures based on mean-variance approach, e.g., HM and TM, are more applicable for the condition when the returns of a sample possess an asymmetric distribution (Tee, 2009, Dichtl and Drobetz, 2011). However, dynamic performance measures are more applicable when the returns of a sample have a non-normality distribution. However, analyses of this study provide very interesting findings in responding to the existing literature.

Glabadanidis (2014) reports profitability of the moving average market timing measures relative to the existing traditional timing measures by comparing the Sharpe ratios of the moving average market timing measures with those from the existing traditional timing measures. He finds higher profitability of the moving average market timing measures because they have higher Sharpe ratios. Since the AD-based market timing measures are also constructed from moving average methodology, this study examines profitability of the AD-based market timing measures as well. This study finds several interesting findings by examine the descriptive statistics of daily and monthly data. First, the daily and monthly average returns of the AD-based market timing measures are substantially greater than those from the traditional market timing measures. Second, these spreads in average returns come with a less return standard deviation for the AD-based market timing measures, and thus the AD-based market timing measures appear to dominate the traditional market timing measures in a mean-variance sense. Third, the traditional market timing measures have a less return skewness than the AD-based market timing measures. This feature makes the AD-based market timing measures very attractive to investors who possess a preference for high return skewness. Fourth, the same results can be found for high return kurtosis. Fifth, the trade-off between risk and return is tremendously improved as observed by much greater Sharpe ratios for the AD-based market timing measure returns relative to the Sharpe ratios of the traditional market timing measure returns. These results implicate higher profitability of the AD-based market timing measures relative to their traditional corresponding measures.

The traditional THM and TTM timing models exhibit poor timing evidence in most of the cases. The timing evidence reported in Tables 4-7 and 4-8 for the daily frequency data and in Tables 4-11 and 4-12 for the monthly frequency data confirms these poor timing findings based on less statistical and economic significance. This poor timing evidence for the traditional timing models is consistent with a great number of studies, such as Merton (1981), Henriksson and Merton (1981), Henriksson (1984), Becker et al (1999), and Jiang (2003), among others, who found poor timing evidence of managed portfolios. More findings can be also found in Kryzanowski et al (1996) and Ferson and Schadt (1996). This poor evidence stimulates researchers to propose new timing measures for predicting the movements of market portfolio returns.

For the market timing measures, most of the traditional measures have either statistically insignificant positive coefficients or statistically significant negative coefficients, implying that portfolio managers cannot forecast market portfolio movements using these measures. Only 39% and 47% of the daily traditional THM and TTM timing measures, respectively, and 8% and 17% of the monthly traditional

THM and TTM timing measures, respectively, exhibit statistically significance and positive timing evidence, implying that portfolio managers predict weakly market movements using these two measures. These results are consistent with Henriksson and Merton (1981), Treynor and Mazuy (1966), Becker et al (1999), Jiang (2003), and Jiang et al (2007) who found that managed portfolios obtain statistically insignificant and negative timing evidence using the traditional timing measures. In contrast, this study finds more statistically significant and positive timing evidence for the portfolios using the proposed timing measures. Contrary to primary studies that did not find evidence of portfolio managers' timing skill, this study finds more positive market timing evidence. Specifically, there are much more timing evidence for the daily and monthly NHM and NTM measures so that 52% and 65% of the daily proposed NHM and NTM timing measures, respectively, and 21% and 56% of the monthly proposed NHM and NTM timing measures, respectively, exhibit statistically significance and positive timing evidence, implying that portfolio managers predict better market movements using the proposed timing measures. In this sense, this study finds three main results on the proposed timing measures. First, the measures have significant magnitudes in most of the countries. Second, these magnitudes are higher than the traditional measures. Third, they exhibit further statistical significance. The absence of significant and positive timing evidence implicates low power of the traditional timing models relative to the proposed timing models (e.g., Becker et al., 1999). Since the THM and TTM timing measures are grounded on the mean-variance approach, and the NHM and NTM timing measures are grounded on the mean-AD approach, thus the superiority of proposed measures is consistent with Tavakoli Baghdadabad et al (2013), Tavakoli Baghdadabad (2013, 2014), and Tavakoli Baghdadabad and Glabadanidis (2013) who found better performance of the AD-based measures and their relevant pricing models relative to the traditional mean-variance measures and their relevant pricing models, e.g., CAPM. However, a positive sign for market timing measures is a theoretical basis for the choice of a successful market timer (e.g., Merton, 1981, Henriksson and Merton, 1981). Higher significant magnitudes in the proposed market timing measures indicate that they have a better performance for the forecasting of market movements than the traditional timing measures (e.g., Aragon, 2005, Chrétien et al., 2016). There are five reasons for this superior performance. First, a negative jump possesses a various impact on future volatilities relative to a positive jump, and also an extreme negative jump possesses a further impact on future volatilities relative to a negative jump. Therefore, these jumps can reinforce the timing of future volatilities using the volatility trading strategies (Patton and Sheppard, 2011, Audrino and Hu, 2016). Second, Giambona and Golec (2009) find that volatility timing increases average excess returns on portfolio since these volatilities allow a portfolio manager to take into account excess market risk when he faces high market volatility. Third, extreme volatilities may affect the performance of a portfolio since the extreme losses and their relevant large returns stimulate a market timer to attract greater volatilities when the volatilities of market portfolio rise (e.g., Busse, 1999, Graham and Harvey, 1996). Fourth, the AD-based timing measures take into account two components of risk to predict market movements, consisting of point risk premiums and volatility drags (or loss volatilities). This means that a portfolio manager uses further risk factors (or risk determinants) and further information contents to predict market movements. Fifth, since the drawdowns' information content is resulted from the market volatilities, ADs can well assess these volatilities because their information content has theoretically been formulated as a dynamic measure in these measures. This reason allows ADs to predict more correctly the market movements. This insight is consistent with Copper (2010) who found high predictabilities of the market volatilities. It is also consistent with Poon and Granger (2003), Patton and Sheppard (2011), and Audrino and Hu (2016) who reported that high market volatilities are able to reinforce market timing ability. However, the findings of this study detect that the proposed timing measures possess high statistical and economic significance, and exhibit better predictability of a portfolio manager relative to the traditional measures. Regardless of the findings reported by Bollen and Bassu (2001) on the superiority of the daily market timing relative to the monthly market timing, poor market timing estimated from the monthly frequency data relative to the daily frequency data in this study can be consistent with Goetzmann et al (2000) and Jiang et al (2007). They found that timing measures are biased downward when using monthly returns and the measures at the monthly frequency data underestimate a portfolio manager's timing skill.

The findings show that Sweden and Singapore at the daily frequency data, and Switzerland and Singapore at the monthly frequency data have the highest AD-based timing measures. In contrast, Ireland and Newzeland at the daily frequency data, and Finland and Denmark at the monthly frequency data have the lowest AD-based timing measures. As observed in the basic results, most countries exhibit better AD-based timing estimates at the daily frequency data than at the monthly frequency data. This distinction in the results can happened due to the existence of monthly frequency data biases as reported in Goetzmann et al (2000) and Jiang et al (2007). They found that timing measures are biased downward when using monthly returns, and the measures at the monthly frequency data underestimate a portfolio manager's timing skill.

The findings report that the proposed NHM and NTM timing models exhibit much more evidence of a portfolio manager's selection skill at the daily frequency relative to the proposed NHM and NTM timing models at the monthly frequency. For example, the daily NHM and NTM timing models estimate significant and positive selection skills for portfolio managers with the same ratio of 82% relative to the monthly NHM and NTM timing models that possess much low statistical and positive evidence with the ratios of 0% and 4%, respectively. This implicates higher power of the daily timing models than of the monthly timing models. Contrary to Bollen and Busse (2001), who believed that standard estimates of stock selection are robust to data frequency since these tests are more a function of research sample length relative to data frequency, the proposed timing models of this study report higher evidence of selection ability over the daily data because these data consider more information content for the choice of a share relative to the monthly data.

The results of portfolio managers' selection skills in the daily traditional timing models show that Portugal managers have the highest performance for the choice of an efficient portfolio, while Irish managers have the lowest performance. An efficient portfolio is a virtual basket composed from a series of shares active in a country, where the shares have the lowest correlation coefficients with each other. Higher intercepts estimated from the daily proposed timing models for Portugal managers are consistent with the average mean of portfolio returns reported in Table 4-1, where Portugal managers earn the highest average mean of portfolio returns. For the monthly frequency data, the traditional and proposed timing models report the same results so that the highest selection abilities estimated from the THM and TTM timing models are related to Japan and Ireland, respectively, and the highest selection abilities estimated from the NTM timing model are related to Finland. Note that the

NHM timing models do not report positive evidence of a portfolio manager's selection ability.

The portfolio managers' selection skill estimated from the AD-based timing models represents several points. First, most of the models highlight less statistical (intercept t-statistics) and economic (intercept magnitude) significance than the traditional timing models. This implies that a portfolio manager does not exhibit a high skill in picking the portfolios using the AD-based timing models. This happens for two possible reasons. First, the choice of a portfolio constrained by AD may negatively affect a portfolio manager's ability to track a benchmark and hence reduce the region of a feasible portfolio (Alexander and Baptista, 2006). Second, a portfolio manager who selects the best performing portfolio also exhibits a poor timing performance and vice versa. Given the above insight, the AD-based timing measures exhibit higher timing performance and hence lower selection ability. For example, selection skills and market timing skills of Hong Kong and Japan in the daily NHM models and Austria, Ireland, New Zealand, and Norway in the daily NTM models highlight a negative relation. This implication is consistent with Kao et al. (1998) who found that a portfolio manager with high selection skill tends to fare poorly in market timing. Fletcher (1995) also highlights that if the trade-off of a portfolio manager's selection skill and market timing skill is actual, he often focuses on selecting mispriced shares (or share picking) relative to market timing. As an interesting finding, there is a negative relation between selection skill and timing skill in most of the tests, especially the AD-based timing models. Regardless of the above two reasons for this relation, there are other three potential reasons as in Kok et al (2004). First, nonlinearities of the timing models can impose the option-like features of shares (Jagannathan and Korajcyzk, 1986). Second, misspecifications of the timing models (Fletcher, 1995). Third, the presence of negatively correlated sampling errors on the selection and timing measures and their timing models (Coggins et al., 1993). However, Kok et al (2004) states that there is not a unique reason for this negative relation.

The findings of this study also highlight that the daily return frequency in the AD-based timing measures can increase the power of market timing in comparison with the monthly frequency. This result is consistent with Bollen and Busse (2001) who found the same findings for the timing ability of mutual funds' managers. The findings also exhibit that portfolio managers may reflect more aggressive trading behaviour at the daily frequency rather than at the monthly frequency, which can be also consistent with Bollen and Busse (2001).

4.15 Chapter Summary

This chapter first examines the two mostly-common statistical tests of normality and unit root, and finds that the sample data is not distributed normally and follows a stationary trend. Subsequently, it uses the two mostly-common statistical tests of Wald and Redundant to understand whether market timing measures added to standard performance evaluation models make significant values on dependent variable of the models, portfolio excess returns. It then examines portfolio managers' selection and market timing abilities using the AD-based timing measures and their relevant timing models. Next, it compares the results of these new market timing measures and their relevant timing models with the traditional market timing measures and their relevant timing models. In next step, this study tests the research hypotheses and interprets the findings deviated from these statistical analyses.

Finally, a discussion section is organized to make a theoretical and logical link between the empirical findings of this study and the existing literature.

Overall, when estimating the timing models formed on portfolio features such as book-to-market, size, and momentum, this study finds that the traditional market timing skills exhibit less statistically positive timing evidence, while new market timing measures exhibit more timing evidence. These new timing measures provide further benefits of the statistical power of an improved model. The positive timing evidence in most of the suggested timing measures presents high economic significance as in Jiang et al (2007), indicating that the AD-based market timing can be an very important tool for investment decisions.

Chapter 5 : Conclusion

5.1 Introduction

This chapter contains seven subsections. The first subsection is the chapter introduction. The second subsection contains a summary of this study, including the performance evaluation concepts, the portfolio managers' selection and market timing skills, the research objective, and the research contribution. The third subsection presents summarily the main results of this study. The fourth subsection represents main implications and recommendation policies. The fifth subsection contains some suggestions for future studies. The sixth subsection presents the research limitations. Finally, a chapter summary is presented as the last subsection.

5.2 A Summary of Survey

The portfolios in various security classes are the most important economic and financial intermediaries in lending financial sources to the world economies (e.g., Huhmann, 2005). These portfolios help rational investors to follow proper investment strategies and obtain positive risk-adjusted returns in financial markets. Such a role of the portfolios in the markets stimulates market practitioners to respond a key question on whether a portfolio manager has sufficient managerial abilities to predict market movements and to select an efficient portfolio. A large number of the empirical studies document these two portfolio managers' abilities, market timing skill and selection skill, in the literature. These two abilities are important for three reasons (Prather and Middleton, 2006). First, good performance of a portfolio causes some biases in the Efficient Market Theory. This responds to a key question whether any market participant (e.g., portfolio manager) possesses monopolistic access to any relevant information for price formation. Second, a rational investor tends to obtain potential benefits by professional fund-management skills. Third, a portfolio manager's performance evaluation is an essential function for investment companies to provide compensation schemes for employing and keeping high quality managers.

A portfolio manager's market timing skill is defined as the ability of a manager to predict market movements. A summarily review of the literature exhibits that most of the empirical studies follow two approaches. The first approach is based on the classical analysis using the classical measures that assess portfolio managers' selection and timing abilities (e.g., Grinblatt and Keloharju, 2000). This approach develops the performance persistence concepts (e.g., Goetzmann and Ibbotson, 1994) and employs various timing models to generate abnormal returns, as indicator of a portfolio manager's selection skill, and to consider the upward returns of the squared risk premium (Treynor and Mazuy, 1966) and the market risk premium (Henriksson and Merton, 1981), as indicators of a portfolio manager's timing skills (Fama and French, 1993, Carhart, 1997, Du et al., 2009). The second approach is based on dynamic models, in general, and technical analyses, in particular, that add technical timing measures to asset pricing models for simultaneously estimating both selection skill and market timing skill of a portfolio manager (e.g., Glabadanidis, 2014, 2015, 2017).

Despite the classical timing measures have unique and effective features for the evaluation of a portfolio manager's timing skill, they suffer some limitations (Chen et al., 2010). These limitations in the existing classical timing measures along with the potential features of other risk measures in the risk management literature, such as dynamic risk measures, provide the possibility to propose alternative timing measures. The reasons are consisting of (i) the lack of dynamic timing measures in the existing literature and the unique features of these measures, especially technical timing measures, in comparison with the classical timing measures, (ii) the existing performance measures ignore information regarding the varying nature of the economy, (iii) the superiority of AD measure extracted from the mean-drawdown approach relative to variance (or standard deviation) extracted from the mean-variance approach, (iv) the lack of sufficient positive timing evidence resulted from the existing timing measures, (v) the existing classical timing measures ignore the effect of worst market losses occurred over the holding period of an investment, (vi) the low forecasting power of the existing timing measures especially when stock market is faced with extreme volatilities, (vii) the existing timing measures focus on point gains (positive spreads between market excess returns and free risk returns (or their squared spreads) and thus these measures do not allow to evaluate the worst losses occurred over the investment period of a portfolio, and (viii) the lack of adequate power of standard performance evaluation models to exhibit the evidence of abnormal performance.

Given the limitations of the existing classical timing measures, the unique and superior features of dynamic timing measures, and the superiority of mean-drawdown approach relative to the mean-variance approach, this analysis proposes two AD-based market timing measures grounded on the mean-AD approach, and incorporates them with the moving average dynamic approach in order to assess the performance of a portfolio manager. These new measures consider simultaneously point timing and extreme (loss) volatility drags (or drawdowns).

The research purpose is to examine portfolio managers' timing and selection abilities based on the AD timing approach, and to compare their performance with the traditional approach. The timing measures are constructed using the two mostly-common timing measures of Treynor and Mazuy (1966) and Henriksson and Merton (1981) to examine the forecasting power of the AD timing measures relative to their traditional corresponding timing measures. Another purpose is to compare the daily performance of the AD timing models with the monthly performance of the AD timing models.

5.3 Main Results

This study conducted different analyses based on the research objectives, the research hypotheses, and the research questions, and obtained very interesting findings as follows:

- The portfolio managers have significant timing skills using the AD-based timing measures to predict market movements.
- The portfolio managers have significant selection skills using the AD-based timing models to select efficient portfolios.
- The prediction power of the AD timing measure in the Treynor and Mazuy (1966) form is better than the power of traditional Treynor and Mazuy (1966) timing measure based on higher statistical and economic significance.
- The prediction power of the AD timing measure in the Henriksson and Merton (1981) form is better than the power of traditional Henriksson and Merton (1981) timing measure based on higher statistical and economic significance.

- The daily performance of the AD timing measures in the Henriksson and Merton (1981) form is better than the monthly performance.
- The daily performance of the AD timing measures in the Treynor and Mazuy (1966) form is better than the monthly performance.

Despite the main results obtained from the basic analyses, this study obtains more detailed and straight results as:

- This study finds higher profitability of the AD market timing measures relative to the traditional market timing measures in both daily and monthly frequencies.
- The proposed timing models at the daily frequency report higher evidence of selection ability because the daily data consider more information content for the choice of a share relative to the monthly data.
- The AD-based timing measures have higher timing skill than the traditional timing measures.
- For the daily frequency data, portfolio managers' timing skills estimated from the AD-based timing models show that Swedish and Singaporean managers have the highest performance for predicting the market movements, while Irish and New Zealander managers have the lowest market timing.
- For the monthly frequency data, portfolio managers' timing skills estimated from the AD-based timing models show that Swiss and Singaporean managers have the highest performance for predicting

the market movements, while Finnish and Danish managers have the lowest market timing.

- The AD-based timing models at the daily frequency have better performance in predicting market movements relative to the AD-based timing models at the monthly frequency.
- For the daily frequency data, portfolio managers' selection skills estimated from the AD-based timing models show that Portuguese managers have the highest performance for the choice of an efficient portfolio, while Irish managers have the lowest performance.
- For the monthly frequency data, portfolio managers' selection skills estimated from the AD-based timing models show that Finnish managers have the highest performance for the choice of an efficient portfolio, while Irish managers have the lowest performance.
- The AD-based timing measures can increase the power of market timing at the daily return frequency in comparison with the monthly return frequency.
- The portfolio managers may reflect more aggressive trading behaviour at the daily frequency rather than at the monthly frequency.

5.4 Implication and Recommendation Policies

From the perspective of a portfolio manager, higher profitability of the AD-based market timing measures implies that risk-seeking portfolio managers (or investors), who often tend to have a higher preference for the risk of portfolio returns, may use the AD-based market timing measures because these measures create higher risk-adjusted returns.

From the perspective of a rational investor, the same implication can be defined for risk-loving investors who tend to use these dynamic measures.

Finally, these dynamic measures are more applicable during the financial crisis periods due to the presence of further volatilities and loss drags (drawdowns) during the periods.

5.5 Future Studies

This study examined the performance of portfolio managers using dynamic risk measures of average drawdown, and found the relatively superior performance of this measure relative to the existing timing measures. Given the superior performance and the potential features of this measure, this study suggests the following future studies:

- This study suggests studying the AD-based timing measures on professionally managed funds such as mutual funds, hedge funds, funds of funds, and etc.
- This study examined the performance of share-based portfolio managers based on the AD-based timing measures. It here proceeds to suggest examining the performance of bond-based portfolio managers using these measures.
- The professionally managed fund databases are often categorized using different features. For example, they classify the funds based on management styles, management strategies, and other characteristics. Using these features, this study suggests studying the performance of portfolio managers based on the AD-based timing measures.

- This study examined the performance of portfolio managers for stocks active in 23 developed countries, it here proceeds to suggest examining the performance of portfolio managers for stocks active in emerging countries.

5.6 Research Limitations

The performance evaluation of portfolio managers is often conducted on managed portfolios, such as mutual funds, hedge funds, funds of funds, and etc. Majority of these portfolios are managed by professional managers, and the specialized database often produces these data. However, I could not access to these data during this study.

5.7 Chapter Summary

This chapter presents a summary review of the research objectives, the research hypotheses, and the research contributions. It then presents main findings of the statistical and econometric analyses conducted in Chapter 4. Subsequently, it provides main implications and policy recommendations to help market practitioners in order to have actual uses of the suggested timing measures under real condition. Next, it presents the research limitations. Finally, it presents suggestions for future studies to develop the basic idea of this study. From the perspective of a portfolio manager, higher profitability of the AD-based market timing measures implies that risk-seeking portfolio managers (or investors) may use the AD-based market timing measures because these measures create higher risk-adjusted returns. From the perspective of an investor, the same implication can be defined for risk-loving investors who tend to use these dynamic measures. Finally, these dynamic measures are more applicable during the financial crisis periods due to the presence of further volatilities and loss drags (drawdowns) during the periods.

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Appendix:

Appendix.1: List of Publications

1. TAVAKOLI BAGHDADABAD, M.R. & MALLIK, G. 2018 “Global Risk Co-Moments and Carry Trade Strategy,” *The Journal of Fixed Income*, 27(04), 73-99.

2. TAVAKOLI BAGHDADABAD, M.R. & MALLIK, G. 2017 “Global Idosyncratic Risk Moments,” *Emirical Economics*, 1-34.

3. TAVAKOLI BAGHDADABAD, M.R. 2015 “Maximum Drawdown and Risk Tolerances,” *Review of Pacific Basin Financial Markets and Policies*, 18(01), 1550003.

4. TAVAKOLI BAGHDADABAD, M.R. 2014 “Average Drawdown Risk Reduction and Risk Tolerances,” *Research in Economics*, 68(03), 264-276.

5. TAVAKOLI BAGHDADABAD, M.R., MAT NOR, F. & IBRAHIM, I. 2013 “Mean-Drawdown Risk Behavior: Drawdown Risk and Capital Asset Pricing,” *Journal of Business Economics and Management*, 14 (sup1), S447-S469.

6. TAVAKOLI BAGHDADABAD, M.R. & GLABADANIDIS, P. 2013 “Average drawdown risk and capital asset pricing,” *Review of Pacific Basin Financial Markets and Policies*, 16(04), 1350028.

7. TAVAKOLI BAGHDADABAD, M.R. & GLABADANIDIS, P. 2013 “Evaluation of Malaysian mutual funds in the maximum drawdown risk measure framework,” *International Journal of Managerial Finance*, 9(3), 247-270.

8. TAVAKOLI BAGHDADABAD, M.R. 2013 “The effects of drawdown risk reduction on the US hedge funds,” *Journal of Derivatives & Hedge Funds*, 19(1), 50-73.

9. TAVAKOLI BAGHDADABAD, M.R., MAT NOR, F. & IBRAHIM, I. 2012 “Optimized drawdown risk in evaluating the performance of Malaysian mutual funds,” *Journal of Islamic Accounting and Business Research*, 3(2), 138-162.

10. TAVAKOLI BAGHDADABAD, M.R., MAT NOR, F. & IBRAHIM, I. 2011 “An Empirical Analysis of Funds’ alternative Measures in the Drawdown Risk Measure (DRM) Framework,” *Journal of Advanced Studies in Finance*, 2 (2 (4)), 16.

Appendix 2: The results of the research hypothesis tests using SPSS

Table A-2-1: The results of the first research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Daily NTM	23	2.8174	4.21500	.87889

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Daily NTM	3.206	22	.004	2.81739	.9947	4.6401

Table A-2-2: The results of the second research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Daily NHM	23	.0769	.16746	.03492

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Daily NHM	2.201	22	.038	.07687	.0045	.1493

Table A-2-3: The results of the third research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Monthly NTM	23	5.1822	10.22942	2.13298

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Monthly NTM	2.480	22	.024	5.18217	.7586	9.6057

Table A-2-4: The results of the fourth research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
Monthly NHM	23	3.9000	6.98009	1.45545

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
Monthly NHM	2.720	22	.014	3.90000	.8816	6.9184

Table A-2-5: The results of the fifth research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
α of Daily NTM	23	.0167	.01965	.00410

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
α of Daily NTM	4.068	22	.001	.01667	.0082	.0252

Table A-2-6: The results of the sixth research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
α of Daily NHM	23	.0161	.01953	.00407

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
α of Daily NHM	3.965	22	.001	.01614	.0077	.0246

Table A-2-7: The results of the seventh research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
α of Monthly NTM	23	.5661	1.21001	.25230

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
α of Monthly NTM	2.270	22	.035	.56613	.0429	1.0894

Table A-2-8: The results of the eighth research hypothesis test

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
α of Monthly NHM	23	.3562	1.14421	.23858

One-Sample Test

	Test Value = 0					
					95% Confidence Interval of the Difference	
	t	df	Sig. (2-tailed)	Mean Difference	Lower	Upper
α of Monthly NHM	1.532	22	.150	.35625	-.1385	.8510

Table A-2-9: The results of the ninth research hypothesis test

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	TTM	.8505	46	10.28977	1.51714
	NTM	3.9998	46	7.82769	1.15413

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	TTM & NTM	46	.783	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	TTM - NTM	-3.24930	6.41031	.94515	-5.05293	-1.24568	-3.420	45	.002

Table A-2-10: The results of the tenth research hypothesis test

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	THM	.9148	46	3.61525	.53304
	NHM	1.9884	46	5.25057	.77415

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	THM & NHM	46	.919	.000

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
					95% Confidence Interval of the Difference				
		Mean	Std. Deviation	Std. Error Mean	Lower	Upper			
Pair 1	THM - NHM	-1.10361	2.40057	.35394	-1.78649	-.36073	-3.120	45	.004

Table A-2-11: The results of the eleventh research hypothesis test

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Monthly NTM	.7039	23	2.47304	.51566
	Daily NTM	2.8174	23	4.21500	.87889

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Monthly NTM & Daily NTM	23	.128	.560

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	Monthly NTM - Daily NTM	-2.15348	4.60551	.96031	-4.10505	-.12191	-2.22	22	.039

Table A-2-12: The results of the twelfth research hypothesis test

T-Test

Paired Samples Statistics

		Mean	N	Std. Deviation	Std. Error Mean
Pair 1	Monthly NHM	3.9000	23	6.98009	1.45545
	Daily NHM	.0769	23	.16746	.03492

Paired Samples Correlations

		N	Correlation	Sig.
Pair 1	Monthly NHM & Daily NHM	23	.163	.457

Paired Samples Test

		Paired Differences					t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean	95% Confidence Interval of the Difference Lower	Upper			
Pair 1	Monthly NHM - Daily NHM	3.86313	6.95475	1.45017	.81567	6.83059	2.684	22	.015