Passive and Active Currency Portfolio Optimisation

by

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I certify that all material in this thesis which is not my own work has been identified and that no material has previously been submitted and approved for the award of a degree by this or any other University

Signature: …………………………………………………………..

To my parents and my wife

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Abstract

This thesis examines the performance of currency-only portfolios with different strategies, in out-of-sample analysis.

I first examine a number of passive portfolio strategies into currency market in out-of-sample analysis. The strategies I applied in this chapter include sample-based mean-variance portfolio and its extension, minimum variance portfolio, and equally-weighted risk contribution model. Moreover, I consider GDP portfolio and Trade portfolio as market value portfolio for currency market. With naïve portfolio, there are 12 different asset allocation models. In my out-of-sample analysis, naïve portfolio performs reasonably well among all 12 portfolios, and transaction cost does not seriously affect the results prior to transaction cost analysis. The results are robust across different estimation windows and perspectives of investors from different countries.

Next, more portfolio strategies are examined to compare with naïve portfolio in currency market. The first portfolio strategy called 'optimal constrained portfolio' in this chapter is derived from the idea of maximising the quadratic utility function. In addition, the timing strategies, a set of simple active portfolio strategies, are also considered. In my out-of-sample analysis with rolling sample approach, naïve portfolio can be beaten by all the strategies discussed in this chapter.

In chapter six, the characteristics of currency are exploited to construct a currency only portfolio. Firstly, the pre-sample test proves that the characteristics, both fundamental and financial, are relevant to the portfolio construction. I then examine the performance of parametric portfolio policies. The results show that while fundamental characteristics can bring investor benefits of active portfolio management, financial characteristics

cannot. Moreover, I find the relationship between characteristics of currency and weights of optimal portfolio.

The overall results show that currencies can be thought of as an asset in their own right to construct optimal portfolios, which have better performance than naïve portfolio, if suitable strategies are used. In addition, ‘lesser’ currencies, indeed, bring significant benefits to the investors.

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Abbreviation

Forex	Foreign Exchange Market
OC	Optimal Constrained portfolio
PPP	Parametric Portfolio Policy
CRRA	Constant Relative Risk Aversion
BEER	Behavioural Equilibrium Exchange Rate model
VaR	Value at Risk
CVaR	Conditional Value at Risk
MDD	Maximum Drawdown
GDP	Gross Domestic Product
CEQ	Certainty-Equivalent
ERC	Equally-weighted Risk Contribution portfolio
VT	Volatility Timing portfolio
RR	Reward-to-Risk portfolio
EWMA	Exponentially Weighted Moving Average
SMA	Simple Moving Average
GMVP	Global Minimum Variance Portfolio
CML	Capital Market Line
HICP	Harmonised Index of Consumer Prices
RIR	Real Interest rates
TNT	Traded to Non-Traded Goods (Productivity)
TOT	Term of Trade
GC	Government Consumption
CPI	Consumer Price Index

Chapter One

Introduction

1.1 Background

Markowitz portfolio theory, widely considered as a cornerstone of modern portfolio theory, was derived by Markowitz in 1952. He assumes that investors are only concerned with the mean and variance of a portfolio's return. Due to preference of higher returns with the same risk, investors will choose tangency portfolio. The idea of this strategy seems right. However, due to moments estimated by sample analogues, the implementation of this model performs poorly out of the sample (Michaud, 1989). A number of studies have focused on this topic leading to the development of this model with some adjustments. Other studies also tried to create alternative methods for constructing portfolios that could beat the market. All these models have been empirically applied to stock and/or bond markets for efficiency testing.

Investors were starting to realise that investment diversification cannot only be done in their own country, but also around the world, with the latter resulting in additional benefits. Grubel (1968) describes and quantifies the benefits derived from international diversification, and concludes this diversification as a new source of gains. In their deliberations, Levy and Sarnat (1970) not only further support the Grubel's findings, but also suggest investing in both developed and developing countries, because less correlated returns can reduce overall portfolio variance as well as risk. In the two decades prior to 1970, due to relatively stable exchange rates, international investments did not need to consider foreign currency holdings for the international diversification.

However, due to collapse of the Bretton Woods system, the currency exchange rates are able to float freely, which can be considered as a source of financial risk. Eun and Resnick (1988) argue that the studies from Grubel (1968) and Levy and Sarnat (1970) are overstating the actual gains made from international diversification, because of the factor that parameter uncertainty is not accounted. The risks inherent to foreign exchange rates can eliminate or substantially reduce the profit made on an international portfolio.

International investment in bonds and equities, therefore, introduces an additional source of risk, which is due to floating-free exchange rates. A number of studies have addressed this risk by hedging strategies that sell the expected foreign currency returns at forward rate. For example, Black (1989) introduced the concept of 'universal hedging' which suggests that investors should always hedge their foreign assets equally for all countries but never 100%. The effectiveness of hedging strategy is dependent upon an investor's ability to estimate future returns. Glen and Jorion (1993), Larsen Jr and Resnick (2000) and Topaloglou et al. (2008) had similar findings supporting the fact that hedged portfolios dominate non-hedged portfolios. More research on hedging strategy include Schmittmann (2010), who studied the impact of hedging the currency risk from the perspectives of different national investors over period including the last financial crisis period, and Fonseca et al. (2011), who extend the robust model to include currency option as a hedging instrument.

However, currencies are increasingly thought of as an asset in their own right. Levy and Sarnat (1978) report achievement of significant gains from holding foreign currencies from a US investor perspective. They firstly calculate mean and standard deviations of monthly return on the holding of foreign currencies from 1959 to 1973. In the periods prior to 1970, the mean returns were either negligible or negative. However, after 1970, the mean returns for most of the currencies are significantly positive, and fluctuations were enlarged. And then, they optimised that most currencies provide a higher rate of return than the Standard and Poor's Common Stock Index did. They also analysed and confirmed the gains from diversification for only currencies portfolios and portfolios of foreign currency and country's stock index. The basic concept of their report is to treat foreign currencies as an investment asset not a hedge tool. According to BIS Triennial Survey (2007), there are $3.2 trillion being exchanged on a daily basis ($4 trillion in 2010), which indicates that the Foreign Exchange Market (Forex) could be considered as the biggest single market in the world. So, more and more currencies could be considered as another type of asset, which I could invest in and find speculating opportunity like I have done in the stock or bond market.

1.2 Motivation

The existing research on portfolio optimisation for currencies is not extensive. Some studies try to use active portfolio management to find out the speculating opportunity in Forex. Dunis et al. (2011) uses cointegration introduced by Engle and Granger (1987) to diversify a currency trading portfolio, in order to find the benefit, if any. In general, cointegration-based optimization strategies add value, but, as all optimization techniques, they should be used cautiously. Schmittmann (2010) applies currency carry trading strategy with MGARCH-based carry-to-risk portfolio optimization to construct a portfolio containing Brazilian real and Mexican peso. They found that this dynamic approach leads to a significant surplus profit in times of either very low or very high volatility. Cao et al. (2009) introduce a novel portfolio optimization method for foreign currency investment. They use support vector machines and neural network and moving average to predict exchange rates and build a portfolio by adopting multi-objective portfolio optimization technique by maximising the return and minimizing the risk. The results show superior return performance of optimal portfolio compared with single currency investment. However, the studies mentioned above regarding currency portfolio optimisation are not systematic, and include only a small number of currencies.

Moreover, very few studies have considered passive portfolio investment among currencies. A most relevant research about passive currency-only portfolios is written by Levy and Sarnat (1978). They simply applied basic idea of modern portfolio theory by sample mean and standard deviation to construct a set of efficient portfolios. They analysed Tobin's separation theorem and illustrated the statistics and composition of tangency portfolio. Furthermore, they conclude that an investor will not hold domestic cash in his portfolio, but blend the optimal portfolio with riskless bonds. However, they did not compare results to other portfolios constructed using different methodologies. Recently, a number of robust models and alternative methods were created to develop the performance of Markowitz model. But, few researches applied these methods into construction of currency-only portfolio.

Based on the considerations above, my thesis provides a comprehensive analysis of both passive and active portfolio management models in currency portfolio optimization. As I have already indicated, researchers always study currencies as a hedge tool to reduce the risk, at cost, on international investments, but are limited to find out optimal solutions for the gain from exchange rate fluctuations by portfolio optimization strategy. So, the gap in the literature is to analyse the performance of optimal portfolios for currency only portfolio. This study aims at filling this gap. Filling this gap is important to investors who desire to take a position on foreign currencies, due to the nature and magnitude of their economic activities, such as central bank, international investment trusts, and large multinational corporations.

1.3 Contribution and Empirical Results

The first contribution of the thesis is the systematic examination of the out-of-sample performance of currency only portfolios. As discussed before, the literature about the performance of currency only portfolio is limited, and methods for evaluating are simple, and the number of currencies is small. So, in my thesis, the evaluation methods I use are comprehensive, including not only trade-off between return and risk but also downside risks. A total of 29 currencies are included in this thesis, which almost include all free-floating currencies without high correlation. So, I call portfolio including 29 currencies as all currencies portfolio. I consider naïve portfolio as benchmark to compare other optimal portfolios. Moreover, I use three chapters to investigate the performance of currency portfolios with various strategies from passive to active. In the next several paragraphs, I will show what strategies I use and results of their performance.

In Chapter four, I examine a number of passive portfolio strategies into currency market in an out-of-sample analysis. The strategies I applied in this chapter include sample-based mean-variance portfolio, its extension, minimum variance portfolio, and equally-weighted risk contribution model. Moreover, I consider GDP portfolio and Trade portfolio as market value portfolio for the currency market. With naïve portfolio, there are 12 different asset allocation models. In the out-of-sample analysis, the results show that the sample-based mean-variance portfolio works very badly with low Sharpe ratio and horrible downside risk, because of an estimation error. Moreover, the minimum variance portfolios, with and without short-sale constraint, has the best performance and exposure to the lowest downside risk. The naïve portfolio and equally-weighted risk contribution portfolio also perform reasonable well. I also take account of transaction cost, and compare the results before and after transaction cost. But, transaction cost does not seriously affect the rankings from before transaction cost analysis.

In Chapter five, more portfolio strategies are examined to compare with naïve portfolio in currency market. The first portfolio strategy is called as optimal constrained (OC) portfolio, which is based on the mean-variance portfolio and target portfolio return to be the conditional mean of naïve portfolio. In addition, the timing strategies, a set of simple active portfolio strategies, are also considered. For my analysis about currency only portfolio, optimal constrained and volatility timing portfolio consistently outperform naïve portfolio in all terms of evaluation I used. The transaction cost does not change the conclusion, although it reduces the performance of portfolios. In addition, I find that exponentially weighted moving average is more efficient to estimate conditional expected moments than simple moving average to reduce estimation error.

In chapter six, I examine an alternative active portfolio strategy, called parametric portfolio policy (PPP). Its weights are calculated as linear function of characteristics of currency plus benchmark weights. The results of my out-of-sample analysis about currency only portfolio display that fundamental characteristics can give CRRA investor benefits of active portfolio management, but financial characteristics cannot. But, considering both classes of characteristics together worsens the performance of PPP portfolio. If the investors are safety-first rather than CRRA investor, the PPP portfolio still is their choice in a way. Although a high level of turnover of PPP portfolios, the transaction cost does not change my conclusions.

The second contribution of the thesis is the examination of international diversification benefit from investing in currencies of developing countries. The fact about more gains from investing globally has been proved again and again by the literature, since the studies by Grubel (1968) and Levy and Sarnat (1970). After free-floating, some studies (e.g. Black, 1989; Larsen Jr and Resnick, 2000; Fonseca et al., 2011) provide empirical evidence that international investment benefit can still be gained by hedging floating risk using currency derivatives. But, there are few studies (only Dunis et al., 2011) that focus on the benefit of global investment for currency. Once I invest in Forex, the currencies bought are already from different countries. Therefore, globally investing or international investment, in this thesis, means that investors invest in both developed and developing countries' currencies. Due to the fact that currencies of developing countries are less traded compared to currencies of developed countries; the developing countries' currencies are often referred to as 'lesser' currency in the rest of this thesis. I firstly examine the performance of portfolios which only contains G10 currencies. And then, I compare it with the performance of portfolios, which use same strategies but contain G10 currencies and 'lesser' currencies. This is the first study to examine benefit from investing in 'lesser' currencies, using vast portfolio strategies. This method is different from the study by Dunis et al. (2011), which added 'lesser' currencies one by one. The results from chapter four and chapter five show that the performance of all currencies portfolio is significantly better than that of G10 currencies portfolio. So, I can conclude that adding 'lesser' currencies can help investors gain the huge benefit from diversification.

The third contribution of the thesis is to provide a guide to construct currencies portfolio by using their fundamental characteristics, and examine the performance of this strategy in out-of-sample. The basic idea I used in this thesis is from a study by Brandt et al. (2009). In equity market, they adjust portfolio weights from market weights by characteristic of stocks, and name this strategy as parametric portfolio strategy. But, there are challenges when this strategy is applied into currency market. Firstly, currency has its own characteristics, which are not the same as stocks. Although Barroso and Santa-Clara (2011) examine the performance of currency only portfolio constructed by parametric portfolio policy, the characteristics they only focus on are financial variables, which are calculated by the historical performance of currency. But, fundamental variables, the factors that determine currency exchange rate, can also be considered to construct portfolio weights. Therefore, in chapter six, the fundamental characteristics of currency also are investigated to construct currency only portfolio. The results from the pre-sample test prove that the characteristics, both fundamental and financial, are relevant to the portfolio construction. Secondly, unlike equity market, there is no market portfolio with value-weighted average. So, I consider two portfolio weights as benchmark weights. One is naïve weights, and another one is volatility timing portfolio weights. The results from out-of-sample analysis of chapter six confirm that the choice of benchmark weights is not important to the investor. In addition, I find that the PPP portfolios allocate considerably more wealth to currencies with small interest rate spread, large real interest rates differential, strong productivity differential, and small term of trade differential.

1.4 Organisation of This Thesis

The remainder of this thesis is organised as follows. In Chapter two, a critical analysis of existing literature on portfolio management is undertaken. This is help in justifying the research objectives and questions. In order to give readers a complete picture, the evaluation methods are also mentioned.

In chapter three, I describe the data used in this thesis. The description includes data collection and the method of currency return calculation. Moreover, I discuss the statistics of currency return and relevant data. In addition, the method of taking account of transaction cost is introduced.

In Chapter four, I test 12 different optimal passive portfolios in currency market. The out-of-sample analysis confirms that the naïve portfolio performs very well, which is consistent with existing literature for equity market. But, minimum variance portfolio has the best performance. The results indicate a support of good performance of naïve portfolio.

In Chapter five, I analyse several active portfolio strategies, which have been proved to have better performance than naïve portfolio for equity market by existing literature. The main results show the same conclusion. But, for the robustness check, the results are inconclusive. Both chapters have two datasets---only G10 currencies and G10 currencies with 'lesser' currencies. The comparison shows significant international diversification benefit.

In Chapter six, I investigate characteristics of currency to construct optimal portfolio, and test the performance of this portfolio. The results of pre-sample test show that both financial and fundamental characteristics are relevant to the portfolio construction. And, the results of out-of-sample analysis show that PPP portfolio with fundamental characteristics has the best performance, which can beat naïve portfolio.

The last chapter concludes the results of the thesis and gives directions for future research. This chapter brings together the work of the dissertation by showing how the initial research plan has been addressed in such a way that conclusions may be formed from the evidence of the dissertation. This will also outline the extent to which each of the aims and objectives has been met. Research questions are also reintroduced in order to give a clear understanding to the reader.

Chapter Two

Literature Review

In this chapter, I firstly review the literature related to portfolio management, which has been considerably advanced since seminal works of Markowitz (1952). Because of the factor that the moments of return are estimated with significant errors, an extensive literature review makes significant effort to handle this estimation error in the purpose of improving performance of portfolio. The popular approach applied in a vast literature is Bayesian approach to estimation error, including purely statistical approach relying on diffuse-priors (Barry, 1974; Brown, 1979), idea of shrinkage estimation (James and Stein, 1961; Jorion, 1986), and recent model depend on the asset-pricing model (Pástor and Stambaugh, 2000; Wang, 2005). Another equally rich set of approach is related to non-Bayesian approach to estimation errors. This includes rules about robust portfolio with uncertainty of parameters and model (Garlappi et al., 2007), Three-fund combination portfolio (Kan and Zhou, 2007; DeMiguel et al., 2007), Optimal constrain portfolio to target conditional expected portfolio return to naïve portfolio return (Kirby and Ostdiek, 2010), and the simplest way to put short-sale constrains into portfolios construction (Frost and Savarino, 1988; Chopra, 1993; Jagannathan and Ma, 2003). In addition, there are alternative strategies, beyond to Markowitz's model (1952), also developed and tested in recent literature, such as a strategy to weight risk contribution equally (Neukirch, 2008b; Maillard et al., 2008), a rule focusing on changes in volatility through time (Fleming et al., 2003; Kirby and Ostdiek, 2010), a novel approach to directly construct portfolio based on only characteristics of assets (Brandt et al., 2009), and the simple non-optimised naïve portfolio (DeMiguel et al., 2007).

In the second part of this section, a critical analysis of literature pertaining to the characteristics of currency is undertaken. The frequent trading strategy in currency market is carry trade, which buys currency with high interest rate and sells currency with low interest rate (Bilson, 1981; Fama, 1984; Burnside et al., 2008). Besides carry trade, other two currency trading strategies, currency moment and value, are also profitable (Menkhoff et al., 2012b; Okunev and White, 2003; Burnside et al., 2011; Asness et al., 2013). Barroso and Santa-Clara (2011) conclude this three currency trading strategies as financial characteristics of currency. In addition to financial characteristics, the approach of behavioural equilibrium exchange rate (BEER), which extended from relative purchasing power parity, determine exchange rate by some economic factors (Clark and MacDonald, 1999). These economic factors can be considered as fundamental characteristics of currency, and are employed in the literature by different sets (Komárek et al., 2005; Lane and Milesi-Ferretti, 2001, MacDonald and Dias, 2007; Cheung et al., 2005).

The final part of this section is to review the method of evaluating performance of portfolio in the literature. Sharpe (1994) defines a famous and standard performance measure as Sharpe ratio, which trade-off between return and standard deviation of return. There are also other measures considered in the literature to trade-off return and risk. But, Caporin and Lisi (2009) conclude that the results from others are similar to it from Sharpe ratio. Recently, there alternative approaches to measure risk have been developed. One is related to the Drawdown, which represent the maximum loss at time t from time 0 (Biglova et al., 2004; Ortobelli et al., 2005; Rachev et al., 2008). Another risk measure is based on the quantiles of series of returns. The simple version is always called as value at risk (Beder, 1995). Due to significant loss in global financial crisis by use of VaR (Kidd, 2012), investors have adopted a conditional value at risk, which was first proposed by Embrechts et al. (1999) and measure tail risk.

2.1 Portfolio Strategies

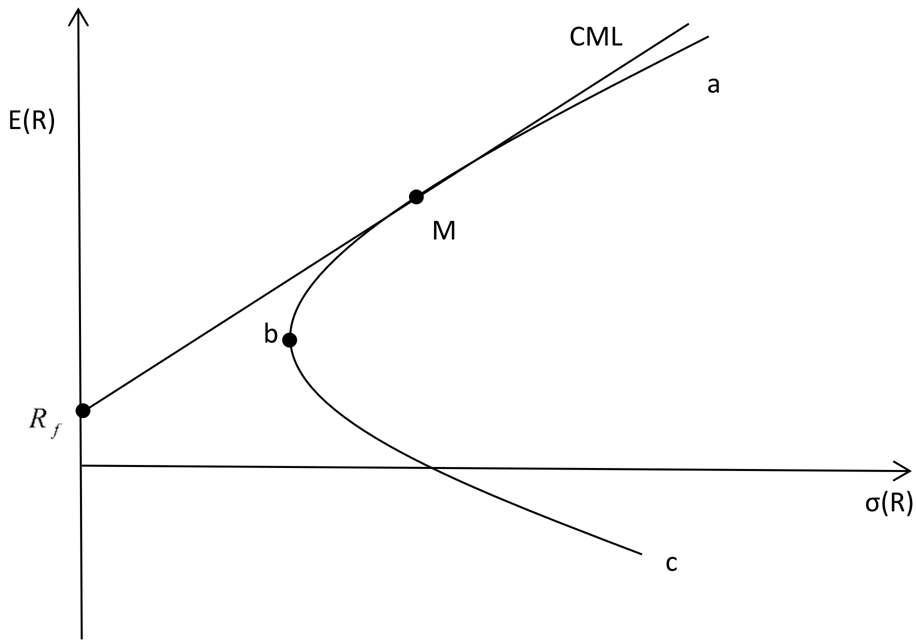
2.1.1 Markowitz Model and Sample-based Mean-Variance Portfolio

In financial markets, the risk has been dealt with a long history. When shares of the East India Company began trading in Amsterdam in 1602, the first stock market was built (Perold, 2004). But, the trade-off between risk and return is formally stated by Morgenstern and Von Neumann (1944), who also develop the utility function of this trade-off.

Markowitz (1952, 1959) firstly considers variance as a measure of risk formally, and then tries to construct portfolios by the risk-return trade-off. He assumes that investors are risk averse and the only matter they care about is the mean and variance of return of portfolios for the holding period. According to these assumptions, investors will choose the portfolios which have minimum variance for a given expected return or maximum expected return for a given variance. Figure 2.1 demonstrates all possible portfolios the investors faced for mean and variance analysis. When there are only risky assets taken into account, the efficient frontier is curve above point b, which represents global minimum variance portfolio (GMVP). But, if considering about risk free asset, the efficient frontier is now a straight line through R_f and M, which is the tangency portfolio. This straight line is also referred to as Capital market line by Sharpe (1964) and Lintner (1965), and the tangent point M is called market portfolio as well.

Figure 2.1 Mean-Variance Analysis

The figure plots the flexible and efficient set of mean and variance analysis of Markowitz, and Capital market line of Sharpe (1964) and Linter (1965). E(R) is the expected return and σ(R) is the standard deviation of returns. When there are only risky assets, point b represents the global minimum variance portfolio (GMVP). The curve abc and the area within belong to flexible set. But, the only curve above point b is efficient, called efficient frontier. When there is a risk free asset, M represents risk free rate and Market portfolio, which is the tangent point from risk free rate R_f. the straight line from R_f and M is the new efficient frontier.



A vast amount of literature, e.g. DeMiguel et al. (2007), Kolusheva (2008), Brandt (2009) Kirby and Ostdiek (2010), derives a formula of tangency portfolios weights from mean-variance utility function. According to Markowitz model above, investors choose the optimal combination lies on CML. This combination has a vector of risky asset weights x and $(1-\iota_N' x)$ of risk free asset, where ι_N is an N-dimensional vector of ones and N is number of risky assets. The exact position of investor is determined by his tolerance for risk. Therefore, they use γ to denote relative risk aversion of investor, and select x, N*1 vector, by maximise expected utility function:

$$\max_x x'\mu - \frac{\gamma}{2} x'\Sigma x \tag{2.1}$$

In which μ is an N-dimensional vector of the expected excess returns over risk free rate, $\boldsymbol{\Sigma}$ is N*N matrix of variance and covariance of expected excess returns. The solution of the problem is:

$$x^* = \frac{1}{\gamma}\Sigma^{-1}\mu \tag{2.2}$$

The vector of relative weights in risky only asset portfolio (tangency portfolio) is:

$$w_{TP} = \frac{x^*}{|\mathbf{1}_N' x^*|} \tag{2.3}$$

After taking equation 2.2 into equation 2.3, they have tangency portfolio weights:

$$w_{TP} = \frac{\Sigma^{-1}\mu}{\mathbf{1}_N'\Sigma^{-1}\mu} \tag{2.4}$$

In order to construct portfolio, investor has to estimate the expected excess return μ and variance-covariance $\boldsymbol{\Sigma}$. The simplest way used by Markowitz (1952, 1959) is 'plug-in' approach, which is to estimate μ and Σ by using their historical sample analogues (sample mean $\hat{\mu}$,N*1 vector, and sample variance-covariance matrix $\hat{\boldsymbol{\Sigma}}$, N*N matrix).

This strategy is referred as ‘sample-based mean-variance portfolio’ or ‘Plug-in estimates’ mean-variance portfolio, and the vector of its weights is calculated as follow:

$$w^{SB} = \frac{\hat{\Sigma}^{-1}\hat{\mu}}{\mathbf{1}'_N\hat{\Sigma}^{-1}\hat{\mu}} \tag{2.5}$$

The problem of this sample based strategy is ignorance of estimation error. In the next section, the literature related to this error will be reviewed.

2.1.2 Error in Estimation and Extension Models

The fact that error in estimation is reason of poor performance of sample-based mean-variance portfolio in out-of-sample is well documented in the literature. As noted in a number of studies, Kolusheva (2008) concludes that the sensitivity to small change in inputs data is the root of failure of sample-based mean-variance portfolio in out-of-sample analysis. Chopra (1993) finds that mean-variance portfolios can be vastly different, even estimates are slightly changed. This analysis has also been done by Best and Grauer (1991). Dickinson (1974) recognizes the impact of parameter uncertainty on optimal portfolio selection, and point out that this approach is seriously hampered by estimation error, according to practical application of portfolio analysis. Jobson and Korkie (1980) clearly illustrate the reason of imprecision of plug-in estimates, according to a simple example, which only considers one risky asset in the universe. They use a typical stock with μ =8% and σ =20% to calculate the standard error of the plug-in estimator, which is large relative to the magnitude of true value. Michaud (1989) points out that the estimation error in sample-based parameters leads to extreme weights that fluctuate substantially over time and perform poorly out of sample. This has motivated that sample-based mean-variance optimizers are ‘error maximisers’, which is widespread view in academic literature.

Therefore, the vast literature made efforts to reduce estimation errors. A prominent role to solve estimation error is acted by the Bayesian approach. Under this approach, μ and $\boldsymbol{\Sigma}$ are estimated by using predictive distribution of asset returns. In order to obtain this distribution, the conditional likelihood is integrated over μ and $\boldsymbol{\Sigma}$ with respect to a certain subjective prior. The studies implement this approach in different ways. Firstly, Stein (1956) and James and Stein (1961) firstly pioneer an application of the idea of shrinkage estimation. In order to mitigate the error for estimating expected returns, they shrink the sample mean of individual asset returns toward 'grand' mean across all assets. Jorion (1986) not only shrink the estimate of mean by taking grand mean to be mean of minimum-variance portfolio, but also use traditional Bayesian-estimation methods to account for estimation error in the covariance matrix. Because of combining both a shrinkage approach and a traditional Bayesian estimation, the portfolio constructed under this approach is called as 'Bayes-stein' portfolio, which was applied into practice by DeMiguel et al. (2007). Secondly, Barry (1974) and Brown (1979) provide a correction based on a diffuse prior. In their approach, the estimation risk is reduced by inflating the covariance matrix. But, because the estimator of expected returns is still a sample mean, the effect of this correction is negligible. Finally, Pástor (2000) and Pástor and Stambaugh (2000) recently proposed the Bayesian 'Data-and Model' approach, which depends on a particular asset-pricing model the investor believes in. Under this approach, the shrinkage target and factor are determined by the investor's belief related to an asset-pricing model and its validity. Then, according to Bayesian 'Data-and Model' approach, Wang (2005) provides a method to obtain estimators for the mean and variance-covariance matrix of asset return. DeMiguel et al. (2007) implements it using three different asset-pricing models: the CAPM, the three-factor model (Fama and French, 1993) and four-factor model (Carhart, 1997).

In addition to Bayesian approach, the set of non-Bayesian approaches are also equally rich in the literature for reducing estimation error. Merton (1980) points out that the expected returns are very hard to estimate from historical returns. He concludes that errors in the estimates of expected returns are larger than those in the estimate of variance-covariance matrix. For this reason, the global minimum variance portfolio, which does not incorporate information on the expected return, is influenced by the recent vast literature (Best and Grauer, 1992; Chan et al., 1999; Ledoit and Wolf, 2003a). This minimum variance portfolio can be thought of as a special case of mean-variance portfolio, when all risky assets in the universe have the same expected return. In this special case, if the variance-covariance matrix is a scale of the identity matrix as well, the weights of mean-variance portfolio will be the same for all risky assets. This equalled weighted portfolio, referred to as naïve portfolio, completely ignores the data without any optimization and estimation. But, DeMiguel et al. (2007) provide strong empirical evidence that many optimal portfolios cannot beat the naïve portfolio. They analyse the out-of-sample performance of naïve portfolio against numerous other optimization strategies. In the real world, Benartzi and Thaler (2001) investigate many participants in defined contribution plan, and show naïve portfolio is a popular strategy. Windcliff and Boyle (2004) argue that naïve portfolio is not naïve as it appears, and shows that it can provide protection against very bad outcomes. In order to help reduce estimation error, there is another simple method, which only allows non-negative weights (short-sale constraints) in optimizing process (Frost and Savarino, 1988; Chopra, 1993). They also explain that the short-sale constraints are similar to shrinkage of expected return towards zero. In addition, a wide range of literature has made an effort to develop new approaches to deal with estimation risk remains with respect to variance-covariance matrix, such as, imposing a strong structure by using constant correlation (Elton and Gruber, 1976), applying single index approach which determines a covariance based on the level of relationship (Sharpe, 1963). An approach to estimate covariance matrix by using means of shrinkage estimators (Ledoit and Wolf, 2003a; Kempf and Memmel, 2003), and a new one-step approach which directly estimates optimal portfolio weights rather than estimate return distribution parameters first and then optimise portfolio weights (Kempf and Memmel, 2003). However, Jagannathan and Ma (2003) prove that for the minimum-variance portfolio, a short-sale constraint imposing have the same effect as shrinking the element of the covariance matrix.

2.1.3 Combination Portfolio

In recent years, there has emerged an alternative idea to construct portfolio by combining other portfolios. This idea tries to apply shrinkage to portfolio weights of N*1 vector directly as the form of:

$$X = cx^c + dx^d \quad st.\ \mathbf{1}'_N X = 1 \tag{2.6}$$

in which x^c and x^d, N*1 vectors, are two reference portfolios chosen by the investor. Instead of first estimating expected returns and variance and then building portfolios with these estimators, the mixture portfolio is constructed directly. There are two mixture portfolios accepted in the literature.

The first mixture portfolio is proposed by Kan and Zhou (2007) who combine sample-based mean-variance portfolio and the minimum-variance portfolio. Theoretically, if the parameters are known, a mean-variance investor should invest their wealth in two funds: the risk-free asset and the tangency portfolio (Markowitz, 1952). But, in practice, the parameters are unknown and the standard theory uses sample-based tangency portfolio instead. There are a number of studies, which use Bayesian predictive approach to deal with parameter uncertainty (estimation error) (see, e.g., Kandel and Stambaugh, 1995; Barberis, 2000; Pástor, 2000; Pástor and Stambaugh, 2000; Xia, 2002; Tu and Zhou, 2004). Alternatively, Garlappi et al. (2007) study robust portfolio rules that maximises the worst case performance when model parameters fall within a particular confidence interval. However, Kan and Zhou (2007) argue that combining with another risky portfolio can help an investor to diversify estimation risk caused by sample-based tangency portfolio. The reason of their argument is that the estimation errors of both portfolios are not perfectly correlated. The choice of c and d in equation 2.6 is dependent upon the estimation errors of two portfolios, their correlation, and their risk-return trade-offs, or alternatively to the expected utility of a mean-variance investor. In addition to sample-based tangency portfolio, Kan and Zhou (2007) use global minimum-variance portfolio as the third fund, due to only variance-covariance matrix concerned, which can be estimated in higher accuracy than expected return. This combination portfolio is known as 'three fund' portfolio strategy. As mentioned in preceding paragraphs that the expected returns are more difficult to estimate and have more estimation errors than variance-covariance matrix, one may wish to avoid expected return but accept variance-covariance matrix. So, DeMiguel et al. (2007) are motivated to consider a portfolio which combines naïve portfolio with global minimum variance portfolio.

2.1.4 Equally-weighted Risk Contribution Portfolio

The concepts of risk contribution are widely mentioned in areas of risk management, asset allocation and active portfolio management (Litterman, 1997; Lee and Lam, 2001; Clarke et al., 2002; Winkelmann, 2004). They all define two terms of the risk – standard deviation and VaR. However, Sharpe (2002) rejects the concept of risk contribution, because it is just defined through a mathematical calculation, but with litter economic justification. Chow and Kritzman (2001) emphasize that because of clear financial interpretation, the marginal contribution to VaR is useful. The reason of it is probably that financial industry places more focus on its financial interpretation rather than the initial mathematical definition (Qian, 2005). Qian (2005) answers the question about whether risk contribution has an independent, intuitive financial interpretation. Using theoretical proof and empirical evidence, he concludes that risk contribution has sound economic interpretation. In addition, he also expresses that in terms of standard deviation, risk contribution is easy to calculate and enough to depict the loss contribution. On the other hand, in terms of VaR, risk contribution although it's more precise in theory, it is difficult to compute in practice. Neukirch (2008a) supports the equally-weighted risk contribution portfolio (ERC). The idea is to equalize risk contribution of components of the portfolio. The risk contribution can be calculated by product of weight with its marginal risk contribution. Maillard et al. (2008) Implemented ERC into practice (equity US sectors portfolio, agricultural commodity portfolio and global diversified portfolio).

2.1.5 Optimal Constrained Portfolio

Kirby and Ostdiek (2010) propose a new kind of shrinkage strategies, which set conditional expected portfolio return for constructing mean-variance model as return of naïve portfolio rather than an original aggressive portfolio return. When close to sight into the models used in DeMiguel et al. (2007) research, part of the reason for poor performance of mean-variance portfolios is conditional expected excess returns they set their target on. They tend to be very aggressive. Specifically, when calculating the weights for optimal portfolio, they target a return, which always exceeds 100% per year. This unusual return can magnify the effect of estimation errors and turnover, and then leads to poor out-of-sample performance. Lehmann and Casella (1998) state that the weights of naïve portfolio are the common choice for a good shrinkage point, when investors try to improve the estimation of the mean of a multivariate distribution. After that, Tu and Zhou (2008) demonstrate that the naïve portfolio constitutes a reasonable shrinkage target, and propose a new strategy which shrinkage three-fund portfolio towards the naïve portfolio, and degree of shrinkage is determined by the level of estimation risk. Inspired by this idea, Kirby and Ostdiek (2010) consider the return from naïve portfolio instead of previous unusual return as target conditional expected portfolio return for constructing mean-variance models. This strategy is referred to as optimal constrained portfolio.

2.1.6 Timing Strategies

There is a new class of active portfolio strategies proposed to exploit sample information related to volatility dynamics. Fleming et al. (2003) advises that rebalanced portfolio weights depend on changes in the estimated conditional variance-covariance matrix of asset returns. After using futures contracts for an analysis, they name this strategy as 'volatility timing', and find that it has superior performance. Based on this idea, Kirby and Ostdiek (2010) are motivated to study the potential for this strategy to outperform naïve portfolio. Because of features of naïve portfolio, they implement volatility timing strategy in the setting of avoiding short sales and keeping turnover as low as possible:

$$w_{i,t}^{VT} = \frac{\left(1/\hat{\sigma}_{i,t}^{2}\right)^{\eta}}{\sum_{i=1}^{N}\left(1/\hat{\sigma}_{i,t}^{2}\right)^{\eta}} \tag{2.7}$$

Where $\hat{\sigma}_{i,t}^{2}$ the estimated conditional volatility of the excess is return on the i the risky asset, and $\eta \geq 0$, is a measure of timing aggressiveness. According to the above equation, there are four notable features of this new strategy: 1, not require optimization 2, not require covariance 3, not generate negative weights 4, and allow the sensitivity of the weights to volatility changes.

Ledoit and Wolf (2003a, 2003b) propose an aggressive shrinkage method, which set the off-diagonal elements of variance-covariance matrix to be zero. On the one hand, estimating $N(N-1)/2$ fewer parameters can significantly reduce the estimation risk. On the other hand, diagonal variance-covariance can strictly keep the non-negative weights of portfolio. Moreover, the tuning parameter η gives investor the flexibility to adjust the portfolio weights in response to volatility changes. If η=0, the investor will not have adjustment to weights, which means naïve portfolio thought time. If η>1, the information loss as a result of setting off-diagonal elements to be zero will be compensated to some extent. To sum up, Kirby and Ostdiek (2010) finally provide weights to reflect a general class of volatility-timing strategy as equation 2.7.

Because of ignoring information of conditional expected return in volatility-timing strategies, Kirby and Ostdiek (2010) also propose a reward-to-risk timing strategies which takes account of conditional expected return or its determinants (beta). After empirical analysis, they conclude that their timing strategies (volatility-timing and reward-to-risk timing) can outperform naïve portfolio, even after taking account of a high transaction cost.

2.1.7 Parametric Portfolio Policy

Brandt et al. (2009) propose a novel approach to optimizing portfolios with large numbers of assets, which model portfolio weights directly based on the characteristics in the cross-section of equity return. Beyond using traditional modelling which first model the return distribution and subsequently characterize the portfolio choice, Ait-Sahalia and Brandt (2001) firstly determine directly the dependence of the optimal portfolio weights on the predictive variables. They think that the single index helps investor determine which economic variables they should track. So, they combine the predictor into this index. They also set that the expected utility is CRRA preference.

Nigmatullin (2003) extends his nonparametric approach to incorporate parameter and model uncertainty in a Bayesian setting. Brandt and SANTA - CLARA (2006) further research his previous study about optimal portfolio weights as a function of the predictors. They model the weight in each asset class (stocks, bonds, and cash) as a separate function of a common set of macroeconomic variables. In their approach, the assets have fundamentally different characteristics. In contrast, based on these literatures, Brandt et al. (2009) continue their study which is related to each asset with the same function of asset-specific variables. They produce parametric portfolio policies which obtain the weights by a simple linear function:

$$w_{i,t}^{PPP} = \overline{w}_{i,t} + \frac{1}{N}\theta'\hat{x}_{i,t} \tag{2.8}$$

where $\overline{w}_{i,t}$ is the weight of stock i at date t in a benchmark portfolio, $\hat{\theta}$ is a S*1 vector of coefficients to be estimated by maximising CRRA utility, and $\hat{x}_{i,t}$ are a S*1 vector of the characteristics of stock i, S is the number of characteristics and is considered in the policy. The equation 2.8 can be interpreted as the idea of active portfolio management, which deviate weights from passive benchmark portfolio based on the information (here, e.g. the characteristics of assets) gathered by the investor.

The characteristics need to be standardized cross-sectional with zero mean and standard deviation of one. The cross-sectional distribution of raw x_{it} (unstandardized characteristics) may be nonstationary. Due to unreliable analysis with nonstationary time series, the standardization can transform the distribution to become stationary through time. This is the first reason of standardizing characteristics. The second reason is that average of $\theta^{'}\hat{x}$ is zero, which means to keep the sum of portfolio weights to be one. In addition to standardization, the term of $1/N$ allows changes in number of assets at any point of time. Finally, the coefficients θ are constant across asset and through time, which implies that the portfolio weight for each asset depends only on the characteristics but not historic return.

There are a number of conceptual advantages which the parametric portfolio policy has. Firstly, the strategy focuses directly on the portfolio weights to avoid an annoying and difficult step of estimating the joint distribution of returns. Secondly, the dimensionality of variable need to be estimated is tremendously reduced. If there is a case of N assets, traditional mean-variance strategy requires estimating N first and $(N^2+N)/2$ second moments of return. But, Brandt et al's strategy ignores the joint distribution of returns, and models only the N portfolio weights. So, this reduction helps investor to mitigate the estimation errors. Finally, this strategy captures the relationship between characteristics and moments of returns. Brandt et al. (2009) implement their strategy to the stock market, and consider market weights as a benchmark. The characteristics of stock taken account by them are the size of firm, book-to-market ratio and one year lagged return. They also provide several extension of this strategy to cooperate modification, mainly including short-sale constraints and transaction cost.

2.2 Characteristics of Currency

From now on, the literature pertaining to currency characteristics is reviewed. This section is divided into two parts. The first part will review the financial (technical) characteristics, which are based on change in price of currency. The second part is concerned with the fundamental characteristics, which is related to economic factors of a pair of countries in currency.

2.2.1 Financial Characteristics

Carry Trade

Bilson (1981) and Fama (1984) document a strategy, which is motivated by the failure of uncovered interest parity. This strategy, normally called carry trade, is constructed by borrowing currency with low interest rate and investing currency with high interest rate. With support from Burnside et al. (2008), carry trade been proven that it has a very good performance. The reason of return from carry trade is discussed with considerable effort in existing literature. Lustig et al. (2011) explain that carry premium is a result of the compensation for the risk an investor bears. In their paper, the risk factor is constructed by return of currency with high-interest rate minus currency with low-interest rate. There are also other risk factors constructed by literature, such as liquidity squeezes by Brunnermeier et al. (2008) and foreign exchange volatility by Menkhoff et al. (2012a), and these systematic risks are timing-varying, as proven by Christiansen et al. (2011). 'Peso problem', proposed by Jurek (2014) and Farhi and Gabaix (2008), could be another explanation of carry premium.

Currency Momentum and Value (Long-term Reversal)

In addition to carry trade, studies also focus on alternative investment styles. Menkhoff et al. (2012b) build a currency only portfolio with momentum strategy, and document its properties. This strategy is simply to buy assets with high short-term return and to sell assets with low short-term return. Okunev and White (2003) illustrate that this currency momentum still works in FX markets. Burnside et al. (2011) combine carry trade with momentum to improve the performance. Besides only momentum strategy, Asness et al. (2013) examine a combination portfolio, which include equally weighted currency value and momentum portfolios. They measure currency value as the negative of the long-term return, which then is adjusted by the change in CPIs of pair of currencies. Due to the implicit idea of reversed return in a long term, this strategy is also noted as 'long-term reversal' by Barroso and Santa-Clara (2011), and they are essentially the same. Jordà and Taylor (2012) study a simple combination, which includes three portfolios of carry, momentum and the real exchange rate. Finally, Barroso and Santa-Clara (2011) investigate a more complex combination portfolio with application of parametric portfolio policies derived by Brandt et al. (2009). The characteristics they try to use are not only related to the strategies of carry trade, momentum and long-term reversal (value), but also include real exchange rate and current account of corresponding countries. However, their pre-sample analysis shows that real exchange rate and current account are not relevant, and their coefficients are not significant. So, they drop these two variables in an out-of-sample analysis. In addition, Kroencke et al. (2013) conduct an extensive out-of-sample experiment about performance of foreign exchange investment strategies. After carefully hedging a portfolio with the stock and bond, they combine this portfolio with the above three currency trading strategies; they find out that these three strategies generate significant improvements.

2.2.2Fundamental Characteristics

Characteristics related to fundamentals are not the real exchange rate itself, but factors that determine real exchange rates. Next, the literature related to determinants of exchange rates is reviewed.

Purchasing Power Parity

Cassel (1921) proposes the traditional purchasing power parity, which posits that the exchange rate between two countries will be identical to the ratio of price levels of those two countries. Or, in the relative version of purchasing power parity, the change in two countries' expected inflation rates will be equal to the change in their exchange rates.

Flood (1981) and Mussa (1982) prove that the purchasing power parity cannot be expected to hold in presence of real shocks. Manzur (1990) tests purchasing power parity with two parts-short run and long run. For the short-run, the results are consistent with the evidence of Frenkel (1980) and Lothian (1985), who prove that purchasing power parity does not hold up well at all in the short run. For the long run, the finding supports purchasing power parity, which also are proved by Hakkio (1984). The deviation from purchasing power parity could be explained by Dornbusch (1976), who argues that the purchasing power parity deviations arise simply due to sticky prices of goods. Dornbusch (1976) and Frenkel (1978) express the sticky-price monetary model, which shows the determinations of exchange rates are related to money, GDP, interest rate and inflation rate.

Behavioural Equilibrium Exchange Rate Model (BEER)

Furthermore, Balassa (1964) argues that the relative price of non-traded goods tend to be higher in richer countries. This is the productivity bias hypothesis which is considerably supported by Bhagwati (1984), Isard (1977), and Kravis and Lipsey (1978), and for broad price indices, the models drops the assumption in purchasing power parity. So, the productivity based model includes characteristics in sticky-price monetary model incorporating productivity, and relate real exchange rates to economic fundamentals. Lots of effort has been devoted to this field (Faruqee, 1994; Stein, 1995; Bayoumi and Symansky, 1994; MacDonald, 1999; Kramer, 1995; Hinkle and Montiel, 1997). Finally, Clark and MacDonald (1999) propose the behavioural equilibrium exchange rate (BEER) model, which models real exchange rates. In their paper, the variables include term of trade, relative price of non-traded to traded goods (productivity differential), net foreign assets, relative stock of government debt, and real interest rate. For empirical studies, authors often use different sets of fundamentals variables when they apply BEERs model. Komárek et al. (2005) chose a set of determinants additionally consisting of degree of openness, foreign direct investment, government consumption, but drop relative stock of government debt. MacDonald and Dias (2007) keeps two variables in the original model--terms of trade and real interest rate, and add other variables of net exports and GDP per capita.

2.3 Performance Evaluation Methods

2.3.1 Traditional Performance Measures

Sharpe (1966) proposes a ratio known as reward-to-variability ratio to measure the performance of mutual funds. Then, this method is very popularly used, but named differently, such as Sharpe Index (Radcliffe, 1997) and Sharpe measure (Elton and Gruber, 1991). But, in a revision of Sharpe (1994), he redefines this ratio as Sharpe ratio. Moreover, there are two versions of Sharpe ratio. The ex-ant Sharpe ratio focuses on the use of the ratio for making decisions, which is defined as follows:

$$\tilde{d} \equiv \tilde{R}_P - \tilde{R}_B \tag{2.9}$$

Let $\tilde{R}_P$ represent the return on fund in the next period and $\tilde{R}_B$ the return on a benchmark portfolio or risk free rate.

$$S \equiv \frac{\bar{d}}{\sigma_{\tilde{d}}} \tag{2.10}$$

In which $\bar{d}$ be the expected value of $\tilde{d}$, and $\sigma_{\tilde{d}}$ is the predicted standard deviation of $\tilde{d}$.

However, the elements from this Sharpe ratio are expected value which is difficult to be determined. So, there is another version, called the ex-post Sharpe ratio, which indicates the historic average differential return per unit of historic variability of the differential return.

$$S_{pi} = \frac{\hat{\mu}_{Pi,t}}{\sigma_{\hat{r}_{Pi,t}}} \tag{2.11}$$

Let $\hat{r}_{Pi,t}$ represent the excess return on portfolio i at time t, $\hat{\mu}_{Pi}$ represent the average of $\hat{r}_{Pi,t}$ and $\sigma_{\hat{r}_{Pi,t}}$ represent the standard deviation of $\hat{r}_{Pi,t}$.

Treynor (1964) proposes another standard performance measure, which is written as follows:

$$Tr = \frac{\hat{\mu}_{Pi,t}}{\beta_i} \tag{2.12}$$

where β_i is coming from the empirical estimates of the CAPM model (Sharpe 1964; Lintner, 1965; Mossin, 1969), and calculated according to regression with formula as follows:

$$\hat{r}_{Pi,t} = \alpha_i + \beta_i \hat{r}_{B,t} + \varepsilon_{Pi,t} \tag{2.13}$$

The intercept in the above equation is Jensen Alpha (Jensen, 1968). However, this measure simply is a reward measure. If I consider risk, the measure can be called Appraisal ratio:

$$AR = \frac{\alpha_i}{\sigma_{\varepsilon_{Pi,t}}} \tag{2.14}$$

The difference between the Sharpe and Treynor ratios is how to measure the risk. There are several other measures which are derived from different ways to measure the risk.

Konno and Yamazaki (1991) propose a ratio called expected return over mean absolute deviation ratio:

$$ERMAD = E\left[\hat{r}_{Pi,t}\right]/E\left[\left|\hat{r}_{Pi,t} - E\left[\hat{r}_{Pi,t}\right]\right|\right] \qquad (2.15)$$

In addition, Young (1998) suggests that the expected return over Minimax ratio

$$ERMM = E\left[\hat{r}_{Pi,t}\right]/\max(\max \hat{r}_{t=1}^{T} - \min \hat{r}_{t=1}^{T}) \qquad (2.16)$$

Caporin and Lisi (2009) contribute a ratio called the expected return over the range ratio

$$EER = E\left[\hat{r}_{Pi,t}\right]/(\max \hat{r}_{t=1}^{T} - \min \hat{r}_{t=1}^{T}) \qquad (2.17)$$

Modigliani and Modigliani (1997) propose a rather different measure, the Risk Adjusted Performance, which is defined as:

$$RAP = \left(E\left[\hat{r}_{Pi,t}\right] - E\left[\hat{r}_{B,i}\right]\right)\frac{\sigma\left[\hat{r}_{B,t}\right]}{\sigma\left[\hat{r}_{Pi,t}\right]} - E\left[\hat{r}_{B,t}\right] \qquad (2.18)$$

After comparing these performance measures over a dataset that contains the stocks included in the S&P 1500 index, Caporin and Lisi (2009) summarize that all 6 measures provided almost similar results to the Sharpe ratio in terms of asset ranking. They analyse rank correlation of performance measures with the Sharpe ratio over different sample lengths. Consequently, all correlations are bigger than 0.9 excepting 3 out of 42.

2.3.2 Comparison of Sharpe Ratios

It is also important to test whether the Sharpe ratio of strategies between two portfolios are statistically different. I calculate the p-values of these differences. The method is suggested firstly by Jobson and Korkie (1981), and then Memmel (2003) makes the correction simplify the test statistics without loss of its statistical properties.

Especially, given two portfolios, one is referred as 'i', and the other is portfolio k, with $\hat{\mu}_{Pi}$, $\hat{\mu}_{Pk}$, $\hat{\sigma}_{Pi}$, $\hat{\sigma}_{Pk}$, $\hat{\sigma}_{Pi,Pk}$ as their mean, standard deviation and covariance which are estimated over a sample of size T-M. The null hypothesis is $\frac{\hat{\mu}_{Pi}}{\hat{\sigma}_{Pi}} - \frac{\hat{\mu}_{Pk}}{\hat{\sigma}_{Pk}} = 0$, and the test statistic, which is asymptotically distributed as a standard normal, is:

$$\hat{z} = \frac{\hat{\mu}_{Pi}\hat{\sigma}_{Pk} - \hat{\mu}_{Pk}\hat{\sigma}_{Pi}}{\sqrt{\hat{\vartheta}}} \tag{2.19}$$

$$\hat{\vartheta} = \frac{1}{T-M}\left(2\hat{\sigma}_{Pi}^{2}\hat{\sigma}_{Pk}^{2} - 2\hat{\sigma}_{Pi}\hat{\sigma}_{Pk}\hat{\sigma}_{Pi,Pk} + \frac{1}{2}\hat{\mu}_{Pi}^{2}\hat{\sigma}_{Pk}^{2} + \frac{1}{2}\hat{\mu}_{Pk}^{2}\hat{\sigma}_{Pi}^{2} - \frac{\hat{\mu}_{Pi}\hat{\mu}_{Pk}}{\hat{\sigma}_{Pi}\hat{\sigma}_{Pk}}\hat{\sigma}_{Pi,Pk}^{2}\right) \tag{2.20}$$

In addition to p-value, the return-loss can be considered as the additional return, which strategy k needs to perform as well as the portfolio i in terms of the Sharpe ratio. The formula of return-loss for portfolio k is:

$$re-loss_{Pk} = \frac{\hat{\mu}_{Pi}}{\hat{\sigma}_{Pi}}\hat{\sigma}_{Pk} - \hat{\mu}_{Pk} \tag{2.21}$$

2.3.3 Risk Measure based on Drawdown

In addition to the standard deviation, there are alternative approaches to measure risk (Biglova et al., 2004; Ortobelli et al., 2005; Rachev et al., 2008). One of possible measures is based on Drawdowns. The Drawdown represent, at time t, the maximum loss an investor may have suffered from 0 to t. According to order drawdown and compute quantities, the risk measure could be such as maximum drawdown or second largest drawdown. The relative formula is showed as follows:

Drawdown: $$D_t = \min\left(D_{t-1} + \hat{r}_{Pi,t}, 0\right) \qquad D_0 = 0 \tag{2.22}$$

Maximum drawdown: $$D_1 = \min\left\{D_{t=1}^{T}\right\} \quad (2.23)$$

The Second largest drawdown: $$D_2 = \min\left\{D_{t=1}^{T} - D_1\right\} \quad (2.24)$$

Young (1991) suggests Calmar ratio, which is the ratio between the expected return and the maximum drawdown. Kestner (1996) introduces a Sterling ratio, which is the ratio between the expected returns and the N largest drawdown. Burke (1994) proposes the Burke ratio, which is the ratio between the expected return and the second order non-central moment of the N largest drawdown. The relative formula is showed as follows:

Calmar ratio: $$CR = \frac{\hat{\mu}_{Pi}}{-D_1} \quad (2.25)$$

Sterling ratio: $$SR = \frac{\hat{\mu}_{Pi}}{-\frac{1}{w}\sum_{j=1}^{w} D_j} \quad (2.26)$$

Burke ratio: $$BR = \frac{\hat{\mu}_{Pi}}{\left(\frac{1}{w}\sum_{j=1}^{w} D_j^2\right)^{\frac{1}{2}}} \quad (2.27)$$

Where w is the number of value used in the computation of the risk measure. Eling and Schuhmacher (2007) fix this w is 5. However, Caporin and Lisi (2009) conclude that ‘there is no need to consider the Sterling and Burke indices computed over different numbers of drawdowns.

2.3.4 Risk Measure based on Quantiles

Beder (1995) concludes approaches to calculating value at risk (VaR). The VaR is defined as the maximum loss on an asset/portfolio that can be expected over a certain time interval with a certain degree of confidence. There are two approaches to calculate VaR. One is related to historical data, or nonparametric approach, which uses historical distribution of the returns in order to compute the appropriate loss. The other one is to simulated data, or parametric approach, which assumes the returns follow a normal distribution with mean and standard deviation calculated by historical data. However, a major criticism of VaR is about subadditivity, which is described by Jorion (2007) as 'merging two portfolios cannot increase risk'. And, he uses an example to prove that VaR violates the principle of subadditivity. Moreover, Albanese (1997) argues that due to a lack of subadditivity in VaR, the measure can lead to a higher concentration of credit risk, while managing credit portfolio risk. Kidd (2012) concludes that the reason for significant loss in a global financial crisis is to improperly understand and use VaR, and ignore tail risk. So, a number of investors try to adopt conditional value at risk (CVaR), which is designed to measure the risk of extreme losses.

Embrechts et al. (1999) firstly propose expected shortfall, which also is called conditional value at risk (CVaR). This measure, an extension of VaR, represents the expected loss of portfolio value given that a loss is occurring at or below the q-quartile. Kidd (2012) states 'CVaR quantifies tail risk and has been shown to be subadditive'. Rockafellar and Uryasev (2000) show another advantage of CVaR, which is that the optimization in portfolio risk by CVaR is easier than VaR. But, CVaR is not perfectly and not absolutely superior to VaR, because it has defects as well. Yamai and Yoshiba (2002) argued that in order to generate a reliable estimate, a large number of observations are required for CVaR. Compared to VaR, CVaR is more sensitive to estimation errors. So, Lim et al. (2010) conclude that both VaR and CVaR are used frequently and therefore complement each other.

2.4 Conclusion

Since Markowitz (1952) proposes a seminal work to make the rule for constructing portfolio, the modern portfolio management has been developed vastly in the academic literature and in practice. Empirical studies show very poor performance of this model with sample-based mean and variance-covariance in out-of-sample analysis. The key problem of the failure can be attributed to errors in estimation. So, considerable effort from literature is focused on how to handle this estimation error, and then finally to improve the performance of portfolios.

On the one hand, a lot of literature tries to mitigate estimation errors by using the Bayesian approach. On the other hand, equally, non-Bayesian approaches also are used to reduce the estimation errors in a number of literatures. However, recent studies tend to propose alternative ways to construct portfolio, beyond to Markowitz's model and its robust extension. I reviewed literature related to these three classes of portfolio strategies. One of strategies, called parametric portfolio policy, needs characteristics of currency. So, next, I reviewed literature about characteristics to determine the price of currency.

The characteristics of currencies can be divided into two parts: financial (technical) and fundamental (economic). The financial characteristics are from profitable currency trading strategies, and related to change in currency price. There are three main trading strategies in currency market. The most popular strategy in literature is referred to as carry trade, which is to invest in currency with high interest rates and sell currency with low interest rate. The other two are referred to as currency monument and value. The currency monument is based on the idea of price rising after rising in the last short time. Conversely, the currency value strategy holds that price will decrease after it increases for a long time. So, this strategy is called long-term reverse. The fundamental characteristics are the economic factors, which can determine the price of currency. The theory of behavioural equilibrium exchange rate (BEER) has modelled how to analyse these factors. But, literature implements this model slightly different in practice.

Lastly, the performance of portfolios needs to be evaluated by a reasonable method. The Sharpe ratio is the most common evaluation method, because it takes account of both return and risk. In spite of the fact that there are other alternative methods, literature has summarised that the results from these alternatives is not different to the results from Sharpe ratio. In addition to the standard deviation, there are other risk measures mentioned more frequently. Drawdown is one of these risk measures. It measures the maximum loss during the certain time periods. Another risk measure is to capture the loss of portfolio at specific quantile. Both of the value at risk and conditional value at risk belong to this class. Because they have their own advantages and disadvantages, researchers would like to use both of them complementarily.

Chapter Three

Data

Before analysing the performance of currency only portfolio constructed using various strategies, the methods of calculating the currency return, taking account transaction cost are firstly introduced, followed by summarising the statistics of currency return. The methodology of currency return calculation introduced in this chapter will be implemented in the next three chapters, as well as the transaction cost method, but the sample and its period might not be the same. The G10 currencies are considered as the first dataset (9 currencies in total and another one, US dollar, as based currencies), as they are the most 10 heavily traded currencies in the world. The corresponding countries and area include Australia, Canada, Japan, New Zealand, Norway, Sweden, Switzerland, UK and Euro Zone. For the second datasets, I add ‘lesser’ currencies, which are mostly from developing countries, to bring a diversification benefit to the portfolio. The corresponding countries include Brazil, Chile, Colombia, Czech, Egypt, Hungary, Iceland, India, Indonesia, Israel, Mexico, Peru, Philippines, Poland, Russia, Singapore, South Africa, Taiwan, Thailand and Turkey. So, the second data set has 29 currencies in total.

3.1 Currency Return

3.1.1 Method of Calculation

To calculate currency returns, it is assumed that an investor at time t to buy currency i for S_t^i, and hold it until time t+1, and sell it at t+1 for S_{t+1}^i, where S_t^i and S_{t+1}^i are the price of one foreign currency unit expressed in home currency. The Investor also earns interest at foreign countries risk free rate during t and t+1. So, the return for the investor should be

$$R_{t+1}^i = \frac{S_{t+1}^i(1+R_{f,t}^{foreign}) - S_t^i}{S_t^i} \tag{3.1}$$

In the analysis, the plan is to include 29 currencies, which required the gathering of risk free rates of 29 countries. However, there is difficulty in choosing an appropriate risk free rate. In order to avoid having to make an arbitrary decision on the most appropriate risk free rate for each country, an alternative way to calculate selected returns is available. In the forward exchange market, the forward rate of currency is calculated as follows (CIP, covered interest parity).

$$F_{t,t+1}^i = S_t^i \frac{(1+R_{f,t}^{US})}{(1+R_{f,t}^{foreign})} \tag{3.2}$$

Combining formula 1 and 2, I obtain the formula as follow.

$$R_{t+1}^i = \frac{S_{t+1}^i(1+R_{f,t}^{us}) - F_{t,t+1}^i}{F_{t,t+1}^i} \tag{3.3}$$

This formula also can be explained as an investor buying currency at t for $F_{t,t+1}^i$ and selling it at t+1 for S_{t+1}^i; meanwhile the investor can earn US risk free rate, this interest also is taken into account for forward buying and spot selling. Comparing to gather the risk free rate for each country, the forward rate is easier to obtain from the database. The advantage of using the last formula is only US risk free rate concerned. For now, the return calculated is called ‘raw return’, but in this thesis uses excess return, which is return over risk free rate. Therefore, risk free rate is subtracted from raw return. The formula of excess return is as follows.

$$r_{i,t+1} = (\frac{S_{t+1}^{i} - F_{t,t+1}^{i}}{F_{t,t+1}^{i}})(1 + R_{f,t}^{us}) \tag{3.4}$$

In the next sub-section, the source and data description for spot rate, forward rate, risk free rate and GDP and trade data is described.

3.1.2 Spot Rate

The spot rate data are collected from WM/Reuters FX Indexes in DataStream from 28th October 1997 till 13th March 2012 with weekly frequency. We, then, convert them to USD/ foreign currency, if they are not. For the robustness check, I convert them again to UK/foreign currency, EU/foreign currency and Japanese Yen/foreign currency. For each currency pair, I have 751 observations in almost 15 years. According to graphic checking, it can be confirmed that that all 29 currencies are floated to each other, with no fixed rate over the period Selected.

3.1.3 Forward Rate

The same period forward rate data is collected from DataStream. However, in the case of some currencies, there are no forward rates available from 28th October 1997. So, I simulate the forward rate for these currencies and period of absence by using formula 3.2 in the last subsection. The question now is that not all countries have 3-month T-bill from DataStream. So, pairs of following interest rate shown in Table 3.1 are used instead of 3-month T-bill.

Forward rates for the period after 23th March 2004 are simulated, and compared to actual forward rates. The difference between the calculated forward rates and the actual forward rates is calculated. The percentages are computed by these differences over the actual forward rates. The average and standard deviation of these percentages are demonstrated in Figure 3.1. From the figure, all averages and standard deviations of percentages, which are no more 0.7%, can be considered to be very small. In addition to statistical analysis, the calculated forward rates along with the actual forward rates are graphed. As per Figure 3.2, for each currency, the line which represents the forward rate from DataStream coincides with the line which represents the calculated forward rate. So, I can confirm that there is no significant difference between the two rates and the two rates are almost the same. It can be assumed that the simulated forward rates are reliable, 751 observations of forward rates covering a 15 year period were reviewed.

Table 3.1 List of currencies with absent forward rate

The first column of table lists currencies that do not have forward rate in DataStream. The next column provides the date of forward rate is available. The last two columns lists the names of risk free rates used for local countries and corresponding name of risk free rates for the US. All risk free rates are collected from DataStream with weekly frequency, and then divided by 52 to obtain weekly rate.

Currencies	Absence until	Interest rate	Corresponding US interest rate
Iceland Krona	23/03/2004	Treasure bond yield 10 years	Treasure bond yield 10 years
Israeli Shekel	23/03/2004	T-bill secondary 3 month	T-bill secondary 3 month
Brazilian Real	23/03/2004	Saving account	CD second market 6 month
Colombian Peso	23/03/2004	Fixed term deposit	Conventional fixed mortgages
Egyptian Pound	23/03/2004	91 Day T-Bill	Treasury constant MAT 3 month
Peru New Sol	23/03/2004	Interbank interest rate	Average of interbank interest rate
Russian Rouble	23/03/2004	Interbank 8 to 30 day	Interbank 1 MTH
Chilean Peso	23/03/2004	CD 30 Days	CD 1 month

Figure 3.1 Statistics of percentage of difference between calculated FWD and quoted FWD over quoted FWD

The purpose of this figure is to compare the calculated forward rates with the quoted forward rates for the eight currencies, which do not have forward rate for the part of sample period. The method used is to firstly take the difference between two values, and then calculate the percentage of this difference over quoted forward rates. Finally, this figure demonstrates the average and standard deviation of this percentage.

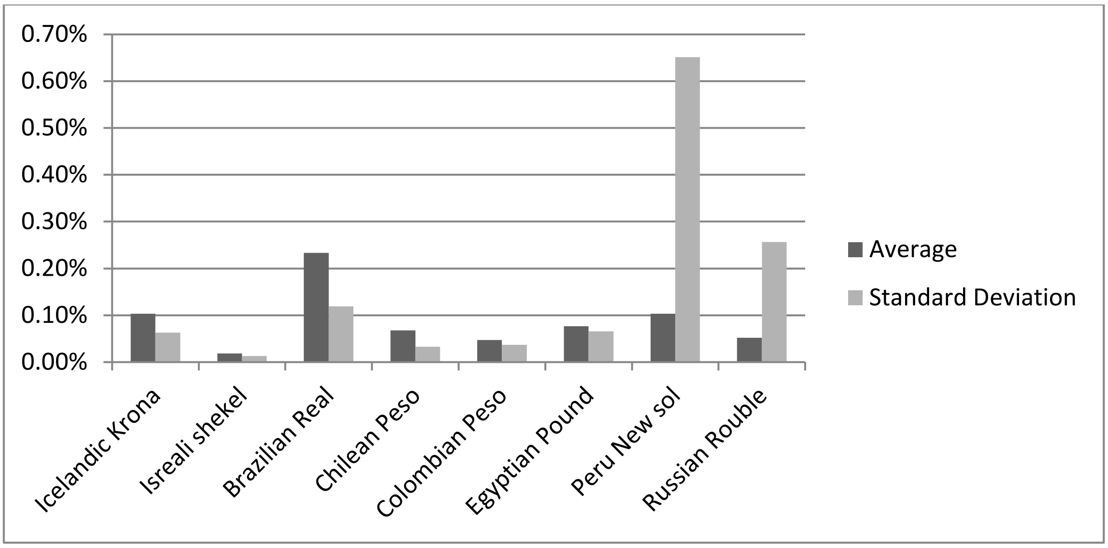


Figure 3.2 Comparison of calculated FWD with quoted FWD

This figure compares the forward rate from source with the calculated forward rate. The currencies reported here are that their forward rates are not available for the whole sample period. And, the period is from 2014 to 2012, which the forward rates of these currencies are available for. For each currency, the blue line (referred as WMD) is the forward rate from WM/Reuters FX Indexes in DataStream, and the red line (referred as calculated) represents the forward rate I calculated by

$$F_{t,t+1}^{i} = S_{t}^{i}\,\frac{(1+R_{f,t}^{US})}{(1+R_{f,t}^{foreign})}$$

3.1.4 Risk Free Rate

In this thesis, risk free rates are required in order to calculate currency return and sharp ratio. There are risk free rates of three countries and one zone collected from DataStream for the same period with weekly frequency. US risk free rates are used for base samples. For robustness checking, Japanese, UK, and Euro zone risk free rates are necessary. US 3 month T-bill interest rate is used for analysis of US investors' perspective, UK 3 month gilt for analysis of perspective of UK investors, and Japanese commercial paper 1 month for analysis of perspective of Japanese investors. As far as Euro zone investors are concerned, it is a more complicated process. There is a need to obtain weights of the countries within the Eurozone. Fortunately, the European Central Bank (ECB) provides this kind of weights, and updates them yearly on its website. The ECB calculates these weights based on GDPs, and use them to calculate Harmonised Index of Consumer Prices (HICP) for Eurozone by a weighted average of countries' price index. After reweighting, the six largest weights add up to 1. This is then followed by collecting these six countries' risk free rates from DataStream. The home-made euro risk free rate is calculated by using the weighted-average method. Table 3.2 demonstrates the re-weighted weights and the names of risk free rate used for these six countries.

Table 3.2 Weights and names of risk free rate of six euro countries

This table lists two components of euro risk free rate in my calculation. One is weights, which obtained from the European Central Bank's website. I reweight six largest weights of countries adds to one. Other one is the name of risk free rate for each country.

	France	Germany	Italy	Spain	Netherland	Belgium
1997	23.7%	37.3%	19.6%	9.6%	5.7%	4.1%
1998	23.7%	37.3%	19.7%	9.6%	5.7%	4.1%
1999	22.8%	37.3%	20.3%	9.8%	5.5%	4.3%
2000	22.5%	37.4%	19.7%	9.8%	6.1%	4.3%
2001	23.0%	34.7%	21.0%	11.7%	5.9%	3.7%
2002	22.9%	34.3%	21.6%	11.5%	5.8%	3.8%
2003	23.0%	33.5%	21.5%	12.2%	6.1%	3.7%
2004	23.3%	32.8%	21.7%	12.5%	6.0%	3.7%
2005	23.3%	32.7%	21.6%	12.8%	5.9%	3.7%
2006	22.9%	32.4%	21.5%	13.5%	5.9%	3.8%
2007	23.5%	32.0%	20.7%	13.9%	6.0%	3.9%
2008	23.5%	31.0%	21.3%	14.6%	5.7%	3.9%
2009	23.8%	30.2%	21.4%	14.8%	5.9%	3.9%
2010	24.2%	30.4%	21.1%	14.6%	5.9%	3.7%
2011	24.1%	30.2%	21.5%	14.8%	5.6%	3.8%
2012	23.9%	30.8%	21.1%	14.4%	5.7%	4.1%
Name	France T-Bill 3 Month	Money market 3 month	Italy T-Bill AUCT. GROSS 3 MONTH	SPAIN T-Bill 1-3 MONTH	NTHRLAND EU-GLDR 3M	BELGIUM TREASURY BILL 3 MONTH

3.1.5 GDP and Trade

In the CAPM world, for the equity, the optimal strategy is the value-weighted market portfolio. So, in this thesis, I attempt to identify market portfolio. But, due to no direct value for the currencies, indirect methods are used to determine the currency value. For the currency market, the total value of currency can be considered as the value of this country, which can be represented by GDPs. Alternatively, the currency rate is closely related to trade. The change in currency rate affects bilateral trade, and the sum of import and export may be considered as value of currency. So, GDPs and the sum of bilateral trade is used to construct two benchmark market portfolios. As a result of a delay in releasing GDP data and trade from national statistics authorities, the previous year's GDPs and trade data obtained from DataStream, is used to calculate weights for a whole currency year returns. GDPs collected are under expenditure approach at current market price, but is dominated by local currencies. I therefore firstly, convert them to US dollars using year end spot rate. In the robustness checking, the trades of most members of the Eurozone with developing countries are not available, so I do not construct trade portfolio of 29 currencies for euro investor.

3.2 Summary Statistics

In this section, the statistics of currency returns, risk free rate and GDP and trade weights all related to the perspective of US investors are summarised. From other investors' perspectives, the conclusions of statistics are almost similar to what I conclude from US investors.

3.2.1 Currency Return

The statistics of returns on 29 currencies are well documented in Table 3.3. From this table, the Polish zloty has the highest average weekly return, while the new Turkish lira has lowest return of -2.41% (annualized return of -125%). Because of a chronic inflation experienced in Turkey from the 1970s through to the 1990s, the lira depreciated in value. This also led to the highest standard deviation of returns of the lira. According to the maximum and minimum return during sample period, the Russian rouble can be considered as very volatile with maximum return of 99% and minimum return of -45%. This can be partly attributed to the 1998 Russian financial crisis resulting in a 70% drop in value against the US dollar. In addition to the new Turkish lira and Russian rouble, there are several other currencies with the anomalously kurtosis and skewness, which indicate that the distribution of returns of these currencies significantly deviate from the norm. These currencies, which include Icelandic krona, Brazilian real, Egyptian pound, Peru new sol and Philippine peso, went through the same challenges as the Russia and Turkey, experiencing a huge drop in value due to rapid economic decline. In sharp contrast, the G10 currencies do not have an anomaly as evidenced by the available statistics. A critical analysis of available data from year to year shows the anomalies of emerging currencies vanishing with no immediate financial impact. Ccorrelations are also analysed for each full calendar year. All correlations are less than 0.85 I can therefore conclude that there are no clearly defined correlations between any two currency returns.

Table 3.3 Statistics of 29 currencies returns

This table shows the results of statistics of 29 currencies returns for the time period from 4/11/1997 to 13/3/2012. 'Mean' represents the average return, and 'SD' represent standard deviation of currencies returns. The high moments of returns are reported in column 7 and 8, which use 'SK.' and 'KU.' to represent skewness and kurtosis respectively. The last two columns give maximum and minimum returns in the period for each currency. Because the weekly return is calculated before, the results are also based on weekly frequency. But, for the convenience to compare with other data, I also report the annualized mean and standard deviation, which is referred to as 'Annualized Mean' and 'Annualized SD' respectively in the table. The process of annualizing used is simple transformation. For example, the mean is multiplied by 52 to get annualized mean, and standard deviation is multiplied by square root of 52 to get annualized standard deviation.

Name	NO.of Ob	Mean	Annualized Mean	SD	Annualized SD	SK.	KU.	MAX	MIN
AUSTRALIAN $	750	0.16%	8.47%	1.85%	13.37%	-0.16	4.26	7.14%	-9.36%
CANADIAN $	750	0.11%	5.62%	1.35%	9.75%	0.55	9.32	2.08%	-6.35%
ICELANDIC KRONA	750	0.06%	3.25%	2.12%	15.27%	2.97	48.72	1.61%	-10.56%
ISRAELI SHEKEL	750	0.10%	5.34%	1.11%	8.01%	-0.50	2.32	3.55%	-5.19%
JAPANESE YEN	750	0.05%	2.77%	1.47%	10.61%	0.69	3.86	10.25%	-5.88%
NEW ZEALAND	750	0.16%	8.18%	1.99%	14.33%	-0.14	2.76	9.79%	-10.56%
NORWEGIAN KRONE	750	0.12%	6.05%	1.67%	12.07%	-0.28	1.49	3.29%	-7.44%
SINGAPORE	750	0.06%	3.19%	0.85%	6.11%	-0.01	6.11	5.67%	-4.54%
SWEDISH KRONA	750	0.07%	3.87%	1.68%	12.11%	-0.26	1.12	4.06%	-7.81%
SWISS FRANC	750	0.08%	4.22%	1.50%	10.85%	0.03	1.12	4.48%	-6.52%
UK £	750	0.07%	3.56%	1.30%	9.37%	-0.24	2.32	2.54%	-7.99%
EURO	750	0.07%	3.80%	1.44%	10.38%	0.20	1.93	2.67%	-4.15%
BRAZILIAN REAL	750	0.10%	5.01%	2.38%	17.18%	-1.90	17.95	13.03%	-23.34%
CHILEAN PESO	750	0.03%	1.38%	1.48%	10.69%	-0.12	1.90	2.10%	-6.81%
COLOMBIAN PESO	750	0.13%	6.68%	1.70%	12.28%	-0.26	5.56	5.30%	-8.78%
CZECH KORUNA	750	0.16%	8.28%	1.81%	13.08%	-0.38	1.32	4.40%	-8.33%
EGYPTIAN POUND	750	0.09%	4.59%	0.78%	5.62%	-13.75	276.95	1.08%	-16.39%
HUNGARIAN FORINT	750	0.18%	9.38%	2.03%	14.66%	-0.57	2.72	2.17%	-12.13%
INDIAN RUPEE	750	0.09%	4.45%	0.83%	6.00%	-0.43	6.40	2.83%	-4.36%
INDONESIAN RUPIAH	750	0.11%	5.60%	3.63%	26.20%	0.04	23.50	31.97%	-26.61%
MEXICAN PESO	750	0.16%	8.08%	1.42%	10.26%	-0.05	6.38	3.30%	-8.93%
PERU NEW SOL	750	0.15%	8.00%	0.81%	5.84%	2.25	23.22	1.85%	-4.48%
PHILIPPINE PESO	750	0.12%	6.35%	1.28%	9.25%	-1.20	22.52	6.66%	-12.58%
POLISH ZLOTY	750	0.20%	10.37%	2.03%	14.61%	-0.79	3.38	3.22%	-10.67%
RUSSIAN ROUBLE	750	0.11%	5.73%	4.53%	32.65%	11.68	320.07	98.86%	-44.92%
SOUTH AFRICA RAND	750	0.16%	8.19%	2.31%	16.64%	-0.55	3.29	4.16%	-14.76%
TAIWAN NEW $	750	0.04%	1.90%	0.66%	4.77%	-0.10	4.22	3.16%	-3.40%
THAI BAHT	750	0.13%	6.76%	1.35%	9.75%	0.63	29.84	13.73%	-11.54%
NEW TURKISH LIRA	750	-2.41%	-125.26%	11.48%	82.78%	-3.81	13.31	2.23%	-57.96%

3.2.2 Risk Free Rate

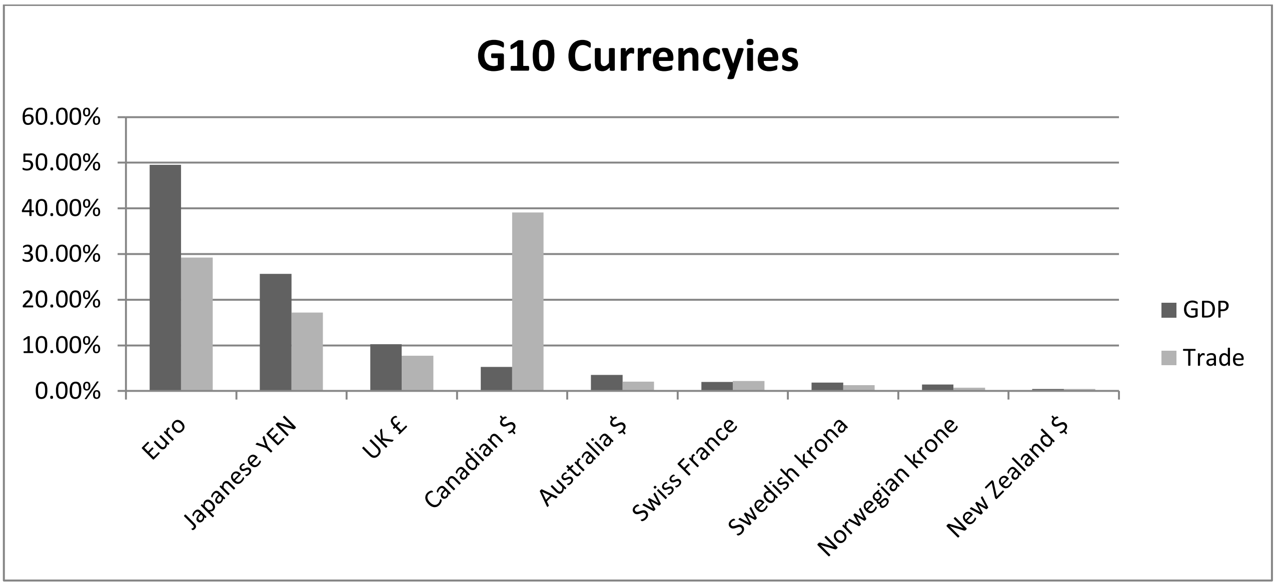
US 3 month T-bills have a weekly return with mean of 0.05%, standard deviation of 0.04%, skewness of 0.13, kurtosis of -1.51, maximum return of 0.12% and minimum return of almost 0. A tiny standard deviation indicates that the risk is very small, so, which can be considered as risk free rate. As minimum return and positive skewness show that all return are above 0, this is rational for the risk free rate. A negative kurtosis indicates a relatively flat distribution.

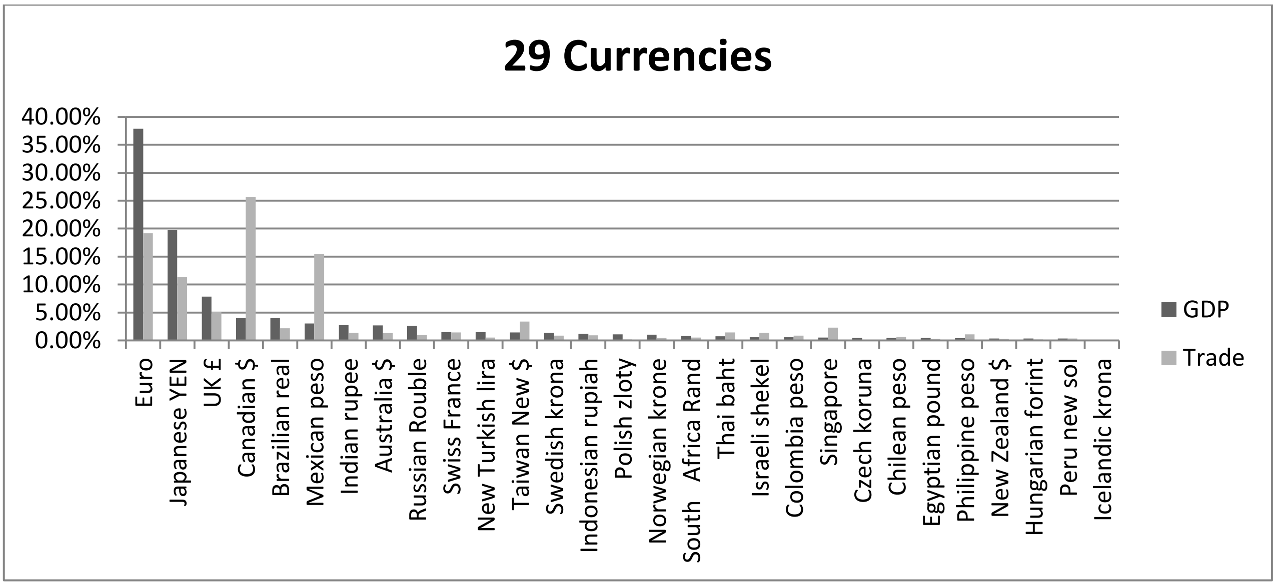
3.2.3 GDP and Trade

The first chart of Figure 3.3 documents average weights of each currency in G10 currencies for GDP and trade portfolios, and the second chart shows this in 29 currencies. Because of no significant difference between the weights of each year, the average weights are representative. Due to being members of the North America Free Trade Association, Canada and Mexico have the largest weights in trade portfolio, but small weights in GDP portfolio, while the euro zone has the largest weights in GDP portfolio for both G10 and 29 currencies. According to the above factors, the GDP and trade portfolios have significantly different weights in some countries, which may lead to significantly different returns for these two portfolios. One disadvantage of these two portfolios is transaction cost of rebalancing, compared to value-weighted portfolio in equity with no rebalancing cost.

Figure 3.3 Average weight of each currency for GDP and Trade portfolios

This bar chart reports average percentages of each country/area's GDP and trade volume to/from US over sum of all currencies/area's GDP and trade volume to/from US. I firstly compute these percentages for every year from 1997 to 2012, then reports only average of them. The percentages reported can be considered as average weights of each currency for GDP and Trade portfolios. There are two datasets used in this thesis. So, the first chart reports the results for the portfolios containing only G10 currencies. The second consider portfolios containing all 29 currencies.





3.3 Turnover and Adjustments for Transaction Cost

Considering transaction cost bigger than zero, any changes in portfolio weights will result in reduced returns. The portfolio turnover is computed, defined as the fraction of invested wealth traded at rebalance date. The formula is shown as follows:

$$\tau = \frac{1}{T-M} \sum_{t=1}^{T-M} \sum_{j=1}^{N} \left(\left| \hat{w}_{k,j,t+1} - \hat{w}_{l,j,t^+} \right| \right) \tag{3.5}$$

$\hat{w}_{k,j,t+1}$ is the weights of portfolio k in asset j at time t+1, and $\hat{w}_{k,j,t^+}$ is weights of the portfolio k before rebalancing at t+1 in asset j. Note that if one dollar is invested in portfolio at time t, the investment in asset j will be $\hat{w}_{k,j,t}(1+r_{j,t+1})$ dollar at time t+1 before rebalancing. Hence, before the portfolio k is rebalanced, the weight in asset j at time t+1 is:

$$\hat{w}_{k,j,t^+} = \frac{\hat{w}_{k,j,t}(1+r_{j,t+1})}{\sum_{j=1}^{N} \hat{w}_{k,j,t}(1+r_{j,t+1})} \tag{3.6}$$

Increases in portfolio turnover can lead to portfolio performance after transaction cost to deteriorate. According to equation 3.4 and 3.5, turnover increases with the variance of the portfolio weights across time, and these are dependent on the sampling variation in $\hat{\mu}_t$ and $\hat{\Omega}_t$, which may change with length of estimation window.

As far as transaction costs are concerned, Lesmond et al. (2004) argue that they are relevant to assess the performance of an investment strategy. So, one valid concern is about performance after taking account of these costs. To calculate transaction cost, one half of the bid-ask spread is used as a percentage of the min-quote, applied by Barroso and Santa-Clara (2011), although this method may overstate transaction costs (Mancini et al., 2013). Transaction cost of currency I at time t is calculated as:

$$c_{i,t} = \frac{F^{ask}_{i,t,t+1} - F^{bid}_{i,t,t+1}}{F^{ask}_{i,t,t+1} + F^{bid}_{i,t,t+1}} \tag{3.7}$$

Portfolio returns are then adjusted for these costs as:

$$\tilde{r}_{Pi,t} = (1 + \hat{r}_{Pi,t})(1 - \sum\nolimits_{j=1}^{N} c_{j,t} \tau_{Pi,j,t}) - 1 \tag{3.8}$$

In which $\tau_{Pi,j,t}$ are turnover for asset j in portfolio I at time t.

3.4 Conclusion

In this section, two common methods are introduced, which will then be applied into of the rest of the chapters. The first one is a method of calculating the return of currency. To enable calculation and data collection to be easy, the forward rate is used to replace the spot rate at time t+1. So, the calculation for each currency successfully avoids gathering all risk free rates from different countries, but, only concerns US risk free rate. The second method introduced is how to take account of transaction cost into a portfolios return. The turnover is calculated at the end of each time point as sum of changes in weights for rebalancing. Transaction cost of currency is not fixed, but is dependent on bid and ask forward rate. The return of portfolio after transaction cost is obtained followed by computation of, turnover and transaction.

The data is collected weekly, mainly from DataStream. But, some forward rates are not available for the sample period. Covered interest parity is used to calculate the unavailable forward rates. Moreover, after statistics and graphing check, the calculated forward rate can be considered as a reliable source. According to the statistics of currency return, the G10 currencies have a more stable performance than ‘lesser’ currencies and the correlations confirm that all 29 currencies are not highly correlated to each other.

Chapter Four

Currency Portfolio Management: Passive Portfolios vs Naïve Portfolio

4.1 Introduction

International investment has become increasingly important since the advent of free floating exchange rates and the removal of capital controls. The risk inherent to foreign exchange rates can eliminate or substantially reduce the profit made on an international investment. Therefore, instruments, such as forwards and options, were used to hedge this risk (Black, 1989); (Glen and Jorion, 1993); (Larsen Jr and Resnick, 2000); (Topaloglou et al., 2008); (Fonseca et al., 2011). However, increasingly currencies are thought of as an asset in their own right. Levy and Sarnat (1978) report the achievement of significant gains from holding foreign currencies from investor US investor perspective. They also analyse and confirm the gains from diversification for only currencies portfolios and portfolios of foreign currency and country's stock index.

In contrast, the studies which consider passive portfolio investment among currencies are not many. A most relevant research about passive currency-only portfolios is written by Levy and Sarnat (1978). They simply apply basic idea of modern portfolio theory by sample mean and standard deviation to construct set of efficient portfolios. A number of robust models and alternative methods have been created to improve and enhance the performance of Markowitz model. But, few researches apply these methods into construction of currency-only portfolio.

This chapter adds to this literature by considering a number of portfolio optimization methods applied to currency-only portfolio. As mentioned in preceding paragraphs, the gap in literature is passive optimization for portfolio with currency only. This study fills this gap, which is important to investors who desire to take a position in foreign currencies, due to nature and magnitude of their economic activities, such as central banks, international investment trusts, and large multinational corporations.

Portfolio optimization has been extensively studied in equity and bond markets, both analytically and empirically. Since Markowitz (1952) derived the optimal rules for allocating wealth with risky assets, a number of studies focused on this topic resulting in the development of this model with some adjustments. Other studies tried to create alternative methods for constructing portfolio to beat the market. All these models have been empirically applied to the stock market or bond market for testing efficiency.

Problem with estimation error attracted considerable effort to solve it with purpose of improving the performance of the Markowitz model. James and Stein (1961) and Jorion (1986) design a shrinkage form to handle the error in estimating expected returns Pástor (2000) and Black and Litterman (1992) improve an asset pricing model to estimate the expected return. Goldfarb and Iyengar (2003) introduce the ‘robust’ portfolio rules. Kan and Zhou (2007) design their rules to optimally diversify portfolio across market and estimation risk. Some approaches are to constrain the portfolio weights, e.g. Frost and Savarino (1988) impose the short selling constraints for the portfolio optimization. The purpose of these methods is to improve the properties of the portfolio weights, and they did.

However, DeMiguel et al. (2007) show that in the equity market, it is very difficult to beat the naïve portfolio. In their analysis, they use various US indices and international indices, and consider various asset-allocation models all derived from Markowitz’s model. And then, they compared the performances of the optimal portfolios against naïve portfolio, and summarised that no single model consistently outperforms the naïve portfolio.

Alternative methods are developed based on other thoughts with same goal of improving the out of sample performance of portfolio. Maillard et al. (2008) introduce a new optimal strategy called equally-weighted risk contribution, which considers the amount of risk an individual contributed to portfolio. From their empirical evidence regarding two asset classes, equity US sectors portfolios and agricultural commodity portfolios, naïve portfolio is inferior in terms of performance and for any measure of risk, and minimum variance portfolio achieves higher Sharpe ratio but expose to higher drawdown as well. However, in the class of global diversified portfolio dataset, the ERC strategy has the best performance in terms of Sharpe ratio.

The conclusions made from other asset classes may not be consistent with that from currency market. Jylhä and Suominen (2011) prove that profit-seeking capital in currencies has a relatively minor role during most of the floating exchange rate area. Taylor (1982) also states that the most important actors in the currency market, central banks; do not seek profits at all. This characteristic of currency market is not for other asset classes. Therefore, the conclusions may be different.

In this chapter, as already indicated, a number of passive portfolio strategies are applied into the currency market. In this chapter, the main objective is to analyse the performance of various optimal portfolio models for the class of currency exchange market, and find out the most efficient strategy for investors. To do this, an evaluation of the out-of-sample performance of various portfolio construction policies is done. The policies include sample-based mean-variance portfolio policy and its extension, which are applied in DeMigual's research (2007), equally-weighted risk contribution model, which was introduced by Maillard et al. (2008), equally-weighted portfolio (1/n or naïve portfolio), GDP portfolio, and trade portfolio. Similar to DeMigual's (2007) research, this analysis relies on a 'rolling sample' approach, but with an estimation window of 5 years. I also take account of transaction cost, and compare the results before and after transaction cost. In robustness check, the estimation window is changed to 1, 3 and 10 years, and results analysed from foreign investors' perspective (UK, Japan and euro zone).

In contrast to DeMigual's (2007) research, methodologies related to the risk management are applied in order to evaluate the performance of different portfolio models. The reason of focusing more on risk is that investors regardless of speculator or hedger in Forex do not like high risk exposure. Considering investor systemic risk, the Treynor ratio and Jansen alpha are also accepted in performance evaluation. Because Dunis et al. (2011) concludes good performance of lesser currencies in most case of portfolios, both cases also need to be considered with and without lesser currencies. In contrast to their method of adding lesser currencies one by one, two datasets are used. One consists of G10 currencies, which are considered to be the 10 most liquid currencies in the world. Another one consists of 29 currencies around the world. This setting of datasets is more practical in the real world.

The first finding of this chapter is that, out of 12 different portfolio models, the sample-based mean-variance portfolio perform badly for out-of-sample analysis in all terms including Sharpe ratio, VaR, maximum drawdown (expose to extreme risk). Although this finding was shown in the literature with regard to other asset classes, such as equity in DeMigual's (2007) research, this is proven to be also true using evaluation methods related to risk across datasets of currency market with and without lesser currency.

The second finding is that the short sale constraints help but not a lot. Although, imposing constraints on most of strategies lead to a modest improvement, these improvements do not change portfolio rankings. As far as turnover is concerned, the constraints substantially reduce it, but the benchmark portfolios still have the lowest turnover among the 12 portfolios. This is almost consistent with DeMigual's (2007) findings. They state that unconstrained policies perform much worse than any of the strategies that constrain short sales. But, in this chapter, one constrained policy appears to be lower Sharpe ratio than unconstrained one.

The third finding is that 1/N portfolio (naïve) performs reasonably well. Despite the fact that the 1/N portfolio does not have the best performance in sharp ratio, CEQ and risk measures, it has a very low turnover, which would help the portfolio exceed others perhaps if I take account of transaction costs. Furthermore, in three benchmark portfolios (naïve, GDP and trade), the 1/N portfolio has the highest Sharpe ratio. In addition, 1/N portfolio's return-loss and p-value of Sharpe ratio against others prove that the performance of 1/N portfolio is not far behind others. This indicates that the main conclusion of DeMigual et al (2007) could be accepted by an asset class of currency exchange market.

The next finding is that the minimum variance portfolio works best. In general, this portfolio has the best performance among portfolios in terms of all measures except turnover, although, regarding the dataset with 29 currencies, the minimum variance portfolio have slight low CEQ than ERC portfolio. Comparing to the analysis of Mailard et al (2008), the same conclusions are reached, which are the worst performance for naïve portfolio and the best for minimum variance portfolio for ERC strategy. In addition, it can be said that ERC portfolio has much lower turnover than minimum variance portfolio. Although DeMigual et al (2007) do not form an opinion on the performance of minimum variance portfolio, the tables in their research show that minimum variance portfolio performs best for most of the datasets in Sharpe ratio and CEQ. This is consistent with the conclusion reached in this thesis.

The final finding is that Transaction cost does not seriously affect the results from before transaction cost analysis. The main evaluation indexes have no significant change after taking account of transaction costs for all portfolio models except three models. The exceptions include sample mean-variance (mv) portfolio, Bayes-stein shrinkage (bs) portfolio and combination portfolio with mean-variance and minimum variance (mv-min). The relative large change of these three portfolios is due to large turnovers. However, the change does not have impact on my results, because of poor performance of these three portfolios from before transaction cost analysis. The large turnovers make performance even poor after transaction cost analysis. According to six main evaluation indexes, the results from before and after transaction cost are almost the same. The minimum variance (min) portfolio can be considered as the best performance portfolio. The naïve portfolio has relative good performance, and the sample mean-variance portfolio performs badly. Although there are inconsistent results for several samples, they are very small, and it can be concluded that there is no effect to results after taking account of transaction cost.

The rest of the chapter is organised as follows. In section 4.2a description of passive portfolio strategies is made as well as the evaluation methods used in this chapter. Section 4.3 presents the results from empirical work while section 4.4 concludes.

4.2 Empirical Framework

In this section, a brief description of each portfolio optimisation model and performance measure is provided. The detail is introduced in Chapter Two; Literature review.

4.2.1 Portfolio Construction Models

4.2.1.1 Naïve Portfolio ('1/n'), GDP Portfolio ('GDP') and Trade Portfolio ('trade')

Na ïve portfolio involves holding a portfolio weight $w_t^{ew} = \frac{1}{N}$ in each of the N risky assets.

GDP and trade portfolios are applied by using weights of GDP and sum of export and import of corresponding countries, respectively. Due to a delay in releasing data of GDPs and trade from national statistics authorities, last year's data is used to calculate weights for a whole current year returns. These strategies completely ignore the data, and are considered as one of the benchmarks in evaluation performance.

4.1.3 Sample-based Mean-variance Portfolio ('mv')

Markowitz (1952) derives the mean-variance portfolio, which suggests that investors optimise the trade-off between the mean and variance of portfolio return. To implement his model, sample mean and sample covariance matrix of historic excess return are plugged into the original formula provided by Benninga (2000). Note that this approach completely ignores the possibility of estimation error.

$$w_t^{mv} = \frac{\hat{\mathbf{\Omega}}_t^{-1}\hat{\mu}_t}{\sum \hat{\mathbf{\Omega}}_t^{-1}\hat{\mu}_t} \tag{4.1}$$

In which $\hat{\mathbf{\Omega}}$ is N*N variance-covariance matrix of historical excess returns, $\hat{\mu}$ is N*1 vector of mean of historical excess returns, and N is number of currencies.

4.2.1.3 Bayes-Stein Shrinkage Portfolio ('bs')

In order to solve estimation error, this portfolio combines both a shrinkage approach and a traditional Bayesian estimation, and hence, it is known as the 'Bayes-Stein' portfolio (James and Stein, 1961). In this analysis, this model is implemented by using the estimator proposed by Jorion (1986). He takes the 'grand mean' to be the mean of minimum-variance portfolio, and solve out the shrinkage estimator. The formula used in this chapter is shown below.

$$\hat{\mu}^{bs} = (1-\hat{\theta})\hat{\mu} + \hat{\theta}\overline{\mu}^{\min} \tag{4.2}$$

In which $\overline{\mu}^{\min}$ is the mean of the minimum-variance portfolio and shrinkage estimator can be re-formed as follows.

$$\hat{\theta} = \frac{N+2}{(N+2) + M(\hat{\mu} - \overline{\mu}^{\min})'\hat{\mathbf{\Omega}}^{-1}(\hat{\mu} - \overline{\mu}^{\min})} \tag{4.3}$$

$$\hat{\mathbf{\Omega}}^{bs} = \hat{\mathbf{\Omega}}\left(1 + \frac{1}{M+\hat{\vartheta}}\right) + \frac{\hat{\vartheta}}{M(M+1+\hat{\vartheta})} \frac{1_N 1_N'}{1_N'\hat{\mathbf{\Omega}}^{-1}1_N} \tag{4.4}$$

In which $\hat{\vartheta}$ is defined as $M\dfrac{\hat{\theta}}{1-\hat{\theta}}$. M is number of observations, N is number of assets, $\mathbf{1}_{\boldsymbol{N}}$ is vector of ones, $\hat{\mu}^{bs}$ and $\hat{\mathbf{\Omega}}^{bs}$ are estimators of N*1 vector of expected return and N*N covariance matrix. The portfolio weight obtained by $\hat{\mu}^{bs}$ and $\hat{\mathbf{\Omega}}^{bs}$ is:

$$w_t^{bs} = \frac{\hat{\mathbf{\Omega}}_t^{bs-1}\hat{\mu}_t^{bs}}{1_N'\hat{\mathbf{\Omega}}_t^{bs-1}\hat{\mu}_t^{bs}} \tag{4.5}$$

4.2.1.4 Optimal Three Fund Portfolio ('mv-min')

Kan and Zhou (2007) propose to invest in another risky portfolio to diversify the estimation risk which sample tangency portfolio has. They choose the minimum-variance portfolio as another risky portfolio, because the weights of minimum-variance portfolio are just relative to covariance matrix but not sample means. The weights will be estimated with higher accuracy. The form of a portfolio rule is as follows:

$$\hat{x}_t^{mv-\min} = \frac{1}{\gamma}\left(c\hat{\mathbf{\Omega}}_t^{-1}\hat{\mu}_t + d\hat{\mathbf{\Omega}}_t^{-1}1_N\right) \tag{4.6}$$

In which c and d maximise utility of a mean-variance investor. So, Kan and Zhou (2007) derive the following formula to decide the weights.

$$\hat{x}_t^{mv-\min} = \frac{(M-N-1)(M-N-4)}{\gamma M(M-2)}\left[\left(\frac{\hat{\varphi}_a^2}{\hat{\varphi}_a^2 + N/M}\right)\hat{\mathbf{\Omega}}_t^{-1}\hat{\mu}_t + \left(\frac{N/M}{\hat{\varphi}_a^2 + N/M}\right)\hat{\mu}_t^{\min}\hat{\mathbf{\Omega}}_t^{-1}1_N\right] \tag{4.7}$$

Defining the Incomplete Beta function:

$$B_x(a,b) = \int_0^x y^{a-1}(1-y)^{b-1}dy \tag{4.8}$$

$$\hat{\varphi}_a^2 = \frac{(M-N-1)\hat{\varphi}^2 - (N-1)}{M} + \frac{2(\hat{\varphi}^2)^{\frac{N-1}{2}}(1+\hat{\varphi}^2)^{-\frac{M-2}{2}}}{MB_{\hat{\mu}^2/(1+\hat{\varphi}^2)}\left(\frac{N-1}{2},\frac{M-N+1}{2}\right)} \tag{4.9}$$

$$\hat{\varphi}^2 = \left(\hat{\mu}_t - \hat{\mu}_t^{\min}\right)'\hat{\mathbf{\Omega}}_t^{-1}\left(\hat{\mu}_t - \hat{\mu}_t^{\min}\right) \tag{4.10}$$

The weights of this three fund portfolio are:

$$w_t^{mv-\min} = \frac{\hat{x}_t^{mv-\min}}{1_N'\,\hat{x}_t^{mv-\min}} \tag{4.11}$$

4.2.1.5 Mixture of Equally Weighted and Minimum-variance Portfolio ('1/n-min')

Because expected returns are more difficult to estimate than covariance, DeMiguel et al. (2007) is motivated to consider a portfolio which combines 1/n portfolio with minimum-variance portfolio. The portfolio is considered as follows.

$$w_t^{1/n-\min} = c\frac{1}{N}1_N + d\hat{\mathbf{\Omega}}_t^{-1} \quad s.t. 1_N'\,\hat{w}_t^{1/n-\min} = 1 \tag{4.12}$$

Again, c and d are chosen to maximise the expected utility of a mean-variance investor, and is derived as follows:

$$c = 1 - d 1_N^{'} \hat{\Omega}_t^{-1} 1_N \quad (4.13)$$

$$d = \frac{(M-N-1)\left(1_N^{'}\hat{\mathbf{\Omega}}_t^{-1}1_N\right)\left(1_N^{'}\hat{\mathbf{\Omega}}_t 1_N\right) - N^2 M}{N^2(M-N-2)k\left(1_N^{'}\hat{\mathbf{\Omega}}_t^{-1}1_N\right) - 2MN^2\left(1_N^{'}\hat{\mathbf{\Omega}}_t^{-1}1_N\right) + (M-N-2)\left(1_N^{'}\hat{\mathbf{\Omega}}_t 1_N\right)\left(1_N^{'}\hat{\mathbf{\Omega}}_t^{-1}1_N\right)} \quad (4.14)$$

$$k = \frac{M^2(M-2)}{(M-N-1)(M-N-2)(M-N-4)} \quad (4.15)$$

4.2.1.6 Short-sale-constrained Portfolio ('ss')

We also consider the above strategies with constraints of short selling, which impose an additional non-negativity constraint on the portfolio weights in the corresponding optimization problems.

Jagannathan and Ma (2003) find that, with a constraint on short sales, 'the sample covariance matrix performs almost as well as those constructed using factor models, shrinkage estimators or daily return.' As a result of this finding, the performance of the models which have been developed to deal with estimation errors on covariance matrix, such as Best and Grauer (1992), are not evaluated.

4.2.1.7 Equally-weighted Risk Contribution Portfolio ('erc')

Neukirch (2008a) supports the equally-weighted risk contribution portfolio (ERC). The idea is to equalise risk contribution of components of the portfolio. The risk contribution can be calculated by product of weight with its marginal risk contribution. Maillard et al. (2008) implement ERC into practice (equity US sectors portfolio, agricultural commodity portfolio and global diversified portfolio).

Starting to set an original vector of weights w_t, the risk of the portfolio is

$$\sigma_t = \sqrt{w_t^{'} \hat{\mathbf{\Omega}}_t w_t} \tag{4.16}$$

In which $\hat{\Omega}_t$ is N*N variance and covariance matrix. The marginal contribution is

$$\partial_{w_{i,t}} \sigma = \frac{\partial \sigma_t}{\partial w_{i,t}} = \frac{w_{i,t}\sigma_{i,t}^2 + \sum_{i \neq j} w_{j,t}\sigma_{ij,t}}{\partial w_{i,t}} \tag{4.17}$$

Where $w_{i,t}$ is weight of asset i, $\sigma_{i,t}^2$ is variance of asset i, $\sigma_{ij,t}$ is covariance of asset i and asset j. In vector for,

$$\partial \sigma_t = \frac{\hat{\mathbf{\Omega}}_t w_t}{\sqrt{w_t^{'} \hat{\mathbf{\Omega}}_t w_t}} \tag{4.18}$$

So, the risk contribution of the asset i is:

$$\sigma_{i,t} = w_{i,t} \partial_{w_{i,t}} \sigma \tag{4.19}$$

The ERC problem can be written as follows:

$$w_t^{erc} = \left\{ w_t^{erc} \in [0,1];\ w_t^{erc'} \mathbf{1}_N = 1;\ \sigma_{i,t} = \sigma_{j,t} \right\} for\ all\ i\ and\ j \tag{4.20}$$

4.2.2 Performance Evaluation Method

4.2.2.1 Traditional Performance Measures

In this chapter, in order to assess the portfolio performance, the ex-post Sharpe ratio (Sharpe, 1966, 1994), is used first; which indicates the historic average differential return per unit of historic variability of the differential return. I let $\hat{r}_{Pi,t}$ represent the excess return on portfolio i at time t, $\hat{\mu}_{Pi}$ represent the average of $\hat{r}_{Pi,t}$ and $\sigma_{\hat{r}_{Pi,t}}$ represent the standard deviation of $\hat{r}_{Pi,t}$. So, the ex-post Sharpe ratio can be written as follows.

$$S_{pi} = \frac{\hat{\mu}_{Pi,t}}{\sigma_{\hat{r}_{Pi,t}}} \tag{4.21}$$

We use Memmel's method to test the statistical difference of Sharpe ratios between each strategy and naïve portfolio[1]. In addition to Sharpe ratio, I also apply Treynor measure and Jansen Alpha to evaluate the performance. The benchmark for calculating β_i is GDP portfolio, which is more like market portfolio.

The return-loss also is computed as follows:

$$re-loss_{Pi} = \frac{\hat{\mu}_{ew}}{\hat{\sigma}_{ew}} \hat{\sigma}_{Pi} - \hat{\mu}_{Pi} \tag{4.22}$$

4.2.2.2 Certainty-Equivalent (CEQ)

We define CEQ return as the riskless rate that an investor is willing to accept rather than adopting a risky portfolio i. The formula is given as:

$$CEQ_i = \hat{\mu}_{Pi} - \frac{\gamma}{2} \hat{\sigma}_{Pi}^2 \tag{4.23}$$

The results reported are for the case of γ=5, which is the risk aversion of an investor. However, I also calculate CEQ in the case of 1 and 10 (without reporting),

4.2.2.3 Maximum Drawdown

The maximum drawdown is the maximum loss an investor may have suffered during whole period. The relative formula is shown as follows:

Drawdown: $D_t = \min\left(D_{t-1} + \hat{r}_{Pi,t}, 0\right) \quad D_0 = 0$

[1] Specially, given two portfolios, one is 1/n portfolio referred as 'ew', another one is portfolio i, with $\hat{\mu}_{ew}$, $\hat{\mu}_{Pi}$, $\hat{\sigma}_{ew}$, $\hat{\sigma}_{Pi}$, $\hat{\sigma}_{Pi,ew}$ as their mean, standard deviation and covariance which are estimated over a sample of size T-M. The null hypothesis is $\hat{\mu}_{ew} / \hat{\sigma}_{ew} - \hat{\mu}_{Pi} / \hat{\sigma}_{Pi} = 0$, and the test statistic, which is asymptotically distributed as a standard normal, is: $\hat{z} = \frac{\hat{\mu}_{ew}\hat{\sigma}_{Pi} - \hat{\mu}_{Pi}\hat{\sigma}_{ew}}{\sqrt{\hat{\vartheta}}}$, with $\hat{\vartheta} = \frac{1}{T-M}(2\hat{\sigma}_{ew}^2\hat{\sigma}_{Pi}^2 - 2\hat{\sigma}_{ew}\ddot{\sigma}_{Pi}\hat{\sigma}_{ew,Pi} + \frac{1}{2}\hat{\mu}_{ew}^2\hat{\sigma}_{Pi}^2 + \frac{1}{2}\hat{\mu}_{Pi}^2\hat{\sigma}_{ew}^2 - \frac{\hat{\mu}_{ew}\hat{\mu}_{Pi}}{\hat{\sigma}_{ew}\hat{\sigma}_{Pi}}\hat{\sigma}_{ew,i}^2)$

$$\text{Maximum drawdown: } D_1 = \min\left\{D_{t=1}^{T}\right\} \tag{4.24}$$

Young (1991) suggests a measurement, called Calmar ratio, to compute the ratio between the expected return and the maximum drawdown:

$$\text{Calmar ratio } CR = \frac{\hat{\mu}_{Pi}}{-D_1} \tag{4.25}$$

4.2.2.4 Risk Measure based on Quantiles

In this chapter, value at risk (VaR), will be used; which expects the maximum loss at certain degree of possibility during a certain time period, to evaluate the downside risk of portfolios. This certain degree of possibility is set at 95%, and the certain time period is one week because of weekly return. Moreover, both methods, variance-covariance approach and historical simulation, are applied in calculation of VaR. In addition to VaR, I also use conditional value at risk (CVaR), which focuses more on the tail risk of distribution.

4.2.3 Estimation Method

In the out-of-sample analysis, a method named ‘rolling-sample’ approach is implemented. Specifically, given total number of T weekly returns for each asset, I use an estimation window of length M. I start from t=M+1 and use the data in the previous M weeks to estimate the parameters needed for a particular strategy. And then, these parameters are used to construct corresponding optimal portfolio at time t. This process continued by adding the return for the next period and dropping the earliest return, until the end of dataset. The outcome of ‘rolling window’ approach is a series of T-M weekly out-of-sample returns. In this chapter, the main analysis is based on T=750, M=260 (5 years). But, robustness checking is with M=520 (10 years), M=52 (1 year), M=156 (3 years).

4.3 Empirical Results

4.3.1 Main Results

Table 4.1 contains the results of the various performances for 12 passive portfolios related to G10 currencies from investor US investor perspective. From table 4.1, according to p-value, I find that Sharpe ratios of half of optimal portfolios are statistically significantly different from Sharpe ratio of naïve portfolio. Although, there are 4 portfolios performing better than naïve portfolio based on return-loss, in general, the naïve portfolio still performs well. The combination of naive portfolio and minimum variance slightly improve the Sharpe ratio of minimum variance, but constrains in minimum variance portfolio have more improvement, which results in the highest Sharpe ratio among all portfolios.

According to Treynor and Jensen alpha, because of the negative value of beta, mean variance portfolio and Bayes-Stein shrinkage portfolio looks like having good performance as outlined by Treynor, but, actually, negative Jensen alpha indicates that it does not work well. From these two evaluation indexes, there is a consistent conclusion regarding the best performance of minimum variance portfolio. With total risk of standard deviation, the minimum variance portfolios (both with and without constrains) work best. The comparison of CEQ returns in table 4.1 confirms the conclusions from the previous analysis. In fact, especially for the risk aversion of 5 and 10, there are only three cases that the CEQ returns from optimizing models are superior to the CEQ return

Table 4.1 The evaluation results for portfolios with G10 currencies

This table documents the evaluation of performance of each optimal portfolio strategy for G10 currencies and US investor perspective. The US dollar is treated as the based currency. The estimation window is 5 years. In the first column of the table, the ‘1/n’ refers to na ïve portfolio, which is equally-weighted , ‘ mv‘ refers to the mean-variance portfolio, ‘min’ refers to minimum variance portfolio, ‘SS’ refers to the portfolios with short-sale constrains, ‘GDP’ refers to GDP portfolio, ‘TRADE’ refers to trade portfolio, ‘ERC’ refers to equally-weighted risk contribution portfolio, ‘‘MV AND MIN’ refers to combination of mean-variance portfolio and minimum variance portfolio, ‘1/N AND MIN’ refers to combination of na ïve portfolio and minimum variance portfolio, ‘bs’ refers to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, ‘μ’ means sample average return. ‘σ’ means sample standard deviation, ‘SR’ means Sharpe ration, which uses returns over risk free rate. ‘vs 1/n’ means that optimal portfolio compare with naïve portfolio. in this category, there are two comparisons, one is called ‘p-val’, which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called‘re-loss’ refer to return-loss, ‘traditional’ means other traditional performance measure-Treynor and Jensen Alpha (referred as ‘α’ in table), the benchmark I used for this method is GDP portfolio. ‘CEQ’ means certainty-equivalent return, I use three value of risk aversion, 1, 5 and 10. ‘VaR’ means Value at risk and ‘VCV’ refer to computing value at risk at possibility of 95% with variance –covariance approach, ‘Historical’ refer to compute value at risk at possibility of 95% with historical simulation, ‘CVaR’ means conditional value at risk, or called expected shortfall. ‘’VCV’ and ‘historical’ have same meanings as what refer to VaR. ‘τ’ means turnover. The last two columns are related to the DrawDown. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use ‘n/a’ to represent that it cannot be calculated due to extreme returns. For drawdown, this means more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

	μ	**σ**	**SR**	**vs1/n**		**traditional**		**CEQ**			**VaR**		**CVaR**		**turnover**	**Drawdown**	
				p-val	**re-loss**	**Treynor**	**α**	**1**	**5**	**10**	**VCV**	**Historical**	**VCV**	**Historical**		**maximum**	**CR**
1/n	5.45%	9.38%	0.58	1.00	0.00%	5.42%	1.95%	5.01%	3.25%	1.05%	2.03%	1.98%	2.58%	2.71%	0.01	23.94%	0.23
mv	-180.21%	1038.17%	-0.17	0.00	782.99%	44.47%	-166.12%	n/a	n/a	n/a	240.27%	6.28%	300.43%	143.92%	37.45	n/a	n/a
mv-ss	2.45%	10.60%	0.23	0.00	3.70%	2.63%	-0.79%	1.89%	-0.36%	-3.17%	2.37%	2.53%	2.99%	3.44%	0.14	39.21%	0.06
min	4.69%	7.24%	0.65	0.50	-0.49%	6.95%	2.34%	4.43%	3.38%	2.07%	1.56%	1.53%	1.98%	1.99%	0.05	13.16%	0.36
min-ss	4.68%	7.02%	0.67	0.39	-0.60%	6.84%	2.30%	4.43%	3.44%	2.21%	1.51%	1.53%	1.92%	1.91%	0.02	14.99%	0.31
GDP	3.48%	8.51%	0.41	0.01	1.46%	3.48%	0.00%	3.12%	1.67%	-0.14%	1.87%	1.86%	2.37%	2.34%	0.01	18.25%	0.19
Trade	4.34%	8.25%	0.53	0.48	0.45%	4.90%	1.26%	4.00%	2.64%	0.93%	1.80%	1.76%	2.28%	2.33%	0.01	18.89%	0.23
erc	5.13%	8.45%	0.61	0.77	-0.22%	5.54%	1.91%	4.77%	3.34%	1.56%	1.83%	1.76%	2.32%	2.42%	0.01	21.64%	0.24
bs	-55.61%	292.07%	-0.19	0.00	225.19%	110.01%	-53.86%	n/a	n/a	n/a	67.69%	2.77%	84.62%	42.12%	12.07	n/a	n/a
mv-min	-160.21%	757.43%	-0.21	0.00	599.98%	-112.81%	-312.55%	n/a	n/a	n/a	178.60%	3.51%	222.49%	142.93%	29.93	n/a	n/a
1/n-min	4.74%	7.25%	0.65	0.46	-0.53%	6.67%	2.27%	4.47%	3.42%	2.11%	1.56%	1.57%	1.98%	2.01%	0.04	13.97%	0.34
bs-ss	3.91%	9.01%	0.43	0.03	1.32%	4.67%	1.00%	3.50%	1.88%	-0.15%	1.98%	2.09%	2.50%	2.91%	0.11	29.44%	0.13

from the naïve portfolio, and one is minimum variance portfolio. As far as downside risk is concerned, the results from value at risk, expected shortfall and maximum drawdown tell me that the minimum variance portfolio has the lowest risk, while mean-variance portfolio has the highest risk. Market portfolios and naïve portfolio is in the middle rankings. However, these portfolios have the lowest turnover, which may help improve performance of market portfolios and naïve portfolio if I consider transaction costs. The large turnover leads to worse performance of mean-variance portfolio. The equally-weighted risk contribution portfolio (erc) also performs well, and has all performance measures slightly superior to those from naïve portfolio, but not superior to these from minimum variance portfolio.

Table 4.2 shows that adding 'lesser' currencies can help to diversify and improve the performance, in general. Specifically, Sharpe ratios of most portfolios with all currencies are bigger than 0.6, while those of the most portfolios with g10 currencies are less than 0.6, and the same situation occurs for risk measures. Generally, all models have better performance with all currencies dataset than they have with g10 currencies dataset. The focus is now on the comparison of performance of portfolios only for all currencies. According to p-value, it can be observed that Sharpe ratios of the most of optimal portfolios are statistically significant different from Sharpe ratio of naïve portfolio. But, based on return-loss, there are more than 4 portfolios performing better than naïve portfolio. The portfolio with the highest Sharpe ratio is also minimum variance portfolio with constrains, but, there is no improvement for combination portfolio. The results from Treynor and Jensen alpha are different from those in g10 currencies cases. Because of less systematic risk in mean-variance portfolio and Bayes-Stein shrinkage portfolio, they have the superior performance, but it also has the largest total risk based on standard deviation. However, differently, CEQ return is not consistent with results of Sharpe ratio anymore. In fact, naïve portfolio and erc portfolio and erc

Table 4.2 The evaluation results for portfolios with all currencies

This table documents the evaluation of performance of each optimal portfolio strategy for 29 currencies and US investor perspective. This means that the US dollar is treated as the based currency. The estimation window is 5 years. In the first column of table, the '1/n' refers to na ïve portfolio, which is equally-weighted , ' mv' refers to mean-variance portfolio, 'min' refers to minimum variance portfolio, 'SS' refer to the portfolios with short-sale constrains, 'GDP' refers to GDP portfolio, 'TRADE' refers to trade portfolio, 'ERC' refers to equally-weighted risk contribution portfolio, ''MV AND MIN' refers to combination of mean-variance portfolio and minimum variance portfolio, '1/N AND MIN' refers to combination of na ïve portfolio and minimum variance portfolio, 'bs' refers to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, 'μ' means sample average return. 'Σ' means sample standard deviation, 'SR' means Sharpe ration, which use returns over risk free rate. 'vs 1/n' means that optimal portfolio compare with naïve portfolio. in this category, there are two comparisons, one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called're-loss' refer to return-loss, 'traditional' means other traditional performance measure-Treynor and Jensen Alpha (referred as 'α' in table), the benchmark I used for this method is GDP portfolio. 'CEQ' means certainty-equivalent return, I use three value of risk aversion, 1, 5 and 10. 'VaR' means Value at risk and 'VCV' refer to computing value at risk at possibility of 95% with variance –covariance approach, 'Historical' refer to compute value at risk at possibility of 95% with historical simulation, 'CVaR' means conditional value at risk, or called expected shortfall. ''VCV' and 'historical' have same meanings as what refer to VaR. 'τ' means turnover. The last four columns are related to the DrawDown. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use 'n/a' to represent that it cannot be calculated due to extreme returns. For drawdown, this means more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

	μ	σ	SR	vs 1/n		traditional		CEQ			VaR		CVaR		turnover	DrawDown	
				p-val	re-loss	Treynor	α	1	5	10	VCV	Historical	VCV	Historical		maximum	CR
1/n	6.06%	7.39%	0.82	1.00	0.00%	6.96%	2.30%	5.79%	4.70%	3.33%	1.57%	1.67%	2.00%	2.30%	0.01	21.74%	0.28
mv	13.36%	36.72%	0.36	0.00	16.78%	78.33%	12.62%	6.62%	-20.35%	-54.06%	8.12%	1.03%	10.25%	4.01%	1.60	n/a	n/a
mv-ss	3.57%	3.22%	1.11	0.13	-0.92%	15.45%	2.57%	3.51%	3.31%	3.05%	0.67%	0.60%	0.85%	0.97%	0.04	7.11%	0.50
min	2.49%	2.53%	0.98	0.34	-0.41%	17.10%	1.86%	2.46%	2.33%	2.17%	0.53%	0.55%	0.68%	0.75%	0.05	6.82%	0.37
min-ss	3.39%	2.66%	1.27	0.03	-1.20%	17.36%	2.54%	3.35%	3.21%	3.03%	0.54%	0.51%	0.70%	0.79%	0.02	6.68%	0.51
GDP	4.33%	7.77%	0.56	0.00	2.05%	4.33%	0.00%	4.02%	2.81%	1.30%	1.69%	1.69%	2.14%	2.20%	0.01	19.47%	0.22
Trade	4.41%	7.26%	0.61	0.03	1.55%	5.16%	0.71%	4.15%	3.09%	1.78%	1.57%	1.45%	1.99%	2.15%	0.01	20.12%	0.22
erc	5.04%	4.77%	1.06	0.17	-1.13%	9.25%	2.68%	4.93%	4.47%	3.90%	0.99%	1.04%	1.27%	1.43%	0.01	14.47%	0.35
bs	10.81%	27.89%	0.39	0.00	12.08%	67.57%	10.11%	6.92%	-8.64%	-28.09%	6.15%	0.79%	7.77%	3.03%	1.18	29.23%	0.37
mv-min	10.34%	26.00%	0.40	0.00	10.99%	16.62%	-3.38%	6.96%	-6.56%	-23.46%	5.98%	1.00%	7.49%	5.14%	2.73	77.34%	0.13
1/n-min	2.54%	2.57%	0.99	0.32	-0.43%	15.70%	1.84%	2.51%	2.38%	2.21%	0.54%	0.56%	0.69%	0.77%	0.05	7.23%	0.35
bs-c	3.46%	3.10%	1.12	0.11	-0.92%	16.48%	2.56%	3.42%	3.23%	2.99%	0.64%	0.60%	0.82%	0.92%	0.04	6.96%	0.50

portfolio the highest CEQ return, while minimum variance portfolio with constraint is the second highest. Minimum variance portfolio has the lowest risk as well, regarding the various risk measures. As discussed in g10 currencies cases, due to lower turnover, the market and naïve portfolio may perform better when transaction costs are taken into account. Equally-weighted risk contribution (erc) portfolio performs better than naïve portfolio, and performs worse than minimum variance portfolio in all terms of measures except CEQ return.

4.3.2 Results after Transaction Cost

In order to investigate how the turnover impacts portfolio ^performances, portfolio returns are calculated after taking account of transaction costs. All performance measures in before transaction cost analysis have been calculated in this section, but, for comparison, the 8 main evaluation indexes of before and after transaction analysis are exhibited in same table. From Table 4.3 and Table 4. 4, I can find that there is no significant change after taking account of transaction costs for all portfolio models except three models. The exceptions include sample mean-variance (mv) portfolio, Bayes-stein shrinkage (bs) portfolio and combination portfolio with mean-variance and minimum variance (mv-min). The relative large change of these three portfolios is due to large turnover. However, the change does not have an impact on the conclusion of this thesis, because of poor performance of these three portfolios from before transaction cost analysis. The large turnovers make performance even worse in after transaction cost analysis. The lowest turnover of GDP portfolio (trade portfolio for all currencies sample base) is not enough to move the portfolio to top rankings. Account to six main evaluation indexes, the results from before and after transaction cost are almost similar. The minimum variance (min) portfolio can be considered as the best performance portfolio. The naïve portfolio has relative good performance and the

Table 4.3 Comparison of results from before and after transaction cost for G10 currencies

This table compares the evaluation of performance of each optimal portfolio strategy before transaction cost to that after transaction cost. The estimation window is 5 years. The database is related to G10 currencies. The left side reports the result of before transaction cost analysis. The right side reports the result of after transaction cost analysis. I only report selected evaluation indexes. In the first column of table, the ‘1/n’ refers to naïve portfolio, ‘ mv‘ refers to mean-variance portfolio, ‘min’ refers to minimum variance portfolio, ‘SS’ refers to the portfolios with short-sale constrains, ‘GDP’ refers to GDP portfolio, ‘TRADE’ refer to trade portfolio, ‘ERC’ refers to equally-weighted risk contribution portfolio, ‘‘MV AND MIN’ refers to combination of mean-variance portfolio and minimum variance portfolio, ‘1/N AND MIN’ refer to combination of naïve portfolio and minimum variance portfolio, ‘bs’ refers to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, ‘SR’ means Sharpe ration, which use returns over risk free rate. There are two comparisons to na ïve portfolio, one is called ‘p-val’, which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called ‘re-loss’ refer to return-loss, ‘CEQ’ means certainty-equivalent return with risk reversion of 5. ‘VaR’ means Value at risk, ‘CVaR’ means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use ‘n/a’ to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

	Results before transaction cost									**Results after transaction cost**							
	SR	**vs 1/n**		**CEQ**	**VaR**	**CVaR**	**DrawDown**		**Turnover**	**SR**	**vs 1/n**		**CEQ**	**VaR**	**CVaR**	**DrawDown**	
		p-val	**re-loss**				**Max DD**	**CR**			**p-val**	**re-loss**				**Max DD**	**CR**
1/n	0.58	1.00	0.00%	3.25%	1.98%	2.71%	23.94%	0.23	0.01	0.58	1.00	0.00%	3.23%	1.99%	2.71%	23.95%	0.23
mv	-0.17	0.00	782.99%	n/a	6.28%	143.92%	n/a	n/a	37.45	-0.22	0.00	753.60%	n/a	6.51%	151.15%	n/a	n/a
mv-ss	0.23	0.00	3.70%	-0.36%	2.53%	3.44%	39.21%	0.06	0.14	0.23	0.00	3.74%	-0.41%	2.54%	3.46%	39.61%	0.06
min	0.65	0.50	-0.49%	3.38%	1.53%	1.99%	13.16%	0.36	0.05	0.66	0.45	-0.55%	3.43%	1.53%	2.00%	13.34%	0.36
min-ss	0.67	0.39	-0.60%	3.44%	1.53%	1.91%	14.99%	0.31	0.02	0.68	0.33	-0.70%	3.54%	1.53%	1.92%	15.02%	0.32
GDP	0.41	0.01	1.46%	1.67%	1.86%	2.34%	18.25%	0.19	0.01	0.42	0.01	1.39%	1.73%	1.86%	2.35%	18.26%	0.19
Trade	0.53	0.48	0.45%	2.64%	1.76%	2.33%	18.89%	0.23	0.01	0.52	0.48	0.45%	2.62%	1.77%	2.33%	18.90%	0.23
erc	0.61	0.77	-0.22%	3.34%	1.76%	2.42%	21.64%	0.24	0.01	0.61	0.71	-0.27%	3.38%	1.76%	2.42%	21.65%	0.24
bs	-0.19	0.00	225.19%	n/a	2.77%	42.12%	n/a	n/a	12.07	-0.24	0.00	212.28%	n/a	2.84%	43.66%	n/a	n/a
bs-c	0.43	0.03	1.32%	1.88%	2.09%	2.91%	29.44%	0.13	0.11	0.44	0.03	1.29%	1.90%	2.09%	2.93%	29.72%	0.13
mv-min	-0.21	0.00	599.98%	n/a	3.51%	142.93%	n/a	n/a	29.93	-0.27	0.00	573.30%	n/a	3.78%	142.65%	n/a	n/a
1/n-min	0.65	0.46	-0.53%	3.42%	1.57%	2.01%	13.97%	0.34	0.04	0.66	0.41	-0.59%	3.48%	1.57%	2.02%	14.10%	0.34

Table 4. 4 Comparison of results from before and after transaction cost for ALL currencies

This table compare the evaluation of performance of each optimal portfolio strategy before transaction cost to that after transaction cost. The estimation window is 5 years. The database is related to 29 currencies. The left side reports the result of before transaction cost analysis. The right side reports the result of after transaction cost analysis. I only report selected evaluation indexes. In the first column of table, the ‘1/n’ refer to naïve portfolio, ‘ mv‘ refer to mean-variance portfolio, ‘min’ refer to minimum variance portfolio, ‘SS’ refer to the portfolios with short-sale constrains, ‘GDP’ refer to GDP portfolio, ‘TRADE’ refer to trade portfolio, ‘ERC’ refer to equally-weighted risk contribution portfolio, ‘‘MV AND MIN’ refer to combination of mean-variance portfolio and minimum variance portfolio, ‘1/N AND MIN’ refer to combination of naïve portfolio and minimum variance portfolio, ‘bs’ refer to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, ‘SR’ means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called ‘p-val’, which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called ‘re-loss’ refer to return-loss, ‘CEQ’ means certainty-equivalent return with risk reversion of 5. ‘VaR’ means Value at risk, ‘CVaR’ means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use ‘n/a’ to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

	Results before transaction cost									Results after transaction cost							
	SR	vs 1/n		CEQ	VaR	CVaR	DrawDown		Turnover	SR	vs 1/n		CEQ	VaR	CVaR	DrawDown	
		p-val	re-loss				Max DD	CR			p-val	re-loss				Max DD	CR
1/n	0.82	1.00	0.00%	4.70%	1.67%	2.30%	21.74%	0.28	0.01	0.81	1.00	0.00%	4.62%	1.67%	2.30%	21.78%	0.27
mv	0.36	0.00	16.78%	-20.35%	1.03%	4.01%	n/a	n/a	1.60	0.23	0.00	21.17%	-24.27%	1.27%	5.11%	51.13%	0.16
mv-ss	1.11	0.13	-0.92%	3.31%	0.60%	0.97%	7.11%	0.50	0.04	1.06	0.16	-0.82%	3.18%	0.60%	0.98%	7.20%	0.48
min	0.98	0.34	-0.41%	2.33%	0.55%	0.75%	6.82%	0.37	0.05	0.91	0.52	-0.26%	2.14%	0.56%	0.76%	6.98%	0.33
min-ss	1.27	0.03	-1.20%	3.21%	0.51%	0.79%	6.68%	0.51	0.02	1.25	0.04	-1.15%	3.12%	0.51%	0.79%	6.65%	0.50
GDP	0.56	0.00	2.05%	2.81%	1.69%	2.20%	19.47%	0.22	0.01	0.56	0.01	1.96%	2.83%	1.69%	2.20%	19.50%	0.22
Trade	0.61	0.03	1.55%	3.09%	1.45%	2.15%	20.12%	0.22	0.01	0.60	0.03	1.55%	3.02%	1.45%	2.16%	20.14%	0.22
erc	1.06	0.17	-1.13%	4.47%	1.04%	1.43%	14.47%	0.35	0.01	1.05	0.17	-1.12%	4.42%	1.05%	1.43%	14.52%	0.34
bs	0.39	0.00	12.08%	-8.64%	0.79%	3.03%	29.23%	0.37	1.18	0.26	0.00	15.37%	-11.74%	0.95%	3.87%	40.55%	0.17
bs-c	1.12	0.11	-0.92%	3.23%	0.60%	0.92%	6.96%	0.50	0.04	1.07	0.15	-0.81%	3.08%	0.61%	0.94%	6.82%	0.49
mv-min	0.40	0.00	10.99%	-6.56%	1.00%	5.14%	77.34%	0.13	2.73	0.24	0.00	14.78%	-10.66%	1.43%	6.94%	86.38%	0.07
1/n-min	0.99	0.32	-0.43%	2.38%	0.56%	0.77%	7.23%	0.35	0.05	0.92	0.48	-0.29%	2.20%	0.56%	0.78%	7.38%	0.32

sample mean-variance portfolio performs badly. So far, it can be concluded that there is no effect to the conclusion after taking account of transaction costs.

4.3.3 Robustness for Different Lengths of Estimation Windows

Table 4.5 contains the results from robustness with a 1 year estimation window including both g10 currencies and all currencies. For g10 currencies, constraint on mean-variance portfolio has the highest Sharpe ratio, but this portfolio has large downside risk. Based on the term of return-loss and CEQ return, naïve portfolio performs well because of only two portfolios which perform better than naïve portfolio. In terms of Sharpe ratio, compared to analysis of a 5 year estimation window, the minimum variance portfolio is no longer superior to naïve portfolio and equally-weighted risk contribution (erc) portfolio, and the latter two portfolios have similar performance. But, there is a consistent conclusion to analysis of 5 year estimation window from risk measures: minimum variance portfolio (both without and with short-sale constraint) has the lowest downside risk. Moreover, Calmar ratio indicates that minimum variance portfolio performs better than naïve portfolio. Comparison of the left and right sides of table 4.5, n improvement can be seen by adding 'lesser' currencies in all cases except naïve portfolio. In the analysis of all currencies, Bayes-Stein shrinkage (bs) portfolio with constraint has the highest Sharpe ratio, and with the lowest maximum drawdown. So, this portfolio can be considered as the best performance. Although some evaluation indexes cannot confirm the best performance of minimum variance portfolio, the downside risks show the lowest value at risk and conditional value at risk of this portfolio. Unfortunately, the naïve portfolio has negative Sharp ratio because of much lower average return. The larger maximum drawdown indicates that naïve portfolio also faces a large downside risk. The reason for lower return and large loss may be partly due to significant depreciation in some 'lesser' currencies over a long period, such as

Table 4.5 Robustness results for 1 year estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor perspective. The estimation window is 1 years. The first panel report the result of before transaction cost analysis. The second panel report the result of after transaction cost analysis. I only report selected portfolios in the second panel. In the first column of table, the ‘1/n’ refer to naïve portfolio, ‘ mv‘ refer to mean-variance portfolio, ‘min’ refer to minimum variance portfolio, ‘SS’ refer to the portfolios with short-sale constrains, ‘GDP’ refer to GDP portfolio, ‘TRADE’ refer to trade portfolio, ‘ERC’ refer to equally-weighted risk contribution portfolio, ‘‘MV AND MIN’ refer to combination of mean-variance portfolio and minimum variance portfolio, ‘1/N AND MIN’ refer to combination of naïve portfolio and minimum variance portfolio, ‘bs’ refer to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, ‘SR’ means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called ‘p-val’, which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called ‘re-loss’ refer to return-loss, ‘CEQ’ means certainty-equivalent return with risk reversion of 5. ‘VaR’ means Value at risk, ‘CVaR’ means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use ‘n/a’ to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.36	1.00	0.00%	1.28%	1.88%	2.50%	23.94%	0.13	0.01	-0.21	1.00	0.00%	-2.83%	1.86%	2.32%	57.33%	-0.03	0.01
mv	0.05	0.00	94.90%	n/a	11.66%	66.43%	n/a	n/a	53.45	0.31	0.00	-88.10%	n/a	2.94%	12.83%	n/a	n/a	13.52
mv-ss	0.38	0.80	-0.14%	1.35%	2.13%	2.98%	20.43%	0.18	0.26	1.44	0.00	-5.62%	4.62%	0.54%	1.11%	8.69%	0.57	0.19
min	0.32	0.46	0.28%	1.05%	1.44%	2.02%	16.33%	0.14	0.24	0.39	0.00	-2.85%	1.31%	0.45%	1.27%	16.16%	0.12	0.35
min-ss	0.33	0.44	0.24%	1.06%	1.46%	1.87%	17.40%	0.12	0.07	0.49	0.00	-2.82%	1.58%	0.39%	1.02%	15.00%	0.13	0.08
GDP	0.14	0.00	1.84%	-0.53%	1.83%	2.24%	26.09%	0.04	0.01	-0.05	0.00	-1.12%	-1.76%	1.66%	2.10%	42.20%	-0.01	0.01
Trade	0.29	0.08	0.52%	0.80%	1.55%	2.15%	18.89%	0.12	0.01	0.34	0.00	-3.54%	1.15%	1.35%	1.92%	20.12%	0.11	0.01
erc	0.37	0.98	-0.01%	1.33%	1.72%	2.25%	20.65%	0.14	0.02	0.42	0.00	-2.96%	1.44%	0.93%	1.53%	20.16%	0.10	0.11
bs	0.05	0.00	41.33%	n/a	4.67%	27.19%	n/a	n/a	26.89	0.36	0.00	-35.46%	n/a	1.61%	7.72%	n/a	n/a	7.34
bs-ss	0.27	0.05	0.92%	0.25%	1.98%	3.15%	27.18%	0.10	0.31	1.45	0.00	-5.45%	4.49%	0.50%	1.05%	8.38%	0.57	0.14
mv-min	0.27	0.00	48.42%	n/a	6.79%	20.39%	n/a	n/a	33.76	0.44	0.00	-74.56%	n/a	1.50%	5.66%	n/a	n/a	8.04
1/n-min	0.35	0.76	0.10%	1.22%	1.45%	2.01%	18.18%	0.13	0.15	0.08	0.00	-1.30%	-0.13%	0.62%	1.35%	27.97%	0.01	0.28

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.36	1.00	0.00%	1.27%	1.88%	2.51%	23.95%	0.13	-0.22	1.00	0.00%	-2.91%	1.86%	2.33%	57.42%	-0.03
mv	-0.12	0.00	126.75%	n/a	14.97%	69.82%	n/a	n/a	0.02	0.00	-32.79%	-491.18%	4.38%	22.25%	n/a	n/a
min	0.28	0.08	0.60%	0.71%	1.45%	2.03%	17.09%	0.11	0.32	0.00	-1.67%	0.07%	0.48%	1.34%	18.83%	0.03
GDP	0.14	0.00	1.79%	-0.50%	1.83%	2.24%	26.12%	0.04	-0.06	0.00	-1.20%	-1.77%	1.67%	2.10%	42.26%	-0.01
erc	0.37	0.96	-0.02%	1.33%	1.72%	2.25%	20.75%	0.14	0.32	0.00	-2.51%	0.94%	0.93%	1.54%	21.42%	0.07
bs-ss	0.21	0.00	1.49%	-0.34%	2.01%	3.18%	29.18%	0.07	1.28	0.00	-4.92%	3.93%	0.51%	1.08%	8.82%	0.48
1/n-min	0.32	0.34	0.30%	1.01%	1.46%	2.03%	18.81%	0.12	-0.14	0.08	-0.35%	-1.13%	0.64%	1.39%	30.20%	-0.02

the new Turkish lira. ‘erc’ portfolio also is ranked in the middle of naïve portfolio and minimum variance portfolio, based on all terms of measure. According to panel B of table 4.5, it can be deduced that there is no significant effect on the conclusion transaction costs are taken into account.

When the length of estimation window is extended to 3 years, from Table 4.6, it similar results to analysis of 5 years estimation window are found: best performance of minimum variance portfolio, good performance of naïve portfolio and ‘erc’ portfolio, improvement by adding ‘lesser’ currencies, no significant effect of transaction costs on performance rankings, and the fact that short-sale constraint helps to enhance the performance. Unlike analysis of 5 years estimation window, adding ‘lesser’ currencies reduce the rankings of performance of naïve portfolio.

From the previous tables, in terms of Sharpe ratio, longer estimation window has better performance of optimal portfolios for the most of cases. In terms of other measures, trend also likely exists. As discussed in preceding paragraphs, estimation error leads to poor portfolio performance. In this thesis, longer estimation window means more accuracy to estimate, which leads to better performance. I continue to extend length of estimation window to 10 years. Unfortunately, the results of Table 4.7 indicate that the portfolios with 10 years estimation window are not superior to the portfolios with other lengths. The reason of violation of the previous trend may be partly because of much longer window and much more irrelevant information contained, again more errors in estimation. In terms of risk measure, minimum variance portfolio has the lowest downside risk in either g10 currencies or all currencies datasets, consistent with the previous analysis. However, regarding Sharpe ratio, naïve portfolio has the best performance with g10 currencies dataset, while ERC portfolio is the best with all currencies dataset. For the g10 currencies dataset, minimum variance portfolio

Table 4.6 Robustness results for 3 year estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor perspective. The estimation window is 3 years. The first panel report the result of before transaction cost analysis. The second panel report the result of after transaction cost analysis. I only report selected portfolios in the second panel. In the first column of table, the '1/n' refers to na ïve portfolio, ' mv' refer to mean-variance portfolio, 'min' refers to minimum variance portfolio, 'SS' refers to the portfolios with short-sale constrains, 'GDP' refers to GDP portfolio, 'TRADE' refers to trade portfolio, 'ERC' refer to equally-weighted risk contribution portfolio, ''MV AND MIN' refer to combination of mean-variance portfolio and minimum variance portfolio, '1/N AND MIN' refer to combination of naïve portfolio and minimum variance portfolio, 'bs' refers to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, 'SR' means Sharpe ration, which uses returns over risk free rate. There are two comparisons to naïve portfolio, one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called 're-loss' refer to return-loss, 'CEQ' means certainty-equivalent return with risk reversion of 5. 'VaR' means Value at risk, 'CVaR' means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use 'n/a' to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.61	1.00	0.00%	3.42%	1.94%	2.59%	23.94%	0.23	0.01	-0.11	1.00	0.00%	-2.34%	1.92%	2.41%	53.42%	-0.02	0.01
mv	-0.35	0.00	93.26%	n/a	6.91%	29.08%	n/a	n/a	6.88	0.08	0.00	-12.97%	n/a	2.20%	21.46%	98.71%	0.05	10.07
mv-ss	0.38	0.00	2.11%	1.38%	2.14%	2.96%	29.84%	0.12	0.16	0.61	0.00	-3.86%	2.54%	0.53%	1.30%	17.23%	0.19	0.08
min	0.63	0.78	-0.18%	3.18%	1.48%	1.96%	12.60%	0.35	0.07	0.99	0.00	-2.85%	2.39%	0.45%	0.76%	7.62%	0.34	0.08
min-ss	0.58	0.79	0.14%	2.80%	1.49%	1.87%	14.87%	0.26	0.03	1.36	0.00	-3.43%	3.03%	0.42%	0.68%	6.06%	0.52	0.03
GDP	0.39	0.00	1.80%	1.49%	1.81%	2.26%	18.25%	0.17	0.01	0.16	0.00	-2.04%	-0.25%	1.67%	2.15%	31.67%	0.04	0.01
Trade	0.47	0.04	1.03%	2.18%	1.61%	2.23%	18.89%	0.20	0.01	0.44	0.00	-3.76%	1.84%	1.41%	2.02%	20.12%	0.15	0.01
erc	0.62	0.84	-0.13%	3.37%	1.74%	2.27%	20.91%	0.24	0.01	0.68	0.00	-3.66%	2.60%	1.00%	1.41%	15.19%	0.21	0.03
bs	-0.18	0.00	22.27%	-25.02%	2.96%	8.87%	88.30%	-0.06	2.33	0.05	0.00	-8.20%	-58.62%	1.57%	15.56%	93.83%	0.03	6.12
bs-ss	0.45	0.02	1.38%	2.01%	2.08%	2.66%	24.49%	0.16	0.13	0.63	0.00	-3.79%	2.58%	0.50%	1.21%	15.97%	0.20	0.06
mv-min	0.49	0.16	9.85%	n/a	2.99%	9.84%	n/a	n/a	7.14	0.74	0.00	-37.43%	-15.21%	1.17%	7.64%	56.91%	0.57	6.38
1/n-min	0.64	0.68	-0.26%	3.27%	1.48%	1.97%	14.25%	0.31	0.06	0.93	0.00	-2.69%	2.23%	0.45%	0.78%	9.69%	0.25	0.08

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.41	1.00	0.00%	3.41%	1.94%	2.59%	23.95%	0.23	-0.12	1.00	0.00%	-2.43%	1.93%	2.42%	53.48%	-0.02
mv	-0.28	0.00	95.77%	n/a	7.20%	29.29%	n/a	n/a	-0.29	0.01	12.49%	-145.20%	4.50%	26.38%	99.93%	-0.20
min	0.42	0.80	-0.16%	3.16%	1.49%	1.96%	12.81%	0.34	0.88	0.00	-2.57%	2.09%	0.46%	0.78%	7.99%	0.28
GDP	0.26	0.00	1.75%	1.54%	1.81%	2.26%	18.26%	0.18	0.16	0.00	-2.14%	-0.24%	1.67%	2.15%	31.70%	0.04
erc	0.42	0.80	-0.17%	3.39%	1.74%	2.28%	20.93%	0.24	0.65	0.00	-3.58%	2.47%	1.00%	1.42%	15.33%	0.20
bs-ss	0.30	0.02	1.42%	1.96%	2.09%	2.67%	24.75%	0.16	0.59	0.00	-3.62%	2.34%	0.52%	1.23%	16.08%	0.19
1/n-min	0.43	0.69	-0.25%	3.25%	1.49%	1.98%	14.42%	0.31	0.82	0.00	-2.42%	1.94%	0.46%	0.79%	10.04%	0.21

Table 4.7 Robustness results for 10 year estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor perspective. The estimation window is 10 years. The first panel report the result of before transaction cost analysis. The second panel report the result of after transaction cost analysis. I only report selected portfolios in the second panel. In the first column of table, the '1/n' refer to naïve portfolio, ' mv' refer to mean-variance portfolio, 'min' refer to minimum variance portfolio, 'SS' refer to the portfolios with short-sale constrains, 'GDP' refer to GDP portfolio, 'TRADE' refer to trade portfolio, 'ERC' refer to equally-weighted risk contribution portfolio, ''MV AND MIN' refer to combination of mean-variance portfolio and minimum variance portfolio, '1/N AND MIN' refer to combination of naïve portfolio and minimum variance portfolio, 'bs' refer to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, 'SR' means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called 're-loss' refer to return-loss, 'CEQ' means certainty-equivalent return with risk reversion of 5. 'VaR' means Value at risk, 'CVaR' means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use 'n/a' to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.29	1.00	0.00%	0.17%	2.52%	3.16%	23.94%	0.14	0.01	0.34	1.00	0.00%	1.02%	2.06%	2.80%	21.74%	0.15	0.01
mv	-0.37	0.00	23.94%	-45.86%	8.06%	13.30%	66.73%	-0.20	1.26	0.00	0.00	4.33%	-3.96%	2.27%	4.47%	31.38%	0.00	0.45
mv-ss	0.04	0.00	3.69%	-4.84%	3.39%	4.47%	33.09%	0.02	0.13	0.15	0.00	1.11%	0.03%	1.24%	2.00%	20.79%	0.04	0.06
min	0.02	0.00	2.24%	-1.50%	1.68%	2.25%	18.90%	0.01	0.03	0.17	0.01	0.68%	0.27%	1.03%	1.30%	12.49%	0.05	0.04
min-ss	0.12	0.00	1.40%	-0.67%	1.83%	2.31%	19.23%	0.05	0.01	0.27	0.33	0.28%	0.71%	1.10%	1.34%	14.37%	0.08	0.02
GDP	0.12	0.00	1.69%	-1.19%	2.15%	2.52%	18.25%	0.06	0.01	0.21	0.02	1.16%	-0.12%	2.04%	2.47%	19.47%	0.10	0.01
Trade	0.14	0.00	1.51%	-1.04%	2.13%	2.70%	18.89%	0.07	0.01	0.23	0.04	0.99%	0.05%	2.05%	2.66%	20.12%	0.10	0.01
erc	0.29	0.92	0.05%	0.38%	2.17%	2.86%	22.00%	0.13	0.01	0.41	0.46	-0.43%	1.60%	1.43%	2.01%	17.21%	0.16	0.01
bs	-0.34	0.00	9.41%	-10.56%	3.19%	5.07%	34.54%	-0.15	0.41	0.00	0.00	3.22%	-2.22%	1.81%	3.34%	25.13%	0.00	0.31
bs-ss	-0.06	0.00	4.31%	-4.46%	2.83%	3.78%	31.25%	-0.02	0.11	0.16	0.00	1.00%	0.13%	1.16%	1.87%	19.85%	0.04	0.05
mv-min	0.12	0.07	3.59%	-8.07%	2.69%	6.75%	29.71%	0.08	0.90	-0.01	0.00	2.96%	-1.86%	1.71%	3.02%	23.61%	0.00	0.27
1/n-min	0.04	0.00	2.09%	-1.36%	1.75%	2.29%	18.89%	0.02	0.03	0.18	0.01	0.66%	0.31%	1.04%	1.31%	12.66%	0.06	0.04

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.29	1.00	0.00%	0.14%	2.52%	3.17%	23.95%	0.14	0.33	1.00	0.00%	0.89%	2.07%	2.82%	21.78%	0.14
mv	-0.42	0.00	25.62%	-47.91%	8.09%	13.51%	69.17%	-0.22	-0.09	0.00	5.26%	-5.09%	2.30%	4.55%	32.38%	-0.04
min	0.03	0.00	2.09%	-1.38%	1.69%	2.26%	18.98%	0.01	0.13	0.00	0.79%	0.12%	1.04%	1.31%	12.66%	0.04
GDP	0.13	0.00	1.55%	-1.07%	2.15%	2.53%	18.26%	0.07	0.22	0.04	0.98%	-0.07%	2.04%	2.48%	19.50%	0.10
erc	0.29	0.98	-0.02%	0.42%	2.18%	2.87%	22.01%	0.13	0.39	0.44	-0.44%	1.51%	1.43%	2.02%	17.26%	0.15
bs-ss	-0.06	0.00	4.27%	-4.45%	2.83%	3.80%	31.42%	-0.02	0.13	0.00	1.11%	-0.06%	1.18%	1.89%	20.08%	0.04
1/n-min	0.05	0.00	1.95%	-1.24%	1.76%	2.30%	18.97%	0.02	0.14	0.00	0.76%	0.15%	1.04%	1.32%	12.83%	0.04

performs very poorly in terms of Sharpe ratio, but constraint significantly improves this performance. According to the measure of return-loss, no portfolio performs better than naïve portfolio. The performance of 'ERC' portfolio is followed by the naïve portfolio without a statistically significant difference. As far as all currencies analysis is concerned, firstly, adding 'lesser' currencies results in diversification benefits. The constraint of short-sale improves moderately the performance of minimum variance portfolio. However, there is only one portfolio which outperforms the naïve portfolio based on the negative return-loss. As I concluded before, panel B indicates that transaction cost does not change the rankings of performance of portfolios.

Although I apply different estimation window lengths to analyse performance, the comparison discussed before is based on different evaluation period. This may lead to a flawed performance evaluation. Sharpe ratios are analyses for comparability of various portfolios with different lengths of estimation window but the same evaluation period. In Table 4.8, panel A, panel B and panel C show Sharpe ratio results with different estimation windows in evaluation period of the last 5 years, the last 10 years and the last 12 years respectively. Comparison between left and right side of table 4.8 indicates that adding 'lesser' currencies help portfolios gain more benefits of diversification except the cases of market portfolios with the longest evaluation period. With the most recent period, the performance of the mean variance portfolio with short-sale constraint appears to be better, but while the performance of the minimum variance portfolio is improved by longer evaluation periods. However, the conclusion for evaluating the most recent period is contradictory results regarding my previous analysis and theory of estimation error. So, I do not state the conclusion just based on the Sharpe ratio. In addition to considering Sharpe ratio, the focus is also on the maximum drawdown for analysis. Because of consistent results with the precious analysis: 1) the lowest risk for minimum variance portfolio for all estimation windows and all evaluation periods;

Table 4.8 Comparing Sharpe ratio for same evaluation period with different lengths of estimation windows

This table show Sharpe ratios of different portfolios of different estimation window, but evaluated in same period. Each row is Sharpe ratio with same length of estimation window, but different portfolio. So, each column represent Sharpe ratio of one portfolio, but different estimation window. The results, in panel A, are evaluated in same period (the last 5 years). The results, in panel B, are evaluated in same period (the last 10 years). The results, in panel C, are evaluated in same period (the last 12 years). There are only selected portfolios reported in table. the '1/n' refer to naïve portfolio, ' mv' refer to mean-variance portfolio, 'min' refer to minimum variance portfolio, 'SS' refer to the portfolios with short-sale constrains, 'GDP' refer to GDP portfolio, 'ERC' refer to equally-weighted risk contribution portfolio, '1/n - min' refer to combination of naïve portfolio and minimum variance portfolio, 'bs' refer to bayes-Stain shrinkage portfolio.

	G10 Currencies							All currencies						
	1/n	**mv**	**min**	**GDP**	**erc**	**bs-ss**	**1/n-min**	**1/n**	**mv**	**min**	**GDP**	**erc**	**bs-ss**	**1/n-min**
Panel A: Evaluation in the last 5 years														
1 year	0.29	0.40	0.14	0.13	0.32	-0.15	0.16	0.33	-0.01	0.05	0.22	0.40	0.10	0.79
3 years	0.29	-0.80	0.40	0.13	0.33	0.65	0.22	0.33	-0.25	0.40	0.22	0.37	-0.59	0.86
5 years	0.29	0.43	0.26	0.13	0.31	-0.41	-0.05	0.33	-0.23	-0.01	0.22	0.46	0.09	0.41
10 years	0.29	-0.42	0.03	0.13	0.29	0.05	-0.06	0.33	-0.09	0.13	0.22	0.39	-0.09	0.13
Panel B: Evaluation in the last 10 years														
1 year	0.58	0.03	0.54	0.42	0.63	-0.20	0.42	0.81	0.01	1.05	0.56	0.88	0.09	1.74
3 years	0.58	-0.44	0.74	0.42	0.63	0.44	0.64	0.81	-0.01	1.47	0.56	0.96	0.02	1.87
5 years	0.58	-0.22	0.66	0.42	0.61	-0.46	0.44	0.81	0.23	0.91	0.56	1.05	-0.43	1.07
Panel C: Evaluation in the last 12 years														
1 year	0.61	-0.01	0.39	0.39	0.60	-0.20	0.39	-0.12	0.04	0.51	0.16	0.59	0.14	1.25
3 years	0.61	-0.41	0.63	0.39	0.63	0.36	0.44	-0.12	-0.29	0.88	0.16	0.65	0.29	0.59

2) 'lesser' currencies reduce the risk of most portfolios except naïve portfolios, not report here. Another point noted from table 4.8 is that 'erc' portfolio is consistently superior to naïve portfolio in both terms of Sharpe ratio.

According to analysis in this subsection, it can be stated that, in general, the conclusions of performance measure results with different length of estimation windows are consistent with conclusions made from 5 year estimation window analysis. Although, in terms of Sharpe ratio, there are some inconsistent conclusions, most of them are consistent. Moreover, measures related to downside risk consistently all support minimum variance portfolio either with or without short-sale constraint. In addition, I conclude that, before extending estimation window to 10 years, the performance roughly is enhanced with increasing estimation window.

4.3.4 Robustness for Investor Perspectives from Different Countries

For the more comprehensive robustness, I also build analysis related to perspectives of other countries investor, including investors from the UK, investors from euro zone and investors from Japan. The estimation window considered here is 5 years.

4.3.4.1 UK Investor

Table 4.9 documents the results for the UK investor and based on both G10 currencies and all currencies dataset. I can find some inconsistencies with conclusions from US investor perspective. Firstly, in all terms of evaluation measures, naïve portfolio has the best performance, and equally-weighted risk contribution (erc) portfolio is ranked only second. According to p-value, these two portfolios have no significant different sharp ratio, but others appear differently at any reasonable significance level. Minimum variance portfolios both with and without constraint are in the middle of the pack. Mean-variance portfolio has the largest downside risk. Along with low sharp ratio, it can be concluded this is the worst performance of mean-variance portfolio. This is consistent with analysis from a US investor perspective.

Regarding to all currencies sample base, right side of table 4.9 shows that naïve portfolio also has the largest Sharpe ratio, there is no portfolio which can be superior to naïve portfolio according to return-loss. CEQ returns also support the naive portfolio has the best performance. According to risk measure of maximum drawdown, the results indicate that the portfolio with the lowest downside risk is erc or naïve portfolio rather than minimum variance portfolio or GDP portfolio. The ranking of three portfolios is similar in ranking to the previous analysis of G10 currencies, with the best performance of naïve portfolio and the worst performance of mean variance portfolio. Similar conclusions are reached for both G10 currencies and all currencies cases. In addition, in both cases, the minimum variance portfolio still performs well, though not the best.

An analysis of UK results shows inconsistencies with findings and conclusions reached for US investors. Generally speaking, there are many inconsistences: 1) the best performance no longer belongs to minimum variance portfolio. 2) Naïve portfolio performs best in the case of G10 currencies. 3) It can be stated that the findings on the benefits of adding lesser currencies in terms of downward risk are generally inconclusive. However, mean-variance portfolio usually performs poorly as outlined in the preceding paragraphs.

A comparison of the difference between before and after taking transaction cost is made, the results of which are shown in panel B of table 4.9. According to these results, it can be deduced that there is no impact on rankings of portfolio performance for all terms of evaluation measures in both cases of g10 and all currencies sample bases, although some portfolios, show a relatively significant change for evaluation measures.

Table 4.9 Robustness results for perspective of UK investors

This table documents the evaluation of performance of each optimal portfolio strategy from a UK investor perspective. The estimation window is 5 years. The first panel report the result of before transaction cost analysis. The second panel report the result of after transaction cost analysis. I only report selected portfolios in the second panel. In the first column of table, the '1/n' refers to naïve portfolio, ' mv' refer to mean-variance portfolio, 'min' refers to minimum variance portfolio, 'SS' refers to the portfolios with short-sale constrains, 'GDP' refers to GDP portfolio, 'TRADE' refers to trade portfolio, 'ERC' refer to equally-weighted risk contribution portfolio, 'mv-min' refer to combination of mean-variance portfolio and minimum variance portfolio, '1/n-min' refer to combination of naïve portfolio and minimum variance portfolio, 'bs' refer to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, 'SR' means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called 're-loss' refer to return-loss, 'CEQ' means certainty-equivalent return with risk reversion of 5. 'VaR' means Value at risk, 'CVaR' means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use 'n/a' to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.58	1.00	0.00%	2.80%	1.31%	1.70%	14.95%	0.26	0.01	0.67	1.00	0.00%	3.55%	1.47%	1.88%	10.21%	0.47	0.01
mv	0.29	0.00	106.82%	n/a	10.00%	35.68%	n/a	n/a	30.08	0.42	0.01	350.40%	n/a	78.99%	199.51%	n/a	n/a	830.47
mv-ss	0.30	0.00	2.50%	0.70%	2.09%	2.68%	18.14%	0.15	0.12	0.46	0.01	1.98%	2.10%	1.84%	2.76%	17.06%	0.25	0.13
min	0.25	0.00	2.36%	0.52%	1.35%	1.87%	23.28%	0.08	0.04	0.26	0.00	3.08%	0.57%	1.34%	2.08%	18.06%	0.11	0.16
min-ss	0.29	0.00	2.08%	0.77%	1.36%	1.85%	21.93%	0.09	0.03	0.42	0.00	1.80%	1.73%	1.33%	1.87%	14.32%	0.21	0.07
GDP	0.14	0.00	3.37%	-0.37%	1.57%	2.22%	22.77%	0.05	0.01	0.25	0.00	3.12%	0.51%	1.49%	2.09%	18.78%	0.10	0.01
Trade	0.28	0.00	2.25%	0.69%	1.50%	2.05%	17.10%	0.12	0.01	0.36	0.00	2.28%	1.27%	1.43%	1.98%	15.19%	0.17	0.01
erc	0.55	0.72	0.23%	2.58%	1.31%	1.71%	16.37%	0.23	0.01	0.64	0.74	0.24%	3.24%	1.43%	1.80%	10.56%	0.42	0.01
bs	0.29	0.00	30.61%	n/a	3.87%	11.86%	n/a	n/a	5.95	0.42	0.01	269.00%	n/a	60.24%	151.66%	n/a	n/a	351.38
bs-ss	0.35	0.00	2.11%	1.13%	2.23%	2.83%	19.08%	0.17	0.11	0.45	0.00	2.08%	2.00%	1.91%	2.78%	17.70%	0.23	0.13
mv-min	0.49	0.38	23.41%	n/a	4.55%	13.63%	n/a	n/a	15.85	0.59	0.47	83.75%	n/a	31.84%	148.48%	n/a	n/a	317.44
1/n-min	0.39	0.01	1.31%	1.52%	1.35%	1.77%	19.91%	0.14	0.03	0.40	0.00	1.92%	1.60%	1.36%	1.88%	15.50%	0.18	0.10

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.58	1.00	0.00%	2.79%	1.31%	1.70%	14.97%	0.26	0.66	1.00	0.00%	3.47%	1.47%	1.88%	10.23%	0.47
mv	0.25	0.00	119.52%	n/a	10.54%	36.48%	n/a	n/a	0.16	0.00	739.51%	n/a	83.15%	272.24%	n/a	n/a
min	0.24	0.00	2.43%	0.44%	1.35%	1.88%	23.40%	0.07	0.21	0.00	3.43%	0.14%	1.35%	2.10%	19.19%	0.08
GDP	0.15	0.00	3.32%	-0.34%	1.57%	2.22%	22.78%	0.05	0.26	0.00	3.04%	0.52%	1.49%	2.09%	18.81%	0.10
erc	0.55	0.72	0.23%	2.57%	1.31%	1.71%	16.39%	0.23	0.63	0.73	0.25%	3.16%	1.43%	1.80%	10.59%	0.41
bs-ss	0.35	0.00	2.15%	1.08%	2.23%	2.84%	19.14%	0.17	0.41	0.00	2.36%	1.63%	1.92%	2.80%	17.83%	0.21
1/n-min	0.39	0.00	1.34%	1.47%	1.35%	1.78%	19.99%	0.13	0.36	0.00	2.15%	1.29%	1.38%	1.89%	16.42%	0.16

4.3.4.2 Japanese Investor

Table 4. 10 contains the results of performance measures for all portfolios based on the Japanese investor perspective with an estimation window of 5 years, and for both G10 currencies and all currencies datasets. From the left side of this table, it shows that there are entirely smaller Sharpe ratios than other previous cases, which indicates that G10 currencies portfolios have a poor performance; bs portfolio with constraint has the largest Sharpe ratio, while bs portfolio without constraint has the lower Sharpe ratio. This means that the constraint on this portfolio improves its performance significantly. Moreover, the evidence from downside risk measures and CEQ return also supports this conclusion. However, results from downside risk measures indicate that the best one is the minimum variance portfolio, and constraint on minimum variance portfolio does not help much. According to the return-loss, there are just two portfolios superior to the naïve portfolio, while it has moderate downside risk. This indicates that naïve portfolio performs well. When I focus on erc portfolio, although the Sharpe ratio of this portfolio is lower than Sharpe ratio of naïve portfolio, p-value indicates that there is not much statistical significant difference between the two ratios. The results from value at risk, expected shortfall and maximum drawdown all indicate that 'erc' portfolio has lower downside risk relative to naïve portfolio. In general, all of naïve portfolio, minimum variance portfolio and erc portfolio have good performance in different aspects.

With regards to all currencies datasets, the one with the highest Sharpe ratio is mean-variance portfolio, but it takes a huge total risk. This large total risk leads to significant reduction of CEQ return with increasing level of risk aversion. Moreover, its downside risk is very high as well. So, mean-variance portfolio cannot be generally considered as the best performance.. From measure of return loss, naïve portfolio is superior to more than half of portfolios, and naïve portfolio has a low downside risk according to its

Table 4. 10 Robustness results for perspective of Japanese investors

This table documents the evaluation of performance of each optimal portfolio strategy from a Japanese investor perspective. The estimation window is 5 years. The first panel report the result of before transaction cost analysis. The second panel report the results of after transaction cost analysis. Only selected portfolios in the second panel are reported. In the first column of table, the ‘1/n’ refer to naïve portfolio, ‘ mv‘ refers to mean-variance portfolio, ‘min’ refers to minimum variance portfolio, ‘SS’ refers to the portfolios with short-sale constrains, ‘GDP’ refers to GDP portfolio, ‘TRADE’ refer to trade portfolio, ‘ERC’ refer to equally-weighted risk contribution portfolio, ‘mv-min’ refers to a combination of mean-variance portfolio and minimum variance portfolio, ‘1/n-min’ refers to combination of naïve portfolio and minimum variance portfolio, ‘bs’ refer to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, ‘SR’ means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called ‘p-val’, which is the p-value of the difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called ‘re-loss’ refers to return-loss, ‘CEQ’ means certainty-equivalent return with risk reversion of 5. ‘VaR’ means Value at risk, ‘CVaR’ means conditional value at risk, or called expected shortfall. These two are computed at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use ‘n/a’ to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.25	1.00	0.00%	-0.71%	2.96%	4.24%	34.99%	0.09	0.01	0.35	1.00	0.00%	0.62%	2.70%	4.01%	32.77%	0.12	0.01
mv	0.24	0.87	9.50%	n/a	13.39%	42.18%	n/a	n/a	18.79	0.63	0.01	-94.22%	n/a	24.23%	61.00%	n/a	n/a	107.14
mv-ss	0.13	0.00	1.84%	-3.73%	3.62%	5.42%	46.68%	0.04	0.15	0.37	0.67	-0.32%	0.09%	3.29%	4.94%	38.30%	0.14	0.09
min	0.02	0.00	2.08%	-1.81%	1.94%	2.61%	30.85%	0.01	0.07	0.09	0.00	2.30%	-1.21%	1.86%	2.64%	30.31%	0.03	0.21
min-ss	0.12	0.00	1.19%	-0.91%	2.03%	2.91%	27.08%	0.04	0.02	0.13	0.00	1.92%	-0.82%	1.97%	2.94%	27.51%	0.04	0.03
GDP	0.00	0.00	2.53%	-2.52%	2.27%	3.44%	35.03%	0.00	0.01	0.10	0.00	2.61%	-1.73%	2.32%	3.58%	32.94%	0.03	0.01
Trade	0.07	0.00	1.87%	-1.93%	2.35%	3.52%	31.44%	0.02	0.01	0.13	0.00	2.24%	-1.34%	2.33%	3.51%	29.27%	0.05	0.01
erc	0.23	0.46	0.25%	-0.71%	2.77%	4.00%	33.64%	0.08	0.01	0.32	0.49	0.31%	0.40%	2.55%	3.85%	31.83%	0.11	0.01
bs	0.26	0.95	-0.88%	n/a	5.28%	12.19%	n/a	n/a	6.79	0.62	0.01	-67.45%	n/a	19.10%	47.35%	n/a	n/a	458.17
bs-c	0.32	0.13	-0.93%	-0.24%	3.18%	4.60%	37.60%	0.12	0.15	0.39	0.44	-0.60%	0.34%	3.29%	4.93%	38.01%	0.15	0.10
mv-min	0.19	0.33	47.48%	n/a	5.37%	50.04%	n/a	n/a	20.43	0.26	0.23	19.93%	n/a	20.08%	55.75%	n/a	n/a	80.71
n/1-min	0.11	0.00	1.26%	-1.00%	1.94%	2.66%	31.38%	0.03	0.05	0.20	0.00	1.33%	-0.23%	1.90%	2.70%	30.04%	0.06	0.16

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.23	1.00	0.00%	-0.99%	2.96%	4.24%	35.00%	0.08	0.32	1.00	0.00%	0.30%	2.70%	4.02%	32.79%	0.11
mv	0.23	0.99	0.72%	n/a	13.63%	43.83%	n/a	n/a	0.30	0.86	3.62%	n/a	29.20%	63.51%	n/a	n/a
min	-0.01	0.00	2.15%	-2.09%	1.94%	2.62%	30.99%	0.00	0.01	0.00	2.76%	-1.91%	1.87%	2.67%	31.62%	0.00
GDP	-0.02	0.00	2.55%	-2.77%	2.27%	3.45%	35.05%	-0.01	0.07	0.00	2.59%	-2.00%	2.32%	3.58%	32.97%	0.02
erc	0.21	0.39	0.26%	-0.98%	2.77%	4.01%	33.64%	0.07	0.29	0.44	0.32%	0.09%	2.55%	3.86%	31.85%	0.10
bs-ss	0.30	0.12	-0.91%	-0.57%	3.19%	4.61%	37.80%	0.11	0.36	0.44	-0.57%	-0.10%	3.29%	4.95%	38.29%	0.14
1/n-min	0.08	0.00	1.32%	-1.27%	1.94%	2.67%	31.52%	0.02	0.13	0.00	1.68%	-0.83%	1.91%	2.73%	31.11%	0.04

value at risk, expected shortfall and maximum drawdown. Although minimum variance portfolio has the lowest downside risk, its Sharpe ratio is also very small. For minimum variance, the constraints do not help much, because overall they improve their Sharpe ratio, but also increase their downside risk in term of VaR and CVaR. The p-value of Sharpe ratio for erc portfolio against naïve portfolio is 0.89, which means two ratios do not show a statistically significant difference at confident level of 85%. Furthermore, the downside risks of these two portfolios are almost the same.

To sum up analysis of results from Japanese investors, the conclusions are not consistent with the conclusions reached before in the analysis of US investors. The performance of minimum variance portfolio is not the best among all portfolios, but it still works well together with naïve portfolio and erc portfolio. But, the one consistent conclusion reached is to do with the benefit of adding 'lesser' currencies.

Panel B of table 4.10 exhibits the results after taking account of transaction cost. According to this table, five out of six evaluation indexes indicate that there is no effect on the performance ranking due to taking account of transaction cost. 'bs' with short-sale constraint perform best in terms of sharp ratio and CEQ, while minimum variance with constraint portfolio has the lowest downside risk. However, when I eliminate transaction cost effect for Japanese investor for all currencies sample base, the significant changes of rankings occur. Regarding Sharpe ratio and return-loss, the mean variance portfolio performs better than naïve portfolio and has top ranking before transaction cost. After taking transaction costs, the mean variance portfolio performs worse than naïve portfolio and bs with constraint portfolio fall in top 1. As far as downside risk is concerned, it cannot be concluded which portfolio has the lowest downside risk in the first place. But, after taking account of transaction cost, minimum variance portfolio with constraint can be considered as the one with the lowest downside risk among all portfolios. The results of after transaction cost, shows that there are similar conclusions could be summarised between two sample bases (g10 and all currencies), which cannot be done before taking account of transaction cost.

4.3.4.3 Investor from Euro Zone Countries

In this subsection, the results of performance measures from portfolios based on the perspective of euro zone investor are analysed, which is shown in Table 4.11. In the left side of table 4.11, results of Sharpe ratio indicate that naïve portfolio performs best, while return-loss measure shows that non-portfolio can be superior to naïve portfolio, and this conclusion is also supported by CEQ return. Moreover, maximum drawdown shows the lowest downside risk for naïve portfolio. It can therefore be concluded that that naïve portfolio has the best performance in general, even though minimum variance portfolio with constraint has the lowest value at risk and expected shortfall. According to p-value, the Sharpe ratios of bs portfolio with constraint are not statistically different from those of naïve portfolio, but it has higher downside risk. This indicates that bs portfolio performs no better than naïve portfolio. Due to lower Sharpe ratio, minimum variance portfolio does not work better than native and erc portfolio. The rankings of these three portfolios are also true, according to CR, SR and BR, which are ratios derived from using drawdown factor instead of standard deviation as risk.

For all currencies dataset, the conclusion is slightly inconsistent with analysis for G10 currencies. From the right side of the table 4.11, combination of mean-variance portfolio and minimum variance portfolio has substantially large Sharp ratio, but the downside risks of it are also very high. Minimum variance portfolio with lower downside risk, however, has exposure to negative Sharpe ratio, while mean-variance portfolio faces a terrible downside risk. So, the portfolios with good performance, overall, are naïve portfolio and erc portfolio, which have above average Sharpe ratio

Table 4.11 Robustness results for perspective of Euro zone investors

This table documents the evaluation of performance of each optimal portfolio strategy for Euro zone investor perspective. The estimation window is 5 years. The first panel report the result of before transaction cost analysis. The second panel report the result of after transaction cost analysis. Selected portfolios in the second panel are the only ones reported. In the first column of table, the '1/n' refer to naïve portfolio, ' mv' refers to mean-variance portfolio, 'min' refers to minimum variance portfolio, 'SS' refers to the portfolios with short-sale constrains, 'GDP' refer to GDP portfolio, 'TRADE' refer to trade portfolio, 'ERC' refer to equally-weighted risk contribution portfolio, 'mv-min' refer to combination of mean-variance portfolio and minimum variance portfolio, '1/n-min' refers to combination of naïve portfolio and minimum variance portfolio, 'bs' refers to bayes-Stain shrinkage portfolio. For the evaluation methods, in the first two rows of the table, 'SR' means Sharpe ration, which use returns over risk free rate. There are two comparisons to naïve portfolio, one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/n, another one is called 're-loss' refer to return-loss, 'CEQ' means certainty-equivalent return with risk reversion of 5. 'VaR' means Value at risk, 'CVaR' means conditional value at risk, or called expected shortfall. I compute these two at possibility of 95% with historical simulation approach. The last columns are related to the maximum DrawDown and Calmar ratio. There are extreme weights at some time points for some portfolios, which lead to extreme returns. This return seriously impact evaluation methods for DrawDown. So, I use 'n/a' to represent that it cannot be calculated due to extreme returns. For drawdown, this means that more than 100% will loss. For other evaluation indexes, this means extreme value, which cannot be easily reported in the table.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/n	0.29	1.00	0.00%	0.79%	1.26%	2.05%	15.36%	0.12	0.01	0.41	1.00	0.00%	1.65%	1.53%	2.20%	11.48%	0.25	0.01
mv	-0.10	0.00	106.82%	n/a	13.65%	49.78%	n/a	n/a	24.29	-0.57	0.00	711.46%	n/a	57.87%	247.64%	n/a	n/a	237.01
mv-ss	0.08	0.00	2.50%	-1.89%	2.07%	3.24%	33.94%	0.02	0.14	0.43	0.85	-0.12%	1.81%	1.70%	2.48%	17.70%	0.19	0.11
min	0.01	0.00	2.36%	-0.76%	1.07%	1.75%	24.28%	0.00	0.03	0.00	0.00	2.11%	-0.66%	0.97%	1.64%	14.73%	0.00	0.11
min-ss	0.03	0.00	2.08%	-0.61%	1.05%	1.74%	23.32%	0.01	0.02	0.10	0.00	1.52%	-0.10%	0.92%	1.55%	16.02%	0.03	0.03
GDP	-0.14	0.00	3.37%	-3.16%	1.78%	2.46%	30.85%	-0.04	0.01	-0.02	0.00	3.53%	-1.84%	1.72%	2.42%	24.18%	-0.01	0.01
erc	0.22	0.72	0.23%	0.44%	1.17%	1.90%	16.84%	0.08	0.01	0.37	0.50	0.25%	1.31%	1.17%	1.87%	10.57%	0.21	0.01
bs	-0.10	0.00	30.61%	n/a	5.76%	17.63%	n/a	n/a	9.74	-0.55	0.00	537.38%	n/a	42.79%	185.12%	n/a	n/a	729.07
bs-c	0.24	0.00	2.11%	-0.44%	2.29%	3.46%	29.84%	0.09	0.14	0.43	0.83	-0.14%	1.82%	1.70%	2.45%	17.74%	0.19	0.11
mv-min	-0.23	0.38	23.41%	n/a	6.53%	20.20%	n/a	n/a	15.62	0.42	0.90	-6.11%	n/a	25.94%	116.97%	n/a	n/a	239.62
n/1-min	0.04	0.01	1.31%	-0.55%	1.04%	1.77%	23.60%	0.01	0.03	0.09	0.00	1.66%	-0.21%	0.97%	1.60%	13.69%	0.03	0.09

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/n	0.28	1.00	0.00%	0.75%	1.27%	2.05%	15.38%	0.12	0.40	1.00	0.00%	1.55%	1.53%	2.21%	11.55%	0.24
mv	-0.17	0.00	86.96%	n/a	14.20%	49.65%	n/a	n/a	-1.05	0.00	n/a	n/a	79.92%	244.19%	n/a	n/a
min	0.00	0.00	1.59%	-0.81%	1.07%	1.76%	24.39%	0.00	-0.06	0.00	2.35%	-0.97%	0.98%	1.66%	16.10%	-0.02
GDP	-0.14	0.00	3.67%	-3.15%	1.78%	2.47%	30.87%	-0.04	-0.02	0.00	3.43%	-1.86%	1.72%	2.43%	24.24%	-0.01
erc	0.22	0.11	0.37%	0.40%	1.17%	1.90%	16.88%	0.08	0.35	0.46	0.26%	1.21%	1.17%	1.87%	10.66%	0.20
bs-ss	0.23	0.32	0.57%	-0.55%	2.30%	3.48%	30.10%	0.08	0.39	0.93	0.05%	1.52%	1.71%	2.47%	18.01%	0.17
1/n-min	0.03	0.00	1.38%	-0.60%	1.04%	1.77%	23.70%	0.01	0.03	0.00	1.87%	-0.49%	0.97%	1.61%	14.96%	0.01

(according to return-loss) and much lower downside risk.

For the euro zone investor, the naïve and erc portfolio have very good performances in general. However, minimum variance portfolio has various performances in G10 dataset and all dataset. Constraints on the portfolios do not help too much. Adding 'lesser' currencies can help most portfolios gain from benefit of diversification, when the two tables are compared.

We also investigated the effect of transaction cost for euro zone investors. According to panel B of table 4.11, there is no transaction cost impact on performance rankings of portfolio for G10 currencies sample base. However, for the all currencies sample base, there is a different ranking after taking account of transaction cost compared to that before transaction cost. When transaction cost is not taken into account, the best performance portfolio is bs portfolio with constraint (based on Sharpe ratio and CEQ). Due to a large turnover, which leads to transaction fee and offset benefits, this portfolio performs worse than naïve portfolio after taking into account transaction costs, and naïve portfolio is ranked to top 1. Although the rankings based on Sharpe ratio have been changed, the conclusion of all currencies sample base related to good performance of naïve and erc portfolio is not changed.

Although the conclusions related to the rank of portfolios are inconsistent for different countries' investors, there are still some common features to all investors. In addition to the benefit of adding 'lesser' currencies, all market portfolios have lower turnover and all mean-variance portfolios work badly, especially in exposure to downside risk. In addition, the transaction cost has no significant impact on conclusions made before transaction cost.

4.4 Conclusions

In this chapter, 12 portfolio strategies are applied, including sample-based mean-variance portfolio, its extensions, minimum variance portfolio, market portfolios and equally-weighted risk contribution portfolio, into currency market. The main motivation for this research was to find how the performances of these portfolios are in a currencies trading portfolio, and which one, if any, is the most optimal. For the US dollar portfolios using US dollar as the base currency, the minimum variance portfolios, with and without short-sale constraint, has the best performance and exposure to the lowest downside risk. The constraint help, indeed, improves the performance but not too much. The naïve portfolio and equally-weighted risk contribution portfolio also performs reasonably well, in general, while the mean variance portfolio works very badly. This portfolio has horrible downside risk, even though it sometimes has moderate Sharp ratio, which is also offset by its significant high downside risk. Although there is a small variation in results from analysis of different lengths of estimation window, overall, this robustness check also supports the conclusions. Two datasets are set to test the benefit of diversification from currencies pairs from developing countries. Comparing both results, it can be concluded that adding 'lesser' currencies can help investors gain the benefit from diversification, which can be proved by all cases in robustness check.

However, the UK pound portfolio, Japanese yen portfolio and euro portfolio cannot give consistent conclusion with the US dollar portfolio. The issue of which portfolio optimization method works best to determine the portfolio weights yields mixed conclusions here. For the UK pound portfolios, the best performance no longer belongs to minimum variance portfolio, which works badly. Moreover, Naïve portfolio no longer performs well in the case of G10 currencies, but GDP portfolio does. As far as Japanese yen portfolios are concerned, the performance of minimum variance portfolio is not the best among all portfolios, but it still works well together with naïve portfolio and erc portfolio. Furthermore, the short sale constraint on bs portfolio does help too much for the performance. Regarding the euro portfolios, the naïve and erc portfolios have very good performance in general. However, minimum variance portfolio has various performances in G10 dataset and all datasets. Although there are these inconsistences, the conclusions related to performance of sample-based mean-variance portfolio and benefit of adding 'lesser' currencies are consistent with all cases analysed in this chapter.

In addition, from results of turnover in all cases, it shows that turnovers for market portfolios are very low. This means that benefits can be derived from this, and the conclusion may be different. So, we, then, take account of transaction to test the effect of turnover for each model, the results show that transaction cost has no significant impact on the conclusion reached before, although performance of three out of 12 portfolios has a significant change.

We have summarised that the mean-variance optimization does not have outperformance relative to other optimizations. But, some literature argues that mean-variance portfolio used in Demiguel's research tends to be very aggressive, while Kirby and Ostdiek (2010) introduce an idea with details of the process. The results from this new idea show that the mean-variance portfolio outperforms naïve portfolios for most of the equity dataset. In the next chapter I will apply this new idea into currency market, and test whether it works or not for only currency portfolio.

Chapter Five

Currency Portfolio Management: Timing Strategies

5.1 Introduction

In Chapter four, I compared the performance of passive optimal portfolios to that of benchmark portfolio (naïve portfolio) for the foreign currency market. As discussed in previous chapters, while many efforts are devoted to overcome the estimation errors of Markowitz model by Bayesian process, some literature try to use alternative ways to construct a portfolio which can beat the market. Besides estimating errors to expected returns and standard deviation of returns, another reason for poor performance of mean-variance portfolio is that the targeting of expected excess return is very aggressive. Specifically, when calculating the weights for mean-variance portfolio in DeMiguel et al. (2007) research, an expected excess return, which is targeted, always exceeds 100% per year. This unusual return can magnify the effects of both estimation risk and turnover. As I have reviewed in chapter two, Kan and Zhou (2007) use an innovative approach to develop a three fund asset allocation strategy that optimally diversifies across both factor and estimation risk. Tu and Zhou (2008) further demonstrate that the naïve portfolio constitutes a reasonable shrinkage target, and propose a new strategy which shrinkage three-fund portfolio towards the naïve portfolio. And, the degree of shrinkage is determined by the level of estimation risk. Inspired by this idea, Kirby and Ostdiek (2010) consider the return from naïve portfolio instead of previous unusual return as the target of conditional expected excess return for constructing mean-variance models. They use the DeMiguel et al. (2007) datasets to confirm that the new strategy outperforms naïve portfolio. But, after taking account of transaction costs, the conclusion is not clear.

The conclusion from DeMiguel et al. (2007) paper gives researchers a challenge, on how to use sample information related to mean and variance to construct a more efficient portfolio. According to Fleming et al. (2003) study, they propose a guideline about volatility-timing portfolio to outperform naïve portfolio. These volatility-timing portfolios are constructed by a class of active portfolio strategies in which rebalance of portfolio weights is based on changes in the estimated conditional covariance matrix of returns. Based on this idea, Kirby and Ostdiek (2010) implement volatility timing in the setting of avoiding short sales and keeping turnover as low as possible. This class of portfolio strategies try to mitigate effect of estimation error by exploit volatility dynamic in sample information. There are four notable features of these strategies: 1, no requirement to optimise 2, no requirement to obtain the covariance matrix inversion 3, no negative weights 4, and allowance for the sensitivity of the weights to volatility changes. Because of ignoring information of conditional expected returns in the volatility-timing strategies, they also propose a reward-to-risk timing strategies, which takes account of the conditional expected return. After empirical analysis, they conclude that their portfolio strategies can outperform naïve portfolio, even after taking account of a high transaction cost.

This chapter continues to investigate the strategies by Kirby and Ostdiek (2010) with currency market, which is used in the last chapter. I evaluate the performance of only currencies portfolio across the strategies stated in Kirby and Ostdiek (2010) to find out if the same conclusion can be reached similar to the one made in the stock market.

As performance evaluation in chapter four, besides Sharpe ratio, I also use other evaluation methods related to downside risk, which was not considered in Kirby and

Ostdiek (2010)'s research. Because risk management is more and more important nowadays, I consider downside risk as a main part of the evaluation analysis. As in chapter four, I have two datasets, G10 currencies and all currencies, rather than add other currencies one by one (Dunis et al., 2011).

In contrast to Kirby and Ostdiek (2010)'s research, I calculate conditional moments using not only simple moving average, but also exponentially weighted moving average (EWMA), which weights the current information more heavily than past information. EWMA is widely applied by researchers in a number of literature, such as the calculation of VaR (Bredin and Hyde, 2004; Billio and Pelizzon, 2000; Brooks and Persand, 2003), forecasting correlation (Campa, 1998), estimating volatility (JP Morgan's RiskMetrics; Balaban et al., 2006), accounting problem (Kodde and Schreuder, 1984; McLeay et al., 1997) and trading rules (Pavlov and Hurn, 2012). The advantage of EWMA is quicker to respond to current fluctuations than a simple moving average, and solve a classic trade-off: more data I have and less relevant information I get. I therefore apply EWMA into the calculation of conditional moments for optimal constrained portfolio and timing strategies.

The first finding of this chapter is that, again, the performance is improved by adding 'lesser' currencies, because these 'lesser' currencies can bring investor diversification benefit. This finding, actually, has been proven in the last chapter. But, in the robustness check about estimation window of 1 and 3 years, the performance of naïve portfolio cannot agree this improvement. As discussed in chapter four, the reason for this disagreement is that some countries of 'lesser' currencies suffered currency crisis in early years. This reason is also considered as a serious disadvantage if investors only apply naïve portfolio passively. In this chapter, I use the same period as the main results analysis to evaluate the performance in the analyses of 1 year and 3 years estimation window. Results from all analysis, including main results and robustness checks, further confirm the benefit of adding currencies of developing countries to the portfolio.

The second finding is that the portfolios, optimal constrained (OC) portfolio and volatility timing (VT) portfolio, which are investigated in this chapter, have better performance than naïve portfolio has. Indeed, in the case of all currencies dataset, RR portfolio outperforms minimum variance (Min) portfolio. In this dataset, the performance of VT portfolio is better than that of OC portfolio, and the former portfolio has very low turnover. Moreover, robustness check of different lengths of estimation window also affirms this finding. However, when I consider the perspective of investors from different countries other than the US, the results show the best performance of naïve portfolio. Even so, some evaluations, such as Var and CVaR, confirm that OC and VT portfolios have less downside risk than naïve portfolio has. Furthermore, this robustness check confirms that VT portfolio outperforms OC portfolio.

The third finding is that, in construction of timing strategy portfolio, taking into account the information of conditional expected returns can improve the performance of all currencies analysis, but cannot for G10 currencies analysis. Due to low variation in expected returns across G10 currencies, this will only deliver bits of useful information, but more estimation errors lead to bad performance. Because of the fact that currencies dataset includes 29 currencies, expected returns of currencies have relatively high variation. My robustness checks also make sure this finding, except 10 years estimation window, which has different evaluation periods than others.

The next finding is that, after comparison using two different estimation methods-simple moving average (SMA) and exponential weighted moving average (EWMA), it can be concluded that EWMA is more efficient, and leads to better performance. By using EWMA instead of SMA to estimate conditional expected moments, the performance of all portfolios is boosted in all terms of evaluation indices. My robustness checks of 1 and 3 years estimation windows totally confirm this finding. However, 10 years estimation window analysis does not absolutely support EWMA. Under the circumstance of considering only downside risk, the performance of the portfolios is improved by EWMA. Furthermore, the results from the robustness check about UK investors give a very ambiguous conclusion about whether the portfolios with EWMA have better performance than these portfolios with SMA. After investigating the performance of the portfolio considering Japanese investors, I can roughly support EWMA. Finally, robustness check related to euro zone investor contradicts this finding. Therefore, except euro zone investor, all robustness checks further prove this finding to a certain extent.

The final finding is that, transaction cost has insignificant effect for G10 currencies analysis, but it displays a noticeable impact on the performance of some portfolios for all currencies analysis. Due to small transaction cost in G10 currencies, the performance cannot be hugely changed by taking transaction cost. But, relatively large transaction cost exists in 'lesser' currencies. Therefore, in all currencies analysis, the portfolios, with high level of turnover, suffer declining performance by taking transaction cost. And, the results from all robustness checks are consistent with this finding.

The rest of the chapter is organised as follows. In section 5.2, a detailed description of the optimal constrained portfolio and timing strategy portfolios. Section 55.3 conducts Monte Carlo experiment to investigate issues of estimation risk on OC and sample-based mean-variance portfolios, and observe the turnover of out-of-sample. In section 5.4, I present the results from empirical work. Finally, section 5.5 gives a conclusion of this chapter.

5.2 Portfolio Strategies

In this chapter, some portfolios already discussed in the last chapter will be used again. In order to investigate the relative performance of other portfolios, I again consider naïve portfolio as benchmark portfolio, which weights risky assets equally. Because of good performance, the minimum variance (Min) portfolio, which tries to minimise the portfolio's standard deviation, and equally-weighted risk contribution (erc) portfolio, which equalises risk contribution for each risky asset in portfolio, will also be analysed in this chapter. In the Monte Carlo experiment, I will also report the sample-based mean-variance (mv) portfolio, which completely ignores the estimation errors, to show the improvement from optimal constraints (OC) portfolio. The details of these portfolios are given in the last chapter. In addition to these old portfolios, other active portfolio strategies proposed by Kirby and Ostdiek (2010) will be introduced in this section.

5.2.1 Optimal Constrained Portfolio

In order to understand this portfolio, I start with presenting the fundamental portfolio management knowledge, which is maximising the quadratic utility function to get optimal weights. The quadratic utility function is shown as follows:

$$Q(\omega_{P,t}) = \omega_{p,t}^{'}\mu_t - \gamma/2\ \omega_{p,t}^{'}\mathbf{\Omega}_t^{'}\omega_{p,t} \tag{5.1}$$

Where $\omega_{p,t}$ is N*1 vector of the weights of portfolio at time t, μ_t is the N*1 conditional mean vector of the excess risky-asset return, $\mathbf{\Omega}_t$ is the N*N conditional covariance matrix of excess risky-asset return, and γ denotes the investor's coefficient of relative risk aversion.

There is no constraint on the sum of risky assets weights. But, the portfolios in this chapter should constrain their weights to sum of one to confirm that different performance is not a result of different allocations between risk free and risky assets. So, in order to exclude the risk-free asset, I impose a constraint $\omega_{p,t}^{'} 1_N = 1$; and, the first-order condition for the constrained problem is

$$\mu_t - \delta_t 1_N - \gamma \mathbf{\Omega}_t \omega_t^{oc} = 0 \tag{5.2}$$

In which δ_t is the Lagrange multiplier associated with the constraint.

From equation 5.2, I can get optimal weights of constrained portfolio is

$$\omega_t^{oc} = \frac{1}{\gamma} \mathbf{\Omega}_t^{-1} \mu_t + \frac{\delta_t}{\gamma} \mathbf{\Omega}_t^{-1} 1_N \tag{5.3}$$

From equation 5.3, I can note that the first term on the right side is proportional to sample-based mean-variance (mv) portfolio, $\omega_t^{mv} = \frac{\mathbf{\Omega}_t^{-1} \mu_t}{1_N^{'} \mathbf{\Omega}_t^{-1} \mu_t}$ and the second is proportional to minimum variance (min) portfolio, $\omega_t^{Min} = \frac{\mathbf{\Omega}_t^{-1} 1_N}{1_N^{'} \mathbf{\Omega}_N^{-1} 1_N}$. After solving for δ_t and substitute the resulting expression into equation 5.3, I obtain

$$\omega_t^{oc} = X_t^{mv} \left(\frac{\mathbf{\Omega}_t^{-1} \mu_t}{1_N^{'} \mathbf{\Omega}_t^{-1} \mu_t} \right) + \left(1 - X_t^{mv}\right) \left(\frac{\mathbf{\Omega}_t^{-1} 1_N}{1_N^{'} \mathbf{\Omega}_t^{-1} 1_N} \right) \tag{5.4}$$

In which $X_t^{mv} = \frac{1_N^{'} \mathbf{\Omega}_t^{-1} \mu_t}{\gamma}$, is the fraction of wealth allocated to tangency portfolio in version of no constraint. After multiplying both sides of equation 5.4 by vectors of conditional expected excess return of assets, conditional expected excess return on the portfolio is given by

$$\mu_{p,t} = X_t^{mv} \mu_t^{mv} + \left(1 - X_t^{mv}\right) \mu_t^{Min} \tag{5.5}$$

Solving $X_{TP,t}$ will give new expression of equation 5.4 as:

$$\omega_t^{oc} = \left(\frac{\mu_{p,t} - \mu_t^{Min}}{\mu_t^{mv} - \mu_t^{Min}}\right)\left(\frac{\mathbf{\Omega}_t^{-1}\mu_t}{1_N \mathbf{\Omega}_t^{-1}\mu_t}\right) + \left(1 - \frac{\mu_{p,t} - \mu_t^{Min}}{\mu_t^{mv} - \mu_t^{Min}}\right)\left(\frac{\mathbf{\Omega}_t^{-1}1_N}{1_N \mathbf{\Omega}_t^{-1}1_N}\right) \tag{5.6}$$

We refer to the portfolio in equation 5.6 as the optimal constrained (OC) portfolio. This OC portfolio can be considered as a constrained version of 'three fund strategy' by Kan and Zhou (2007). However, the final weights of portfolio is decided by the target return, $\mu_{p,t}$, rather than maximising utility function. Also, the min and mv portfolio do not play important role, because any two portfolios on efficient frontier can construct the whole frontier.

5.2.2 Timing Strategies

According to the results from simulation to be introduced in section 5.3, OC portfolio has a large turnover. This turnover may reverse the performance of OC portfolio if plausible assumptions about transaction costs are applied. The turnover of OC portfolio can be reduced perhaps by using some techniques proposed in the literature to show the improvement on the performance of mean-variance portfolio[2]. But, besides improving performance, it would be beneficial to have a simple strategy, which also has outstanding features similar to naïve portfolio, such as easy and wide applicability, low turnover, nonnegative weights and no optimization. The reason for this requirement is that investors likely prefer a simple strategy to a complicated portfolio (Maillard et al., 2008). Fortunately, Kirby and Ostdiek (2010) propose a class of simple active strategies to exploit the historical information about mean and variance of returns.

[2] I have already given the detail of their works in the previous chapters, including Pastor and Stambaugh (2000), Wang (2005), Garlappi, Uppal and Wang (2007), Kan and Zhou (2007), DeMiguel, Garlappi and Uppal (2007), Jagannathan and Ma (2003), MacKinlay and Pastor (2000), and Ledoit and Wolf (2004).

In chapter two, an aggressive method of shrinkage by Ledoit and Wolf (2003a), (2003b) has already been reviewed and this entails the use of a diagonal covariance matrix. Without this setting, weights in one or more assets will be negative. A strategy will be characterized by extreme weights, while it has negative weights[3]. If all of the estimated correlations are set to zero, the N (N-1)/2 fewer parameters need to be estimated from the data. This means less estimation risk. Although this setting will result in the loss of information, Kirby and Ostdiek (2010) prove the reduction in estimation risk could outweigh the loss of information.

So, firstly, assuming all of the estimated pair-wise correlations between the excess risky-asset returns are zero, the weights for the sample minimum variance portfolio are given by

$$\hat{\omega}_{it}^{VT} = \frac{\left(1/\hat{\sigma}_{it}^{2}\right)}{\sum_{i=1}^{N}\left(1/\hat{\sigma}_{it}^{2}\right)} \tag{5.7}$$

Due to no flexibility in determining how portfolio weights respond to volatility changes, a general class of volatility-timing strategies is given by

$$\hat{\omega}_{it}^{VT} = \frac{\left(1/\hat{\sigma}_{it}^{2}\right)^{\eta}}{\sum_{i=1}^{N}\left(1/\hat{\sigma}_{it}^{2}\right)^{\eta}} \quad \text{where } \eta > 0 \tag{5.8}$$

η is the tuning parameter which measure timing aggressiveness. Moreover, setting $\eta > 1$ should compensate to some extent for the information loss.

When there is a need to take into account information of conditional expected returns, the formula is given by:

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[3] This conclusion has been proved in the chapter three. The performance of portfolio with short sale constrain is better than the performance of same portfolio without short sale constrain. Moreover, turnover of former portfolio is less than that of latter

$$\hat{\omega}_{it}^{RR} = \frac{\left(\hat{\mu}_{it}^{+} / \hat{\sigma}_{it}^{2}\right)^{\eta}}{\sum_{i=1}^{N}\left(\hat{\mu}_{it}^{+} / \hat{\sigma}_{it}^{2}\right)^{\eta}} \tag{5.9}$$

Because of the nonnegative weights needed, the conditional expected return which is less than zero should be set as zero, e.t., $\hat{\mu}_{it}^{+}$=max($\hat{\mu}_{it}$, 0). The equation 5.9 is considered as a reward to risk timing strategy. In this strategy, the investors are assumed to have strong opinion about positive conditional expected return, and drop any asset from consideration, when it is estimated to have negative conditional expected return.

5.3 Monte Carlo Experiment

We apply a simple Monte Carlo experiment to investigate the issues of estimation risk in empirical relevance. I use two datasets examined in the last chapter, and each of them consists of weekly returns on foreign currencies from a US investor perspective. The first dataset is constructed by G10 currencies, while the second one contains both G10 currencies and currencies from developing countries. The sample size is 750 observations.

For highlighting an effect of the estimation risk on the OC and sample based mean-variance portfolio, I are going to compare performance of in-sample and out-of-sample analysis. The in-sample scenario reflects the time invariant mean and variance whole population, which are true moments I assume I do know. However, out-of-sample scenario investigates the case with unknown moments, which means the mean and variance are time variant and I need to estimate them. There are three evaluation indices considered in this section, Sharpe ratio, value at risk and condition value at risk, which have already been viewed in the last chapter. In addition, for the out-of-sample analysis, I will investigate turnover as well. The calculation method of turnover is discussed in chapter three. To provide additional points of reference, naïve portfolio and minimum variance portfolio are also reported here.

5.3.1 The Experiment

There are 750 observations in the original sample, which are then divided into two parts. The first part, including the first 260 observations (5 years), is used to estimate parameters. So, I call this part an estimation window (h=260). The second part, including the rest of observations, is for out-of-sample performance evaluation. I consider it as evaluation window (T=490). For the experiment, we, firstly, would like to generate a new sequence by resampling data. The first part of new sequence is obtained by randomly drawing h times with replacement from the first part of the original sequence. The second part of new sequence is obtained by randomly drawing T* times with replacement from the second part of original sequence. So, now, I have new sequence with h+T* observations. In in-sample analysis, I calculate the sample mean vector and covariance matrix for the second part of the new sequence. And then, I construct each portfolio for time T* by the weights implied by sample mean vector and covariance matrix I calculated before. In order to approximate expected portfolio return and variance, I use the sample moments, because the error in approximating goes to zero as T*trend to be unlimited and I set T*=1000000.

In out-of-sample analysis, I use rolling sample approach to construct the portfolio. I use the first part of new sequence as initial estimates of portfolio weights, and multiply this weight by return of next period to get return of portfolio. Then, I roll forward to the next period until I reach period h+T*.

Finally, to construct OC portfolio, I have to specify a target estimated conditional expected return, e.g. $\mu_{p,t}$. Firstly, naïve portfolio can be considered as reasonable shrinkage target (Tu and Zhou, 2008). And, this simple strategy also is used by DeMiguel et al. (2007) to replace sample-based mean-variance portfolio in ‘three-fund’ strategy proposed by Kan and Zhou (2007). Secondly, the weights of OC portfolio are sensitive to the target return chosen, and it is expected that naïve portfolio has very low turnover. So, in practice, I set the target return to be equal to conditional expected excess return of naïve portfolio. i.e., $\mu_{p,t} = \hat{\mu}_t' 1_N / N$. However, occasionally, if a conditionally inefficient portfolio exists, I replace $\mu_{p,t} - \mu_t^{Min}$ with $|\mu_{p,t} - \mu_t^{Min}|$ for equation 5.6.

5.3.2 Results of the Experiment

I document results for the simulation experiment. For both datasets-G10 currencies and all currencies, the Sharpe ratio of mean-variance portfolio is the largest in in-sample analysis, and downside risk lie within an acceptable range, which indicates that once I know the true population moments, the mean-variance portfolio will have the best performance. But, for out-of-sample analysis, the Sharpe ratio of mean-variance portfolio is extremely low, and downside risk is extremely high. This striking change can be explained by estimation error. In out-of-sample analysis, unknown moments have to be estimated according to historical returns. This error from estimating lead to that weights are not true and time-invariant, finally bad performance of sample-based mean-variance portfolio. This conclusion can be proved by other portfolios, which also yield additional insights.

There is no difference between in-sample and out-of-sample analysis for naïve portfolio. Construction of naïve portfolio does not need to estimate moments, so there is no estimation error. As far as minimum variance portfolio is concerned, the performance gets worse from in-sample to out-of-sample analysis in both terms of Sharpe ratio and

Table 5.1 Evidence from Monte Carlo Simulation

This table documents the impact of estimation window and turnover of rebalance. A sequence with length of h+T* is generated by randomly drawing from original empirical distribution for each dataset including G10 currencies and all 29 currencies. Specifically, this sequence is generated by drawing h=260 times with replacement from the first 260 observation of dataset to obtain the sample used to initialize the rolling estimates, and T*=1000000 times with replacement from the rest observation of dataset to obtain the sample used for the Monte Carlo integration. These two analyses are done to reflect the impact of estimation window. One is in-sample analysis, which calculates return of each portfolio by true, time-invariant weights calculated by moments of T* observations. The other is out-of-sample analysis, which calculated return of each portfolio by rolling estimation window and rebalance weekly, so weights are time-variant. The strategies include naïve portfolio (Naïve), optimal constrained portfolio (OC), mean-variance portfolio (TP) and minimum variance portfolio (min), while OC portfolio target the estimated conditional expected excess return of naïve portfolio. In each case, Sharpe ratio, value at risk and conditional value at risk is reported, as well as turnover for out-of-sample analysis.

	In-sample			**Out-of-sample**			
Panel A: G10 currencies							
	SR	**VaR**	**CVaR**	**SR**	**VaR**	**CVaR**	**τ**
Naïve	0.081	2.03%	2.58%	0.081	2.03%	2.58%	0.008
OC	0.105	1.54%	1.96%	0.078	1.59%	2.02%	0.099
TP	0.141	3.13%	4.00%	0.002	3549.70%	4452.34%	126.922
min	0.063	1.48%	1.87%	0.062	1.51%	1.91%	0.042
Panel B: ALL currencies							
	SR	**VaR**	**CVaR**	**SR**	**VaR**	**CVaR**	**τ**
Naïve	0.113	1.57%	2.00%	0.113	1.57%	2.00%	0.009
OC	0.270	0.59%	0.77%	0.146	0.79%	1.01%	0.108
TP	0.339	1.38%	1.82%	0.001	4282.35%	5371.06%	486.812
min	0.116	0.55%	0.71%	0.087	0.74%	0.94%	0.052

downside risk, but this change is not significant. Due to only second moments needed to construct minimum variance portfolio, the estimation error will be smaller than constructing mean-variance portfolio. This factor also indicates that the estimation error mostly belongs to the first moment, and error from estimating the second moment is not a big problem. Although OC portfolio also is constructed by estimating the first and second moments, it is implemented by targeting the conditional expected return of the naïve portfolio. According to equation 5.6, OC portfolio is some kind of combination of mean-variance portfolio and minimum variance portfolio. So, in in-sample analysis, it performs between these two portfolios in both terms of evaluation. Although, with presence of estimation error (out-of-sample analysis), OC portfolio also has depressed performance, this changes is not too much. Moreover, Sharpe ratio of OC portfolio in out-of-sample analysis is higher than both of mean-variance portfolio and minimum variance portfolio, because I target conditional expected return of naïve portfolio, which do not have estimation error. In the case of all currencies dataset, OC portfolio even has larger Sharper ratio and lower downside risk than naïve portfolio has. This indicates that the OC portfolio can outperform naïve portfolio, sometimes.

The results of turnover also further prove that mean-variance portfolio has the worst out-of-sample performance. The significant large turnover will distort the performance more when I take accounts transaction cost for out-of-sample analysis. In addition, compared to naïve portfolio, OC portfolio has a turnover which over 10 times than what the naïve portfolio has in both cases of G10 currencies and all currencies. This may indicate that the outperformance of OC portfolio might be vanished when I take account of transaction cost in my out-of-sample analysis.

5.4 Empirical Results

5.4.1 Preparation before Analysis

As outlined in chapter three, I use the rolling-sample approach to conduct out-of-sample analysis with two datasets (G10 currencies and all currencies). The sample includes 750 observations from 1997 to 2012 for each currency's return. The methods used to evaluate the performance of portfolios include Sharpe ratio, p-value, return-loss, certainty equivalent return (CEQ), value at risk, conditional value at risk, maximum drawdown and Calmar ratio. The setting of these evaluation methods is the same as the robustness check section in chapter four, details of which have been given.

Most of the setting related to constructing and evaluating timing strategies has been discussed previously. But, there are other two parameters which will be specified in this section. The first one is tuning parameter, η, in equation 5.8 and 5.9, which shows the extent to which investors are responding to volatility changes. I consider the same setting similar to the one used by Kirby and Ostdiek (2010), who set this tuning parameter to be equal 1, 2 and 4 respectively. But, in this thesis robustness check analysis, I will consider only one of the settings. The setting of $\eta = 1$ is just a choice of the baseline analysis, because it does not give any compensation for information loss. But, the setting of $\eta = 4$ is too aggressive in response to the changes of volatility, and the weights will be allocated to the asset with lowest conditional standard deviation more heavily. So, I choose value of 2 as tuning parameter in robustness analysis.

In order to be consistent with the analysis in chapter four, I apply simple moving average (SMA) in rolling sample analysis. But, Akgiray (1989) uses different decay factor to prove that using EWMA (exponentially weighted moving average) techniques are more powerful than the equally weighted scheme. Moreover, J.P Morgan (1996), in their introduction document for Risk metrics software, applies EWMA technique in order to calculating Value at Risk. Then this model is widely used for estimating conditional VCV matrices. So, I also try to use EWMA technique to estimate volatility. There are other evidences shows that EWMA is good technique for calculating time variant volatility. For example, Tse (1991) found a slower reaction to the changes in volatility in GARCH forecasts compared to EWMA techniques. Then, Guermat and Harris (2002) forecast value at risk with allowing time variating in variance and kurtosis of portfolio returns by using EWMA and GARCH model. Finally, Horasanlı and Fidan (2007) use equally weighted, exponentially wiehgted and GARCH model in portfolio selection problem derived from Markowitz mean-variance portfolio theory. They conclude that exponentially weighted technique is superior to the equally weighted and GARCH (1,1). In addition to volatility, Conrad and Kaul (1988) use weekly evidence to reveal the time-variance in expected return. And, they model conditional expected return by an exponentially weighted sum of past returns. So, I will apply EWMA technique to estimate both conditional expected returns and volatility for timing strategy. Recently, Pavlov and Hurn (2012) apply EWMA technique to generate buy and sell signals for trading rules based on moving-average. In their paper, EWMA is expressed as:

$$EWMA_t = \lambda EWMA_{t-1} + (1-\lambda)V_t \tag{5.10}$$

From equation 5.10, I can see that the EWMA in the current period is decided by weighing between EWMA in the last period and value in the current period. The question about how to weight is answered upon choosing the value of λ. Therefore, the second parameter I would like to specify is lambda, λ, called smoothing factor or decay factor in literature. A famous investment management company, JP Morgan, chooses lambda to be 0.94 in their RiskMetrics^{TM}. And, this setting is also applied in some literature. But, the decay factor of 0.94 is usually used only for daily return. Moreover, a certain value for lambda seems quite arbitrary in the cases used in this thesis, and does not take account of the number of observations included in the estimation window. Because of different lengths of estimation window analysed, using the same value of lambda will not be fair for each case. With certain value of lambda, for the cases with different lengths of estimation window, the weights allocated to the nearest period are the same, but the weights allocated to the oldest period are not the same. Even, the weights for the oldest period are close to zero. In this thesis, the value of lambda is based on the number of observations. The weights for the current period should be relatively the same for all cases. And, for the oldest period, the weights will also be relatively the same for all cases. Therefore the method used by Pavlov and Hurn (2012) is replicated, in which they set lambda to be related to the number of periods in the estimation window, N as follows

$$1-\lambda=\frac{2}{N+1} \tag{5.11}$$

This setting ensures that weight for the current period in EWMA is almost twice as in simple moving average regardless of the length of estimation window, if N is large enough e.g. $N>10$. Term of $N+1$ in equation 5.11 makes sure that there is not too heavy weight allocated to the value of the current period if N is small. For example, if $N=2$, according to equation 5.10 and 5.11, the weight for the current period is 2/3. But, when $N+1$ is replaced with N, the weight for the current period is 1, which does not make sense. In addition to lambda, the initial value of EWMA, $EWMA_0$, be calculated to be simply moving average.

So, I give the weight of most recent period as $2/(N+1)+(1/N)*\lambda^N$, and the weight of the earliest period is $(2/(N+1))*\lambda^{N-1}+(1/N)*\lambda^N$. Specifically, when a 5 year estimation window is used ($N = 260$), the lambda is 0.992. The weight for the last period is 0.00818, and for the first period is 0.00156. When I use 1 year estimation window ($N = 52$), the lambda is 0.962. The weight for the last period is 0.04000, and for the first period is 0.00790. When I use 3 years estimation window ($N = 156$), the lambda is 0.987. The weight for the last period is 0.01360, and for the first period is 0.00261. If I multiply the weights with N , in the case of 5 years estimation window, this value is 2.1 for the last period and 0.4 for the first period. In the case of 1 year and 3 year estimation window, this value is also 2.1 for the last period and 0.4 for the first period. So, comparing weights from EWMA and weights from SMA, I confirm that the ratios are the same for all cases. This is means that they have relatively the same weights.

In order to investigate the efficiency of timing strategies, I also report results for the portfolios that have good performance in chapter four. The portfolios include minimum variance portfolio, naïve portfolio and equally weighted risk contribution portfolio. In addition, I also consider OC portfolio, and apply EWMA into OC portfolio.

5.4.2 Main Results

5.4.2.1 Results for G10 Currencies

From Table 5.2, which documents the results of portfolios including G10 currencies only, I can see that the optimal constrained (OC) portfolio has larger Sharpe ratio than naïve portfolio has. This is also confirmed by the negative return-loss, but p-value statistically proves that two Sharpe ratio have no significant difference. According to the downside risk, OC portfolio has less risk than naïve portfolio. Moreover, Calmar ratio, which takes maximum drawdown to consider as risk in the calculation of Sharpe ratio, also confirms that OC portfolio has better performance than naïve portfolio. Although

Sharpe ratio shows that minimum variance portfolio does not work better than OC portfolio, the Calmar ratio and downside risk do not agree with this. The conclusion reached with regards to OC portfolio is that it is not completely consistent with what I got from simulation analysis. However, due to the fact that there is no statistically significant difference between Sharpe ratios, based on the downside risk, both analysis can prove that OC portfolio outperforms naïve portfolio but not minimum variance portfolio. Incidentally, the performance of OC portfolio is better than equally weighted risk contribution (ERC) portfolio in all terms of evaluation for G10 currencies analysis.

As far as timing strategies are concerned, OC portfolio consistently has better performance than all timing strategies. But, it is still useful to discuss the detail of the performance of these strategies, and compare them to the benchmark, naïve portfolio. P-values of three volatility timing (VT) portfolios indicate that their Sharpe ratios are not statistically different from the Sharpe ratio of naïve portfolio. Moreover, small return-loss and difference of certainty-equivalent returns (CEQ) can confirm that volatility timing portfolios and naïve portfolio have similar performance according to Sharp ratio. Therefore, downside risk can be considered as a determinant to judge the performance of portfolios. The low VaR, CVaR and maximum drawdown indicates that volatility timing strategies outperform naïve portfolios. Although Calmar ratio does not totally agree with this conclusion, due to tiny differences and more attention on risk, the conclusion about outperformance of volatility timing portfolio is approved in this thesis analysis.

Table 5.2 Performance of the portfolios for G10 currencies

This table documents the evaluation of performance of each optimal portfolio strategy for US investor's perspective. This means that I treated US dollar as the based currency. The estimation window is 5 years. The database includes g10 currencies. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR' in panel A and panel B. The number in the bracket followed by 'VT' and 'RR' is tuning parameter applied in those strategies; I choose this parameter as 1, 2 and 4. In panel A, the conditional expected moments are estimated by simple moving average (sma). In panel B, I use exponentially weighted moving average to estimate conditional expected moments. The first part shows results from before transaction cost analysis, so I tagged them with 'results before transaction cost'. The second part shows results from after transaction cost analysis, so I tagged them with 'results after transaction cost'. In both parts, I apply same evaluation methods. For these methods, 'SR' refers to Sharpe ratio, 'vs 1/N' means that optimal portfolio compare with naïve portfolio. In this category, there are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost.

	Results before transaction cost									**Results after transaction cost**							
	SR	**vs 1/n**		**CEQ**	**VaR**	**CVaR**	**DrawDown**		**Turnover**	**SR**	**vs 1/n**		**CEQ**	**VaR**	**CVaR**	**DrawDown**	
		p-val	**Re-loss**				**Maximum**	**CR**			**p-val**	**re-loss**				**Maximum**	**CR**
1/N	0.58	1.00	0.00%	3.25%	1.98%	2.71%	23.94%	0.23	0.01	0.58	1.00	0.00%	3.23%	1.99%	2.71%	23.95%	0.23
Min	0.65	0.50	-0.49%	3.38%	1.53%	1.99%	13.16%	0.36	0.05	0.66	0.45	-0.55%	3.43%	1.53%	2.00%	13.34%	0.36
ERC	0.61	0.77	-0.22%	3.34%	1.76%	2.42%	21.64%	0.24	0.01	0.61	0.71	-0.27%	3.38%	1.76%	2.42%	21.65%	0.24
Panel A: Simple moving average (SMA)																	
OC	0.69	0.32	-0.81%	3.80%	1.54%	2.07%	16.13%	0.33	0.10	0.68	0.32	-0.81%	3.79%	1.55%	2.08%	16.30%	0.32
VT(1)	0.57	0.88	0.11%	3.06%	1.89%	2.48%	22.23%	0.22	0.01	0.57	0.91	0.08%	3.07%	1.89%	2.49%	22.25%	0.22
VT(2)	0.56	0.85	0.13%	2.96%	1.78%	2.33%	20.84%	0.22	0.01	0.57	0.90	0.08%	3.00%	1.78%	2.34%	20.87%	0.23
VT(4)	0.58	1.00	0.00%	3.05%	1.74%	2.23%	19.23%	0.24	0.02	0.59	0.90	-0.09%	3.13%	1.75%	2.24%	19.28%	0.25
RR(1)	0.43	0.01	1.58%	1.74%	2.10%	3.22%	31.80%	0.14	0.07	0.42	0.01	1.64%	1.68%	2.10%	3.23%	32.00%	0.14
RR(2)	0.34	0.00	2.50%	0.83%	2.24%	3.27%	33.49%	0.10	0.10	0.33	0.00	2.54%	0.77%	2.25%	3.29%	33.76%	0.10
RR(4)	0.20	0.00	3.97%	-0.63%	2.46%	3.43%	36.53%	0.06	0.14	0.20	0.00	3.97%	-0.65%	2.46%	3.45%	36.89%	0.06
Panel B: Exponentially Weighted Moving Average (EWMA)																	
OC	0.69	0.30	-0.87%	3.88%	1.51%	2.04%	13.24%	0.41	0.15	0.68	0.33	-0.80%	3.80%	1.52%	2.05%	13.68%	0.39
VT(1)	0.57	0.90	0.09%	3.07%	1.87%	2.47%	22.08%	0.22	0.01	0.57	0.93	0.06%	3.08%	1.87%	2.48%	22.10%	0.23
VT(2)	0.56	0.85	0.13%	2.96%	1.81%	2.33%	20.61%	0.23	0.02	0.57	0.90	0.08%	2.99%	1.81%	2.33%	20.65%	0.23
VT(4)	0.57	0.92	0.07%	2.97%	1.69%	2.26%	19.10%	0.24	0.03	0.58	0.97	-0.03%	3.05%	1.69%	2.26%	19.16%	0.24
RR(1)	0.47	0.14	1.03%	2.21%	1.99%	2.85%	22.77%	0.19	0.08	0.46	0.11	1.10%	2.13%	1.99%	2.86%	23.02%	0.19
RR(2)	0.37	0.00	1.98%	1.27%	2.15%	2.92%	22.30%	0.16	0.11	0.36	0.00	2.05%	1.18%	2.16%	2.94%	22.75%	0.15
RR(4)	0.22	0.00	3.45%	-0.18%	2.19%	3.14%	27.07%	0.08	0.16	0.22	0.00	3.50%	-0.24%	2.20%	3.16%	27.68%	0.07

When I try to take account of rewards into timing strategies, all indices of evaluation show no improvement. P-values decreasing to approach zero means that the differences of Sharpe ratios between rewards-to-risk (RR) portfolios and naïve portfolio are statistically significant. Moreover, RR portfolios have more downside risk than naïve portfolio. According to these results, I conclude that when considering rewards, the timing strategies deteriorate to underperform naïve portfolio. So, based on the G10 currencies dataset, I find no support for RR portfolio. This may be because of low variation in expected returns across 9 currencies, which perhaps then deliver little useful information but relatively more estimation errors. This reason may also explain that performance gets worse while tuning parameter, η, goes large.

As discussed before, I also apply exponentially weighted moving average (EWMA) instead of simple moving average (SMA) to estimate the conditional expected moments for constructing timing portfolios, as well as OC portfolio. Generally speaking, the performance of portfolios is improved by using EWMA rather than SMA. Although most of Sharpe ratios do not change, the lower return-loss and larger CEQ can prove this improvement. Furthermore, the downside risk of portfolios related to EWMA is less than those of portfolios related to SMA. This finding is consistent with the fact that EWMA can more efficiently estimate conditional expected moments than SMA.

As far as turnover and transaction costs are concerned, comparing results before transaction cost to those after transaction, I find that taking transaction cost in this analysis only has a slight effect on the performance of the portfolios. The portfolios, which consider both return and volatility, have much larger turnover than the portfolios, which only consider the volatility. Therefore, the transaction cost will have more harm on the performance of former portfolios than the latter. But, according to my results, the changes for all portfolios are very small. Due to the most frequently traded currencies included in my dataset, the transaction cost should be very low for efficient market. Therefore, transaction cost almost has no impact on the performance of the portfolios regardless of how large the turnover is.

5.4.2.2 Results for All Currencies

After analysing the portfolios for G10 currencies, I turn to the all currencies dataset. If the hypothesis related to the reason of unimpressive performance of RR portfolio is correct, I should have strong evidence to show the outperformance of RR portfolio in this dataset. Because of the fact that the other 20 currencies from developing countries have more variant sample mean return than g10 currencies, then estimating their conditional expected return is more valuable than in the case of g10 currencies analysis. From the point of diversification, I anticipate that the performance in this dataset is integrally better than the performance in g10 currencies dataset.

Table 5.3 reports the out-of-sample performance of the portfolios for all currencies dataset. The layout of the table is the same as that in Table 5.2. As expected, the diversification can bring significant benefits to the portfolio's performance. Most Sharpe ratios in this case are almost twice, sometimes triple, to those in the case of g10 currencies. Similarly, many portfolios have less than half of downside risk which g10 currencies portfolios have. This diversification benefit is also found in the last chapter. But, there is another benefit when 'lesser' currencies are added. I will compare the performance of all these currencies portfolios to find it.

All portfolios display better performance than naïve portfolio, according to downside risk, Calmar ratio and negative return-loss. Although p-values indicate that Sharpe ratios of most of the portfolios are not statistically significantly different from that of naïve portfolio, it does not contradict the fact that all portfolios outperform naïve portfolio. Except RR portfolio, the results of other portfolios are similar to those for g10

Table 5.3 Performance of the portfolios for all currencies

This table documents the evaluation of performance of each optimal portfolio strategy for US investor's perspective. This means that I treated US dollar as the based currency. The estimation window is 5 years. The database includes 29 currencies induced in chapter three. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR' in panel A and panel B. The number in the bracket followed by 'VT' and 'RR' is tuning parameter applied in those strategies; I choose this parameter as 1, 2 and 4. In panel A, the conditional expected moments are estimated by simple moving average (sma). In panel B, I use exponentially weighted moving average to estimate conditional expected moments. The first part shows results from before transaction cost analysis, so I tagged them with 'results before transaction cost'. The second part shows results from after transaction cost analysis, so I tagged them with 'results after transaction cost'. In both parts, I apply same evaluation methods. For these methods, 'SR' refers to Sharpe ratio, 'vs 1/N' means that optimal portfolio compare with naïve portfolio. In this category, there are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost.

	Results before transaction cost									Results after transaction cost							
	SR	vs 1/n		CEQ	VaR	CVaR	DrawDown		Turnover	SR	vs 1/n		CEQ	VaR	CVaR	DrawDown	
		p-val	re-loss				Maximum	CR			p-val	re-loss				Maximum	CR
1/N	0.82	1.00	0.00%	4.70%	1.67%	2.30%	21.74%	0.28	0.01	0.81	1.00	0.00%	4.62%	1.67%	2.30%	21.78%	0.27
Min	0.98	0.34	-0.41%	2.33%	0.55%	0.75%	6.82%	0.37	0.05	0.91	0.52	-0.26%	2.14%	0.56%	0.76%	6.98%	0.33
ERC	1.06	0.17	-1.13%	4.47%	1.04%	1.43%	14.47%	0.35	0.01	1.05	0.17	-1.12%	4.42%	1.05%	1.43%	14.52%	0.34
Panel A: Simple moving average (SMA)																	
OC	0.81	0.97	0.02%	2.45%	0.70%	1.00%	8.12%	0.34	0.14	0.70	0.36	0.38%	2.05%	0.72%	1.02%	8.26%	0.28
VT(1)	0.91	0.56	-0.37%	3.44%	0.96%	1.30%	13.84%	0.28	0.01	0.89	0.59	-0.34%	3.36%	0.96%	1.30%	13.89%	0.28
VT(2)	0.94	0.45	-0.36%	2.58%	0.67%	0.88%	8.46%	0.33	0.02	0.91	0.50	-0.31%	2.49%	0.67%	0.88%	8.47%	0.32
VT(4)	1.06	0.18	-0.71%	2.88%	0.65%	0.88%	10.21%	0.30	0.02	1.04	0.20	-0.67%	2.81%	0.65%	0.88%	10.21%	0.30
RR(1)	0.90	0.61	-0.35%	3.65%	1.05%	1.44%	13.58%	0.31	0.04	0.86	0.73	-0.23%	3.48%	1.06%	1.45%	13.77%	0.29
RR(2)	1.15	0.09	-1.02%	3.32%	0.70%	0.91%	8.75%	0.41	0.04	1.11	0.11	-0.92%	3.18%	0.70%	0.92%	8.82%	0.39
RR(4)	0.97	0.38	-0.45%	2.72%	0.70%	0.93%	10.22%	0.29	0.03	0.94	0.44	-0.38%	2.62%	0.70%	0.94%	10.23%	0.28
Panel B: Exponentially Weighted Moving Average (EWMA)																	
OC	0.83	0.96	-0.02%	2.31%	0.58%	0.89%	8.22%	0.31	0.25	0.55	0.02	0.79%	1.47%	0.60%	0.93%	11.40%	0.15
VT(1)	0.95	0.41	-0.52%	3.49%	0.90%	1.25%	13.03%	0.30	0.01	0.93	0.44	-0.48%	3.40%	0.90%	1.25%	13.10%	0.29
VT(2)	1.09	0.15	-0.75%	2.88%	0.64%	0.82%	8.07%	0.38	0.02	1.05	0.17	-0.68%	2.76%	0.64%	0.83%	8.09%	0.37
VT(4)	1.12	0.12	-0.86%	3.00%	0.63%	0.84%	10.18%	0.32	0.02	1.09	0.13	-0.80%	2.89%	0.63%	0.85%	10.18%	0.30
RR(1)	1.03	0.23	-0.94%	4.16%	1.03%	1.44%	12.33%	0.38	0.05	0.98	0.30	-0.77%	3.95%	1.03%	1.45%	12.49%	0.36
RR(2)	1.38	0.02	-1.76%	4.12%	0.69%	0.92%	6.56%	0.67	0.05	1.32	0.02	-1.61%	3.93%	0.69%	0.93%	6.76%	0.62
RR(4)	1.33	0.02	-1.54%	3.80%	0.69%	0.90%	8.93%	0.45	0.05	1.27	0.03	-1.40%	3.63%	0.69%	0.91%	9.19%	0.42

currencies dataset. OC and volatility timing portfolio can beat naïve portfolio but minimum variance portfolio. But, OC portfolio consistently outperforms all volatility timing (VT) portfolios. If $\eta = 2$ and $\eta = 4$, the Value at risk and conditional Value at risk of VT portfolio are less than those of OC portfolio, while their Sharpe ratios are also higher than OC portfolios. Comparing Panel B to Panel A of Table 5.3, the benefit of using EWMA rather than SMA also can be found as in the case of g10 currencies.

It is worth noting that the performance of RR portfolios change completely when I consider all currencies dataset, and it is compelling. With $\eta = 2$, RR portfolio has the biggest Sharpe ratio and Calmar ratio. Furthermore, if estimation method of EWMA is used, the Sharpe ratio of this RR portfolio can be considered to be statistically significantly different from Sharpe ratio of naïve portfolio according to p-value, and its maximum drawdown is less than the minimum variance portfolio's. Although other downside risks of RR portfolios is not less than the minimum variance portfolio and some VT portfolios, this slight difference cannot reject its outstanding Sharpe ratio and Calmar ratio. Similarly, mentioned in preceding paragraphs, impressive performance of RR portfolios can support that the hypothesis for this thesis is correct.

The conclusion regarding turnover and transaction cost partly differs from the results obtained for G10 currencies analysis. Firstly, unlike the results based on G10 currencies dataset, turnover of RR portfolios remain a low level. This can be explained by more efficient RR portfolio in this case than in the case of G10 currencies. The only portfolio with relatively high level of turnover is OC portfolio. For example, turnover of OC portfolio with EWMA is 0.25 while the highest turnover during all other portfolios is 0.5. Secondly, transaction cost, indeed, affects performance of OC portfolio. After taking transaction cost, positive return-loss indicates that Sharpe ratio of OC portfolio with EWMA is lower than that of naïve portfolio, and p-value shows that this difference is no longer statistically insignificant. Moreover, its Calmar ratio is reduced to half of what I get before taking transaction cost. The market of currencies from developing countries is not as efficient as the market of g10 currencies. This inefficient market leads to a large gap between bid and ask price, and then large transaction cost. Due to low level of turnover, the performance of other portfolios seems to be not affected by transaction cost. So, the high level of turnover and large transaction cost of some currencies lead to this dramatic drop of performance of OC portfolio.

5.4.3 Robustness Check for Different Lengths of Estimation Windows

As in chapter four, I conduct robustness analysis by changing the lengths of estimation windows. However, unlike what was done in chapter four, it is important to evaluate the performance of the portfolios in the same period for all cases. It seems to be more reasonable and comparable when I compare the performance across different lengths of estimation windows. So, the period used to evaluate the performance of the portfolios here is the same as the period used to evaluate them in the main analysis with 5 years estimation window. This is more convincing to support validate the conclusions reached from the main results.

5.4.3.1 Results for 1 year Estimation Window

The results of analysis related to estimating conditional expected moments in 1 year window are documented in Table 5.4. Generally speaking, this robustness analysis can almost support the conclusions reached in the main findings. In particular, with respect to the G10 currencies dataset, there are four consistent conclusions reached. The first one is that naïve portfolio cannot outperform other portfolios based on the downside risk. When rewards are considered to construct timing strategy portfolios, the Sharpe

Table 5.4 Robustness results for 1 year estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor's perspective. This means that I treated US dollar as the based currency. The estimation window is 1 year. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio, 'VS 1/N' means that optimal portfolio compare with naïve portfolio. In this category, there are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A. Although estimation window I used is 1 year, the period I used to evaluate the performance is same as in main results analysis.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	p-val	re-loss	CEQ	VaR	CVaR	Max DD	CR	Turnover	SR	p-val	re-loss	CEQ	VaR	CVaR	Max DD	CR	Turnover
1/N	0.58	1.00	0.00%	3.25%	1.98%	2.71%	23.94%	0.23	0.01	0.82	1.00	0.00%	4.70%	1.67%	2.30%	21.74%	0.28	0.01
Min	0.58	0.98	-0.02%	3.00%	1.60%	2.22%	14.06%	0.32	0.27	1.49	0.01	-1.81%	3.86%	0.47%	0.81%	4.71%	0.86	0.36
ERC	0.62	0.64	-0.36%	3.50%	1.85%	2.41%	20.59%	0.26	0.02	0.98	0.32	-0.77%	4.15%	1.04%	1.54%	15.40%	0.31	0.10
OC-SMA	0.46	0.14	0.98%	2.11%	1.77%	2.38%	17.47%	0.22	0.42	1.03	0.24	-0.85%	3.73%	0.82%	1.38%	12.64%	0.33	0.63
VT-SMA	0.53	0.55	0.38%	2.71%	1.84%	2.40%	21.53%	0.21	0.05	1.39	0.01	-1.64%	3.79%	0.44%	0.74%	7.46%	0.54	0.06
RR-SMA	0.47	0.15	1.08%	2.17%	2.17%	2.86%	14.28%	0.31	0.19	1.98	0.00	-3.24%	5.33%	0.51%	0.91%	7.72%	0.72	0.09
OC-EWMA	0.51	0.45	0.56%	2.55%	1.78%	2.40%	16.54%	0.26	0.54	1.14	0.10	-4.60%	11.24%	3.23%	4.54%	25.01%	0.66	0.04
VT-EWMA	0.57	0.92	0.07%	3.00%	1.82%	2.30%	19.08%	0.24	0.06	1.52	0.01	-1.89%	3.92%	0.41%	0.73%	6.63%	0.62	0.07
RR-EWMA	0.48	0.22	0.94%	2.30%	2.15%	2.90%	16.09%	0.28	0.25	1.89	0.00	-3.67%	6.20%	0.55%	0.98%	5.36%	1.21	0.12

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	p-val	re-loss	CEQ	VaR	CVaR	Max DD	CR	SR	p-val	re-loss	CEQ	VaR	CVaR	Max DD	CR
1/N	0.58	1.00	0.00%	3.23%	1.99%	2.71%	23.95%	0.23	0.81	1.00	0.00%	4.62%	1.67%	2.30%	21.78%	0.27
Min	0.54	0.67	0.29%	2.68%	1.61%	2.24%	14.20%	0.29	1.05	0.19	-0.63%	2.61%	0.51%	0.86%	5.80%	0.48
ERC	0.62	0.61	-0.39%	3.51%	1.86%	2.41%	20.62%	0.26	0.88	0.65	-0.32%	3.65%	1.04%	1.55%	15.55%	0.27
OC-SMA	0.41	0.02	1.44%	1.65%	1.78%	2.40%	17.74%	0.19	0.48	0.00	1.32%	1.56%	0.89%	1.50%	16.35%	0.12
VT-SMA	0.53	0.57	0.37%	2.71%	1.84%	2.41%	21.59%	0.20	1.36	0.02	-1.46%	3.44%	0.46%	0.76%	7.62%	0.47
RR-SMA	0.44	0.07	1.31%	1.93%	2.18%	2.87%	14.50%	0.29	1.84	0.00	-2.83%	4.87%	0.53%	0.94%	7.98%	0.63
OC-EWMA	0.43	0.05	1.25%	1.85%	1.87%	2.44%	16.88%	0.21	1.13	0.10	-4.57%	11.05%	3.23%	4.56%	25.07%	0.65
VT-EWMA	0.57	0.90	0.08%	2.97%	1.82%	2.30%	19.17%	0.24	1.47	0.01	-1.65%	3.52%	0.42%	0.75%	6.88%	0.53
RR-EWMA	0.44	0.07	1.31%	1.92%	2.16%	2.92%	16.68%	0.25	1.70	0.00	-3.09%	5.60%	0.57%	1.04%	5.98%	0.99

ratio is decreased, and VaR and CVaR are increased. The second one shows that the results do not support RR portfolios. Moreover, according to the changes of most evaluation indices from estimation method of SMA to EWMA, the third one is that EWMA can improve the performance of portfolios. After comparing results before taking transaction cost to those after taking transaction cost, the last one supports the fact that transaction cost does not affect the performance significantly regardless of turnover value. In addition, there are some inconsistent points when I make these consistent conclusions. For example, the question about whether OC portfolio outperforms timing strategies portfolio is ambiguous, and maximum drawdown is decreased after taking account of rewards in timing strategy. VaR and CVaR of RR portfolio is higher than those of naïve portfolios. But, because these inconsistent points are inconspicuous, the conclusions reached cannot be totally rejected.

In response to the all currencies dataset, the results are robust to the conclusions from main results analysis. Firstly, comparing to results of G10 currencies analysis, adding 'lesser' currencies delivers huge diversification benefits, except that downside risk of OC portfolio with estimation method of EWMA (referred as OC-EWMA portfolio) is increased, but its Sharpe ratio and Calmar ratio is raised significantly as well. Secondly, in addition to that downside risk of OC-EWMA portfolio is higher than that of naïve portfolio, all other portfolios consistently outperform naïve portfolio in all terms of evaluation. Moreover, timing strategy portfolios have better performance than OC portfolio. Thirdly, although the advantage of using EWMA is not expressed consistently, most of the terms of evaluation index can also display improvement from application of estimation method of EWMA. Finally, unlike analysis related to G10 currencies dataset, RR portfolio has outstanding performance, which can be considered to be better than the performance of minimum variance portfolio. In addition, turnover of RR portfolio remains at low level, which is just half of the original to G10 currencies analysis. With high level of turnover, e.g. OC portfolio, the transaction cost has obvious impact on the performance. For example, after taking transaction cost, I find that the drop of Sharpe ratio and Calmar ratio of OC portfolio with turnover of 0.63 is significant. These conclusions are totally consistent with analysis for the main results using 5 years estimation window.

5.4.3.2 Results for 3 years Estimation Window

According to Table 5.5, which documents the results related to 3 years estimation window, I find that the conclusions made in the main results analysis are also tenable in this case. Firstly, making comparison between the left and the right side of table, I can easily find that 'lesser' currencies can bring the portfolio lots of diversification benefits. This has already been proven in chapter four, and confirmed in the previous discussion in this chapter. I will not mention this conclusion again in the following robustness check analysis, which also can show this benefit.

Next, OC portfolio displays a better performance than naïve portfolio and other timing strategies portfolio in the case of G10 currencies dataset, however, this portfolio can only beat naïve portfolio but not timing strategy portfolios in the case of all currencies dataset. Based on the case of G10 currencies dataset, OC portfolio has higher Sharp ratio, as well as Calmar ratio, and less downside risk than volatility timing and reward-to-risk portfolios. But, as far as all currencies dataset is concerned, I cannot generally say that all evaluation indices indicate outperformance of OC portfolio against timing strategy portfolios, because some indices do not agree to that.

For example VaR and CVaR of volatility timing portfolio is less than OC portfolio. Even, RR portfolio with an estimation method of EWMA (referred as RR-EWMA portfolio) has outstanding Sharpe ratio and Calmar ratio, while its downside risk also

Table 5.5 Robustness results for 3 years estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor's perspective. This means that I treated US dollar as the based currency. The estimation window is 3 years. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio. There are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A. Although estimation window I used is 3 year, the period I used to evaluate the performance is same as in main results analysis.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/N	0.58	1.00	0.00%	3.25%	1.98%	2.71%	23.94%	0.23	0.01	0.82	1.00	0.00%	4.70%	1.67%	2.30%	21.74%	0.28	0.01
Min	0.74	0.16	-1.15%	4.05%	1.55%	2.05%	12.60%	0.43	0.08	1.59	0.00	-1.72%	3.42%	0.43%	0.60%	5.23%	0.68	0.08
ERC	0.63	0.62	-0.37%	3.47%	1.80%	2.36%	20.91%	0.25	0.01	0.99	0.30	-0.83%	4.25%	1.06%	1.49%	15.19%	0.32	0.03
OC-SMA	0.65	0.47	-0.57%	3.58%	1.60%	2.15%	14.07%	0.36	0.15	1.53	0.01	-2.00%	4.10%	0.55%	0.75%	5.65%	0.76	0.21
VT-SMA	0.54	0.63	0.32%	2.78%	1.80%	2.36%	21.16%	0.21	0.02	1.48	0.01	-1.63%	3.52%	0.54%	0.72%	6.91%	0.53	0.02
RR-SMA	0.46	0.09	1.13%	2.08%	1.97%	2.78%	28.70%	0.14	0.11	1.56	0.00	-2.05%	4.13%	0.58%	0.79%	7.30%	0.59	0.05
OC-EWMA	0.72	0.21	-1.10%	4.12%	1.55%	2.13%	14.15%	0.40	0.21	1.26	0.04	-1.27%	3.44%	0.54%	0.86%	7.41%	0.49	0.26
VT-EWMA	0.57	0.85	0.13%	2.96%	1.80%	2.33%	20.51%	0.23	0.02	1.48	0.01	-1.64%	3.52%	0.53%	0.72%	6.94%	0.53	0.03
RR-EWMA	0.54	0.65	0.37%	2.85%	2.11%	2.82%	16.34%	0.30	0.13	1.84	0.00	-2.82%	4.89%	0.58%	0.83%	5.18%	0.98	0.06

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/N	0.58	1.00	0.00%	3.23%	1.99%	2.71%	23.95%	0.23	0.81	1.00	0.00%	4.62%	1.67%	2.30%	21.78%	0.27
Min	0.74	0.16	-1.15%	4.05%	1.55%	2.06%	12.81%	0.42	1.46	0.01	-1.45%	3.12%	0.44%	0.61%	5.54%	0.59
ERC	0.63	0.58	-0.42%	3.51%	1.80%	2.36%	20.93%	0.25	0.96	0.33	-0.75%	4.12%	1.07%	1.50%	15.33%	0.31
OC-SMA	0.65	0.51	-0.51%	3.51%	1.61%	2.16%	14.38%	0.35	1.29	0.03	-1.35%	3.44%	0.59%	0.78%	6.19%	0.59
VT-SMA	0.55	0.70	0.25%	2.83%	1.80%	2.37%	21.19%	0.22	1.43	0.01	-1.55%	3.41%	0.55%	0.72%	6.95%	0.51
RR-SMA	0.44	0.05	1.27%	1.93%	1.97%	2.79%	28.91%	0.14	1.49	0.01	-1.88%	3.94%	0.59%	0.80%	7.60%	0.54
OC-EWMA	0.70	0.27	-0.95%	3.96%	1.55%	2.15%	14.33%	0.38	0.96	0.38	-0.44%	2.60%	0.55%	0.91%	10.45%	0.27
VT-EWMA	0.57	0.91	0.08%	2.99%	1.80%	2.34%	20.56%	0.23	1.44	0.01	-1.53%	3.36%	0.53%	0.73%	6.98%	0.50
RR-EWMA	0.52	0.50	0.53%	2.67%	2.12%	2.83%	16.46%	0.29	1.75	0.00	-2.59%	4.64%	0.59%	0.85%	5.32%	0.91

stays at very low level. This portfolio can also be considered to be better than minimum variance portfolio.

Once more, the results of both cases of G10 currencies dataset and all currencies dataset show that EWMA is more efficient to estimate conditional expected moments than SMA, and then it leads to the factor that the performance of the portfolio is improved. From the table, it can be seen that if I change estimation method from SMA to EWMA, most of Sharpe ratios and Calmar ratio is increased, and most of downside risk is reduced, only with one exception.

In addition, the results of G10 currencies dataset cannot support RR portfolio, but those of all currencies dataset do strongly support RR portfolio. All indices based on the case of g10 currencies analysis indicate that the performance of RR portfolio is not better than that of VT portfolio (low Sharpe ratio and Calmar ratio with high downside risk). This means that taking account of reward will not develop the performance of timing strategy portfolio. However, as the hypothesis in the previous sections states, because of more variation in expected returns across currencies for all currencies dataset than G10 currencies dataset, RR portfolio constructed by all currencies has better performance than VT portfolio constructed by same currencies.

Finally, the effect of transaction cost is insignificant for G10 currencies analysis, but it is noticeable to some portfolios with a high level of turnover for all currencies analysis. The turnover of OC-EWMA portfolio is 0.21, while that of naïve portfolio is only 0.01. But, due to low transaction cost in trading G10 currencies, the performance of OC-EWMA portfolio is not significantly reduced. Its Sharpe ratio and Calmar ratio are only decreased by 0.02 after taking transaction cost. Unlike high level to turnover of RR portfolio in G10 currencies analysis, RR portfolio retains its turnover at low level in all currencies analysis. Unfortunately, OC-EWMA portfolio still has a high turnover, 0.26, in an analysis related to all currencies dataset. Moreover, due to subtraction of transaction cost from portfolio return, the Sharpe ratio is reduced by 0.3, from 1.26 to 0.96. So, the effect of transaction cost is considered to be significant to all currencies analysis, while it is insignificant to G10 currencies analysis.

5.4.3.3 Results for 10 years Estimation Window

In this subsection, I turn to focus on 10 years estimation window, which is longer than what I use in the main results analysis. However, due to longer estimation window, the evaluation period will be shortened. Consequently, I cannot use the same evaluation period as in the main results analysis. I therefore, can only report the evaluation results for the period of the last 5 years. Although evaluating the performance with different period lengths is not very fair and suitable to the comparison, it is still valuable in some ways to analyse the results of this case.

The evaluation results related to 10 years estimation window are documented in Table 5.6, which shows some inconsistences with the main results analysis. According to p-value of zero and positive return-loss, naïve portfolio has better Sharpe ratio than OC and timing strategy portfolios have with statistically significant differences for both cases of G10 and all currencies datasets. In contrast, downside risks of those portfolios, except RR portfolio in the case of G10 currencies dataset, are less than naïve portfolios. However, Calmar ratios support the performance of Sharpe ratio. So, if the risk is the only major concern of an investor, investor, the naïve portfolio does not outperform others, but if an investor also has an interest about return, naïve portfolio should be the best choice, because the difference of downside risk is not large. The same situation happens when I compare the performances of OC portfolio and timing strategy portfolios.

Table 5.6 Robustness results for 10 years estimation window

This table documents the evaluation of performance of each optimal portfolio strategy for US investor's perspective. This means that I treated US dollar as the based currency. The estimation window is 10 years. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio. There are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A. because the estimation window I used is 10 year, I can only report the evaluation results for the period of the last 5 years.

Panel A: Results before transaction cost

	G10 Currencies									**All Currencies**								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/N	0.29	1.00	0.00%	0.17%	2.52%	3.16%	23.94%	0.14	0.01	0.34	1.00	0.00%	1.02%	2.06%	2.80%	21.74%	0.15	0.01
Min	0.02	0.00	2.24%	-1.50%	1.68%	2.25%	18.90%	0.01	0.03	0.17	0.01	0.68%	0.27%	1.03%	1.30%	12.49%	0.05	0.04
ERC	0.29	0.92	0.05%	0.38%	2.17%	2.86%	22.00%	0.13	0.01	0.41	0.46	-0.43%	1.60%	1.43%	2.01%	17.21%	0.16	0.01
OC-SMA	0.04	0.00	2.35%	-1.77%	2.00%	2.55%	20.27%	0.02	0.09	0.04	0.00	1.41%	-0.37%	1.10%	1.54%	15.60%	0.01	0.08
VT-SMA	0.14	0.00	1.53%	-1.11%	2.19%	2.92%	22.70%	0.06	0.01	0.21	0.01	0.72%	0.40%	1.40%	1.63%	16.74%	0.07	0.01
RR-SMA	0.10	0.00	2.71%	-3.38%	2.96%	4.18%	29.67%	0.04	0.05	0.13	0.00	1.52%	-0.36%	1.65%	2.29%	23.61%	0.04	0.05
OC-EWMA	0.08	0.00	1.75%	-1.05%	1.81%	2.33%	20.50%	0.03	0.11	-0.10	0.00	1.56%	-0.67%	0.85%	1.17%	12.55%	-0.03	0.12
VT-EWMA	0.17	0.00	1.19%	-0.71%	2.16%	2.80%	21.72%	0.08	0.01	0.21	0.01	0.63%	0.43%	1.15%	1.45%	15.28%	0.07	0.01
RR-EWMA	-0.20	0.00	6.20%	-6.43%	3.04%	4.03%	36.89%	-0.07	0.11	0.03	0.00	1.75%	-0.63%	1.25%	1.89%	19.93%	0.01	0.06

Panel B: Results after transaction cost

	G10 Currencies								**All Currencies**							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/N	0.29	1.00	0.00%	0.14%	2.52%	3.17%	23.95%	0.14	0.33	1.00	0.00%	0.89%	2.07%	2.82%	21.78%	0.14
Min	0.02	0.00	2.09%	-1.38%	1.69%	2.26%	18.98%	0.01	0.13	0.00	0.79%	0.12%	1.04%	1.31%	12.66%	0.04
ERC	0.29	0.98	-0.02%	0.42%	2.18%	2.87%	22.01%	0.13	0.39	0.44	-0.44%	1.51%	1.43%	2.02%	17.26%	0.15
OC-rolling	0.04	0.00	2.27%	-1.71%	2.01%	2.57%	20.42%	0.02	-0.02	0.00	1.59%	-0.61%	1.11%	1.55%	15.93%	0.00
VT-rolling	0.14	0.00	1.46%	-1.07%	2.20%	2.94%	22.71%	0.06	0.19	0.01	0.75%	0.30%	1.41%	1.63%	16.79%	0.06
RR-rolling	0.09	0.00	2.81%	-3.52%	2.97%	4.21%	29.76%	0.04	0.10	0.00	1.67%	-0.61%	1.66%	2.31%	23.81%	0.03
OC-EWMA	0.08	0.00	1.66%	-0.98%	1.83%	2.34%	20.78%	0.03	-0.18	0.00	1.82%	-0.97%	0.86%	1.19%	13.03%	-0.05
VT-EWMA	0.17	0.00	1.10%	-0.64%	2.17%	2.81%	21.75%	0.08	0.19	0.01	0.65%	0.35%	1.15%	1.46%	15.35%	0.06
RR-EWMA	-0.22	0.00	6.37%	-6.63%	3.06%	4.06%	37.14%	-0.07	-0.03	0.00	1.98%	-0.93%	1.27%	1.91%	20.33%	-0.01

Again, taking return into timing strategy portfolio cannot improve its performance in the case of G10 currencies dataset. However, in the case of all currencies dataset, this is still useless in terms of making the performance better. For both cases, the Sharpe and Calmar ratios of VT portfolios are better than those of RR portfolio, while former downsides are consistently higher than the latter. In addition, only OC and VT portfolios for G10 currencies analysis have improved performance when EWMA is applied instead of SMA to estimate moments. But, RR portfolio has worse performance than before. Moreover, for all currencies analysis, only decreasing downside risk can confirm this improvement, but not Sharpe and Calmar ratio. So, unlike previous analyses, the advantage of EWMA is ambiguous, here. If risk is considered as the only evaluation to the performance, EWMA can be concluded roughly to improve the performance of portfolios.

As far as results after taking transaction cost are concerned, the reduction of the performance is not significant due to transaction cost for both cases of G10 and all currencies datasets. After comparing Panel B to Panel A of Table 5.6, I find that there is almost unchanged to all evaluation indices for G10 currencies analysis. As explained, the reasons for this tiny effect of transaction cost are small transaction costs and low turnover. Although transaction cost is relatively large for the case of all currencies dataset, low turnover also leads to the factor that the performance of the portfolios is not affected significantly.

In summary, the results related to 1 year and 3 years estimation windows can confirm the conclusions obtained from the main results analysis (5 years estimation window). Although conclusions from results of 10 years estimation window are not consistent mostly, this analysis just evaluates the performance of the portfolios in the last 5 year period, which is different to the evaluation period of the main results analysis. Moreover, in some ways, analysis of 10 years estimation window also has robustness to my main results analysis.

5.4.4 Robustness Check for Investor Perspectives from Different Countries

As in chapter four, I also conduct robustness check analysis in a different direction, which considers perspectives of investors from other countries. I will still use 5 years estimation window, and the countries include the United Kingdom, Japan, and euro zone as whole.

5.4.4.1 United Kingdom (UK) Investor

Results related to the perspective of investors from United Kingdom (UK) are documented in Table 5.7, and these results only partly support the conclusions of the main results analysis. According to this table, all positive return-loss means that Sharpe ratio of naïve portfolio is higher than that of other portfolios for both cases of G10 and all currencies datasets, and p-value indicates that most of the differences between Sharpe ratios are statistically significantly different. And, other evaluation indices also confirm the best performance of naïve portfolio. Furthermore, all evaluation indices display that volatility timing portfolio has better performance than OC portfolio. Based on Sharpe ratio and Calmar ratio, timing strategy portfolios and OC portfolio outperform minimum variance portfolio.

Table 5.7 Robustness results for perspective of UK investors

This table documents the evaluation of performance of each optimal portfolio strategy for UK investor's perspective. This means that I treated British pound as the based currency. The estimation window is 5 years. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio. There are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/N	0.58	1.00	0.00%	2.80%	1.31%	1.70%	14.95%	0.26	0.01	0.67	1.00	0.00%	3.55%	1.47%	1.88%	10.21%	0.47	0.01
Min	0.25	0.00	2.36%	0.52%	1.35%	1.87%	23.28%	0.08	0.04	0.26	0.00	3.08%	0.57%	1.34%	2.08%	18.06%	0.11	0.16
ERC	0.55	0.72	0.23%	2.58%	1.31%	1.71%	16.37%	0.23	0.01	0.64	0.74	0.24%	3.24%	1.43%	1.80%	10.56%	0.42	0.01
OC-SMA	0.30	0.00	2.03%	0.85%	1.41%	1.91%	21.49%	0.10	0.07	0.35	0.00	2.52%	1.22%	1.46%	2.26%	15.14%	0.18	0.21
VT-SMA	0.44	0.05	1.02%	1.83%	1.31%	1.79%	18.08%	0.17	0.01	0.51	0.06	1.11%	2.34%	1.39%	1.80%	12.23%	0.29	0.01
RR-SMA	0.26	0.00	2.65%	0.46%	1.86%	2.51%	16.80%	0.13	0.10	0.56	0.24	0.91%	2.86%	1.55%	2.28%	14.01%	0.32	0.08
OC-EWMA	0.25	0.00	2.31%	0.55%	1.40%	1.89%	22.70%	0.08	0.09	0.33	0.00	2.72%	1.03%	1.47%	2.34%	16.60%	0.16	0.27
VT-EWMA	0.44	0.07	0.98%	1.86%	1.27%	1.79%	18.50%	0.17	0.02	0.50	0.04	1.20%	2.24%	1.40%	1.81%	12.89%	0.26	0.02
RR-EWMA	0.40	0.02	1.57%	1.60%	1.98%	2.55%	15.16%	0.23	0.12	0.57	0.27	0.85%	2.89%	1.67%	2.16%	11.80%	0.37	0.11

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/N	0.58	1.00	0.00%	2.79%	1.31%	1.70%	14.97%	0.26	0.66	1.00	0.00%	3.47%	1.47%	1.88%	10.23%	0.47
Min	0.24	0.00	2.43%	0.44%	1.35%	1.88%	23.40%	0.07	0.21	0.00	3.43%	0.14%	1.35%	2.10%	19.19%	0.08
ERC	0.55	0.72	0.23%	2.57%	1.31%	1.71%	16.39%	0.23	0.63	0.73	0.25%	3.16%	1.43%	1.80%	10.59%	0.41
OC-SMA	0.29	0.00	2.08%	0.79%	1.42%	1.92%	21.69%	0.10	0.29	0.00	2.93%	0.73%	1.49%	2.29%	16.00%	0.14
VT-SMA	0.43	0.05	1.04%	1.80%	1.31%	1.79%	18.10%	0.17	0.50	0.05	1.12%	2.26%	1.39%	1.81%	12.35%	0.28
RR-SMA	0.25	0.00	2.76%	0.33%	1.86%	2.52%	17.18%	0.12	0.53	0.13	1.09%	2.60%	1.56%	2.30%	14.33%	0.29
OC-EWMA	0.24	0.00	2.37%	0.48%	1.41%	1.90%	22.95%	0.07	0.24	0.00	3.30%	0.37%	1.48%	2.37%	17.01%	0.11
VT-EWMA	0.44	0.06	1.00%	1.83%	1.28%	1.80%	18.53%	0.16	0.49	0.03	1.21%	2.16%	1.40%	1.81%	13.02%	0.26
RR-EWMA	0.38	0.01	1.70%	1.46%	1.98%	2.56%	15.29%	0.22	0.52	0.12	1.10%	2.56%	1.68%	2.17%	11.93%	0.34

Similar to the main results analysis, taking returns cannot improve the timing strategy portfolio for G10 currencies analysis, but it helps investors to have better performance than VT portfolio has if all currencies dataset is considered. In the case of G10 currencies dataset, Sharpe ratio of RR portfolio is smaller than that of VT portfolio, while RR portfolio has more downside risks, except maximum drawdown, than VT portfolio has. Although maximum drawdown is less to RR portfolio than VT portfolio, Calmar ratio indicates that VT portfolio outperforms RR portfolio. However, in the case of all currencies dataset, Sharpe ratio shows a better performance of RR portfolio than VT portfolio. Admitting that RR portfolio is riskier than VT portfolio, the difference between two portfolios' downside risk is very small. Moreover, RR portfolio has higher Calmar ratio than VT portfolio has.

The role of using EWMA instead of SMA to estimate conditional expected moments is not clear here for both G10 and all currencies analysis. In the G10 currencies analysis, VaR and CVaR of OC and VT portfolios have slight decrease after using EWMA. But, maximum drawdown of these two portfolios is increased. Moreover, these two portfolios have lower Sharpe ratio/CEQ and Calmar ratio for estimation method of EWMA than SMA. Correspondingly, the estimation method of EWMA increases Sharpe ratio/CEQ and Calmar ratio of RR portfolio. And, maximum drawdown of this portfolio is lower with EWMA than SMA. But, this portfolio has VaR and CVaR, which are larger in EWMA than SMA. According to results from all currencies analysis, a similar situation happens, other than the fact that all downside risks of three portfolios are raised because of using EWMA.

With respect to transaction costs, the performance of the portfolio with G10 currencies dataset is not affected significantly. By comparison, in the case of all currencies dataset, transaction cost, indeed, has impact on the performance of some portfolios. All portfolios in G10 currencies analysis have low level of turnover. Therefore, comparing the results before to after taking transaction cost, I find that the changes of all evaluation indices are very slight. However, the turnover of OC portfolio in all currencies analysis remains at relatively high level. So, after taking transaction cost, this portfolio has a big drop in Sharpe ratio and Calmar ratio. The reason for this change also includes high transaction cost for developing countries' currencies. Although the impact is not ignorable, the ranking of the performance is unchanged.

5.4.4.2 Japanese (JP) Investor

According to Table 5.8, which reports the results of analysis related to perspective of investors from Japan, I find that, like the UK investor analysis, some conclusions are not consistent with the conclusion of the main results analysis. Firstly, based on Sharpe ratio and Calmar ratio in both cases of G10 and all currencies datasets, I can conclude that other portfolios cannot beat naïve portfolio, although some downside risk of other portfolios is less than that of naïve portfolio. Furthermore, these two ratios of OC portfolio are lower than those of VT portfolios. With lower maximum drawdown, I roughly conclude that VT portfolio has better performance than OC portfolio.

Secondly, unlike results related to main results analysis, I find evidence not only in all currencies analysis to support RR portfolio, but also in G10 currencies analysis. For both cases, Sharpe ratio and Calmar ratio are increased due to taking account of returns in timing strategy. However, the downside risk in the case of G10 currencies dataset is also raised to a large extent. It can therefore be said that I find evidence to prove the advantage of use of return in the case of G10 currencies dataset. But, I cannot conclude that RR portfolio has better performance than VT portfolio.

Table 5.8 Robustness results for perspective of JP investors

This table documents the evaluation of performance of each optimal portfolio strategy for Japanese investor's perspective. This means that I treated Japanese yen as the based currency. The estimation window is 5 years. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio. There are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A.

Panel A: Results before transaction cost

	G10 Currencies									**All Currencies**								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/N	0.25	1.00	0.00%	-0.71%	2.96%	4.24%	34.99%	0.09	0.01	0.35	1.00	0.00%	0.62%	2.70%	4.01%	32.77%	0.12	0.01
Min	0.02	0.00	2.08%	-1.81%	1.94%	2.61%	30.85%	0.01	0.07	0.09	0.00	2.30%	-1.21%	1.86%	2.64%	30.31%	0.03	0.21
ERC	0.23	0.46	0.25%	-0.71%	2.77%	4.00%	33.64%	0.08	0.01	0.32	0.49	0.31%	0.40%	2.55%	3.85%	31.83%	0.11	0.01
OC-SMA	0.06	0.00	2.02%	-2.03%	2.12%	3.34%	35.20%	0.02	0.16	0.18	0.00	1.53%	-0.49%	2.16%	2.79%	33.43%	0.05	0.27
VT-SMA	0.18	0.00	0.77%	-0.84%	2.40%	3.57%	32.05%	0.06	0.01	0.21	0.00	1.33%	-0.40%	2.28%	3.42%	29.68%	0.07	0.01
RR-SMA	0.24	0.66	0.19%	-1.14%	3.15%	4.63%	38.57%	0.08	0.10	0.24	0.00	1.25%	-0.60%	2.58%	3.92%	35.88%	0.08	0.08
OC-EWMA	0.16	0.07	0.89%	-0.84%	2.06%	3.02%	28.15%	0.06	0.22	0.24	0.04	0.97%	0.10%	1.97%	2.64%	31.08%	0.07	0.33
VT-EWMA	0.18	0.00	0.75%	-0.75%	2.40%	3.43%	31.32%	0.06	0.01	0.20	0.00	1.42%	-0.46%	2.24%	3.37%	29.28%	0.07	0.01
RR-EWMA	0.20	0.11	0.73%	-1.47%	3.03%	4.52%	40.49%	0.06	0.13	0.30	0.27	0.54%	0.11%	2.61%	3.99%	34.13%	0.10	0.12

Panel B: Results after transaction cost

	G10 Currencies								**All Currencies**							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/N	0.23	1.00	0.00%	-0.99%	2.96%	4.24%	35.00%	0.08	0.32	1.00	0.00%	0.30%	2.70%	4.02%	32.79%	0.11
Min	-0.01	0.00	2.15%	-2.09%	1.94%	2.62%	30.99%	0.00	0.01	0.00	2.76%	-1.91%	1.87%	2.67%	31.62%	0.00
ERC	0.21	0.39	0.26%	-0.98%	2.77%	4.01%	33.64%	0.07	0.29	0.44	0.32%	0.09%	2.55%	3.86%	31.85%	0.10
OC-SMA	0.02	0.00	2.12%	-2.36%	2.13%	3.36%	35.57%	0.01	0.10	0.00	2.06%	-1.28%	2.18%	2.82%	34.72%	0.03
VT-SMA	0.16	0.00	0.79%	-1.10%	2.41%	3.57%	32.07%	0.05	0.18	0.00	1.36%	-0.70%	2.28%	3.43%	29.75%	0.06
RR-SMA	0.21	0.57	0.22%	-1.47%	3.15%	4.64%	38.66%	0.07	0.21	0.00	1.28%	-0.96%	2.59%	3.94%	36.29%	0.07
OC-EWMA	0.13	0.03	1.02%	-1.20%	2.07%	3.03%	28.74%	0.04	0.14	0.00	1.63%	-0.82%	1.99%	2.69%	33.14%	0.04
VT-EWMA	0.15	0.00	0.78%	-1.01%	2.40%	3.44%	31.36%	0.05	0.17	0.00	1.46%	-0.77%	2.24%	3.38%	29.37%	0.06
RR-EWMA	0.17	0.06	0.81%	-1.84%	3.04%	4.54%	40.71%	0.05	0.26	0.10	0.71%	-0.39%	2.63%	4.02%	35.09%	0.08

Finally, estimation method of EWMA can help some portfolios to improve their performance, but not all of them. For both G10 and all currencies analysis, because all terms of evaluation have development, using EWMA to replace SMA can improve the performance of OC and VT portfolios. Moreover, this improvement for OC portfolio is obvious, while VT portfolio does not have obvious improvement. In contrast, RR portfolio with SMA has less downside risk than what EWMA has. Furthermore, Sharpe ratio and Calmar ratio are higher to RR portfolio with SMA than EWMA for G10 currencies analysis. However, as with all currencies analysis, EWMA increases Sharpe ratio and Calmar ratio of RR portfolio. In addition to previous inconsistent points, the conclusion about the effect of transaction cost is consistent with the main results analysis. By comparison with the results before taking transaction cost, results after transaction cost for the case of G10 currencies dataset display almost unchanged evaluation indices. This indicates insignificant effect of transaction cost, even if turnover is high. However, in the case of all currencies dataset, transaction cost is meaningful to the portfolio with high level of turnover. For example, due to the fact that OC-EWMA portfolio has high turnover of 0.33, its Sharpe ratio is decreased from 0.24 to 0.14 when I take account of transaction cost.

5.4.4.3 Euro zone (EZ) Investor

The results about analysis related to perspectives of investors who comes from euro zone countries are documented in Table 5.9. From this table, I can only find evidence to support some of the conclusions made in the main results analysis. The first evidence is about adding returns into building of timing strategy portfolio. In the case of G10 currencies dataset, VT portfolio has higher Sharpe ratio and Calmar ratio than RR portfolio has, while downside risk of VT portfolio is less than that of RR portfolio. This means that taking account of returns cannot boost the performance of timing strategy portfolio. However, when I consider the case of all currencies dataset, the advantage of constructing timing strategy portfolio with both volatility and return can be found. As to all currencies analysis, Sharpe ratio and Calmar ratio of RR portfolio is higher than that of VT portfolio. Although more downside risk is attributed to RR portfolio than VT portfolio, the huge improvement on Sharp ratio and Calmar ratio confirms better performance of RR portfolio than VT portfolio.

The second evidence is related to turnover and effect of transaction cost. As far as G10 currencies dataset is concerned, most portfolios remain with low turnover, and only RR portfolio has high turnover, 0.14 for SMA and 0.19 for EWMA. With this high level of turnover, RR portfolio still has almost unchanged performance after taking transaction cost. So, this means that transaction cost has insignificant effect to the performance regardless of the level of turnover for the case of G10 currencies dataset. But, as in the main results analysis, the situation for the case of all currencies dataset is different. Sharpe ratio and Calmar ratio is dropped hugely for OC portfolio, whose turnover stays at high level. Therefore, transaction cost can impact on the portfolio with high turnover, when I consider all currencies analysis.

In addition to supporting evidence, from the results of Table 5.9, I also can find some inconsistent conclusions with the main results analysis. In the first place, naïve portfolio can be considered as having the best performance. In G10 currencies analysis, return-loss indicates that naïve portfolio has higher Sharpe ratio than others have, and p-value confirms this difference is statistically significant. The highest Calmar ratio of naïve portfolio also agrees the best portfolio of naïve portfolio. VaR and CVaR of some portfolios are lower than those of naïve portfolio. But, naïve portfolio has the lowest maximum drawdown. In all currencies analysis, although p-value indicates no statistically significant difference between Sharpe ratios of naïve portfolio

Table 5.9 Robustness results for perspective of EZ investors

This table documents the evaluation of performance of each optimal portfolio strategy for euro zone investor's perspective. This means that I treated euro as the based currency. The estimation window is 5 years. In the first three columns of table, the '1/N' refers to naïve portfolio, which is equally-weighted. The 'Min' refers to minimum-variance portfolio, and the 'ERC' refers to equally weighted risk contribution portfolio. I also report the performance of optimal constrained portfolio referred as 'OC', and volatility timing portfolio referred as 'VT' and reward-to-risk portfolio referred as 'RR'. The tuning parameter applied in those strategies is 2, e.t $\eta = 2$. The abbreviation after these portfolios presents the estimation method I used. 'SMA' refers to simple moving average, and 'EWMA' refers to exponentially weighted moving average. The first part shows results from the case of G10 currencies dataset, so I tagged them with 'G10 currencies'. The second part shows results from the case of all currencies dataset, so I tagged them with 'all currencies'. The results before taking transaction cost are showed in panel A, while the results after taking transaction cost are showed in panel B. For the evaluation methods, 'SR' refers to Sharpe ratio. There are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' means Value at risk and conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'Maximum', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in panel A.

Panel A: Results before transaction cost

	G10 Currencies									All Currencies								
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**Turnover**
1/N	0.29	1.00	0.00%	0.79%	1.26%	2.05%	15.36%	0.12	0.01	0.41	1.00	0.00%	1.65%	1.53%	2.20%	11.48%	0.25	0.01
Min	0.01	0.00	2.36%	-0.76%	1.07%	1.75%	24.28%	0.00	0.03	0.00	0.00	2.11%	-0.66%	0.97%	1.64%	14.73%	0.00	0.11
ERC	0.22	0.72	0.23%	0.44%	1.17%	1.90%	16.84%	0.08	0.01	0.37	0.50	0.25%	1.31%	1.17%	1.87%	10.57%	0.21	0.01
OC-rolling	0.05	0.00	1.41%	-0.60%	1.03%	1.85%	25.85%	0.01	0.07	0.15	0.00	1.46%	0.05%	1.01%	1.84%	15.63%	0.05	0.16
VT-rolling	0.09	0.00	1.07%	-0.26%	1.04%	1.78%	22.24%	0.02	0.01	0.19	0.00	1.20%	0.31%	1.06%	1.73%	14.31%	0.08	0.01
RR-rolling	0.03	0.00	2.53%	-2.14%	1.93%	3.14%	32.86%	0.01	0.14	0.40	0.93	0.05%	1.62%	1.58%	2.42%	16.76%	0.18	0.09
OC-EWMA	0.06	0.00	1.31%	-0.50%	1.01%	1.79%	23.84%	0.02	0.09	0.13	0.00	1.56%	-0.05%	1.02%	1.86%	11.06%	0.06	0.20
VT-EWMA	0.07	0.00	1.22%	-0.40%	1.06%	1.83%	23.42%	0.02	0.02	0.16	0.00	1.41%	0.10%	1.02%	1.75%	15.00%	0.06	0.02
RR-EWMA	0.01	0.00	2.59%	-2.11%	1.94%	3.01%	31.62%	0.00	0.19	0.32	0.14	0.67%	1.00%	1.58%	2.51%	17.76%	0.13	0.13

Panel B: Results after transaction cost

	G10 Currencies								All Currencies							
	SR	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**	**SR**	**p-val**	**re-loss**	**CEQ**	**VaR**	**CVaR**	**Max DD**	**CR**
1/N	0.28	1.00	0.00%	0.75%	1.27%	2.05%	15.38%	0.12	0.40	1.00	0.00%	1.55%	1.53%	2.21%	11.55%	0.24
Min	0.00	0.00	1.59%	-0.81%	1.07%	1.76%	24.39%	0.00	-0.06	0.00	2.35%	-0.97%	0.98%	1.66%	16.10%	-0.02
ERC	0.22	0.11	0.37%	0.40%	1.17%	1.90%	16.88%	0.08	0.35	0.46	0.26%	1.21%	1.17%	1.87%	10.66%	0.20
OC-rolling	0.04	0.00	1.43%	-0.65%	1.03%	1.86%	26.14%	0.01	0.08	0.00	1.78%	-0.34%	1.01%	1.87%	16.19%	0.03
VT-rolling	0.08	0.00	1.09%	-0.31%	1.05%	1.79%	22.28%	0.02	0.18	0.00	1.22%	0.21%	1.06%	1.74%	14.44%	0.07
RR-rolling	0.01	0.00	2.64%	-2.33%	1.94%	3.16%	33.26%	0.00	0.37	0.69	0.21%	1.36%	1.59%	2.43%	17.08%	0.16
OC-EWMA	0.05	0.00	1.33%	-0.56%	1.01%	1.79%	24.21%	0.01	0.05	0.00	1.96%	-0.52%	1.03%	1.90%	11.77%	0.02
VT-EWMA	0.06	0.00	1.24%	-0.46%	1.06%	1.83%	23.48%	0.01	0.14	0.00	1.45%	-0.01%	1.02%	1.75%	15.17%	0.05
RR-EWMA	-0.01	0.00	2.74%	-2.32%	1.94%	3.02%	32.16%	0.00	0.27	0.02	0.95%	0.61%	1.60%	2.53%	18.05%	0.11

and RR portfolio, the other evaluation indices also show the best performance of naïve portfolio. So, naive portfolio performs best during portfolios for both datasets. In addition, OC portfolio is no longer better than timing strategy portfolios, even it underperforms VT portfolio according to most of the evaluation indices.

Next, I find that estimation method of EWMA, cannot bring benefits to investors. I compare the performance of portfolios with SMA to the performance of these portfolios with EWMA. Based on the case of G10 currencies dataset, only OC portfolio has slight improvement. But, Sharpe ratio of other two portfolios, VT and RR, is decreased, while downside risk of them is also increased. In the case of all currencies dataset, according to the changes of most of the evaluation indices, all three portfolios have worse performance when I use EWMA than SMA to estimate conditional moments.

To sum up, these robustness checks about different countries' investors do not fully support all conclusions made in the main results analysis. On one hand, unlike conclusions from the main results analysis, all robustness checks generally conclude that naïve portfolio has the best performance, and VT portfolio outperforms OC portfolio. Moreover, the conclusions about the role of using EWMA instead of SMA are different for analyses to investors from different countries. An analysis of UK investors does not result in a clear conclusion, while analysis of EZ investors denies the advantage of using EWMA. Only JP investor confirms that EWMA can improve the performance of some portfolios. On the other hand, as far as the effect of transaction cost and evidence to support RR portfolios are concerned, the results of these three robustness checks almost display same conclusions reached in the main results analysis.

5.5 Conclusion

In this chapter, I investigate the performance of optimal constrained (OC) portfolio and two timing strategy portfolios, volatility timing (VT) portfolio and reward-to-risk (RR) portfolio for currency market, and compare them to three passive portfolios, which have good performance in chapter four. The main motivation for this research was to know, in currencies trading portfolio, whether these portfolios can consistently outperform naïve portfolio. In addition, in order to reduce estimation error, I also use exponentially weighted moving average (EWMA) instead of simply moving average (SMA) to estimate conditional expected moments for the portfolios investigated in this chapter. Before I started to do the main research, I conducted a Monte Carlo experiment to understand estimation error, and find improvement on OC portfolio. Due to this error, the Sharpe ratios of all portfolios except naïve portfolio are lower for out-of-sample analysis than in sample analysis, while downside risk is raised. But, change for OC portfolio is not too much. In out-of-sample, I roughly consider that OC portfolio has the best performance. Only one disadvantage of OC portfolio is that it has high level of turnover. Hence, the motivation is to use timing strategy to reduce portfolio turnover.

For the US investor using US dollar as the base currency with 5 years estimation window, there are five main conclusions made. Firstly, again, 'lesser' currencies can give investors an obvious diversification benefit, and then improve the performance. Secondly, OC and VT portfolio consistently outperforms naïve portfolio in all terms of evaluation. Thirdly, taking account of return into timing strategy portfolio improved its performance for all currencies analysis, but did not for G10 currencies analysis. Therefore, in the case of all currencies dataset, RR portfolio had better performance than OC and VT portfolios had, and it can also beat minimum variance portfolio. Next, I found that EWMA is more efficient to estimate conditional expected moments than

SMA to reduce estimation error. Finally, transaction cost did not affect the performance of portfolio significantly regardless of the level of turnover in the case of G10 currencies dataset. But, in the case of all currencies dataset, this effect was very obvious for the portfolios which have a high turnover. In addition to this main results analysis, I also conducted a robustness check to investigate whether the conclusions reached are supported by different lengths of estimation window or other countries' investors. Overall, robustness check about different lengths of estimation window confirmed conclusions reached.

However, robustness checks related to the perspectives of investors from other countries cannot give consistent conclusions with the main results analysis. There are two main inconsistent conclusions. The first one was related to comparison of the performance to naïve portfolio. The results from robustness checks for investors from three countries/areas, UK, Japan and euro zone, all showed that naïve portfolio has the best performance in general. But, some portfolios have less downside risk than naïve portfolio has. The second one was about the role of using EWMA. According to the results of the analysis for UK investor, it is not clear whether portfolios with EWMA are better than the ones with SMA. With respect to the analysis for euro zone investors, the results displayed that using EWMA to replace SMA is useless for improving the performance of the portfolios. As far as other conclusions are concerned, my robustness checks had results almost consistent with the main results analysis.

We investigated the performance of OC and timing strategy portfolios for only currency market. These portfolios are derived from mean-variance model in order to beat naïve portfolio. However, these strategies also depend on estimation of expected return and standard deviation of return of currencies. But, once estimating, the error exists. Is there a possibility of extending to avoid this estimation error? Brandt et al. (2009) give out a strategy named as parametric portfolio policy. This strategy decides weights based on the characteristics of assets. So, in the next chapter, this strategy will be applied into the currency market and test if it works or not.

Chapter Six

Currency Portfolio Management: Exploiting Characteristics

6.1 Introduction

All discussion and analysis in preceding chapters are related to the estimation of expected returns and its covariance matrix. The conclusion shows that the estimation error impacts performance of portfolio significantly. Although a number of researcher and literature put lots effort on it to improve the performance, the previous analysis, DeMiguel et al. (2007) have proved that all extension of Markowitz's mean-variance model cannot beat the naïve portfolio. Kirby and Ostdiek (2010) provide simple active portfolio strategies, called timing strategies, which can outperform naïve portfolio. Furthermore, chapter five of this thesis shows that these strategies can beat naïve portfolio in some cases of currencies only portfolio. Unlike extensions of mean-variance portfolio, the timing strategies rather exploit sample information about the means and variance of return than focus on optimization method. But, the point is that these strategies still need to require investors to estimate the first and second moments of returns of foreign exchange. The main purpose of this chapter is to apply strategies, which do not require estimating the moments of return, into currency only portfolio. It is a fact that the return is calculated by exchange rate, and the rate is determined by some economic factors. I am therefore motivated by following two questions in the first place to find an alternative approach. Can the factors that determine exchange rate be used to construct a portfolio? Can I build an optimised portfolio by exploiting the characteristics of currency?

Fortunately, Brandt et al. (2009) provide a guide to answer these questions. They recommend parametric portfolio policies (PPP) to exploit the characteristics in the cross-section of equity returns. Specifically, they propose policy weights as a linear function of characteristics of firm plus benchmark weights. Then, by maximising average utility of investors, they estimate coefficients of policy. I consider this alternative strategy as semi-active portfolio, because it seems adjusting benchmark weights by characteristics. The first term is benchmark weights, which represents passive element. The second term is adjustment according to the characteristics of asset, which represents active element. In this chapter, I would like to apply these PPP strategies into currency only portfolio. But, to implement this, there are two challenges. One is to select a benchmark portfolio for currency market. Another one is the choice of the relevant characteristics for this policy.

In response to the first challenge, in the paper of Brandt et al. (2009), they consider market portfolio weights as benchmark for empirical application. For the FX market, unlike equity market, there is no market portfolio with value-weighted average. Instead, I can use GDP or trade weights to construct a market portfolio. However, chapter four of this thesis has already proved that these two portfolios perform worse than naïve portfolio. Parametric portfolio policy will be used to adjust a benchmark weight which has a good performance itself. Therefore, the naïve portfolio could be one of the choices for the benchmark. In addition, in chapter five, it was concluded that volatility timing (VT) portfolio has better performance than naïve portfolio in some ways. Moreover, the features of VT portfolio are similar to the features of naïve portfolio. Although VT portfolio requires estimating moments, only variance of return needs to be estimated.

Therefore, in our empirical application, I consider these two portfolios, naïve portfolio and VT portfolio, as my benchmark.

With respect to the second challenge, characteristics of currency return are classified, which are then exploited to construct portfolio, into two parts. The first class is the financial characteristics, which are derived from three most widely applied currency trading strategies in practice. One of them is carry trade constructed by borrowing currency with low interest rate and investing currency with high interest rate (Fama, 1984). This strategy is based on a failure in uncovered interest rate parity, and performs very well (Burnside et al., 2008). However, it is also well known that the carry trade faces a substantial crash risk (Brunnermeier et al., 2008; Menkhoff et al., 2012a; Christiansen et al., 2011). Luckily, since 2008, the other famous currency trading strategies, the momentum and value, has major development (Menkhoff et al., 2012b; Burnside et al., 2011; Asness et al., 2013; Jordà and Taylor, 2012). But, these studies establish one of the strategies or combine them by a simple portfolio (equal weights), and none of them tries to have optimal portfolio. So, Barroso and Santa-Clara (2011) explore this undeveloped area by applying parametric portfolio policy. However, in their approach, the portfolio they build consists of zero sum long-short portfolio and 100% investing in risk free asset, but not benchmark portfolio. This thesis original idea is to consider characteristics as an opinion of investors to adjust benchmark weights. Therefore, as discussed before, the naïve portfolio and VT portfolio are used as a benchmark, and no investment in risk free assets. I consider carry trade (forward discounts), currency momentum (short term return) and currency value (long term return) as financial characteristics in my empirical analysis.

The second class is fundamental characteristic. Unlike equity which has characteristics related to fundamentals of a firm, the fundamental characteristics of currency mostly are related to economic factors of pair countries, and these factors can determine real exchange rate. The Approach of modelling exchange rate I considered is Behavioural Equilibrium Exchange Rate (BEER), which extends the relative purchasing power parity by recognising that the exchange rate is determined by a wide range of macroeconomic factors. Since Clark and MacDonald (1999) propose BEER model, a different set of macroeconomic variables are employed in the literature (Komárek et al., 2005; Lane and Milesi-Ferretti, 2001; MacDonald and Dias, 2007; Cheung et al., 2005). These models generally offer superior performance in terms of both medium run valuation and short run dynamics. Hence, the most relevant variables are chosen and, importantly, they also have to comply with the constraint of data availability. The final set chosen includes (1) the real interest rate differential, (2) the productivity differential, (3) the term of trade differential, and (4) the fiscal differential. Adding three characteristics related to trading strategies, produces seven characteristics. Moreover, I ran a pre-sample test to determine which characteristics were relevant. This is followed by a comprehensive out-of-sample analysis with 22 years of weekly returns of G10 currencies to see how PPP portfolio performs.

Moreover, in contrast to researches by Brandt et al. (2009) and Barroso and Santa-Clara (2011), besides the standard constant relative risk aversion (CRRA) utility function, I also apply PPP strategy to practitioner-oriented objective function. Concretely, variance of the portfolio to estimate the coefficients of policy is minimised. As shown in the last two chapters, minimum variance portfolio has very good performance, even the best performance sometimes. I also found that it always has the lowest downside risk. In chapter five, I stated that the investors focus more on risk management; I therefore estimate the coefficients by minimizing variance of portfolio's return instead of maximising utility of investor.

The first finding of this chapter is that the fundamental characteristics are efficient out of the sample for CRRA investors to apply PPP portfolio, but financial characteristics are not. All terms of evaluation, except CEQ return, do not support PPP portfolio with financial predictors. Differently, the PPP portfolio with fundamental predictors performs best in terms of Sharp ratio, CEQ return and Calmar ratio. But, in robustness check related to Japanese investors, the results do not agree with this outperformance completely. For Japanese investors, Sharpe ratio of PPP portfolio is not statistically significantly higher than that of naïve portfolio. Except this disagreement, all other robustness checks also confirm outperformance of PPP portfolio with fundamental predictors.

The second finding is that considering all seven characteristics together worsens the performance of PPP portfolios. Sharpe ratio, Calmar ratio and CEQ return of PPP portfolio decrease significantly when I combine all predictors into one strategy; and downside risks increase. This drop leads to the conclusion that PPP portfolio with all predictors cannot beat naïve portfolio. However, when I consider the perspective of investors from the UK, PPP portfolio with all predictors has better performance than naïve portfolio has in terms of evaluation. Even so, the performance of PPP portfolio is still getting worse after considering all predictors together. For Japanese investors, in terms of CEQ return and Calmar ratio, PPP portfolio is slightly improved. However, these inconsistences cannot fully reject these findings. So, it can be said that the robustness checks generally affirm this finding.

The next finding in this chapter is that the choice of which portfolio weights should be used as benchmark weights in PPP portfolio is not important to the investor. There is no significant change in the values of all evaluation indices when I use VT portfolio weights, instead of naïve weights, as benchmark weights. Therefore, the conclusions remain the same. Furthermore, the results from all robustness checks also consistently support this finding.

The final finding is that investors may still prefer PPP portfolio to naïve portfolio, if they firstly think about safety before making an investment. Based on this consideration, as mentioned before, I estimate coefficients by minimizing a portfolio's variance rather than maximising CRRA utility. The results display that PPP portfolio has lower downside risk than naïve portfolio has. So, given satisfied CEQ returns, the investor may choose PPP portfolio, although its other evaluation indices are not better than naïve portfolio's. This finding is confirmed by robustness check analysis. For UK investor, Sharpe ratio, CEQ return and Calmar ratio of PPP portfolio are higher than those of naïve portfolio. This outperformance does not disagree with the findings of this thesis, but further confirms the finding.

In addition, in this chapter, I document the importance of the currency characteristics for explaining deviation of PPP portfolio weights from naïve weights. Relative to naïve weights, the PPP portfolios allocate considerably more wealth to currencies with small interest rate spread, large real interest rates differential, large productivity differential, and small term of trade differential.

The rest of the chapter is organised as follows. In section 6.2, a description of parametric portfolio policy is given. Section 6.3 focuses on the description of currency characteristics. And, the calculation of predictors is also given in this section. In section 5.4, the results from empirical work are presented. Before out-of-sample analysis, an in-sample test is done. Finally, section 5.5 gives a conclusion of this chapter.

6.2 Portfolio Strategy

In this section, parametric portfolio policy (PPP) will be introduced in detail using different benchmark portfolio; followed by a description of methods to estimate the coefficients of the policy.

6.2.1 Basic Approach

Brandt et al. (2009) introduce a simple linear specification for the portfolio weights function, and his formula showed as follows:

$$w_{i,t}^{ppp} = \overline{w}_{i,t} + \frac{1}{N}\theta^{'}\hat{x}_{i,t} \qquad 6.1$$

where $\overline{w}_{i,t}$ is the weights of asset i at date t in a benchmark portfolio, θ is an S*1 vector of coefficient that need to be estimate. $\hat{x}_{i,t}$ is S*1 vector of the characteristics of asset i, and S is the number of characteristics. This strategy uses a single function of characteristics to estimate weights for all assets over time, rather than one weight for each asset at each point in. This is referred to as a portfolio policy.

Again, the strategy captures the idea of active portfolio management. The first term of the function is benchmark portfolio weights, and the second term, $\theta^{'}\hat{x}_{i,t}$, is active element represents opinion of investor to adjust weights from benchmark according to asset characteristics. These characteristics with zero mean and unit standard deviation are also standardized. The first reason of standardization is that raw characteristics may be nonstationary, but standardized characteristics are surely stationary through time. Secondly, standardization makes sure that sum of deviations from benchmark weights equal to zero, then the weights of the strategy always sum to one. The term of 1/N can help investor apply this strategy to an arbitrary and time-varying number of assets.

Without this term, when the investment opportunities are not changed fundamentally, doubling number of asset will result in twice as aggressive allocation. Importantly, the coefficients, θ , are constant for all assets and time points. Due to constant coefficients across assets, the adjustment of weight for each asset is decided by only the characteristics but not historic performance. This means two assets with similar characteristics will have similar adjustments even if they have significantly different historic returns. Coefficients' being constant through time means that the coefficients estimated by maximising conditional expected utility of investor at given period are the same for all periods. So, they also are assumed to maximise the unconditional expected utility of an investor.

In this chapter, with respect to the benchmark portfolio, I firstly use naïve portfolio, which equally weight all assets in the portfolio. The equation 6.1 is re-written corresponding to naïve portfolio as follows:

$$w_{i,t}^{ppp} = w^{naive} + \frac{1}{N}\theta^{'}\hat{x}_{i,t} \qquad 6.2$$

Secondly, as discussed in section 6.1, I consider VT portfolio instead of naïve portfolio as benchmark. So, the equation 6.1 is re-written as follows to present that VT portfolio is concerned.

$$w_{i,t}^{ppp} = w_{i,t}^{VT} + \frac{1}{N}\theta^{'}\hat{x}_{i,t} \qquad 6.3$$

In empirical analysis, I will conduct an out-of-sample analysis to investigate performance of PPP strategy. Details of the method used about estimating coefficients are given in the next subsection 6.2.2. In addition, the detail of VT portfolio is given in the last chapter.

6.2.2 Method of Estimating θ

We have introduced the idea about PPP portfolio. Now, the problem is how to estimate coefficients of characteristic. Firstly, for the choice of the portfolio weights, investors would like to maximise the conditional expected utility of investor related to the portfolio return.

$$\max E_t[u(r_{p,t+1})] \qquad 6.4$$

Due to $r_{p,t+1} = \sum_{i=1}^{N} w_{i,t} r_{i,t+1}$ the equation 6.4 can be expressed as

$$\max_{\{w_{i,t}\}_{i=1}^{n}} E_t[u(\sum_{i=1}^{N} w_{i,t} r_{i,t+!})] \qquad 6.5$$

In the linear policy case 6.1, the optimization problem is

$$\max E_t[u(\sum_{i=1}^{N} (\overline{w}_{i,t} + \frac{1}{N}\theta^{'}\hat{x}_{i,t}) r_{i,t+!})] \qquad 6.6$$

Secondly, the important ingredient of the portfolio choice problem is the investor's objective function. There are many choices of objective function that can be applied to this approach, for example, HARA preference, behaviourally motivated utility functions and practitioner-oriented objective functions. But, in this chapter, I will use standard CRRA preference to this thesis approach, and the equation is shown below followed with the expansion form of portfolio return:

$$u(r_{p,t+1}) = \frac{(1+r_{p,t+1})^{1-\gamma}}{1-\gamma} = \frac{(1+\sum_{i=1}^{N}(w_{i,t} = \overline{w}_{i,t} + \frac{1}{N}\theta^{'}\hat{x}_{i,t}) r_{i,t+1})^{1-\gamma}}{1-\gamma} \qquad 6.7$$

where γ is a relative risk aversion, and it is set as being equal to 5 as indicated in a number of literature. The main advantage of CRRA utility is that it penalizes higher-order moments, unlike mean-variance utility which cares about first and second moments. As far as expected utility is concerned, Brandt et al. (2009) and Barroso and Santa-Clara (2011) calculate expected utility based on simple average by using the sample counterparts. However, I will apply exponentially weighted moving average (EWMA) instead of simple moving average (SMA) to estimate expected utility of investors. The details of how to apply EWMA has been provided in Chapter 5.

Alternatively, as mentioned before, I also consider a practitioner-oriented objective function in optimal portfolio policy. Due to good performance of minimum variance portfolio with the lowest downside risk, I estimate the coefficients of PPP strategy by minimizing the variance of returns of portfolio for estimation period.

6.2.3 Transaction Cost

In this chapter is concerned with the performance of optimal portfolios after taking into consideration transaction cost. To do this, in previous chapters, I subtract the effect of transaction cost from return of portfolio for evaluation period. This means that I take account of transaction cost only when I evaluate the performance of the portfolio. However, in this chapter, the coefficients, θ, are constant in estimation period, but weights are not. This may lead to unneglectable effect of transaction cost to the return of portfolio in estimation period. So, I also take account of transaction cost when estimating coefficients of characteristics of currency. Specifically, the utility function related to case of taking transaction cost is, now, expressed as follows:

$$u(\tilde{r}_{p,t+1}) = \frac{((1+\sum_{i=1}^{N}(\overline{w}_{i,t} + \frac{1}{N}\theta'\hat{x}_{i,t})r_{i,t})(1-\sum_{i=1}^{N}c_{i,t}\tau_{i,t}))^{1-\gamma}}{1-\gamma} \qquad 6.8$$

where $c_{i,t}$ the transaction is cost of currency i at time t, and $\tau_{i,t}$ is turnover for currencies i in optimal portfolio at time t. The methods used to calculate transaction cost and turnover have been introduced in chapter three. I then maximise expected conditional utility relative to the above equation 6.8 to estimate coefficients of characteristics. The same process is also applied into estimation about practitioner-oriented objective function.

6.3 Data

We have already described the calculation of return for currency portfolio in chapter three. I still use the same approach for calculation, but extend the period to the end of 2014. In this section, I focus on description of characteristics of currency used. The following economic data is from DataStream.

6.3.1 Financial Characteristics

The first three characteristics considered in this chapter are related to three famous currency trading strategies. These variables are determined by historical or present performance of currency. So, I call them financial characteristics. The calculation to build these three variables in my optimization exercise is:

Carry Trade:

We use the log of forward discount, also referred to as interest rate spread, on currency, and denote them as $CT_{i,t} = \ln(\frac{F_{i,t,t+1}}{S_{i,t}})$. I also denote the cross-sectional mean and standard deviation across all countries available at time t as μ_{CT_t} and σ_{CT_t} respectively. I standardize the forward discount as: $ct_{i,t} = \frac{CT_{i,t} - \mu_{CT_t}}{\sigma_{CT_t}}$.

Currency Momentum:

We use the log of cumulative currency appreciation in the last four week. So, I calculate them as $CM_{i,t} = \ln(\frac{S_t}{S_{t-4}})$. I also apply cross-sectional standardizations according to $cm_{i,t} = \frac{CM_{i,t} - \mu_{CM_t}}{\sigma_{CM_t}}$, where μ_{CM_t} and σ_{CM_t} is mean and standard deviation of cumulative appreciation cross all countries.

Currency Value:

We use the log of the cumulative real currency change in two years. The formula used to calculate this variable is $CV_{i,t} = \ln(\frac{S_{i,t-4} CPI_{i,t-4} CPI^{US}_{t-104}}{S_{i,t-104} CPI_{i,t-104} CPI^{US}_{t-4}})$. I use two month lag to ensure the CPI is known. This means that the CPI used in the formula is actually CPI of the country two months ago, but published currently. To avoid overlap with currency momentum, I only explore the real currency change between $t-104$ to $t-4$. Again, I standardize this variable cross-sectionally, and denote as $cv_{i,t}$.

6.3.2 Fundamental Characteristics

Another class of characteristics in this chapter is related to economic factors of pair countries. These economic factors chosen are determiners to model currency exchange rate based on BEER model. I calculate the variables in the empirical analysis as follows. In addition to calculation, I also give the reason about why these economic factors should be concerned.

Real Interest Rates Differential:

According to uncover interest parity (UIP), in order to equalise the yields in domestic and foreign currency, a currency with a positive interest rate is expected to depreciate.

Similarly, if interest rate differential increases, the demand for the currency with relatively higher interest rate will be higher, due to portfolio reallocation. So, I are suggesting that a positive interest rate differential with respect to foreign currency should result in contemporaneous appreciation of domestic currency.

We define real interest rates as long term interest rates (usually 10-year government bond yield) adjusted by a change in CPI from the last year. Specifically, the formula used to calculate the real interest rates is $RIR_{i,t} = \frac{1+bond_{i,t}}{1+\Delta CPI_{t,t-52}}$, where $\Delta CPI_{t,t-52}$ present the rate change from year to year. I obtain the variable by log of quotient of two countries' real interest rates, expressed as $RIRD_{i,t} = \ln(\frac{RIR_t^{US}}{RIR_{i,t}})$. And then, I denote the cross-sectional standardization form of this variable as $rird_{i,t}$.

Relative Price of Non-traded to Traded Goods (Productivity):

If domestic average productivity is higher than foreign economy, the domestic inflation will be higher, and then typically lead to results in an appreciation of the domestic currency. This is associated with the Balassa-Samuelson effect. This effect states that when growth of productivity is relatively higher in domestic tradable sector than in non-tradable sector, the wages in the tradable sector tend to increase. Under perfect labour mobility, due to equalization of wages in two sectors, the price of non-tradable goods will increase. This leads to an increase in overall price level in the domestic economy with respect to the foreign economy and higher demand for domestic currency relative to the foreign currency. Finally, appreciation of the real exchange is induced by an increase in productivity.

We define this one as the ratio of CPI to domestic wholesale or producer price index (PPI), and denote it as $TNT_{i,t} = (\frac{CPI_{i,t}}{PPI_{i,t}})$. And then, I calculate variables in log as formula of $TNTD_{i,t} = \ln(\frac{TNT_t^{US}}{TNT_{i,t}})$. Finally, the cross-sectional standardization form of $TNTD_{i,t}$ is denoted as $tntd_{i,t}$

Term of Trade:

The term of trade is a ratio of export price to import price, which is related to current accounts and the balance of payments. In a phenomenon of positive shock to term of trade (a greater rise of export price than risk of import price), rising exports revenues provide increased demand for the country's currency, which leads to appreciation.

We denote export and import price index as $EXPRIN_{i,t}$ and $IMPRIN_{i,t}$, respectively. So, I define terms of trade as $TOT_{i,t} = \frac{EXPRIN_{i,t}}{IMPRIN_{i,t}}$, and the variable is calculated in logs by $TOTD_{i,t} = \ln(\frac{TOT_t^{US}}{TOT_{i,t}})$. Again, I need cross-sectional standardization form of this variable, which denote as $totd_{i,t}$.

Government Consumption:

In the short run, the greater government consumption will induce greater demand of non-tradable goods, which then increases the overall domestic price level. Consequently, an appreciation occurs. But, in the long run, growing consumption means more budget deficit, which could be considered as an unstable economy leading to depreciation.

We consider this variable as log of the ratio of the US government expense, $EXPEN_t^{US}$, to foreign government expense, $EXPEN_{i,t}$, and the government expense is defined as a ratio of government consumption, $GOV_{i,t}$, to nominal GDP, $GDP_{i,t}$. The formula is as follows:

$$GC_{i,t} = \ln(\frac{EXPEN_t^{US}}{EXPEN_{i,t}}) \text{, where } EXPEN_{i,t} = \frac{GOV_{i,t}}{GDP_{i,t}} .$$

After conducting cross-sectional standardization, the variable is $gc_{i,t}$.

6.4 Empirical Analysis

6.4.1 Pre-sample Test

Before conducting out-of-sample analysis, I would like to test the relevance between variables and weights. To do this, I divide this subsection into two parts. In the first part, I conduct an in-sample analysis for the period from November 1992 to October 1997. I apply PPP portfolios with different variable classes to compare their performance. These classes include seven classes, which only contain single variable respectively, and one class contains three variables responding to financial characteristics, and one class contains four variables responding to fundamental characteristics, and the final class contains all seven variables. So, I have ten PPP portfolios in total. In the second part, I perform a bootstrap to obtain the p-value of coefficients to make sure that the coefficients are different from zero. Specifically, I re-sample 1000 random samples of the same size as the original, drawn with replacement from original sample. Then, I re-estimate coefficient of variables for each sample. After this, the distribution of coefficient is constructed, and the p-value is based on student t-statistics with null hypothesis of zero mean.

6.4.1.1 In sample Analysis

The results of the performance of ten PPP portfolios are shown in

Table 6.1. According to the Sharpe ratio, the carry trade delivers the best performance in all single variable strategies related to financial predictors, with Sharpe ratio of 0.074. But, carry trade strategy has more crash risk than others, because of higher Kurtosis and left-skewness, as well as the lowest minimum return. When I consider combining three financial predictors (including carry trade, currency momentum and currency value) in a strategy, the improvement of Sharp ratio with an increase of almost 30%, compared to carry trade strategy, is significant.

As far as fundamental predictors are concerned, the strategy with productivity predictor (tntd) has the largest Sharpe ratio of 0.177. Moreover, these four strategies have similar crash risk, except productivity strategy with minimum return of -8.65%. To combine four fundamental predictors together, I construct a portfolio which improves Sharpe ratio by 23% compare to productivity strategy. However, it has significant potential risk to crash, based on extremely large kurtosis. Then, the risk is reduced by adding three financial predictors. Compared to the strategy with three financial predictors, the strategy including all variables increases the Sharpe ratio by only 5%. Although, in terms of Sharpe ratio, financial predictors do not improve this strategy too much, the crash risk is reduced. Especially, kurtosis indicated 21% crash risk reduced. After analysing performance of all strategies, I may suggest that there is evidence to support relevance of variables. The more evidence needed is related to statistical significance of coefficients of variables.

Table 6.1 performance of each strategy for in sample analysis

This table shows the in sample performance of investment strategies for the period of pre-sample (1992-1997). The aversion coefficient used in CRRA utility is five. The 'max' and 'min' represent the maximum and minimum of one week return in the sample. The 'mean' is the average return of sample weekly return. The standard deviation, kurtosis and skewness have abbreviation as 'Std', 'Kurt' and 'Skew' in this table respectively. The 'SR' stands for Sharpe ratio. The first 7 rows show the results of a strategy based on using only one characteristic as variable at a time. The next 2 rows show the results of a strategy combining different variables. The last row shows the results of a strategy combining all variable simultaneously. See description of the characteristics variables in the text.

Variable	Max	Min	Mean	Std	Kurt	Skew	SR
ct	7.91%	-14.57%	0.20%	2.71%	6.499	-0.880	0.074
cm	6.93%	-6.34%	0.04%	1.43%	7.542	-0.186	0.031
cv	6.02%	-4.83%	0.09%	1.55%	4.259	0.388	0.055
rird	2.62%	-6.78%	0.03%	1.20%	6.687	-1.067	0.025
tntd	12.88%	-8.65%	0.54%	3.05%	4.156	-0.047	0.177
totd	2.42%	-2.44%	0.01%	0.76%	4.110	-0.044	0.017
gc	1.89%	-2.59%	0.01%	0.57%	4.233	-0.209	0.018
ct,cm,cv	12.74%	-11.20%	0.31%	3.41%	4.156	-0.013	0.091
rird,tntd,totd,gc	37.52%	-9.99%	1.06%	4.89%	14.600	1.675	0.218
all	44.81%	-14.92%	1.44%	6.29%	11.487	1.518	0.229

6.4.1.2 P-value of Bootstrap

Table 6.2 summarises the statistical significance of coefficients of variables for both single variable and combination strategies. For single variable strategies, coefficients of all variables are significant at 2% level. Moreover, considering combined strategies for financial predictors, I conclude that the coefficients are statistically significantly different from zero, according to p-value of zero. I have known that Burnside et al. (2011) give explanations of profitability of carry trade and momentum strategies. Comprehensive evidence on the return premium to value and momentum strategies is provided by Asness et al. (2013). Barroso and Santa-Clara (2011) also prove that the carry trade, momentum and value are strong relevant to optimal portfolio. Furthermore, for a strategy with fundamental predictors, p-values of coefficients of these variables are zero. The economic factors determine the exchange rate, and therefore have connection to the return of currency. These factors can be used to construct optimal portfolio. Moreover, the zero p-values confirm that the variables responding to these economic factors are relevant to PPP portfolio. After considering all predictors in a strategy, the p-value of zero displays all coefficients are different from zero in statistically significant level.

The statistical significance of coefficients of variables confirms the conclusion made previously. All variables are relevant for the optimization. I will apply all characteristics (including both financial predictors and fundamentals) in my parametric portfolio policy for out-of-sample practice.

Table 6.2 coefficients of variables and their p-value from a bootstrap process

This table shows the coefficient estimates and bootstrapped p-value (in brackets). To obtain the p-value, I randomly draw 260 times with replacement from original sample to generate a new sample of the same size as the original sample. Then I re-estimate the optimal coefficient for a new sample. I repeat this step 1000 times to have 1000 random samples and 1000 coefficients, and this is distribution of coefficient. The p-value is based on student t-statistics with null hypothesis of zero mean. 'ct' is carry trade (forward discount). 'cm' is currency momentum (short term return). 'cv' is currency value (long term return). 'rird' is real interest rate differential. 'tntd' is productivity differential. 'totd' is term of trade differential. 'gc' is government consumption differential.

strategy	ct	cm	cv	rird	tntd	totd	gc
ct	-5.93 (0.00)	- -	- -	- -	- -	- -	- -
cm	- -	2.33 (0.00)	- -	- -	- -	- -	- -
cv	- -	- -	-3.63 0.02	-	- -	- -	- -
rird	- -	- -	- -	3.08 (0.00)	- -	- -	- -
tntd	- -	- -	- -	- -	7.73 (0.00)	- -	- -
totd	- -	- -	- -	- -	- -	-0.61 (0.00)	- -
gc	- -	- -	- -	- -	- -	- -	1.49 ((0.00)
ct,cm,cv	-6.36 (0.00)	2.60 (0.00)	-3.18 (0.00)	- -	- -	- -	- -
rird,tntd,totd,gc	- -	- -	- -	5.18 (0.00)	14.60 (0.00)	-2.11 (0.00)	5.47 (0.00)
all	-2.70 (0.00)	0.54 (0.00)	-7.62 (0.00)	7.29 (0.00)	16.11 (0.00)	-5.63 (0.00)	7.73 (0.00)

6.4.2 Out-of-sample Analysis

In this section, an out-of-sample analysis is performed to check robustness of the selected strategies. Parameters for parametric portfolio policy are estimated by initial 260 weeks of the sample, which is 5 years from 11.1992-11.1997. The first portfolio is constructed using these parameters. I then re-estimate parameters every week, using an expanding estimation window until the end of the sample, 30/12/2014. Expending estimation window, unlike rolling window I have done in the last two chapters, adds new week data into window, but not drop the oldest data. The reason I use expending window rather than rolling window is to minimise the problem of look-ahead bias, which led by delaying availability of fundamental predictors.

As discussed in the section of pre-sample analysis, all seven variables are incorporated into optimization strategy. But, taking in isolation, there are two additional optimization strategies considered as well. One only includes three financial predictors, and the other one only includes four fundamental predictors. Thus, I can find out which kind of predictors has contribution for the portfolios. Besides three PPP strategies, I also perform other optimization strategies for comparing, as well as benchmark naïve portfolio. Mean-variance strategy is considered as it is a cornerstone of modern portfolio theory. I also perform minimum-variance portfolio, because it has good performance in chapter one analysis. Optimal constraints portfolio discussed in chapter two beats most other portfolios. In addition to simple application, again, there is another reason that naïve portfolio is treated as the benchmark portfolio. This is from the conclusion of chapter one, which states that no optimal strategies can beat naïve portfolio consistently for all terms of evaluation. So, the first part of this section analyses the PPP strategy, which uses naïve weights as benchmark weights and apply CRRA utility function to estimate coefficients. Because the motivation of this research is to find out optimal weights derived from naïve weights by active components (financial and fundamental predictors), in order to test if the active components work, I compare performance of naïve portfolio to PPP strategies. As already introduced, I also try to use VT portfolio weights as benchmark weights in PPP strategy. This analysis is done in the second part of this section. In addition, I minimise variance of portfolio return to estimate coefficients in the third part of this section.

Due to the fact that economic factors of most developing countries are not available for the whole period from 1992 to 2014, I only investigate the PPP portfolio for G10 currencies for this period. Then, I conduct robustness check analysis based on the perspectives of investors from different countries.

6.4.2.1 Basic Case

Table 6.3 shows the results of PPP portfolio with my first scenario, which adjusts portfolio weights from naïve weights and estimate coefficients by maximising constant relative risk aversion (CRRA) utility function. In addition to performance of this portfolio, the table also gives the results of naïve portfolio and other optimal portfolios to make comparison. As far as PPP portfolio with financial predictors is concerned, although the Sharpe ratio of it is higher than that of naïve portfolio, the p-value of 0.49 indicates that there is not statistically significantly different between two ratios. CEQ of 1.11% for naïve portfolio means that investors would like to choose naïve portfolio when certain return is lower than 1.11%. But, CEQ for PPP portfolio with financial predictors indicates that this certain return is 2.04%. So, when there is a certain return between 1.11% and 2.04% in the universe of investment, the investor will choose this PPP portfolio rather than naïve portfolio. Downside risks are higher for PPP portfolio with financial predictors than naïve portfolio. Moreover, they have the same Calmar ratios. Therefore, only CEQ supports PPP portfolio with financial predictors, but other evaluations display that naïve portfolio performs better than PPP portfolio with financial predictors.

To consider only four fundamental predictors, I find that the performance of this PPP portfolio is better than that of naïve portfolio, as well as PPP portfolio with financial predictors. According to p-value and return-loss, I can see that Sharpe ratio of PPP portfolio with fundamental predictors is statistically significantly higher than Sharpe ratio of naïve portfolio. CEQ of 5.20% indicates that investors more prefer this portfolio than naïve portfolio and PPP portfolio with financial predictors, when universe of investment has certain return less than 5.20%. PPP portfolio with fundamental predictors, indeed, has higher downside risks than naïve portfolio has. But, this portfolio has Calmar ratio of 0.13 which is higher than 0.06 for naïve portfolio. So, considering both of return and risk, PPP portfolio with fundamental predictors performs better than naïve portfolio and PPP portfolio with financial predictors.

For the strategy I combine all predictors, the performance is not improved and even gets worse. The PPP portfolio's Sharpe ratio decreases from 0.33 for fundamental predictors, to 0.20 for financial predictors, and finally to 0.18 for all predictors (For comparison, Sharpe ratio of naïve portfolio is 0.18). CEQ return of the portfolio, with all predictors, drops to 1.27% from 5.20% for fundamental predictors. This means that the investor only chooses PPP portfolio with all predictors when the highest certain return in the universe of investment is less than 1.27%. Moreover, the downside risks increase, and Calmar ratio decreases. Compared to naïve portfolio, most of evaluation indices show that PPP portfolio with all predictors cannot beat naïve portfolio.

Table 6.3 Performance of portfolios related to naïve portfolio

This table documents the evaluation of performance of PPP portfolios for US investor's. This means that the US dollar is used as the as the base currency. I maximise the CRRA utility to estimate the coefficients, and treated naïve weights as benchmark weights. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'vs 1/N' means that optimal portfolio compare with naïve portfolio. In this category, there are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the 1/N, another one is called 're-loss' refer to return-loss. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost. The second part documents the performance after taking account of transaction cost. For each part, I report seven portfolios. The '1/N' refers to naïve portfolio, which is equally-weighted. 'PPP' represents three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'. 'Other' represents other optimal portfolios, including sample based mean-variance portfolio as 'Mean-var', minimum-variance portfolio as 'Min-var' and optimal constrained portfolio as 'OC'.

		SR	vs 1/N		CEQ	VaR	CVaR	DD		Turnover
			p-value	**re-loss**				**MDD**	**CR**	
				No transaction cost						
1/N		0.18	1.00	0.00%	1.11%	1.81%	2.41%	25.16%	0.06	0.01
PPP	**Financial**	0.20	0.49	-0.48%	2.04%	4.19%	6.32%	56.75%	0.06	0.53
	Fundamental	0.33	0.00	-3.89%	5.20%	5.32%	8.11%	62.68%	0.13	0.75
	All	0.18	0.95	-0.07%	1.27%	5.83%	8.64%	68.69%	0.07	1.03
Other	**Mean-var**	-0.01	0.00	46.62%	-304.41%	9.74%	47.01%	N/A	-0.02	382.02
	Min-var	0.08	0.00	0.65%	0.31%	1.42%	1.98%	21.76%	0.03	0.02
	OC	0.10	0.00	0.51%	0.48%	1.44%	2.03%	22.86%	0.03	0.03
				with transaction cost						
Naïve		0.17	1.00	0.00%	1.10%	1.81%	2.41%	25.23%	0.06	-
PPP	**Financial**	0.19	0.70	-0.24%	1.77%	3.85%	5.91%	54.56%	0.06	-
	Fundamental	0.29	0.01	-2.72%	4.08%	5.05%	7.76%	60.11%	0.11	-
	All	0.14	0.39	0.81%	0.45%	5.42%	8.23%	67.61%	0.05	-
Other	**Mean-var**	-0.25	0.00	1232.88%	-42679.14%	10.05%	313.37%	N/A	-6.88	-
	Min-var	0.08	0.00	0.67%	0.29%	1.42%	1.98%	21.81%	0.02	-
	OC	0.10	0.00	0.55%	0.42%	1.44%	2.04%	22.95%	0.03	-

With respect to other optimal portfolios, they cannot outperform naïve portfolio in terms of considering both return and risk. Because of negative Sharpe ratio and Calmar ratio and ridiculous downside risk, sample based mean-variance portfolio performs the worst among all portfolio strategies. Moreover, its CEQ return indicates that investor will never choose this portfolio, due to the fact that certain returns will always be higher than -304.41%. Another two optimal portfolios reported here do not have better performance than naïve portfolio for some terms of evaluation. So, if I take account of both return and risk to evaluate the performance, these two optimal portfolios cannot outperform all PPP portfolios.

The transaction cost impact on the performance of some portfolios in a way. In addition to high level turnover of sample-based mean-variance portfolio, the PPP portfolios also have a large turnover. Although transaction cost leads to the fact that Sharpe ratio of PPP portfolio, with fundamental predictors decreasing from 0.33 to 0.29 and its Calmar ratio decreases from 0.13 to 0.11, these two ratios are still higher than those of naïve portfolio. Furthermore, p-value of 0.01 indicates that Sharpe ratios of naïve portfolio and PPP portfolio with fundamental predictors have statistically significant difference. However, transaction cost makes PPP portfolio with all predictors have a lower Sharpe ratio and Calmar ratio than naïve portfolio has. There is no significant effect on three portfolios, including naïve portfolio, minimum variance portfolio and OC portfolio. From the table, I can find that downside risks of three PPP portfolios decrease slightly after taking account of transaction costs. This is an unusual situation when I investigate the effect of transaction cost in the last two chapters. For other optimal portfolios, I remove the trading cost for the returns of portfolio when I evaluate them, then the downside risks should increase. In previous cases and after taking transaction cost, the portfolios are the same, and the only difference is whether or not I should remove the trading cost. But, for the PPP portfolios, I also take account of transaction cost when estimating the coefficients to construct portfolios. So, there are two different portfolios in the cases before and after taking transaction cost. The new portfolio may have lower downside risks than the original one. After taking transaction cost in evaluation process, the downside risks of new portfolio can still be lower than those of original portfolio.

6.4.2.2 Benchmark as Volatility Timing Portfolio

In this section, I consider weights of volatility timing (VT) portfolio as benchmark in PPP strategy, and keep constant relative risk aversion (CRRA) utility function in estimation process. In addition, I also investigate the performance of VT portfolio for comparison. The results, shown in Table 6.4, are similar to the last section. Therefore, the conclusions also are similar to the last section.

Although negative CEQ return means that the investor will never choose VT portfolio, other evaluation indices support VT portfolio rather than PPP portfolio with financial predictors. Sharpe ratio of PPP portfolio with financial predictors is 0.19, higher than 0.16 for Sharpe ratio of VT portfolio. But, p-value indicates that there is no statistically significant difference between two Sharpe ratios. PPP portfolio with financial predictors has much more downside risk than VT portfolio has, and both portfolios have almost similar Calmar ratio.

As far as four fundamental predictors are concerned, PPP portfolio has better performance than VT portfolio has, if the investor cares about trade-off between return and risk. Comparing to VT portfolio, which Sharpe and Calmar ratios of 0.16 and 0.05 respectively, Sharpe ratio of 0.33 and Calmar ratio of 0.13 for PPP portfolio with fundamental predictors are very high. P-value also confirms that Sharp ratios for two portfolios have statistically significant difference. However, if only downside risks are concerned, they are higher for this PPP portfolio than VT portfolio.

Table 6.4 Performance of portfolios related to volatility timing portfolio

This table documents the evaluation of performance of PPP portfolios for US investor's perspective. This means that I treated US dollar as the based currency. I maximise the CRRA utility to estimate the coefficients, and treated VT portfolio weights as benchmark weights. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'vs VT' means that optimal portfolio compare with VT portfolio. In this category, there are two comparisons; one is called 'p-val', which is the p-value of difference between the Sharpe ratio of each strategy from that of the VT portfolio, another one is called 're-loss' refer to return-loss. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost. The second part documents the performance after taking account of transaction cost. For each part, I report four portfolios. The 'VT' refers to volatility timing portfolio, which is introduced in the last chapter. 'PPP' represents three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'.

		SR	vs VT		CEQ	VaR	CVaR	DD		turnover
			p-value	**re-loss**				**MDD**	**CR**	
No transaction cost										
VT		0.16	1.00	0.00%	-0.21%	1.61%	2.21%	23.17%	0.05	0.01
PPP	**Financial**	0.19	0.45	-0.51%	1.73%	3.90%	6.24%	57.13%	0.06	0.52
	Fundamental	0.33	0.00	-4.14%	5.00%	5.29%	8.05%	62.73%	0.13	0.74
	All	0.17	0.72	-0.37%	1.09%	5.75%	8.57%	68.77%	0.06	1.03
with transaction cost										
VT		0.16	1.00	0.00%	-0.23%	1.61%	2.21%	23.19%	0.05	-
PPP	**Financial**	0.17	0.60	-0.31%	1.51%	3.68%	5.82%	54.96%	0.05	-
	Fundamental	0.29	0.01	-3.13%	4.03%	4.99%	7.76%	60.66%	0.11	-
	All	0.13	0.58	0.50%	0.30%	5.41%	8.15%	68.03%	0.05	-

If all predictors are considered in one strategy, the performance for this portfolio is getting worse in all terms of evaluation indices. The Sharpe ratio and Calmar ratio of PPP portfolio drop from 0.33 and 0.13 for financial predictors to 0.17 and 0.06 for all predictors, respectively. Change of CEQ indicates that the certain return investor is expecting decreases from 5% to 1.09%. Moreover, all downside risks of PPP portfolio increase, when the strategy considers both financial and fundamental predictors together.

With a high level of turnover for all three PPP portfolios, the transaction cost has impact on their performances, especially Sharpe ratios, but the conclusions remain the same. Due to low level of turnover, all evaluation indices for VT portfolio are almost unchanged. For PPP portfolios, these evaluation indices are not unchanged. For example, turnover of 1.03 makes Sharpe ratio of PPP portfolio with all predictors to decrease from 0.17 to 0.13, and CEQ drops from 1.09% to 0.3%. However, these impacts are not enough to change the conclusion made about rankings of performance.

According to the discussion in this and the last sections, I find that Fundamental characteristics can help investors to improve benchmark portfolio by applying PPP strategy. Financial characteristics cannot give investor benefits of active portfolio management in out-of-sample analysis. Moreover, considering both two classes of characteristics together do not boost the performance of the portfolio, even lead to worse performance than considering two classes of characteristics separately. In addition, I realise that the choice of benchmark portfolio is not very important to the performance of PPP portfolio, as long as they have similar features.

6.4.2.3 Minimizing Variance of Return of Portfolio

In this subsection, I estimate coefficients for PPP strategy by minimizing variance of return of portfolio instead of maximising CRRA utility function. I consider both of two cases about benchmark portfolio weights. One is to assume that benchmark weights equal to naïve weights. For another one, VT portfolio is considered as benchmark portfolio. As illustrated in previous sections, I also report the performance of benchmark portfolios (naïve and VT portfolios) for comparison. The results are shown in Table 6.5. It should be noted that I do not report the results of return-loss in this table, but, instead, I give out two kinds of p-value. The first p-value represents the difference between relative optimal portfolios and naïve portfolio. And, the second p-value is about VT portfolio.

With respect to treating naïve portfolio as benchmark, although the PPP portfolios cannot beat naïve portfolio based on the Sharpe ratio and Calmar ratio, these portfolios are less risky than naïve portfolio. Sharpe ratios indicate that the performance of PPP portfolios is not better than that of naïve portfolio, except PPP portfolio with financial predictors. Especially, zero p-values point out that the difference between their Sharp ratios is statistically significant. Moreover, Calmar ratios also confirm outperformance of naïve portfolio when the investor wants to find trade-off between reward and risk. Nevertheless, because of the fact that the estimation method for coefficients is to minimise variance of return of portfolios, I assume that investors are more concerned about downside risk than return. According to VaR, CVaR and maximum drawdown, I can conclude that three PPP portfolios have lower downside risk than naïve portfolio has. Furthermore, the lowest CEQ return during these three PPP portfolios is 0.48%. This means that the investor will choose these portfolios if certain return is lower than 0.48% annually. In practice, this certain return can be considered as risk free rate. For

Table 6.5 Performance of portfolios related to minimum variance

This table documents the evaluation of performance of PPP portfolios for US investor's perspective. This means that I treated US dollar as the based currency. I minimise variance of return of portfolio to estimate the coefficients. Two cases are reported here. One is that I treat naïve weights as benchmark weights. Another one is treat VT portfolio as benchmark weights. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'p-value' means that p-value of difference between the Sharpe ratio of each strategy from that of relative benchmark portfolio. As I mentioned, there are two benchmark portfolios. 'vs 1/N' 'reports the p-value against naïve portfolio, and 'vs VT' reports the p-value against VT portfolio. I do not report return loss in this table. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost. The second part documents the performance after taking account of transaction cost. For each part, I report eight portfolios. The '1/N' refers to naïve portfolio, which is equally-weighted, and 'VT' refers to volatility timing portfolio, which introduced in the last chapter. The rest of portfolios are divided into two categories. The category of 'Naïve portfolio' includes PPP portfolios which consider naïve weights as benchmark weights. The category of 'VT portfolio' includes PPP portfolios which consider VT portfolio weights as benchmark weights. There are three PPP portfolios included in each category. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'.

		SR	p-value		CEQ	VaR	CVaR	DD		turnover
			vs 1/N	vs VT				MDD	CR	
No transaction cost										
1/N		0.18	1.00	-	1.11%	1.81%	2.41%	25.16%	0.06	0.01
VT		0.16	-	1.00	-0.21%	1.61%	2.21%	23.17%	0.05	0.01
Naïve portfolio	**Financial**	0.18	0.76	-	1.13%	1.77%	2.30%	26.08%	0.06	0.05
	Fundamental	0.11	0.00	-	0.53%	1.57%	2.15%	22.78%	0.03	0.05
	All	0.10	0.00	-	0.48%	1.52%	2.11%	22.18%	0.03	0.07
VT portfolio	**Financial**	0.14	-	0.35	0.76%	1.63%	2.14%	21.93%	0.05	0.04
	Fundamental	0.06	-	0.00	0.18%	1.50%	2.06%	24.56%	0.02	0.03
	All	0.06	-	0.00	0.20%	1.46%	2.03%	23.43%	0.02	0.05
with transaction cost										
Naïve		0.17	1.00	-	1.10%	1.81%	2.41%	25.23%	0.06	-
VT		0.16	-	1.00	-0.23%	1.61%	2.21%	23.19%	0.05	
Naïve portfolio	**Financial**	0.17	0.95	-	1.06%	1.77%	2.31%	26.37%	0.05	-
	Fundamental	0.10	0.00	-	0.13%	1.52%	2.07%	23.49%	0.02	-
	All	0.09	0.00	-	0.37%	1.52%	2.11%	22.41%	0.03	-
VT portfolio	**Financial**	0.13	-	0.16	0.69%	1.63%	2.14%	21.98%	0.04	-
	Fundamental	0.04	-	0.00	0.02%	1.46%	2.02%	24.46%	0.01	-
	All	0.05	-	0.00	0.12%	1.46%	2.04%	23.90%	0.01	-

comparison, I find that annual risk free rates for 1 month and 3 months at the end of 2014 are 0.03% and 0.04% respectively[4]. So, CEQ returns of portfolios can satisfy the investor. It is assumed, the investor may prefer PPP portfolio to naïve portfolio because of low level of downside risk. Therefore, in some ways, this analysis supports PPP portfolios.

In the case of letting benchmark weights equal to VT portfolio weights, the results are not changed much, and the conclusions are almost similar to those of naïve portfolio. P-value indicates that the Sharpe ratios of two PPP portfolios are statistically significantly different from Sharpe ratio of VT portfolio. Based on the Sharpe ratio and Calmar ratio, PPP portfolios do not outperform VT portfolio. But, their downside risks consistently are less than VT portfolio's. And, PPP portfolio with all predictors has the lowest downside risk. Moreover, evaluation about CEQ return supports PPP portfolios. The lowest CEQ return of these PPP portfolios is 0.18%, which is higher than 0.04% risk free rate for 3 month from US T-bill, but CEQ return of VT portfolio is negative. Therefore, like conclusions reached in is more analysis of the first case, with enough CEQ return, the investor, who more concerned with risk than return, may choose PPP portfolio rather than VT portfolio.

Due to lower level of turnover, the transaction cost effect on the performance of PPP portfolios is not significant. The largest turnover for PPP portfolios is 0.07, which is very small, comparing to 1.03 in table 6.3 and table 6.4 which display the performance of PPP portfolios estimated by maximising CRRA utility function. Sharpe ratio after taking account of transaction cost only decreases by 0.01 for all PPP portfolios in both cases. The change of downside risks is also tiny, even some of downside risks is unchanged. Therefore, I can conclude that transaction cost has an impact on the performance of PPP portfolios for the cases in this subsection. Then, the conclusions

[4] These sources are from official website of U.S. Department of the Treasury.

made before taking account of transaction cost are not changed after taking account of transaction cost.

6.4.3 Robustness Check

As done in previous chapters, I also conduct robustness check to test whether my conclusions are consistent with different situations. But, unlike the previous chapter, in this chapter, I only consider perspectives of investors from other countries than US. Because of the fact that I use extending sample rather than rolling sample to estimate coefficients, the robustness check for using different lengths of estimation window will not be very meaningful. If I apply 1 year and 5 years estimation window, for example, the estimation windows will be mainly different in early period. With extending the estimation windows, in later years, the difference will be shrinking. So, the 1 year or 5 years only represents initial length of estimation windows, not length for whole period. Moreover, I use EWMA to weight the historical information. Therefore, the length of initial estimation windows is not very important to this thesis analysis.

6.4.3.1 UK Investors

In this subsection, in order to perform a robustness check, I investigate the performance of PPP portfolio related to the perspectives of investor from the United Kingdom. So, the base currency is Great British pound (GBP) rather than the US dollar. The results are shown in Table 6.6. I report the performance of naïve and VT portfolio in the first two rows for comparison with PPP portfolios. I firstly consider naïve portfolio as benchmark weights, and use CRRA utility function to estimate coefficients. The results of PPP portfolios related to this case (case one) are given out in Panel A. Secondly, I keep estimation method as CRRA, but to use VT portfolios weights to represent benchmark weights. This case is referred as case two, and the results are reported in

Table 6.6 Robustness results for perspective of UK investors

This table documents the evaluation of performance of PPP portfolios for UK investor's perspective. This means that I treated British pound as the base currency. The performance of naïve portfolio and VT portfolio is reported in the first two rows, and referred as '1/N' and 'VT' respectively. I firstly consider naïve weights as benchmark weights, and use CRRA utility function to estimate coefficients. The results of PPP portfolios related to this case are given in Panel A. In Panel B, I keep estimation method as CRRA, but use VT portfolios weights to represent benchmark weights. In Panel C, I report the results of the case, which estimate coefficients by minimizing variance of return of portfolio and treat naïve weights as benchmark weights. For each panel, there are three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'. In the last panel, Panel D, I report the performance of two optimal portfolios, including minimum-variance portfolio as 'Min-var' and optimal constrained portfolio as 'OC'. The right side of table shows the results before taking account of transaction cost. The left side of table shows the results after taking account of transaction cost. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'p-value' means that p-value of difference between the Sharpe ratio of each strategy from that of relative benchmark portfolio. As I mentioned, there are two benchmark portfolios. 'vs Naive' 'reports the p-value against naïve portfolio, and 'vs VT' reports the p-value against VT portfolio. I do not report return loss in this table. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost.

	No transaction cost									With transaction cost							
	SR	P-value vs		CEQ	VaR	CVaR	DD		turnover	SR	P-value vs		CEQ	VaR	CVaR	DD	
		Naive	VT				MDD	CR			Naïve	VT				MDD	CR
1/N	0.14	1.00	-	0.69%	1.38%	1.74%	17.85%	0.05	0.01	0.13	1.00	-	0.67%	1.38%	1.74%	18.04%	0.05
VT	0.10	-	1.00	0.43%	1.28%	1.73%	18.91%	0.03	0.01	0.10	-	1.00	0.41%	1.29%	1.73%	19.11%	0.03
Panel A: Naïve portfolio and CRRA utility function																	
Financial	0.27	0.01	-	3.35%	4.20%	6.33%	42.79%	0.12	0.65	0.22	0.05	-	2.30%	3.83%	5.71%	42.74%	0.09
Fundamental	0.30	0.00	-	4.19%	4.65%	7.28%	46.84%	0.14	0.77	0.23	0.05	-	2.55%	4.48%	6.75%	45.00%	0.10
All	0.25	0.02	-	3.19%	5.83%	8.69%	57.73%	0.11	1.15	0.16	0.58	-	0.95%	5.28%	7.97%	59.43%	0.06
Panel B: VT portfolio and CRRA utility function																	
Financial	0.26	-	0.00	3.05%	4.20%	6.29%	42.65%	0.11	0.64	0.21	-	0.02	2.02%	3.81%	5.67%	42.60%	0.08
Fundamental	0.28	-	0.00	3.66%	4.55%	7.26%	46.33%	0.13	0.77	0.20	-	0.02	2.09%	4.29%	6.73%	43.76%	0.10
All	0.23	-	0.01	2.66%	5.81%	8.63%	57.64%	0.10	1.15	0.14	-	0.36	0.45%	5.31%	7.92%	59.14%	0.05
Panel C: naïve portfolio and minimum variance of return of portfolio																	
Financial	0.20	0.02	-	1.10%	1.40%	1.79%	15.11%	0.09	0.04	0.19	0.03	-	1.01%	1.40%	1.79%	15.17%	0.08
Fundamental	0.18	0.05	-	1.00%	1.39%	1.75%	16.10%	0.08	0.02	0.18	0.06	-	0.96%	1.39%	1.75%	16.36%	0.07
All	0.27	0.00	-	1.60%	1.42%	1.81%	14.75%	0.12	0.05	0.25	0.00	-	1.48%	1.43%	1.82%	14.84%	0.11
Panel D: other optimal strategies																	
Min-var	0.04	0.00	0.00	0.04%	1.31%	1.73%	23.38%	0.01	0.02	0.03	0.00	0.00	0.00%	1.31%	1.73%	23.74%	0.01
OC	0.05	0.00	0.00	0.14%	1.32%	1.74%	22.37%	0.02	0.03	0.04	0.00	0.00	0.07%	1.32%	1.74%	23.04%	0.01

Panel B. Thirdly, In panel C, I report the results of case three, which estimates coefficients by minimizing variance of return of portfolio and treat naïve portfolio as benchmark weights. As discussed before in the analysis of US investors, the choice of benchmark weights is not important to the performance of PPP portfolios. Moreover, from panel A and Panel B of Table 6.6, I also can find that the results for different benchmark weights are similar. So, here, I do not report the results of the case, which consider VT portfolio weights as benchmark weights and use minimum variance to estimate coefficients. Finally, I give the performance of other optimal portfolios, minimum variance and optimal constrained portfolios, in Panel D.

As far as case one is concerned, the results mainly support the conclusions made before from US investor analysis. The PPP portfolio with fundamental predictors has the highest Sharpe ratio, and zero p-value indicates that its Sharpe ratio is statistically higher than naive portfolio's. Moreover, the highest Calmar ratio of 0.14 proves the best performance of this PPP portfolio. CEQ return of PPP portfolio with fundamental predictors indicates that the investor will prefer this portfolio to a certain return if the certain return in universe is less than 4.19%. So, like the analysis based on US investor, if both of return and risk are considered in performance evaluation, the PPP portfolio with fundamental predictors has the best performance. But, downside risks for PPP portfolios are higher than those of naïve portfolio very much. Combining both fundamental and financial predictors in one PPP portfolio cannot improve the performance. Its Sharpe ratio, Calmar ratio and CEQ return decrease, and downside risks are increased. In addition to these consistent conclusions, there is one conclusion, which is not consistent to the analysis based on US investor. Although the performance of PPP portfolio is getting worse after considering all predictors together, it still has better performance than naïve portfolio based on the evaluation related to trade-off of return and risk. Due to high level of turnover for PPP portfolios, the performance of these portfolios has obvious drop. For example, Sharpe ratio of the PPP portfolio with all predictors decreases from 0.25 to 0.16. And, P-value of 0.58 indicates that its Sharpe ratio is no longer statistically significantly different from naïve portfolio's Sharpe ratio.

With respect to case two, the conclusion is also consistent to the analysis based on the perspective of US investor, which is that the choice of benchmark is not important to the performance of PPP portfolios. On the other hand, the values of various evaluation indices are not changed too much. The largest differences of Sharpe ratio and Calmar ratio between case one and two are 0.02 out of 0.25 and 0.01 out of 0.11 respectively. Especially, for downside risk, VaR of PPP portfolio with financial predictors stay at 4.20% in both cases, and the biggest change, 0.5% out of 46.84%, happens on maximum drawdown of PPP portfolio with fundamental predictors. On the other hand, the main conclusions are the same for case one and case two. Combining both classes of predictors together cannot improve the performance of PPP portfolio in any term of evaluation. Moreover, all PPP portfolios also have better performance than benchmark portfolio (here, referred to VT portfolio) if both risk and return are considered in evaluation, but downside risk is higher for PPP portfolios than VT portfolios. Transaction cost leads to a significant decrease in Sharpe ratio, then p-value of 0.36 indicates that the difference of Sharpe ratio between PPP portfolio with all predictors and VT portfolio is not statistically significant. So, the choice of benchmark weights is not relevant to efficiency of characteristics of currency in PPP portfolio strategy as long as the benchmark portfolios have similar features.

In response to case three, I find some inconsistent conclusions to the analysis based on the perspective of US investor. Firstly, Sharpe ratios of PPP portfolios are all higher than naïve portfolio, and these differences are statistically significant at confidence level of 95% according to p-values. The lowest Calmar ratio of PPP portfolios is 0.09, which is higher than that of naïve portfolio. CEQ returns indicate that the investor will choose PPP portfolios if certain return is between 0.69% and 1.00%. Secondly, although VaR and CVaR do not support PPP portfolios, downside risk related to maximum drawdown prefer PPP portfolio to naïve portfolio. Finally, according to Sharpe ratios, Calmar ratios and CEQ returns, the performance of PPP portfolio is improved by considering all characteristics of currency together. In addition to these inconsistent conclusions, there is a consistent conclusion. Due to low turnover, the transaction cost has little effect on the performance of PPP portfolios. There are tiny decreases/increases after taking account of transaction cost for all evaluation indices.

Like results from the perspective of US investor, the two optimal portfolios, minimum-variance portfolio and constrained optimal portfolio, cannot beat two benchmark portfolios. Their Sharp ratios are lower than naïve and VT portfolios' very much. Moreover, the CEQ return and Calmar ratio also prove this underperformance. Although they have very similar value at risk and conditional value at risk, the maximum drawdowns of benchmark portfolios are higher than these two optimal portfolios.

6.4.3.2 Japanese Investors

Here, I focus on the perspectives of Japanese investor to conduct an analysis of PPP portfolios. So, now, the Japanese yen is a based currency. And, the results are shown in Table 6.7. The format of this table is similar to the format of Table 6.6. Besides naïve portfolio and VT portfolio, in four panels, I report the performances related to three cases of PPP portfolios and two other optimal portfolios.

Table 6.7 Robustness results for perspective of JP investors

This table documents the evaluation of performance of PPP portfolios for Japanese investor's perspective. This means that I treated Japanese yen as the base currency. The performance of naïve portfolio and VT portfolio is reported in the first two rows, and referred as '1/N' and 'VT' respectively. I firstly consider naïve weights as benchmark weights, and use CRRA utility function to estimate coefficients. The results of PPP portfolios related to this case are given in Panel A. In Panel B, I keep estimation method as CRRA, but use VT portfolios weights to represent benchmark weights. In Panel C, I report the results of the case, which estimate coefficients by minimizing variance of return of portfolio and treat naïve weights as benchmark weights. For each panel, there are three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'. In the last panel, Panel D, I report the performance of two optimal portfolios, including minimum-variance portfolio as 'Min-var' and optimal constrained portfolio as 'OC'. The right side of table shows the results before taking account of transaction cost. The left side of table shows the results after taking account of transaction cost. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'p-value' means that p-value of difference between the Sharpe ratio of each strategy from that of relative benchmark portfolio. As I mentioned, there are two benchmark portfolios. 'vs 1/N' 'reports the p-value against naïve portfolio, and 'vs VT' reports the p-value against VT portfolio. I do not report return loss in this table. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost.

	No transaction cost									With transaction cost							
	SR	p-value		CEQ	VaR	CVaR	DD		turnover	SR	p-value		CEQ	VaR	CVaR	DD	
		Naïve	VT				MDD	CR			Naïve	VT				MDD	CR
Navie	0.39	1.00	-	3.87%	2.66%	3.82%	35.04%	0.13	0.01	0.38	1.00	-	3.84%	2.66%	3.82%	35.07%	0.13
VT	0.37	-	1.00	3.40%	2.42%	3.50%	32.26%	0.12	0.01	0.36	-	1.00	3.38%	2.42%	3.50%	32.32%	0.12
Panel A: Naïve portfolio and CRRA utility function																	
Financial	0.38	0.84	-	5.55%	4.52%	6.90%	60.79%	0.12	0.50	0.31	0.18	-	3.21%	4.16%	6.17%	56.67%	0.09
Fundamental	0.47	0.13	-	9.05%	5.82%	8.99%	66.40%	0.19	0.86	0.38	0.85	-	6.20%	5.24%	8.15%	64.81%	0.14
All	0.47	0.14	-	9.76%	6.68%	10.54%	73.84%	0.20	1.18	0.39	0.98	-	6.87%	6.00%	9.46%	71.52%	0.15
Panel B: VT portfolio and CRRA utility function																	
Financial	0.38	-	0.76	5.55%	4.47%	6.80%	60.26%	0.12	0.51	0.30	-	0.29	3.11%	3.96%	6.07%	56.23%	0.09
Fundamental	0.46	-	0.10	8.77%	5.69%	8.94%	65.68%	0.19	0.85	0.37	-	0.96	5.94%	5.19%	8.08%	63.91%	0.14
All	0.46	-	0.09	9.58%	6.77%	10.48%	73.51%	0.20	1.18	0.38	-	0.74	6.70%	5.97%	9.38%	71.10%	0.15
Panel C: naïve portfolio and minimum variance of return of portfolio																	
Financial	0.28	0.00	-	2.41%	2.43%	3.48%	39.10%	0.08	0.10	0.25	0.00	-	2.15%	2.44%	3.49%	39.98%	0.07
Fundamental	0.30	0.01	-	2.58%	2.38%	3.22%	38.57%	0.08	0.05	0.29	0.00	-	2.48%	2.38%	3.23%	39.07%	0.08
All	0.23	0.00	-	1.84%	2.34%	3.21%	41.59%	0.06	0.11	0.20	0.00	-	1.59%	2.34%	3.22%	42.37%	0.05
Panel D: other optimal strategies																	
Min-var	0.39	0.96	0.59	3.34%	2.17%	3.07%	33.98%	0.11	0.03	0.38	0.92	0.69	3.26%	2.17%	3.07%	34.25%	0.11
OC	0.36	0.44	0.81	3.16%	2.31%	3.36%	33.61%	0.11	0.05	0.34	0.28	0.59	3.03%	2.31%	3.36%	33.95%	0.11

The results for the case one give out some conclusions, which are partly inconsistent with the analysis based on US investor. According to p-value, I find that all Sharpe ratios of PPP portfolios cannot be considered to be statistically significantly higher than that of naïve portfolio anymore. Therefore, after trading off between return and risk, I cannot conclude that PPP portfolio with fundamental predictors completely beat naïve portfolio, although CEQ return and Calmar ratio support PPP portfolios. PPP portfolio with all predictors has slightly higher CEQ return and Calmar ratio than PPP portfolio with fundamental predictors has. This proves that considering all characteristics together in the policy somehow improves the performance of PPP portfolio. In addition to two inconsistent conclusions above, the conclusions related to other aspects are consistent with the analysis based on US investor. For example, PPP portfolios have more downside risk than naïve portfolio has.

Comparing results in panel A to Panel B, I find that conclusion about the choice of benchmark portfolio is similar to that in the analysis based on US investor. The changes of values of all evaluation indices are not significant. Then, the conclusions made in case one are also confirmed in case two. Therefore, the choice among different portfolios for benchmark weights is not important for this thesis conclusion. Because of a high level of turnover in both cases, transaction cost has obvious effect on the performance of PPP portfolios. Especially, Sharpe ratios and Calmar ratios drop by around 20% to 25%, and CEQ returns decrease by almost 50%. But, same as the analysis based on US investor, these drops cannot change the conclusions made before taking account of transaction cost.

After I move on to case three, I find that the results from Panel C display similar conclusions to the analysis based on US investor. PPP portfolios can only be supported by evaluations related to value at risk and conditional value at risk. Other terms of evaluation show underperformance of PPP portfolios. According to all terms of evaluation, PPP portfolio with fundamental predictors has the best performance during all three PPP portfolios. CEQ return of this portfolio is 2.58%, which is lower than that of naïve portfolio but higher than risk free rate of Japan. For the reference, I use 3 month 'Gensaki' repo rate as Japanese risk free rate, and at the end of 2014, this rate is around 0.1%. Therefore, based on the CEQ return, the PPP portfolios cannot be rejected by the investor immediately. If the risk of investment is prime consideration to the investor, he may choose PPP portfolio with fundamental predictors rather than naïve portfolio because this portfolio has low downside risk. Moreover, low level of turnover leads to very small effect of transaction cost on the performance of PPP portfolios, thus the conclusions remain unchanged..

6.4.3.3 Euro Zone Investors

In this subsection, I conduct a robustness check based on the perspectives of euro zone investors. So, euro will be treated as the base currency. I use same format as used in the previous two subsections to report the results of this robustness check in Table 6.8. Overall, the conclusions from these results are mostly consistent with the conclusions from analysis based on US investor. In the following paragraphs, I give these consistent conclusions in detail for the three cases.

For case one, the PPP portfolio with fundamental predictors displays an outstanding performance in terms of evaluation related to both risk and return. Firstly, p-value of 0.02 indicates that Sharpe ratio of PPP portfolio with fundamental predictors is statistically significantly higher than Sharpe ratio of naïve portfolio. Although this PPP portfolio has more downside risk than naïve portfolio has, the Calmar ratio of this PPP portfolio is over twice as that of naïve portfolio. Secondly, PPP portfolio with financial predictors has a Sharpe ratio, which is not statistically significantly different from

Table 6.8 Robustness results for perspective of Euro investors

This table documents the evaluation of performance of PPP portfolios for euro zone investor's perspective. This means that I treated euro as the based currency. The performance of na ïve portfolio and VT portfolio is reported in the first two rows, and referred as '1/N' and 'VT' respectively. I firstly consider na ïve weights as benchmark weights, and use CRRA utility function to estimate coefficients. The results of PPP portfolios related to this case are given in Panel A. In Panel B, I keep estimation method as CRRA, but use VT portfolios weights to represent benchmark weights. In Panel C, I report the results of the case, which estimate coefficients by minimizing variance of return of portfolio and treat na ïve weights as benchmark weights. For each panel, there are three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'. In the last panel, Panel D, I report the performance of two optimal portfolios, including minimum-variance portfolio as 'Min-var' and optimal constrained portfolio as 'OC'. The right side of table shows the results before taking account of transaction cost. The left side of table shows the results after taking account of transaction cost. The first column, referred as 'SR', reports the annualised Sharpe ratio of portfolios. In the next two columns, 'p-value' means that p-value of difference between the Sharpe ratio of each strategy from that of relative benchmark portfolio. As I mentioned, there are two benchmark portfolios. 'vs 1/N' 'reports the p-value against naïve portfolio, and 'vs VT' reports the p-value against VT portfolio. I do not report return loss in this table. 'CEQ' means annualised certainty-equivalent return with risk aversion of 5. 'VaR' and 'CVaR' mean weekly Value at risk and weekly conditional value at risk, which both are computed at possibility of 95% with historical sample approach. I report two evaluation indices relevant to drawdown. One is maximum drawdown referred as 'MDD', another one is Calmar ratio referred as 'CR'. Except VaR, CVaR and maximum drawdown, the results of all other indices are annualised. In addition, I report turnover only in the part of no transaction cost. I divided this table into two parts. The first part documents the performance of portfolios without transaction cost.

	No transaction cost									**With transaction cost**							
	SR	**p-value**		**CEQ**	**VaR**	**CVaR**	**DD**		**turnover**	**SR**	**p-value**		**CEQ**	**VaR**	**CVaR**	**DD**	
		Na ïve	**VT**				**MDD**	**CR**			**Na ïve**	**VT**				**MDD**	**CR**
Navie	0.21	1.00	-	1.03%	1.22%	1.65%	20.61%	0.06	0.01	0.21	1.00	-	1.01%	1.22%	1.65%	20.71%	0.06
VT	0.15	-	1.00	0.51%	0.76%	1.18%	18.96%	0.03	0.01	0.15	-	1.00	0.49%	0.76%	1.18%	19.04%	0.03
Panel A: Na ïve portfolio and CRRA utility function																	
Financial	0.30	0.11	-	3.71%	3.89%	6.16%	55.60%	0.09	0.59	0.27	0.20	-	3.09%	3.51%	5.72%	53.28%	0.08
Fundamental	0.37	0.02	-	5.80%	4.74%	7.73%	58.70%	0.14	0.72	0.30	0.11	-	4.13%	4.41%	7.31%	59.27%	0.11
All	0.27	0.28	-	3.64%	5.66%	8.94%	67.39%	0.10	1.08	0.20	0.92	-	1.94%	5.29%	8.27%	66.00%	0.07
Panel B: VT portfolio and CRRA utility function																	
Financial	0.30	-	0.03	3.68%	3.81%	6.12%	55.70%	0.09	0.58	0.28	-	0.04	3.09%	3.52%	5.64%	53.41%	0.08
Fundamental	0.34	-	0.01	5.15%	4.90%	7.72%	57.50%	0.13	0.73	0.27	-	0.05	3.49%	4.51%	7.23%	56.59%	0.10
All	0.25	-	0.13	3.01%	5.46%	8.82%	66.79%	0.09	1.07	0.17	-	0.61	1.34%	5.12%	8.11%	65.35%	0.06
Panel C: na ïve portfolio and minimum variance of return of portfolio																	
Financial	0.13	0.00	-	0.58%	1.23%	1.66%	23.75%	0.03	0.03	0.12	0.00	-	0.50%	1.23%	1.67%	24.11%	0.03
Fundamental	0.35	0.01	-	1.62%	1.01%	1.41%	16.18%	0.11	0.03	0.34	0.00	-	1.64%	1.06%	1.44%	16.19%	0.11
All	0.37	0.00	-	1.75%	0.98%	1.40%	15.98%	0.12	0.06	0.34	0.01	-	1.61%	0.98%	1.41%	16.73%	0.10
Panel D: other optimal strategies																	
Min-var	0.20	0.85	0.16	0.71%	0.71%	1.21%	19.34%	0.04	0.01	0.20	0.79	0.15	0.69%	0.71%	1.21%	19.42%	0.04
OC	0.19	0.63	0.29	0.73%	0.89%	1.34%	20.83%	0.04	0.03	0.17	0.37	0.42	0.66%	0.89%	1.34%	21.07%	0.04

Sharpe ratio of naïve portfolio. Thirdly, according to decrease of Sharp ratio and increase of downside risk, I find that considering all predictors together does not improve but worsens the performance of PPP portfolio. So, like analysis based on US investor, only PPP portfolio with fundamental predictors has better performance than naïve portfolio has, if both of return and risk are considered in evaluation. From results in panel D, I can find that minimum variance portfolio and optimal constrained portfolio perform better than naïve portfolio. But, Sharpe ratios and Calmar ratios still confirm the best performance of PPP portfolio with fundamental predictors. In addition, high turnover leads to big drop of Sharpe ratio of PPP portfolio with fundamental. The Sharpe ratio decreases from 0.37 to 0.30, and the value of p-value increases to 0.11. So, this means that, after taking account of transaction cost, Sharpe ratio of PPP portfolio with fundamental predictors is no longer higher than that of naïve portfolio in statistically significant difference.

Comparing results of case two to case one, I conclude that the choice of benchmarks is not important to investors who want to apply PPP strategy. The changes of all terms of evaluation can be ignored. From case one to case two, for example, Sharpe ratio of PPP portfolio with fundamental predictor decreases by 0.03 from 0.37 to 0.34, and this decrease is largest during all Sharpe ratios. The biggest change for the value of downside risk is VaR of PPP portfolio with all predictors, which lowers to 5.46% from 5.66%. In addition to these tiny changes of performance evaluation, the changes of turnover are also small. For three PPP portfolios, the turnovers decrease by only 0.01 relative to the smallest value of 0.58. Therefore, after taking account transaction cost, the results of case one are also similar to the results of case two. Because of very small change, the main conclusions in case two are same as the conclusion in case one.

The results in panel C about case three display that, except PPP portfolio with financial predictors, other two PPP portfolios have outperformance over naïve portfolio in all terms of evaluation, and other two optimal portfolios in most terms of evaluation. As far as PPP portfolio with financial predictors is concerned, p-value indicates that its Sharpe ratio is statistically significant lower than Sharpe ratio of naïve portfolio. Other evaluation indices also confirm that naïve portfolio has better performance than it has. However, other two PPP portfolios have larger Sharpe ratios than naïve portfolio has. And, p-value proves that these differences are statistically significantly different. Moreover, their downside risk is consistently less than naïve portfolio's. CEQ return and Calmar ratio also confirm outperformance of PPP portfolio with fundamental predictors and PPP portfolio with all predictors. Comparing to the performance of other optimal portfolios, I find that, except VaR and CVaR, all terms of evaluation show better performance of these two PPP portfolios than minimum-variance portfolio and OC portfolios. Although above conclusions are not consistent with the conclusions from analysis based on US investor, overall, the results of this analysis, here, also support PPP portfolios. In addition, transaction cost does not have significant impact on the performance of the portfolios.

6.4.4 Investigation of Coefficients for Out-of-sample Analysis

After discussing the performance of PPP portfolios, I investigate the coefficients corresponding to various predictors for the out-of-sample analysis in this section. Table 6.9 presents the average of estimated coefficients of PPP portfolios related to the basic case, which treats naïve portfolio weights as benchmark weights and use constant relative risk aversion (CRRA) utility function to estimate coefficients. Besides US investors, I also report these estimated coefficients from robustness check analysis.

According to this investigation, I can find how the predictors affect weights of PPP portfolios.

From the signs of coefficients, I can find that the effects of the predictors on weights are consistent for all portfolios and all perspectives of investors from different countries. The coefficients corresponding to carry trade (forward discount or interest rate spread), currency value (long term return) and differential term of trade are negative for all PPP portfolios related to all four countries/area investors, and the coefficients corresponding to other predictors are positive. This means that the deviations of the optimal weights from the benchmark weights decrease with forward discount, long term return and differential term of trade and increase with short term return (currency momentum), differential real interest rate, differential productivity and differential government consumption. Therefore, the investors overweight the currencies have small interest rate spread, short term winning, long term losing, large real interest rates differential, strong productivity differential, small term of trade differential, and great fiscal differential and underweight the currencies have large interest rate spread, short term losing, long term winning, small real interest rates differential, small productivity differential, large term of trade differential, and low fiscal differential. This conclusion is also consistent with the results of Table 6.2 in pre-sample analysis. I can compare the coefficients of each other, because of the fact that predictors are standardized cross-sectionally. Quantitatively, a high differential of productivity leads to the largest overweighting of a currency. However, the short term return, long term return and government consumption have relatively small effect on the weights, since their coefficients are not significant.

Table 6.9 The average of coefficients for all out-of-sample analyses

This table shows the average coefficients corresponding to their predictors for out-of-sample in main analysis and robustness analysis. The results related to my main analysis are reported in the first part, referred as 'US investor'. In the second part, referred as 'UK investor', the results are related to the robustness check based on the perspective of UK investor. The third part, referred as 'Japanese investor ', reports results related to the robustness check based on the perspective of Japanese investor. The final part, referred as 'euro zone investor', reports results related to the robustness check based on the perspective of euro zone investor. For each part, there are three PPP portfolios. The first one is PPP portfolio with only three financial predictors, tagged as 'Financial'. The second one is PPP portfolio with only four fundamental predictors, tagged as 'Fundamental'. The third one is PPP portfolio with all predictors, tagged as 'All'. For each column, 'ct' is predictor of carry trade (forward discount). 'cm' is currency momentum (short term return). 'cv' is currency value (long term return). 'rird' is real interest rate differential. 'tntd' is productivity differential. 'totd' is term of trade differential. 'gc' is government consumption differential.

strategy	ct	cm	cv	rird	tntd	totd	gc
			US investor				
Financial	-3.41	0.94	-0.45	-	-	-	-
Fundamental	-	-	-	4.81	8.39	-2.68	1.32
All	-1.59	0.55	-0.13	5.50	7.94	-2.33	1.07
			UK investor				
Financial	-3.76	1.47	-0.40	-	-	-	-
Fundamental	-	-	-	4.98	7.32	-3.47	1.08
All	-4.11	1.00	-0.08	6.03	5.27	-2.23	1.64
			Japanese investor				
Financial	-4.03	0.16	-0.57	-	-	-	-
Fundamental	-	-	-	4.78	9.43	-4.83	1.21
All	-4.61	0.55	-1.01	5.88	7.37	-4.79	1.33
			euro zone investor				
Financial	-3.76	1.18	-0.32	-	-	-	-
Fundamental	-	-	-	4.52	7.59	-3.58	2.25
All	-3.89	0.75	-0.10	5.74	5.72	-2.60	2.60

6.5 Conclusion

In this chapter, the performance of PPP portfolios with different classes of predictors and different objective functions for currency market is investigated, and compared to the relevant benchmark portfolios and other optimal portfolios, which have good performance as outlined in the last chapter. The main motivation of this research was to find a methodology to construct currency only portfolios based on the characteristics of currencies, and how these portfolios perform in out-of-sample. I tried to apply parametric portfolio policy (PPP), proposed by Brandt, Santa-Clara and Valkanov (2009), to currency only portfolio optimization. I used naïve weights and volatility timing (VT) portfolio weights as benchmark weights. Two objective functions were chosen for estimating coefficients. One is constant relative risk aversion (CRRA) utility function. Another one is practitioner-oriented to minimise variance of return of portfolio. Moreover, I exploited seven characteristics of currency, divided into two classes. The first class is financial characteristics, including forward discount, short long return, and long term return. The second class is fundamental characteristics based on behavioural equilibrium exchange rate model, including real interest rates, productivity, term of trade, and government consumption. Before I began the out-of-sample analysis, I conducted an in-sample analysis to test the relevance of these characteristics to optimization, and the results are satisfactory. Therefore, in out-of-sample analysis, I had three portfolios for each case. One included three financial characteristics, and the other one included four fundamental characteristics, and finally one included all seven characteristics.

There are four main conclusions made in out-of-sample analysis. Firstly, fundamental characteristics can give CRRA investor benefits of active portfolio management, but financial characteristics cannot. Secondly, considering all seven characteristics together worsens the performance of PPP portfolios. Thirdly, the choice of benchmark weights does not have significant effect on the performance of PPP portfolios. Finally, if the investors are not CRRA investor, but they would like to minimise portfolio's variance, PPP portfolios are still their choice in a way. In addition, the transaction cost does not change the conclusions reached, although the Sharpe ratios of PPP portfolio, indeed, decrease distinctly after taking account of transaction cost.

The most conclusions in robustness check analysis are consistent with the above conclusions, but some of them are inconsistent. For UK investors, the inconsistences are related to the case, which estimates coefficients by minimizing variance of return of portfolio. But, these inconsistences cannot reject my conclusion about support of PPP portfolio. For Japanese investor, CRRA investor will not choose PPP portfolio with fundamental predictors based on the term of Sharpe ratio. But, it still has the advantage in terms of Calmar ratio and CEQ return. For euro zone investor, all conclusions are consistent. Therefore, although inconsistent conclusions exist in robustness check analysis, the four main conclusions, are robust from the perspectives of investors from different countries.

The value of coefficients displays a conclusion about how characteristics of currency make that PPP portfolio weights deviate from benchmark weights, and this conclusion is consistent with all cases of out-of-sample analysis. Relative to naïve weights, the PPP portfolios allocate considerably more wealth to currencies with small interest rate spread, large real interest rates differential, strong productivity, and small positive shock to term of trade.

Chapter Seven

Conclusion and Future Research

7.1 Conclusion

This thesis mainly focuses on the currency only portfolio, and considers investment in currency market as a speculating opportunity rather than hedge tool. So, I therefore investigate the out-of-sample performance of various optimal currency only portfolios (passive and active), and compare them to the performance of naïve portfolio. The results show that some of passive portfolio strategies cannot beat naïve portfolio, but the active strategies I investigate in this thesis have better performance than naïve portfolio has.

We analyse 12 passive portfolio strategies, three non-optimal (benchmark) portfolios and 9 optimal portfolios, for currency only portfolio in chapter four. Three benchmark portfolios include naïve portfolio, GDP portfolio and Trade portfolio, and 9 optimal portfolios include sample-based mean-variance portfolio, its extensions, minimum variance portfolio and equally-weighted risk contribution portfolio. Like equity portfolio, the sample-based mean-variance portfolio should have the best Sharpe ratio in-sample. And, its other evaluation indices also kept at a good level. In the out-of-sample analysis, however, the results show that the sample-based mean-variance portfolio works very badly with low Sharpe ratio and horrible downside risk, because of estimation error. Moreover, the minimum variance portfolios, with and without short-sale constraint, has the best performance and exposure to the lowest downside risk. The naïve portfolio and equally-weighted risk contribution portfolio also perform reasonable well. In addition, adding 'lesser' currencies can help investors gain the benefit from diversification. Although transaction cost leads to decreases in the performance of portfolio with high level of turnover, the rankings do not change after taking account of transaction cost.

In chapter 5, I analyse optimal constrained portfolio strategy, which derive from mean-variance optimization with purpose to outperform naïve portfolio, and a class of active portfolio strategies (called as timing strategy), which include volatility timing strategy and reward-to-risk timing strategy, for currency only portfolio. In the literature, for the equity portfolio, the optimal constrained portfolio generally performs better than naïve portfolio in the absence of transaction costs. And, both types of timing strategies can outperform naïve portfolio for a range of equity data after high transaction cost is incorporated. For this thesis analysis about currency only portfolio, optimal constrained and volatility timing portfolio consistently outperform naïve portfolio in all terms of evaluation used. However, taking account of return into timing strategy portfolio improves its performance only for all currencies dataset, but does not for G10 currencies dataset. Similarly, the transaction cost has obvious effect on the performance of optimal constrained portfolio for all currencies dataset. But, in the case of G10 currencies dataset, transaction cost does not affect the performance of optimal constrained portfolio. In addition, it can be concluded that exponentially weighted moving average is more efficient to estimate conditional expected moments than simple moving average to reduce estimation error. Same as chapter 4, 'lesser' currencies can give investor an obvious diversification benefit, and then improve the performance.

In chapter 6, I analyse an alternative active portfolio strategy, which is called PPP portfolios whose weights deviate from benchmark weights based on the characteristics of currencies. I used naïve weights and volatility timing portfolio weights as benchmark weights. And, two objective functions are chosen to estimate coefficients. One is constant relative aversion utility function. Another one is practitioner-oriented to minimise portfolio's variance. Besides all seven characteristics together, I also isolate them with two classes, financial and fundamental characteristics. The results of the out-of-sample analysis about currency only portfolio show that fundamental characteristics can give CRRA investor benefits of active portfolio management, but financial characteristics cannot. The performance of PPP portfolio is worsened if I consider all seven characteristics together. Moreover, the choice of benchmark weights is not important to the investor. If the investors are safety-first rather than CRRA investor, the PPP portfolio still is their choice in a way. Although a high level of turnover of PPP portfolios, the transaction cost does not change the conclusion. In addition, I find that the PPP portfolios allocate considerably more wealth to currencies with small interest rate spread, large real interest rates differential, strong productivity differential, and small term of trade differential.

The overall results indicate that currencies can be thought of as an asset in their own right to construct optimal portfolios, which have better performance than naïve portfolio has, if the suitable strategies are used. Although sample-based mean-variance portfolio and its extensions do not have very good performance, minimum variance portfolio can beat naïve portfolio and other market portfolios of currency. A more advanced version of mean-variance portfolio, optimal constrained portfolio, also has better performance than naïve portfolio has. For active portfolio management, the two active strategies, timing strategy and PPP strategy give investors more benefit than naïve strategy Even, these two active portfolios outperform optimal passive portfolios, e.g. minimum-variance portfolio and optimal constrained portfolios. Moreover, in the analysis of PPP portfolios, I find the relationship between characteristics of currency and deviation of PPP portfolio weights from naïve weights. However, besides what has been researched in this thesis, there are lots things that can be investigated in the future. The next section will give directions to possible future researches.

7.2 Limitation

There is a potential limitation of the empirical analysis in this thesis. I do not consider much more about the impact of outliers when I conduct parametric statistics. The outliers are defined differently, such as Dixon (1950) defines outliers as values that are 'dubious in the eyes of the researcher' and Hawkins (1980) describes an outlier as an observation that 'deviates so much from other observation as to arouse suspicions that it was generated by a different mechanism'. But, then, an outlier is generally considered as a data point which is far away from norm for a variable or population (e.g., Jarrell, 1992; Rasmussen, 1988; Stevens, 1984). Wainer (1976) also introduce fringelier, a special case of outlier.

Most parametric statistics, like means, standard deviation, and correlations, and every statistic based on these, are highly sensitive to outliers. Zimmerman (1998) state that the presence of outlier will lead to inflated error rates and substantial distortions of parameter and statistics estimates. Schwager and Margolin (1982) also argue that outliers can seriously bias or influence estimates. However, in this paper, I only checked the presence of outlier by visual inspection and my experience, but not a certain rule. Simple rules, such as data point three or more standard deviations from means, are simple and effective, although some researchers (e.g., Selst and Jolicoeur, 1994) propose several complex rules. So, the limitation of my empirical analysis is that I do not use a certain rule to identify the outliers of my data. This may lead to a different conclusion.

There is much debate about how to deal with outliers. When the outliers are illegitimately, they should be removed from data in common sense (Bamnett and Lewis, 1994). However, when the outliers are legitimately or the cause is unclear, the issue will be complicated. Judd and McClelland (1989) very support for removal of outliers, and make several strong points. Osborne and Overbay (2004) empirically demonstrate the benefits of outlier removal. But, Orr et al. (1991) ague that data are more like to be representative of the population as a whole if outliers are not removed. In addition to removal, alternative methods to accommodating outliers include transformation (Hamilton, 1992; Osborne, 2002) and ‘robust’ procedures (Bamnett and Lewis, 1994). So, researcher should make decisions on dealing with legitimately by using their training, intuition, reasoned argument and thoughtful consideration.

7.3 Future Research

Although I have undertaken an analysis in my thesis to investigate the performance of currency only portfolios related to various optimal strategies, there are still issues that can be researched in the future.

Firstly, due to the fact that the new strategies will be proposed continuously, it is interesting to investigate their performance for currency only portfolios. I investigated 9 optimal portfolios (adding 3 market portfolios to have total 12 portfolios) in chapter four, but there are other optimal portfolio strategies based on improving the estimation of moments of asset returns can be applied into currency market. Garlappi et al. (2007) propose a strategy for an investor who has multiple priors and ambiguity aversion. In their approach, the multiple priors are characterized by a confidence interval around the estimated expected returns, and a minimization over the priors is used to show investor’s aversion to ambiguity (uncertainty of estimation). Based on Garlappi’s (2007) approach, Fonseca et al. (2011) investigate robust optimization for currency only portfolio. They adjust the original idea to comply a feature of currency, which is a triangular relationship exists among foreign exchange rate. Above is an example about applying other optimal portfolio strategy into currency only portfolio. Another example is Bayesian 'Data-and-Model' approach proposed by Pástor (2000) and Pástor and Stambaugh (2000). This approach is Bayesian portfolio based on belief in a particular asset-pricing model. So, for the future research, I could employ this portfolio strategy to currency market. Because currency differs from equity, asset-pricing model for the currency will also differ from asset-pricing model for equity. For example, I may use currency trading strategies, such as carry trade and momentum trade, to build factors model as asset-pricing model. However, the research of asset-pricing model on currency is limited. For the future research in this direction, I could also pay close attention to more advanced strategies, which may be proposed in the future.

Secondly, rather than weekly data, I could use monthly data to conduct my analysis in the future. In this thesis, I chose to use weekly frequency for data collection. The reason is that I would like to obtain enough observations given that the period is limited. But, for the risk free rate, due to availability of one week and one month T-bills, I only can use 3 month T-bills with weekly frequency to calculate excess return. Moreover, in the literature about portfolio strategy, they mostly prefer monthly data. For example, it includes the papers I mentioned in the thesis, such as DeMiguel et al. (2007), Kan and Zhou (2007) and Brandt, Brandt et al. (2009). With time permitting in the future, I could try to collect data on a monthly basis, and use one month T-bills with monthly frequency to calculate excess return.

Thirdly, more sophisticated estimation techniques could be used to estimate moments of excess return for timing strategies. In chapter five, I used two estimation techniques, simple moving average and exponentially weighted moving average, to estimate variance and mean of currency excess return. From the results, I found that exponentially weighted moving average is more efficient than simple moving average for my timing strategy. So, it would be interesting to know whether more sophisticated estimation techniques can bring investors more benefits. For example, I might use GARCH (1, 1) process to model the daily excess return on each currency. Then, the forecasts of daily excess return variances are calculated to construct forecasts of monthly excess return variances. But, this technique requires me to switch to daily data. So, I could leave this idea to future research.

I also could investigate the reason of inconsistent conclusions in robustness check analysis. In the conclusion sections of my three main chapters, I have stated some inconsistences from robustness check related to perspectives of investors from different countries. Although most of the inconsistences cannot totally reject my main conclusions, they, at a certain extent, affect investor's decision for portfolio strategy. Therefore, it would be interesting to investigate how these inconsistences happen.

Finally, for the PPP portfolio, I could investigate the reason of the fact that financial characteristics cannot give investor benefit of active portfolio management, and whether the benefit from fundamental characteristics is likely to continue going forward. In chapter six, I stated that PPP portfolio with financial predictors cannot beat naïve portfolio, and they have similar Sharpe ratio and Calmar ratio. One of the explanations of this phenomenon may be that the currency market is efficient enough to eliminate the benefit from trading at these financial characteristics. Similarly, the explanation of outperformance of PPP portfolio with fundamental predictors may that the inefficient market cannot eliminate the benefit from trading at four fundamental characteristics. To investigate this, I may test whether the profitability of the PPP portfolios compensate for the risk they bear. However, according to the adaptive markets hypothesis, Lo

(2004) argues that abnormal profitability can persist for some time because the market needs time to fully arbitrage, but not indefinitely. This also opens a question to investigate whether the performance of this PPP portfolio is decreasing, and the outperformance will be eliminated in future. This presents a good opportunity for future research.

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