

CMRI Working Paper 03/2012

**Hedging Effectiveness of SET50 Index Futures:
Empirical Studies and Policy Implications**

Thaisiri Watewai
Faculty of Commerce and Accountancy
Chulalongkorn University

January 2012

Abstract

This paper concerns the hedging effectiveness of the SET50 index futures traded in the Thailand Futures Exchange during January 2008 to December 2009. We measure the level of hedging effectiveness based on the concept of the mean-variance criterion with the inclusion of liquidity and transaction costs. In particular, we construct cost-adjusted mean-variance frontiers of the investment universe including the stocks in the SET50 index, TDEX and the SET50 index futures. The results show that the liquidity cost associated with trading the futures is relatively small, while the transaction cost is relatively large compared to those associated with trading stocks. However, when portfolio managers are allowed to use the futures to manage their portfolios, both *ex-ante* and *ex-post* Sharpe ratios of the cost-adjusted mean-variance frontiers are significantly higher than those when portfolio managers are not allowed to use the futures. It also enables portfolio managers who are required to invest a certain minimum amount in stocks to achieve a lower global minimum variance. The improvement in the cost-and-risk-adjusted return, however, depends also on the ability to forecast the market trend of portfolio managers.

JEL Classification Numbers: C53, C61, G11

Keywords: Hedging effectiveness, liquidity cost, transaction cost, mean-variance frontier, portfolio optimization, factor model, SET50 Index Futures.

E-Mail Address: thaisiri@acc.chula.ac.th

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1 Introduction

SET50 Index Futures, launched by the Thailand Futures Exchange (TFEX), is a stock index futures on SET50 Index which is an index compiled, computed and disseminated by the Stock Exchange of Thailand (SET). TFEX provides futures contracts with maturity in March, June, September and December. The minimum price change of a futures contract is 0.10 index point, which is equivalent to 100 baht¹. SET50 Index Futures is the first product of TFEX, and its popularity has been growing since its first date on April 28, 2006.

A stock index futures is primarily used as a tool to adjust the portfolio exposure to the index where the associated trading cost is expected to be smaller than that associated with trading the stocks in the underlying index directly. How effective to manage the exposure through the stock index futures depends on many factors including the liquidity cost, transaction cost (brokerage commission fees and taxes), and the correlation between the return of the futures and that of the index. In the Thai markets, portfolio managers may choose to use alternative products to manage their portfolio exposures to the SET50 index. These include ThaiDEX SET50 Exchange Traded Fund (TDEX), which is an ETF tracking the SET50 index, and SET50 Index Options, which is a series of European options on the SET50 index. Unfortunately, using the SET50 index options is not practical because the market is highly illiquid. Moreover, holding TDEX requires full capital investment and short selling can be costly. On the other hand, the SET50 index futures market is liquid, and trading the futures only requires margin deposits. In addition, the cost of shorting the futures is small. Nevertheless, the SET50 index futures has a relatively large contract size, and a predetermined expiry date on which any open position will be closed and the transaction cost must be paid. As a result, the benefits from using the futures may not be attractive.

In this paper, we study the hedging effectiveness of the SET50 index futures in managing large equity portfolios where the investment universe includes stocks in the SET50 index, TDEX and the SET50 index futures. We measure the level of hedging effectiveness using the mean-variance efficient frontiers with liquidity and transaction costs included. The mean-variance frontier is chosen as our indicator of hedging effectiveness because (i) it is widely used in the equity fund management industry (see, for example, [10]), (ii) it considers both risk and return, (iii) it can handle different levels of risk aversion, and (iv) incorporating the trading costs is not difficult.

To construct a cost-adjusted mean-variance frontier, we solve a series of mean-

¹Contract multiplier is 1,000 baht per index point.

variance optimization problems which take into account the liquidity and transaction costs for each value of the risk-return trade-off coefficient. Then the frontier corresponding to the case when trading the futures is not allowed is compared with that corresponding to the case when trading the futures is allowed. Likewise, when trading the futures is possible, we measure the contributions of the liquidity and transaction costs to the hedging ineffectiveness of the futures by comparing the mean-variance frontiers when the associated cost is assumed to be zero and when it is not. The understanding of the benefits and costs associated with trading the SET50 index futures will support the decision making process of portfolio managers who are reluctant to use the futures to manage their portfolios. It also helps policy makers make decisions regarding changes in the product structures to facilitate the use of the futures if it is needed.

The rest of the paper is organized as follows. Section 2 provides a brief discussion of the literature in hedging effectiveness. Section 3 describes the mean-variance optimization model that takes into account the liquidity and transaction costs. The estimation method and the fitted liquidity cost curves are provided in Section 4. A factor model used to forecast expected values and covariances of securities returns is proposed in Section 5. We discuss the results of the hedging effectiveness and the trading cost contributions in Section 6. Two extensions are considered in Section 7. The implications for policy makers are discussed in Section 8. We conclude in Section 9.

2 Literature Review

The notion of hedging effectiveness for futures markets has been extensively studied in the literature. One of the main focuses is to determine the optimal hedge ratio² that optimizes a certain objective function. The first group of researchers in this area including, for example, Ederington [12], Johnson [19], and Myers and Thompson [26], considers the minimization of the variance of the hedged portfolio in order to obtain the so-called minimum variance hedge ratio. This framework focuses only on risk and totally ignores expected returns. To incorporate expected return and risk into the notion of hedging effectiveness, another group of researchers including, for example, Cecchetti, Cumby and Figlewski [4], Howard and D'Antonio [16] and Hsin, Kuo and Lee [17], proposes a mean-variance equivalent approach to determine the optimal hedge ratio. Further developments of alternative objective functions are available, for instance, the expected utility maximization (Benninga, Eldor and Zilcha [2]), mean extended-Gini minimization (Cheung, Kwan and Yip [9]), and generalized semivariance minimization (De Jong, De Roon and Veld [11]).

Another direction of research in hedging effectiveness is the development of econometric techniques to estimate the optimal hedge ratio. Examples are Junkus and Lee [20] (OLS), Baillie and Myers [1] (bivariate GARCH), Grammatikos and Saunders [15] (random coefficient), Ghosh [14] (cointegration), Kolb and Okunev [22] (mean extended-Gini), and Lien and Tse [25] (generalized semivariance). We refer the reader to Chen, Lee and Shrestha [8] for a more complete review in futures hedge ratios.

Most of the research works in this area assume away the transaction costs associated with futures trading. Few exceptions are Lence [23] and Lence [24] who considers brokerage fee and initial margin deposit in his works and shows that the economic value of the improvement of complicated estimation techniques for minimum variance hedge ratio is negligible and that when more realistic scenarios are considered (such as brokerage fees and margin deposit) it may be optimal *not* to hedge at all. However, Lence does not consider liquidity costs in his models. In the real world, however, liquidity costs in financial markets cannot be ignored and in fact the existence of liquidity costs of stock trading known as the price impact are widely documented (see, for example, Chan and Lakonishok [6], Keim and Madhavan [21], Sharpe et al. [28]). In this study, we incorporate the liquidity cost of both stocks and futures to emphasize the importance of this component in the hedging effectiveness analysis. To the best of our knowledge, there is no analysis for liquidity cost in the hedging effectiveness literature elsewhere.

²The ratio between the number (or value) of futures contracts and the number (or value) of underlying shares.

Another fundamental yet missing piece in the literature is the interaction between the use of futures and the portfolio choice of stocks. Most, if not all, of the works assume that the portfolio to be hedged is given and fixed. Then the number of futures contracts needed is optimized. In reality, however, decisions for both portfolio choice and hedging should be made together to fully utilize the hedging instrument. In particular, the correlation between stocks and futures and the costs incurred from trading stocks and futures should be considered in making the decision on the portfolio re-balancing. This is because hedging with futures can reduce trading costs of stocks and hence affect the optimal allocation among stocks in his portfolio. Indeed, this is one of the most important benefits from using futures for managing portfolios. We take this joint-decision view into our model.

3 Mean-Variance Model with Liquidity and Transaction Costs

In this section we formulate an optimization problem with mean-variance objective that incorporates liquidity and transaction costs. Given the portfolio weights $\pi_i, i = 1, \dots, N$ for stock i (or TDEX), the percentage of cash position is $\pi_0 = 1 - \sum_{i=1}^N \pi_i$. Denoted by π_f the equivalent weight of SET50 index futures in the portfolio, which is given by $\pi_f = (n_f F \times 1,000)/Y$ where Y is the current portfolio value, F is the futures price, and n_f is the number of futures contracts held in the portfolio. For a long position, $n_f > 0$, and for a short position, $n_f < 0$. The number 1,000 comes from the contract multiplier of 1,000 baht per index point. The optimization problem is to maximize the risk-and-cost-adjusted expected return under a set of constraints.

Liquidity Cost

The liquidity cost is the cost that a buyer or seller has to pay when he trades an illiquid security. This cost can be measured by the amount the buyer pays above or the seller receives below the current value computed from the mid price. Typically, a large buy market order will increase the average price per share paid, and a large sell market order will decrease the average price per share received. The increase in the liquidity cost when the order size increases is known as the price impact or market impact. We model the liquidity cost for security i by an asymmetric quadratic function of traded value

$$L_i = \begin{cases} \alpha_i^+ v^2 & \text{if } v \geq 0 \\ \alpha_i^- v^2 & \text{if } v < 0 \end{cases} \quad (3.1)$$

where v is the traded value, and is positive for buy orders and negative for sell orders, and α_i^+ and α_i^- are the liquidity cost parameters for buy and sell orders of security i , respectively³.

³A (symmetric) quadratic liquidity cost function of order size is proposed by Cetin et al [5] who study the liquidity cost using the U.S. data. They define the liquidity cost for each share of stock bought/sold as the difference between the executed price and its marginal price at the time when the order is submitted. They assume that the marginal stock price follows a Geometric Brownian motion with drift, and that the size of the order affects the executed price through an exponentially linear function. They show that the liquidity cost can be approximated by a quadratic function of the order size. Specifically, for an order flow of size x , the liquidity cost is approximately equal to

$$L \approx \alpha S x^2$$

Transaction Cost

To incorporate the transaction costs (fees and taxes) of trading securities, we introduce a variable transaction cost parameter θ_i and a fixed transaction cost parameter η_i for stock $i, i = 1, \dots, N$. That is, if stock i is traded at the value of v , we will pay the transaction cost of

$$\theta_i |v| + \eta_i.$$

On the other hand, the transaction cost of trading the futures usually depends on the number of contracts traded. Let θ_f and η_f denote, respectively, the associated variable and fixed transaction cost parameters. That is, if n contracts of the futures are bought or sold, we will pay the cost of

$$\theta_f |n| + \eta_f.$$

Note that we are interested in trades from institutional investors which usually have constant variable transaction cost parameters $\theta_i, i = 1, \dots, N, f$ at any traded value v , and zero fixed transaction cost parameters $\eta_i, i = 1, \dots, N, f$. Therefore, we will assume that θ_i does not depend on the traded value, and that there is no fixed transaction cost. Furthermore, we set $\theta_i = 0.2675\%, i = 1, \dots, N$ and $\theta_f = 267.50^4$.

Formulation

Consider a portfolio with current value of Y . Let $\bar{\pi} = [\bar{\pi}_1, \dots, \bar{\pi}_N, \bar{\pi}_f]'$ denote the vector of the current portfolio weights. A re-balance of the current portfolio to a new portfolio $\pi = [\pi_1, \dots, \pi_N, \pi_f]'$ ⁵ will incur liquidity cost

$$L(\pi; \bar{\pi}) = Y^2 \left[\sum_{i: \pi_i > \bar{\pi}_i} \alpha_i^+ (\pi_i - \bar{\pi}_i)^2 + \sum_{i: \pi_i < \bar{\pi}_i} \alpha_i^- (\pi_i - \bar{\pi}_i)^2 \right],$$

and transaction cost

$$R(\pi; \bar{\pi}) = Y \left[\sum_{i=1}^N \theta_i |\pi_i - \bar{\pi}_i| + \frac{\theta_f}{1,000F} |\pi_f - \bar{\pi}_f| \right].$$

where S is the marginal stock price, and α is the liquidity cost parameter which is estimated from a least square regression in which the log-returns of executed prices are regressed on the length of the time intervals between executions, and the differences between signed order flows. Unfortunately, unlike the U.S. markets, the executions in the equity and equity index futures markets in Thailand are mostly driven by marketable limit orders. As expected, we find that the majority of log-returns of executed prices are zeros. Therefore we do not follow their method in estimating the liquidity cost parameter. Instead we directly approximate the piecewise linear liquidity cost curve from the limit order book by an asymmetric quadratic function. The details are given in Section 4.

⁴We assume that the transaction cost is 0.25% for stocks and TDEX, and 250 baht per futures contract. The transaction cost is taxed at 7%.

⁵Note that after the re-balance the value of the portfolio will reduce due to the liquidity and transaction costs. However, $\bar{\pi}$ and π are defined with respect to the value of the portfolio before the re-balance or Y .

However, unlike stocks, futures contracts are predetermined to be expired on their maturity dates. To incorporate this into the decision making process, we assume that each time an investor opens a new position in the futures, he or she will take into account the present value of the associated transaction cost of closing the position at the maturity date. Let t denote the number of days until the maturity date. Then the quantity is

$$\tilde{R}(\pi; \bar{\pi}) = \begin{cases} Y \frac{\theta_f}{1,000F} \frac{|\pi_f - \bar{\pi}_f|}{(1+r_f)^t} & \text{if } 0 \leq \bar{\pi}_f < \pi_f \text{ or } \pi_f < \bar{\pi}_f \leq 0 \\ Y \frac{\theta_f}{1,000F} \frac{|\pi_f|}{(1+r_f)^t} & \text{if } \pi_f < 0 < \bar{\pi}_f \text{ or } \bar{\pi}_f < 0 < \pi_f \\ 0 & \text{otherwise} \end{cases}$$

where r_f is the risk-free rate of return.

Denote by μ and Σ the vector of expected returns, and the variance-covariance matrix of the returns of N stocks (including TDEX) and the futures, respectively. Then the expected return of the portfolio after liquidity and transaction costs is $\pi' \mu + \pi_0 r_f - l(\pi; \bar{\pi}) - r(\pi; \bar{\pi}) - \tilde{r}(\pi; \bar{\pi})$, where $l = L/Y$, $r = R/Y$ and $\tilde{r} = \tilde{R}/Y$ are the percentages of the liquidity and transaction costs to the total wealth. Note that $\tilde{r}$ is included here although it is not paid for at the time of the transaction. The variance of the portfolio return is $\pi' \Sigma \pi$. Our mean-variance objective with liquidity and transaction costs is

$$\max_{\pi} G(\pi) = (1 - \lambda)(\pi' \mu + \pi_0 r_f - l(\pi; \bar{\pi}) - r(\pi; \bar{\pi}) - \tilde{r}(\pi; \bar{\pi})) - \lambda \pi' \Sigma \pi \quad (3.2)$$

where $\lambda \in (0, 1]$ is a risk-return trade-off coefficient. Note that $\lambda = 1$ refers to minimizing the portfolio variance. The cost-adjusted mean-variance frontier can be obtained by maximizing the above objective for various values of λ . In this paper we use $\lambda = 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95, 0.975, 0.99$, and 1.

The following constraints are imposed in the optimization problem:

1. No cash-borrowing: $\pi_0 \geq 0$.
2. No stock short-selling: $\pi_i \geq 0, i = 1, \dots, N$.
3. Limit stock concentration at 20%: $\pi_i \leq 0.2, i = 1, \dots, N - 1$.
4. Limit position by trading value at 50%: $|\pi_i| \leq \frac{0.5 \zeta_i}{Y}, i = 1, \dots, N, f$
where ζ_i is the average daily trading value⁶ of security i .

⁶We use the 22-day average of daily trading values (excluding the maximum and minimum) for each security. The data for stocks are obtained from the Thomson Reuters Datastream database, and the data for TDEX and SET50 index futures are obtained from the Bloomberg database. For the SET50 index futures, we use the product of the volume and the settlement price as a measure of the trading value. It is multiplied by 1,000 to make it consistent with the definition of π_f .

5. Maximum number of futures contracts at 20,000 contracts:

$$-20,000 \leq \frac{\pi_f Y}{1,000F} \leq 20,000.$$

6. Self-financing: $\sum_{i=0}^N \pi_i + l(\pi; \bar{\pi}) + r(\pi; \bar{\pi}) = 1.$

7. Margin deposit at 50,000 baht per futures contract: $\pi_0 \geq 50,000 \frac{|\pi_f|}{1,000F}.$

8. Investment universe: stocks in SET50 index⁷, TDEX and SET50 index futures.

⁷The list of the SET50 index constituents is obtained from the website of the Stock Exchange of Thailand (<http://www.set.or.th/th/market/constituents.html>).

4 Liquidity Cost Curve Estimation

In Section 3 we propose an asymmetric quadratic function of the traded value for the liquidity cost. In this section we describe how to estimate the liquidity cost curve, and we show that the data support the asymmetry between the buy and sell sides.

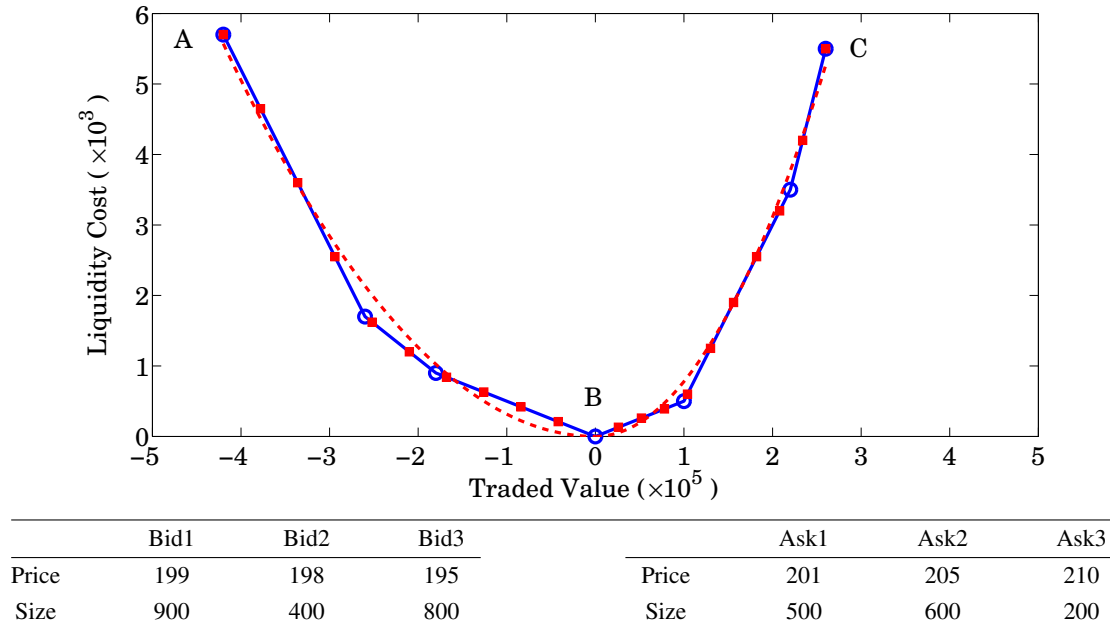
Estimation

Given the current limit order book, which is the collection of bid and ask prices and their associated sizes, we can determine the liquidity cost of a buy/sell market order (assuming that the order can be filled completely), which is equal to the product of the order size and the difference between the average price paid/received and the market mid price. Figure 4.1 illustrates a hypothetical limit order book and its associated liquidity cost curve which is a piecewise linear function of the order value. An order value is defined as the order size multiplied by the market mid price, where a buy order has a positive order value, and a sell order has a negative order value. Note that the magnitude of the slope of the curve is the percentage difference between the bid or ask price and the mid price, and it increases as the magnitude of the order value increases.

To make it computationally tractable, we approximate the piecewise linear liquidity cost curve by two quadratic functions, one for buy orders (positive order values) and another one for sell orders (negative order values). More precisely, for a given security and time, we select ten points evenly-spaced on the negative side of the curve (from points A to B in Figure 4.1), and another ten points evenly-spaced on the positive side of the curve (from points B to C in Figure 4.1). The twenty points of the hypothetical example in Figure 4.1 are shown as the solid squares.

We use the tick data from SET, TFEX and Thomson Reuters to create the three best bid and ask prices and sizes from October 2007 to December 2009 for stock in the SET50 index, TDEX and SET50 index futures (a total of 62 securities). For each security, we select twenty points from the liquidity cost curve for every five minutes starting from 10:15-12:15 and 14:45-16:15 for stocks and TDEX (a total of 44 time points, or 880 data points), and from 10:00-12:15 and 14:45-16:30 for the futures (a total of 50 time points, or 1,000 data points)⁸. Daily liquidity

⁸We select the time intervals this way to avoid the periods during the open and close of the morning and afternoon sessions.

Figure 4.1: A hypothetical limit order book and its liquidity cost curve.

This figure shows a hypothetical limit order book, the associated liquidity cost curve (solid line), and its quadratic approximation (dashed line) as a function of the order value. The circles correspond to the points where slope of the liquidity cost changes, and the solid squares correspond to the points used in fitting the quadratic approximation based on the regression equation

$$L = \alpha_1 v^2 + \alpha_2 v^2 D^+ + \varepsilon$$

where L is the liquidity cost, v is the order value, and D^+ is the dummy variable for buy orders. The estimate of α^- is α_1 and that of α^+ is $\alpha_1 + \alpha_2$. The fitted parameters for this limit order book are $\alpha^+ = 7.7890 \times 10^{-8}$ and $\alpha^- = 3.1582 \times 10^{-8}$.

cost parameters for each security are estimated using the following regression equation

$$L_{it} = \alpha_1 v_{it}^2 + \alpha_2 v_{it}^2 D_{it}^+ + \varepsilon_{it} \quad (4.1)$$

where L_{it} is the liquidity cost, v_{it} is the order value, and D_{it}^+ is the dummy variable for buy orders of point i at time t . The estimate of α^- is α_1 and that of α^+ is $\alpha_1 + \alpha_2$. For each security, we compute the average of the daily parameters, the percentage of number of days that each parameter is significantly different from zero at the 95% confidence level, and the average of r-square. The distribution of these quantities across securities are given in Table 4.1.

As we can see, the results show strong evidence of asymmetry in the liquidity cost curve. Moreover, we find that liquidity cost curve is steeper on the buy side than the sell side. This implies that a buy order incurs higher liquidity cost compared to a sell order with the same order value. The high values of r-square also confirms that the asymmetric quadratic curve is a good approximation to the linear piecewise liquidity cost curve. We provide the average of the

Table 4.1: Statistics of Asymmetric Quadratic Liquidity Cost Curves

	α_1		α_2		R-square
	Estimate ($\times 10^{-8}$)	% Significance	Estimate ($\times 10^{-8}$)	% Significance	
Mean	19.775	1.000	5.196	0.962	0.891
5 Percentile	0.897	1.000	0.058	0.938	0.863
Median	12.567	1.000	2.305	0.963	0.895
95 Percentile	57.758	1.000	20.154	0.980	0.918

This table provides the distribution of security-average estimates of liquidity cost parameters (α_1 and α_2) in the asymmetric liquidity cost curve given by

$$L = \alpha_1 v^2 + \alpha_2 v^2 D^+ + \varepsilon$$

where L is the liquidity cost, v is the order value, and D^+ is the dummy variable for buy orders. The distribution is created using the intra-day data during October 2007 to December 2009 of stocks in the SET50 index, TDEX, and SET50 index futures. The table also provides the distribution of security-average percentage of number of days on which the parameter estimates are statistically different from zero at 95% confidence level. The distribution of the security-average r-square is also given.

daily estimates of the liquidity cost parameters for each security and its rankings in Table 4.2. The results show that the SET50 index futures is relative liquid, and is ranked 16th for the buy order side and 17th for the sell order side out of 62 securities during October 2007 to December 2009. On the other hand, TDEX is ranked 29th for the buy order side, and 30th for the sell order side.

Forecasting

To solve the cost-adjusted mean-variance problem (3.2) *ex-ante*, the forecasted values of α_i^+ and α_i^- for each security i must be available. We use the average of daily α_i^+ and α_i^- during the last ten trading days as the forecasted value of the α_i^+ and α_i^- for the next trading day. We test the forecasting performance using the following regression

$$\alpha_{it}^j = \phi_{it}^j \hat{\alpha}_{it}^j + \varepsilon_{it}^j \quad j = +, - \quad (4.2)$$

where α_{it}^j is the estimate value of daily liquidity cost parameter on day t of security i obtained from (4.1), $\hat{\alpha}_{it}^j$ is the forecasted value of α_{it}^j , and ϕ_{it}^j is the estimated coefficient from regression equation (4.2).

We run regression (4.2) for each security in the SET50 index, TDEX and SET50 index futures using the data from January 2008 to December 2009 (a total of 59 securities). The distribution of the estimate ϕ^+ and ϕ^- is given in Table 4.3. The results show that the average values of ϕ^+ and ϕ^- are quite close to one. The hypothesis testing can reject the null hypothesis of $\phi = 1$ at the 95% confidence level for only one security out of 59 securities. The 5 and 95

Table 4.2: Estimates of Asymmetric Quadratic Liquidity Cost Curves

Ticker	Estimate ($\times 10^{-8}$)		Rank		Ticker	Estimate ($\times 10^{-8}$)		Rank	
	α^+	α^-	α^+	α^-		α^+	α^-	α^+	α^-
ADVANC	1.26	1.14	9	8	MBK	86.30	99.13	59	62
AMATA	35.87	29.00	47	46	MCOT	55.81	39.28	54	53
AOT	17.76	13.39	34	33	MINT	25.69	20.13	42	41
ATC	1.13	1.05	6	7	PS	48.19	41.70	50	54
BANPU	0.81	0.72	3	3	PSL	16.96	14.52	33	34
BAY	3.03	2.68	14	15	PTT	0.42	0.28	1	1
BBL	1.21	1.04	7	6	PTTAR	2.66	2.15	13	13
BEC	10.60	9.50	26	27	PTTCH	4.46	4.01	17	16
BECL	21.29	16.50	36	37	PTTEP	0.52	0.42	2	2
BGH	26.90	23.11	43	45	QH	5.78	6.01	18	20
BH	40.41	32.14	49	48	RATCH	12.80	9.75	30	28
BIGC	71.72	57.76	57	59	RCL	110.58	90.43	62	61
CCET	90.65	68.61	60	60	RRC	1.23	1.17	8	9
CPALL	6.09	5.87	19	18	SCB	1.10	0.98	4	5
CPF	8.88	6.71	25	25	SCC	2.33	1.53	12	10
CPN	23.67	18.69	41	39	SCCC	34.03	29.22	46	47
DELTA	61.63	49.25	55	55	SCIB	26.97	21.34	44	43
DTAC	7.51	6.01	22	19	SSI	52.02	34.58	52	50
EGCO	10.86	7.63	27	26	TCAP	14.41	12.24	31	31
ESSO	18.06	14.77	35	35	THAI	22.27	16.15	38	36
GLOW	28.19	21.12	45	42	TMB	8.81	6.71	24	24
HANA	65.30	50.61	56	56	TOP	1.92	1.60	10	11
IRPC	7.98	6.47	23	22	TPC	94.64	53.61	61	57
ITD	6.91	6.53	21	23	TPIPL	52.19	34.94	53	51
KBANK	1.10	0.90	5	4	TRUE	21.96	19.12	37	40
KK	16.72	12.89	32	32	TSTH	23.41	21.68	39	44
KSL	83.63	54.00	58	58	TTA	2.01	1.93	11	12
KTB	3.24	2.60	15	14	TTW	11.70	10.30	28	29
LH	6.65	6.14	20	21	TUF	23.41	17.74	40	38
MAJOR	39.38	34.27	48	49	TDEX	11.75	10.72	29	30
MAKRO	49.54	37.28	51	52	FUTURES	4.12	4.47	16	17

This table provides the averages of daily estimates of the liquidity parameters of stocks in the SET50 index, TDEX and SET50 index futures and their rankings during October 2007 to December 2009. The parameters are based on the liquidity cost curve given by equation (3.1).

percentiles of the r-squares range from 0.373 to 0.861 for the buy side, and from 0.471 to 0.893 for the sell side. The forecasting method for α^+ and α^- seems to provide reasonable forecasting performance.

Table 4.3: Forecasting Performance of Liquidity Cost Curves

	ϕ^+		ϕ^-	
	Estimate	R-square	Estimate	R-square
Mean	1.005	0.688	0.994	0.744
Standard Deviation	0.034	0.134	0.021	0.113
5 Percentile	0.964	0.373	0.959	0.471
Median	1.000	0.717	0.994	0.757
95 Percentile	1.073	0.861	1.029	0.893
N (Total)	59		59	
N (Reject $\beta = 1$ at 95%)	1		1	

This table provides the analysis of forecasting performance of the liquidity cost curves. The liquidity cost curve is defined by two liquidity cost parameters: α^+ and α^- for buy and sell sides, respectively. For each security, we forecast the daily values of α^+ and α^- using the average of the last ten trading day values of α^+ and α^- , respectively. We use the data from January 2008 to December 2009 for the stocks in the SET50 index, TDEX and SET50 index futures. The following regression is fitted

$$\alpha^j = \phi^j \hat{\alpha}^j + \varepsilon^j \quad j = +, -$$

where $\hat{\alpha}^j$ is the forecasted value of α^j , and the hypothesis $\phi^j = 1$ is tested for $j = +, -$. The results show that, out of 59 securities, the null hypothesis of only one security can be rejected at the 95% confidence level.

5 Factor Model

We employ a dynamic factor model adopted by many fund managers in the equity fund management industry (see Chincarini and Kim [10]) to estimate expected values and variance-covariance matrix of asset returns. This model is based on the arbitrage pricing theory of Ross [27] which combines the economic factor model of Chen, Roll and Ross [7] and the fundamental factor model of Fama and French [13]. In this framework, asset returns are driven by a set of common factors. Let r_{it} denote the excess return of security i at time t , and f_{kt} denote common factor return (or factor premium) k at time t . The excess return of security i follows the following relationship

$$r_{it} = \beta_{it}^1 f_{1t} + \beta_{it}^2 f_{2t} + \cdots + \beta_{it}^K f_{Kt} + \xi_{it} \quad (5.1)$$

where β_{it}^k is the factor exposure (or factor loading) of stock i at time t to factor k . The stock residual return ξ_{it} are assumed to be independent across securities and times.

The Factors

In this paper, we use the fundamental factor model, and utilize the ideas of Fama and French [13] to include a market factor to which the exposure is one, a value factor measured by price-to-earnings ratio (PE), and a size factor measured by the logarithm of market capitalization. We also adopt the work of Carhart [3] which is based on the findings of Jegadees and Titman [18], and include a momentum factor measured by the past twelve-month performance. Lastly, an analyst factor measured by the recommendation score is also included. We obtain the daily data for PEs, market capitalizations, total index returns, and recommendation scores of stocks in the SET50 index from the Thomson Reuters Datastream database. The daily total index return data of TDEX and SET50 index futures are obtained from the Bloomberg database. We use the yield of the one-month treasury bills from the Thai Bond Market Association⁹ as the risk-free rate. The time period for the data is from January 2005 to December 2009. The daily factor returns are estimated from (5.1) using the stocks in the SET50 index as the estimation universe. The descriptive statistics of the daily factor returns are given in Table 5.1. Each of the factors has a positive mean value, but negative skewness (except the value factor). All of the factors exhibit excess kurtosis. The market factor is the most volatile based on the standard deviation and the excess kurtosis. Therefore, the proper use of the futures to reduce the market risk might

⁹The data are available at <http://www.thaibma.or.th/PriceYield.html>.

Table 5.1: Descriptive Statistics of Daily Factor Returns

Statistics	Market	Value	Size	Momentum	Recommendation
Mean	0.00049	0.00015	0.00012	0.00011	0.00018
Standard Deviation	0.01653	0.00357	0.00393	0.00464	0.00363
Skewness	-0.73160	0.13034	-0.09240	-0.08570	-0.54108
Excess Kurtosis	12.42566	2.46402	0.89356	5.25607	3.50108
5 Percentile	-0.02434	-0.00544	-0.00674	-0.00687	-0.00549
Median	0.00023	0.00009	0.00021	0.00014	0.00015
95 Percentile	0.02578	0.00594	0.00626	0.00697	0.00617

This table provides the descriptive statistics of daily factor returns from January 2005 to December 2009. The market factor is the factor that drives each security in the market with unit exposure. The value factor is measure by the common movement of the securities with similar price-to-earnings (PE) ratio. The size factor is the factor whose exposure is the logarithm of market capitalization. The recommendation factor captures the co-movements of security returns with similar recommendation values. The results show that all of the factors have positive average returns, but negative skewness (except the value factor). The market factor has the highest standard deviation and excess kurtosis, and is a major source of uncertainty for the asset returns.

significantly improve the risk-adjusted return of the portfolio performance.

Mean and Variance Forecasts

We use exponentially weighted sample means and sample covariances of the past one-year daily factor returns as the estimates of the expected factor returns and covariances, respectively. Similarly, we estimate the stock residual variances by one-year exponentially weighted sample variances. The estimate of the expected return of security i can then be computed as

$$\mu_i = r_f + \beta_i^1 \bar{f}_1 + \beta_i^2 \bar{f}_2 + \cdots + \beta_i^K \bar{f}_K$$

and the estimate of the covariance between securities i and j is

$$\sigma_{ij} = \sum_{j=1}^K \sum_{k=1}^K \beta_i^j \beta_j^k \omega_{jk} + v_{ij}$$

where $\bar{f}_k$ is the expected return of factor k , ω_{jk} is the covariance between factors j and k , and v_{ij} is the variance of ξ_i if $i = j$ and zero otherwise. The estimates of the expected factor returns and covariances, and those of the stock residual variances are recomputed daily.

6 Hedging Effectiveness and Cost Contributions

In this section we measure the level of hedging effectiveness of the SET50 index futures and the impact of liquidity and transaction costs associated with trading the futures on the performance of managing a large portfolio. The level of hedging effectiveness is measured by comparing the cost-adjusted mean-variance frontiers of portfolios when the SET50 index futures is and is not included in the investment universe. Similarly, to measure the impact of a cost component, we compare the cost-adjusted mean-variance frontiers when the cost is and is not present.

To construct the cost-adjusted mean-variance frontiers, we use the optimization model developed in Section 3 and the forecasting model for liquidity cost curves, and that for means and covariances of security returns developed in Sections 4 and 5, respectively. In particular, we consider a portfolio management problem with a large portfolio size and daily trading frequency starting from January 2008 to December 2009. The initial portfolio has a value of one billion baht in terms of cash and securities. We assume that the portfolio is optimal according to the *zero-cost* risk-adjusted return objective

$$\max_{\pi} G(\pi) = (1 - \lambda)(\pi' \mu + \pi_0 r_f) - \lambda \pi' \Sigma \pi$$

at the end of the first day. After the returns on the second day are realized, the portfolio can be re-balanced with some trading costs. The re-balance decision will be based on maximizing the risk-and-cost-adjusted expected return objective (3.2) subject to all the constraints. After the returns are realized on the third day, the portfolio is re-balanced based on objective (3.2) again. The process repeats until the end of December 2009. Note that all profits and losses are accumulated to the next day and will affect the portfolio performance over the remaining time period. The results of the dynamic trading will be analyzed both *ex-ante* and *ex-post*.

Ex-Ante Analysis

The *ex-ante* analysis uses the estimate of the after-cost expected return and the estimate of the portfolio variance *before* the portfolio re-balance of each day to construct the daily cost-adjusted mean-variance frontiers. Then the daily frontiers are averaged to obtain the *ex-ante* frontiers. The series of optimization problems are solved under each of the following five scenarios:

- Trading futures is not allowed (MV)
- Trading futures is allowed, but with liquidity and transaction costs (MV_{FLT})
- Trading futures is allowed, but with liquidity cost (MV_{FL})
- Trading futures is allowed, but with transaction cost (MV_{FT})
- Trading futures is allowed, and is free of trading costs (MV_F)

Figure 6.1 shows the annualized *ex-ante* cost-adjusted mean-variance frontiers under each of the five scenarios. It also provides the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line) assuming the constant Sharpe ratio¹⁰:

$$\mu_p = r_f + SR\sigma_p \quad (6.1)$$

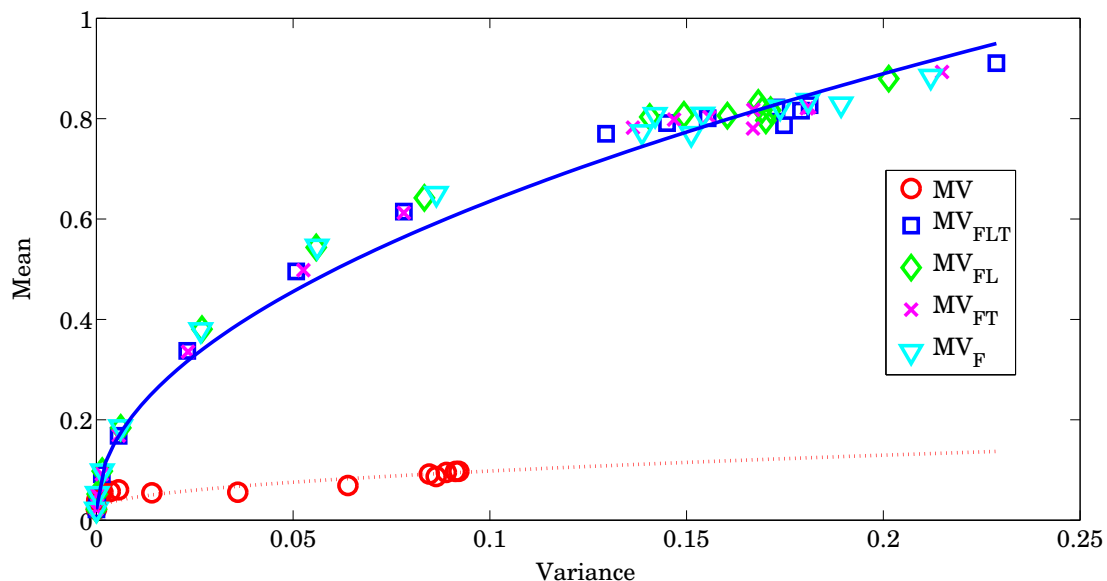
where μ_p and σ_p are the expected value and standard deviation of the portfolio return, respectively, and SR is the portfolio's Sharpe ratio. The fitted Sharpe ratio is obtained from minimizing the mean square error of expected returns in equation (6.1). The fitted annualized Sharpe ratio of MV is 0.241 and that of MV_{FLT} is 1.940. On the *ex-ante* basis, it implies that the optimal use of the SET50 index futures can generate additional 1.699 units of expected return for every unit increase in the portfolio's standard deviation, which is a very significant improvement in the portfolio performance.

On the other hand, there is not much difference in the cost-adjusted mean-variance frontiers whether or not the liquidity and/or transaction costs are taken into account. In other words, the benefits of using the futures to hedge market risk or to speculate the market trend are much greater than the costs associated with trading the futures.

Ex-Post Analysis

Despite the fact that the *ex-ante* cost-adjusted mean-variance frontier is significantly improved when fund managers are allowed to use the futures, the *ex-post* performance may or may not lead to the same conclusion. This is because the *ex-ante* analysis always guarantees a superior (or the same) performance when the fund manager has an additional option to invest. In this section we measure the portfolio performance and the benefits from the futures based on the realized gains and losses. Figure 6.2 shows the realized annual returns and variances under each of the five scenarios for the different values of the risk-return trade-off coefficients λ , and the fitted cost-adjusted mean-variance frontier under the assumption of constant Sharpe ratio for scenarios MV (dotted line) and MV_{FLT} (solid line). From the figure we can see that, like the *ex-ante* case, the realized returns and variances do not depend much on the inclusion and exclusion of the liquidity and transaction costs associated with trading the futures.

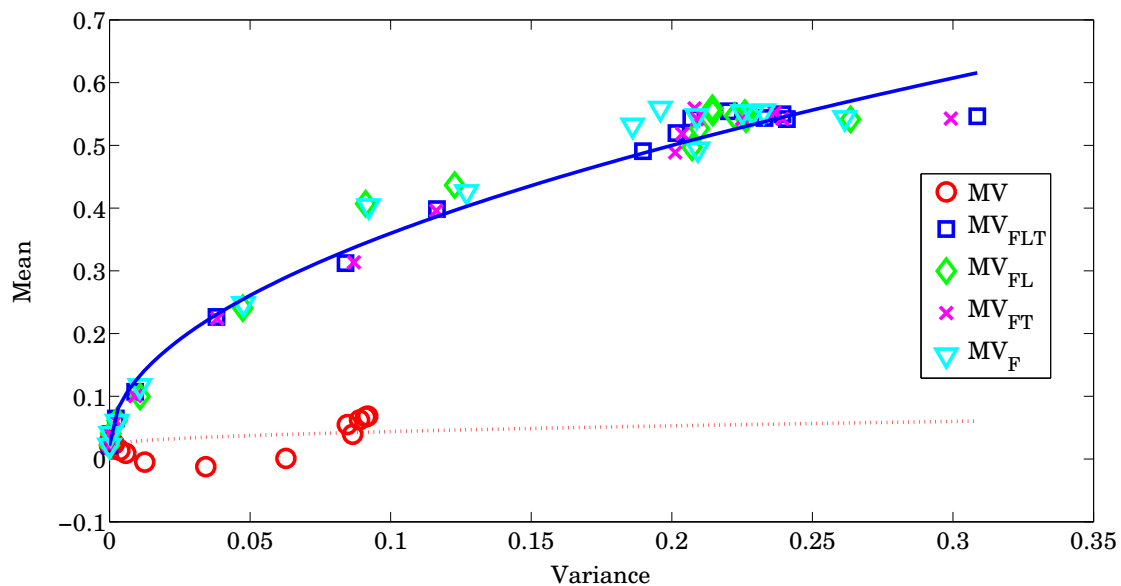
¹⁰The Sharpe ratio is constant along the mean-variance frontier when there are no constraints, and liquidity and transaction costs.

Figure 6.1: Annualized *ex-ante* cost-adjusted mean-variance frontiers.

This figure provides the annualized *ex-ante* cost-adjusted mean-variance frontiers under the five scenarios (MV, MV_{FLT} , MV_{FL} , MV_{FT} and MV_F), and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line). The fitted frontiers are based on the minimum mean square error of the constant Sharpe ratio equation $\mu_p = r_f + SR\sigma_p$ where μ_p and σ_p are the expected value and standard deviation of the portfolio return, respectively, and SR is the portfolio's Sharpe ratio. The fitted Sharpe ratio of MV is 0.241 and that of MV_{FLT} is 1.940.

The *ex-post* analysis confirms a significant advantage of fund managers who use the futures in an optimal way. More precisely, the fitted mean-variance frontier of MV corresponds to a Sharpe ratio of 0.070, and that of MV_{FLT} corresponds to a Sharpe ratio of 1.069, which are lower than the Sharpe ratios in the *ex-ante* cases. However, the *ex-post* benefit of the futures, which is an increase in a Sharpe ratio of 0.999, is still significant.

Figures 6.3 and 6.4 show the *ex-post* liquidity and transaction costs, respectively, associated with trading the futures, stocks and both futures and stocks for scenarios MV and MV_{FLT} for each value of the risk-return trade-off coefficient λ . It can be seen from Figures 6.3 and 6.4 that as fund managers become more concerned about risk (λ increases), they reduce trading activities for both stocks and the futures which can be observed by the lower total liquidity and transaction costs for both scenarios MV and MV_{FLT} . Moreover, regardless of the level of risk-return trade-off coefficient λ , the liquidity cost associated with trading the futures is relatively very small compared to the total liquidity cost (less than 4%), while the transaction cost associated with trading the futures is a large proportion of the total transaction cost (more than 90%). This suggests that the transaction cost is the major trading cost component that fund managers have to consider when they choose to manage their portfolios with the futures. Nev-

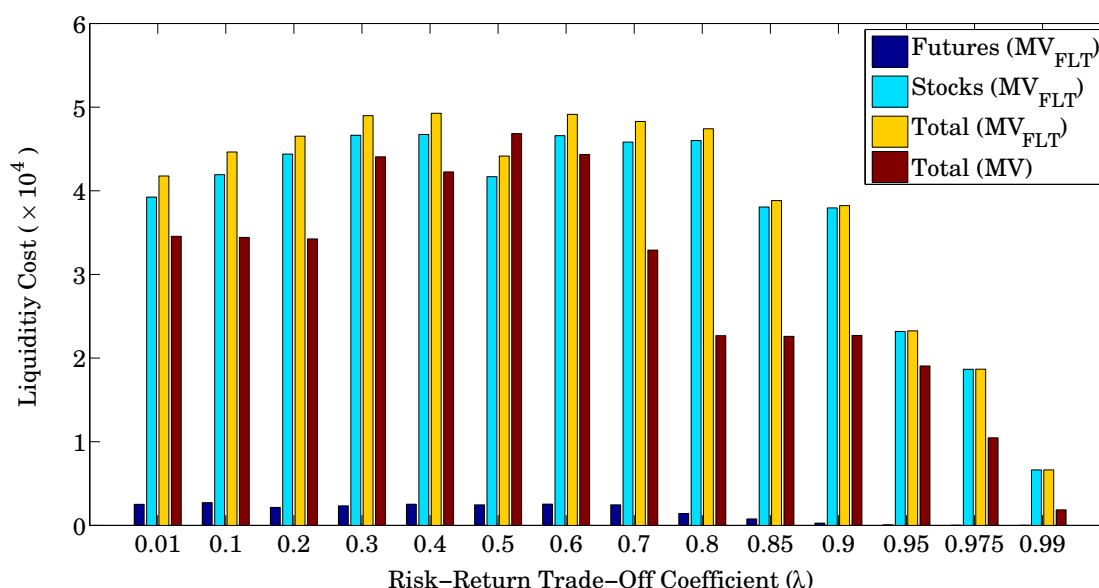
Figure 6.2: Annualized *ex-post* cost-adjusted mean-variance frontiers.

This figure provides the annualized *ex-post* cost-adjusted mean-variance frontiers under the five scenarios (MV, MV_{FLT} , MV_{FL} , MV_{FT} and MV_F), and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line). The fitted frontiers are based on the minimum mean square error of the constant Sharpe ratio equation $\tilde{\mu}_p = r_f + SR\tilde{\sigma}_p$ where $\tilde{\mu}_p$ and $\tilde{\sigma}_p$ are the realized value and standard deviation of the portfolio return, respectively, and SR is the portfolio's Sharpe ratio. The fitted Sharpe ratio of MV is 0.070 and that of MV_{FLT} is 1.069.

ertheless, as shown by Figure 6.2, when fund managers use the futures in an optimal way, the associated trading costs are small compared to the gained benefits.

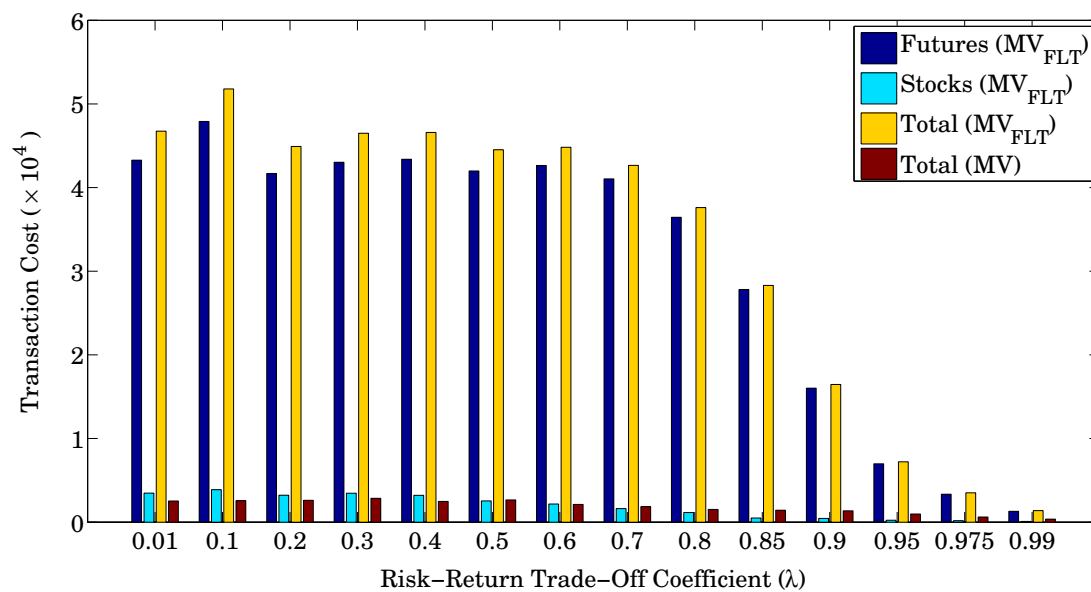
Panels (a), (b) and (c) of Figure 6.5 provide the cumulative returns of the SET50 index (the market), the portfolio value for MV, and the portfolio value for MV_{FLT} , and panels (d), (e) and (f) show the time-series of the portfolio weights for stocks in MV, stocks in MV_{FLT} , and the futures in MV_{FLT} . Panels (a) and (d) correspond to $\lambda = 0.1$, panels (b) and (e) correspond to $\lambda = 0.5$, and panels (c) and (f) correspond to $\lambda = 0.9$. As expected, the portfolio weights given to stocks for MV are lower as λ , or equivalently the level of risk aversion, increases. In addition, the weights are lower during the market downturn and higher during the market upturn. The result shows that the cumulative returns of the portfolio values for MV over the study period are higher than that of the SET50 index. This suggests that the factor model in Section 5 provides a reasonable forecasting performance.

Unlike the scenario MV, the weights given to stocks for MV_{FLT} are lower during the market downturn, but are quite stable during the market upturn. However, the resulting portfolio's cumulative returns for MV_{FLT} are higher than those for MV. This is because fund managers for MV_{FLT} use the futures to increase the market exposure during the market upturn

Figure 6.3: Averages of daily *ex-post* liquidity costs.

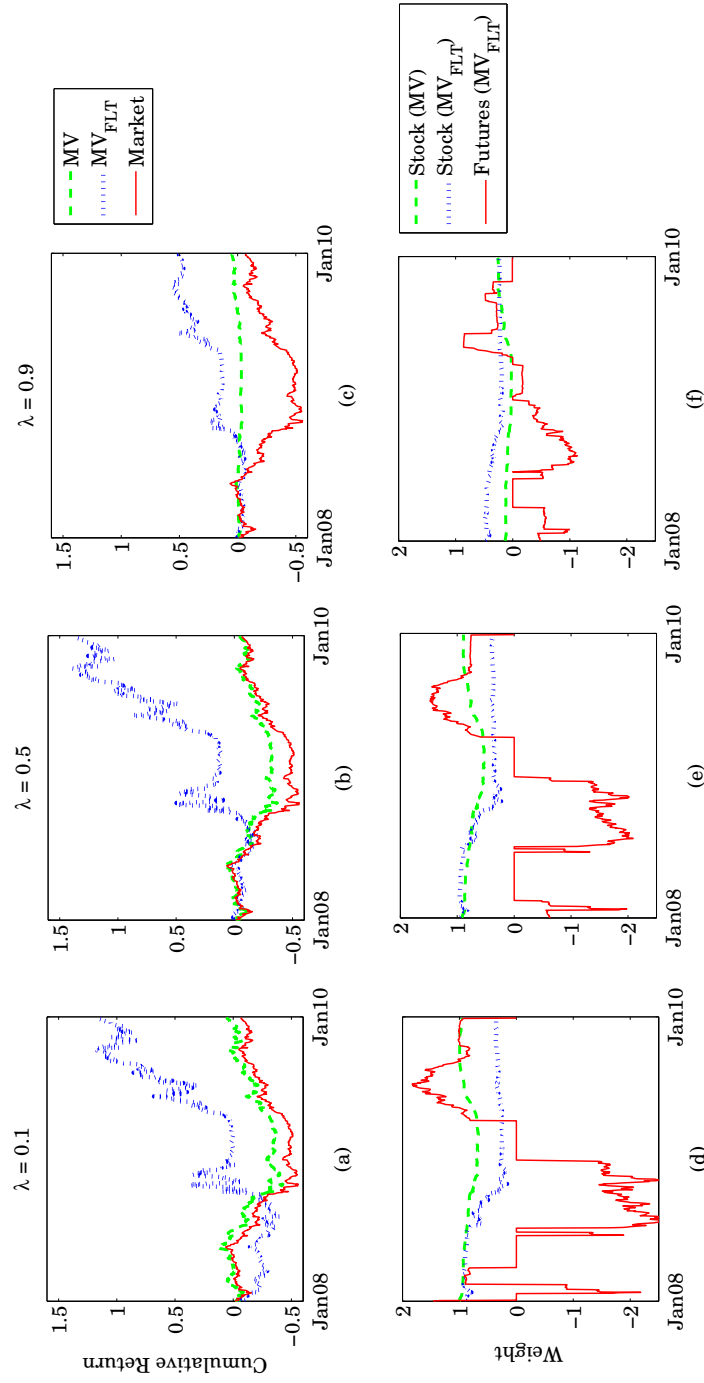
This figure provides the averages of daily *ex-post* liquidity costs associated with (i) trading the futures, (ii) trading the stocks and TDEX, and (iii) trading all securities (total) for scenario MV_{FLT} , and the averages of daily *ex-post* total liquidity costs for scenario MV for each value of the risk-return trade-off coefficient.

and decrease the market exposure during the market downturn as suggested by the weights given to the futures in panels (d), (e) and (f) of Figure 6.5. This analysis clearly shows the advantage of fund managers who can use the futures to control the market exposure over those who cannot. Nonetheless, it is important to note that the realized benefits from the futures may depend on the ability to forecast the market trend of fund managers, and on the constraints faced by fund managers. In the next section, we will provide an example where the benefits of the futures are small, or even negative, when a naive forecasting model is used, and another example to show an additional benefit of the futures when fund managers are required to invest at least a certain percentage of portfolio values in stocks.

Figure 6.4: Averages of daily *ex-post* transaction costs.

This figure provides the averages of daily *ex-post* transaction costs associated with (i) trading the futures, (ii) trading the stocks and TDEX, and (iii) trading all securities (total) for scenario MV_{FLT} , and the averages of daily total transaction costs for scenario MV for each value of the risk-return trade-off coefficient.

Figure 6.5: Ex-post portfolio's cumulative returns and portfolio weights.



Panels (a), (b) and (c) of this figure provide the time-series of the portfolio's cumulative returns during January 2008 to December 2009 for scenarios MV (dashed line) and MV_{FLT} (dotted line) compared to the cumulative returns of the SET50 index (solid line), which is the market. The values of the risk-return trade-off coefficient λ for panels (a), (b) and (c) are 0.1, 0.5 and 0.9, respectively. Panels (d), (e) and (f) provide the portfolio weights in stocks for MV (dashed line), portfolio weights in stocks for MV_{FLT} (dotted line), and portfolio weights in the futures for MV_{FLT} (solid line). The values of the risk-return trade-off coefficient λ for panels (d), (e) and (f) are 0.1, 0.5 and 0.9, respectively.

7 Extensions

In this section we consider two extensions. The first one concerns the use of a naive forecasting model to forecast means and covariances of security returns. The second extension regards an additional restriction on the minimum stock holdings in the portfolio. We show that the benefits from including the futures in the investment universe may change due to the forecasting model used and the constraint faced by fund managers.

Naive Forecasting Model

In this section we adopt a naive forecasting model for means and covariances of security returns to show that the benefits from using the futures depend also on the forecasting ability of fund managers. This naive model only uses historical returns to generate forecasts of means and covariances. More precisely, we use the one-year equally weighted sample means of the stock returns as the estimates of the expected returns, and the five-year equally weighted sample covariances as the estimates of the stock covariances. Figures 7.1 and 7.2 show the *ex-ante* and *ex-post* cost-adjusted mean-variance frontiers and the fitted frontiers for the scenarios MV (dotted line) and MV_{FLT} (solid line). The benefit from using the futures on the *ex-ante* basis is an increase of 0.372 in the Sharpe ratio (from 0.470 to 0.842). However, using the futures on the *ex-post* basis results in a decrease of 0.311 in the Sharpe ratio (from 0.012 to -0.299¹¹). This example therefore provides evidence of the loss from using the futures when a poor forecasting model is employed.

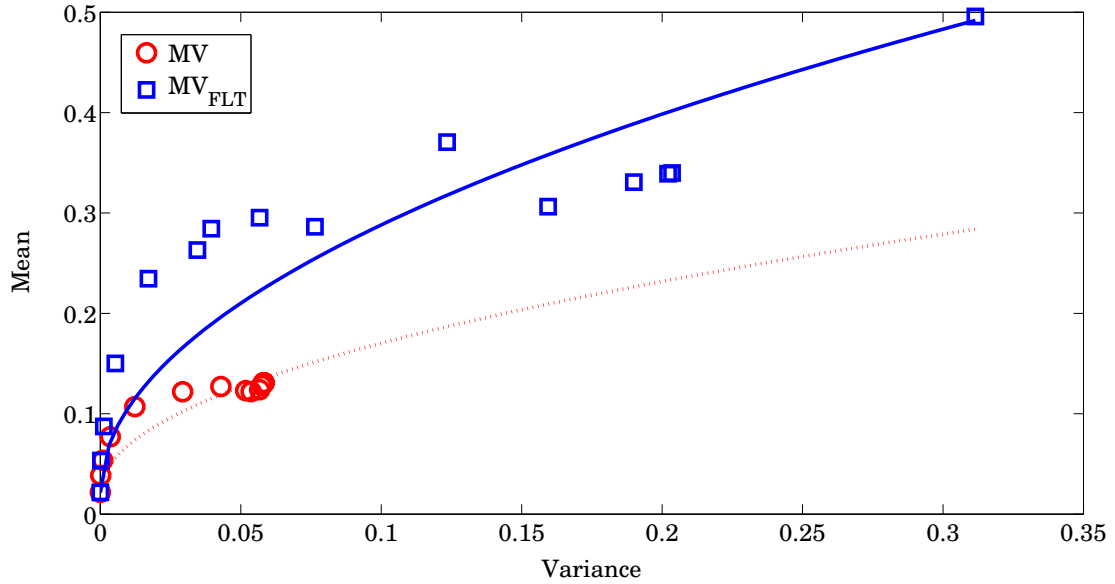
Minimum Stock Holdings

Some mutual funds have a policy to hold stocks for at least a certain percentage of the fund value. For example, the long term equity fund or LTF in Thailand is a fund that is required to hold stocks in the Stock Exchange of Thailand for an annual average of at least 65% of their net asset values. In return, the amount invested in the fund for a minimum of five calendar years will be eligible for a tax deduction. In this section we evaluate the benefits of using the futures when fund managers are faced with such the constraint.

Figure 7.3 shows the annualized *ex-ante* cost-adjusted mean-variance frontiers and the fitted frontiers for MV (dashed line) and MV_{FLT} (solid line). The frontiers are fitted based

¹¹ A negative Sharpe ratio is equivalent to having returns lower than the risk-free rate.

Figure 7.1: Annualized *ex-ante* cost-adjusted mean-variance frontiers with the naive forecasting model.



This figure provides the annualized *ex-ante* cost-adjusted mean-variance frontiers under scenarios MV and MV_{FLT} , and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line). The fitted frontiers are based on the minimum mean square error of the constant Sharpe ratio equation $\mu_p = r_f + SR\sigma_p$ where μ_p and σ_p are the expected value and standard deviation of the portfolio return, respectively, and SR is the portfolio's Sharpe ratio. The fitted Sharpe ratio of MV is 0.470 and that of MV_{FLT} is 0.842.

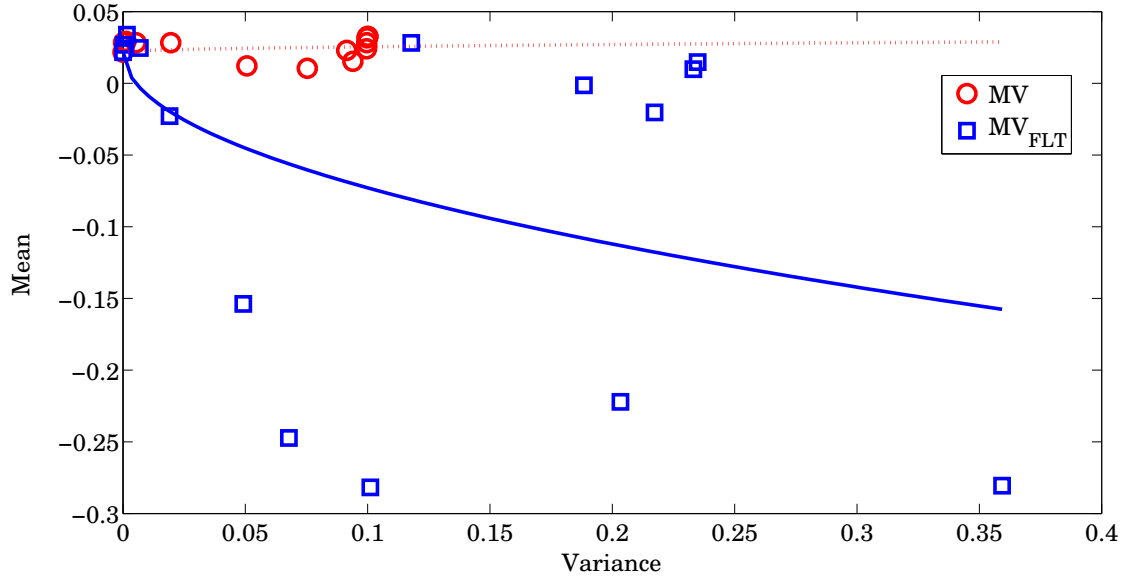
on minimizing the mean square error of the portfolio's expected return from the following equation¹²

$$\mu_p = \mu_0 + SR_0 \sqrt{\sigma_p^2 - \sigma_0^2} \quad (7.1)$$

where σ_0^2 is the global minimum variance of the portfolio return, μ_0 is the expected value of the portfolio return at the global minimum variance, and SR_0 is a measure of the risk-adjusted return similar to the Sharpe ratio, but is referenced to the mean and variance at the global minimum variance (μ_0 and σ_0^2) instead of those of the risk free asset. Let us call SR_0 the global minimum

¹²This equation represents mean-variance frontiers when a fixed proportion of the portfolio value is required to invest in risky assets, and there are no other constraints, nor liquidity and transaction costs.

Figure 7.2: Annualized *ex-post* cost-adjusted mean-variance frontiers with the naive forecasting model.



This figure provides the annualized *ex-post* cost-adjusted mean-variance frontiers under scenarios MV and MV_{FLT} , and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line). The fitted frontiers are based on the minimum mean square error of the constant Sharpe ratio equation $\mu_p = r_f + SR\sigma_p$ where μ_p and σ_p are the expected value and standard deviation of the portfolio return, respectively, and SR is the portfolio's Sharpe ratio. The fitted Sharpe ratio of MV is 0.012 and that of MV_{FLT} is -0.299.

variance Sharpe ratio¹³. The fitted frontier for MV is

$$\mu_p = 0.0036 + 0.4275\sqrt{\sigma_p^2 - 0.1917^2},$$

and that for MV_{FLT} is

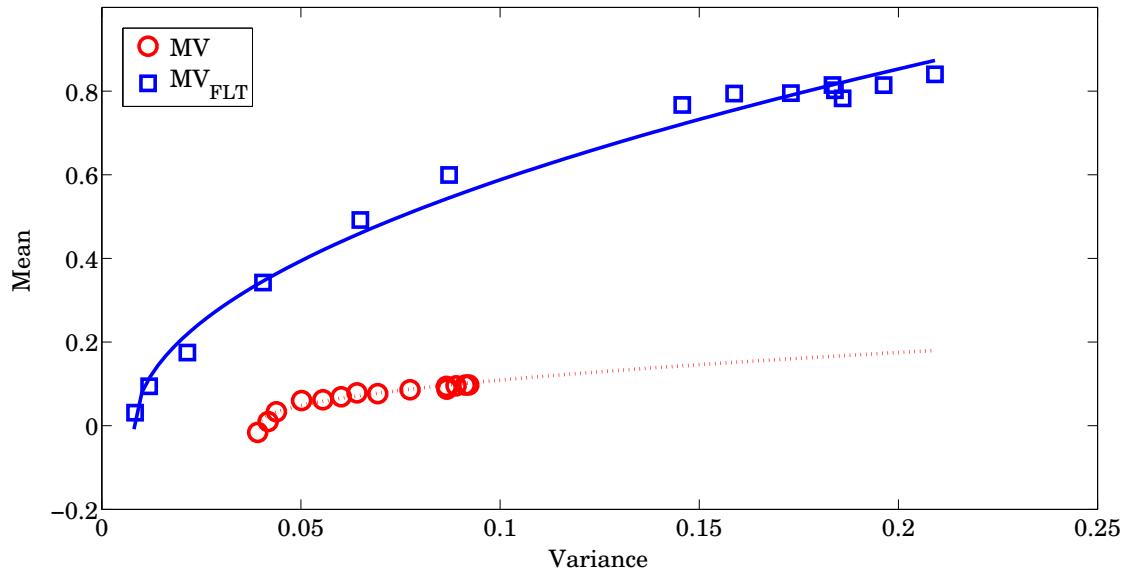
$$\mu_p = -0.0083 + 1.9659\sqrt{\sigma_p^2 - 0.0899^2}.$$

There are two clear advantages of fund managers who use the futures to manage their portfolios under the minimum stock holdings constraints that can be seen from the fitted frontiers. Firstly, the global minimum variance Sharpe ratio significantly increases from 0.4275 to 1.9659, an increase of 1.5384. Secondly, the global minimum standard deviation of the portfolio return reduces from 0.1917 to 0.0899. In other words, fund managers who use the futures may

¹³The terminology for the global minimum variance Sharpe ratio used here is not a general name for SR_0 in equation (7.1). We use this terminology for our convenience to refer to SR_0 .

reduce their annual portfolio standard deviation on the *ex-ante* basis to 8.99%, while those who do not use the futures have to hold the portfolios with the annual standard deviation of at least 19.17%. This illustrates how much short positions of the futures can reduce market risk, and consequently the portfolio risk. The *ex-post* analysis leads to the same conclusions. Specifically, the use of the futures on the *ex-post* basis increases the minimum global variance Sharpe ratio of 1.0634 (from 0.2380 to 1.3014), and reduces the global minimum variance from 20.10% to 5.64%. The *ex-post* cost-adjusted mean-variance frontiers are given in Figure 7.4.

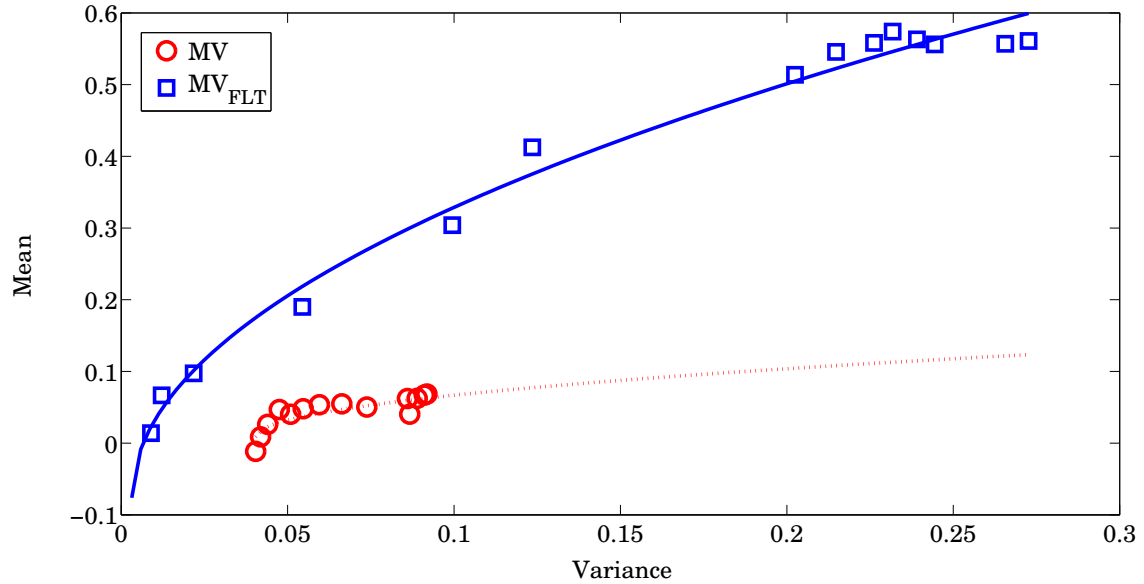
Figure 7.3: Annualized *ex-ante* cost-adjusted mean-variance frontiers with 65% minimum stock holdings constraint.



This figure provides the annualized *ex-ante* cost-adjusted mean-variance frontiers under scenarios MV and MV_{FLT} , and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line) when the 65% minimum stock holdings constraint is imposed. The fitted frontiers are based on the minimum mean square error of equation $\mu_p = \mu_0 + SR_0 \sqrt{\sigma_p^2 - \sigma_0^2}$ where μ_p and σ_p are the expected value and standard deviation of the portfolio return, respectively, μ_0 and σ_0 are the expected value and standard deviation at the global minimum variance, respectively, and SR_0 is the portfolio's global minimum variance Sharpe ratio. The fitted frontier parameters of MV are $\mu_0 = 0.0036$, $\sigma_0 = 0.1917$, $SR_0 = 0.4275$, and those of MV_{FLT} are $\mu_0 = -0.0083$, $\sigma_0 = 0.0899$, $SR_0 = 1.9659$.

Like the case when there is no minimum stock holdings constraint in Section 6, the major part of the liquidity cost comes from that associated with trading stocks, while the major part of the transaction cost comes from that associated with trading the futures for scenario MV_{FLT} . Interestingly, as the risk-return trade-off coefficient λ increases, the total liquidity and transaction costs for MV increase, but those for MV_{FLT} decrease. This shows that when fund managers are not allowed to use the futures, trading costs become higher as they need to maintain a minimum of 65% of stocks in their portfolios and at the same time to keep the portfolio

Figure 7.4: Annualized *ex-post* cost-adjusted mean-variance frontiers with 65% minimum stock holdings constraint.

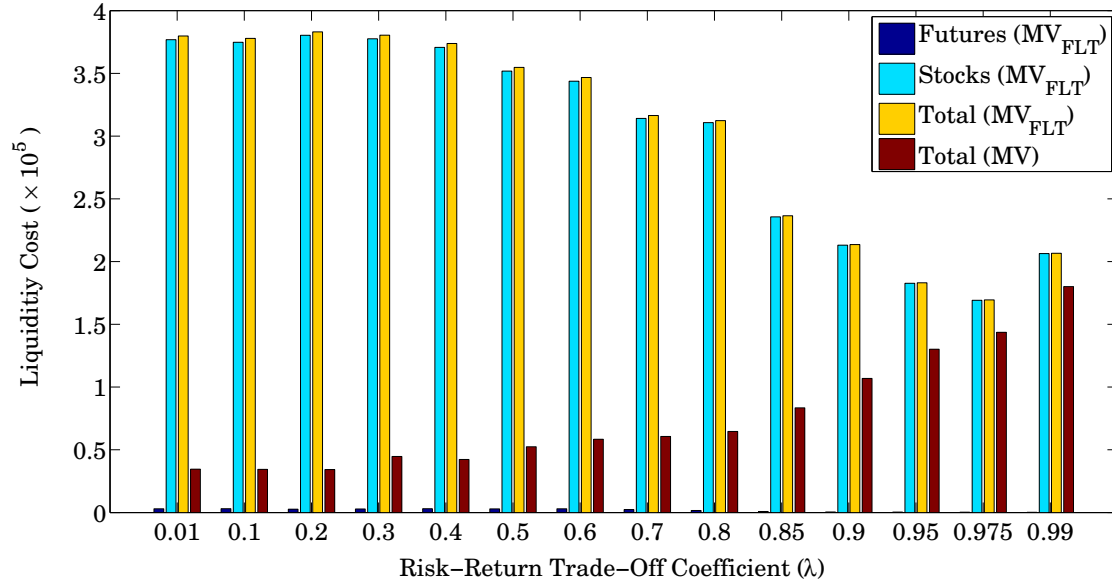


This figure provides the annualized *ex-post* cost-adjusted mean-variance frontiers under scenarios MV and MV_{FLT} , and the fitted mean-variance frontiers for MV (dotted line) and MV_{FLT} (solid line) when the 65% minimum stock holdings constraint is imposed. The fitted frontiers are based on the minimum mean square error of equation $\tilde{\mu}_p = \mu_0 + SR_0 \sqrt{\tilde{\sigma}_p^2 - \sigma_0^2}$ where $\tilde{\mu}_p$ and $\tilde{\sigma}_p$ are the realized value and standard deviation of the portfolio return, respectively, μ_0 and σ_0 are the expected value and standard deviation at the global minimum variance, respectively, and SR_0 is the portfolio's global minimum variance Sharpe ratio. The fitted frontier parameters of MV are $\mu_0 = 0.0087$, $\sigma_0 = 0.2010$, $SR_0 = 0.2380$, and those of MV_{FLT} are $\mu_0 = -0.0762$, $\sigma_0 = 0.0564$, $SR_0 = 1.3014$.

variance lower. On the other hand, when they are allowed to use the futures, it becomes easier to keep the portfolio variance smaller with the use of the futures, and this leads to lower trading costs as minimizing risk becomes more important. Nevertheless, both liquidity and transaction costs for MV_{FLT} are higher than those for MV for all values of λ . It is, however, worth paying the costs in exchange for a significant improvement in the portfolio performance as shown by the cost-adjusted mean-variance frontiers. The annualized *ex-post* liquidity and transaction costs are provided in Figures 7.5 and 7.6, respectively.

Figure 7.7 shows the portfolio weights given to stocks and futures for scenarios MV and MV_{FLT} for the cases where the 65% minimum stock holdings constraint is and is not imposed at $\lambda = 0.9$. In particular, panel (a) of Figure 7.7 shows the time-series of weights given to stock for MV (dotted line) and MV_{FLT} (dashed line) and that given to the futures for MV_{FLT} (solid line) when there is no 65% minimum stock holdings constraint, while panel (b) shows the same time-series when the constraint is imposed. It is clear that when the constraint is present,

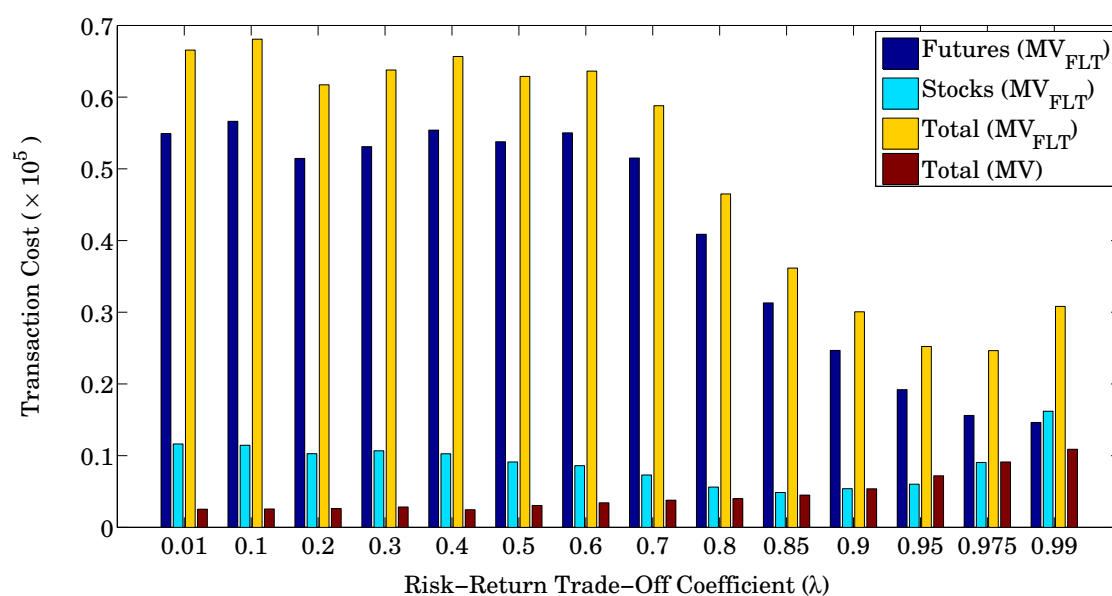
Figure 7.5: Averages of daily *ex-post* liquidity costs with 65% minimum stock holdings constraint.



This figure provides the averages of daily *ex-post* liquidity costs associated with (i) trading the futures, (ii) trading the stocks and TDEX, and (iii) trading all securities (total) for scenario MV_{FLT} , and the averages of daily *ex-post* total liquidity costs for scenario MV for each value of the risk-return trade-off coefficient λ when the 65% minimum stock holdings constraint is imposed.

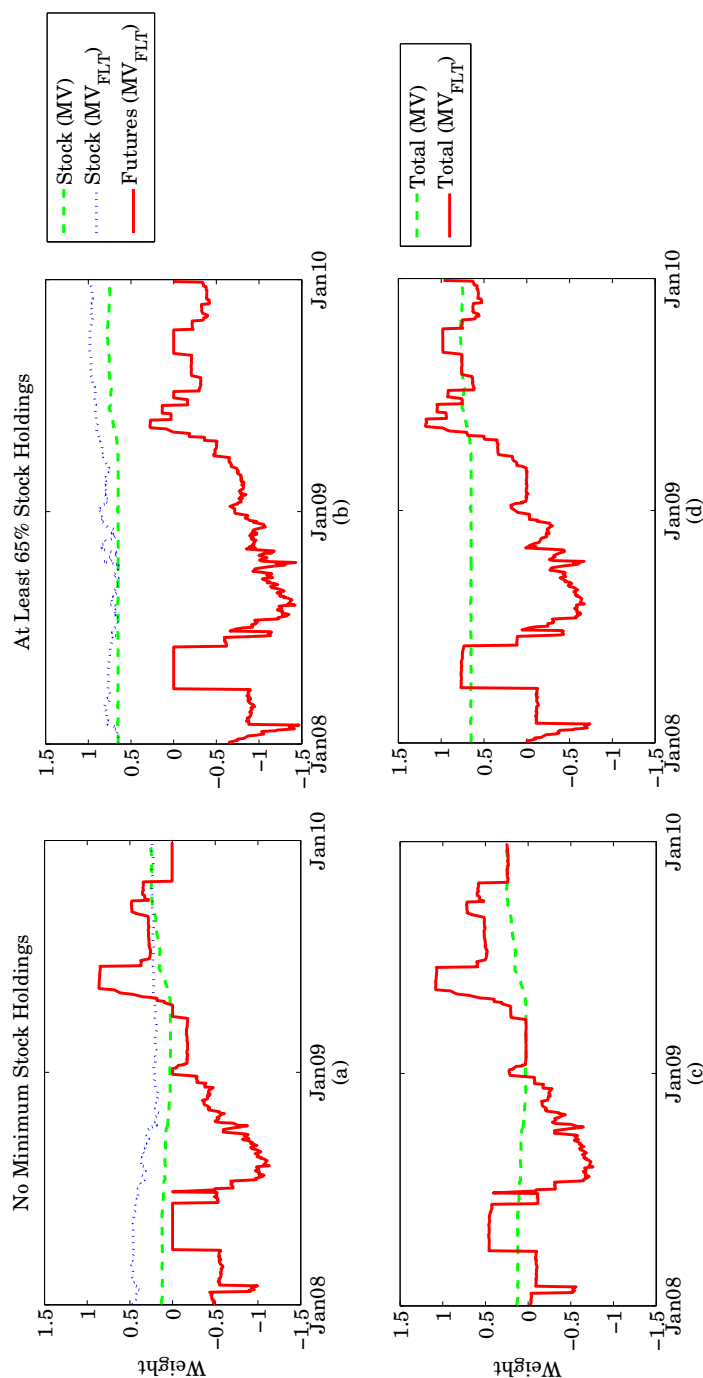
the weights given to stocks are higher for both MV and MV_{FLT} , and the weights given to the futures for MV_{FLT} are lower. The lower level of the futures weights is to compensate the higher stock positions due to the 65% minimum stock holdings constraint. In fact, we can see from panel (b) that the futures weights are almost always negative. Thus, in this case where the risk-return trade-off coefficient λ is high, the futures is used as a market risk hedging tool even during the market upturn. Panels (c) and (d) of Figure 7.7 show the total weights given to stock and futures for MV and MV_{FLT} when fund managers are and are not free from the constraint, respectively. As we can see, the total weights given to stocks and the futures for MV_{FLT} in panels (c) and (d) are similar. This is because the futures are used to keep the total market exposure remain stable whether or not the constraint is imposed.

Figure 7.6: Averages of daily *ex-post* transaction costs with 65% minimum stock holdings constraint.



This figure provides the averages of daily *ex-post* transaction costs associated with (i) trading the futures, (ii) trading the stocks and TDEX, and (iii) trading all securities (total) for scenario MV_{FLT} , and the averages of daily *ex-post* total transaction costs for scenario MV for each value of the risk-return trade-off coefficient λ when the 65% minimum stock holdings constraint is imposed.

Figure 7.7: Ex-post portfolio weights with 65% minimum stock holdings constraint.



This figure provides the time-series of the portfolio weights during January 2008 to December 2009. Panels (a) and (b) of this figure provide the weights given to stocks for scenarios MV (dashed line) and MV_{FLT} (dotted line), and the weights given to the futures for MV_{FLT} (solid line) where panel (a) corresponds to the case when no 65% minimum stock holdings constraint is imposed, and panel (b) corresponds to the case when the constraint is imposed. Panels (c) and (d) provide the portfolio weights in stocks for MV (dashed line) and the total weights given to stocks and the futures for MV_{FLT} (solid line) where panel (c) corresponds to the case when no 65% minimum stock holdings constraint is imposed, and panel (d) corresponds to the case when the constraint is imposed. The value of the risk-return trade-off coefficient λ is 0.9.

8 Policy Implications

This study addresses both *ex-ante* and *ex-post* analyses on the hedging effectiveness of the SET50 index futures. The results of the study show that the level of hedging effectiveness of SET50 index futures is very high (an increase of 1.699 in the *ex-ante* Sharpe ratio and 0.999 in the *ex-post* Sharpe ratio), and that the liquidity and transaction costs associated with trading the futures are minimal compared to the benefits although the transaction cost is relatively high compared to that associated with trading stocks. However, to gain the advantage from using the futures, fund managers must have a skill to forecast the market trend reasonably well. In this study, we assume that the fund manager manages portfolios based on a fairly complicated factor model, and show that it provides a good forecast for the market trend during the study period. Furthermore, it is shown that a poor forecasting model may lead to a worse performance when the futures is included in the investment universe.

Based on this study, policy makers can be ensured that the current market structure and the liquidity for the SET50 index futures well facilitate investors with large portfolio values (one billion baht in this study) to utilize the benefits of the futures. However, the realized benefits depend also on the ability to forecast the market trends, and constraints faced by fund managers. Moreover, fund managers must understand the role of the futures in improving the *risk-adjusted* performance, and do not be misled by the fact that using a short position of the futures to hedge the market risk may reduce the realized return during the market upturn. In fact, given that fund managers can forecast the market trend reasonably well, hedging the market risk by shorting the futures can improve the *risk-adjusted* performance on both *ex-ante* and *ex-post* bases.

9 Conclusions

We study the hedging effectiveness of the SET50 index futures based on the notion of mean-variance criterion with liquidity and transactions costs during January 2008 to December 2009. We model liquidity cost curves by asymmetric quadratic functions of the order values where the price impacts from buy orders and sell orders of the same size may differ. We find strong evidence of asymmetry in the liquidity cost curves. The liquidity level of the SET50 index futures is relatively high compared to those of stocks in the SET50 index. The transaction costs are assumed to be proportional to the traded values for stocks and the number of traded contracts for the futures. A fundamental factor model is used to generate forecasts for means and covariances of security returns. We find that the market factor has the highest risk in terms of the variance and excess kurtosis. A cost-and-risk-adjusted expected return objective is maximized subject to a set of constraints with daily trading frequency. We measure the benefits of the futures using the Sharpe ratio of the fitted cost-adjusted mean-variance frontiers. The results show that the benefits obtained from using the futures are significant on both *ex-ante* and *ex-post* bases, and the trading costs associated with trading the futures are minimal compared to the benefits. However, the transaction cost associated with trading the futures is relatively high compared to the transaction cost of trading stocks.

Two extensions are studied in this paper. The first one assumes a naive forecasting model. It is shown that using the poor forecasts from the naive model can lead to losses when the fund managers are allowed to use the futures. The second one concerns the 65% minimum stock holdings constraint imposed on the long term equity fund or LTF in Thailand. We find that with this constraint, the use of the futures provides a lower global minimum variance as well as a higher Sharpe ratio. That is, it generates a wider range and the higher level of the risk-adjusted returns. The findings ensure the benefits of the futures over the costs although the realized benefits depend on the ability of fund managers to forecast the market trend reasonably well.

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