IMPLEMENTING BLACK-LITTERMAN USING EQUITY ANALYST CONSENSUS: EVIDENCE FROM SET50

BY

MISS BOONMAYTAR NANNAR

AN INDEPENDENT STUDY SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE PROGRAM IN FINANCE (INTERNATIONAL PROGRAM)
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ABSTRACT

This study document that the Black-Litterman asset allocation model, which incorporates analyst consensus revision, outperforms the market for both monthly and quarterly rebalancing basis after transaction cost, as it provides the higher average return while keep the risk lower. Moreover, we show that equal-weighted favorable revision consensus portfolio performs impressively above the market as well. Thus, using analyst consensus, a public information, helps investor gaining an abnormal return. This affirms that the SET50 is a semi-strong form market inefficient.

Keywords: Black-Litterman, Analyst consensus, Market efficiency

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Ms. Boonmaytar Nannar

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LIST OF ABBREVIATIONS

Symbols/Abbreviations	Terms
BL	Black-Litterman
MVO	Mean Variance Optimization
P1_MW	Market cap. weighted of favorable consensus portfolio
P2_MW	Market cap. weighted of unfavorable consensus portfolio
P1_EW	Equal weighted of favorable consensus portfolio
P2_EW	Equal weighted of unfavorable consensus portfolio
EMH	Efficient market hypothesis

CHAPTER 1
INTRODUCTION

When Markowitz framework was introduced in 1952, it became a groundbreaking framework which considerably changes the way how investors invest at that time. The framework helps investors determining and allocating the weight of assets within a portfolio so as to maximize the expected return of the investment portfolio and minimizing the potential risk. Afterward, an asset allocation has gained so much interest that no shortage of literature exploring about its importance. The studies from Brinson et al. [1986], Hensel et al. [1991], Ibbotson and Kaplan [2000] and Kritzman [2006] provided a similar conclusion that the asset allocation is very important attribution in portfolio performance.

Although Markowitz framework provides the simply and intuitive approach to portfolio construction, but the problems still can be found when applying the model in practice. The first problem is input sensitivity, a small change in input may lead to huge change in asset weight of portfolio. As a result of an unstable portfolio. Secondly, the highly concentrated portfolio, instead of well-diversified one. Result from overweighting assets with high expected returns and low volatility in a risk-minimizing procedure. This also known as the error-maximizing problem.

Throughout the years, there have attempted to remedy those problems. For example, the resampling technique and the Bayesian approach. However, among the potential remedies to the input sensitivity of Markowitz model, Da Silva et al. [2009] suggest that the Black-Litterman framework shows the most strong theoretical conceptual of all techniques. It also largely mitigates error-maximizing problem according to Idzorek [2005].

The Black-Litterman model, hereafter BL model, allows investors to put their unique investment view into optimize process and combine the views with market equilibrium data in order to form a new optimal portfolio. The model points out that, when changing the view of one asset, it will affect its expected return and also other assets due to a correlation. Therefore, the error in estimating expected return in one asset will be extended to all other correlated assets, so that a robust optimal portfolio can be derived and yield more stable mean variance efficient portfolio. For this reason, it provides more practical framework in implementing the model.

The comparative advantages of the BL model over the other models have been studied by Schottle et al. [2010]. They made a comparison between BL model and Bayesian approach, two of the most well-known models in combining information. They suggest that the BL model allows more possibilities for incorporate experts' opinion in both absolute and relative term. While in the Bayesian approach, only the absolute return of each asset can be made and this may lead to the misleading in the optimization framework. Moreover, Cheung [2010] summarized that BL model does not require the users to have views or forecast data of all assets in the universe. This advantage helping us to avoid using uninformative forecast and it also allows to put a confident level of the uncertain views.

Even though the BL model is quite popular among practitioners, but far from here, there is a few pieces of literatures that studied in Thai equity market and all of them furnish the use of the BL model in quantitative manners so as to construct a view. Leelaprachakul [2011] studied the BL model with GARCH model as views input, while Wachirapansathit [2013] taking views from momentum factor.

This study aims to 1) provide an application of the BL model by using investment strategy based on equity analyst consensus as private views to optimize a portfolio weight 2) analyze and compare the BL portfolio performance to the market and other benchmark portfolios 3) grant an important implication for individual investors or fund managers whom use analysts' consensus and/or analysts' opinion to making investment decisions and 4) the result also imply the economic value of equity analysts' consensus whether it helps investors to gain abnormal return. This is to confirm that there is no existence of semi-strong form of efficient market hypothesis (EMH) in Thai equity market.

The data of this study will cover from 2006 – 2015 to ensure that the portfolio is constructed in every market condition. We use Bloomberg analysts' consensus of the stocks comprising the SET50 index instead of an individual analyst since the consensus provides more informative data according to Elton et al. [1986].

The contribution of the study is to focus the use of BL model based on the revision of analyst consensus. We blend the advantages of methods used by previous studies to construct unique private views, which should be more informative.

For the sample period, we found that the BL model using analyst consensus as private views outperformed the market for both monthly and quarterly rebalancing basis after transaction cost. Especially for quarterly rebalancing, the BL portfolio performed impressively, beat all other benchmark portfolios. The result of this study suggests the economic value of analysts' consensus, an investor aiming to use such a trading strategy is able to gain a superior return.

The remainder of this paper consists of the following section: Section 2 review the previous relevant studies. Section 3 Theoretical framework explains the insight and literature regarding the BL model and also efficient market hypothesis. The research designation and methodology are explained in Section 4. Section 5 describes the data used in the study. The results and conclusion are shown in section 6 and 7 respectively.

CHAPTER 2
REVIEW OF LITERATURE

Before the BL model was introduced in 1992, asset allocation approaches often based on historical data such as historical averages, equal means, and risk-adjusted equal means, or based on the assumption that assets across different countries would yield the equal mean return (Black and Litterman, [1992]). However, after the introduction of the BL model, it has become popular among both practitioners and academic researchers with its intuitive way to solve the serious problem of classical mean-variance framework. There are several research papers that explored on the application and also the limitation of the model.

As mentioned above, one serious problem of Markowitz model is a highly concentrated portfolio. Cheung [2010] and Jones et al. [2007] indicated that using the BL model can have less extreme portfolio weights. The intuition is, the model takes market equilibrium return as portfolio's starting point and tiles out toward investor's private view if it exists. Hence, it results in the balanced portfolio and less likely to run into unstable or corner solution compared to other approaches. A further study comparing portfolio performance between BL model and the classical mean-variance framework was conducted by Hirani and Wallstrom [2014]. They simulated past performance of portfolio using the total return of the stocks included in OMXS 30 from Jan 2003 – Dec 2013 for both models. Applying an investment strategy which prefers high dividend stocks as private view, the result shows that BL model has superior performance, gaining the higher Sharpe ratio and lower volatility.

Since Black and Litterman [1992] did not clue up how to choose a view, many papers studied to incorporate difference types of views into the model. He et al. [2013] and Chen et al. [2015] studied the implementation of an equity analyst's recommendations and target price into the model. While Fabozzi et al. [2006] introduce and suggest a method to combine trading strategies, for example, factor model and cross-sectional ranking variables, as private views into the BL model.

He et al. [2013] studied economic value of equity analyst's recommendations using BL model in Australian equity market. They separated analyst's recommendation rating into groups in order to construct private views. Unfortunately, the market adjusted return of the portfolio using this approach did not turn significant statistically. The paper suggested that we should require a more substantial change in consensus recommendation before adjusting portfolio weights. Since the result did not satisfy the paper's hypothesis, we found some papers studied about an informative of analyst consensus. Boni and Womack [2006] show that the Recommendation change strategy, which is to long all net upgrade and to short all net downgrade stocks within the industry, yields a significant mean return and higher Sharpe ratio than the Consensus level strategy, which considers analyst consensus at one point of time. Note that Consensus level strategy is logically similar to the way of He et al. [2013] using analyst's recommendation to construct private views. Another study of analyst consensus investment value is from Barber et al. [2001]. They show that the favorable consensus portfolios, which recommendation rating are above 3.5, beat the market return.

As the paper intension to optimize a portfolio using BL model with analyst consensus as private views, we will construct optimal portfolio following to He et al. [2013] suggestion, but basically change the way of picking winner and loser stocks to constructing private view. This point we follow the strategy from Boni and Womack [2006] and Barber et al. [2001].

Our hypothesis is the performance of BL portfolio, which incorporate views of analyst consensus, will be improved compare to the benchmark portfolios. If the performance of the BL portfolio outperform the market, it will be concluded that there is no existence of semi-strong form due to the trading strategy using public information yields us an abnormal return, as the securities price is not fully and instantaneously reflect new public information so the holder of that information has the opportunity to buy (sell) the security before its price move toward the new fair value overtime, which is against the Efficient market hypothesis proposed by Fama [1970].

CHAPTER 3
THEORETICAL FRAMEWORK

3.1 Black-Litterman model

The BL model is an asset allocation model introduced by Fischer Black and Robert Litterman in 1992. It involves with combining two sources of information, market view and investor's view, in portfolio optimization process. The main benefit of the model is that it yields a well-diversified and stable mean-variance efficient portfolio since it anchors a starting point with market capitalization portfolio weight.

In this section, we explain the insight of the model separating into three parts as following.

3.1.1 The Black-Litterman model basic assumption and starting point

The BL model assumes the distribution of assets' return (r) to be normal distribution with unknown mean (μ) and known covariance (∑)

$$r \sim N(\mu, \Sigma) \tag{1}$$

Note that our study also assumes a normal distribution of asset return because 1) it is consistent with other mainstream theories in finance and 2) according to Giacometti et al. [2007], the BL model with other assumptions of asset return distribution, including t-student distribution and stable distribution, did not yield much different result from using a normal distribution.

Since ∑ is assumed to be known, it can be computed from historical data. On the other hand, the true expected excess return (μ), is explicitly exposed to an uncertainty. Therefore, the model also assumes the expected return to be the normal distribution.

$$\mu \sim N(\mu^e, \tau\Sigma) \tag{2}$$

, where μ^e represents the best expected excess return estimation of μ and $\tau\Sigma$ represents the uncertainty of this estimation. To come up with the estimation of μ^e, the BL model set up the basic idea indicating that if an investor has no private view or only has a public information and common techniques, then the market portfolio should be the best portfolio choice for the investor. The reason is, if we believe in the semi-strong form of market efficiency hypothesis, it suggests the market has already taken all public information into account and only with a superior private insight and techniques can the investor make abnormal returns. Therefore, the starting point is the CAPM

$$E(R_i) - R_f = \beta[E(R_m) - R_f] \tag{3}$$

, where $E(R_i), E(R_m)\ and\ R_f$ represent an expected return of a security, expected return of a market and risk-free rate respectively. The β measures a systematic risk of a security which can be defined as

$$\beta = \frac{cov(R_i,R_m)}{\sigma_m^2} \tag{4}$$

, where σ_m^2 is variance of the market portfolio return. So we can rewrite CAPM in the equation (3) as

$$E(R_i) - R_f = \frac{cov(R_i,R_m)}{\sigma_m^2}\left[E(R_m) - R_f\right]$$

$$= \frac{E(R_m)-R_f}{\sigma_m^2}\sum_{i=1}^{N} cov(R_i,R_j)w_j \tag{5}$$

Hereafter the term $E(R_i) - R_f$ will be represented by μ^e. The same result of equation (5) can also be derived from utility maximization problem. Assume quadratic utility function,

$$\max \quad \text{utility} = w^T \mu^e - \frac{1}{2} w^T \sum w \tag{6}$$

$$\text{FOC} \qquad \mu^e = \lambda \sum w_m \tag{7}$$

Equation (7) express in matrix form where $\sum$ represent covariance matrix of assets return and w_m is the equilibrium market portfolio weights while λ is the market risk aversion coefficient, characterize risk-return tradeoff. As equation (5) and (7) provide the same result, so we can define λ as equation (8). The equation shows the rate of excess return that investor forgoes to lowering the portfolio volatilities.

$$\lambda = \frac{E(R_m)-R_f}{\sigma_m^2} \tag{8}$$

Hence, we rewrite the Equation (7) as

$$\mu^e = \frac{E(R_m)-R_f}{\sigma_m^2} \sum w_m \tag{9}$$

, noted that μ^e implies market equilibrium return shown in form of excess return and $\sum$ represents covariance matrix.

Then, reverse optimization the equation (9) by assuming market is in equilibrium, so w_m is a market capitalization weight of assets, we will come up with the estimation of μ^e which is a market view. This process of derivation μ^e refers to implied market equilibrium approach.

The intuition behind the equation (9) is that since μ^e represents the expected return in form of excess return of assets against the market, the equation (9) shows that the excess return positively depends on the specified market risk premium. Here, we may interpret λ as the price of market risk and $\sum w_m$ as the quantity of risk. So, the higher market risk premium, the higher excess return. More generally, the implied market equilibrium return will be equal to market return plus market risk premium of each asset.

3.1.2 Expressing an investor's private views

The BL model has no requirement for investor to have views for all assets within a universe. Furthermore, it allows incorporating views in both absolute and relative form. An absolute view, for example, can be stated as asset A will have excess return of 5%. While a relative view, expected return will be compared to other assets such as asset A will outperform asset B by 0.5%. Noted that these views are not sure thing, it faces with some level of uncertainty.

To improve portfolio stability and simplification, a few basic set up of constructing a view is required under the BL model. First, views are uncorrelated to each other. Therefore, a view covariance matrix (Ω) is diagonal. Second, views are fully invested. The meaning is that, if we state an absolute view, sum of invested asset weights under the view is one. A relative view, on the other hand, relies on self-finance method so the summation of those weights is zero. Here, we represent the investor's K views on N assets as the following matrix,

$$P \cdot \mu = Q + \varepsilon \, , \varepsilon \sim N(0, \Omega) \tag{10}$$

The matrix P, KxN matrix, represents the weight of assets involved in each view. From reviewing previous research paper, there have 2 major schemes to impose those weights. First is market capitalization weight scheme from Idzorek [2005] and He et al [2013]. They specify the weight of each asset by dividing asset's market capitalization to the aggregate market capitalization that involves in the particular view. Second is equal weight scheme from Satchell and Scowcroft [2000], so the weight of view-involved asset equal to one divided by the number of those assets. However, Walters [2014] suggest that, in practice, the weight should be a mixture depending on how is the process which we use to estimate the view's return.

The examples of constructing matrix P in each scheme is shown below, given that there have three assets and 2 views. View 1 is an absolute view with involved only asset A. And View 2 is relative view which asset B and C outperforms asset D and E.

Market capitalization weight scheme

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0.7 & 0.3 & -0.7 & -0.3 \end{bmatrix}$$

Equal weight scheme

$$P = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0.5 & 0.5 & -0.5 & -0.5 \end{bmatrix}$$

Where under Market capitalization weight scheme, the relative weight of each asset is equal to its market capitalization divided by total market capitalization of either the outperforming or underperforming assets of that particular view. Obviously, sum of absolute view row is equal to one, while the relative view row is equal to zero.

According to Idzorek [2005], the equal weight scheme ignores market size effect of the securities, causing a large change in optimal weight of the smaller market size securities. Thus, the market-cap weight scheme is applied into this study.

The vector Q, Kx1 vector, represents the expected excess returns of the portfolios from the views described in matrix P. We obtain the vector by backtesting the trading strategy. Detail is shown in section4.

The matrix Ω, KxK matrix, represents the covariance matrix of view error term showing the level of uncertainty in each view. We can also interpret the matrix Ω as view confidence which reflects the view uncertainty to constructing the new combined portfolio. Matrix Ω and view confidence have an inverse relationship. It means that the higher confidence in views, the lower uncertainty and the more investor's optimal portfolio move out of the starting point to have higher weight on the view portfolio. The BL model assumes the matrix to be diagonal which means views are independent and uncorrelated.

According to Walters [2014], there have several approaches to specify the matrix Ω including

1. *Proportional to the variance of the prior.*

   This is the most common approach used by many pieces of previous literature such as He and Litterman [1999] and Meucci [2006]. The matrix will be specified by

   $$\Omega = \mathrm{diag}(\mathrm{P}(\tau\Sigma)P^{T}) \tag{11}$$

   Where τ is a scalar indicating uncertainty of the implied market excess return. So, the idea is that it assumes the uncertainty or variance of views will be proportional to the variance of assets.

2. *Using a confident interval around an estimated mean return.*

   Under this approach, we need to specify an interval around mean return and find a probability that the actual data will fall into this interval then translate into a standard deviation under a normal distribution. So, we compute for the variance.

3. *Using the variance of residuals in a factor model.*

   This approach appropriates for investors who use a factor model to constructing their private view. We can directly compute for the variance of residual, which is a part of the factor model regression, in order to form matrix Ω.

4. *Using Idzorek's method to specify the confidence along the weight dimension.*

The proportional to the variance is used in this study as it was used by the majority of previous studies. Moreover, using this approach, the posterior return is irrelevant to the value of τ which is the most abstract and has different interpretation of its meaning among previous studies. Thus, our result is not matter to the parameter τ.

3.1.3 Combining an investor's views with market view

BL model uses the Bayesian approach, referred to a mixed estimation strategy, in combining two sources of data, which is the market view and private views, to have a posterior distribution of expected excess returns and it will be used as critical input for the mean-variance portfolio choice decision. The posterior return vector then based on Bayesian updating expected risk and return and can be calculated by

$$\mu_{BL} = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}\,[(\tau\Sigma)^{-1}\mu^{e} + P'\Omega^{-1}Q] \tag{12}$$

Where τ represents a scalar indicating uncertainty on the implied market equilibrium return estimation. The value can vary from 0 to 1. The more τ close to zero, the more that a new optimal portfolio weight will close to market portfolio. Otherwise, it will close to private view. Since τ is an abstract factor and difficult to determine, Black and Litterman [1992] assume V= τ∑, the covariance matrix of the expected return is simply proportional to the historical variance. However, some interpret it as the estimation SE of the equilibrium implied return. It could be used to adjust the aggressiveness in overweighting or underweighting stock given the views according to He et al. [2013].

If substituting the equation (10) into equation (12) we can rewrite the equation as following,

$$\mu_{BL} = [(\tau\Sigma)^{-1} + P'\Omega^{-1}P]^{-1}\,[(\tau\Sigma)^{-1}\mu^{e} + P'\Omega^{-1}P\hat{\mu}] \tag{13}$$

The equation (13) shows that the new combined expected return (μ_{BL}) is a linear weight between market confidence and view confidence in expected return. The market and view confidence weight can be shown as

$$w_m = [(\tau\sum)^{-1} + P'\Omega^{-1}P]^{-1}[(\tau\sum)^{-1}]$$

$$w_Q = [(\tau\sum)^{-1} + P'\Omega^{-1}P]^{-1}(P'\Omega^{-1}P)$$

Where $w_m + w_Q = I$

Therefore, the more we are confident in the view, the more the new combined optimal portfolio tilts away from market equilibrium. For the extreme case when investor has no private view, the value of $\Omega = Q = 0$ or the confidence in the view is zero. So, the new combined expected return becomes $\mu_{BL} = \mu^e$ That is, investor who has no private view will hold market portfolio.

The variable τ is the most abstract variable in BL model and the original paper did not explain in the detail about how to come up with its value, so the literatures interpret and impose the value differently. Black and Litterman [1992] set the value of τ close to zero as the uncertainty in a mean should have less uncertainty than in the return. On the contrary, Satchell and Scowcroft [2000] often set τ equal to one. While He et al. [2013] decide to vary the value of τ to be 0.01, 0.05 and 0.10 to study the impact of the portfolio return.

In order to construct the optimal weighted portfolio, we then put the variables μ_{BL} into mean-variance optimization process to find the BL portfolio weights. As a result, the BL model will yield us a stable optimal portfolio.

3.2 Efficient Market Hypothesis (EMH)

The efficient market hypothesis proposed by Eugene Fama describe as "A market where there are large numbers of rational, profit maximizers actively competing, with each trying to predict future market values of individual securities, and where important current information is almost freely available to all participants. In an efficient market, competition among the many intelligent participants leads to a situation where, at any point in time, actual prices of individual securities already reflect the effects of information based both on events that have already occurred and *on events which, as of now, the market expects to take place in the future. In other words, in an efficient market at any point in time the actual price of a security will be a good estimate of its intrinsic value." (Fama [1970])*

From above definition of EMH, in an efficient market, securities prices is instantaneously reflect all available information about individual stocks and stock market so that the investors can only earn an average rate of return. In this condition, the securities price is equal to its intrinsic value or fair price. In fact, each market has different level of efficiency depend on how relevant information is easily and freely available. Thus, Fama identified three distinct level at which a market might actually be efficient as follow,

3.2.1 Strong Form of EMH

The strongest form states that a market is efficient when all information, include those are not available to common investor (insider information), is accurately and rapidly reflect in the securities prices. The market prices already incorporate information of all individual investor in the market so that even the insider cannot gain abnormal return from information they have.

3.2.2 Semi-Strong Form of EMH

A slightly less strict class of EMH, it says that a market is efficient when all public information, include historical data, is already incorporate in current market price which meaning that neither fundamental nor technical data can be used to earn superior return. It imply that investors may have superior return only if they hold an insider information.

3.2.2 Weak Form of EMH

The least strict class of EMH, known as the random walk theory, it claim that a market is efficient if the historical price movements and volume data is calculated into a current securities prices. Hence, we cannot use this type of data to seek an abnormal return due to the fact that all investors also hold this information. An investor who pursues the superior return can earn profits by using fundamental analysis.

CHAPTER 4
RESEARCH METHODOLOGY

This study would like to find whether equity analyst consensus could help improving portfolio performance by using BL model. The portfolio will be rebalanced on monthly and quarterly basis. The result would also imply the economic value of equity analysts' recommendation in Thailand. In order to translate equity analyst consensus into the views, we will follow He et al. [2013], Boni and Womack [2006] and Barber et al. [2001] suggestions.

The process of this study is the following steps,

4.1 Equilibrium implied rate of return

Compute equilibrium implied rate of return as the prior distribution of asset representing the market view. The computation follows equation (9)

The inputs are the market capitalization weight of each asset on the rebalance date and the covariance matrix which calculated on a daily basis of five-year historical return data.

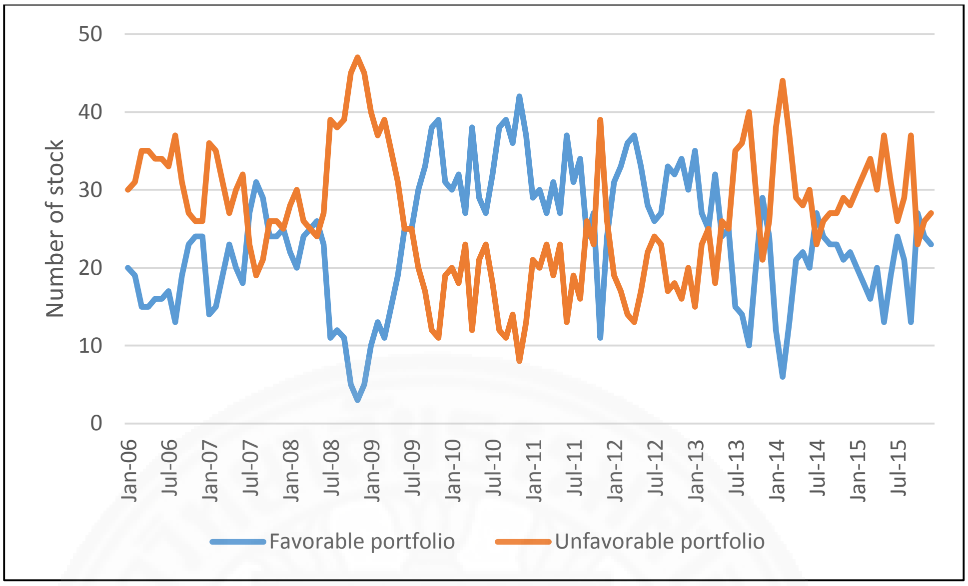
The risk aversion coefficient (λ) can be computed by following the equation (8). As a result of the risk aversion coefficient in SET50 equal to 1.9, in line with Fabozzi et al. [2006] that set the coefficient = 2

4.2 Construct view expression

To translating equity analyst consensus into the views, we follow He et al. [2013] suggestion that separates private views into groups based on equity analysts' consensus ranging from the most favorable to the most unfavorable portfolio. But, to pick winner or loser stocks that falls in each group we follow recommendation change strategy from Boni and Womack [2006] and Barber et al. [2001] as show below,

- Portfolio 1 – All net upgrade or net unchanged consensus stocks. And consensus recommendation are within buy range. (Favorable portfolio)
- Portfolio 2 – otherwise. (Unfavorable portfolio)

Figure 4.1: Number of stock corresponding to each view



Following the criteria above, number of stocks corresponding to each view are shown in figure4.1. The minimum stock in the favorable portfolio was three stocks in November 2008, during the Great Financial Crisis. However, after the economic recovery, analyst consensus became bullish causing a rapid reduction in a number of stock in the unfavorable portfolio which hit the lowest point at eight stocks in November 2010.

Since views of the BL model are expressed as following equation (10),

$$P \cdot \mu = Q + \varepsilon \, , \varepsilon \sim N(0, \Omega)$$

We need to define each of these matrixes. To define view matrix (Q), we track back the relative performance of those portfolios against the market. Using monthly return of the portfolios and rolling five-year estimation periods to compute performance of each consensus recommendation portfolio (R_{pi}), then minus a market return (R_m) at the same period to find out how much is it over/underperform the market. It is assumed that the rate of over/underperform to the market will continue over the next year. These relative portfolio performances are inputs to construct the view matrix.

$$Q = \begin{bmatrix} R_{p1} - R_m \\ R_{p2} - R_m \\ R_{p3} - R_m \end{bmatrix}$$

Table4.1: Performance of consensus portfolios and SET50 over 5-year rolling periods

	Average monthly return		
Estimated period	Portfolio 1	Portfolio 2	SET50
2001-2005	3.2%	1.6%	2.5%
2002-2006	2.5%	1.1%	1.9%
2003-2007	2.7%	1.3%	2.1%
2004-2008	0.7%	-0.9%	-0.2%
2005-2009	1.5%	0.5%	0.8%
2006-2010	1.8%	1.1%	1.2%
2007-2011	1.9%	1.2%	1.4%
2008-2012	1.8%	1.4%	1.3%
2009-2013	2.2%	2.2%	2.1%
2010-2014	1.5%	1.2%	1.4%

Matrix P identifies N assets (In this study, we focus on SET50, so N = 50) involved in each view by setting weight position in the respective consensus portfolio to achieve matrix Q relative performance compare to the market. This study uses a market capitalization weighting scheme. For example, if an asset falls in portfolio1 (Favorable portfolio), we have to long this asset equal to its market capitalization dividing by the total market capitalization of portfolio1. Simultaneously, short position all asset in the market portfolio equal to its market capitalization to the aggregate value of the index.

The example of P matrix can be shown below, assuming asset1 and asset 2 fall into portfolio 1, asset 3 and asset 4 are in portfolio 2 and asset 5 and asset 6 are in portfolio 3. Those assets that are not involved to a particular view will be shorted equal to its market capitalization to the aggregate value of the index.

$$P = \begin{bmatrix} W_{p1} - W_{m1} & W_{p2} - W_{m2} & -W_{m3} & -W_{m4} & -W_{m5} & -W_{m6} & -W_{m7} \cdots -W_{m50} \\ -W_{m1} & -W_{m2} & W_{p3} - W_{pm} & W_{4p} - W_{m1} & -W_{m5} & -W_{m6} & -W_{m7} \ldots -W_{m50} \\ -W_{m1} & -W_{m2} & -W_{m3} & -W_{m4} & W_{p5} - W_{m5} & W_{p6} - W_{m6} & -W_{m7} \cdots -W_{m50} \end{bmatrix}$$

The error term (ε) represents the uncertainty of the view which the BL model assumed to be normal distributed random variable with zero mean, while the variance of the error term (Ω) is diagonal matrix representing view confidence computed by proportional to the variance of the prior approach, $\Omega = \mathrm{diag}(\mathrm{P}(\tau\Sigma)P^T)$

4.3 Update return and perform optimization process

Updating return on Bayesian approach follows the equation (12). Then use the variables μ_{BL} as inputs in the mean-variance optimization process to find the optimal weights of the portfolio by solving the problem of maximizing utility function,

$$\max\ w_*^T \mu_{BL} - \frac{1}{2}\lambda w_*^T \sum\ w_* \tag{14}$$

Subject to $w^T\mathbf{1} = 1$ and $w_i \geq 0$ (i = 1,..., 50)

4.4 Evaluate performance and portfolio turnover

To measure the portfolio performance, we take two evaluation dimensions. The first is financial performance dimension and the second is allocation stability.

Financial performance dimension, we compare portfolio financial performance based on monthly return data for both gross and net return after transaction cost, including 0.15% commission fee and 7% tax on commission fee. And the following are tools used to measure portfolio financial performance,

1. *Market adjusted returns* – to measure portfolio excess return, we simply compute market adjusted returns by using portfolio mean return minus market mean return.

2. *CAPM model* – to evaluate active return performance of portfolio by using monthly time series and compute for the α_i value, which identifies a portfolio return that take out the market explainable return effect.

$$R_{p,t} - R_{f,t} = \alpha_i + \beta_i(R_{m,t} - R_{f,t}) \tag{15}$$

3. *Sharpe ratio* – a mainstream performance measure which indicates how well a portfolio is performing compared to a risk-free return, taking into account of the additional total risk involved with holding the portfolio.

$$\frac{\overline{R_{p,t}} - R_{f,t}}{\sigma_{p,t}} \tag{16}$$

It is calculated by minus the rate of portfolio return to the risk free rate, 3-month government bill rate, then dividing by the standard deviation of the portfolio return. The Sharpe ratio compare the portfolio return adjusted total risk.

4. *Sortino ratio* - a modification of the Sharpe ratio. Instead of using standard deviation, the excess portfolio return is adjusted by downside deviation. It corrects a flaw of Sharpe ratio that punish the ratio with upside volatility (good risk).

$$\frac{\overline{R_{p,t}} - R_{f,t}}{\sigma_d} \tag{17}$$

Where σ_d is a standard deviation of negative stock returns.

Allocation stability dimension, we calculate the portfolio turnover by the percentage of portfolio's holding that has been sold on the next rebalance period. Then, compare among the portfolio. The portfolio turnover will help to see whether it is possible for fund manager to implement the investment strategy in practice as the high turnover ratio indicates low stability asset allocation and difficult to implement in large fund size.

CHAPTER 5
DATA

This paper will study the BL model with an investment strategy based on equity analysts' consensus for the constituents of the SET50 index. And the time period of the study covers from January 2006 through December 2015.

To form views as the model input, we use the historical analysts' consensus from Bloomberg database. The coverage of analysts' consensus in SET50 from the Bloomberg database for the last ten years reached 100% every year. To see how consensus had been revised, we use the function BEst Standard to track the consensus changed/maintained in a month. The Bloomberg database provides a recommendation rating ranging from 1 to 5 where the rating of 5 represents the strong buy tone and the rating of 1 represents strong sell tone. From the table 5.1 shown descriptive statistics of analyst consensus for SET50 constituent stock, it is obviously that recommendation distribution is asymmetry. Most of the recommendation consensus are on a buy rating. In other word, analysts' recommendation tend to be positive bias because they need to maintain a good relationship with a company to obtain information in the future. Using consensus change strategy to separate consensus into two groups, group1 is the favorable portfolio and group2 is the unfavorable portfolio), can help reducing distribution asymmetry and analysts' consensus should be more informative.

In order to compute portfolio return, we use total return including the net dividend received and other benefits that investor should gain from investment in a specific period.

The others market data to be used in this study including stock closing prices and market capitalizations are provided by SETSMART, while the risk-free rate (proxy three-month Treasury bill rate) is from Bank of Thailand.

Table 5.1: Descriptive statistics of analyst consensus for SET50 constituent stock

Year	% of stocks covered	Average rating	Recommendation distribution					Consensus group distribution	
			1	2	3	4	5	1	2
2006	100%	3.45	0.67%	12.67%	34.67%	40.67%	11.33%	36.83%	63.17%
2007	100%	3.67	0.17%	8.50%	27.50%	48.50%	15.33%	44.83%	55.17%
2008	100%	3.99	0.00%	3.00%	18.67%	51.00%	27.33%	30.67%	69.33%
2009	100%	3.69	0.00%	10.02%	26.88%	46.58%	16.53%	48.17%	51.83%
2010	100%	4.09	0.33%	4.50%	9.00%	56.67%	29.50%	67.83%	32.17%
2011	100%	4.20	0.00%	4.50%	5.50%	52.00%	38.00%	55.33%	44.67%
2012	100%	3.95	0.00%	3.83%	16.33%	56.50%	23.33%	63.33%	36.67%
2013	100%	3.79	0.50%	7.17%	21.67%	52.00%	18.67%	46.67%	53.33%
2014	100%	3.74	1.17%	8.00%	25.83%	47.17%	17.83%	39.00%	61.00%
2015	100%	3.76	0.67%	5.67%	23.50%	58.50%	11.67%	39.67%	60.33%

CHAPTER 6
RESULTS AND DISCUSSION

The study focuses on monthly and quarterly portfolio rebalancing to compare portfolio performance in risk, return and trading cost incurred aspect. The BL portfolio will be compared to these following portfolios,

1. SET50 index as market portfolio
2. Equal weighted of SET50 (SET50_EW)
3. Mean variance portfolio (MVO)
4. Market cap. weighted of favorable consensus portfolio (P1_MW)
5. Market cap. weighted of unfavorable consensus portfolio (P2_MW)
6. Equal weighted of favorable consensus portfolio (P1_EW)
7. Equal weighted of unfavorable consensus portfolio (P2_EW)

The result suggests that, for monthly rebalancing, the equal weighted of favorable consensus portfolio (P1_EW) performs surprisingly with the highest mean return and risk-adjusted statistic. However, for quarterly rebalancing, the result follows our hypothesis that the BL portfolio performs admirably as it gains much of the upside, while still preventing large volatility of portfolio return.

6.1 Monthly portfolio performance

From table 6.1, all portfolios beat the market return, except unfavorable consensus portfolios, including P2_MW and P2_EW, which have monthly mean return of 0.235% and 0.266% lower than the market. Whereas, it is obviously that the best performance portfolio is P1_EW with achieving the highest mean return of 1.685% and also keep the risk lowest. As we see from the table 6.1, the portfolio generates the largest Sharpe and Sortino ratio of 0.225 and 0.373 respectively.

Now consider the BL portfolio performance. It earns monthly mean return of 1.411%, 0.538% higher than the market and a CAPM adjusted return of 0.639% which p-value indicates that it is statistically significant, thus it is able to generate a positive abnormal return. However, the overall risk-return performance still underperforms the P1_EW. Furthermore, the BL portfolio with monthly rebalancing may not practical for a large fund size due to the highest monthly turnover of 44%. While the MVO portfolio provides the lowest turnover of 12%.

The performance of MVO is better than BL portfolio in an aspect of return as it posts a positive monthly raw return of 1.583%, 0.711% above the market and an abnormal return is also significant statistically. But its risk performance is poor. The MVO portfolio has the highest volatility, excluding the unfavorable consensus portfolios, so that the Sharpe ratio is a little better than the BL portfolio and the Sortino ratio is eventually lower than the BL portfolio.

Figure 6.1: Monthly equity curve before transaction cost

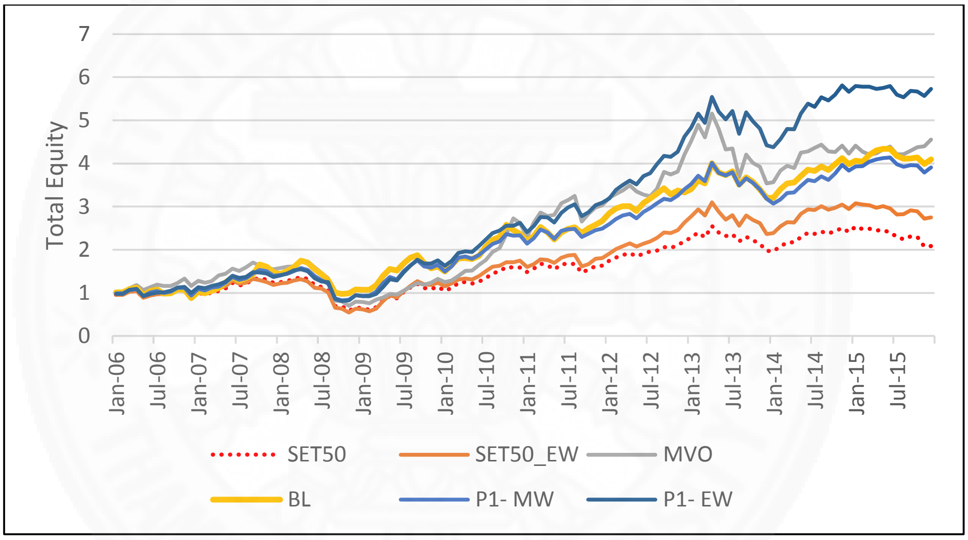
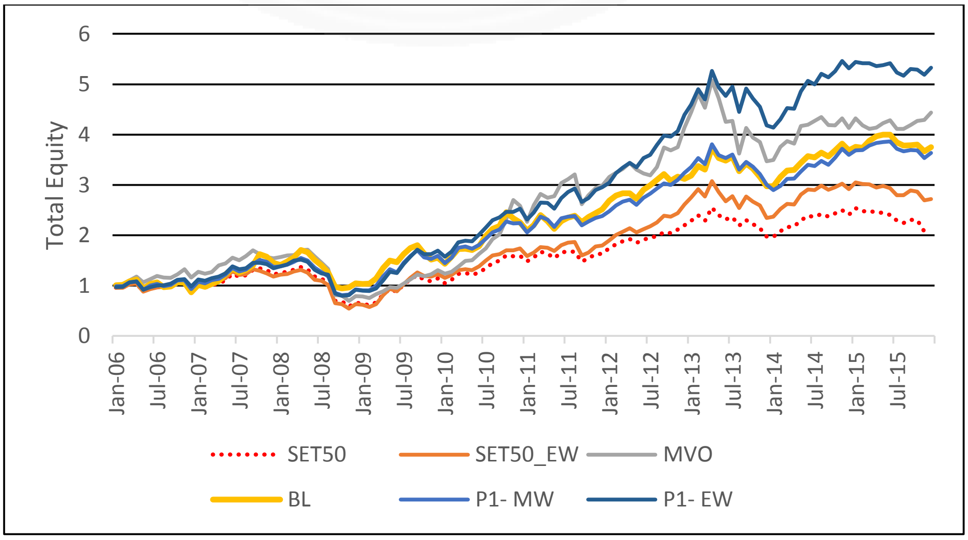


Figure 6.2: Monthly equity curve net of transaction cost



6.2 Quarterly portfolio performance

The MVO portfolio gains the highest quarterly mean return of 4.822%, 1.937% above the market. Unfortunately, a CAPM adjusted return of 2.199% turns insignificant statistically due to its high volatility of portfolio return.

The top performance portfolio for quarterly rebalancing is the BL portfolio which captured a strong quarterly mean return of 4.430% and a CAPM adjusted return of 1.914%. As its lowest volatility among the others, it gains the largest risk-adjusted return ratio for both Sharpe and Sortino ratio as shown on the table 6.2.

Consider the portfolio after transaction cost, the performance of the BL was lowered to nearly the same level as P1_EW. The Sharpe ratio was reduced from 0.313 to 0.305 and the Sortino ratio from 0.612 to 0.594 comparing to the Sharpe and Sortino ratio of P1_EW which equal to 0.298 and 0.569 respectively. The fact that the performance after transaction cost of these two portfolios are closely make the BL approach seeming to have less attractiveness as its complexity. In addition, the BL portfolio turnover of 218% annually is relatively high, even though it reduced from 526% annually on monthly rebalancing basis. The dynamic change of analysts' consensus is the cause of a highly port turnover, as the net upgrade stocks in the last month probably turn to be net downgrade stocks in the following month that may largely affects a change in an optimal portfolio weights.

For the quarterly rebalancing, we summarize that, if not consider the transaction cost, the BL portfolio performs the best and its performance has improved from the result of monthly rebalancing. As we see from the annualized data, the mean return improved for 60 bps and the volatility stayed in the same level, while the others increased. But the performance after transaction cost, the BL performed a little better than the P1_EW portfolio. But, with its complication and a higher portfolio turnover, the P1_EW is more interesting. For the others portfolios, including MVO P2_MW and P2_EW, the result show that it fail to generate abnormal return as the CAPM adjusted returns are insignificant.

Figure 6.3: Quarterly equity curve before transaction cost

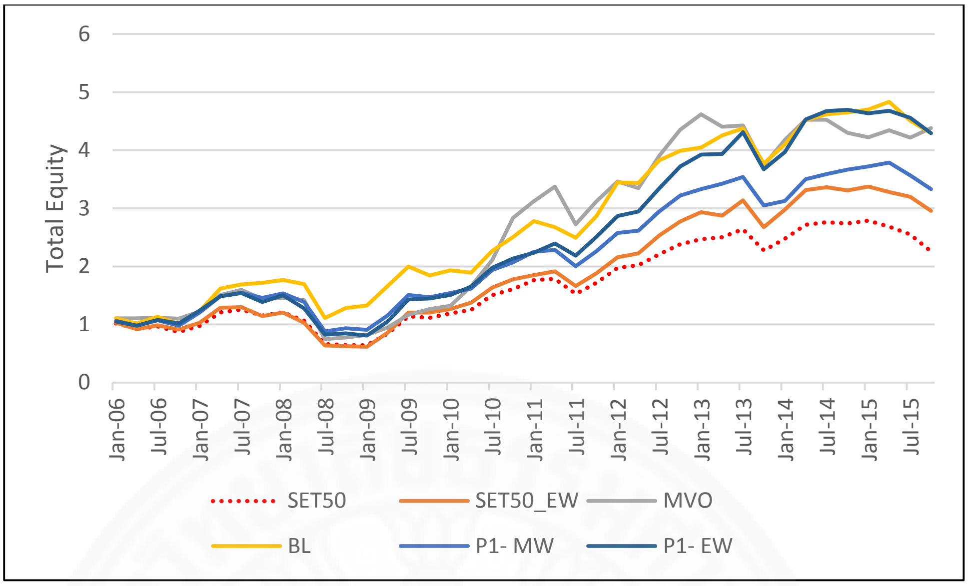
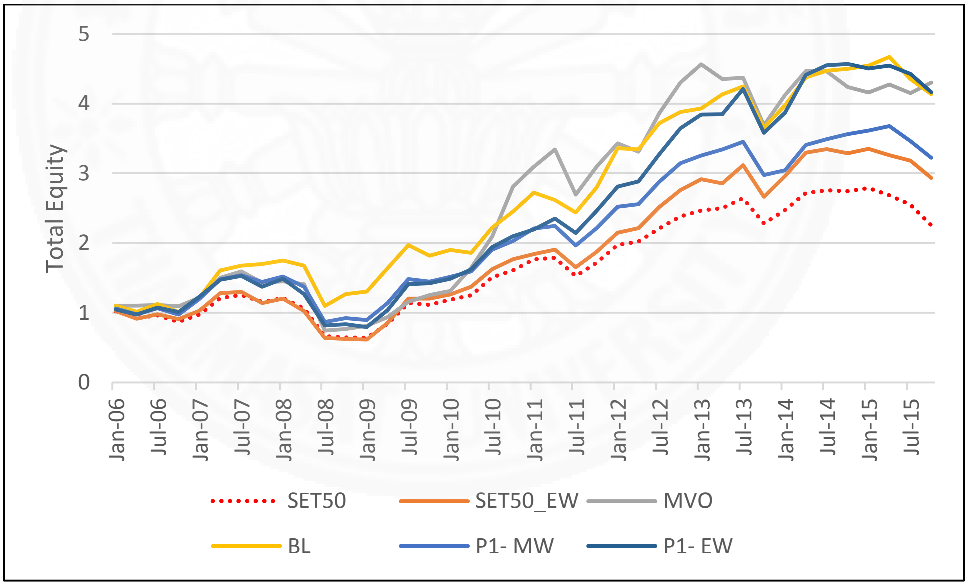


Figure 6.4: Quarterly equity curve net of transaction cost



6.3 The effect of infrequency rebalancing and implication for investor

Reducing a frequency of rebalancing from monthly to quarterly basis, we observe that 1) The BL portfolio performance has improved and 2) the P1_EW, a simple approach, performs very well for both rebalancing basis but the performance declined as less frequency rebalancing was applied. Here, we provide reasons behind and implication for investor.

The performance of the BL portfolio, which using analysts' consensus as private views, has improved from the mean return of 18.3% to 18.9% annually when rebalancing less frequent from monthly to quarterly basis. Hence, the securities prices are not immediately reflect the new information of analysts' view as the theory claim, but it takes some time to absorb the new information and gradually move toward the new fair price overtime. As the result from figure 6.5, the initial fund of the quarterly BL portfolio grown further and most of the time staying higher than the monthly BL portfolio. This is an evidence that there is no existence of the semi-strong form of EMH in the SET50. Our finding is different from the previous studies of Barber et al. [2001] and He et al. [2013], which studied trading strategies based on analysts' consensus in the US and Australian stock market respectively. Those two studies provide a similar conclusion, but contrary to our result, that the less frequent rebalancing, the less likely for investor to capture an abnormal return. Hence, we assert that Thai stock market is less efficient than US and Australian stock market.

Another observation is the P1_EW earns a remarkable portfolio return for both rebalancing basis and outperforms the other strategies even though it is a straightforward approach. This is beyond our expectation, but from reviewing some previous studies, the equal-weighted scheme often performs well. Plyakha et al. [2012] examined the performance of equal, market and price weighted portfolios of stocks in the US markets and found that the equal-weighted portfolio return exceeds the others because the equal-weighted scheme is implicitly a contrarian strategy which is to buy poorly performing stocks and to sell well performing stocks to maintain equally weight portfolio when rebalancing. A contrarian strategy exploits these reversal in stock prices, thus, an abnormal return of the equal-weighted portfolio will decline as we reduce the rebalancing frequency. This conform to Greenblatt [2011] that the equal-weighted scheme outperforms the market-cap weighted scheme as it helps correcting the systematic flaws of investing too much in stocks that already overpriced and too little of the underpriced stocks. As well, our result is in line to these studies as the abnormal return of the equal-weighted portfolio, P1_EW was lowered from 11.3% to 7.1% annually when we reduce the rebalancing frequency.

An important implication for common investors is that they can use an investment strategy based on analysts' consensus to obtain a superior return, as our portfolios which based on consensus, consist of BL P1_EW and P1_MW, can beat the market return with significant statistically abnormal return. The equal-weighted scheme seems to be a good choice for short rebalancing period, that is monthly basis or shorter. But for quarterly rebalancing, it is unclear which portfolio between BL and P1_EW performs better after transaction cost. However, both of them are not practical for a large fund size due to a highly portfolio turnover. The relatively low portfolio turnover is the MVO portfolio. But using of the MVO approach, a fund manager or investor has to beware of its return volatility and a larger maximum drawdown, especially for a crisis period or sharp declining in market return. The figure 6.6, show that the MVO approach is least prevent the portfolio value from downside risk comparing to the BL portfolio and equal-weighted portfolio.

Table 6.1: Monthly rebalancing portfolio performance

										After trading cost items				
Portfolio	Mean return	Excess market return	Mean CAPM adjusted return*	SD	Downside deviation	Max Drawdown	Sharpe ratio	Sortino ratio	Turnover	Trading cost	Return net of trading cost	Sharpe ratio	Sortino ratio	Return net of market and trading cost
Panel A: Monthly data														
P1_MW	1.360%	0.488%	0.565%	6.5%	3.9%	47.5%	0.175	0.296	36%	0.060%	1.300%	0.166	0.279	0.427%
			(0.004)**											
P2_MW	0.637%	-0.235%	-0.276%	7.7%	4.7%	61.5%	0.055	0.089	39%	0.065%	0.573%	0.046	0.075	-0.300%
			(0.1303)											
P1_EW	1.685%	0.813%	0.898%	6.5%	3.9%	47.3%	0.225	0.373	36%	0.060%	1.625%	0.216	0.356	0.753%
			(0)**											
P2_EW	0.606%	-0.266%	-0.329%	8.1%	5.0%	62.6%	0.048	0.077	32%	0.054%	0.552%	0.042	0.066	-0.320%
			(0.1414)											
BL	1.411%	0.538%	0.639%	6.8%	3.8%	44.3%	0.177	0.315	44%	0.073%	1.338%	0.166	0.294	0.465%
			(0.0327)**											
MVO	1.583%	0.711%	0.771%	7.6%	4.9%	59.3%	0.180	0.278	12%	0.022%	1.561%	0.177	0.273	0.689%
			(0.0454)**											
SET50_EW	1.132%	0.259%	0.240%	7.4%	4.6%	58.8%	0.124	0.200	4%	0.009%	1.123%	0.122	0.198	0.251%
			(0.0947)											
Market (SET50)	0.872%			7.0%	4.4%	57.4%	0.093	0.148						
Panel B: Annualized data														
P1_MW	17.6%	6.6%	7.0%	22.6%	13.4%	47.5%	0.662	1.122	433%	0.724%	16.8%	0.625	1.060	5.3%
P2_MW	7.9%	-3.1%	-3.3%	26.7%	16.4%	61.5%	0.199	0.324	464%	0.776%	7.1%	0.168	0.274	-3.5%
P1_EW	22.2%	11.2%	11.3%	22.6%	13.6%	47.3%	0.868	1.437	435%	0.722%	21.3%	0.829	1.374	9.4%
P2_EW	7.5%	-3.5%	-3.9%	27.9%	17.5%	62.6%	0.176	0.282	382%	0.643%	6.8%	0.152	0.243	-3.8%
BL	18.3%	7.3%	7.9%	23.4%	13.1%	44.3%	0.671	1.197	526%	0.874%	17.3%	0.627	1.119	5.7%
MVO	20.7%	9.8%	9.7%	26.3%	17.0%	59.3%	0.689	1.066	140%	0.258%	20.4%	0.677	1.048	8.6%
SET50_EW	14.5%	3.5%	2.9%	25.6%	15.9%	58.8%	0.463	0.747	46%	0.105%	14.3%	0.458	0.739	3.0%
Market (SET50)	11.0%			24.3%	15.4%	57.4%	0.344	0.546						

* The number in the parentheses are p-value pertaining to the null hypothesis that the associated return is zero

** Abnormal return are significant at the 5% leve

Table 6.2: Quarterly rebalancing portfolio performance

										After trading cost items				
Portfolio	Mean return	Excess market return	Mean CAPM adjusted return*	SD	Downside deviation	Max Drawdown	Sharpe ratio	Sortino ratio	Turnover	Trading cost	Return net of trading cost	Sharpe ratio	Sortino ratio	Return net of market and trading cost
Panel A: Quarterly data														
P1_MW	3.799%	0.914%	1.106%	12.2%	6.6%	43.2%	0.258	0.475	47%	0.083%	3.716%	0.251	0.461	0.8%
			(0.0313)**											
P2_MW	2.539%	-0.346%	-0.663%	15.0%	7.7%	54.3%	0.126	0.244	54%	0.096%	2.443%	0.120	0.231	-0.4%
			(0.1773)											
P1_EW	4.506%	1.620%	1.731%	12.7%	6.6%	47.6%	0.304	0.583	46%	0.081%	4.425%	0.298	0.569	1.5%
			(0.002)**											
P2_EW	2.767%	-0.119%	-0.441%	15.2%	7.7%	55.8%	0.140	0.274	46%	0.082%	2.684%	0.134	0.263	-0.2%
			(0.4431)											
BL	4.430%	1.544%	1.914%	12.1%	6.2%	37.0%	0.313	0.612	54%	0.095%	4.334%	0.305	0.594	1.4%
			(0.035)**											
MVO	4.822%	1.937%	2.199%	14.0%	8.3%	53.2%	0.299	0.502	24%	0.048%	4.775%	0.295	0.495	1.9%
			(0.1053)											
SET50_EW	3.688%	0.803%	0.664%	13.9%	7.2%	52.6%	0.218	0.423	8%	0.021%	3.7%	0.217	0.420	0.8%
			(0.106)											
Market	2.885%			12.9%	7.1%	49.1%	0.173	0.315						
Panel B: Annualized data														
P1_MW	16.1%	4.0%	4.5%	24.4%	13.3%	43.2%	0.553	1.017	189%	0.332%	15.7%	0.538	0.989	3.4%
P2_MW	10.6%	-1.5%	-2.6%	30.0%	15.5%	54.3%	0.265	0.514	217%	0.385%	10.1%	0.251	0.487	-1.8%
P1_EW	19.3%	7.2%	7.1%	25.4%	13.2%	47.6%	0.658	1.261	182%	0.323%	18.9%	0.643	1.234	6.3%
P2_EW	11.5%	-0.5%	-1.8%	30.3%	15.4%	55.8%	0.294	0.579	183%	0.329%	11.2%	0.283	0.556	-0.8%
BL	18.9%	6.9%	7.9%	24.1%	12.3%	37.0%	0.677	1.322	218%	0.382%	18.5%	0.659	1.287	5.9%
MVO	20.7%	8.7%	9.1%	27.9%	16.6%	53.2%	0.649	1.090	95%	0.191%	20.5%	0.641	1.077	7.8%
SET50_EW	15.6%	3.5%	2.7%	27.8%	14.4%		0.467	0.904	32%	0.082%	15.5%	0.463	0.898	3.2%
Market	12.1%			25.8%	14.2%	49.1%	0.367	0.666						

* The number in the parentheses are p-value pertaining to the null hypothesis that the associated return is zero ** Abnormal return are significant at the 5% level

Figure 6.5: Comparison of the total equity between monthly and quarterly rebalancing of the BL portfolio

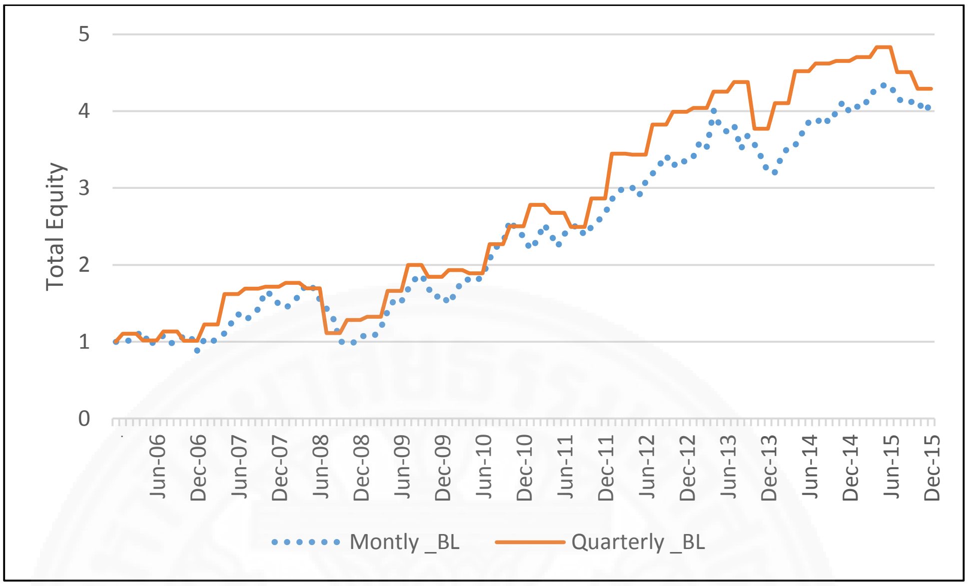
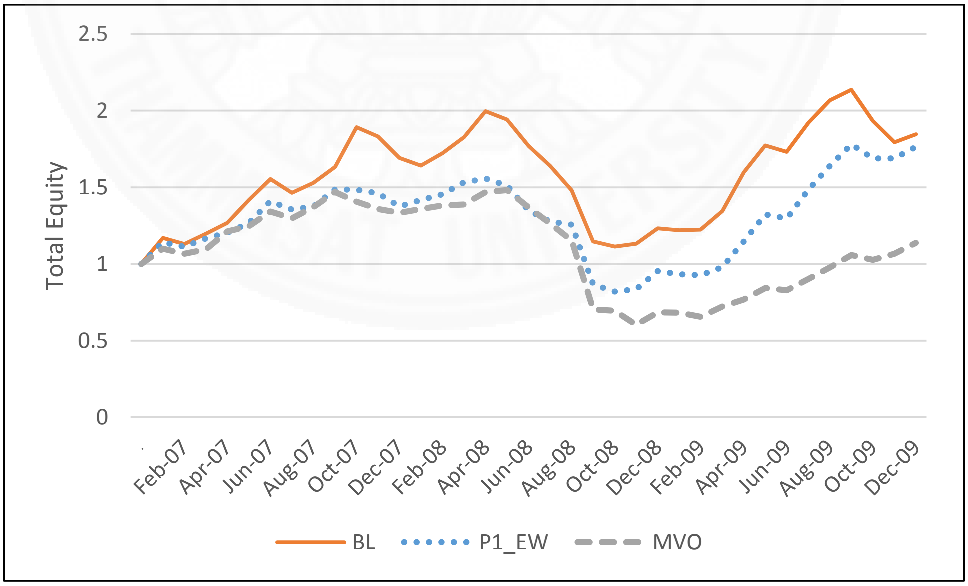


Figure 6.6: The total equity during the downturn period from 2007 – 2009 show the portfolio capability of preventing the downside risk.



CHAPTER 7
CONCLUSIONS AND RECOMMENDATIONS

The goals of this paper have been to provide an application of the BL model using analyst consensus as private views and analyze the BL portfolio performance, both gross and net return of transaction cost, comparing to the market, mean-variance and consensus group portfolios. Over the 2006 to 2015 period we find that the BL portfolio, which overweight (underweight) stocks with favorable (unfavorable) analysts' consensus, earns a positive abnormal return and higher risk-adjusted return than the market for both monthly and quarterly rebalancing basis. Yet, in conjunction with monthly rebalancing, the BL portfolio still underperforms the mean-variance and the equal-weighted favorable consensus portfolio (P1_EW). The performance of the BL has improved with quarterly rebalancing so it produced more stable and higher abnormal return that the risk-adjusted statistics overcome all other portfolios, because the securities prices are not immediately reflect the new information of analysts' consensus. If taking a transaction cost into account, the performance of the BL was lowered to nearly the same level as P1_EW. With the complication of the BL approach, the P1_EW seems to be more interesting. However, our finding also indicates that the abnormal return of portfolio in an equal-weighted scheme are diminishing when reduce the rebalancing frequency.

The result of this study suggests the economic value of analysts' consensus, an investor aiming to use such a trading strategy can gain a superior return. The equal-weighted scheme seems to be a good choice for a short rebalancing period investment. Otherwise, the BL approach will be more appropriated as it is relatively more capable of preventing the portfolio value from the downside risk. However, both of these two portfolios not practical for a large fund size due to a highly portfolio turnover.

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BIOGRAPHY

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