Chapter 14
Constructing Mean Variance Efficient Frontiers Using Foreign Large Blend Mutual Funds

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14.1 Introduction

Mutual funds are efficient investment vehicle for small investors. The buy and hold strategy is the prevailing way of investing in mutual funds because of the trading cost and tax considerations. Since the emergence of online trading platforms, the trading cost has come down significantly. Now it is the time to evaluate strategies of more actively managed portfolios of mutual funds. In this study, we show how to use mean-variance portfolio selection methods to construct and manage portfolios of mutual funds, with the focus on funds categorized as foreign large blend by Morningstar. There are two reasons we choose this category of mutual funds. First, total foreign equity markets are as large as the US equity market now, and mutual funds are still the best way to get exposures to it. Second, this category of mutual fund is under-studied. Most researchers focus on the relative performance of US equity mutual funds. We report that: (1) The performance predictive variables that work for US equity mutual funds can also work for foreign large blend mutual funds; (2) the mean-variance approach can effectively diversify the risk of portfolios for this category of mutual funds too. The risk of the minimum variance portfolio could be 6 percentage points less than the risk of the expected-return maximizing portfolio while the realized return is only about 2 percentage points less; (3) the mean-variance approach can produce portfolios with higher Sharpe ratios than the Sharpe ratio of either the index funds or the category average which are the benchmark of

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this study. Some efficient portfolios can outperform these two benchmarks by more than 2 percentage points while having the same risk levels even after transaction cost.

This paper is organized as following. In Sect. 14.2, we briefly state the single-period mean-variance portfolio selection problem with turnover constraints, and describe how we compute the *ex post* mean-variance efficient sets. In Sect. 14.3, we present two variance-covariance models and also a broad review of expected return models used for US equity mutual funds. In Sect. 14.4, we describe the data source, define the investable universe, and discuss the assumptions on transaction cost. In Sect. 14.5, we present various *ex post* efficient frontiers by varying expected return models, risk models, turnover constraints, and upper bounds. We conclude that various expected return models can be used as input for mean-variance optimizations to generate 2 percentage points more returns than benchmarks while having the same or less risk.

14.2 Single-Period and *Ex Post* Mean Variance Efficient Frontier

The mean variance portfolio construction method proposed by Markowitz (1952, 1959) assumes that an investor should maximize the expected portfolio return for a given risk level, or equivalently, minimize the risk for a given expected portfolio return. The complete efficient portfolio set can be traced out by the quadratic problem:

$$\min x^T Cx - \lambda_E \mu^T x \tag{14.1}$$

where μ is the expected return vector, C is the variance-covariance matrix, and x is the portfolio weights, $\lambda_E \geq 0$ is the risk return trade off parameter. The choice of λ_E reflects the investor's risk tolerance. The more risk adverse an investor is, the smaller would be his λ_E.

In this study, we impose the no-shorting constraint, i.e., $x_i \geq 0$ for all i, an universal upper bound, i.e.,

$$x_i \leq \text{ upper bound}, \quad \text{for all } i, \tag{14.2}$$

and budget constraints $\sum x_i = 1$, i.e., fully invested. We also consider turnover constraints in terms of total buying and selling

$$\left(\sum\nolimits_{i=1}^{N} \left|x_i - x_i^o\right|\right)/2 \leq \text{ turnover} \tag{14.3}$$

where x_i^o is previous period's portfolio weight of security i in the universe.

Using the mean-variance framework requires the investor to estimate the mean-variance parameters (μ, C), and make decisions on upper bounds, turnover, and λ_E. We refer the estimation methodology of (μ, C) together with decisions on upper bounds and turnover constraints as an investment strategy. For each period t and λ_E, the transaction cost-adjusted return $R(t, \lambda_E)$ can be easily calculated for the corresponding efficient portfolio generated at the beginning of the period. The λ_E parametric realized mean-variance set of returns $R(t, \lambda_E)$ (for $t = 0$ to period T) generated by the same strategy for all λ_E are called the *ex post* efficient frontier. We will use *ex post* efficient frontier as the criteria to evaluate investment strategies.

14.3 Risk Models and Expected Return Models

The multifactor linear model is the standard risk model. Here we assumes that the return of any mutual fund can be modeled by Eq. (14.4) with four factors, i.e., market factor R_{M}, size factor R_{SMB} (small cap portfolio minus large cap portfolio), value factor R_{HML} (high Book/Price portfolio minus low Book/Price portfolio), and momentum factor R_{WML} (last year winner portfolio minus loser portfolio).

$$R_p - R_f = \alpha_p + \beta_{\mathrm{mp}}\left(R_M - R_f\right) + \beta_{\mathrm{smbp}} * R_{\mathrm{SMB}} + \beta_{\mathrm{hmlp}} R_{\mathrm{HML}} + \beta_{\mathrm{wmlp}} * R_{\mathrm{WML}} + \epsilon_p \tag{14.4}$$

Once the betas were estimated by regressing mutual fund returns to factor returns, the variance-covariance risk matrix C can be calculated by

$$C = \beta F \beta' + \sum \tag{14.5}$$

where F is variance-covariance of factor returns and $\sum$ is the residual diagonal risk matrix. Fama and French (1992, 1996) developed this factor model for stocks. It has been adopted by mutual fund researchers since Carhart (1997). The factor returns used in this study are downloaded from French's data library. Table 14.1 shows the sample statistics of the factor returns.

The relatively low correlations and negative correlations among the factor returns make it a very attractive risk model. One can skip the regressions in Eq. (14.4) and calculate the variance-covariance matrix directly from fund's historical returns by Eq. 14.6.

$$C_{ij} = \sum\nolimits_{t=0}^{T} \left(R_{it} - \overline{R}_i\right) * \left(R_{jt} - \overline{R}_j\right) / T \tag{14.6}$$

We call Eq. (14.6) the historical model and will compare it with the factor model (Eq. 14.5). At the beginning of each period, previous 5 years' monthly returns are used to estimate betas of Eq. (14.4), factor model (Eq. 14.5), and historical model (Eq. 14.6).

Table 14.1 Global factor returns, February 2004–January 2014

Start date	Mkt	SMB	HML	WML
200402	12.77	7.42	8.68	3.75
200502	19.32	6.13	5.85	22.19
200602	17.00	−4.50	7.92	−0.70
200702	0.16	−8.19	−1.84	11.80
200802	−40.93	0.69	−5.13	19.53
200902	38.67	7.39	2.99	−40.31
201002	20.97	6.46	−0.76	13.07
201102	−3.64	−2.20	−8.42	2.19
201202	16.79	−4.19	9.19	10.56
201302	17.93	2.32	1.81	22.03
Average	9.90	1.13	2.03	6.41
Std	21.27	5.69	6.05	18.30
Corr				
Mkt	1.00	0.36	0.59	−0.48
SMB		1.00	0.18	−0.21
HML			1.00	−0.11
WML				1.00

There are numerous ways to estimate the expected return vector μ. Three groups of data have been shown to contain information of future returns. The first group of data consists of the raw returns, like past year's return, past 3 years' return, etc. The second group of data consists of risk-adjusted returns, like Treynor Index, Sharpe Ratio, and Jensen's alpha. This group of data measures the fund manager's stock selection skills by taking into account the portfolio's risk. The third group of data is the mutual fund's characteristics, like expense ratios, annual turnover rates, and top holdings concentrations. These three groups of data have been studied extensively in the literatures for US equity funds. We will review them in detail accordingly.

14.3.1 Raw Return

Can past performance of mutual funds be indicative of future performance? Hendricks et al. (1993) found strong evidence that last year's winners will continue to do well this year for US growth equity mutual funds using data from 1974 to 1988. Carhart (1997) studied the all equity mutual fund data from 1962 to 1993 and concluded that funds with the highest returns last year will have higher returns than average fund returns this year. Carlson (1970) using data from 1948 to 1967, and Brown and Goetzmann (1995) using data from 1970 to 1989, also found support of persistence of raw returns. However some researchers, like Brown et al. (1992), argue that the persistence is the result of survivor bias of the test database. In this study we show that the performance still persists even after control for survivor bias. Since the return from the manager's skill is small when compared to the return of risk factors, the underlying risk exposures and the persistence of risk factor returns are the main determinants of persistence of raw performance. If raw returns are used as the sole selection criteria for mutual fund, then high risk mutual funds are most likely to be recommended. If the risk factor returns reverse themselves, then last year's winners will perform poorly. Table 14.3 shows that the 2007s top winner decile portfolio underperformed the bottom loser decile portfolio by almost 4 % during the 2008 market crash. When the market reversed itself in 2009, the 2008s winner decile portfolio underperformed the loser decile portfolio by 9.04 %.

14.3.2 Risk-Adjusted Return

The risk-adjusted return is the standard performance measurement. The risk model has evolved from the single factor model to multifactor models like Eq. (14.4). Treynor (1965) is the first one to adjust raw returns to evaluate mutual fund performance. He created the Treynor Index, which is the raw return divided by the mutual fund's beta against market. Sharpe (1966) created the Sharpe ratio as the mutual fund performance measurement, which is the excess return divided by the standard deviation of the mutual fund's return. The Shape ratios based on the return and volatility from 1954 to 1963 are positively correlated with the Sharpe ratios calculated using the data from 1944 to 1953. Jensen (1969) used the regression alpha of fund returns to market returns to evaluate the performance of mutual funds. More recently, Carhart (1997) proposed the four factor model Eq. (14.4) to study the risk-adjusted returns using data from 1962 to 1993. He found the top decile portfolio based on previous years' returns did outperform the bottom decile. Most researchers, like Pastor and Stambaugh (2002a, b), Elton et al. (1996), Carhart (1997) found that the relative risk-adjusted performance persist from formation period to post formation period.

14.3.3 Mutual Fund Characteristics

The Index fund industry and academies have long argued that active fund managers can't beat the market on average because of the expenses. Kinnel (2010) reported that expense ratio is the most reliable predictor of mutual fund's future success. He sorted funds into quintiles by expense ratios and category, and found that least expensive fund group always out performs the most expensive fund group. Academies have studied the fund characteristics too. Carhart (1997) documented a negative effect for fees. Cremers and Petajisto (2009) found a negative effect of fund size on performance.

All the researchers mentioned above concluded that past relative performance can be used to forecast future relative performance. Based on the conclusion of previous studies, we will study the following information variables (Table 14.2).

Table 14.2 Definition of information variables

Alpha = regression alpha of Eq. (14.4) using previous 5 years' monthly returns. It is the long-term risk-adjusted return
ERatio = reported fund expense ratio for the previous year
LQRet = the previous quarterly return before the formation time
LY1Ret = the previous year's return before the formation time
LY3Ret = the previous 3 years' cumulative return before the formation time
TI1 = LY1Ret/β_{mp}, where β_{mp} is the market beta in Eq. (14.4) estimated by using previous 5 years' monthly returns. This is the modified 1-year Trenyor Index
TI3 = LY3Ret/β_{mp}, where β_{mp} is the market beta in Eq. (14.4) estimated by using previous 5 years' monthly returns. This is the modified 3-year Tranyor Index
SR1 = LY1Ret/σ_p, where σ_p is the monthly standard deviation estimated by using previous 5 years' monthly returns. This is the modified 1-year Sharpe ratio
SR3 = LY3Ret/σ_p, where σ_p is the monthly standard deviation estimated by using previous 5 years' monthly returns. This is the modified 3-year Sharpe ratio
Assets = the asset under management at the end of the previous year

14.4 Data and Universe

All the mutual fund data are from Morningstar Principia. Morningstar assigns each mutual fund to a category according to the fund's objective. Starting from January 2000, we download the monthly return, expense ratio, total net asset value, turnover ratio, and Morningstar ratings for all the mutual funds. At the end of January of each year, by that time the mutual fund's characteristic data is available, we will reconstruct our universe by considering only those mutual funds that have more than \$100 million assets under management. Elton et al. (1996) found that 1-year survival rate is 98% for fund with AUM more than 15 million. Our AUM cutoff makes our universe free of survivor bias. For the foreign large blend category, there are 117 funds with average expense ratio 1.28% at end of year 2003, and 264 funds with average expense ratio 0.90% at the year end of 2013. Since we need 5 year's return data to calculate alpha and betas in (Eq. 14.4), we further eliminate those mutual funds which don't have 5 years returns. The reported annual return is cumulative return from February of the report year to the January of the next year. The bottom decile return is calculated as the larger returns of the worst two decile portfolio returns. We do this because Carhart (1997) has shown that the difference in returns from the worst two decile portfolios is un-proportionally large when compared to the difference in returns from other adjacent decile portfolios. Table 14.3 reports the return differences.

Another way to look at the predictive power of variables is to examine the information coefficient (Table 14.4). The Table 14.4 presents the results for some of the variables listed in Table 14.2.

Table 14.3 Difference of top decile portfolio return to bottom decile portfolio return

Starting date	ERatio	Alpha	LQRet	LY1Ret	TI1	SR1	LY3Ret	TI3	SR3	Assets
200402	0.64	1.40	−0.40	2.71	2.47	3.08	3.68	3.40	3.41	−0.30
200502	−2.36	4.22	10.61	2.87	2.16	−6.32	3.78	0.36	−1.03	−0.27
200602	2.36	1.12	1.23	2.68	1.42	1.52	3.76	−1.22	−0.77	−2.00
200702	1.57	5.29	4.59	3.86	1.85	3.12	6.16	3.67	2.92	2.03
200802	1.25	2.05	1.34	−3.93	−1.30	−0.05	−4.63	−0.36	−3.28	3.15
200902	2.18	9.94	−11.76	−9.04	7.23	8.53	5.65	8.03	6.20	1.86
201002	0.34	2.50	4.75	4.41	3.04	2.98	1.47	1.42	1.61	0.06
201102	2.11	0.58	0.61	−2.82	−2.11	−1.94	0.40	0.37	0.26	−1.16
201202	1.96	0.23	1.32	−1.72	−0.76	1.00	−2.44	−2.47	−3.61	4.06
201302	−2.41	0.88	0.90	7.51	6.38	6.88	−0.05	0.23	−0.92	3.22
Average	0.76	2.82	1.32	0.65	2.04	1.88	1.78	1.34	0.48	1.07
Std	1.79	2.98	5.61	4.91	3.05	4.21	3.50	3.01	3.08	2.07
T	1.35	2.99	0.74	0.42	2.11	1.41	1.61	1.41	0.49	1.63

Table 14.4 Annual information ratios

Starting date	ERatio	Alpha	LY1Ret	LY3Ret	TI1	SR1	TI3	SR3
200402	0.23	0.21	0.29	0.48	0.38	0.33	0.49	0.49
200502	0.02	0.30	0.13	0.23	0.17	0.06	0.25	0.22
200602	0.27	0.00	0.02	0.24	−0.02	0.02	0.15	0.18
200702	0.20	0.15	0.03	0.35	−0.09	−0.03	0.26	0.28
200802	0.15	0.19	0.02	−0.08	0.10	0.11	0.06	0.06
200902	0.10	0.36	−0.02	0.13	0.14	0.22	0.14	0.15
201002	0.04	0.23	0.26	0.13	0.19	0.22	0.15	0.15
201102	0.20	0.26	0.08	0.30	0.12	0.13	0.28	0.28
201202	0.21	−0.12	0.01	−0.24	0.00	0.02	−0.26	−0.26
201302	−0.09	−0.03	0.49	0.10	0.45	0.44	0.07	0.07
Average	0.13	0.16	0.13	0.16	0.14	0.15	0.16	0.16
Std	0.11	0.15	0.15	0.20	0.16	0.14	0.18	0.18
T	3.93	3.34	2.70	2.61	2.84	3.37	2.72	2.79

Table 14.5 Distribution of minimum initial investment at 2013

Minimum initial investment	0	≤2500	≤5000	≥100,000
Count	30	39	4	52

The positive decile return differences and statistically significant positive information coefficients confirm that these variables are viable expected return models. The data period under consideration is a very special period. We experienced the great financial crises. The market tanked in 2008 and started to bounce back in 2009. Most variables failed in year 2009. In particular, the momentum variables (LQRet, LY1Ret, and LY3Ret) failed more than the risk-adjusted variables like TI3 and SR3.

14.4.1 Transaction Cost, Turnover, and Upper Bound

One of the decision variables of using mean-variance portfolio construction and management process (Eq. 14.1) is the turnover constraint from period to period. The optimal turnover depends on what expected return model to use and what transaction cost per trade the investor expects. The cost per trade is from 7 to 10 dollars for most online trading platforms. So the percentage cost of trading depends on the actual dollars amount traded. For example, 10 dollar fee for 2000 dollar trade translates into 50 basis points of cost, and 10 dollar fee for 4000 dollar trade translates into 25 basis points of cost. This makes higher upper bound a way of lowing transaction cost. For this reason we will run our simulation with two levels of transaction cost and two levels of upper bounds. The two levels of cost are 25 basis points and 0 basis points per trade. The two upper bounds are 10 and 20 %. There are other trade frictions too. One of them is the minimum initial investment. In order to implement the mean-variance portfolio weights, we remove those mutual funds with minimum initial investment more than 2500 dollars from our simulation universe. This deletion does not affect our simulation results. Another trade friction is the fee imposed by mutual funds for frequent traders. They are usually 2 and 1 % if the holding period of the fund is less than 3 and 6 months respectively. For this reason, we will simulate our portfolio construction process on an annual basis.

14.5 *Ex Post* Efficient Frontiers

We will run a series of simulations by varying the expected returns, turnover constraints, risk models, transaction cost, and upper bound. First we would like to settle what risk model to use. Table 14.6 compares the risk-return trade-off curves generated with factor risk model and historical risk model, using Alpha as expected returns with no transaction costs, no turnover constraints, and upper bounds of 10 %. There are no statistically significant differences for these two efficient sets. This is true for other expected return models. From now on we will report ex-post efficient frontiers using factor risk model only.

The next three exhibits validate our expected return models. Tables 14.7, 14.8, and Fig. 14.1 show the benchmark returns, and the efficient frontiers using different expected return models with no transaction cost, and no turnover constraints. The category average returns are reported by Morningstar. Index funds returns are calculated by the average return of the 10 least expensive funds, which turned out to be index funds. The long-term risk-adjusted return Alpha dominates the 1-year momentum variable LY1Ret, which dominates the fund expensive ratio variable ERatio. Alpha mean-variance efficient portfolios with comparable risks are 2 percentage points better than the benchmarks. LY1Ret and ERatio mean-variance efficient portfolios are as good as benchmarks.

Table 14.6 February, 2004–January, 2014, no cost, no turnover constraint

Expected return: Alpha						
Risk model	Factor			Historical		
λ	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9	12.24	25.75	0.42	12.24	25.76	0.42
8	11.95	24.96	0.42	12.07	25.03	0.42
7	11.52	23.98	0.42	11.69	24.00	0.42
6	11.38	23.19	0.43	11.42	23.02	0.43
5	11.28	22.07	0.44	11.33	22.04	0.45
4	11.11	21.05	0.46	11.02	21.19	0.45
3	10.94	20.56	0.46	10.93	20.74	0.45
2	10.73	20.51	0.45	10.65	20.31	0.45
1	10.49	20.15	0.45	10.21	19.75	0.44

Table 14.7 Benchmark returns: February, 2004–January, 2014

Category average			Index funds		
Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9.28	23.37	0.33	8.81	21.24	0.34

Table 14.8 February, 2004–January, 2014, no cost, no turnover constraints

Expected return	LY1Ret			Alpha			ERatio		
λ	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9	10.22	24.12	0.36	12.24	25.75	0.42	8.81	21.24	0.34
8	9.98	23.54	0.36	11.95	24.96	0.42	8.94	21.15	0.35
7	9.50	22.80	0.35	11.52	23.98	0.42	8.82	20.99	0.35
6	9.11	22.09	0.34	11.38	23.19	0.43	8.67	20.83	0.34
5	8.98	20.88	0.36	11.28	22.07	0.44	8.57	20.69	0.34
4	8.92	20.12	0.37	11.11	21.05	0.46	8.55	20.44	0.34
3	9.00	20.04	0.37	10.94	20.56	0.46	8.34	19.93	0.34
2	8.79	20.02	0.36	10.73	20.51	0.45	8.41	19.46	0.35
1	8.90	19.13	0.39	10.49	20.15	0.45	8.61	19.08	0.37

The *ex post* efficient frontier is not as smooth and as concave as ex ante efficient frontier. The main cause is the imperfect estimation of expected returns. Nevertheless, the portfolios with less risk-tolerant parameter, i.e., lower λ_E in ex-ante, do realize less total risk in *ex post*. The mean-variance process is very effective on controlling portfolio risk. In particular, the minimum variance portfolio trades off only 2 % return with 6 % less risk when compared to the return-maximizing portfolio for Alpha model. The conservative portfolios have higher Sharpe ratios than the more risk taking portfolios. The performance of expensive ratio is not as good as expected since it has an average positive IC of 0.13 and highest *t* statistic of 3.93. On the other hand, the least expensive funds are dominated by index funds so one should not expect them to outperform the index fund benchmark. The positive

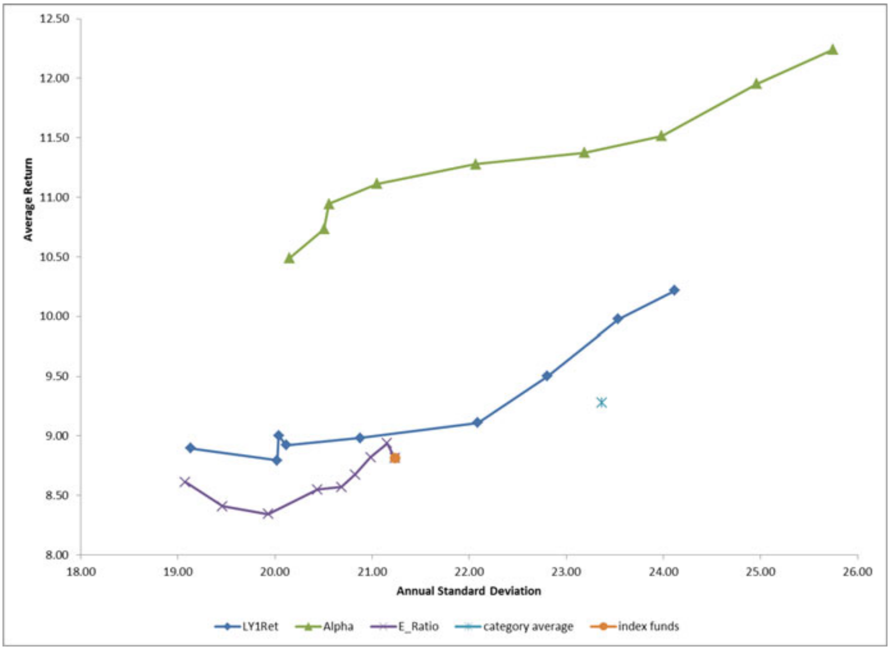

Fig. 14.1 February, 2004–January, 2014, no cost, no turnover constraints

decile portfolio spread and positive IC suggest that we should either combine it with other variables or use it as a constraint to avoid the most expensive funds.

In the presence of transaction cost, we expect the efficient portfolios to underperform no cost-efficient ones by

$$2 \times \text{Cost} \times \text{Turnover} \tag{14.7}$$

Table 14.9 shows the cost effects on momentum LY1Ret model and Alpha model. The performance deduction on LY1Ret model confirms to Eq. (14.7). The resulting portfolios underperform the benchmarks. However, there are no performance deductions for Alpha model. It is possible because the optimizer takes into account the transaction cost, and the portfolios are different. The portfolios with transaction cost turned out to be better for the Alpha model even after the cost.

On one hand, imposing turnover constraints puts an upper bound (Eq. 14.7) on trading cost. On the other hand, it may prevent the optimizer from fully utilizing the predictive information. Table 14.10, Figs. 14.2 and 14.3 show the overall effect of turnover and cost. Adding turnover constraints, the LY1Ret model performs almost 1 % better while Alpha model performs 1 % worse respectively.

All the above simulations are done with 10 % as the upper bound for each position to enforce some diversification. Table 14.11 and Figs. 14.4 and 14.5 show the efficient frontiers by loosening the upper bound from 10 to 20 %. For Alpha

Table 14.9 February, 2004–January, 2014, cost = 0.25%, no turnover constraints

Expected return	LY1Ret			Alpha		
λ	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9	9.69	24.09	0.34	12.18	25.82	0.41
8	9.41	23.21	0.34	11.96	24.56	0.43
7	8.92	22.97	0.32	12.05	23.57	0.45
6	8.73	21.82	0.33	11.30	22.58	0.43
5	9.01	20.83	0.36	11.42	21.90	0.45
4	8.83	20.21	0.36	11.06	20.97	0.46
3	8.90	20.01	0.37	10.81	20.46	0.46
2	8.57	20.05	0.35	10.61	20.49	0.44
1	8.75	19.24	0.38	10.31	20.26	0.43

Table 14.10 February, 2004–January, 2014, cost = 0.25, turnover≤0.25

Expected return	LY1Ret			Alpha		
Λ	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9	11.17	25.36	0.38	11.50	25.04	0.40
8	10.34	22.85	0.39	10.40	22.55	0.39
7	10.08	21.66	0.40	10.30	21.64	0.41
6	10.24	21.51	0.41	10.28	21.50	0.41
5	10.13	20.73	0.42	9.79	20.79	0.40
4	9.64	20.38	0.40	10.70	20.35	0.45
3	9.24	19.56	0.40	10.40	20.28	0.44
2	9.02	19.22	0.39	10.13	20.16	0.43
1	8.73	19.03	0.38	9.68	19.72	0.41

model, the whole efficient frontier shifts to upper-left more than 1 %. The return is more and risk is less. For LY1Ret model, the effect is mixed. The riskier portfolios underperform and the conservative portfolio outperform than the tighter constrained portfolios.

14.5.1 Conclusion

This paper discusses the nontrivial aspects of applying the mean-variance optimization technique to manager portfolios of foreign large blend mutual funds. There are numerous viable expected return models from past performance and fund characteristics. With the right turnover constraints, upper bound, and appropriate risk-return trade-off parameter, efficient portfolios with comparable risk as the benchmarks can outperform the benchmarks more than 2 %.

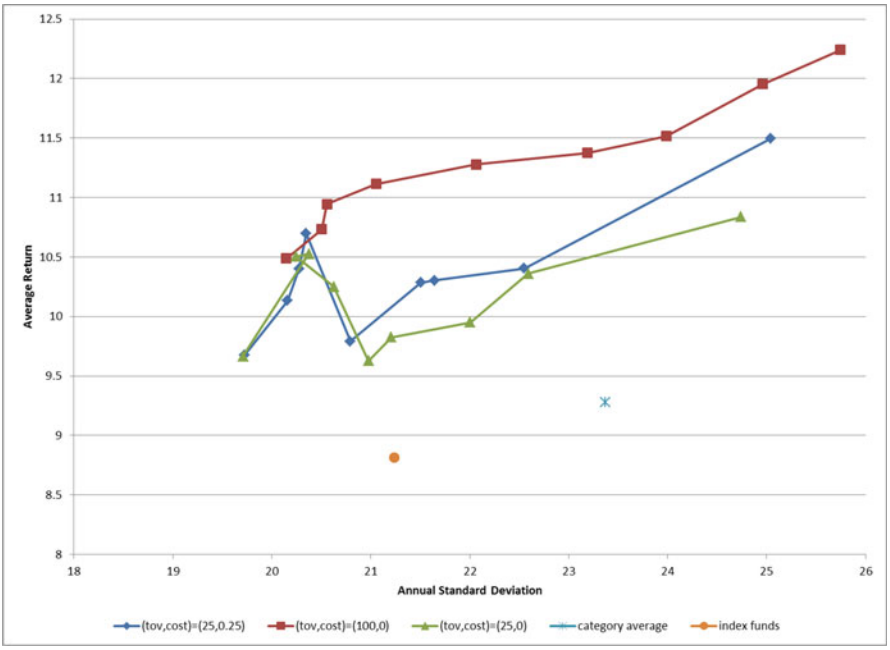

Fig. 14.2 Turnover and cost effect of Alpha model

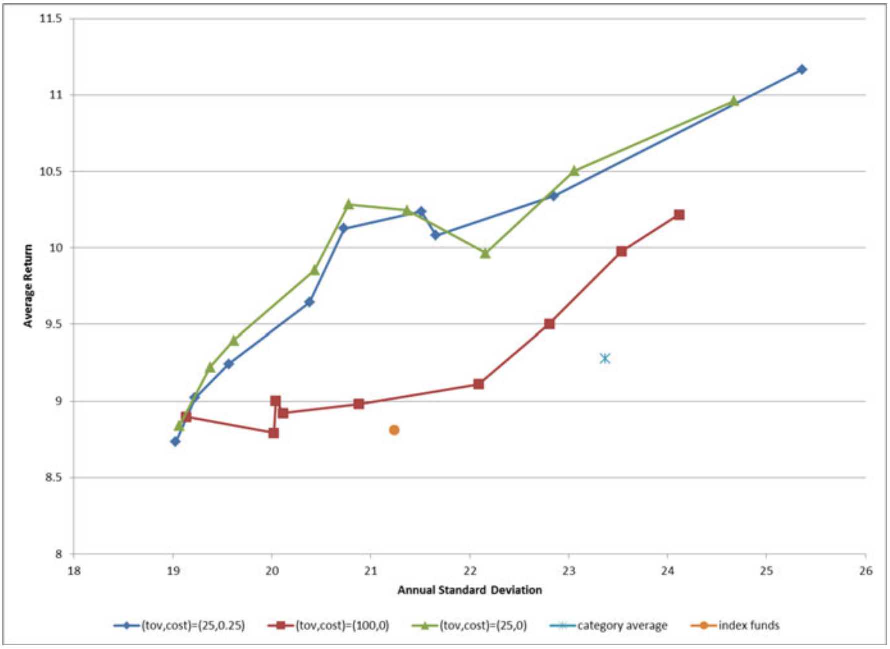

Fig. 14.3 Turnover and cost effect of LY1 model

Table 14.11 February, 2004–January, 2014, cost = 0.0, turnover≤25 %, upper bound≤0.20

Expected return	LY1Ret			Alpha		
λ	Mean	Std	Sharpe ratio	Mean	Std	Sharpe ratio
9	10.25	25.01	0.35	11.32	23.74	0.41
8	9.36	22.65	0.35	10.73	21.27	0.43
7	9.26	21.44	0.36	11.33	20.23	0.49
6	9.92	20.50	0.41	10.80	18.96	0.49
5	10.23	19.53	0.45	10.02	18.66	0.46
4	9.72	19.31	0.43	10.18	18.78	0.46
3	9.38	18.41	0.43	9.74	18.56	0.44
2	9.09	17.57	0.43	9.88	18.27	0.46
1	9.21	17.36	0.44	10.02	18.35	0.46

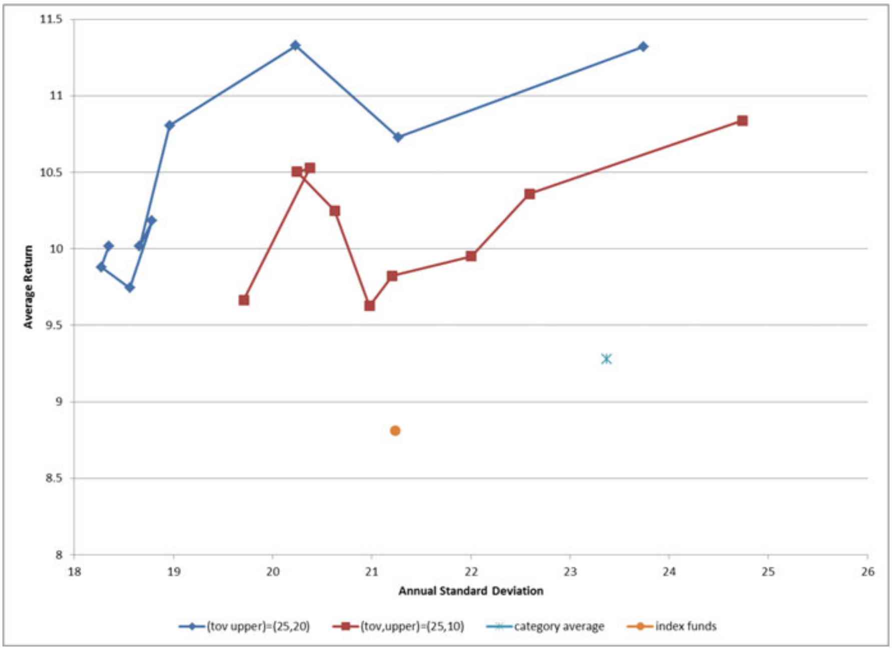

Fig. 14.4 Alpha model with cost = 0.0, turnover≤25 %, upper bound≤0.20

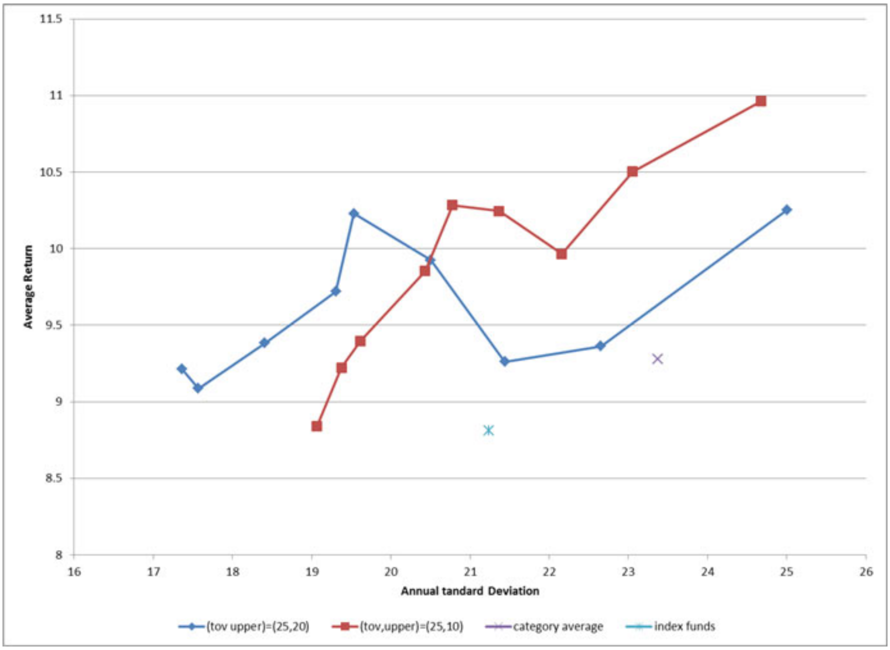

Fig. 14.5 LY1Ret model with cost = 0.0, Turnover≤25 %, upper bound≤0.20

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