Quantitative Strategy

Global Markets Research

Deutsche Bank

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Signal Processing

The rise of the machines

Research Summary
In this report, we introduce our N-LASR (Non-Linear Adaptive Style Rotation) stock-selection model. The model uses machine learning algorithms to select and combine factros. The model adapts to capture seasonal and evolutionary trends in factor peformance.

Using machine learning in global stock selection

Harnessing the power of machine learning
In this report, we introduce our N-LASR (Non-Linear Adaptive Style Rotation) global stock-selection model. The N-LASR model uses machine learning techniques to select and combine factors, taking into account seasonal and evolutionary trends in factor performance. The model shows consistent outperformance, with a long-term average rank IC of 8.6% for the Russell 3000 from 1988 to 2012.

Generalized system works for different sets of factors and universes
We find that N-LASR model works well for both standard factors and technical indicators, and the performance using these two types of factors is relatively uncorrelated which is useful for diversification. In addition, the N-LASR model performs well for different countries and regions, especially for large and developed markets like Europe and Japan

Scalable and less prone to overfitting
The algorithm we used to build N-LASR model is easily scalable with more data, and the performance would increase with a larger factor library. Unlike most other learning methods, the algorithm we use is relatively immune to overfitting.

Highly profitable as a trading strategy
The N-LASR model shows consistent positive performance over the past 14 years. After transaction costs, the Sharpe ratio for the market-neutral portfolio constructed from our N-LASR model is 2.0x from 1998 to 2012, and has remained above 2.0x even after 2008.

Source: gettyimages.com

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A letter to our readers

A quantitative model for a rapidly changing world

Factor performance changes over time, so how to dynamically select useful factors is a challenging problem

The last five years have been challenging for all investors, but perhaps even more so for quantitative investors. Quant, by definition, relies to some extent on historical patterns persisting over time. Unfortunately, in a world dominated by a seemingly never-ending string of macroeconomic crises, the long-term past is proving to be an ineffectual guide to the future. The struggles of tried and true quant factors like value, momentum, and earnings revisions in this type of environment have been well documented. Indeed, in our own research we have always advocated dynamic models to cope with a rapidly changing world; for example our QCD stock-selection model[1] evolves over time to reflect changing market dynamics.

In this report we introduce the next generation of learning models: the N-LASR model

In this report, we launch the next generation of dynamic stock-selection models. We develop a Non-Linear Adaptive Style Rotation (N-LASR) model that draws on the world of machine learning to rapidly adapt to changing market conditions. The model is based on an algorithm called AdaBoost, and is designed to dynamically select useful factors in real-time. This learning algorithm is less susceptible to the overfitting problem compared to other learning algorithms, and is less sensitive to noisy data. The flexibility of the algorithm allows us to make seasonality adjustments by using training data from different time periods, which can help capture the seasonal and recent evolution of the factor performance. We show that our model is useful for a wide range of investors: fundamental managers can improve their stock-selection hit rate by using the N-LASR model to pre-screen their universe, while quantitative managers can use it as a stand-alone alpha source or as an input into a more traditional multifactor model.

N-LASR model works for different style of factors, both standard factors and technical indicators

The N-LASR model works for different types of factors; we find that N-LASR model works well for both standard quant factors as well as technical indicators. The performances of models built using these two factor sets a relatively uncorrelated, so the combination of them would garner useful diversification benefits. Another implication is that our model can be also useful for high frequency investors who trade mainly on high turnover technical indicators.

The N-LASR model outperforms in most geographic regions

The model also works for different stock universes, especially for large developed markets like Europe and Japan, because developed markets have mature and stable financial environments and thus more consistent factor performance. More developed markets also tend to have larger breadth, which is important for data-hungry learning models. Our global N-LASR stock-selection model has significant outperformance for major stock universes compared with traditional multifactor models in almost all markets, including emerging markets.

Our model is actually negatively correlated with market returns

A nice feature of our model is that the performance is negatively correlated with the stock market. The correlation between the long/short decile spread and the S&P 500 total return index is -37%. This means the N-LASR model can be used to hedge the market risk, and can also be used together with other market-correlated trading strategies to diversify the existing portfolios.

Yin, Rocky, Miguel, Javed, John, and Sheng
Deutsche Bank North American Quantitative Strategy

[1] See Luo, et al, [2010c] for details about our QCD model.

Stock Screen

N-LASR stock screen

The screen below (Figure 1 and Figure 2) constitutes the best 30 long and short US stocks derived from our N-LASR (Non-Linear Adaptive Style Rotation) stock selection model. A full list of global stocks is available upon request. The details of our N-LASR model are discussed in the remainder of this report.

Figure 1: Best long ideas as of May 31st, 2012 based on S&P 500 Universe

Ticker	Company Name	GICS Industry Group	N-LASR Score (larger = more likely to outperform)
ALXN	ALEXION PHARMACEUTICALS INC	Health Care	2.23
SPG	SIMON PROPERTY GROUP INC	Financials	2.20
BF.B	BROWN-FORMAN -CL B	Consumer Staples	1.94
JNJ	JOHNSON & JOHNSON	Health Care	1.88
CAG	CONAGRA FOODS INC	Consumer Staples	1.83
HNZ	HEINZ (H J) CO	Consumer Staples	1.75
DLTR	DOLLAR TREE INC	Consumer Discretionary	1.75
CL	COLGATE-PALMOLIVE CO	Consumer Staples	1.74
ABT	ABBOTT LABORATORIES	Health Care	1.73
LLY	LILLY (ELI) & CO	Health Care	1.63
CMG	CHIPOTLE MEXICAN GRILL INC	Consumer Discretionary	1.63
NEE	NEXTERA ENERGY INC	Telecommunication Services	1.62
ISRG	INTUITIVE SURGICAL INC	Health Care	1.61
UPS	UNITED PARCEL SERVICE INC	Industrials	1.59
GIS	GENERAL MILLS INC	Consumer Staples	1.57
GWW	GRAINGER (W W) INC	Industrials	1.55
MRK	MERCK & CO	Health Care	1.54
AEP	AMERICAN ELECTRIC POWER CO	Telecommunication Services	1.54
GR	GOODRICH CORP	Industrials	1.53
BMY	BRISTOL-MYERS SQUIBB CO	Health Care	1.53
CCI	CROWN CASTLE INTL CORP	Telecommunication Services	1.53
HD	HOME DEPOT INC	Consumer Discretionary	1.51
SO	SOUTHERN CO	Telecommunication Services	1.49
WMT	WAL-MART STORES INC	Consumer Staples	1.49
VZ	VERIZON COMMUNICATIONS INC	Telecommunication Services	1.47
IBM	INTL BUSINESS MACHINES CORP	Information Technology	1.46
PRGO	PERRIGO CO	Health Care	1.45
WFM	WHOLE FOODS MARKET INC	Consumer Staples	1.45
KO	COCA-COLA CO	Consumer Staples	1.43
FDO	FAMILY DOLLAR STORES	Consumer Discretionary	1.43

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope,, Deutsche Bank Quantitative Strategy

Figure 2: Best short ideas as of May 31st, 2012 based on S&P 500

Ticker	Company Name	GICS Industry Group	N-LASR Score (more negative = more likely to underperform)
ANR	ALPHA NATURAL RESOURCES INC	Energy	-2.65
MU	MICRON TECHNOLOGY INC	Information Technology	-2.50
FSLR	FIRST SOLAR INC	Information Technology	-2.03
OI	OWENS-ILLINOIS INC	Materials	-1.87
JDSU	JDS UNIPHASE CORP	Information Technology	-1.78
CBG	CBRE GROUP INC	Financials	-1.72
AMD	ADVANCED MICRO DEVICES	Information Technology	-1.72
CNX	CONSOL ENERGY INC	Energy	-1.69
X	UNITED STATES STEEL CORP	Materials	-1.59
BTU	PEABODY ENERGY CORP	Energy	-1.57
WY	WEYERHAEUSER CO	Financials	-1.52
SHLD	SEARS HOLDINGS CORP	Consumer Discretionary	-1.48
NFLX	NETFLIX INC	Consumer Discretionary	-1.44
NFX	NEWFIELD EXPLORATION CO	Energy	-1.40
BAC	BANK OF AMERICA CORP	Financials	-1.33
THC	TENET HEALTHCARE CORP	Health Care	-1.29
ATI	ALLEGHENY TECHNOLOGIES INC	Materials	-1.20
HSP	HOSPIRA INC	Health Care	-1.19
CLF	CLIFFS NATURAL RESOURCES INC	Materials	-1.18
CHK	CHESAPEAKE ENERGY CORP	Energy	-1.17
BHI	BAKER HUGHES INC	Energy	-1.16
GT	GOODYEAR TIRE & RUBBER CO	Consumer Discretionary	-1.14
JCP	PENNEY (J C) CO	Consumer Discretionary	-1.13
AA	ALCOA INC	Materials	-1.13
LNC	LINCOLN NATIONAL CORP	Financials	-1.12
NRG	NRG ENERGY INC	Utilities	-1.11
CSC	COMPUTER SCIENCES CORP	Information Technology	-1.11
S	SPRINT NEXTEL CORP	Telecommunication Services	-1.10
HST	HOST HOTELS & RESORTS INC	Financials	-1.08
FHN	FIRST HORIZON NATIONAL CORP	Financials	-1.07

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope,, Deutsche Bank Quantitative Strategy

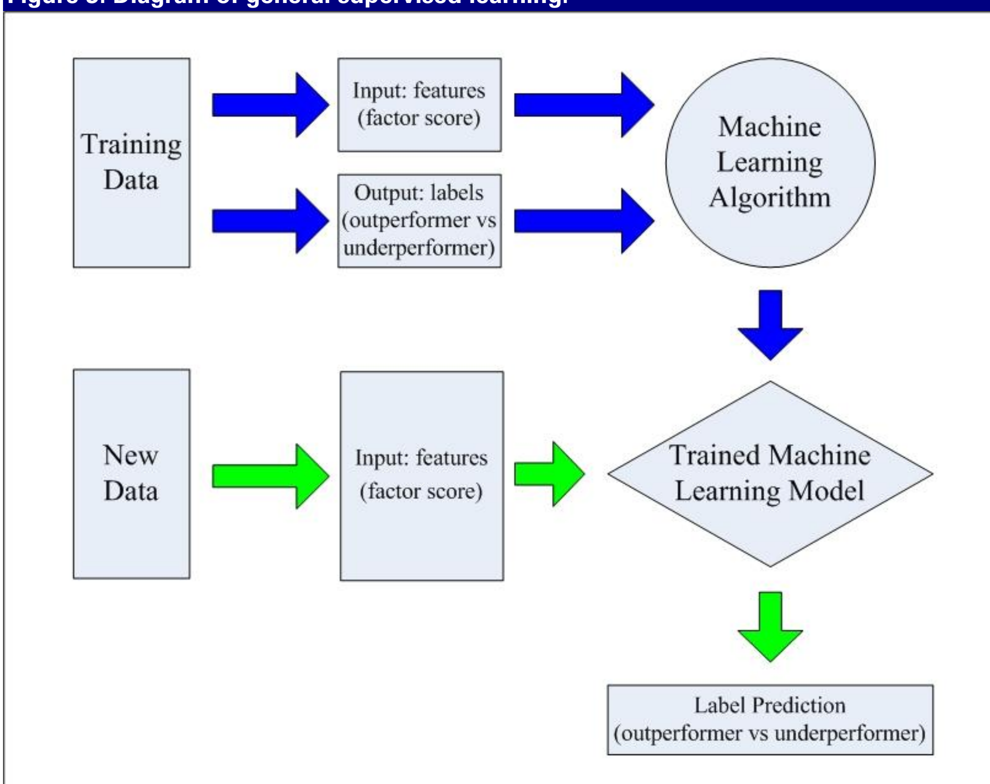
Introducing machine learning

A brief history of machine learning

Machine learning is a branch of computer science that is concerned with the design and development of algorithms that allow computers to perform tasks associated with artificial intelligence (AI), based on empirical data. Such tasks involve recognition, diagnosis, prediction, system control, etc. A powerful machine learning method can capture the inherent characteristics of disparate data and illustrate hidden relationships among observed variables. A major focus of machine learning is to automatically learn to recognize complex patterns and make intelligent decisions based on this analysis. The difficulty of machine learning lies in the generalization from training data in order to produce accurate out-of-sample prediction with new data.

Supervised learning is often used in the application of prediction. This type of learning trains and labels the training samples based on the actual result, which in turn gives feedback about how the learning is progressing. Supervised learning usually consists of a set of training examples. Each training example is a pair consisting of an input feature and a desired output value or label. A supervised learning algorithm analyzes the training data and produces an inferring function between the input feature and the output value. The inferring function should predict the correct output value for any valid input feature. When it comes time to predict outcomes based on out-of-sample data, the trained learning model will output the label prediction. An illustration of supervised learning is shown in Figure 3.

Figure 3: Diagram of general supervised learning.



Source: Deutsche Bank Quantitative Strategy

Supervised learning has a multitude of applications such as handwriting recognition, information retrieval, speech recognition, face detection, and pose estimation, etc.[2] In this paper we aim to utilize machine learning to predict future stock returns based on historical data.

Certain stock selection models pick stocks based on factors that have performed well in the past. However, these models tend to do poorly out-of-sample. The best performing factors typically change over time; therefore, factor timing is a critical component of the stock selection process[3]. Supervised machine learning can serve well for these kinds of purposes.

Our training data consists of historical factor scores as input features and their corresponding forward stock returns as the output labels. The goal is to construct the inferring function between the current factor scores and the future stock returns. Since most machine learning algorithms are designed to handle complex data patterns and relationships, utilizing machine learning for stock selection seems like a natural extension.

Academic evidence

In recent years, machine learning methods for stock selection has become a hot topic in quant finance. As data availability and computing power increases, the question of how machine learning methods may be used to predict stock returns gains more and more attention in both academia and industry.

Machine learning methods have certain advantages over traditional techniques. First, machine learning is well suited to capture the non-linearity often inherent within financial data. Second, machine learning methods are usually data-driven and based on statistical distributions; therefore, it can capture hidden relationships in the data that are normally difficult to discover. Third, machine learning methods can be adapted to new data sources and regions.

In Academic Insight last year, we highlighted a paper titled "Nonlinear Support Vector Machines can Systematically Identify Stocks with High and Low Future Returns". In that paper (Huerta, et al. [2011]), the author explored an interesting machine learning method named Support Vector Machine (SVM) and its application in building stock selection model. Both technical factors and fundamental factors were used to build the SVM. The author constructed portfolios by taking a long position in the highest ranked stocks and a short position in the lowest ranked stocks based on the ranking determined by the classifier output. The author showed that building a stock selection model based on SVM produced annualized returns of 13% (after transaction costs) and a Sharpe ratio of 1.6x.

In Yan, et al. [2006], the author used a machine learning method based on kernel regression to predict weekly equity returns using price and volume data. The return predictability was increased by applying the machine learning method compare with traditional modeling techniques using the same set of predictors. The authors showed that applying machine learning methods to portfolios of stocks can lead to a Sharpe ratio of approximately 1.9x (before transaction costs).

Other research areas where machine learning techniques have been used for stock prediction include TREE models (Luo, et al. [2010d], Salvini, et al. [2010b], and Cahan, et al. [2012]), linear/non-linear regression (Luo, et al. [2010c]), textual analysis of financial news or social

2. See Wu, et al.[2004] and Wang, et al. [2010]

3. Our QCD model is one of the many examples of signal weighting methodologies, see Luo, et al. [2010c]

media articles (Cahan, et al. [2010b]), and Hidden Markov Models (Atsalakis, et al. [2009]). These applications have shown promising results.

Conversely, some academics argue against these black box type models that lack human oversight and input. They contend that financial data may contain a lot of noise, which makes predictability difficult. In addition, the problem of overfitting is a serious one; the model may work well during the training period but collapse out-of-sample. Last but not least, the complexity of these types of models may cause results to be unintuitive and difficult to interpret.

We build our N-LASR (Non-Linear Adaptive Style Rotation) stock-selection model based on a machine learning algorithm called AdaBoost (Schapire [1998]). It can predict and interpret the stock performance by selecting and combining the most effective factors in the previous months. This learning algorithm has been used in stock return prediction (Creamer, et al. [2006, 2010]) in academia. It is less susceptible to the overfitting problem than most learning algorithms, and less sensitive to noisy data. It can be used in conjunction with many learning algorithms to improve their performance.

In this paper, we take a different approach from Creamer, et al. [2006, 2010]. Instead of training with time-series data we use cross-sectional data. Our backtesting shows that the AdaBoost algorithm works well for stock selection. The output of the algorithm is not only a confidence score shows how likely the stock is going to outperform, but also the list of most important factors that are likely to be useful at each point in time in predicting stock returns.

The groundwork for machine learning

Machine learning in a nutshell

We formulate our stock selection model as a binary classification problem. We classify the stocks in our universe into two categories: outperformers and underperformers based on one-month forward stock returns. Outperformers are those stocks with highest one-month forward returns and underperformers are those with lowest one-month forward returns

We construct classifiers based on whether the stock is going to outperform or underperform. The inputs of the classifiers are our stock selection factors, and the outputs are confidence scores. A positive confidence score means we expect the stock to outperform. The higher the confidence score is, the more likely the stock will outperform and vise versa.

The construction of the confidence score has two steps. First is the training step. In this step, we use the end-of-month factor scores for each stock and one-month forward returns as training data to build the classifiers. Essentially, the input vector is the stock factor score and the output label is a binary label of outperformer or underperformer. The power inherent within machine learning methods is the ability to find a predictive relationship between the input vector and the output label. The second step is the actual prediction step. In this step we use the current month factor score as the input for the classifiers we built in the training step, and the output is the confidence score.

Data preparation

Before we build our machine learning framework, we need to "normalize" the data to ensure that the training data used to build the classifiers are as consistent as possible. Most machine learning algorithms are very sensitive to input data. If the training data are not consistent, then the algorithm is more likely to be overfit. Data preparation is crucial to the machine learning algorithms. To some extent, normalizing the data can be even more important than choosing the machine learning algorithm.

Input factor data

We use the cross-sectional ranking of the factors, rather than the factor score itself as the input, and we calculate the factor ranking each month for all the available stocks. This is because what we care about is the relative ranking rather than the absolute returns. The factor score itself will vary from time to time, making the training data inconsistent. Furthermore, the factor score is very easily influenced by market regimes. For example, in a bearish market certain factors may have low values (e.g. price to earnings) for all the stocks. Whereas in a bullish market, factor scores (e.g., price to earnings) may have higher values. If we were to utilize the actual factor scores instead of the "ranked" factor scores, the training data would be inconsistent over time. In addition, we use the ranking of the factors rather than normalizing the factor score by the typical z-score since several factors are heavily skewed. Factor rankings would always produce an even distribution.

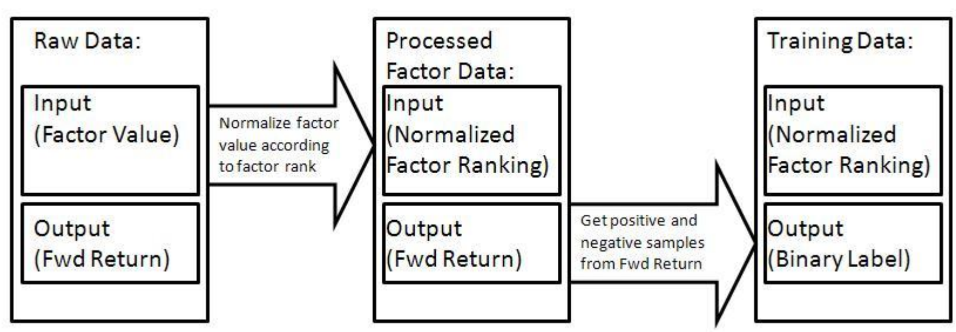
Once we rank each factor cross-sectionally, we divide the factor ranking by the number of stocks to normalize the factor ranking to between (0, 1]. The reason we normalize it between (0,1] is because coverage varies between factors and across time. Normalizing our factor ranking between (0,1] will enable us to be able to compare factors that have varying coverage in a consistent manner.

Labeling training data

After normalizing the factors by rank and coverage, we then assemble the training data. We label the training data using one-month forward returns. We label the top forward return stocks as outperformers, and the bottom forward return stocks as underperformers. We set the stocks in the top 30% as measured by one-month forward return as the outperformers. Similarly we set stocks in the bottom 30% as measured by one-month forward returns as the underperformers. We perform this labeling exercise on a monthly basis. Note that stocks not classified in the top or bottom 30% are disregarded. This is because stocks with insignificant positive or negative forward returns may just be noise, rather than true outperformers or underperformers. If we include those stocks in the training data we potentially reduce the accuracy of the classifiers.

Similar to the factor normalization, we only care about the relative performance; thus, we cross-sectionally label the stocks every month. This means in some good months, underperformers might even have a slightly positive forward return; and some bad months, outperformers might have a slightly negative forward return. In our strategy relative performance is more important, because we want to minimize the extrinsic effects that influence the market, since we want to long (or overweight) the relative good stocks and short (or underweight) the relative bad ones, so we don't care that much about the absolute performance. In addition, most of the binary classification problems in machine learning prefer similar number of outperformers and underperformers in the training data, and this way of collecting the training data will generate a similar number of outperformers and underperformers. Figure 4 illustrate how we prepare the training data.

Figure 4: Data preparation



Source: Deutsche Bank Quantitative Strategy

The AdaBoost algorithm

We use the machine learning algorithm called AdaBoost to build classifiers that can combine the best performing factors in previous months and get a confidence score. The higher the confidence score, the more likely the stock is going to outperform in the next month.

AdaBoost is a very effective machine learning method for classification; the main idea of AdaBoost is that it adaptively builds a sequence of classifiers that are constantly being tweaked to emphasize *misclassified* stocks, thereby slowly improving the classification of stocks that would normally be incorrectly classified. Although certain classifiers can be weak, as long as their performance is not random, the performance of the final model will improve.

In our case, a weak classifier is simply defined by a factor. We divide the factor into quantiles, and calculate the weights of outperformers and underperformers in each quantile. Intuitively, the most effective factors are those which have the largest difference between the weights of outperformers and underperformers in each quantile. Therefore, when the new data falls into a certain quantile, the label of the new data can be determined by the majority of the labels of the training data in that quantile. As such, the value of the weak classifier is determined by the weights of outperformers and underperformers in that quantile. The higher the weight of outperformers relative to the weights of underperformers in that quantile, the higher value the output of that weak classifier will be.

Dividing factors into quantiles is a natural extension of the decision tree (TREE model), in which case the quantile number equals two. By setting quantiles to more than two (in our case we set it to be five because setting this number too large increases the risk of overfitting) our model can much better capture the non-linear payoffs described in our recent paper, Cahan [2012a]. For example, for some factors, the middle quantiles show better performance than the top and bottom quantiles, in which case not only a linear model but also the TREE model would fail to capture the factor payoffs. For the TREE model, no matter where we set the threshold to split the node, the performance would not be satisfying. Therefore, the TREE model would need multiple levels of splits to capture a highly nonlinear pattern. However, in our model, the weak classifier would naturally learn and apply lower value for the top and bottom quantiles and higher value for the middle quantiles, since there are be more underperformers in the middle quantiles for this factor.

Initially, we equally-weighted each observation in the training data, and then the weights are updated in each round after a new weak classifier is found. The weight of each incorrectly classified stock is increased and the weight of each correctly classified stock is decreased, so that the next classifier would focus on the stocks which have so far not been correctly classified.

As discussed above, in each round we choose the most effective weak classifier, which can distinguish the underperformers and underperformers the most. Therefore, that corresponding factor is best performing factor with the current set of weights. Notice that the current best factor itself might not be the best performing factor; it is best performing in the sense that it performs best for those stocks that cannot be classified correctly by previous classifiers. This means the current best performing factors is less correlated with the previous selected factors. This is a good feature of the model, because many of the well performing factors are highly correlated, therefore, combining them can hardly improve the performance. What our machine learning system does is select those factors that are complementary to each other.

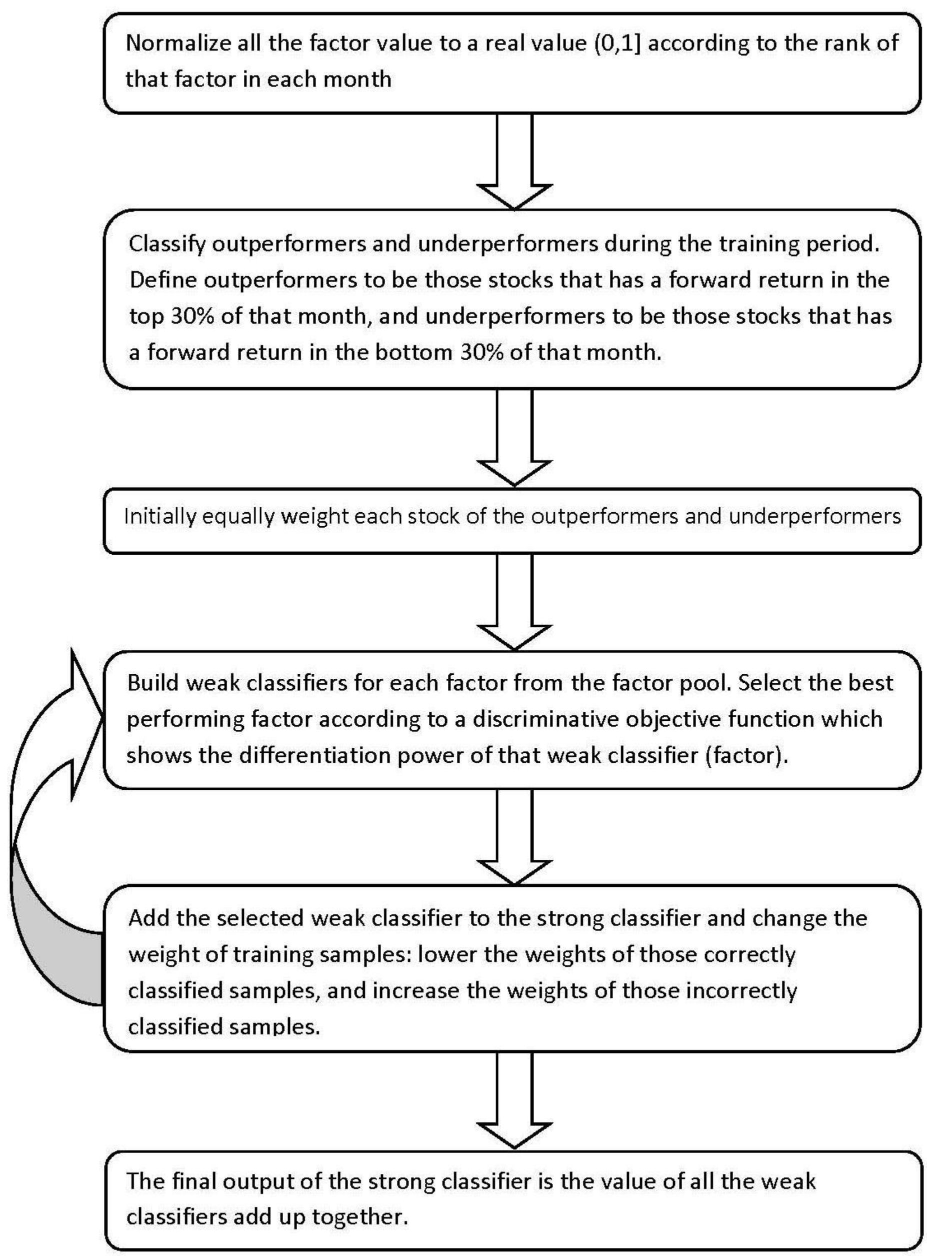
The output of the strong classifier is the sum of all the weak classifiers; it is a real value confidence score of how likely the stock is to be an outperformer. Essentially we can use this confidence score as a new composite factor, which hopefully has better performance than any of the factors comprising it. Notice that the way we combine the factors is non-linear in the sense that the output of current weak classifier is based on the previous factor performance on the training data, since the weights of the training data would change each round after a new classifier is constructed.

The strong classifier we build has good predicting power as long as the factor performance of the current month is similar to the factor performance in our training data. Although the factor performance differs from time to time, the advantage of our model is that even if some factors fail to work, as long as the majority of the factors work our model would still have a good predictive power.

In addition, this method is easily scalable with more factors, because the algorithm will automatically pick the best factors and is not easily overfit. Ideally, the more factors we included in the training process the better performance will be. It is also adaptive, because we train new classifiers each month, which captures the seasonality and evolution in factor performance.

Figure 5 shows a detailed step by step flow chart of our machine learning model.

Figure 5: Flow chart of the machine learning model



Source: Deutsche Bank Quantitative Strategy

Model algorithm details

In this part, we will show the model process and detailed calculation steps.

Given a labeled set of stock $\boldsymbol{S}$= $\{(x_1, y_1), (x_2, y_2),\ldots(x_N, y_N)\}$, where N is the number of stocks in the training data, x_i is the factor score vector for stock $\boldsymbol{i}$, y_i is the corresponding labeling (or classification) for stock $\boldsymbol{i}$, i.e. $y_i = 1$ if a stock has a top 30% forward return, $y_i = -1$ if a stock has a bottom 30% forward return.

In the AdaBoost framework, one weak classifier $\boldsymbol{h}$ is built for each factor $\boldsymbol{k}$ in the factor pool F. The weak classifier is a function from the real value factor space to a real valued classification confidence space. For a stock x_i the factor score is denoted as $f^k(x_i)$ for factor $\boldsymbol{k}$, we assign a weight to each stock denoted as $w(x_i)$.

The weak classifier $\boldsymbol{h}$ is trained as a piecewise function:

If $f(x)$ is in the j^{th} quantile denoted as $f(x) \in \text{quantile}_j$, the value of the weak classifier is:

$$h(x) = \frac{1}{2}\ln\left(\frac{W_+^j + \varepsilon}{W_-^j + \varepsilon}\right)$$

where ε is a small value set as $1/N$ to make the function robust (so that the nominator and denominator won't be 0), and $j = 1,2,\ldots,Q$ is the number of quantiles (in our experiments we set Q=5), and $W_\pm^j$ is the sum of the weights in quantile $\boldsymbol{j}$.

$$W_\pm^j = \sum_{y_i=\pm 1,\, f(x_i)\in quantile_j} w(x_i)$$

Intuitively, the larger the total weight of outperformers in a quantile, the more likely the stock is going to outperform if the future factor score falls into that quantile. Therefore, the more positive $h(x)$ will be. Similarly if the weights of outperformers are smaller than the weights of underperformer, $h(x)$ will be negative.

We define a discriminative objective function, to show how good the weak classifier is:

$$Z = \sum_{j=1}^{n} \sqrt{W_+^j W_-^j}$$

The intuition of this objective function is that a good weak classifier should have strong differentiation power. Because all the weights add up to 1, in each quantile if the difference between W_+^j and W_-^j is large (meaning the weak classifier has strong differentiation power) then the objective function will be small.

We update the weights each round of weak classifier $w_{(l+1)}(x_i) = w_l(x_i)\exp(-y_i\, h_l(x_i))$, where l is the l^{th} layer of weak classifier. If currently the weak classifier correctly classified the stock we decrease the weight $w_l(x_i)$ otherwise we increase the weight. The higher the absolute value of $h_l(x_i)$, the smaller the weight of correctly classified stocks and conversely the larger the weight on the incorrectly classified stocks. In that way, for the next weak classifier we will focus more on the previously misclassified stocks.

We use the AdaBoost algorithm to choose weak classifiers to build one strong classifier that returns the confidence value. Assume $h_l(x)$ is the l-th weak classifier, and $H(\boldsymbol{x})$ is the strong classifier built by weak classifier: $H(\boldsymbol{x}) = \Sigma(h_l(x))$.

Figure 6 gives the full algorithm of our AdaBoost stock selection model.

Figure 6: Algorithm of AdaBoost Stock Selection Model

AdaBoost Algorithm

1. Normalize all the factor value to a real value (0,1] according to the rank:

   Normalized_factor = factor_rank/total_number_of_factors_in_the_month

2. Given stock performance set $S = \{(x_1, y_1), (x_2, y_2), \ldots (x_N, y_N)\}$ and the factor pool F, where y_i {-1,1}, N is the number of stocks in the training sample.

3. Initially equally weighted all the stocks $w_1(x) = 1/N$

4. For $l = 1, \ldots L$

   1) For each factor f^k from the factor pool we build a weak classifier h^k.

      a) Divide the training data into Q quantiles, $X_1, X_2, \ldots X_Q$

      b) For each quantile j we calculate the total weight of outperformers and underperformers

$$W_{\pm}^{j} = \sum_{y_i = \pm 1, f(x_i) \in quantile_j} w(x_i)$$

      c) Calculate the discriminative objective function:

$$Z_l^k = \sum_{j=1}^{n} \sqrt{W_+^j W_-^j}$$

      d) Get a weak classifier:

$$h^k(x) = \frac{1}{2} \ln\left(\frac{W_+^j + \varepsilon}{W_-^j + \varepsilon}\right)$$

   2) Find the best weak classifier according to the discriminative objective function:

$$h_l(x) = h^k(x) \text{ where } k = \arg\min_{f^k \in F} \{Z_l^k\}$$

   3) Update the weights of each stock:

$$w_{(l+1)}(x_i) = w_l(x_i) \exp(-y_i h_l(x_i))$$

   4) Normalize the weight $w_{l+1}(x_i)$ so that they add up to 1.

5. The final strong classifier: $H(x) = \sum_{t=1}^{L} (h_l(x))$

Source: Deutsche Bank Quantitative Strategy

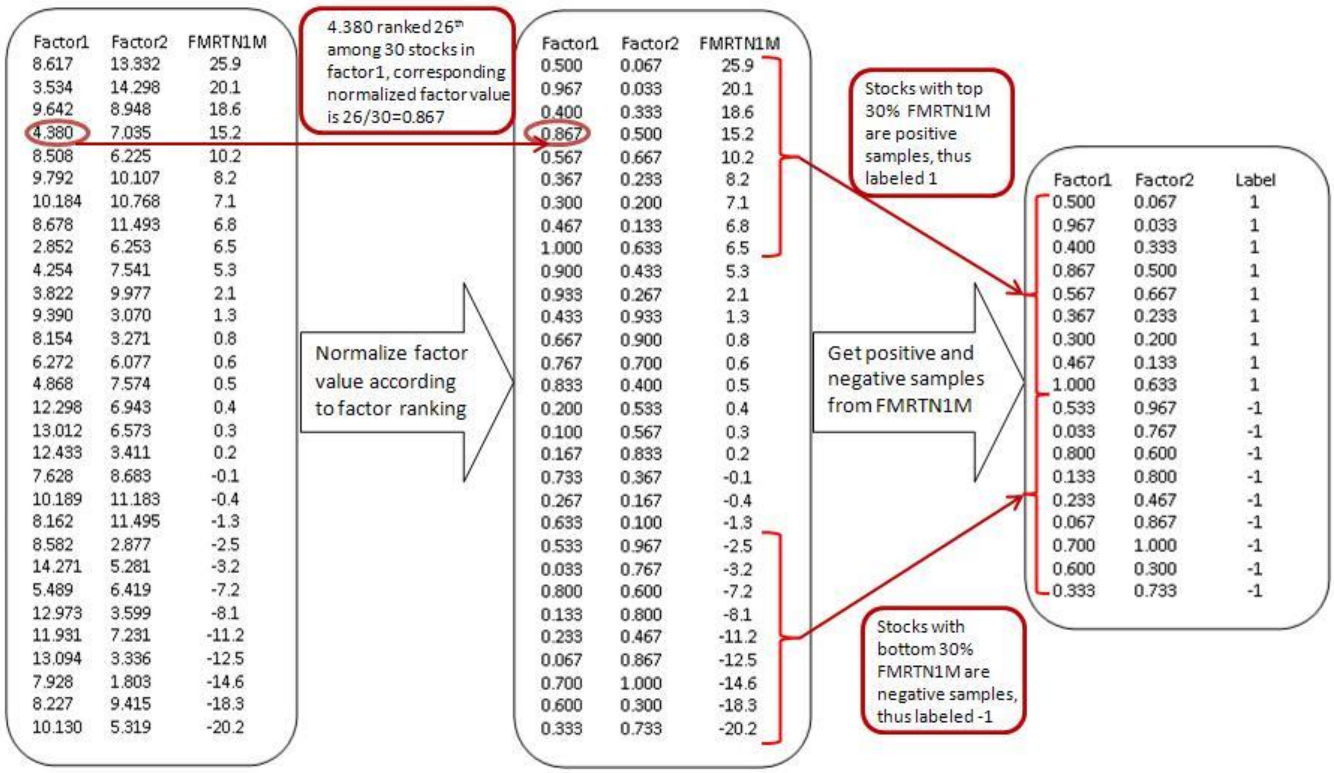
A simple example of machine learning

The best way to understand how our AdaBoost algorithm works is to work through an example. For this simple example we use artificially generated factor scores. Suppose we want to predict month-ahead returns using two factors in the factor pool.

Data preparation

The first step is to construct training set. As discussed earlier, we need to normalize each factor score according to factor ranking and then get the top 30% as outperformers and the bottom 30% as underperformers. Figure 7 shows detailed example of how we prepare the data for training.

Figure 7: Data Preparation for Training



Source: Deutsche Bank Quantitative Strategy

Building a weak classifier

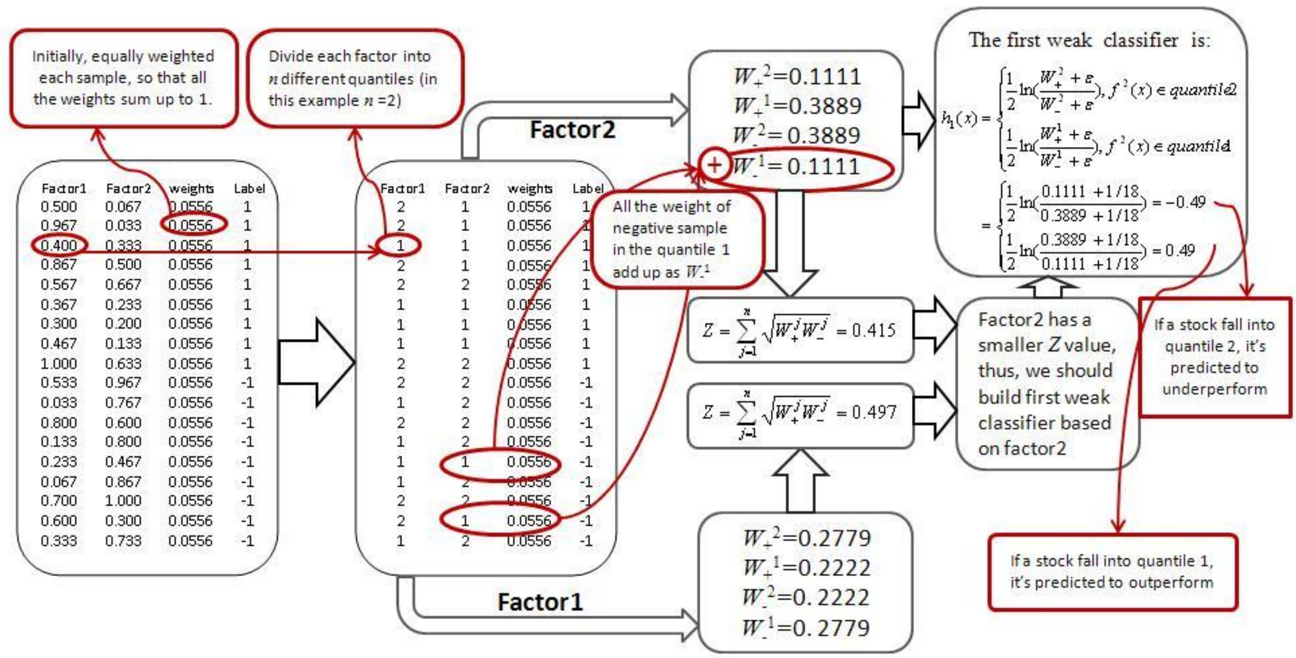
Once we have the training data ready, we equally weight each stock, so that all the weights sum up to 1. In this example, we divide each factor into 2 quantiles. For each factor we calculate the sum of all the outperformers and underperformers' weights in quantile 1 and quantile 2, which are denoted as $W_{\pm}^{j}$, where j refers to quantiles and ± refers to outperforming and underperforming. We calculate the discriminative objective function $Z=\text{sqrt}(W_{+}^{j}W_{-}^{j})$ for each factor. It turns out factor 2 has a smaller Z value, which means factor 2 is currently the best performing factor and can better differentiate outperformers from underperformers. So we construct the weak classifier using factor 2.

The output of the weak classifier is denoted as a piecewise function. If a stock has a factor 2 value in quantile 1 the output of the weak classifier is 0.49, meaning it is more likely to be an outperformer. This is because in the training set there are more outperformers than underperformers in quantile 2. This is naturally defined by the function determine the value of weak classifier:

$$h(x) = \frac{1}{2}\ln\left(\frac{W_{+}^{j} + \varepsilon}{W_{-}^{j} + \varepsilon}\right)$$

We can see that if the weight of underperformers is larger than the weight of outperformers, the output of the weak classifier would have a negative value, indicating the stock is more likely to be underperformers if its factor score falls into this quantile. This is the case when the factor 2 value falls into quantile 2 in this example, the output of the weak classifier would be negative. Figure 8 illustrate how we choose the best performing factor and build the first weak classifier.

Figure 8: Build Weak Classifier



Source: Deutsche Bank Quantitative Strategy

Building a strong classifier

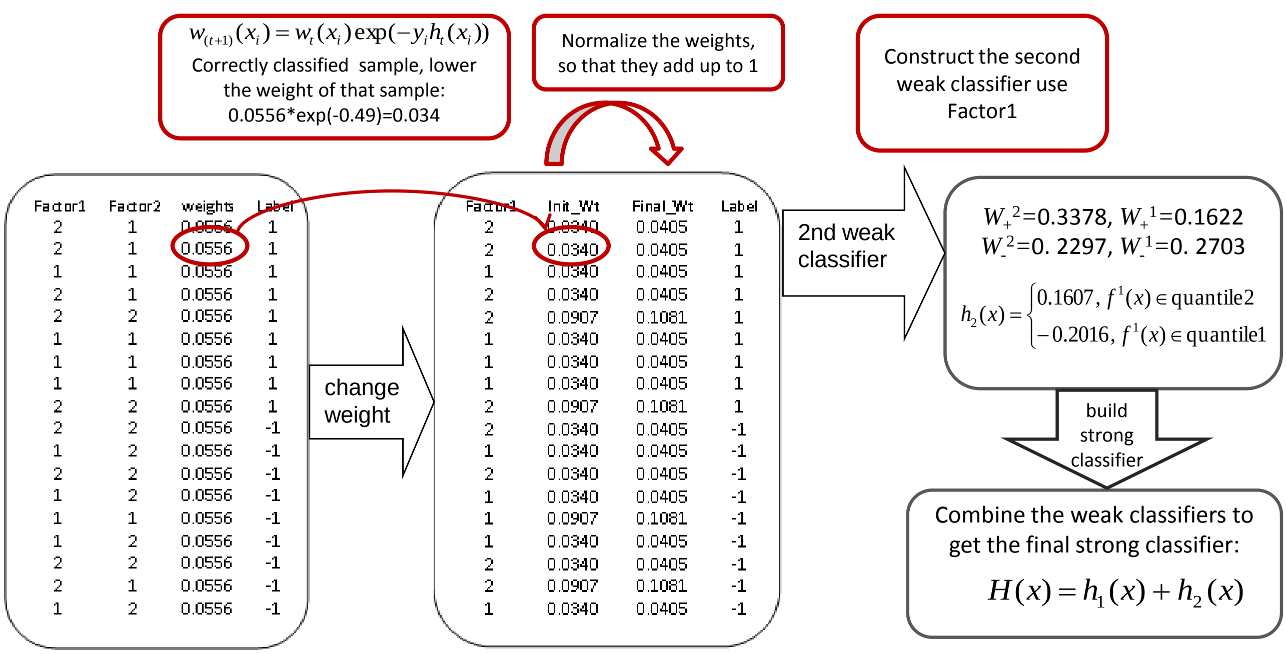
After a weak classifier is built, we change the weights of all the stocks by a multiple of $\exp(-y_i h(x_i))$. This means if the stock label y_i and the output of the latest classifier $h(x_i)$ have the same sign (meaning the last weak classifier correctly classified this stock) we would lower the weights of those stocks. Similar, this multiple can ensure we increase the weights assigned to those misclassified stocks. Therefore, in the next round, the weak classifier would focus on those misclassified stocks. In addition, the larger the absolute value of the weak classifier for those correctly classified stocks, the lower the weights of those stocks will be; and the larger the absolute value of the weak classifier for those misclassified stocks, the higher the weights of those stocks will be. This also makes sense; if the previous weak classifier is confident about the label of a stock but in fact it got misclassified, then this stock should get special attention.

Again we normalized all the weights so that they add up to 1, and find the next weak classifier the same way: choose the factor with the smallest discriminative objective function Z to build the current weak classifier. Notice that, we don't need to exclude previous selected factors, because after the change of weights according to the weak classifier built by factor 2, now factor 1 would have a smaller discriminative objective function value than factor 2. So normally the same factor would not be selected again right away, although it could be selected again after many rounds. But by that time the weights of the training stocks would have changed, so the weak classifier constructed with the same factor would be totally different.

The determination of how many layers of weak classifiers can be set as a fixed number. Normally, the more layers of weak classifiers, the better the performance for the new data will be. However, the incremental benefit from each new classifier will diminish because after certain number of factors have been chosen the rest are correlated with some of the factors already selected. For example, there is no need to set the number of weak classifiers greater than the number of factors. For a small list of uncorrelated factors, we could set the number of layers equal to the factor number, but with a larger set of factors, it is almost certain that many factors would be highly correlated. However, the good thing about the AdaBoost algorithm is that it is less subject to the problem of overfitting, or multi-colinearity. Therefore, the performance of the strong classifier won't decrease significantly when trained with too many layers (although of course training with too many layers is computationally inefficient and unnecessary). Only with larger factor pools and less correlated factors could we train more layers of weak classifiers and still improve performance.

Finally the combination of all the weak classifier is easy; the output of the strong classifier is simply the sum of all the weak classifiers. Figure 9 shows the example of how to build strong classifier after a weak classifier is built in Figure 8.

Figure 9: Build Strong Classifier

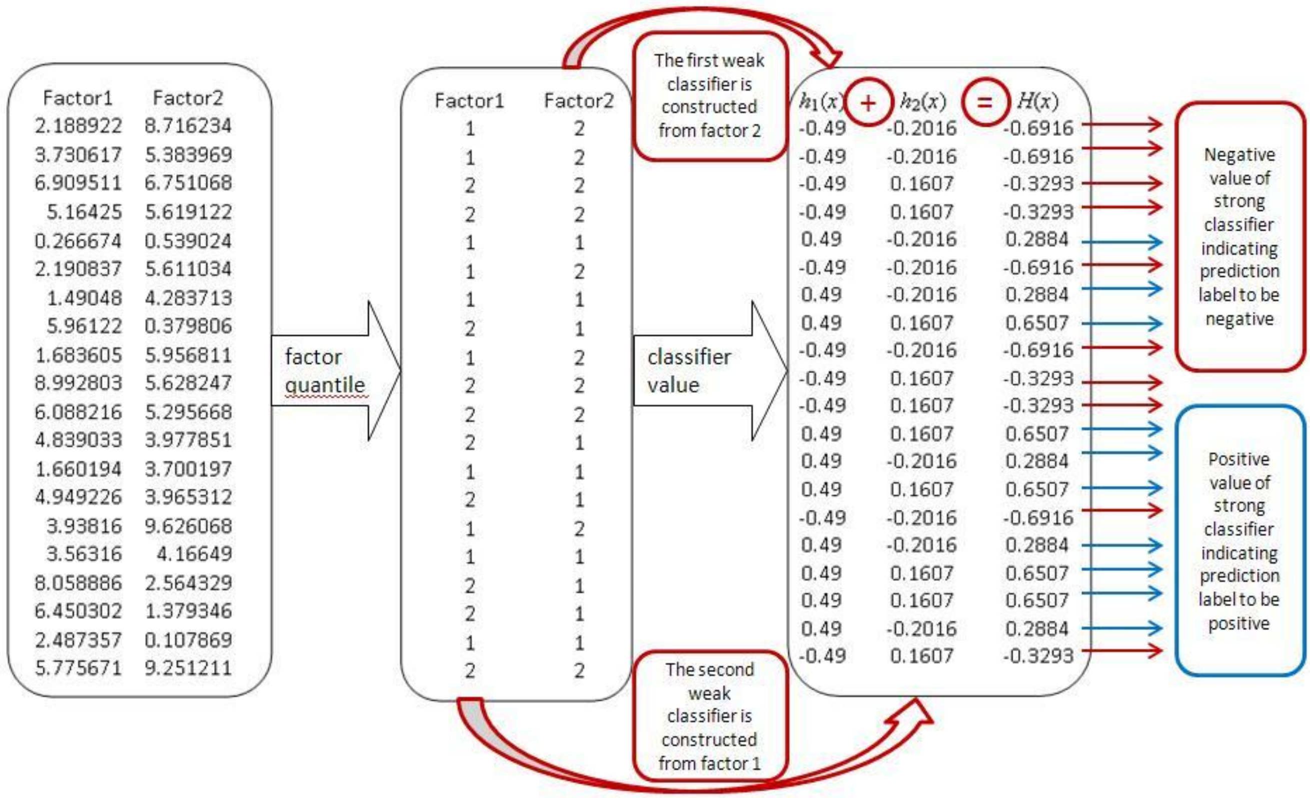


Source: Deutsche Bank Quantitative Strategy

Predicting with new data

After we train our machine learning model, we can predict month-ahead returns using the constructed classifiers with new data. First we transform factor scores into quantiles, and get the corresponding value of the weak classifier, adding up all the weak classifiers, we get the final value of the strong classifier. A positive value of the strong classifier indicates a stock is likely to be an outperformer, and negative value of the strong classifier indicates the opposite. The illustration is shown in Figure 10.

Figure 10: Predicting new data



Source: Deutsche Bank Quantitative Strategy

Baseline N-LASR model performance

Baseline factor universe

We build our baseline N-LASR model using 70 standard factors from our factor library. The list of the 70 factors is shown in Figure 11. These factors are chosen not because they are the best factors; rather it is because they are the common factors used by most investors.

Figure 11: Standard factors used in the N-LASR model

No.	Factor Name	Factor Description	No.	Factor Name	Factor Description
1	EBITDA_EV	EBITDA to EV	36	IBA0_FY1_ROE_R1AVG	IBES FY1 Mean ROE Revision, 1M
2	SAL_EV	Sales to EV	37	IBA0_FY1_ROE_R3AVG	IBES FY1 Mean ROE Revision, 3M
3	PB	Price to Book	38	IBA0_FY1_SAL_R1AVG	IBES FY1 Mean SAL Revision, 1M
4	PE_T12MOB	Price to Earnings	39	IBA0_FY1_SAL_R3AVG	IBES FY1 Mean SAL Revision, 3M
5	PSALES	Price to Sales	40	IBA0_LTG_REV1M_AVG	IBES LTG Mean EPS Revision, 1M
6	CAPEX_DEP_12M	Capex to Dep	41	IBA0_LTG_REV3M_AVG	IBES LTG Mean EPS Revision, 3M
7	BARRY_R	Berry Ratio	42	IBA0_PTG_RTN	Target price implied return
8	CURRENT_R	Current ratio	43	IBA0_REC_AVG	Recommendation, mean
9	DEBT_EQUITY	Long-term debt to equity	44	IBA0_REC_R3AVG	Mean recommendation revision, 3M
10	GROSS_MARGIN	Gross margin	45	IBA0_FY1_EPS_DISP	IBES FY1 EPS dispersion
11	ROA	Return on Assets	46	ABNORMAL_VOL	Normalized abnormal volume
12	ROE	Return on Equity	47	MA_CO_15_36W	Moving average crossover, 15W-36W
13	SAL_TA	Asset Turnover	48	REAL_VOL_1YD	Realized vol, 1Y daily
14	CFY_FY0	Cash flow yield, FY0	49	SKEW_1YD	Skewness, 1Y daily
15	EBP_MDN	Est Book-to-price, median	50	EXP_YLD	Expected dividend yield
16	EPSY_FY0	Earnings yield, FY0	51	EPSY_T12MOB	Operating earnings yield, trailing 12M, Basic
17	EPSY_FY1_AVG	Earnings yield, forecast FY1 mean	52	EPSY_IB5YG	Earnings yield x IBES 5Y growth
18	EPSY_FY2_AVG	Earnings yield, forecast FY2 mean	53	CFY_IS	Operating cash flow yield (income stmt def)
19	FY1_YLD	Dividend yield, FY1	54	FCF_YLD	Free cash flow yield
20	FY2_YLD	Dividend yield, FY2	55	YOY_EPS_G	Year-over-year quarterly EPS growth
21	PE_FY0	Price-to-FY0 EPS	56	P_52WHI	Price-to-52 week high
22	TRL_YLD	Dividend yield, trailing 12M	57	P_52WLO	Price to 52-week low
23	IB0_EPS_5Y_GRO	IBES 5Y EPS growth	58	ROIC	Return on invested capital (ROIC)
24	IB0_EPS_5Y_GTOS	IBES 5Y EPS growth/stability	59	ALTMAN	Altman's z-score
25	IB0_FY1_AVG_EPS_G	IBES FY1 mean EPS growth	60	MERTON	Merton's distance to default
26	IBA0_FY2_AVG_DPS_G	IBES FY2 mean DPS growth	61	ACCR	Accruals (Sloan 1996 def)
27	IBA0_LTG_EPS_AVG	IBES LTG EPS mean	62	PAYOUT_OEPS	Payout on trailing operating EPS
28	RTN12_1M	12M-1M total return	63	CHG_SHARES	YoY change in # of shares outstanding
29	RTN1260D	Total return, 1260D (60M)	64	CHG_DEBT	YoY change in debt outstanding
30	RTN21D	Total return, 21D (1M)	65	RNOA	Return on net operating assets (RNOA)
31	RTN252D	Total return, 252D (12M)	66	CFROE_CF	Cash flow return on equity
32	IB0_FY1_EPS_UPDN1M	IBES FY1 EPS up/down ratio, 1M	67	CFROC_CF	Cash flow return on capital
33	IB0_FY1_EPS_UPDN3M	IBES FY1 EPS up/down ratio, 3M	68	SHORT_COV	# of days to cover short
34	IBA0_FY1_EPS_R1AVG	IBES FY1 Mean EPS Revision, 1M	69	SHORT_FLOAT	Short interest/float
35	IBA0_FY1_EPS_R3AVG	IBES FY1 Mean EPS Revision, 3M	70	FLOAT_TO_1M	Float turnover, 1M

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

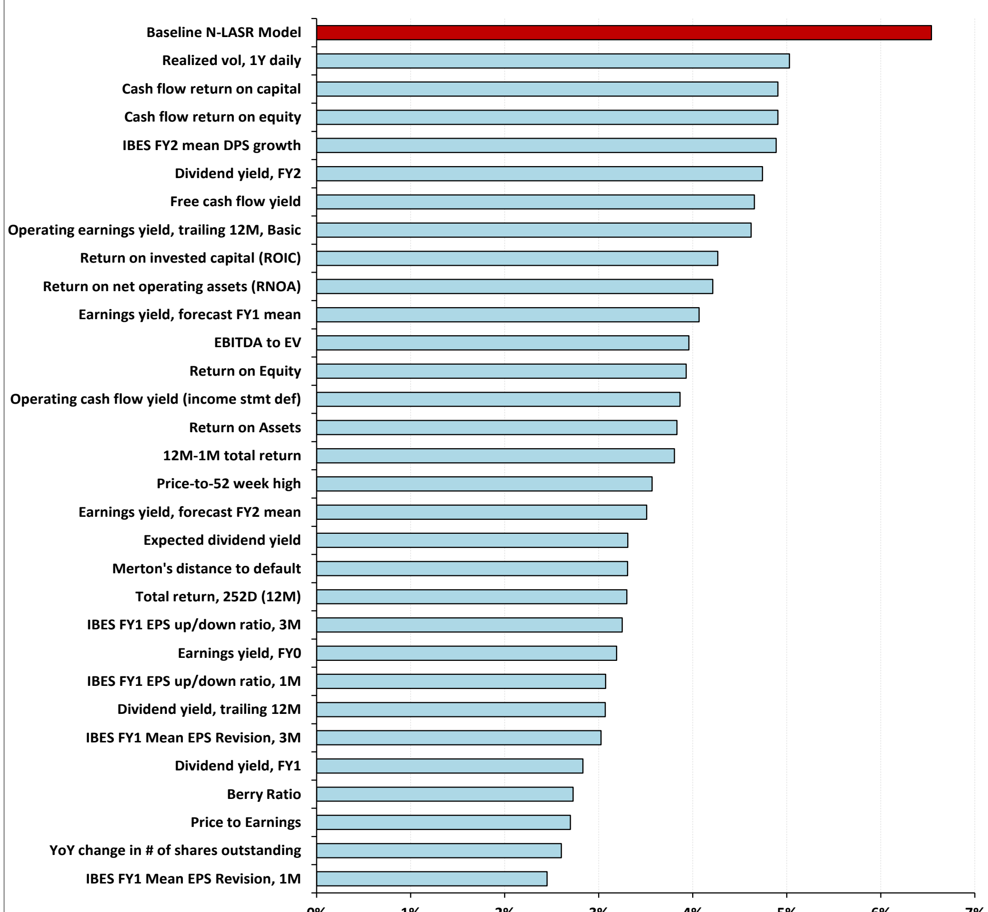
Each of these factors has some predictive power for future stock returns, but many of them have non-linear payoff patterns (see, for example, Cahan et al. [2012]). We train our baseline N-LASR model using a trailing 12 months worth of data with 30 layers of weak classifiers to build the AdaBoost strong classifier. When constructing the weak classifiers, we set the number of quantiles to be 5, because this can capture the non-linear payoffs for the factor while avoiding overfitting. The output of the AdaBoost strong classifier is the score of our N-LASR model.

Now we can see how much the performance increases for our N-LASR model compared to the underlying factors. Our preferred metric is the rank information coefficient (IC), which is the correlation between the ranks of stocks on the factor at the start of each month, versus the rank of the stock returns over the subsequent month. This metrics shows the predictive power of the factor.

Baseline model performance

In Figure 12 we show our baseline N-LASR model, compare with the long-term average performance for the best 30 factors from 1988 to 2012, using the rank IC as our performance metric. Notice that we use the absolute value of the long term average rank IC to compare the performance of the factor, because a negative number is not necessarily bad, it just means that the signal should be traded in the opposite direction, i.e. buy stocks with a low factor score and sell those with a high score.

Figure 12: Long term average Rank IC for best performing factors from 1988 to 2012

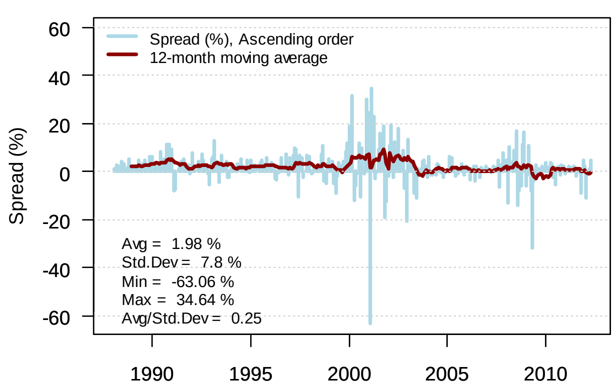


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

From Figure 12 we can see that our baseline N-LASR model on average has good predictive power, the long term rank IC is 7.56%, which is better than all the single factors. A more subtle point to keep in mind is that the N-LASR model only uses information up to each point in time. To harness the predictive power of the best performing single-factors (e.g. Realized Volatility, Cash Flow Return on Capital) we would have needed to somehow know at the start of the backtesting that these would be good factors to use. In other words, while these factors look nice in hindsight, how could be have picked them ex ante? In contrast, the N-LASR model was able to generate comparable (in fact better) performance, with no look-ahead bias.

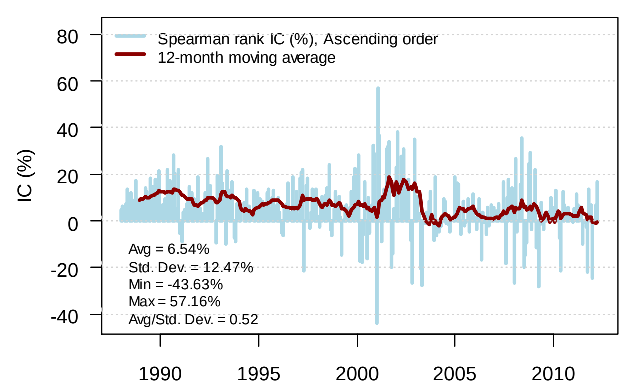
Figure 13 shows the time series for the monthly long short decile spread and Figure 14 shows the time series of rank IC of Baseline N-LASR model, from the 1988 to 2012. We can see that this baseline model performs well with average monthly long short spread of 1.98% and average Rank IC of 6.54%. The annualized Sharpe ratio for the long/short portfolio is 0.79x. This strategy works especially well in early years. In the recent periods, the returns are lower, and the performance is more volatile. We will show how we can further enhance our model with seasonality adjustment in the next section.

Figure 13: Monthly spread of Baseline N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

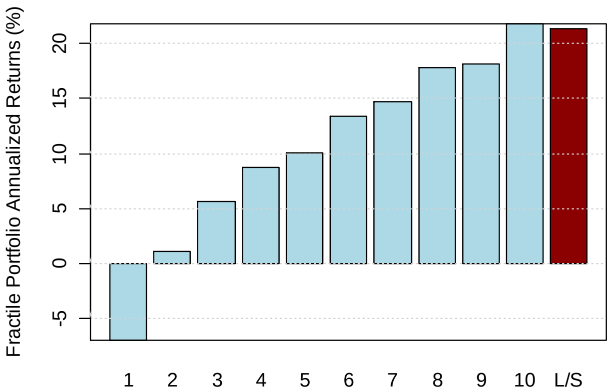
Figure 14: Rank IC of Baseline model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

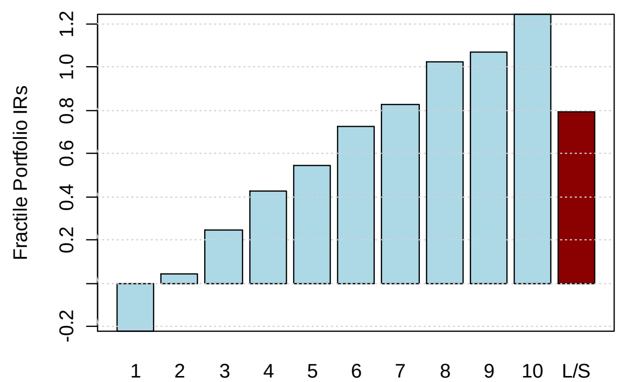
Figure 15 shows the annualized return for each of the decile, and Figure 16 shows the Sharpe ratio for each decile. We can see that the performance of each decile is almost monotonic, which means the higher the factor score the better the performance. An interesting thing to notice is that for this baseline N-LASR model, the long-only portfolio has a higher IR than the long-short portfolio. The reason is because the performance of baseline N-LASR model is still quite volatile, especially on the short side. We will see that in our enhanced N-LASR model, the long/short portfolio has better performance than the long only portfolio. We discuss the enhanced model later in this report.

Figure 15: Annualized decile returns



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 16: Annualized information ratio (IR)/Sharpe ratio



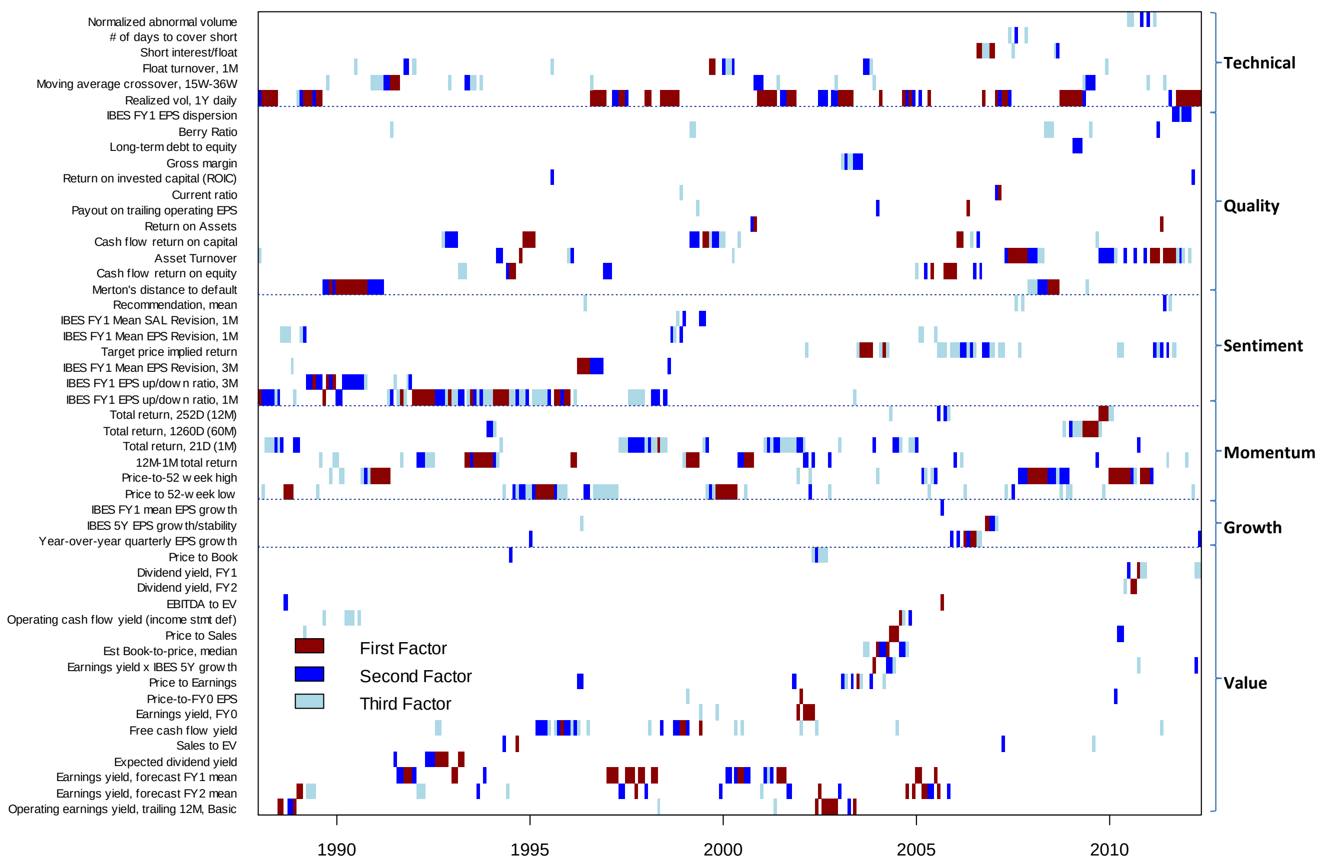
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Looking under the hood

Factor loading

Let's look at the factors we have selected in our model. Figure 17 shows the first three factors selected by our baseline N-LASR model over time. Those factors were sorted into styles of value, growth, momentum/reversal, sentiment, quality, and technicals. Those factors are the most influential factors in our prediction. We can see that the factors evolve through time, indicating our model can adapt to different market condition. For example, during the recent financial crisis, the factor such as Merton's default ratio was often picked up as the first factor. In addition, the first three factor being selected often belong to different style groups, confirming that the N-LASR model will pick factors that are less correlated with each other (since factors across styles tend to have lower correlation).

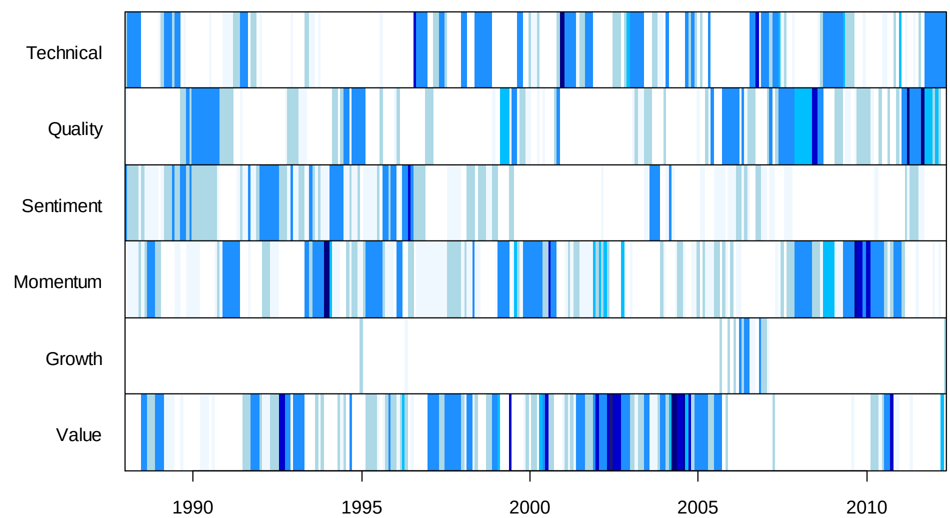
Figure 17: The first three factors sectors selected by Baseline N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 18 shows the styles of factors been selected, we weight the style according to the first three factors that have been picked; the darker the blue the heavier the weight. We can see the importance of factor styles changing over time.

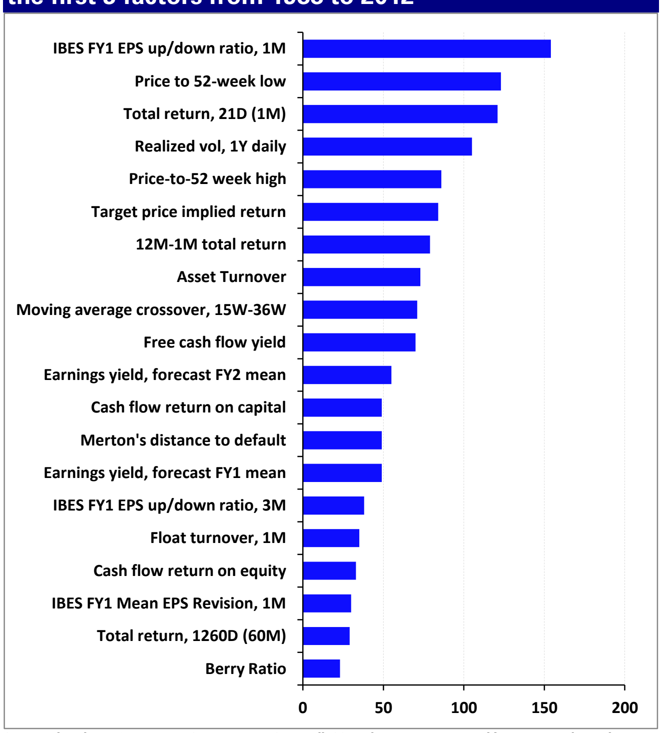
Figure 18: The style of factor been selected



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 19 and Figure 20 show the frequency of the top 20 factors that have been selected as the first three factors for different time periods. The ranking of the top selected factor frequency changed in recent year. We notice that 1 month earnings revisions and price to 52 weeks low were often picked in early years, while asset turnover and price to 52 weeks high were the most frequently picked factors in the recent years.

Figure 19: Frequency of top 15 factors selected as one of the first 3 factors from 1988 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

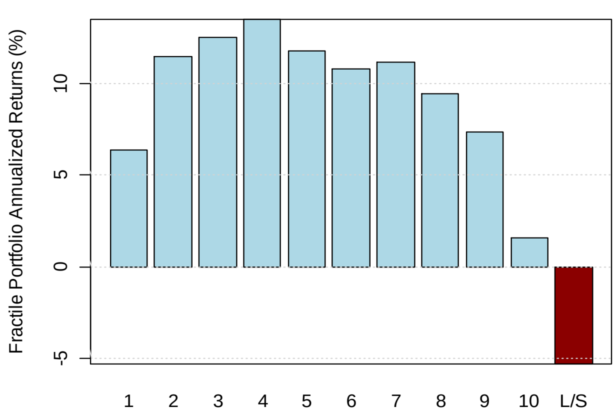
Figure 20: Frequency of top 15 factors selected as one of the first 3 factors from 2008 to 2012

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Machine learning captures factor non-linearity

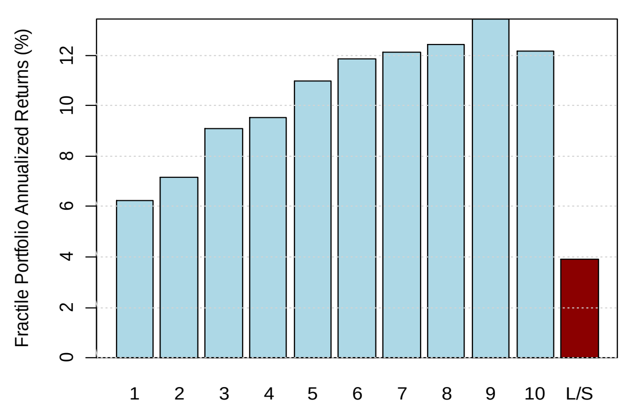
As we mentioned earlier, the way we construct our weak classifier for the N-LASR model can capture the non-linear payoffs of a factor. Take Accruals (Sloan [1996] definition) as an example, Figure 21 shows the decile returns for this factor; we can see that the returns for this factor are highly non-linear. The payoff is inversed "U" shape, where the payoffs for both top and bottom deciles are low and the payoffs for the middle deciles are high.

Figure 21: Decile returns for Accruals (Sloan 1996 def)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 22: Decile returns for classifier based on Sloan

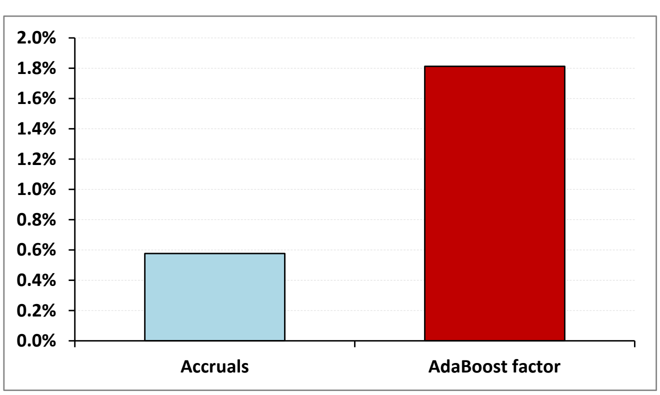


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We construct one layer of weak classifier for this factor (called "AdaBoost factor"), using a trailing 12 months data, and then use the output of the weak classifier as our new factor. Figure 22 shows the decile returns for this transformed factor. And we can see now the payoff of the AdaBoost score is much more linear, where higher decile stocks on average will have higher return.

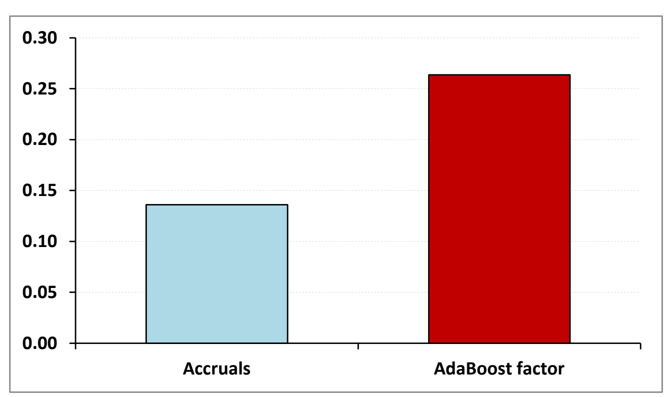
We can show that for the factors with nonlinear payoffs, the weak classifier generally has a better predictive power than the factor itself. Figure 23 shows the long term average rank IC comparison, and Figure 24 shows the comparison of the risk adjusted IC, i.e. long-term average IC divided by the time-series standard deviation of those monthly ICs. In both cases the performance of the AdaBoost factor is much better than the performance of the raw Accruals factor.

Figure 23: Average rank IC for Accruals



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

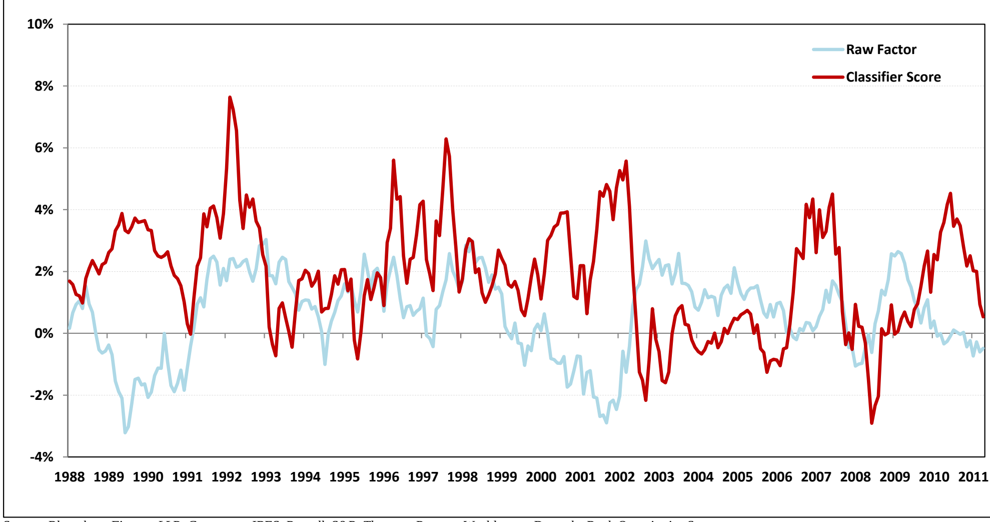
Figure 24: Risk adjusted rank IC for Accruals



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 25 show the trailing 12 month average rank IC for the raw Accruals factor and the AdaBoost factor based on one layer of weak classifier. We can see that the average rank IC is improved most of the time, with AdaBoost algorithm.

Figure 25: Trailing 12 month average rank IC for raw factor and the classifier score of Accruals



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

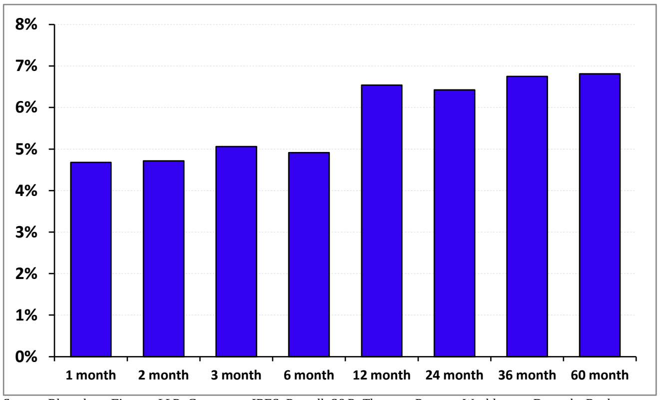
The effects of varying the rolling window

Is a longer training data window better for our model? On one hand, using a longer rolling window will give us more training data and thus can increase the model accuracy, but on the other hand using longer a rolling window introduces more out-of-date data which might not be consistent with the current financial environment.

Figure 26 and Figure 27 show that both the average rank IC and risk-adjusted rank IC increase as the number of training months increase. This is because as a machine learning technique, a model's performance will typically increase with more training data. However, the incremental increase slows down after the rolling window is over 12 months, and even stops at some point.

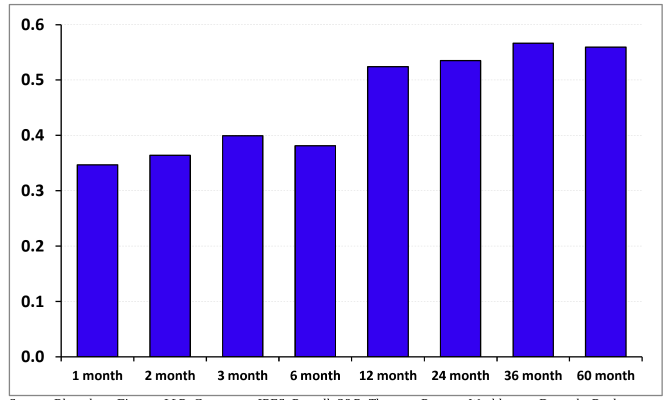
Therefore, we chose 12 months as our baseline, because it balanced the amount of training data and the amount of stale data. Besides, we have better ways to increase the model performance than by simply using a longer historical data window. We will discuss the details in the later section of this report when we describe our enhanced N-LASR model.

Figure 26: Average rank IC for different rolling window



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 27: Risk adjusted IC for different rolling window



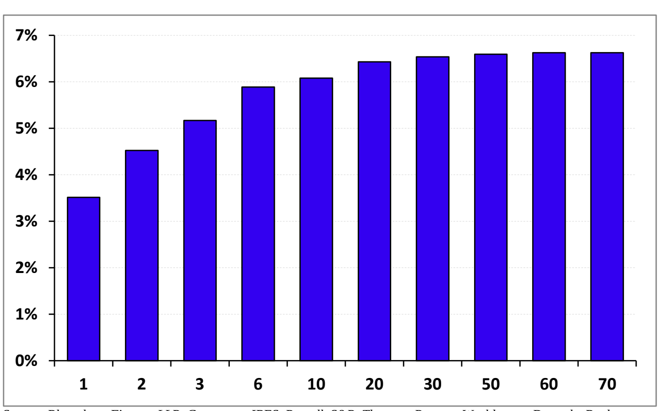
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

What is the optimal number of classifiers?

Do more layers of weak classifier perform better? Indeed, the performance on the training set will definitely better, but what we care about is the out-of-sample backtesting results. Will more layers of weak classifiers cause overfitting? As discussed in Cahan [2012a], for a TREE model without pruning, the performance out-of-sample is poor. Will more layers of weak classifier in our N-LASR model also decrease performance?

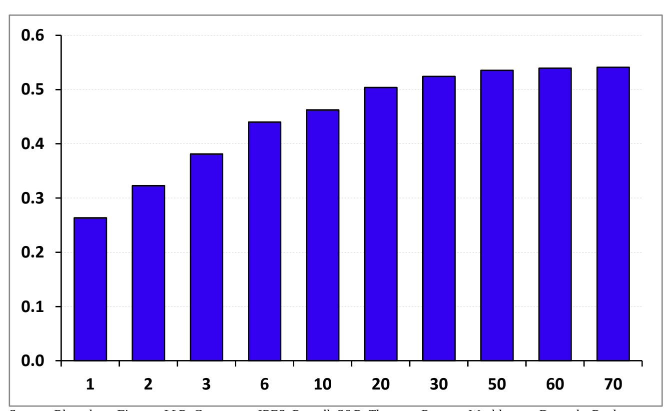
Figure 28 shows the average rank IC and Figure 29 shows the risk-adjusted rank IC for different layers of weak classifiers. We find that the performance of the model increases as the layers of weak classifiers increases, and it increases quickly for the first a few layers, and when the layer number reach a certain level, the increase in performance slows down and eventually flattens. This is because the first selected factors are the best performing factors, and later on many factors are correlated, thus the marginal increase is small. In addition, we find that risk-adjusted returns and rank ICs flatten out later than the absolute term, this means with more layers of weak classifiers the rank IC will be less volatile, and the performance will be more stable. The non-decreasing performance of the model as the layers of weak classifiers increase is a good property, because this means our model is hard to overfit. Even with the number of weak classifiers similar to the number of factors, the model performance won't decrease.

Figure 28: Rank IC for different layers of weak classifiers



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 29: Risk adjusted IC for different layers of classifiers



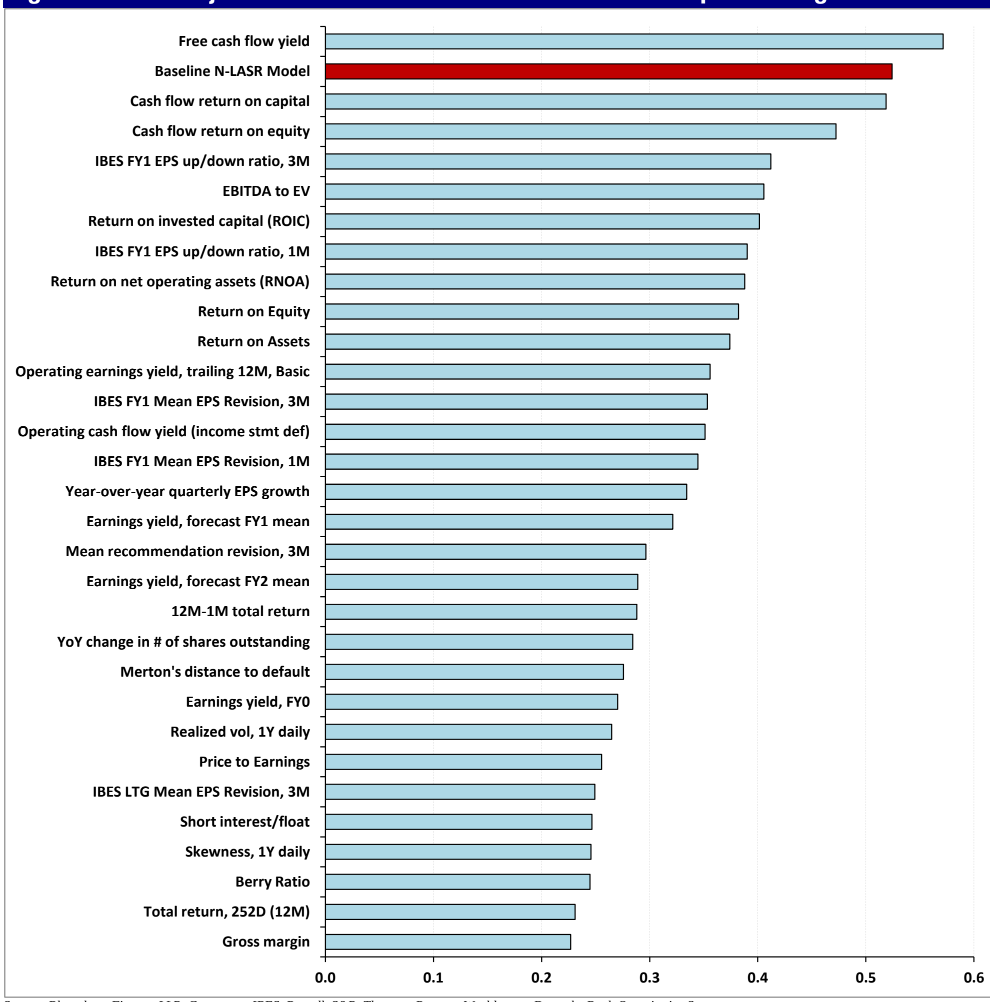
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Building an enhanced model

Enhanced model with seasonality adjustment

Our baseline N-LASR model has shown great predicting power, however, there is one problem: the model performance is too volatile. If we look at the risk adjusted rank IC, our baseline model still not good enough. Figure 30 shows the comparison of risk adjusted rank IC of baseline model compared with the 30 best performing factors.

Figure 30: Risk adjusted rank IC for baseline model and best performing factors

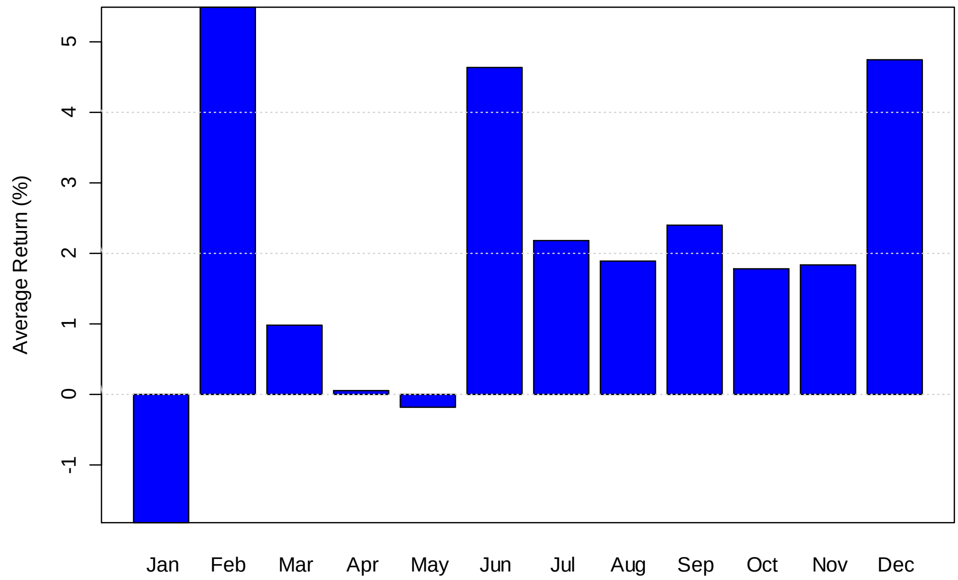


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We can see although our model shows good performance but is not the best – it does not do as well as Free Cashflow Yield. This is mainly due to the volatile performance of baseline model, since the average long term rank IC outperforms all other factors (recall Figure 12).

Why is our baseline N-LASR model not as good as this single factor in term of risk adjusted rank IC? Is there anything wrong with the machine learning method? If we look deeper into the model, we can find that the returns for our model show great seasonality. Figure 31 shows the average return for each month over the entire backtesting period from 1988 to 2012. We can see that our model performs poorly in January, April, and May on average. The regularity of this pattern seems to be beyond a coincidence.

Figure 31: Average return of different month for baseline model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

The reason why our model performs very well on some months and poorly on some others is because many factors have seasonal effects (see Luo et al. [2010c]). Especially for accounting factors, January might be quite different from other months, but the way we train the classifiers simply treats all months equally. The easiest way to solve this problem is to train another strong classifier using data from only the same month from previous years. For example, we could train a January strong classifier using only data from past Januaries. But we also don't want abandon our existing baseline strong classifier, because it captures the trailing 12 month factor performance.

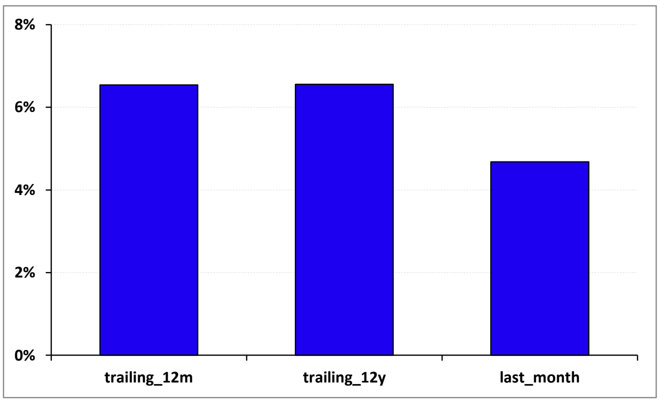
In addition, we also find that sometimes when a sudden event comes along, or the market conditions change, it takes a few months for the baseline N-LASR model to adapt because we use the trailing 12 months data. Therefore, the baseline strong classifier would have some built-in lag. For example, in 2008 when the credit crises started, the market condition started to change in July, but our baseline N-LASR model needed a few months to adapt to the new conditions. Therefore, for July, August and September in 2008 our baseline model showed losses of 14.2%, 7.9% and 5.8% before it was able to adapt to the new conditions. However, if we used only the previous month's data to train a strong classifier, we find that July 2008 would still have similar loss of 13.7%, but for August and September 2008 this one month training data model would have led to positive returns of 4.6% and 10.4% respectively.

Considering the above, we can enhance our model with the following adjustment: we build our enhanced N-LASR stock selection model with three strong classifiers using different training data. The first classifier is our baseline model, which uses the trailing 12 months of data; the second classifier uses the trailing 12 years (if there is less than 12 years historical data, just use all the available years) *in the same month*, which captures the cyclical seasonal effect of the factor; and third classifier uses just the previous one month data, which captures the most recent effect of the factor. For simplicity, for all three strong classifiers we set the number of layers to be 30, which is the same as in the baseline model.

Exploring seasonal effects

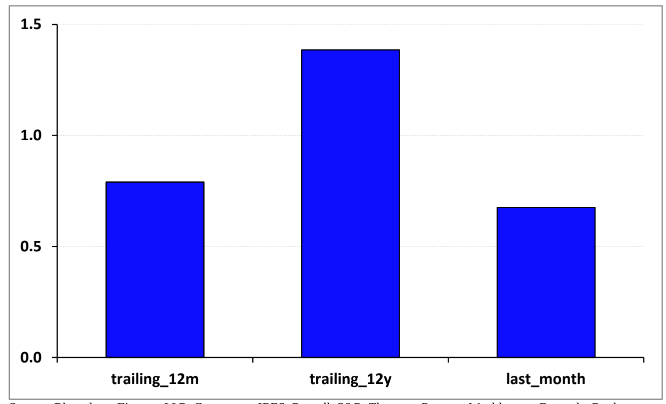
Figure 32 shows the long term average rank IC of three component strong classifiers of our enhanced N-LASR model, and Figure 33 shows the IR for each component. We can see that each of the component classifier shows good predictive power. The classifier trained with last month's data has relatively inferior performance than the other two classifiers, because of the smaller sample size. And the classifier trained with the last 12 years of the same month's data has the highest IR. This is because it captures the seasonal effect of factor performance.

Figure 32: Rank IC for three component classifiers



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 33: IR for three component classifiers



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Whether we can increase the model performance largely depends on the correlation of three component classifiers. Figure 34 shows the correlation of the long-short spread, and Figure 35 shows the correlation of the rank IC. We find that those strong classifiers have weak correlation and even negative correlation. This means the combination of those weak classifiers would increase the model performance.

Figure 34: Correlation for spread

	Trailing 12month	Trailing 12year	Last month
Trailing 12month	100%		
Trailing 12year	-7.3%	100%	
Last month	42%	-12.2%	100%

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope Deutsche Bank Quantitative Strategy

Figure 35: Correlation for rank IC

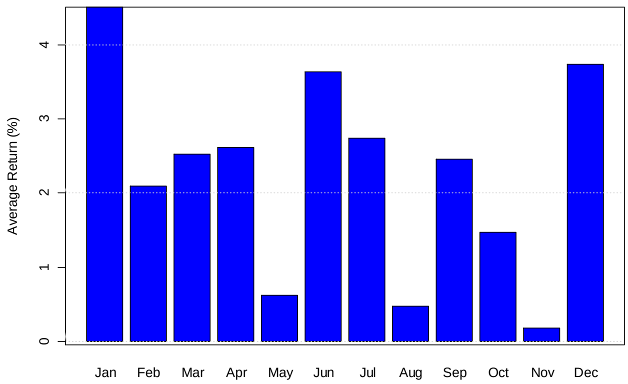
	Trailing 12month	Trailing 12year	Last month
Trailing 12month	100%		
Trailing 12year	21.8%	100%	
Last month	29.5%	1.3%	100%

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope Deutsche Bank Quantitative Strategy

We can further combine the three strong classifiers. One way to combine it is simply by adding the normalized scores of these three classifiers together. The way we normalize the score is at each point date we subtract the mean and divide by the standard deviation. And because the output of the strong classifiers is approximately a normal distribution, doing this will give equal weights to each component of the enhanced model.

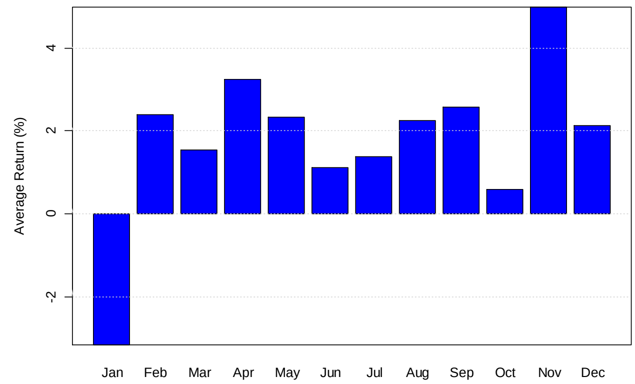
In addition, we notice that there is also seasonality for the trailing 12 year classifier and the last month classifier. Figure 36 and Figure 37 shows the average monthly return for different months for these two classifiers. Interestingly, we find that in January, the trailing 12 years classifier has the best performance, and November has the worst performance. However, the last month classifier has exactly the opposite performance, it is best in November and worse in January.

Figure 36: Monthly decile for seasonal classifier



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 37: Monthly decile for last month classifier



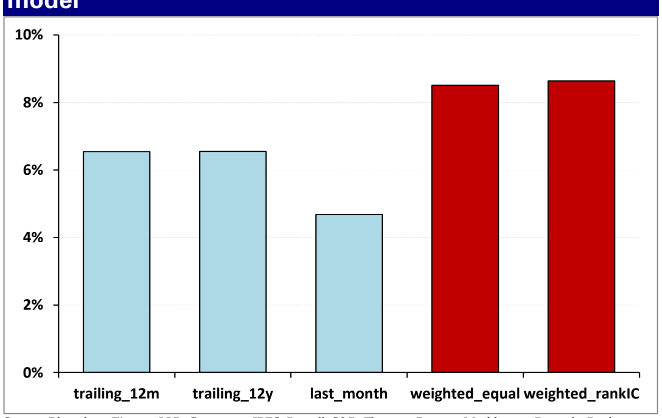
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

This gives us another idea: weight the three strong classifiers by the average rank IC for the same month over the past years. For example, this might result in higher weights for the trailing 12 year classifier in January and lower weights in November. In order not to introduce any look-ahead bias, we set the weights dynamically. Each month the weight of each strong classifier is determined by the average rank IC of each of the three classifiers in that month in the past. (For the first year, since we don't have previous performance of rank IC available, we equally weighted each strong classifier.)

Performance results for enhanced N-LASR

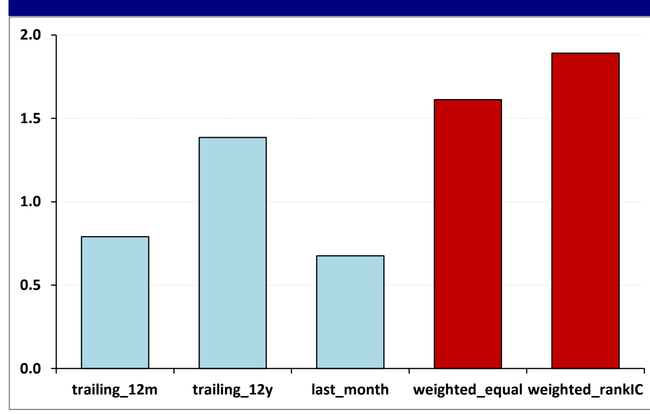
Figure 38 and Figure 39 show the improvement in average rank IC and IR. We find that both the enhanced N-LASR models combining three strong classifiers indeed increase the performance. The enhanced model weighted by rank IC performance does even better than the equally weighted model, and is especially good in terms of IR, because the combination of three strong classifiers diversifies the performance and reduces volatility.

Figure 38: Rank IC improvement for enhanced N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

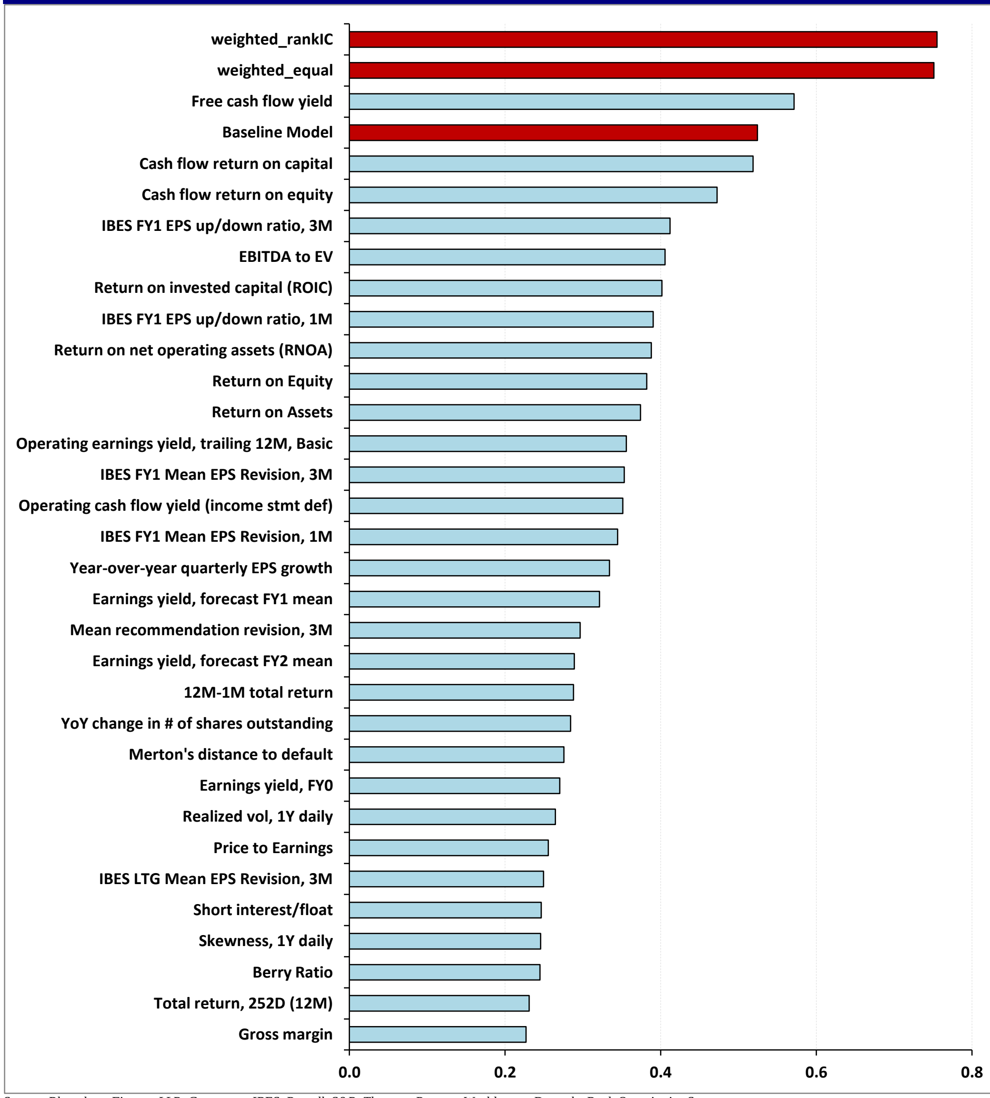
Figure 39: IR improvement for enhanced N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Now, let's look at the risk-adjusted IC again. Figure 40 shows a comparison of risk-adjusted rank IC of the enhanced N-LASR model with the 30 best performing factors and the baseline N-LASR model. Now that our enhanced model shows better performance in the risk-adjusted rank IC, we are more confident that our machine learning model is indeed boosting the performance of the factors in every aspect.

Figure 40: Risk adjusted rank IC for enhanced N-LASR model



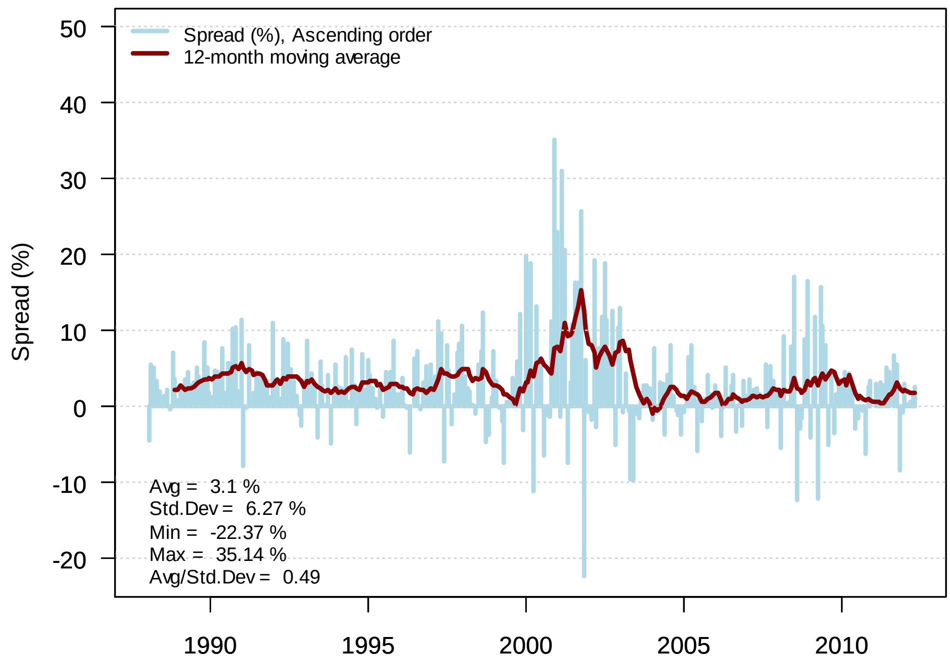
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

For the rest of the report, we will refer to our N-LASR model for US stock universes as the enhanced N-LASR model using the standard 70 factors weighted by the average rank IC, since it has the best performance. In the last session of this report when we build the global N-LASR model we will use equally-weighted enhanced N-LASR models, because other countries may not have the similar seasonality for different component strong classifiers.

Time series results of N-LASR

Figure 41 shows the time series of the long-short decile spread for our N-LASR model from 1988 to 2012. We can see that the performance is very good with an average monthly return spread of 3.1%. The annualized return is 40% over the whole period, and the annualized Sharpe ratio is 1.89x. The performance for the early period is even better, with hardly any losing months. Even for the recent period from 2008 to 2012 the average monthly spread is 2.12%, i.e. 26.0% annualized return, and Sharpe ratio is 1.23x.

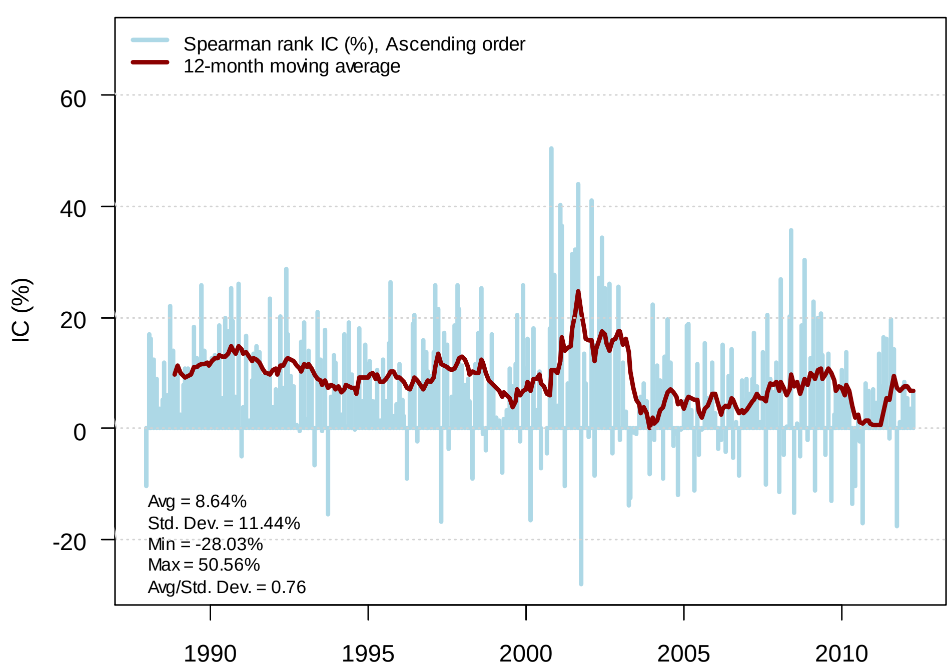
Figure 41: Time series of monthly long/short decile spread for N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 42 shows the time-series of rank IC for our N-LASR model over the period of 1988 to 2012. As expected, the rank IC for the N-LASR model is very high, with an average of 8.64%. The trailing 12 month moving average of rank IC is always above zero, and even the recent period from 2008 to 2012, the average rank IC is 6.23%, and risk adjusted IC is 0.52x.

Figure 42: Time series of monthly rank IC for N-LASR model from 1987 to 2012

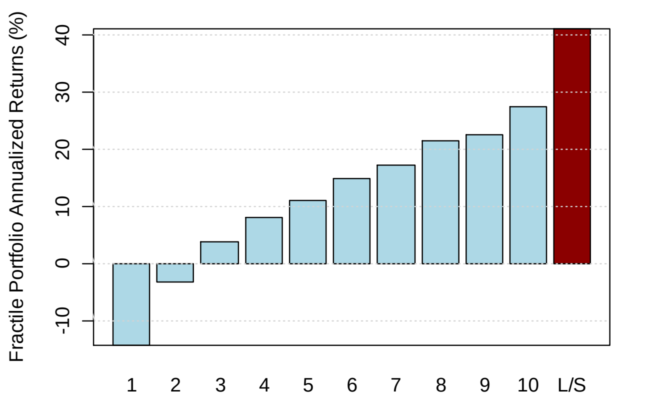


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 43 is the annualized return for each of the decile, and Figure 44 shows the Sharpe ratio for each decile. We can see that the performance of each decile is almost linear: the higher the factor score the better the performance. Even the long-only portfolio has an annualized return of 27.3%, and Sharpe ratio of 1.55x.

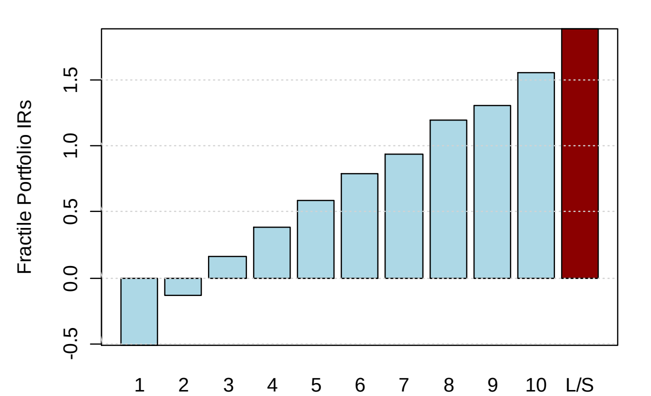
However, with all these results we have not yet considered transaction costs. We elaborate on turnover and transaction costs in the next section.

Figure 43: Annualized decile return for N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 44: Annualized Sharpe ratio for N-LASR model

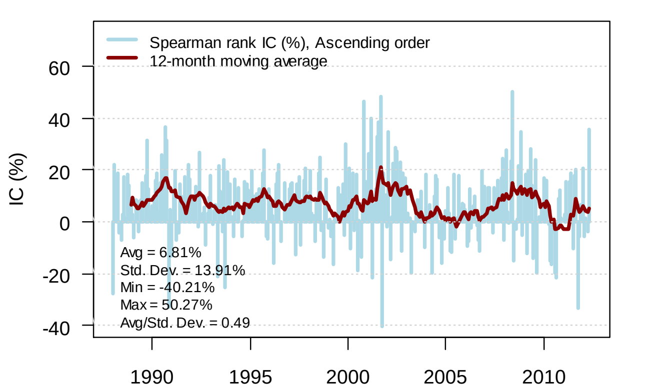


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Backtesting different US stock universes

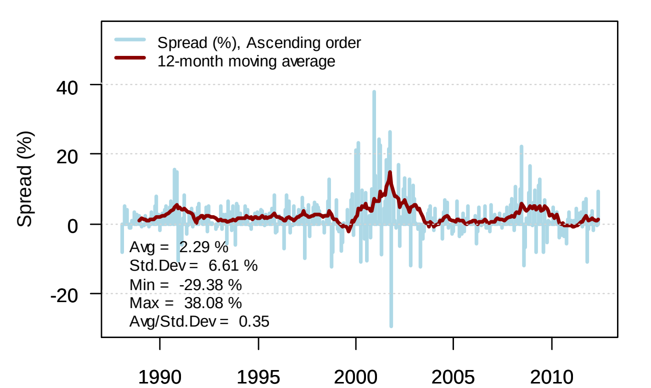
We trained the N-LASR model using the Russell 3000 universe, and backtested the performance on various different US stock universes. The N-LASR model works well for all those universes. Similar to most other quant models, our N-LASR model also has much better predictive power in the small cap universe (as defined by the Russell 2000) than in large cap universe (as defined by the Russell 1000). Also, the N-LASR was a little more effective in selecting growth stocks (as defined by the Russell 3000 Growth) than value stocks (as defined by Russell 3000 Value). Figure 45 and Figure 46 show the performance in the Russell 1000; Figure 47 and Figure 48 show the performance in the Russell 2000; Figure 49 and Figure 50 show the performance for Russell 3000 Growth stocks; Figure 51 and Figure 52 show the performance for Russell 3000 Value stocks.

Figure 45: Time series of monthly rank IC for RUSSEL 1000



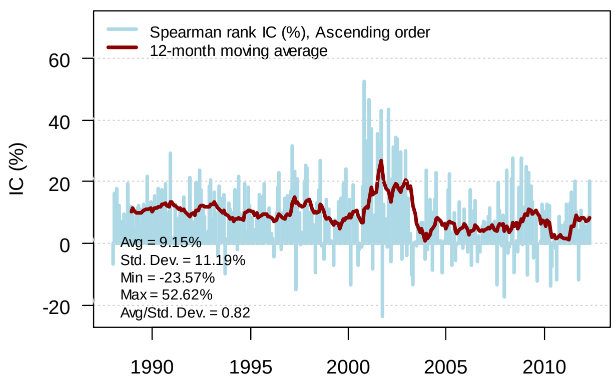
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 46: Time series of monthly long/short decile spread for RUSSLL 1000



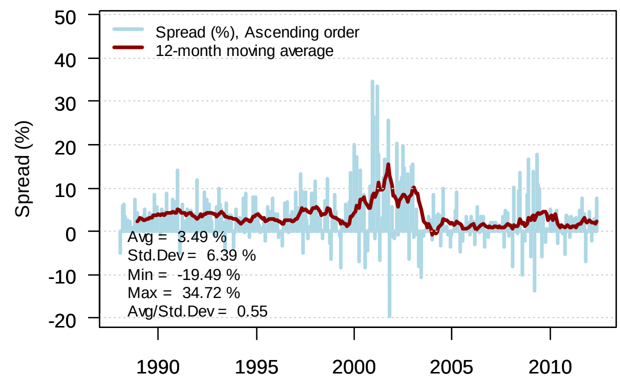
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 47: Time series of monthly rank IC for RUSSEL 2000



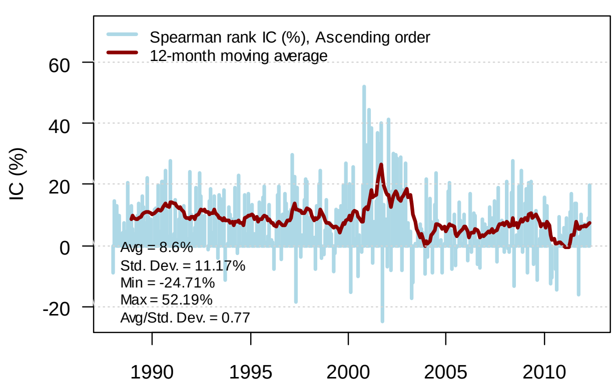
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 48: Time series of monthly long/short decile spread for RUSSLL 2000



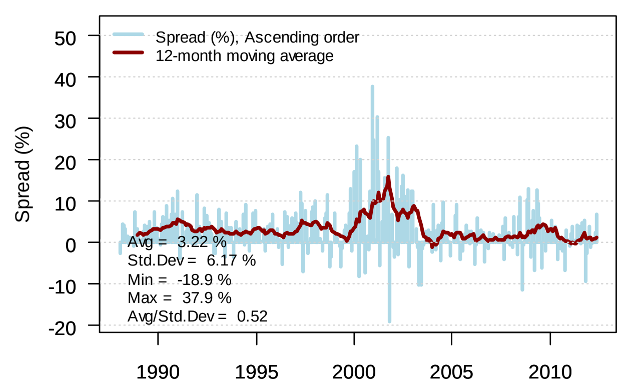
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 49: Time series of monthly rank IC for RUSSEL 3000 growth



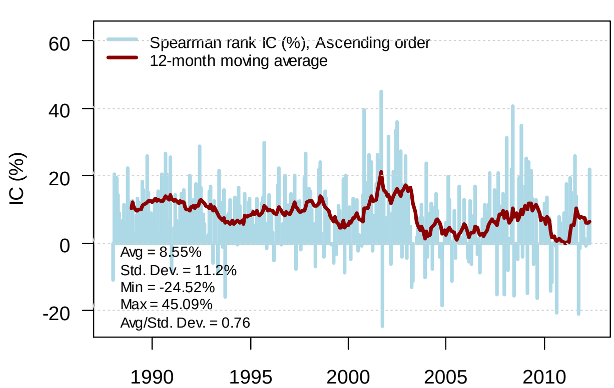
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 50: Time series of monthly long/short decile spread for RUSSLL 3000 growth



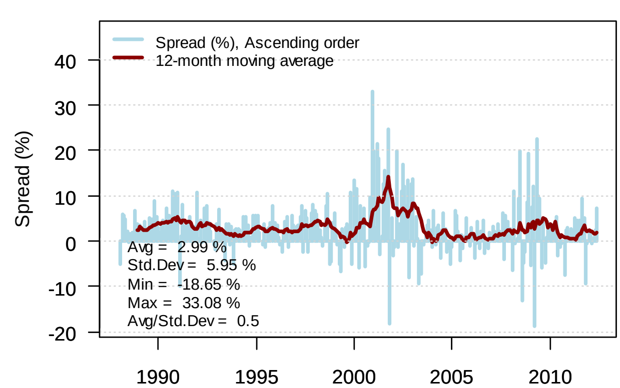
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 51: Time series of monthly rank IC for RUSSEL 3000 value



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 52: Time series of monthly long/short decile spread for RUSSLL 3000 value



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

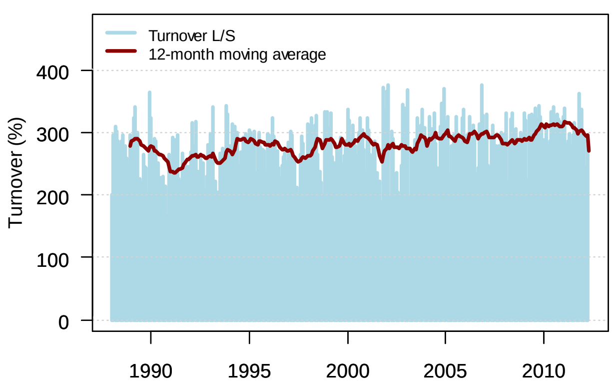
Machine learning as a strategy

What about turnover?

As expected, our N-LASR model has a high turnover, because the goal is to maximize the categorization of forward return, without reference to turnover. This means that transaction cost cannot be ignored.

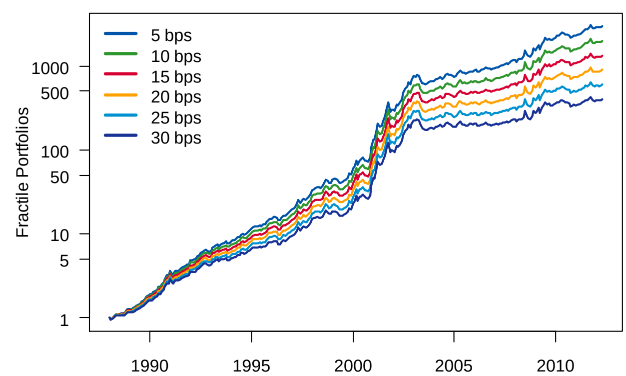
To evaluate whether we can extract any after-cost alpha out of the model, we conduct a real world simulation, longing the top decile and shorting the bottom decile of our N-LASR model. Figure 53 shows the monthly turnover of our model, the average is over 250% (notice this is a two-way turnover for a market neutral portfolio, so the maximum turnover in a given period is 400%). Next, we evaluate the impact of transaction cost by assuming varying degree of linear transaction cost, Figure 54 show the cumulative performance of different level of one-way transaction cost.

Figure 53: Two-way turnover for N-LASR model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

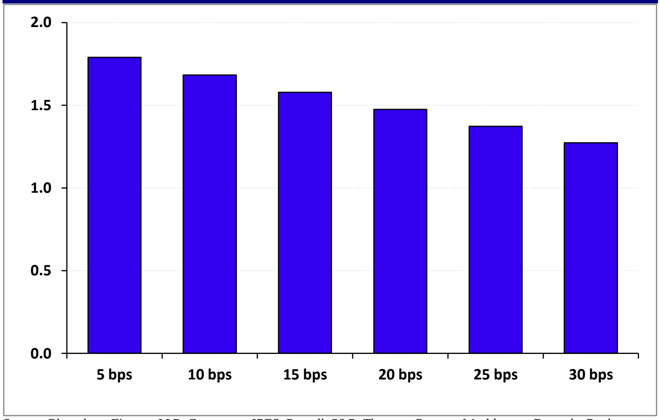
Figure 54: Wealth curve for different levels of transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

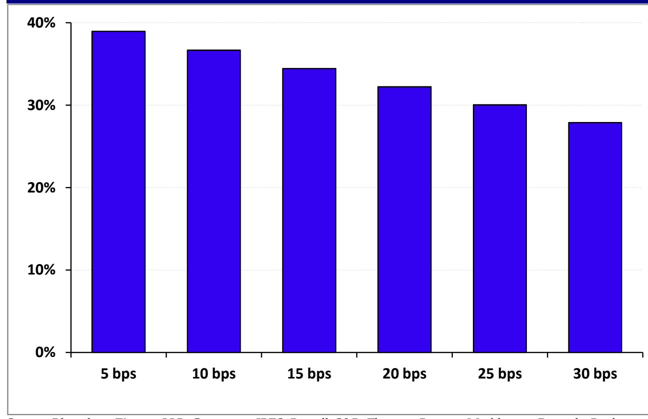
Figure 55 show the IR with different level of transaction cost from 1988 to 2012. Even with 30 bps for one-way linear transaction cost the Sharpe ratio is still reasonably high at almost 1.3x, and Figure 56 show the annualized return for different level of transaction cost, even with 30 bps of transaction cost the return is almost 30% annualized.

Figure 55: Sharpe ratio for different level of transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

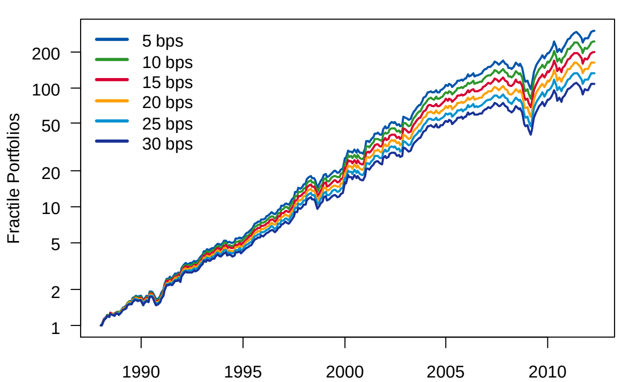
Figure 56: Annualized return for different level of transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

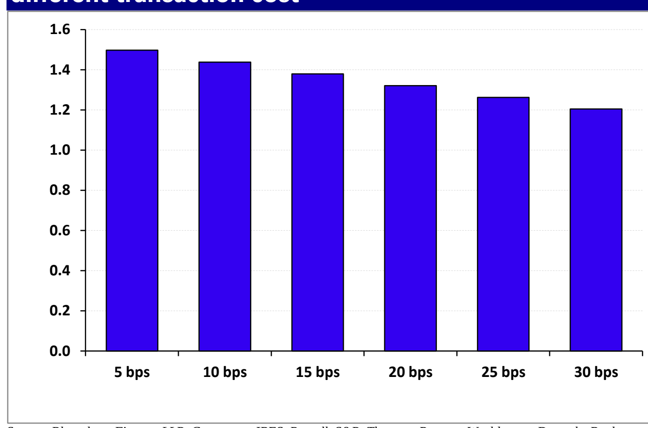
Figure 57 shows the wealth curve of the long-only portfolio with different transaction cost, and Figure 58 shows the Sharpe ratio for different level of transaction cost. Based on these results, even the long only strategy is still very appealing after the high transaction cost.

Figure 57: Wealth curve of the long only portfolio with different transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 58: Sharpe ratio for the long only portfolio with different transaction cost



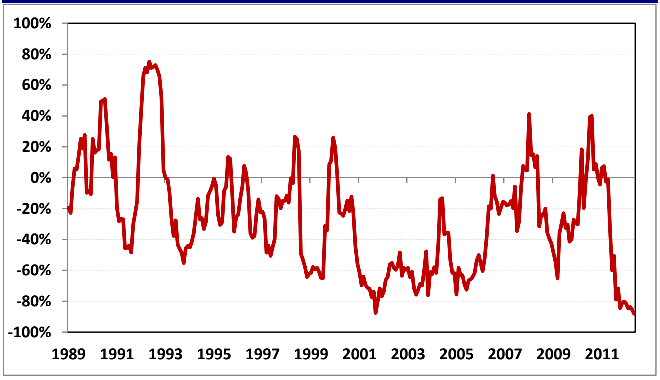
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Model performance relative to the market

An interesting result is that the N-LASR model is not correlated with the market, in fact it actually has a negative correlation. The correlation between the long/short decile return and the S&P 500 total return index is -37%. This means, this strategy can help hedge a long-only strategy.

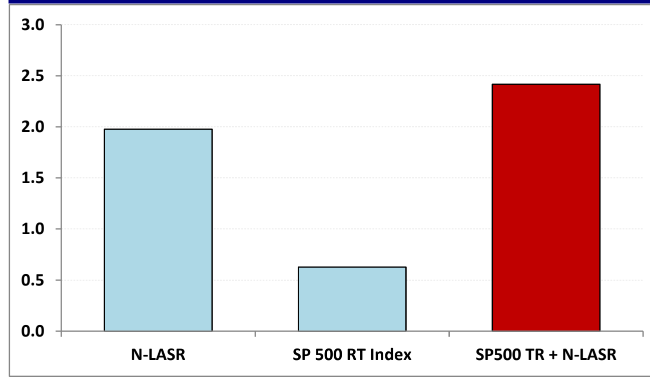
Figure 59 show the trailing 12 month correlation between long/short decile return of the N-LASR model and the S&P 500 total return index. We can see that the correlation is negative for most periods, especially in bear markets – for example, during the period when the IT bubble bust and in the recent financial crisis. Figure 60 shows that a simple, equally-weighted combination of a S&P 500 market portfolio and the N-LASR model does better than either strategy in isolation.

Figure 59: Trailing 12 month correlation between long/short decile N-LASR with S&P500 total return



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 60: Sharpe ratio for the long/short decile N-LASR with S&P500 total return index



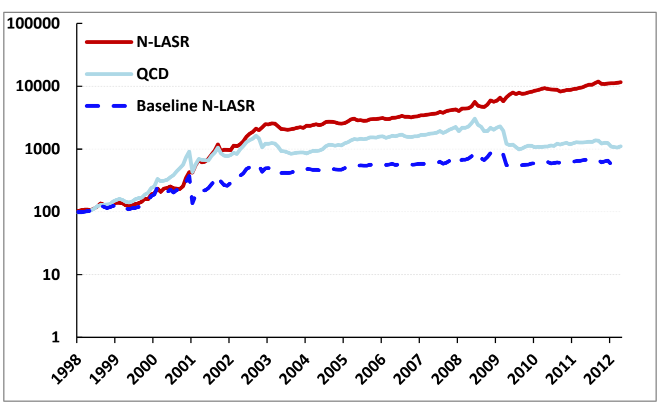
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Model performance compare with other trading strategy

We compare our N-LASR performance with our QCD (Luo et al. [2010c]) model, using long/short decile returns from 1998 to 2012. Figure 61 is the wealth curve for the QCD and our baseline N-LASR model and enhanced N-LASR model. Note the chart uses a log scale on the y-axis. Overall we find that the N-LASR model does significantly better than the QCD model over the backtest period.

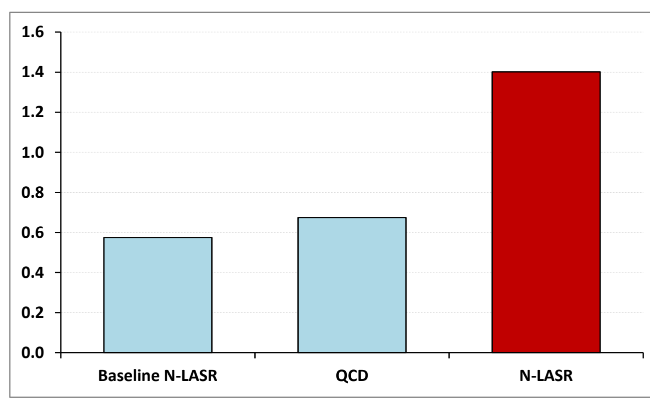
Figure 62 is the comparison of Sharpe ratio for QCD model and our N-LASR models. The baseline N-LASR model has similar performance to QCD, while the enhanced N-LASR model outperforms QCD.

Figure 61: Wealth curve comparison



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 62: Sharpe ratio comparison from 1998 to 2012

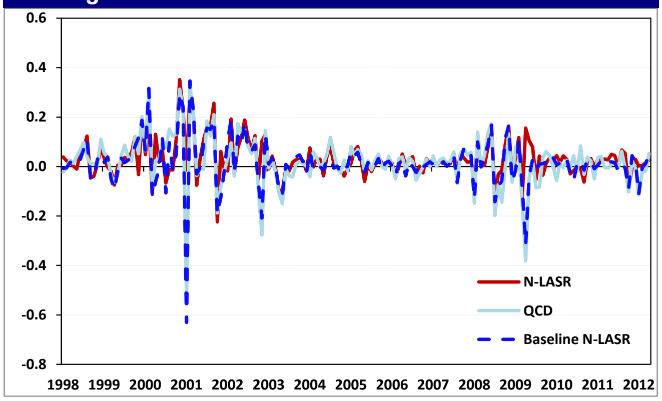


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 63 shows the monthly long/short returns for the N-LASR models and QCD model. We can see that the returns are quite correlated, especially for the baseline model. The overall correlation is over 90% for the N-LASR model and 60% for the enhanced model Figure 64 gives the trailing 12 month correlation of the N-LASR models and the QCD model.

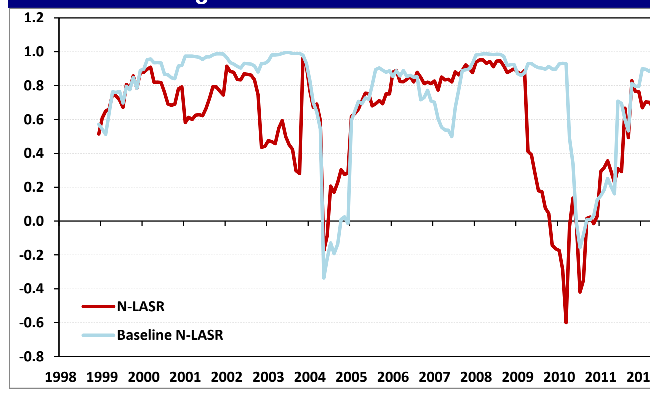
The high correlation of the model is as expected, because both QCD model and N-LASR models use similar underlying factors. For example there is a large draw down in January 2001, for both the QCD model and machine learning models, because that month most of the factors worked differently to how they did in the past. For both the baseline N-LASR model and the QCD model the drawdown is more than 50%, however, because our enhanced N-LASR model combined the seasonal classifier using previous years' January data, that classifier actually worked very well in that month, thus making the overall loss a more manageable 16% rather than over 50%.

Figure 63: Monthly long short decile return for machine learning models and QCD



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 64: Trailing 12 month correlation between machine learning models and QCD



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

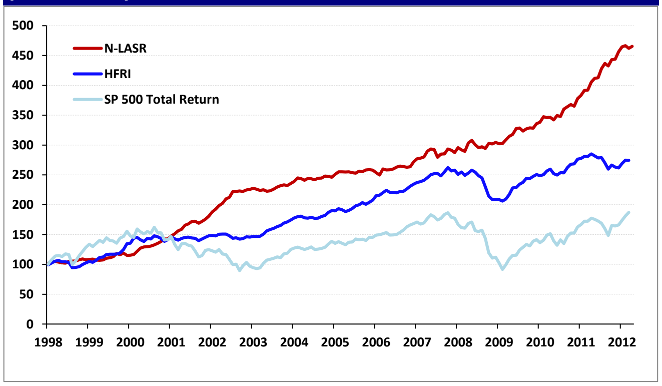
Optimized portfolio comparison

It is important to note that the results above are tilted in favor of the N-LASR model, because the N-LASR model has higher turnover than the QCD model, and we did not consider transaction costs. A fairer comparison is to run a realistically optimized portfolio and compare after-cost returns. To do so we build an optimized, market-neutral portfolio using the following constraints (details see Luo et al. [2010c]):

- Long/short market neutral strategy
- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized volatility of 4%
- Beta neutral
- Turnover constrained at 30% one-way per month (or 360% one-way per year)

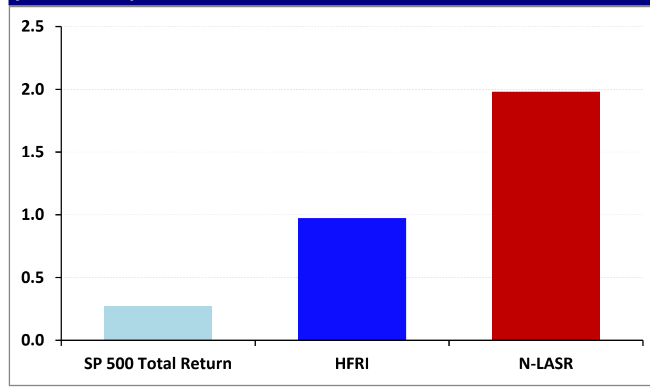
First, we compare the performance of N-LASR model with the market return and hedge fund index. Figure 65 shows the cumulative performance for the S&P 500 total return index, hedge fund return index (HFRI), and our N-LASR model from 1998 to 2012. Our N-LASR model increases steadily throughout time, and does not have big drawdowns, with 11.3% annualized return and 5.7% realized volatility. Figure 66 shows the Sharpe ratio for the S&P 500 total return index and HFRI compared with N-LASR model. As expected, the Sharpe ratio for N-LASR model is higher than both indices.

Figure 65: Cumulative performance from 1998 to 2012 (after cost)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

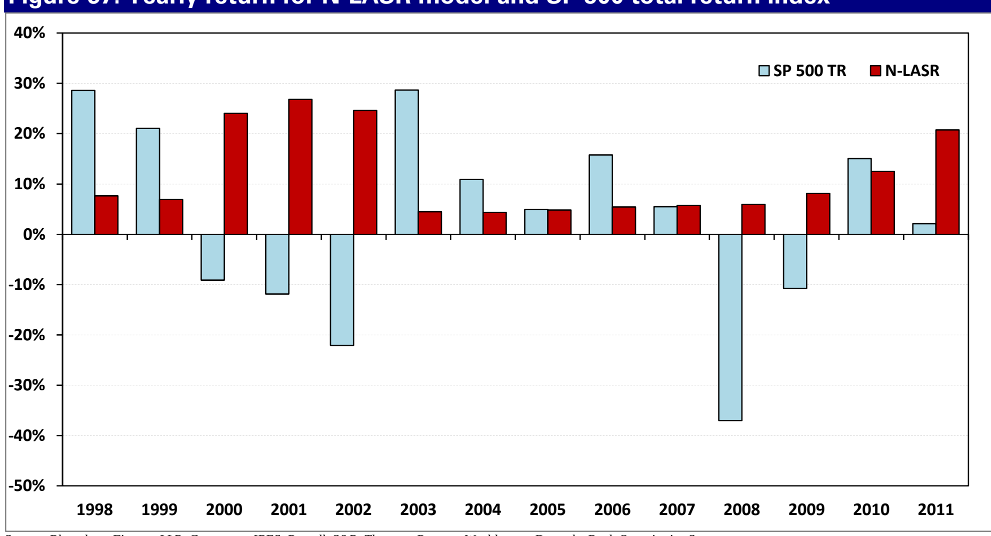
Figure 66: Sharpe ratio comparison from 1998 to 2012 (after cost)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 67 shows the yearly return for the N-LASR model and the S&P 500 total return index. It is interesting to note that the N-LASR model perform extremely well when the market is going down, for example during the period when the IT bubble burst after 2000 and the financial crisis in 2008.

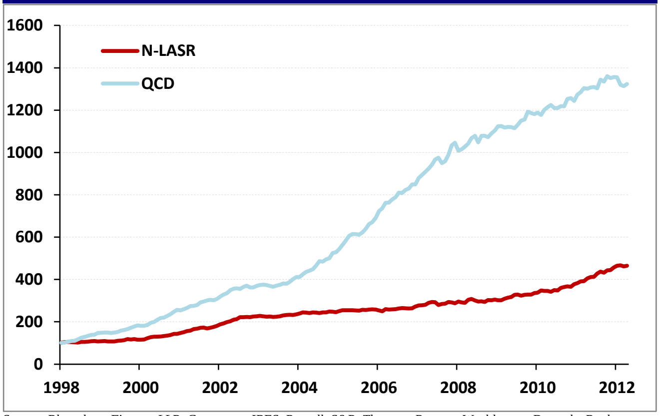
Figure 67: Yearly return for N-LASR model and SP 500 total return index



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

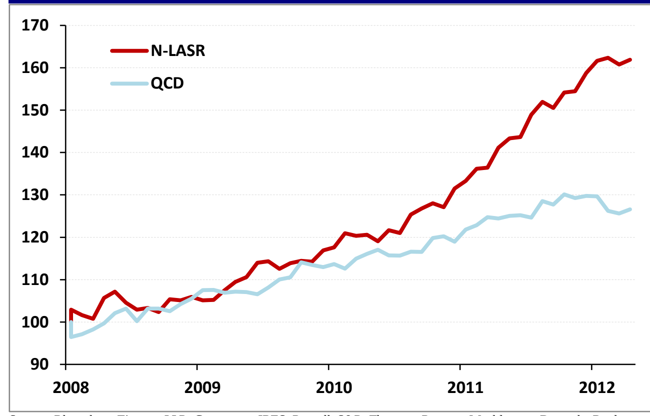
Next we compare the N-LASR model with our existing QCD model. Figure 68 and Figure 69 show the cumulative performance of QCD and N-LASR model from 1998 to 2012 and from 2008 to 2012 respectively. We can see that QCD outperforms N-LASR for the entire period, however, in the recent period N-LASR outperformed QCD. Even in 2008 and 2009, two most challenging years for quantitative investing, the N-LASR model produced an Sharpe ratio of 1.54x while QCD produced an Sharpe ratio of 1.13x. One thing worth noting is that, although for both optimizations we set the target annualized volatility to be 4%, the N-LASR model has realized annualized volatility of 5.2% while the QCD has realized volatility of 6.3%, this is also why the cumulative performance of QCD outperforms N-LASR that much for the entire period.

Figure 68: Cumulative performance from 1998 to 2012 (after cost)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

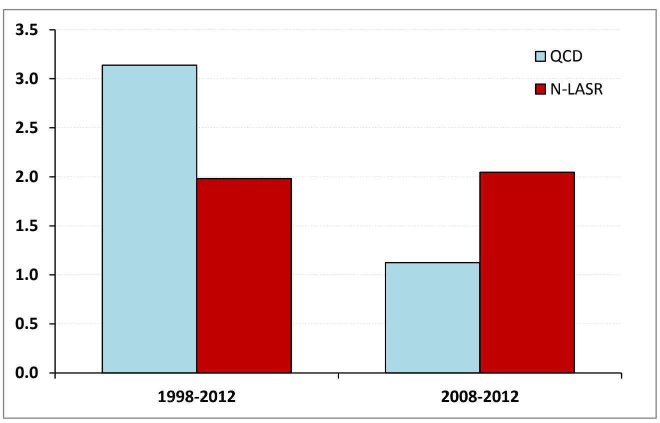
Figure 69: Cumulative performance from 2008 to 2012 (after cost)



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

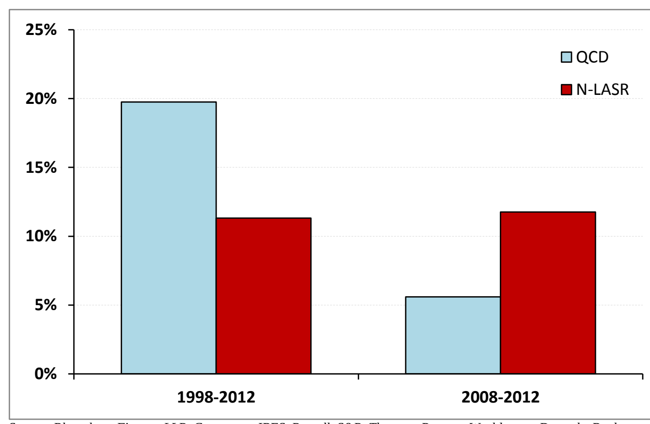
Figure 70 and Figure 71 show the IR and average decile return spread for the QCD and N-LASR model for different time periods. We can see that N-LASR model has a better performance in recent years than the QCD model.

Figure 70: Sharpe ratio for QCD and N-LASR



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

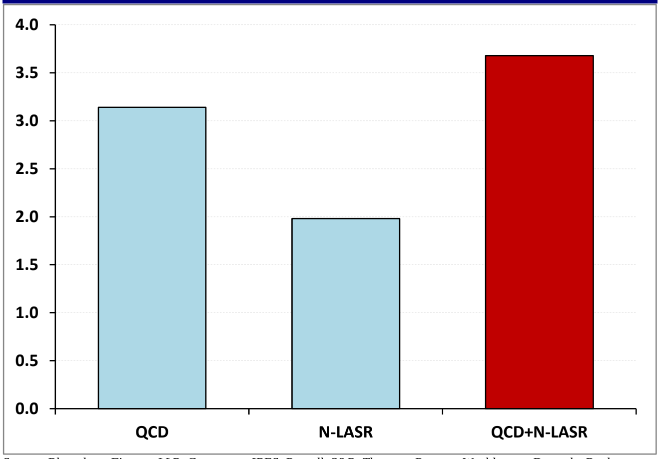
Figure 71: Annualized return for QCD and N-LASR



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

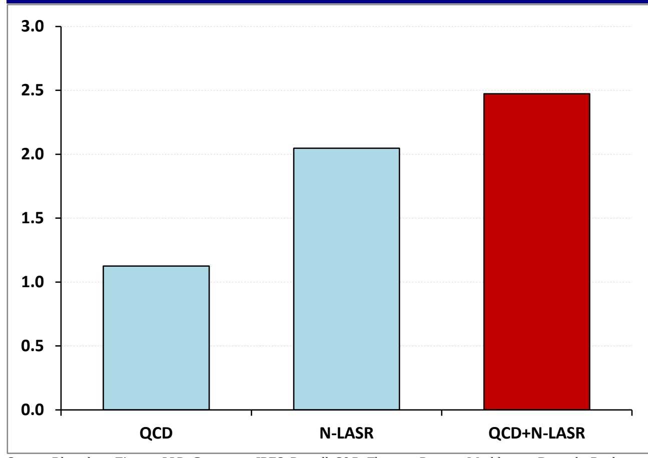
We also find that the correlation between the returns of QCD and N-LASR model is negative 0.8%, which means the combination of two strategies can further increase the Sharpe ratio. Note this number is a lot lower than what we found with the non-turnover controlled signals previously. Figure 72 and Figure 73 show the Sharpe ratio of a strategy that invests half of its asset in QCD and half of its asset in the N-LASR model. We can see the Sharpe ratio for the combined optimized portfolio is 3.67, which is higher than both models. The annualized return is 15.6% and realized volatility is only 4.23%. The Sharpe ratio for the strategy that invest half in QCD and half in N-LASR from 2008 to 2012 also increases to 2.47x, higher than both strategies alone. In reality, if some of the trades in N-LASR and QCD cancel out, the transaction cost will be even lower, which means the combined portfolio will have even higher Sharpe ratio.

Figure 72: Sharpe ratio for different strategy from 1998 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 73: Sharpe ratio for different strategy from 2008 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Adding technical factors

Introducing our technical factors

We also applied our machine learning method on technical factors. Here we use the technical factors defined in our previous paper, Jussa et al. [2011a]. Figure 74 shows the 10 different styles of technical indicators we consider.

Figure 74: Technical factor definitions

Technical Indicator	Definition	Scale	Formula	Period	Variants
Williams %R	The Williams %R is a momentum indicator that attempts to measure overbought (bearish) and oversold (bullish) levels. The scale extends from 0 to -100. The overbought level is considered 0 to -20, and oversold -70 to -100. The nearer the close is to the top of the range, the nearer to zero (higher) the indicator will be.The nearer the close is to the bottom of the range, the nearer to -100 (lower) the indicator will be.	0 to (-100)	W%R = (high_over_period - close) / (high_over_period - low_over_period)	5, 14, 20	Realtive to daily and montly deviations
Close Location Value	The Close Location Value is one of the indicators using the location of Close related to Low and High for the same period. It is, therefore, trying to spot the tendency in the price move of the security. This approach is working by determining the location of the Close compared to the Low and High. The indicator oscillates between -1 and 1, the closer the CLOSE is to the High, the closer it is to one, which is considered a bullish signal. The closer period's CLOSE is to Low, the closer the indicator value is to -1, which is considered bearish.	(-1) to 1	CLV = ((Close - daily_low) - (daily_high-Close)) / (daily_high- daily_low)		Realtive to daily and montly deviations
Accumulation/Distribution Line (AD)	Accumulation/Distribution is a momentum indicator which takes into account changes in price and volume together. The idea is that a change in price coupled with an increase in volume may help to confirm market momentum in the direction of the price move. If the Accumulation/Distribution indicator is moving up the buyers are driving the price move and the security is being accumulated. A decreasing A/D value implies that the sellers are driving the market and the security is being distributed. If divergence occurs between the Accumulation/Distribution indicator and the price of the security a change in price direction is probable. The A/D indicator is defined by fluctuations of the price and volume. The volume serves as a weight factor at the price change. The more factor (volume), the bigger is the contribution of the price change for the defined time period in value of the indicator.		AD = sum(CLV*Volume)	5, 14, 20	Realtive to daily and montly deviations
Percentage Price Oscillator (PPO)	The Percentage Price Oscillator (PPO) is an indicator, based on the difference of two moving averages. To make it oscillate within a convenient range, it is then normalized by dividing by the value of a shorter moving average. The PPO reflects the convergence and divergence of two moving averages. PPO is positive when the shorter moving average is above the longer moving average. The indicator moves further into positive territory as the shorter moving average distances itself from the longer moving average. This reflects strong upside momentum. The PPO is negative when the shorter moving average is below the longer moving average. Negative readings grow when the shorter moving average distances itself from the longer moving average (goes further negative). This reflects strong downside momentum.	Max = 100; no minimum	PPO = 100* (Fast_EMA - Slow_EMA) / Fast_EMA	26 and 12	Realtive to daily and montly deviations
Percentage Volume Oscillator (PVO)	The Percentage Volume Oscillator (PVO) indicator is a difference between two moving averages of volume. As the volume moves reflect the buying / selling pressure, the indicator (at least in theory) can precede the price moves. The 12-day exponential moving average (EMA) and 26-exponential moving average are generally used. Typically, these can be changed to suit longer or shorter time periods.	Max = 100; no minimum	PVO = 100* (Fast_EMA - Slow_EMA) / Fast_EMA	26 and 12	Realtive to daily and montly deviations
Stochastic Oscillator (SO)	The Stochastic Oscillator provides information about the location of a current close in relation to the period's high and low. The closer the close is to the period's high, the higher is the buying pressure, and the closer the close is to the period's low, the more selling pressure is. The indicator is considered bullish, when above 80, and bearish, when below 20.		SO = (recent_close - lowest_low) / (highest_high - lowest_low) ; SMA(SO); SMA(SMA(SO)	n=39	Realtive to daily and montly deviations
Moving Average Convergence Divergence (MACD)	The Moving Average Convergence/Divergence indicator (MACD) is calculated by subtracting the value of a 26-period exponential moving average from a 12-period exponential moving average (EMA). A 9-period dotted exponential moving average (the "signal line") of the difference between the 26 and 12 period EMA is used as the signal line. The basic MACD trading rule is to sell when the MACD falls below its 9 day signal line and to buy when the MACD rises above the 9 day signal line.		DIFF : EMA(CLOSE,SHORT) - EMA(CLOSE,LONG); DEA : EMA(DIFF,M); MACD : (DIFF-DEA),	Short=12;Long=26;and M=9	Realtive to daily and montly deviations
Bollinger Bands (BB)	Bollinger Band Width is used to measure volatility by placing trading bands around a moving average. These bands are charted two standard deviations away from the average, so as the average changes, the value of two standard deviations also changes. As standard deviation is a measure of volatility, the bands are self-adjusting: widening during volatile markets and contracting during calmer periods. The purpose of Bollinger Bands is to provide a relative definition of high and low. By definition prices are high at the upper band and low at the lower band.		BB=(Close-MA(Close,N))/stdev(Close,N)	5, 14, 20	Realtive to daily and montly deviations
Chaikin's Money Flow (CMF)	The Chaikin Money Flow is based upon the assumption that a bullish stock will have a relatively high close price within its daily range and have increasing volume. This condition would be indicative of a strong security. However, if it consistently closed with a relatively low close price within its daily range and high volume, this would be indicative of a weak security. Typically a reading below -0.25 is indicative of strong selling pressure. Conversely, a reading above +0.25 is considered to be indicative of strong buying pressure.		AD:=((CLOSE-LOW)-(HIGH-CLOSE))/(HIGH-LOW)*VOL CMF=SUM(AD,N)/SUM(VOL,N)	20	Realtive to daily and montly deviations
Relative Strength Indicator (RSI)	Relative Strength Index (RSI) is a momentum oscillator that measures the speed and change of price movements. RSI oscillates between zero and 100. Traditionally, and according to Wilder, RSI is considered overbought when above 70 and oversold when below 30. One characteristic of the RSI is that it moves slower when it reaches increased overbought or oversold conditions, and then snaps back very quickly when the market enters even a mild correction. This brings the RSI back to more neutral levels and indicates that the price trend may be able to resume.	0 to 100	RSI = 100 - (100/1+RS) RS = Average Gain / Average Loss	14	Realtive to daily and montly deviations

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Technical quant factors are far different from conventional quantitative factors. Conventional quantitative factors are typically calculated and then compared cross-sectionally. For example, an investor may calculate price-to-book for various companies, and then compare the price-to-book ratio cross-sectionally (i.e. between all the companies at a particular point in time). However, technical indicators are calculated relative to their own history. Therefore, a technical indicator signal is only relevant when compared to its history. So for quant factors based on technical indicators, we compute the deviation of the technical signals relative to their historical deviations. Then we compare these deviations cross-sectionally between all the companies in our universe.

Note that technical factors can be calculated using various windows ranges. For example, the technical factor Williams %R has been traditionally calculated based on a 5, 14 and 20 day window. However, for the purposes of this research, and for simplicity, we utilize a fixed 5 day windows when calculating any technical indicators.

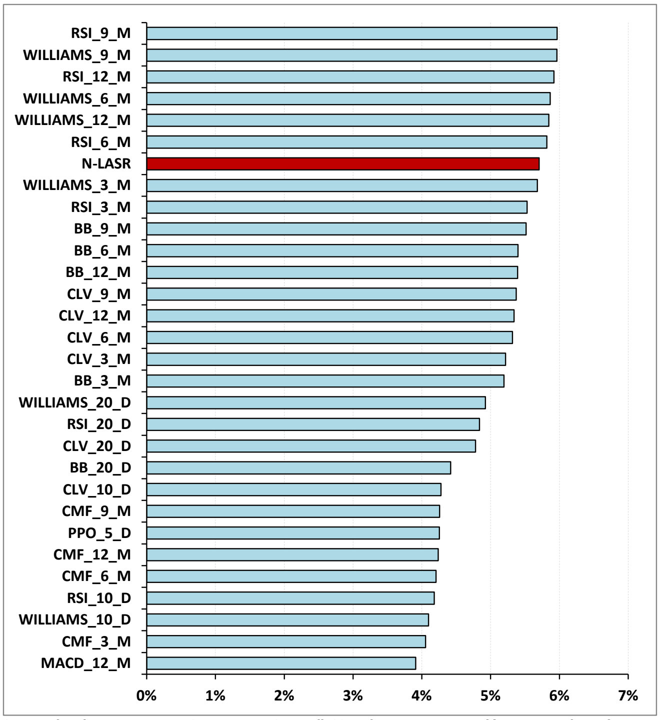
Recall that a technical indicator is typically only relevant when compared to its own history. As such, we build our technical factors based on values relative to their own history. For example, the factor William_10_D is Williams %R using a 5 day window calculated relative to its 10 day historical deviation. Similarly, the factor William_12_M is Williams %R using a 5 day window calculated relative to its 12 month historical deviation. For the purposes of this report, we form various historical deviation periods including 5, 10, 20 days as well as 3, 6, 9, 12 months. For details for technical factors see our previous reports Jussa et al. [2011a] and Le Binh et al. [2011c].

N-LASR performance solely using technical factors

We train enhanced N-LASR model for the technical factors with the same parameters as the N-LASR model trained with standard factors. We will call this the Technical N-LASR model. Figure 75 show the average rank IC for the best performing technical factors compared with the Technical N-LASR model trained with those factors. All the technical factors show good predictive power, and the Technical N-LASR model does not have the highest average rank IC.

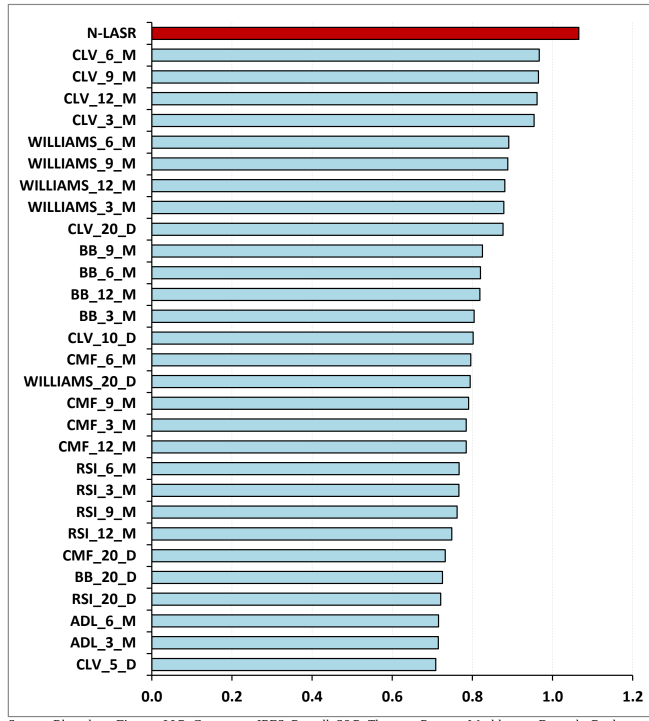
However, Figure 76 shows that the risk adjusted rank IC for the Technical N-LASR is higher than any of the single technical factors. We can conclude that the Technical N-LASR model has more stable performance.

Figure 75: Average rank IC for technical



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

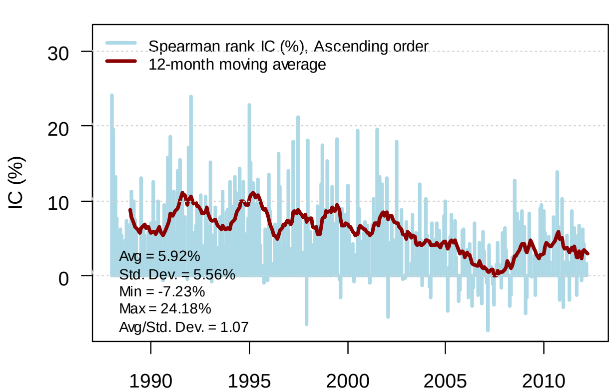
Figure 76: Risk adjusted rank IC for technical



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

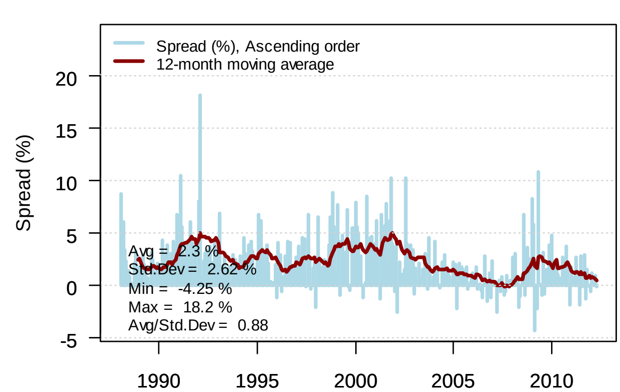
Figure 77 shows the time-series of the rank IC for the Technical N-LASR, we can see that the rank IC is not as high as the N-LASR model but more stable, the risk adjusted rank IC is 1.07 and the trailing 12 month average rank IC is always positive. Figure 78 show the time-series of long short decile spread, the performance for the technical factors is very stable, the Sharpe ratio for the whole period is over 3.0x and the trailing 12 months average spread is always positive. The performance of the model dropped in recent years though.

Figure 77: Rank IC for Technical N-LASR



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

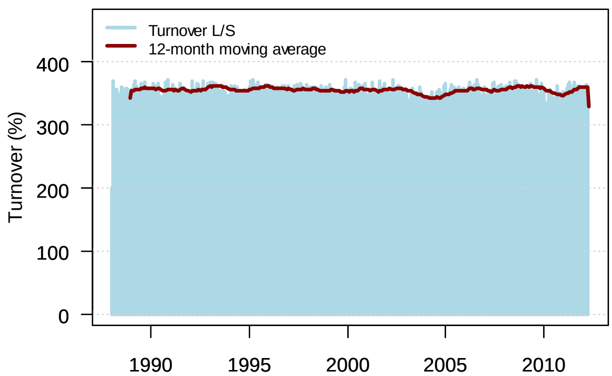
Figure 78: Long/short spread for Technical N-LASR



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

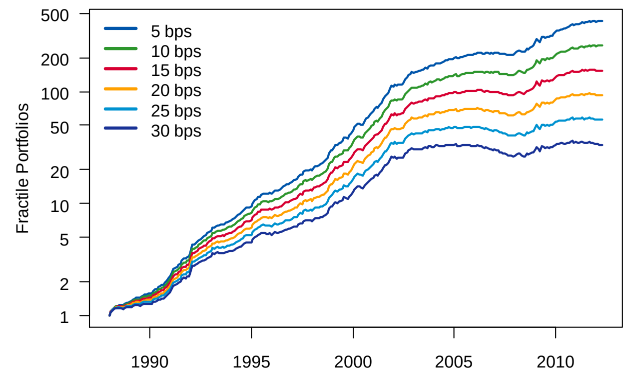
The technical factors usually suffer from the high turnover, Figure 79 shows the time-series of turnover for the Technical N-LASR model. We can see that the turnover is over 350% on average. Will transaction cost kill the profit? Figure 80 shows the wealth curve with different level of transaction cost. We can see that the Technical N-LASR model trained with technical factors is still profitable with a high level of transaction cost. However, the profit in the recent years dropped significantly, especially after 2005.

Figure 79: Turnover of the Technical N-LASR model of technical factors



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

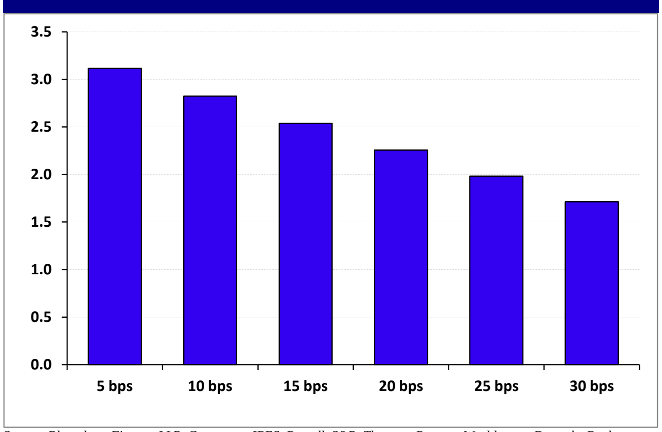
Figure 80: Wealth curve of different transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

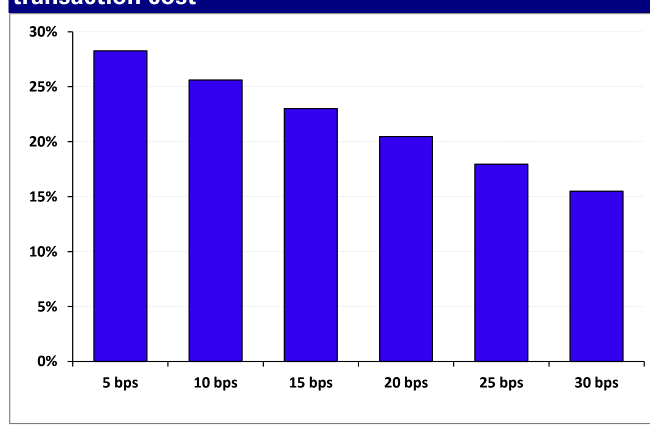
Figure 81 shows the IR for different level of transaction costs, and Figure 82 shows the annualized return for different levels of transaction costs. We can see that the Technical N-LASR is quite profitable with an after-cost Sharpe ratio of 1.7x at 30bps of costs.

Figure 81: IR for different level of transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 82: Annualized return for different level of transaction cost

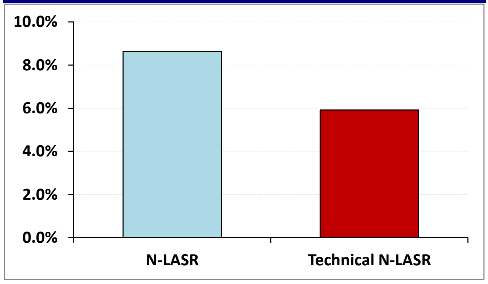


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Comparing N-LASR versus Technical N-LASR

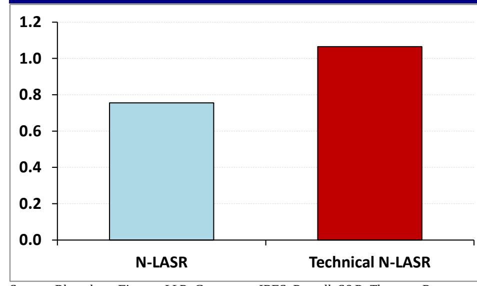
Figure 83, Figure 84, Figure 85 and Figure 86 show factor performance comparisons between N-LASR and Technical N-LASR. We can see that the N-LASR model has higher average rank IC and average long-short spread, while Technical N-LASR model has higher IR and risk adjusted rank IC. This means Technical N-LASR has more stable performance while N-LASR model on average has better raw predictive power.

Figure 83: Rank IC comparison



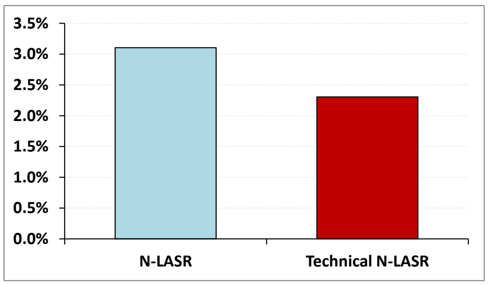
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 84: Risk Adjusted rank IC comparison



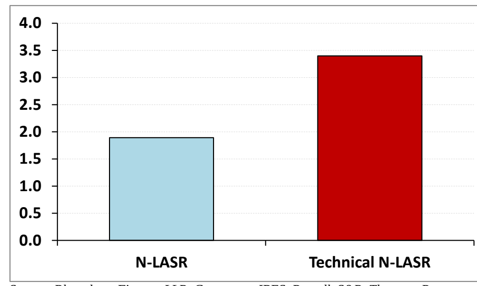
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 85: Average spread comparison



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

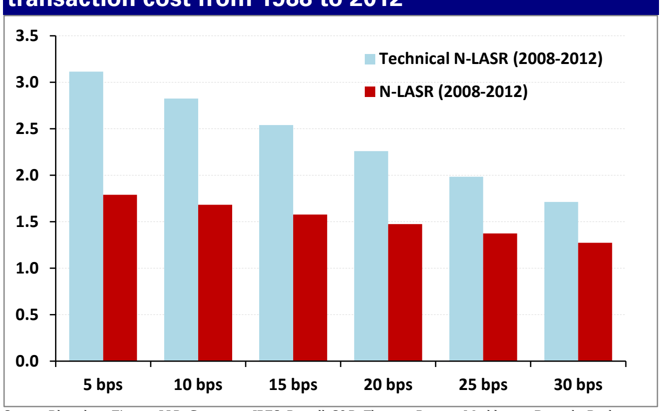
Figure 86: IR comparison



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

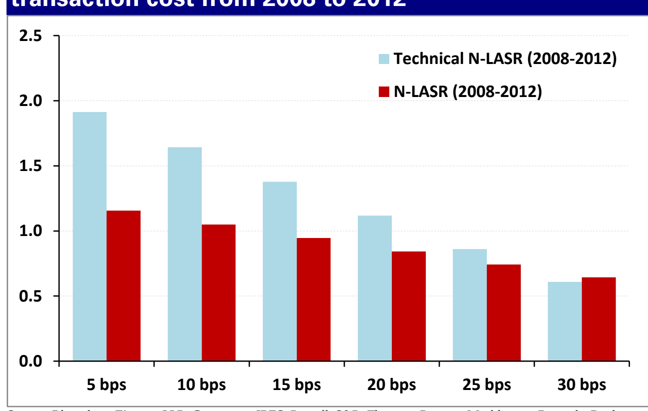
Figure 87 and Figure 88 show the IR of Technical N-LASR with different levels of transaction costs for different time periods. We can see that the Technical N-LASR is easily affected by transaction costs, as the Sharpe ratio drops faster compared with N-LASR model. This is because of the relatively higher turnover and the lower spread. In recent years, both the performances of the N-LASR model and Technical N-LASR have dropped, and the Technical N-LASR dropped even more. The N-LASR model has better performance in 2008 to 2012 if we assume high transaction costs of 30 bps.

Figure 87: IR comparison with different level of transaction cost from 1988 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 88: IR comparison with different level of transaction cost from 2008 to 2012



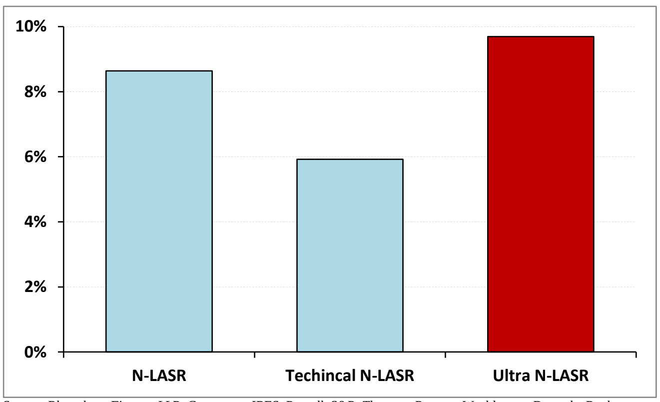
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Ultra N-LASR performance

We find that the performance of the standard factors and technical factors are not correlated. In fact, the correlation between the long-short spread of the two models is -0.8%, so we can combine the N-LASR with the Technical N-LASR and achieves even better results. We call the combined model the Ultra N-LASR model.

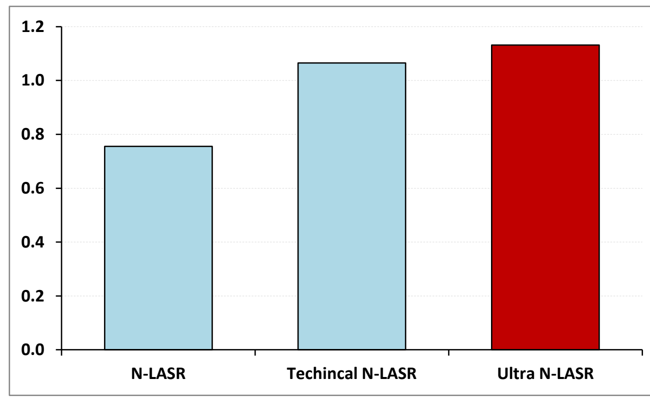
We simply equally-weighted the z-score of the N-LASR and Technical N-LASR model to get the Ultra N-LASR model. We find the performance of the Ultra N-LASR model is better than either model separately. Figure 89 shows the average rank IC improvement and Figure 90 shows the improvement of the risk adjusted IC.

Figure 89: Average rank IC for the three model



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 90: Risk adjusted IC



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

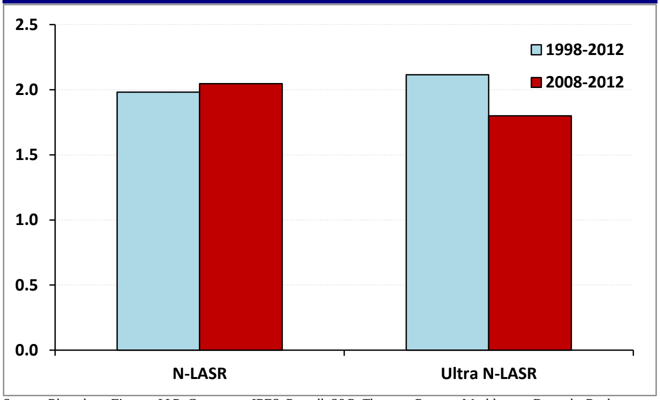
Optimized Ultra N-LASR performance

Again, we use the same approach for portfolio construction as described in QCD (details see Luo et al. [2010c]). We tested the long/short market neutral portfolio for this Ultra N-LASR model, using an optimization with the following parameters:

- Long/short market neutral strategy
- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized volatility of 4%
- Beta neutral
- Turnover constrained at 30% one-way per month (or 360% one-way per year)

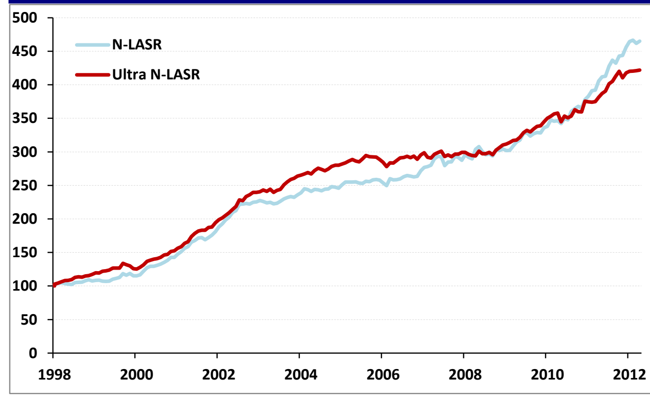
Figure 91 shows the comparison of IR for the N-LASR model and the Ultra N-LASR model. The IR for the Ultra N-LASR model is higher from 1998 to 2012, but lower for the recent period from 2008 to 2012, because the technical factors are not doing well in recent years. Figure 92 shows the wealth curve of two models. We can see that Ultra N-LASR model outperform N-LASR model in the early period, but underperformed in the recent period.

Figure 91: IR for the optimized portfolio of QCD and N-LASR models for different time period



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 92: Wealth curve of QCD and N-LASR models from 1998 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Real life machine learning

A conservative approach: lagging

In the backtesting model, we always get the factor score at the end of the month and assume rebalance on the same day. However, for many of the factors we do not know the value before the market close (for example the factors based on the closing price), thus, we cannot really rebalance at the close on the last day of the month.

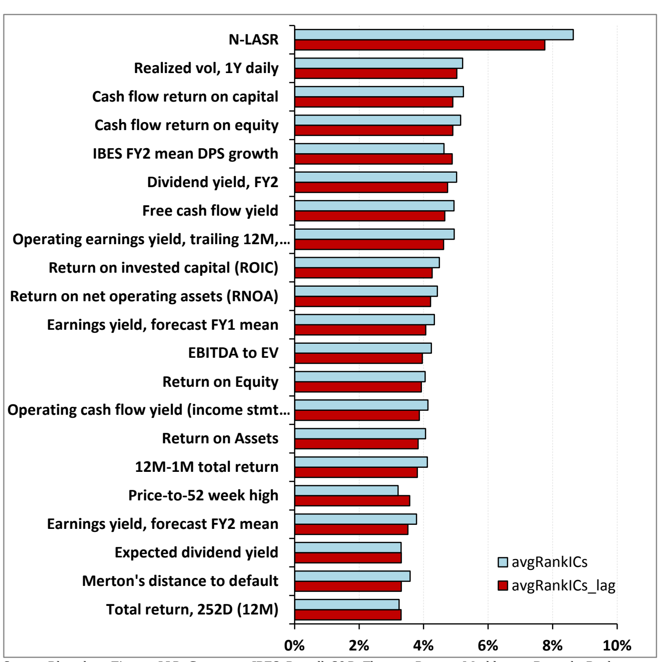
To avoid this look-ahead bias, we can lag the factors by one day, meaning we rebalance on the first day of each month using factor values from the last day of the previous month. How much would this one day lag affect our profitability? If this is still profitable, we can certainly trade real time based on this model. We train our model also based on the forward return from the beginning of the next month to the month after.

Performance of standard factors

Figure 93, Figure 94, Figure 95 and Figure 96 show the performance of the best 20 factors compared with the enhanced N-LASR model. The red bar is the performance with one day lag, and the light blue is the performance without lag.

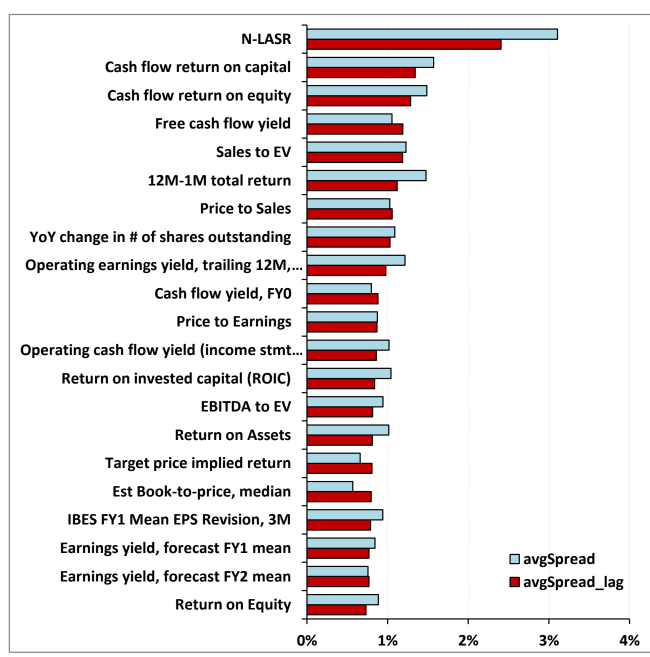
We can see most of the best performing factors' performance dropped with one day lag. This is because by lagging one day and using the next day's closing price, we give up the returns on the first trading day in the next month. However, we would argue that in reality we can still get a price close to the open price instead of the closing prices on the next day; this will capture the return on the first trading day in the month. The performance will be better than lagging one day. Our N-LASR model still outperforms all of the factors by lagging one day. In reality, if we can trade at the open price or a price close to the month-end closing price, the performance for our N-LASR model will be better.

Figure 93: Average Rank IC with one day lag



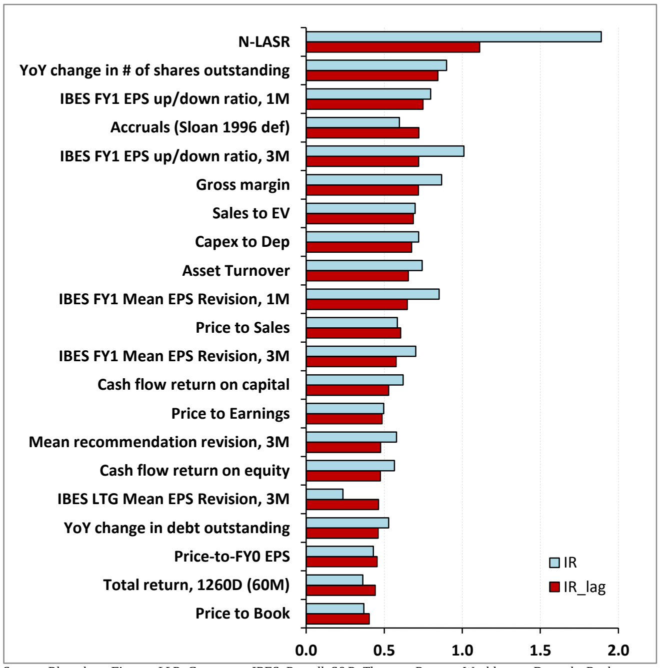
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 94: Average Spread with one day lag



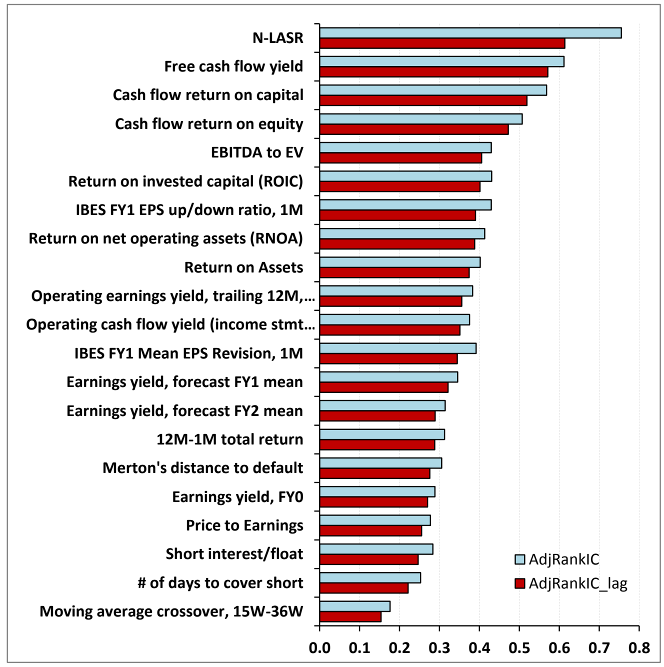
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 95: Sharpe ratio with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 96: Risk adjusted IC with one day lag

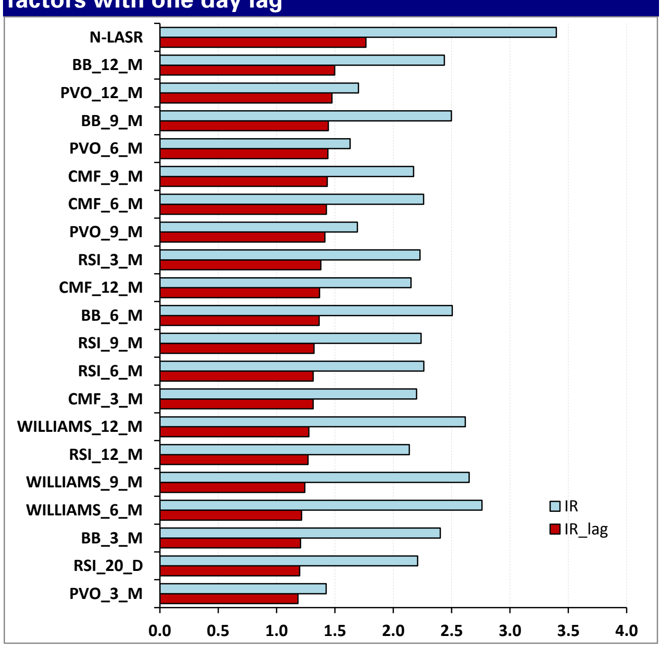


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Lagging has more severe effects for technical indicators

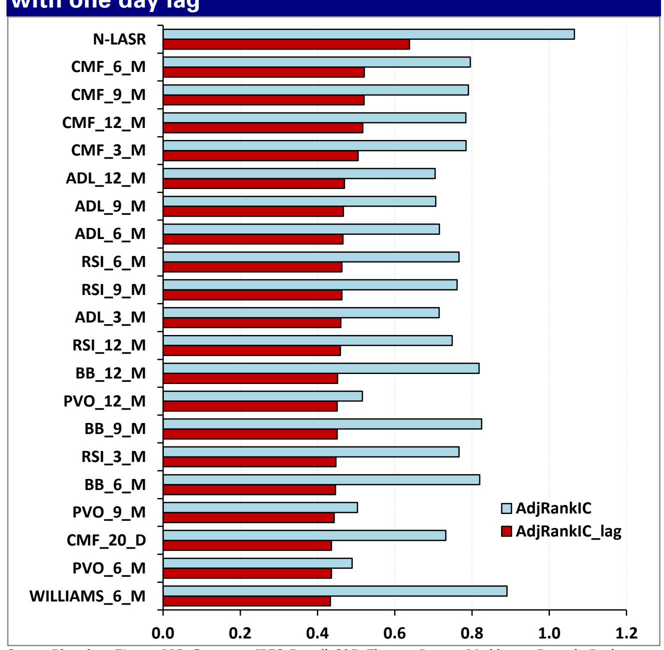
As for the technical factors, we tested how much one day lag would affect our model performance. Figure 97 and Figure 98 shows the IR and risk adjusted rank IC for the Technical N-LASR model with the 20 best performing technical factors with one day lag.

Figure 97: Sharpe ratio of long short decile for technical factors with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 98: Risk adjusted rank IC for technical factors with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

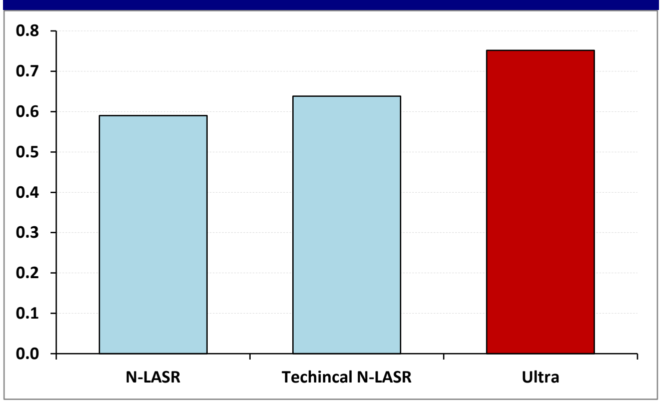
As expected, the performance for the technical factors dropped significantly with one day lag. This is because the technical factors decay quickly, especially the best performing technical factors. Thus, with one day lag single technical factors may not be profitable when we consider transaction costs.

Our Technical N-LASR model still outperforms the individual technical factors. In reality, if we can trade on the open price or a price close to the month-end closing price (for example calculate the technical factor based on the prices 5 minutes before closing and thus trade the stocks at the month-end closing price) then the technical factor can perform much better than shown in Figure 97 and Figure 98. These figures represent the most conservative extreme.

Ultra N-LASR model with one day lag

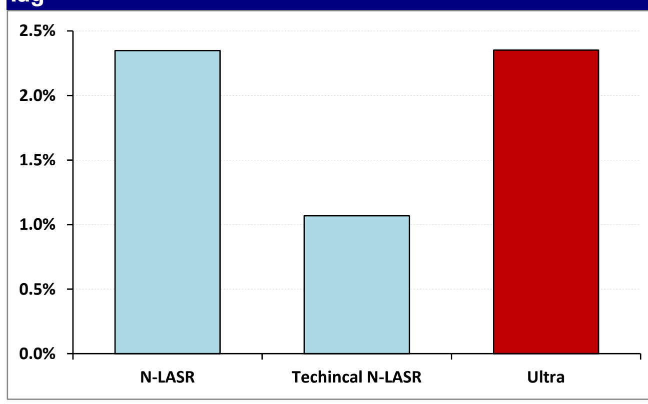
We constructed the Ultra N-LASR model with one day lag by combining the N-LASR and Technical N-LASR; both models were trained and tested with one day lag. Figure 99 show the improvement for the risk-adjusted IC and Figure 100 show the average spread for long short decile. Although the average spread for the Ultra N-LASR model only increase a little bit compared with N-LASR model, it is less volatile so the risk adjusted Rank IC increased quite a lot.

Figure 99: Risk adjusted Rank IC with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

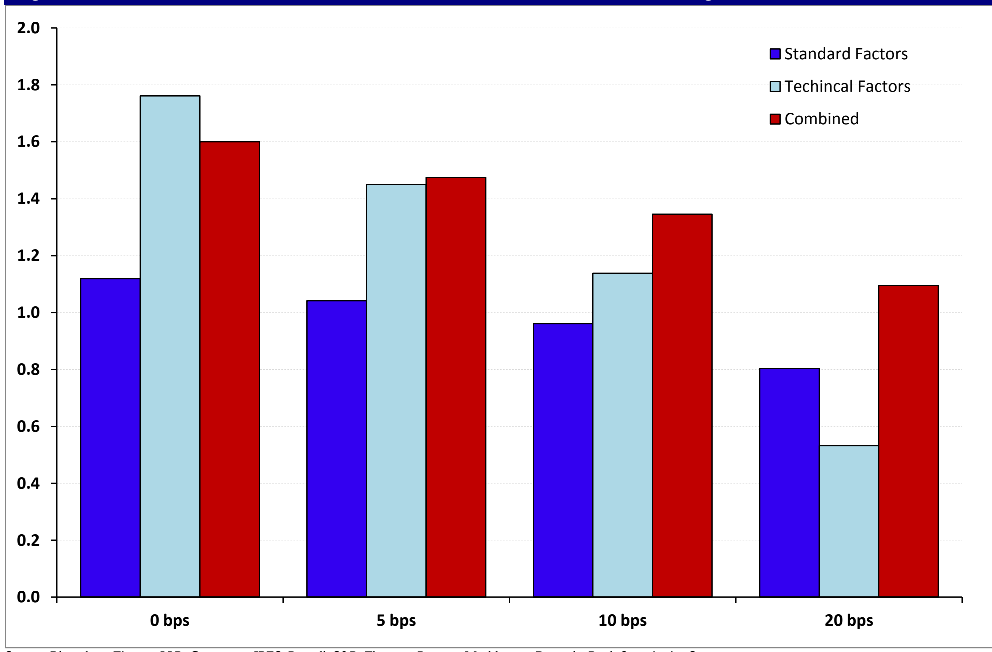
Figure 100: Spread for long short portfolio with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 101 show the Sharpe ratio of long-short decile portfolio for different levels of one-way transaction cost. We find that the Sharpe ratio dropped much more quickly for the Technical N-LASR when the transaction cost increases, because it has higher turnover. Although it has the highest Sharpe ratio if there are no transaction costs, in reality if we consider anything over 10 bps of one way transaction cost, the Ultra N-LASR model would have the best performance.

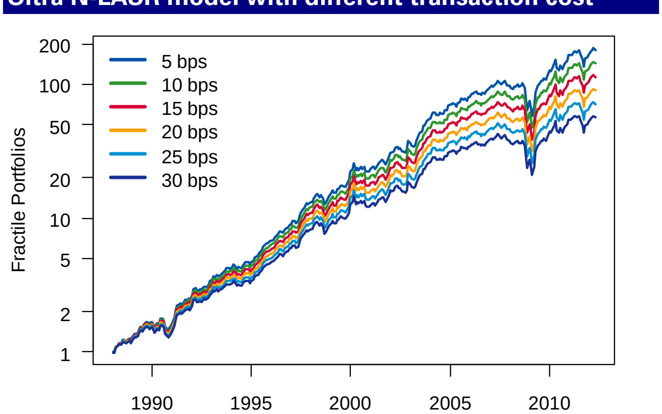
Figure 101: IR with different transaction cost with one day lag



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

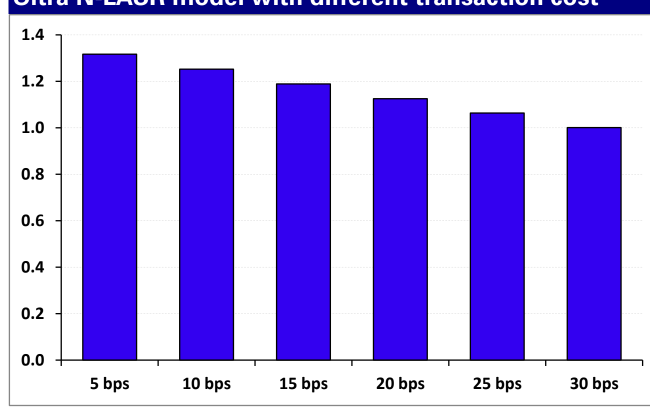
Figure 102 show the long only portfolio of the Ultra N-LASR model with different transaction cost and Figure 103 show the Sharpe ratio with different level of transaction cost. We find that even with 30bps of one way transaction cost, the Ultra N-LASR model is still profitable with Sharpe ratio of 1.0x. This shows that our model is profitable even with one day lag.

Figure 102: Wealth curve of long only portfolio for the Ultra N-LASR model with different transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 103: Sharpe ratio for long only portfolio for the Ultra N-LASR model with different transaction cost



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

A more realistic approach: opening price

A more realistic approach for our back testing is calculating the monthly return based on the open price for first trading day of next month instead of the closing price of current month. Due to the data availability, we only have the open price starting from 2006, thus we use the forward return calculated from month end closing price before 2006 and use open price of next month after 2006 to train the model, and we backtest the model from 2007 to 2012 using open price. In this way, we could get all the factors each month end, and rebalancing the portfolio when the market opens on the first day of next month.

Figure 104 shows the comparison when using month-end close price and next month open price for the N-LASR model. We can see that the overall performance is lower using the next month open price, because the price jumps from close to open. However, the difference is very small; on average only a few bps each month, which we can almost ignore. The average spread is even higher for the open price. Therefore, we would argue our backtesing for N-LASR model using the month-end close prices is fairly realistic.

Figure 104: Comparison of month end close price and next month open price for N-LASR model

	open price	close price
Average Rank IC	6.28%	6.33%
Average Spread	2.14%	2.13%
IR	1.30	1.36
Risk adjusted Rank IC	0.53	0.55
Annualized Return	26.4%	26.5%

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 105 shows the comparison when using month end close price and next month open price for the Technical N-LASR. As expected the difference is larger, however, not that significant compared with using one day lag. The IR for the open price is even higher. This is because the Technical N-LASR using open price has consistently lower spread; therefore, the volatility of the long short decile spread is even lower, result in the higher IR. However, the overall performance is lower, especially in reality when we consider transaction costs. For example, consider 20 bps of transaction costs. The IR for Technical N-LASR using open price will be 0.65x compared with the 0.74x when using the close price. Overall, we would argue that the backtesing for Technical N-LASR model using the month end close prices would be a close approximation to the real situation

Figure 105: Comparison of month end close price and next month open price for N-LASR based on technical factors

	open price	close price
Average Rank IC	2.36%	2.99%
Average Spread	1.12%	1.24%
IR	1.88	1.80
Risk adjusted Rank IC	0.53	0.66
Annualized Return	14.0%	15.5%

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Global results

Country performance

Because of the data availability, we build our global N-LASR model for individual countries based on a subset of the factors we used in the US. Figure 106 shows the 61 factors we used for the global N-LASR stock selection model.

Figure 106: Factors used in the global universe for individual countires

Factor No.	Factor Name	Factor No.	Factor Name
1	Normalized abnormal volume	32	IBES FY1 Mean FFO Revision, 1M
2	ASSET GROWTH	33	IBES FY1 Mean FFO Revision, 3M
3	Berry Ratio	34	IBES FY1 Mean ROE Revision, 1M
4	Capex to Dep	35	IBES FY1 Mean ROE Revision, 3M
5	Cash flow yield, FY0	36	IBES FY2 mean DPS growth
6	Cash flow yield, FY1 mean	37	IBES LTG EPS mean
7	YoY change in debt outstanding	38	IBES LTG Mean EPS Revision, 1M
8	Current ratio	39	IBES LTG Mean EPS Revision, 3M
9	Long-term debt/equity	40	Target price implied return
10	EBITDA to EV	41	Recommendation, mean
11	EBITDA margin	42	Mean recommendation revision, 3M
12	Est Book-to-price, median	43	Moving average crossover, 15W-36W
13	EPS Growth	44	Merton's distance to default
14	Earnings yield, FY0	45	Price/Book
15	Earnings yield, forecast FY1 mean	46	Price-to-FY0 EPS
16	Earnings yield, forecast FY2 mean	47	Price/Earnings
17	Dividend yield, FY1	48	Price/Sales
18	Dividend yield, FY2	49	Realized vol, 1Y daily
19	Gross margin	50	Return on Assets
20	IBES 5Y EPS growth	51	Return on Equity
21	IBES 5Y EPS growth/stability	52	12M-1M total return
22	IBES FY1 mean CFPS growth	53	Total return, 1260D (60M)
23	IBES FY1 mean EPS growth	54	Total return, 21D (1M)
24	IBES FY1 EPS up/down ratio, 1M	55	Total return, 252D (12M)
25	IBES FY1 EPS up/down ratio, 3M	56	Weekly Total Return
26	IBES FY1 Mean CFPS Revision, 3M	57	Sales/EV
27	IBES FY1 Mean DPS Revision, 1M	58	Asset Turnover
28	IBES FY1 Mean DPS Revision, 3M	59	Skewness, 1Y daily
29	IBES FY1 EPS dispersion	60	Dividend yield, trailing 12M
30	IBES FY1 Mean EPS Revision, 1M	61	return on capital
31	IBES FY1 Mean EPS Revision, 3M		

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We need the country universe to be large enough so that we can have sufficient training data, and all the backtesting for the global universes are all done in quintiles rather than deciles. We also require the number of stocks for the selected universe to be more than 100 each month for the training data, thus the backtesting period for different universes start from different times. Figure 107 shows the start date, end date, number of backtesting months and the average number of stocks for different countries.

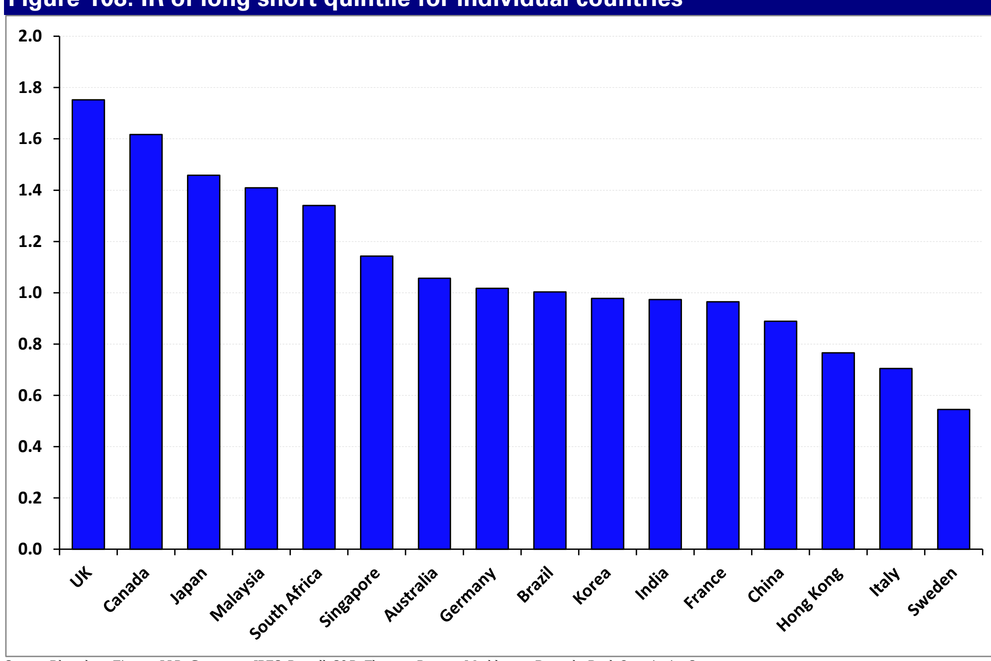
Figure 107: Country start date, end date, number of months and stock number

Country Name	Start Date	End Date	Number of Months	Stock Num
Australia	7/31/1995	4/30/2012	202	236
Brazil	11/30/2005	4/30/2012	78	162
Canada	12/31/1987	4/30/2012	293	411
China	12/31/2002	4/30/2012	113	328
France	7/31/1990	4/30/2012	262	201
Germany	1/31/1997	4/30/2012	184	186
Hong Kong	7/29/1994	4/30/2012	214	157
India	11/30/2005	4/30/2012	78	243
Italy	7/31/1990	4/30/2012	262	152
Japan	7/31/1990	4/30/2012	262	1335
Korea	10/31/2000	4/30/2012	139	273
Malaysia	10/31/2000	4/30/2012	139	112
Singapore	10/31/2006	4/30/2012	67	139
South Africa	11/30/2005	4/30/2012	78	129
Sweden	7/31/2001	4/30/2012	130	136
UK	7/31/1990	4/30/2012	262	514

Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

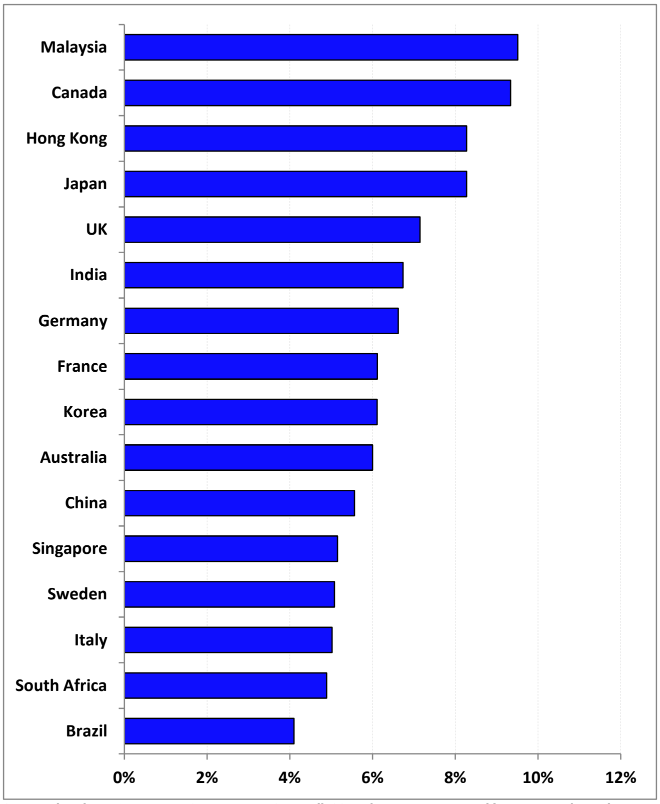
Figure 108, Figure 109, and Figure 110 show the performance in individual countries. We can see that the N-LASR model performs well on all countries. Generally speaking, larger countries have better performance than small countries. This is because the machine learning method needs more training data to have good performance. Developed markets show better performance than emerging markets because developed markets have mature and stable financial environment and thus more consistent factor performance. For example, among all those countries Canada, UK and Japan has the best performance in terms of IR.

Figure 108: IR of long short quintile for individual countries



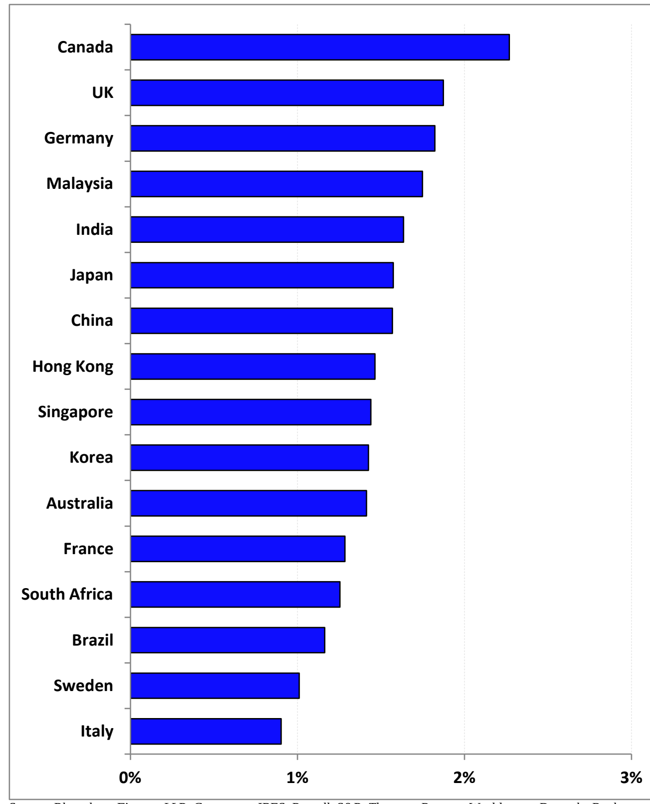
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 109: Average Rank IC for individual countries



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 110: Monthly spread for individual countries



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Regional performance

We construct the following regional universes based on the S&P BMI universe: Asia ex Japan, Europe, EM, DM, and Global. Figure 111 shows the country constituents for each region, their start date, end date, and the average number of stocks in each region. Due to data availability, different regions might start from different time.

Figure 111: Region definition

Region	Start Date	End Date	Average # of Stocks	Constituent Countries
Asia ex Japan	7/29/1994	4/30/2012	1543	Australia, New Zealand, HK, Singapore, China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand
Europe	1/31/1991	4/30/2012	1362	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK
EM	1/31/1991	4/30/2012	1780	Brazil, Chile, Colombia, Mexico, Peru, Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa, Turkey, China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand
DM	1/31/1991	4/30/2012	6863	Canada, USA, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK, Australia, Hong Kong, Japan, New Zealand, Singapore
Global	1/31/1991	4/30/2012	8165	Canada, USA, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, UK, Australia, Hong Kong, Japan, New Zealand, Singapore, Brazil, Chile, Colombia, Mexico, Peru, Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa, Turkey, China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand

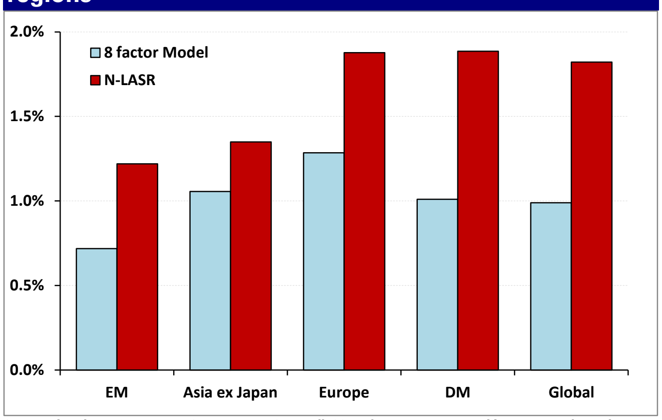
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We compare our model performance with a standard 8-factor model, using the following factors: earnings yield, earnings growth (EPS growth), reversal (return in 21 days), price momentum (total return for the period twelve months ago to 1 month ago), earnings diffusion, ROE, Merton's default ratio, capital utilization (change in number of shares outstanding) We equally weighted the z-score of each factor, and flip the signs for those descending factors. For each region we use the same backtesting period used in the N-LASR model as shown in Figure 111.

We backtested the performance of both models based on the country neutral returns, which is the stock returns minus the country average returns. All the returns are calculated in USD. This country neutrality ensures that we don't take on significant directional exposure to any country. For the N-LASR model, we train the model also using country neutral forward returns, so that it will be consistent with the backtesting. Figure 112, Figure 113, Figure 114 and Figure 115 show the comparison of the model performance between our N-LASR model and 8-factor model.

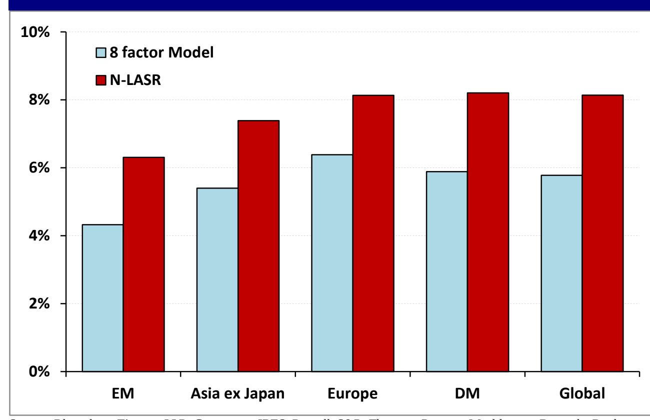
We can see that N-LASR model has a much better performance than the standard 8-factors model in all regions. Again, N-LASR model works better for larger universe compared to smaller universe. In addition, machine learning methods perform better on the developed market than emerging market.

Figure 112: Average monthly spread for different regions



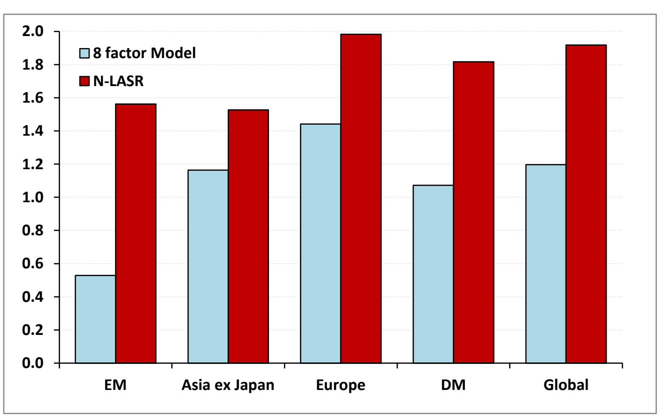
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 113: Average rank IC for different regions



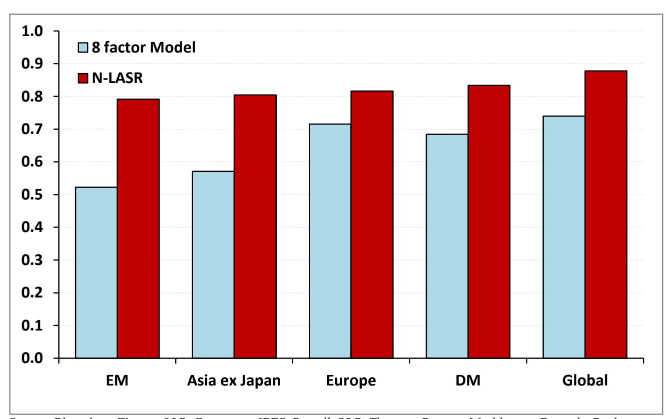
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 114: IR for different regions



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 115: Risk adjusted rank IC for different region

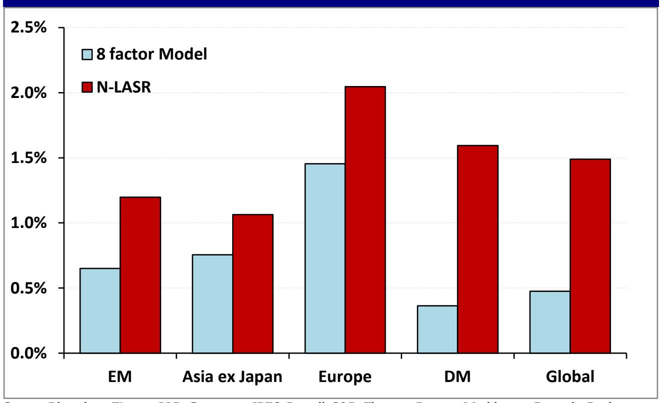


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Consistent outperformance in recent years

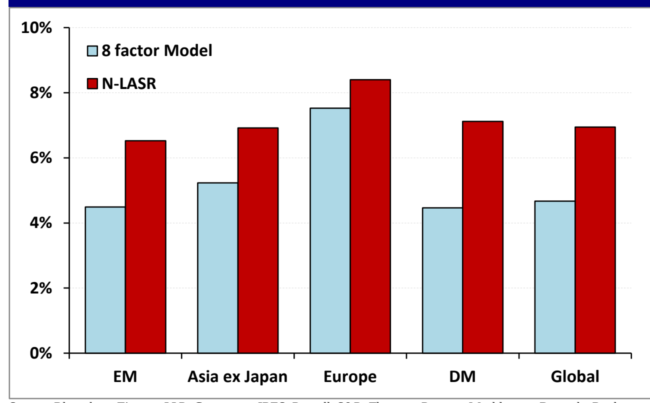
We tested the performance for the same regions for the recent period from 2008 to 2012. Figure 116, Figure 117, Figure 118 and Figure 119 show the performance for the regions in recent years. As we expected, our N-LASR model outperforms the 8-factor model in every aspect for every region.

Figure 116: Average long short quintile spread from 2008 to 2012



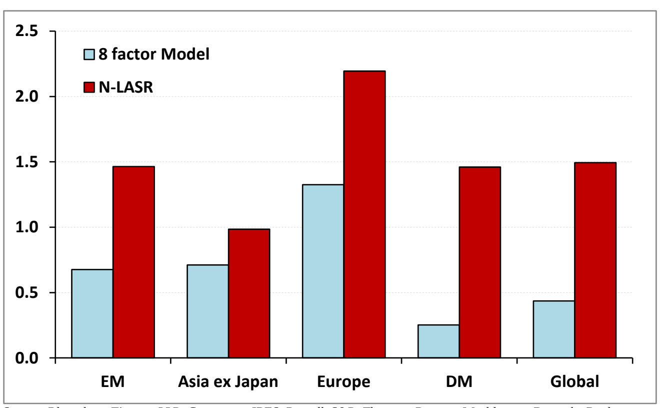
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 117: Average rank IC for different regions from 2008 to 2012



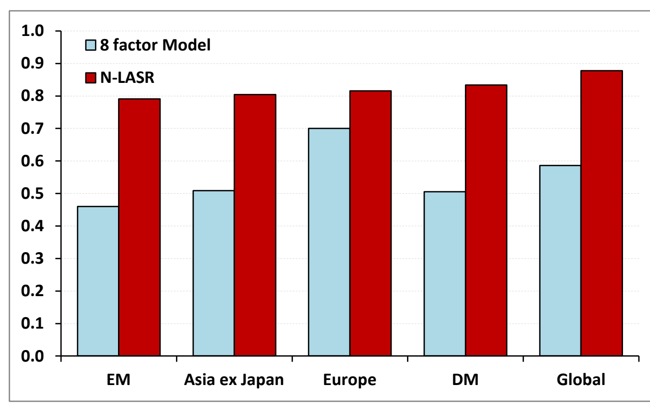
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 118: IR from 2008 to 2012



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 119: Risk adjusted rank IC from 2008 to 2012

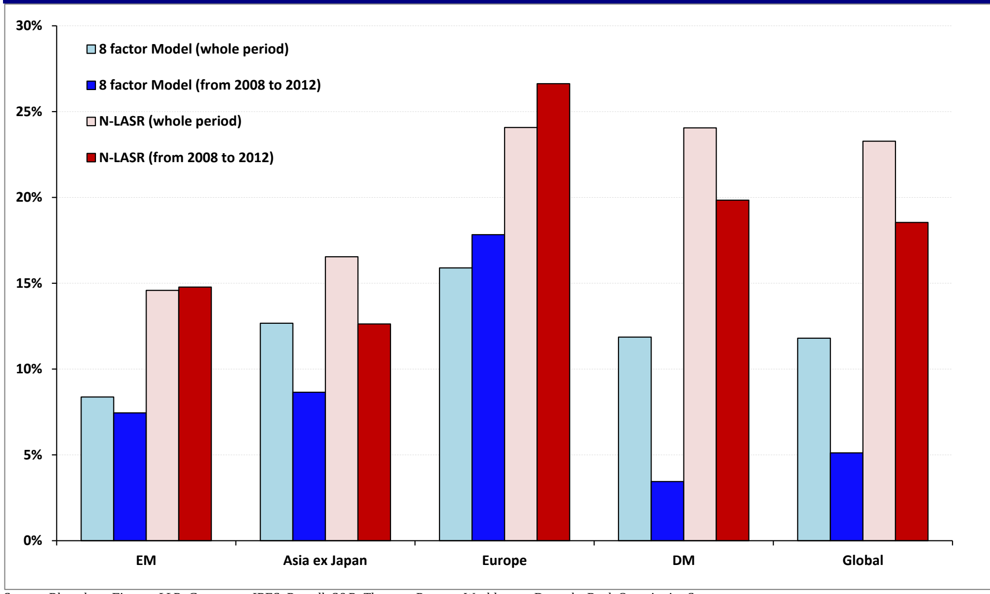


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 120 shows the annualized cumulative return for the long short quintile portfolio in various regions. Interestingly, we notice that the performance of our N-LASR model didn't deteriorate as much in the recent years. In fact, for EM and Europe the performance is even better in recent years. In contrast, the performance for the 8-factor model dropped much more for most regions in the recent years, especially for DM and Global.

The challenge performance for traditional models in the recent years is because some factors have not been working or even flipped signs in the recent years. Our N-LASR model can effectively evolve and adapt to the new market conditions, therefore maintaining similar outperformance. In addition, large universes such as DM and Global contain many countries, so the non-linear payoffs of the factors become a problem for the 8-factor model, while our N-LASR model can capture the non-linear patterns much better.

Figure 120: Annualized accumulative return comparison for different time period



Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

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Appendix 1

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