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The rise of the machines II

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Introducing the second generation of machine learning model

We are introducing our second generation N-LASR (Non-Linear Adaptive Style Rotation) global stock selection model. This N-LASR2 model uses the same machine learning algorithm we used before, but utilizes a new neutralization technique and accounts for different market conditions. The risk adjusted performance for all regions improves significantly.

Neutralizing for sector, country, size and beta biases

We introduce a neutralization technique that can mitigate sector, country, size and beta biases in the model. This is particularly useful for risk management, and reduces the volatility of the model. We show that neutralization at the signal level does better than using constraints on the optimizer to manage these biases.

Adapting to changing market conditions

We introduce a novel approach to capture different market conditions. We train a “hedge” model using the data from those months that cannot be predicted well using this month’s model.

Highly profitable as a trading strategy for all the markets

We construct market neutral portfolios from our N-LASR2 model for 9 regions. They all show consistent positive performance over the past 14 years. Even after setting liquidity constraints and including transaction costs, the Sharpe ratios for the US, Europe ex UK, and Emerging Markets are over 2.6x for the entire history, and remained above 2.0x even after 2008.

Source: gettyimages.com

Deutsche Bank Securities Inc.

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A letter to our readers

Machine learning is back!

In 2012 we introduced our first global stock selection model: the Non-Linear Adaptive Style Rotation (N-LASR) model (Wang, et al. [2012]). The model is based on a machine learning algorithm called AdaBoost (Schapire [1998]), and is designed to dynamically select factors to adapt to changing market conditions. The model continues to show strong predictive power out of sample. In this report, we launch the N-LASR2 model. This model is built on top of our original N-LASR model to make the performance more stable.

Neutralization: A simple but powerful tool to control risk

Normally quant managers do not want high exposures to sectors, countries and beta. We introduce a simple neutralization technique at the raw factor level, before input to the machine learning engine. This will result in an even distribution of signal scores across dimensions we want to avoid tilts towards, such as sectors or size. For example, if we neutralize for sectors, and long the stocks within the top quantile based on the final score, the number of stocks in each sector will be in proportion to the sector size. Thus the final score will be naturally sector neutral. For a single factor, neutralizing the signal or setting a sector constraint at portfolio construction level will not make much difference. However, in our machine learning algorithm it will, because the neutralized signal will be focused more on stock selection rather than sector selection. We can easily neutralize for sector, country, size, and beta at the signal level. This greatly reduces the volatility of the model performance.

A novel approach to capture different market conditions

It is always very difficult to predict the market, and most quant models will suffer in certain market conditions. We introduce a novel approach to adjust for different market conditions. First, we find those months in the history that cannot be predicted well using the current month's model. Then we train another "hedge" model using those months of data. By adding this hedge model as a diversifier, our model can perform well when the market suddenly changes, but also remains highly predictive in normal market conditions.

Superior performance for realistic optimized portfolio all over the world

We build our optimized long/short market neutral portfolio based on the N-LASR2 model for different regions in the world. For most of the regions, the optimized portfolio has consistent performance in recent years from 2008 to 2012. For some regions, such as Emerging Markets, Asia ex Japan and Europe ex UK, the recent years have even better performance compared to the more distant past. We also consider more realistic liquidity constraints, such as an average daily volume constraint. With this liquidity constraint, and after transaction costs, all the regions perform well, especially the US, Europe ex UK, Emerging markets, and Asia ex Japan. The Sharpe ratio of those markets is over 2.0x in the 14 years backtesting period from 1999 to 2012.

Regards,

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

Stock screen

US N-LASR2 stock screen

The screen below (Figure 1 and Figure 2) lists the best 40 long and short ideas for the S&P 500, based on our N-LASR2 (Non-Linear Adaptive Style Rotation) stock selection model. A full list of the Russell 3000 stocks is available upon request.

Figure 1: Best long ideas based on the S&P 500 universe

Ticker	Company Name	GICS Industry Group	N-LASR Score (more positive = more likely to outperform)
HIG	HARTFORD FINANCIAL SERVICES	Financials	1.79
PRU	PRUDENTIAL FINANCIAL INC	Financials	1.72
ACE	ACE LTD	Financials	1.54
TER	TERADYNE INC	Information Technology	1.54
MO	ALTRIA GROUP INC	Consumer Staples	1.53
MSFT	MICROSOFT CORP	Information Technology	1.51
KR	KROGER CO	Consumer Staples	1.50
CNP	CENTERPOINT ENERGY INC	Utilities	1.50
DFS	DISCOVER FINANCIAL SVCS INC	Financials	1.49
GCI	GANNETT CO	Consumer Discretionary	1.48
ACN	ACCENTURE PLC	Information Technology	1.44
FDX	FEDEX CORP	Industrials	1.42
NOV	NATIONAL OILWELL VARCO INC	Energy	1.42
GPS	GAP INC	Consumer Discretionary	1.41
MRO	MARATHON OIL CORP	Energy	1.41
DRI	DARDEN RESTAURANTS INC	Consumer Discretionary	1.38
NVDA	NVIDIA CORP	Information Technology	1.37
QCOM	QUALCOMM INC	Information Technology	1.37
CI	CIGNA CORP	Health Care	1.36
SAI	SAIC INC	Information Technology	1.36
ALL	ALLSTATE CORP	Financials	1.36
MET	METLIFE INC	Financials	1.35
CAG	CONAGRA FOODS INC	Consumer Staples	1.34
AAPL	APPLE INC	Information Technology	1.34
JBL	JABIL CIRCUIT INC	Information Technology	1.32
JPM	JPMORGAN CHASE & CO	Financials	1.32
LSI	LSI CORP	Information Technology	1.31
NBR	NABORS INDUSTRIES LTD	Energy	1.30
TRV	TRAVELERS COS INC	Financials	1.29
OI	OWENS-ILLINOIS INC	Materials	1.28
WYNN	WYNN RESORTS LTD	Consumer Discretionary	1.26
DF	DEAN FOODS CO	Consumer Staples	1.25
COF	CAPITAL ONE FINANCIAL CORP	Financials	1.23
CF	CF INDUSTRIES HOLDINGS INC	Materials	1.19
FTR	FRONTIER COMMUNICATIONS CORP	Telecommunication Services	1.19
AIZ	ASSURANT INC	Financials	1.13
BHI	BAKER HUGHES INC	Energy	1.12
NE	NOBLE CORP	Energy	1.12
FIS	FIDELITY NATIONAL INFO SVCS	Information Technology	1.11
WPI	WATSON PHARMACEUTICALS INC	Health Care	1.10

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

Figure 2: Best short ideas based on the S&P 500 universe

Ticker	Company Name	GICS Industry Group	N-LASR Score (more negative = more likely to underperform)
FHN	FIRST HORIZON NATIONAL CORP	Financials	-1.63
MCD	MCDONALD'S CORP	Consumer Discretionary	-1.61
FISV	FISERV INC	Information Technology	-1.53
FTI	FMC TECHNOLOGIES INC	Energy	-1.44
FSLR	FIRST SOLAR INC	Information Technology	-1.39
PCL	PLUM CREEK TIMBER CO INC	Financials	-1.36
SIAL	SIGMA-ALDRICH CORP	Materials	-1.35
SJM	SMUCKER (JM) CO	Consumer Staples	-1.34
HRL	HORMEL FOODS CORP	Consumer Staples	-1.32
STT	STATE STREET CORP	Financials	-1.31
NFLX	NETFLIX INC	Consumer Discretionary	-1.30
BWA	BORGWARNER INC	Consumer Discretionary	-1.27
DISCA	DISCOVERY COMMUNICATIONS	Consumer Discretionary	-1.22
AN	AUTONATION INC	Consumer Discretionary	-1.21
WM	WASTE MANAGEMENT INC	Industrials	-1.20
SCHW	SCHWAB (CHARLES) CORP	Financials	-1.18
NYX	NYSE EURONEXT	Financials	-1.18
NKE	NIKE INC	Consumer Discretionary	-1.17
WAT	WATERS CORP	Health Care	-1.17
K	KELLOGG CO	Consumer Staples	-1.14
NEE	NEXTERA ENERGY INC	Utilities	-1.12
CPB	CAMPBELL SOUP CO	Consumer Staples	-1.11
MCHP	MICROCHIP TECHNOLOGY INC	Information Technology	-1.09
FAST	FASTENAL CO	Industrials	-1.09
MKC	MCCORMICK & CO INC	Consumer Staples	-1.06
PHM	PULTEGROUP INC	Consumer Discretionary	-1.05
BLK	BLACKROCK INC	Financials	-1.05
XLNX	XILINX INC	Information Technology	-1.05
JCI	JOHNSON CONTROLS INC	Consumer Discretionary	-1.05
HCN	HEALTH CARE REIT INC	Financials	-1.05
D	DOMINION RESOURCES INC	Utilities	-1.01
JNPR	JUNIPER NETWORKS INC	Information Technology	-1.01
SRE	SEMPRA ENERGY	Utilities	-1.00
KMX	CARMAX INC	Consumer Discretionary	-1.00
URBN	URBAN OUTFITTERS INC	Consumer Discretionary	-1.00
FOSL	FOSSIL INC	Consumer Discretionary	-0.97
PLL	PALL CORP	Industrials	-0.97
NI	NISOURCE INC	Utilities	-0.97
SYY	SYSCO CORP	Consumer Staples	-0.94
BDX	BECTON DICKINSON & CO	Health Care	-0.92

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

Global N-LASR2 stock screen

The screen below (Figure 3 and Figure 4) lists the best 40 long and short global stocks with market capitalizations greater than US$ 500 million, based on our N-LASR2 stock selection model. A full list of global stocks is available upon request, including the following regions: Europe ex UK, Asia ex Japan, Japan, Emerging Markets, Canada, UK, Australia and New Zealand, and Global.

Figure 3: Best long ideas for global stocks with over US$ 500 million market capitalizations

Ticker	Company Name	Country	GICS Industry Group	N-LASR Score (more positive = more likely to outperform)
WFC	WELLS FARGO & CO	USA	Financials	8.00
SREN VX	Swiss Re Reg	Switzerland	Financials	7.96
9719 JT	SCSK Corp	Japan	Information Technology	7.46
URS	URS CORP	USA	Industrials	7.25
FL	FOOT LOCKER INC	USA	Consumer Discretionary	7.22
GCI	GANNETT CO	USA	Consumer Discretionary	7.13
SLHN VX	Swiss Life Reg	Switzerland	Financials	7.07
FNF	FIDELITY NATIONAL FINANCIAL	USA	Financials	6.99
WJA	WESTJET AIRLINES LTD	Canada	Industrials	6.94
ACAS	AMERICAN CAPITAL LTD	USA	Financials	6.91
UNH	UNITEDHEALTH GROUP INC	USA	Health Care	6.88
PEABB SS	Peab AB	Sweden	Industrials	6.87
HCC	HCC INSURANCE HOLDINGS INC	USA	Financials	6.85
AFL	AFLAC INC	USA	Financials	6.78
BALN VX	Baloise Hldg Reg	Switzerland	Financials	6.78
CI	CIGNA CORP	USA	Health Care	6.75
773 HK	China Metal Recycling (Holdings) Ltd.	China	Materials	6.58
CSCO	CISCO SYSTEMS INC	USA	Information Technology	6.55
MBFI	MB FINANCIAL INC/MD	USA	Financials	6.46
ANDE	ANDERSONS INC	USA	Consumer Staples	6.45
NDAQ	NASDAQ OMX GROUP INC	USA	Financials	6.44
SEBA SS	SEB-Skand Enskilda Banken A	Sweden	Financials	6.40
ENR	ENERGIZER HOLDINGS INC	USA	Consumer Staples	6.40
604 HK	Shenzhen Investment Ltd.	China	Financials	6.36
HIG	HARTFORD FINANCIAL SERVICES	USA	Financials	6.33
1800 HK	China Communications Construction	China	Industrials	6.28
880 HK	SJM Holdings Ltd.	Hong Kong	Consumer Discretionary	6.27
NDA SS	Nordea AB	Sweden	Financials	6.23
QBR.B	QUEBECOR INC -CL B	Canada	Consumer Discretionary	6.22
RJF	RAYMOND JAMES FINANCIAL CORP	USA	Financials	6.18
AV/ LN	Aviva	UK	Financials	6.17
PACW	PACWEST BANCORP	USA	Financials	6.17
KMPR	KEMPER CORP/DE	USA	Financials	6.16
YZJ SP	Yangzijiang Shipbuilding Hldgs Ltd	China	Industrials	6.11
LRD LN	Laird PLC	UK	Information Technology	6.07
POLI IT	Bank Hapoalim BM Reg	Israel	Financials	6.05
NCCB SS	NCC AB CL B	Sweden	Industrials	6.03
POWF IS	Power Finance Corp Ltd	India	Financials	6.03
MING NO	Sparebanken Midt-Norge	Norway	Financials	5.95
THO	THOR INDUSTRIES INC	USA	Consumer Discretionary	5.93

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

Figure 4: Best short ideas for global stocks with over US$ 500 million market capitalizations

Ticker	Company Name	Country	GICS Industry Group	N-LASR Score (more negative = more likely to underperform)
1211 HK	BYD Co. Ltd. - H Shares	China	Consumer Discretionary	-8.66
CLT.	CELTIC EXPLORATION LTD	Canada	Energy	-8.56
FIO	FUSION-IO INC	USA	Information Technology	-7.90
CYMI	CYMER INC	USA	Information Technology	-7.66
BJC TB	Berli Jucker PCL	Thailand	Industrials	-7.63
IPGP	IPG PHOTONICS CORP	USA	Information Technology	-7.60
2049 TT	Hiwin Technologies Corp	Taiwan	Industrials	-7.48
MMR	MCMORAN EXPLORATION CO	USA	Energy	-7.42
NFLX	NETFLIX INC	USA	Consumer Discretionary	-7.35
958 HK	Huaneng Renewables Corp Ltd	China	Utilities	-7.13
BSFT	BROADSOFT INC	USA	Information Technology	-7.12
APKT	ACME PACKET INC	USA	Information Technology	-7.02
538 HK	Ajisen (China) Holdings Ltd.	China	Consumer Discretionary	-6.99
THR BB	ThromboGenics NV	Belgium	Health Care	-6.93
FARO	FARO TECHNOLOGIES INC	USA	Information Technology	-6.88
CNC	CENTENE CORP	USA	Health Care	-6.79
3110 JT	Nitto Boseki Co	Japan	Industrials	-6.50
BLOOM PM	Bloomberry Resorts Corp.	Philippines	Consumer Discretionary	-6.49
CMG	CHIPOTLE MEXICAN GRILL INC	USA	Consumer Discretionary	-6.42
PG.	PREMIER GOLD MINES LTD	Canada	Materials	-6.40
TET.	TRILOGY ENERGY CORP	Canada	Energy	-6.33
FNSR	FINISAR CORP	USA	Information Technology	-6.30
GBT.A	BMTC GROUP INC -CL A	Canada	Consumer Discretionary	-6.27
OPNT	OPNET TECHNOLOGIES INC	USA	Information Technology	-6.16
IMGN	IMMUNOGEN INC	USA	Health Care	-6.05
NESZ MK	Nestle Malaysia Bhd	Malaysia	Consumer Staples	-6.00
OAS	OASIS PETROLEUM INC	USA	Energy	-6.00
CPACASC1 PE	Cementos Pacasmayo C	Peru	Materials	-5.95
9427 JT	Eaccess Ltd	Japan	Telecommunication Services	-5.94
6268 JT	Nabtesco Corp	Japan	Industrials	-5.85
PXP	PLAINS EXPLORATION & PROD CO	USA	Energy	-5.81
ATML	ATMEL CORP	USA	Information Technology	-5.81
XXIA	IXIA	USA	Information Technology	-5.81
GEM IM	Gemina SpA Ord	Italy	Industrials	-5.80
FVI.	FORTUNA SILVER MINES INC	Canada	Materials	-5.80
5631 JT	Japan Steel Works	Japan	Industrials	-5.77
1387 HK	Renhe Commercial Holdings Co. Ltd.	China	Financials	-5.75
AAON	AAON INC	USA	Industrials	-5.70
ANTO LN	Antofagasta Hldgs	UK	Materials	-5.68
JDSU	JDS UNIPHASE CORP	USA	Information Technology	-5.67

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

Machine learning revisited

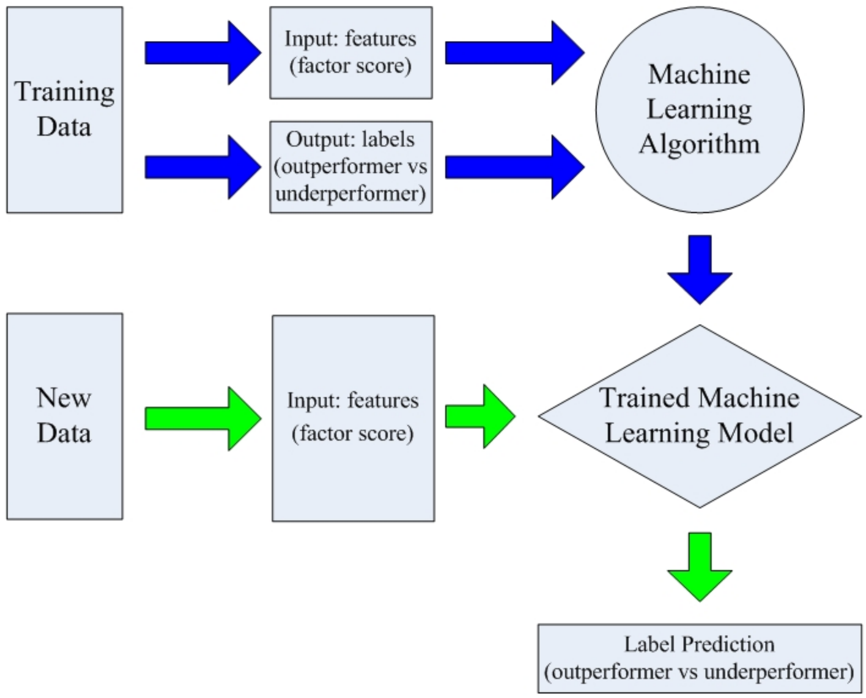
Our previous work on machine learning

Machine learning methods have become more and more popular in the quant world to predict stock returns. The main idea in using machine learning methods to predict future stock returns is to automatically learn to recognize complex data patterns and capture the hidden relationships among financial data, which are normally difficult to see with the human eye.

Machine learning has always been one of our favorite topics; we used machine learning techniques in many our previous research papers, such as TREE models (Luo, et al. [2010c], Salvini, et al. [2011], and Cahan, et al. [2012a]), linear/non-linear regression (Luo, et al. [2010a]), textual analysis of financial news or social media posts (Cahan, et al. [2010,2011,2012b]). Last year we launched our first global stock selection model, which we called N-LASR (Non-Linear Adaptive Style Rotation) (Wang, et al. [2012]). It uses machine learning techniques to select and combine factors, taking into account seasonal and evolutionary trends in factor performance, and has shown strong performance globally since we published last year.

The N-LASR model treats stock selection as a binary classification problem using supervised learning. We classify the stocks in our universe into outperformers and underperformers based on one-month forward stock returns. The construction of the confidence score has two steps: the training step and the prediction step. In the training step, we use the end-of-month factor scores for each stock and one-month forward returns as training data to build the classifiers. In the prediction step, we use the current month factor score as the input for the classifiers we built in the training step, and the output is a confidence score. Figure 5 illustrates how supervised learning is used in stock selection.

Figure 5: Diagram of general supervised learning

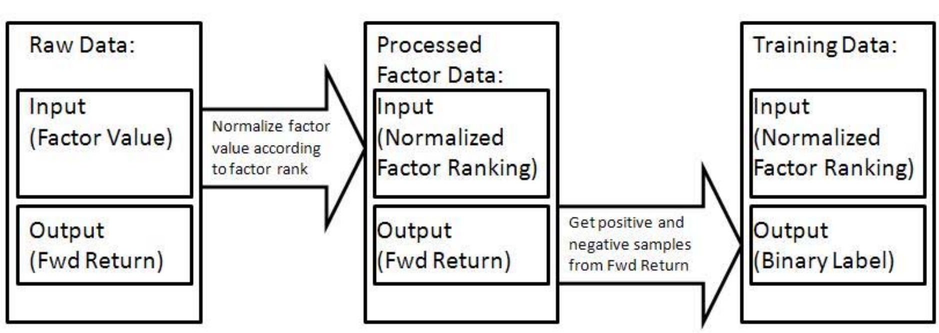


Source: Deutsche Bank Quantitative Strategy

Data preparation

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. Then, we divide the factor ranking by the number of stocks to normalize the factor ranking to between (0, 1]. After normalizing the factors by rank and coverage, we then assemble the training data. We set the stocks in the top 30%, measured by one-month forward return, as the outperformers. Similarly we set the bottom 30% as the underperformers. Note that stocks not classified in the top or bottom 30% are disregarded. We perform this labeling exercise on a monthly basis, and pile the different months' data together as training data. Figure 6 illustrate how we prepare the training data.

Figure 6: Data preparation



Source: Deutsche Bank Quantitative Strategy

AdaBoost algorithm

We use a machine learning algorithm called AdaBoost (Schapire [1998]) 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. 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. 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. This way of defining the weak classifier can transform the non-linear factors into linear factors.

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 focuses on the stocks which have so far not been correctly classified. In each round we choose the most effective weak classifier, which can distinguish the outperformers and underperformers the most with the current set of weights. This means the current best performing factor is less correlated with the previously selected factors. Essentially, 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.

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. We use the value of strong classifier as a new composite factor, which has better performance than any of the factors comprising it.

Figure 7 gives the full algorithm of our AdaBoost stock selection model. For details see Wang, et al. [2012].

Figure 7: 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: $H(x) = \sum_{t=1}^{L} (h_l(\mathrm{x}))$

Source: Deutsche Bank Quantitative Strategy

The N-LASR model

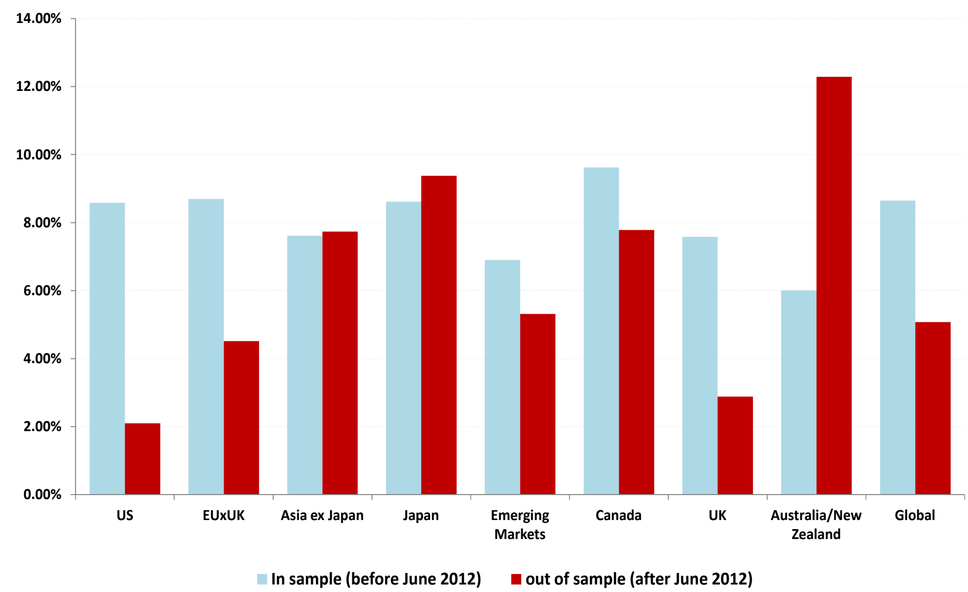
We build our N-LASR stock selection model with three strong classifiers using different training data. The first classifier uses the trailing 12 months of data; the second classifier uses the trailing 12 years (if there is less than 12 years historical data, just use all the available years) *in the 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 the non-US N-LASR model we simply equally weighted the z-score of the value of the three strong classifiers. For the US model we weight the three strong classifiers by the average rank IC for the same month over the past years. In order not to introduce any look-ahead bias, we set the weights dynamically. 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.

Out of sample performance

Figure 8 shows the performance of the N-LASR model for different regions in sample and out of sample. The in sample performance is defined as the average rank IC before June 2012 when our report published, the out of sample performance is the average rank IC after June 2012 till the end of 2012. We can see that the out of sample performance of our N-LASR model is positive for all the regions; most of the regions have similar performance out of sample, but some regions such as Asia ex Japan, Japan and New Zealand even have better performance than in sample. However, for some regions such as the US, Europe ex UK, and UK, the performance drops quite a lot. Of course, six months of live performance is not really enough to draw any real conclusions. As we continue to run the model we will continue to track the out of sample performance.

Figure 8: N-LASR performance in terms of average rank IC for different regions



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

What else can be done?

In our previous version of the N-LASR model, the overall performance is strong; but it can also be quite volatile. This results in the lower average performance out of sample for some regions. There are several aspects that can still improve.

1. The signal score has some sector tilts, which means certain sectors will have higher scores than other sectors. If we construct the portfolio without any sector constraint, we may long stocks from certain sectors, and short stocks from some other sectors. However most managers do not want to take any unnecessary sector exposure.

2. Similar to the sector tilt, for the regional models, the N-LASR model will have some imbedded country bets. Therefore, certain countries will have generally higher or lower N-LASR scores compare to others countries.

3. Like most stocks selection models, the N-LASR model would have a higher score for small cap stocks than large cap stocks. However, in reality large cap stocks are usually more liquid and easier to trade, and the transaction cost for large cap stocks are much lower. Improving the performance for the large cap stocks will have a huge benefit for real world performance.

4. The performance of the N-LASR model is negatively correlated with the market. This is to some extent a good property, since we can hedge market risk. However, the N-LASR model will typically have negative performance when the market rallies. The reason is because many quant factors have some negative beta tilt which hurts the model when the market rallies.

5. The raw signal still has some drawdowns for certain market conditions. If we simply trade the N-LASR score without a risk constraint, the maximum drawdown will be intolerable.

The above issues are common problems in most of the quant models, and could be dealt with at the portfolio construction stage. Portfolio managers can set constraints such as sector neutral, country neutral, beta neutral, and liquidity constraints. However, it is sub-optimal since some of the alpha will be eaten away in this process. Instead, we could have a smarter way to solve these problems at the signal level, which will improve the performance significantly, especially in risk adjusted terms. In the following sections, we will show how we tackle these problems to further improve the performance of the N-LASR model.

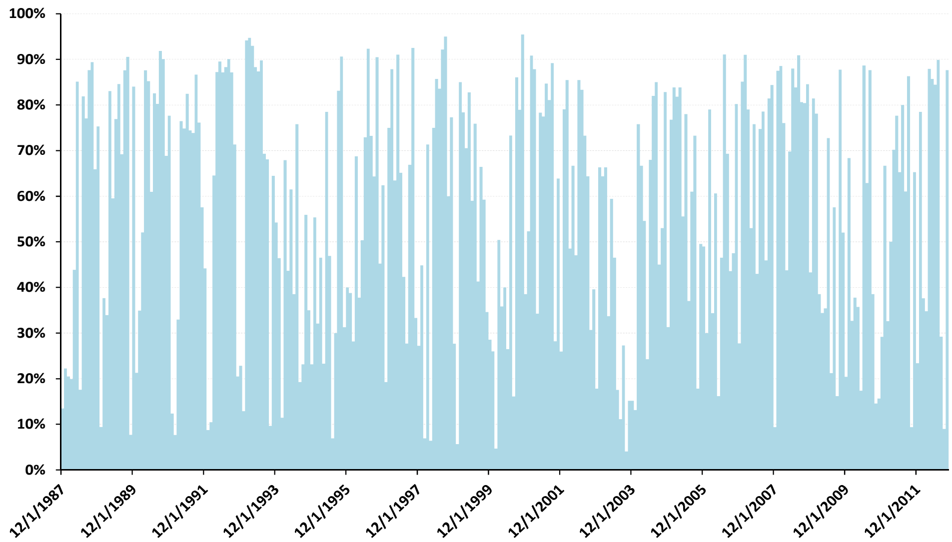
Neutralize for sector and country tilts

Avoiding sector bias

As we know, stocks from different sectors usually have large differences in terms of factor distribution and performance. In our original N-LASR model, we treated all the stocks equally regardless of the sector they belong to. The factor score will naturally tilt towards certain sectors. For example, in the training period, if the Utilities sector outperforms relative to other sectors, then our final N-LASR score will be relatively higher for utility stocks than other sectors. So if we simply long the stocks with a high N-LASR score, we will have a high sector exposure to Utilities sector.

An easy way to look at the sector tilt is to see the percentage of stocks in a sector that are above the median N-LASR score. Ideally, if the score is equally distributed for all the sectors, approximately 50% of the stocks in each sector will be above the universe median score. However, for our original N-LASR score, this is not the case. Figure 9 shows the time series of the percentage of stocks in the Utilities sector are are above the median N-LASR score. As we can see, the percentage of stocks above the median N-LASR score is very volatile, ranging from less than 10% to over 90%. This illustrates that the sector tilt changes over time; there will be positive Utilities exposure in the long/short quantile N-LASR portfolio in some months, while other months will have negative Utilities exposure in the same portfolio. This is because our model is dynamically changing so the sector tilt will also change over time. Of course, certain sectors do perform better than other sectors, meaning this dynamic sector bet might increase the average performance if we are making the right call more often than not. However, taking the sector can be dangerous. For example during the tech bubble, if we tilted towards the tech sector we would have high performance until the bubble burst, followed by a huge drawdown. Most investors cannot afford to have such big drawdowns.

Figure 9: Percentage of stocks in utility sector which is above the median for N-LASR scores for the Russell 3000



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

Sector neutralization to minimize sector risk

To solve this sector exposure problem, sector neutralization could be a good idea. We published a few reports on the topic of factor neutralization (see Luo, et al. [2010b] and Kassam, et al. [2010]). Here we simply introduced a new sector neutralization technique that normalized the factor scores in each sector. Recall that in originally N-LASR we divide the factor ranking by the number of stocks to normalize the factor ranking to between (0, 1]. In the sector neutralization process, we simply normalized the factor scores *in each sector* to (0,1] using the same method. In addition, in the data preparation phase, we define outperformers and underperformers to be the stocks in the top 30% and bottom 30% *in each sector* as measured by one-month forward return.

This sector neutralization technique will focus our algorithm on the relative factor score and stock performance within each sector. The factor score is essentially the percentile within its sector. For example, the outperformers might have negative forward one-month returns as long as they outperform relative to their sectors.

Figure 10 shows an example of the difference between the sector neutral data preparation and the original data preparation. In this example, if we look at the forward return, Utilities stocks outperform Energy stocks. Therefore, in the original data preparation, all the outperformers will be Utilities stocks, and all the underperformers will be Energy stocks. In this case, the final strong classifier for the AdaBoost algorithm is more for classification of Utilities stocks versus Energy stocks; thus, the N-LASR score for the Utilities sector will be higher than the Energy stocks. On the other hand, if we look at the raw factor score, we can see that *within a sector*, higher factor scores usually have higher returns. However, if we use the original data preparation method, since the Utilities sector has generally lower scores and higher returns than Energy stocks, we will get the wrong conclusion: namely that lower factor scores lead to higher returns. This is because the sector effect dominates the factor performance for the raw data. If we use the sector neutral data preparation, we will isolate the sector effect by normalizing the factor score in each sector, and label outperformers and underperformers within each sector. In Figure 10, we find that after sector neutralized data preparation the normalized score is negatively correlated with the label, which means higher raw factor score leads to higher returns.

Figure 10: Example of sector neutral data preparation

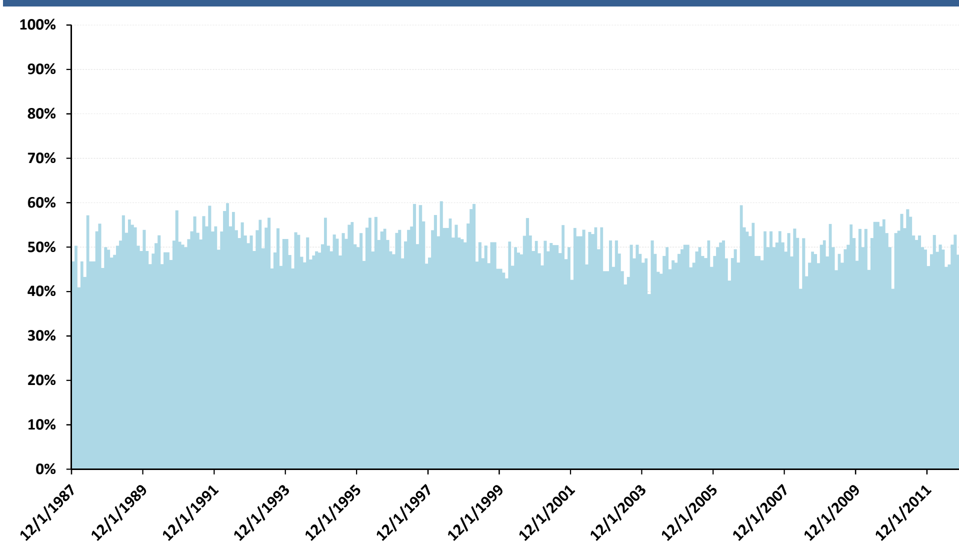
Raw Data			Orignal Data Preparation			Sector Neutral Data Preparation		
sector	raw factor	forward return	factor rank	normalized score	label	factor rank	normalized score	label
utilities	4.16	3.23%	15	0.88	exclude	5	0.71	-1
utilities	4.64	5.36%	9	0.53	1	2	0.29	-1
utilities	4.64	12.78%	8	0.47	1	1	0.14	1
utilities	3.57	6.33%	16	0.94	1	6	0.86	exclude
utilities	4.17	8.30%	14	0.82	1	4	0.57	exclude
utilities	4.60	16.87%	10	0.59	1	3	0.43	1
utilities	3.08	1.81%	17	1.00	exclude	7	1.00	exclude
energy	4.55	-1.62%	13	0.76	exclude	10	1.00	exclude
energy	4.77	-6.38%	4	0.24	-1	4	0.40	exclude
energy	4.57	-12.41%	12	0.71	-1	9	0.90	-1
energy	4.70	-7.46%	6	0.35	-1	6	0.60	-1
energy	4.58	-2.01%	11	0.65	-1	8	0.80	exclude
energy	4.74	3.16%	5	0.29	exclude	5	0.50	1
energy	5.17	3.00%	1	0.06	exclude	1	0.10	1
energy	5.10	2.46%	2	0.12	exclude	2	0.20	1
energy	4.67	0.30%	7	0.41	exclude	7	0.70	exclude
energy	4.79	-6.94%	3	0.18	-1	3	0.30	-1

note: normalized score = factor rank/number of stocks; outperformers: label = 1, underperformers: label = -1

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

We use the sector neutralized factor preparation and train the N-LASR model exactly the same as before. We call this the sector neutral N-LASR. Figure 11 shows the percentage of stocks in the Utilities sector that have an above median score for the sector neutral N-LASR score. We can see that the sector neutral N-LASR scores have approximately 50% of the Utilities stocks that are above the average overall N-LASR score. This means there will be less sector exposure in the sector neutral N-LASR than the original N-LASR. If we compare Figure 11 and Figure 9, we can see that it is much less volatile as well.

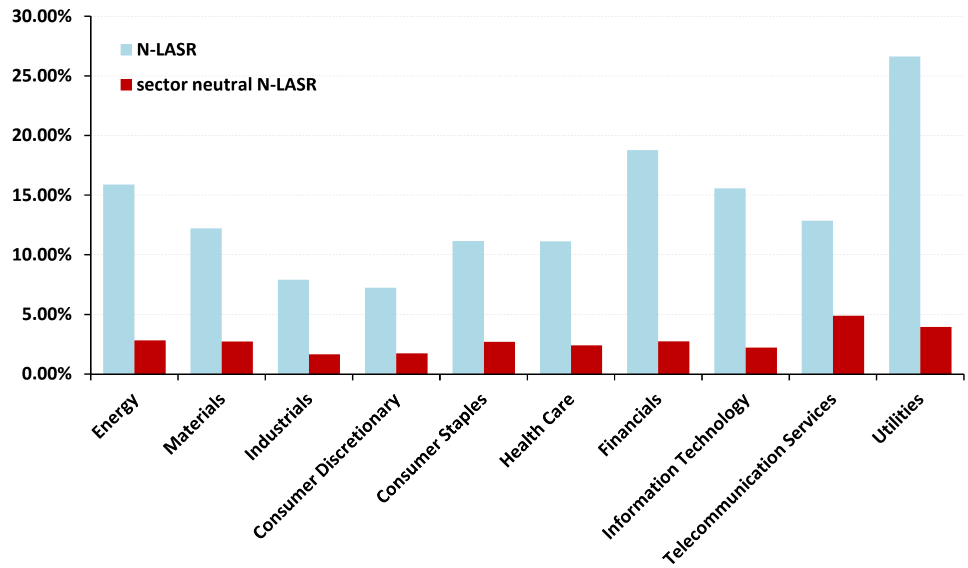
Figure 11: Percentage of stocks in utility sector which is above median for sector neutral N-LASR scores for the Russell 3000



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

Figure 12 shows the standard deviation of the percentage of stocks in each sector that are above the median N-LASR score. For all the sectors, the percentage of the stocks with above average N-LASR scores in that sector are far less volatile for the sector neutral N-LASR.

Figure 12: Standard deviation of percentage of stocks in each sector which is above median N-LASR score



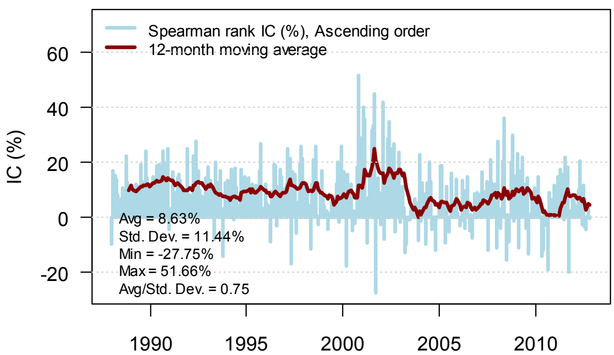
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance comparison after sector neutralization[1]

From the previous section we know the sector neutral N-LASR has less sector exposure in the final score, but what we care about more is whether the performance increases. Figure 13 and Figure 14 show the comparison of rank IC for the N-LASR and the sector neutral N-LASR. We can see that although the average rank IC drops slightly from 8.63% to 8.13%, the risk adjusted the rank IC (defined by the average rank IC divided by the standard deviation of rank IC) increases from 0.75 to 1.1. The number of months where sector neutral N-LASR has negative rank IC is much less than original N-LASR. And the maximum negative rank IC drops more than half from -27.8% to -12.5%. This is exactly as we expected: taking less sector exposure results in lower risk. Although the absolute performance (measure by average rank IC) drops a little, the decrease in the performance is much less than the decrease in risk.

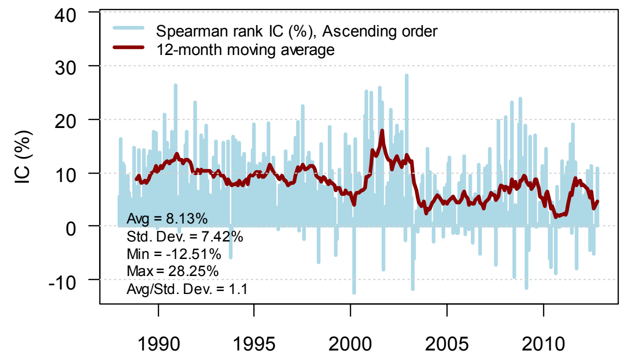
[1]Note: Please note that the N-LASR model is global In this paper, we mostly use the US markets as an example; results for other countries and regions are available upon request.

Figure 13: Rank IC over time for the Russell 3000 from 1987 to 2012 for N-LASR



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

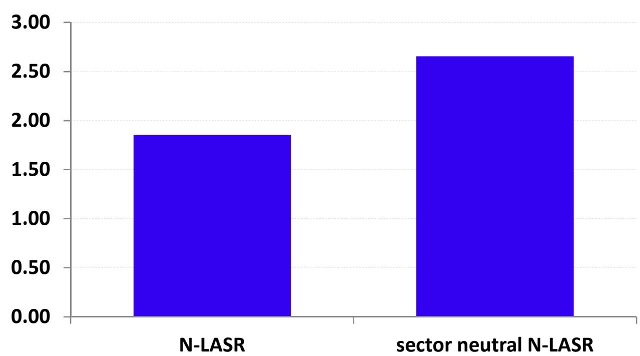
Figure 14: Rank IC over time for the Russell 3000 from 1987 to 2012 for sector neutral N-LASR



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

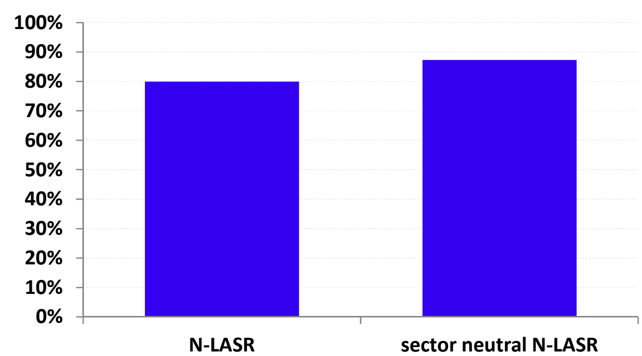
Figure 15 shows the long/short decile Sharpe ratio (before costs) for the Russell 3000 from 1987 to 2012. The sector neutral N-LASR has a more than 40% increase in Sharpe ratio. Figure 16 shows the hit rate for rank IC, which is defined by the number of positive rank IC months divided by the total number of months. As expected, the hit rate for the sector neutral rank IC also is higher than the original N-LASR.

Figure 15: long/short decile Sharpe ratio for the Russell 3000 from 1987 to 2012



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

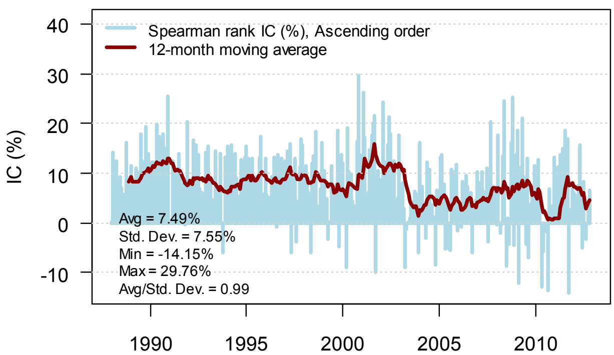
Figure 16: Hit rate of rank IC for the Russell 3000 from 1987 to 2012



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

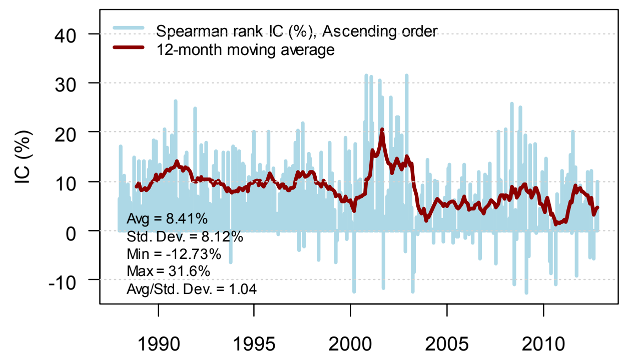
Figure 17 and Figure 18 show the performance in terms of sector neutral rank IC, which is the rank correlation between next month's sector neutral stock returns and the current scores. We define the sector neutral return for a stock as the stock return minus the median return of the sector which this stock belongs to. For the sector neutral rank IC, we find that the sector neutral N-LASR has better performance on a range of metrics: higher average, higher risk adjusted, higher maximum, and higher minimum.

Figure 17: Sector neutral rank IC over time for the Russell 3000 from 1987 to 2012 for N-LASR



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

Figure 18: Sector neutral rank IC over time for the Russell 3000 from 1987 to 2012 for sector neutral N-LASR



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

Sector neutralization at the portfolio construction level versus signal level

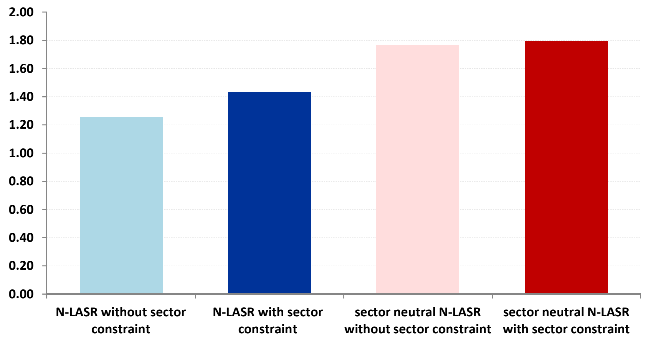
Now we know that sector neutralization for N-LASR increases risk adjusted performance. However, most of the fund managers who do not want sector exposure would set sector constraints at the portfolio construction stage. People would argue we can always set the constraint in the portfolio construction phase, so why bother to neutralize it at signal level? Does sector neutralization at the signal level really add value when we construct the portfolio with a sector constraint?

To answer this question, we compare the performance of an optimized portfolio with and without a sector constraint (maximum 1% sector constraint). We set as little other constraints as possible in order to minimize the effects of other constraints. The constraints we set are maximum leverage constraint (2x maximum leverage, i.e., for $1 capital, the strategy can invests maximum $1 long and $1 short) and volatility constraint (10% annualized volatility).

Figure 19 shows the comparison of Sharpe ratio after transaction costs for the N-LASR and sector neutral N-LASR with and without sector constraints. We can see that the sector neutral N-LASR has much better performance than original N-LASR regardless of sector constraint in the portfolio construction level. This illustrate that sector neutralization at signal level does matter; it will improve the performance even with a sector constraint in portfolio construction. What is more interesting is that the sector neutral constraint at portfolio construction level improves the performance of original N-LASR much more than the sector neutral N-LASR. For the original N-LASR the sector neutral constraint will result in a 15% increase in Sharpe ratio, while the sector neutral N-LASR will only have a 1% increase. This is because the sector constraint won't bind as much for sector neutral N-LASR, therefore the improvement due to the sector constraint won't be as significant.

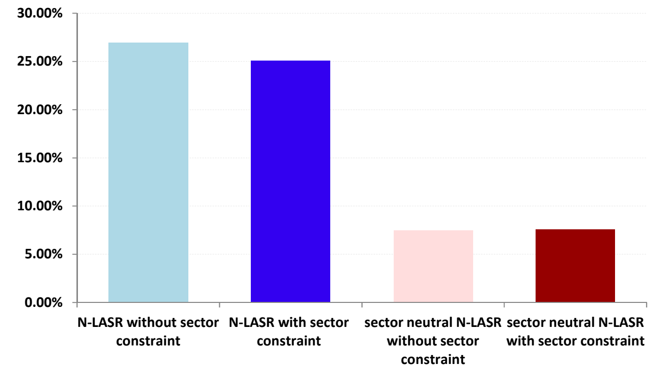
Figure 20 show the comparison of the maximum monthly drawdown after transaction costs for the N-LASR and sector neutral N-LASR with and without sector constraints. We find that the sector neutral N-LASR has significantly lower maximum drawdown than the original N-LASR. The maximum drawdown for sector neutral N-LASR is less than one third of the original N-LASR. Furthermore, with a sector constraint at the portfolio construction level, the maximum drawdown decreased for the original N-LASR but not for the sector neutral N-LASR. This means the sector neutral constraint will have less impact on the sector neutral N-LASR, since the signal is already neutralized for sectors.

Figure 19: Comparison of Sharpe ratio for optimized portfolio (after transaction cost) from 1995 to 2012



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

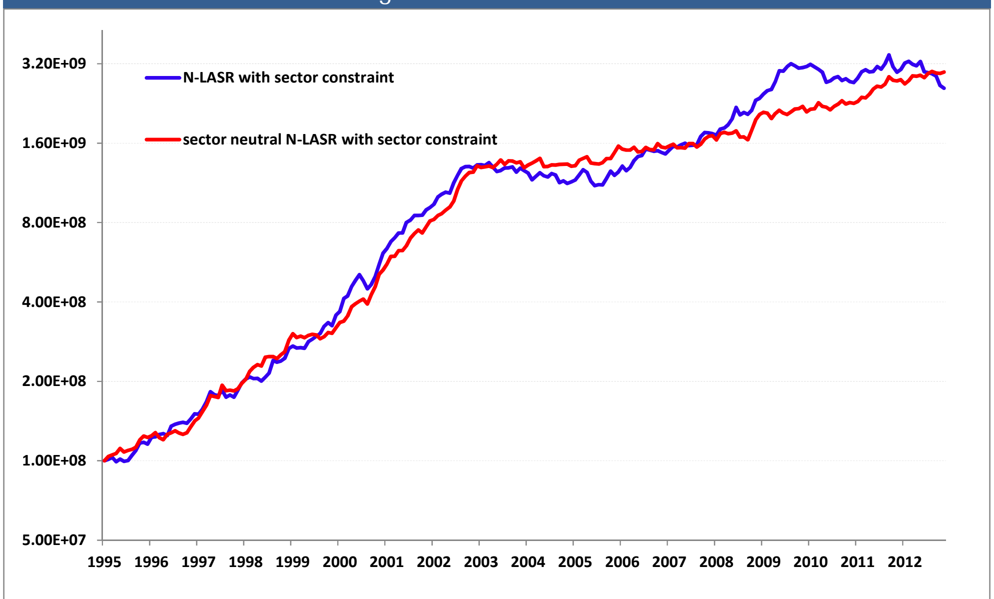
Figure 20: Comparison of max drawdown for optimized portfolio (after transaction cost) from 1995 to 2012



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

Figure 21 shows the wealth curve of the long/short Russell 3000 portfolio after transaction cost for sector neutral N-LASR and original N-LASR with sector constraint. We can see that although the final wealth looks similar, the sector neutral N-LASR has a much smoother wealth curve, with less drawdowns. In addition, in recent years this difference is much more significant than early years. This also suggests that in recent years sector effects play more and more important roles in stock selection.

Figure 21: Wealth curve of the long/short Russell 3000 portfolio after transaction cost for sector neutral N-LASR and original N-LASR with sector constraints



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

To conclude, sector neutralization at the signal level does have superior performance compared to the portfolio construction level. This superior performance not only shows up in a higher Sharpe ratio, but more importantly through much lower drawdowns. This is because sector neutralization at the signal level pays less attention to the factors that differentiate sector performance, and instead focuses more on the general factors that differentiate stock performance across sectors. That is why the stock selection power of sector neutral signal is greater even with a sector neutral constraint.

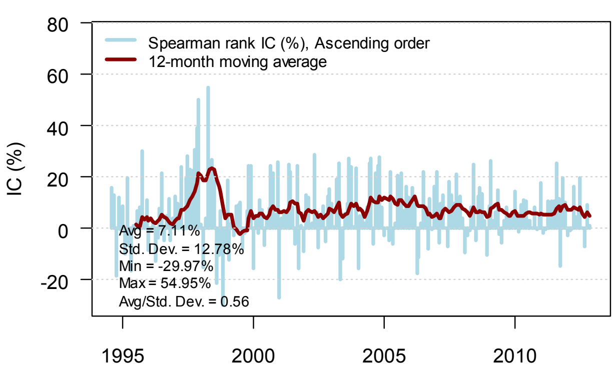
Country neutralization to minimize country effects

For our global and regional N-LASR models, a natural extension of the sector neutralization is country neutralization: normalize the factor score within each country and label outperformers and underperformers for each country. The reason for country neutralization is stocks in different countries might have different characteristics for the same factor and perform differently. Country neutralization can minimize the country exposure in the alpha signal.

We define our country neutral N-LASR model similar to the sector neutral N-LASR model; we simply replace sector with country To make a fair comparison we trained and backtested the original N-LASR model and country neutral N-LASR model both using USD forward returns[2].

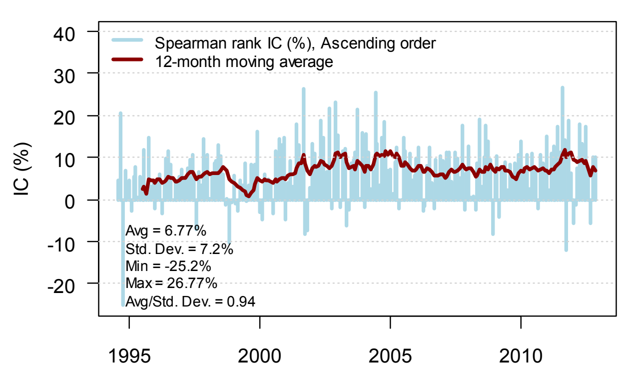
We use emerging markets as an example to demonstrate how the country neutral N-LASR performs. Figure 22 and Figure 23 show the comparison of rank IC for Emerging Markets between the original N-LASR and the country neutral N-LASR. We find a similar conclusion to sector neutralization: the absolute performance (average rank IC) drops a little bit, but the risk adjusted performance almost doubles (measure by risk adjusted rank IC). The number of negative performance months drops significantly, and the max drawdown of the signal also drops.

Figure 22: Rank IC over time for EM from 1994 to 2012 for original N-LASR backtested on USD returns



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

Figure 23: Rank IC over time for EM from 1994 to 2012 for country neutral N-LASR backtested on USD returns

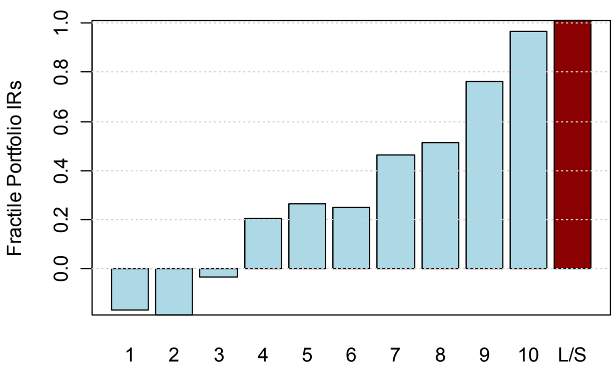


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 24 and Figure 25 compare the decile portfolio Sharpe ratio for EM between the original N-LASR and country neutral N-LASR. Again we find the Sharpe for the long/short decile portfolio increased significantly, more than doubling from less than 1.0x to over 2.5x. And the performance of each decile is more monotonic for the country neutral N-LASR.

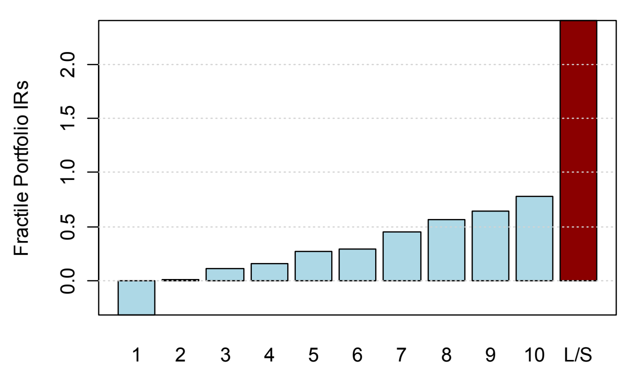
[2] This means that our strategies are currency unhedged.

Figure 24: Decile portfolio Sharpe ratio for EM from 1994 to 2012 for original N-LASR



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

Figure 25: Decile portfolio Sharpe ratio for EM from 1994 to 2012 for country neutral N-LASR



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

Country neutral versus sector neutral

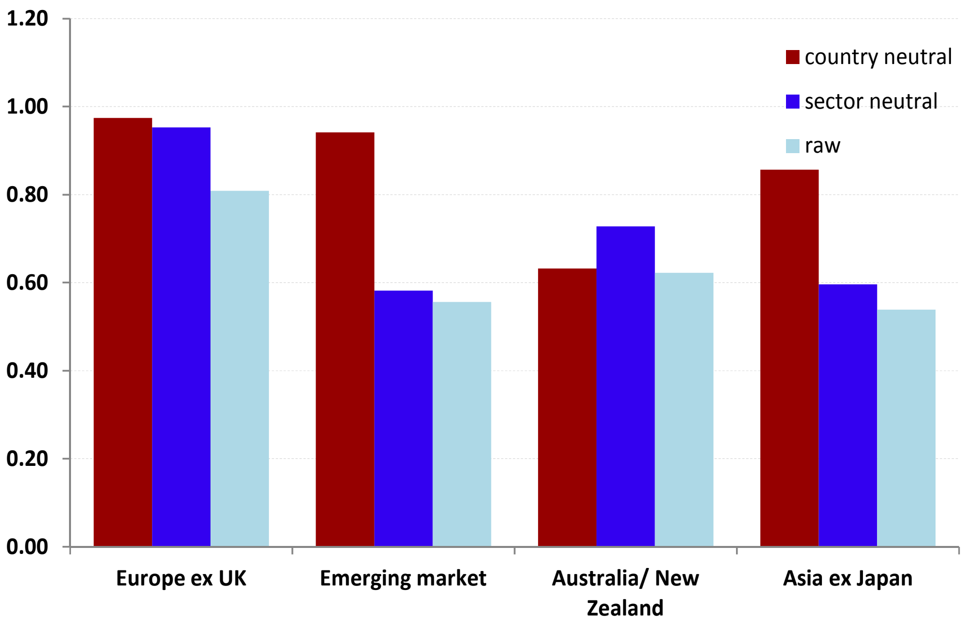
One question people always ask is whether country or sector neutralization plays a more important role in stock selection?

To answer this, we compare the performance of three different N-LASR models using raw factors (original N-LASR), sector neutral factors (sector neutral N-LASR), and country neutral factors (country neutral N-LASR). Figure 26 and Figure 27 show the comparison for risk adjusted rank IC and the long/short decile portfolio Sharpe ratios for different regions. We find interesting conclusions:

- For all the regions, country neutralization has better performance than using raw factors, this suggests that neutralizing for country exposure will increase risk adjusted performance.
- For the Australia/New Zealand region, sector neutralization outperforms country neutralization; this is due to the similarity between these two markets therefore sector difference is more important than country difference.[3]
- For Emerging Markets and Asia ex Japan, country neutral outperforms sector neutral significantly; this is because country effects dominate the sector effect for these markets.
- For Europe ex UK, sector neutral and country neutral have similar performance; this is because European countries are relatively similar, so country effects are less pronounced compared to more geopolitically dissimilar regions.

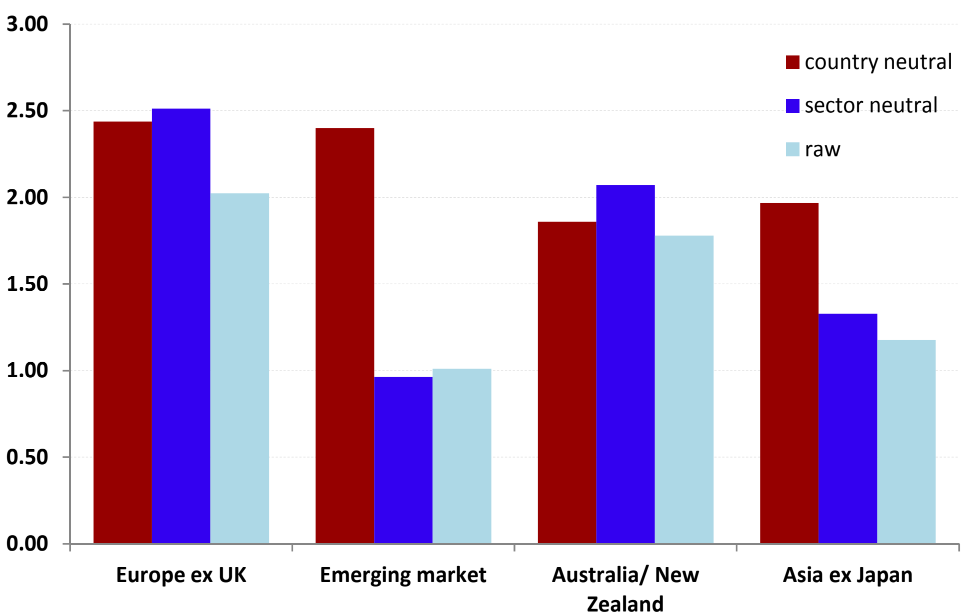
[3] Although one of your authors – a Kiwi – vehemently denies that there is any similarity whatsoever between the two countries, especially when it comes to their respective rugby teams!

Figure 26: Risk adjusted rank IC for different regions, sector vs country neutral



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

Figure 27:Long short decile portfolio Sharpe Ratio, sector vs country neutral



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

Size and beta also matters

The size effect

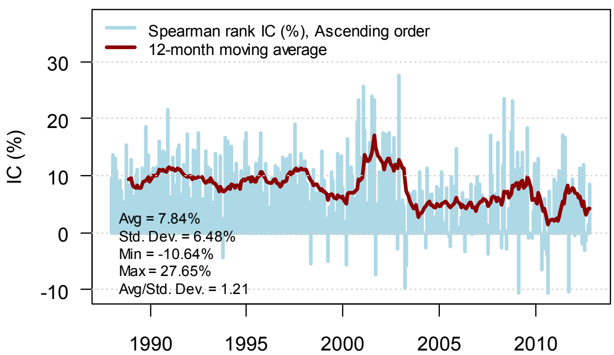
It is well known in finance that small cap stocks outperform large cap stocks (Fama and French [1993]). However, small cap stocks are relatively illiquid and the transaction costs are much higher. They also have a capacity issue; even with a small amount of buying or selling you can easily turn the price against you. In addition, small cap stocks usually are more risky; tilting towards small cap stocks can lead to large drawdowns. Therefore, most managers prefer not to take a size tilt.

Like most other quant models, our N-LASR model will have some embedded size position. This is because in our training data there will be more outperformers for the small cap stocks and thus the final output will be skewed towards small cap stocks. The factors that can differentiate large and small caps will be more likely to be selected.

To neutralize the size effect, we can borrow the ideas from sector neutralization and extend it to size neutralization. Recall that when we neutralize for sectors, we categorize the stocks into sectors, and normalize the factor scores within each category. Similarly, now we can categorize the stocks into two categories: large cap and small cap. Again we normalize the factors within each category. We simply use the median of the market cap as the threshold. Stocks with market cap greater than this threshold would be categorized as large cap stocks, and below this threshold would be categorized as small cap stocks.

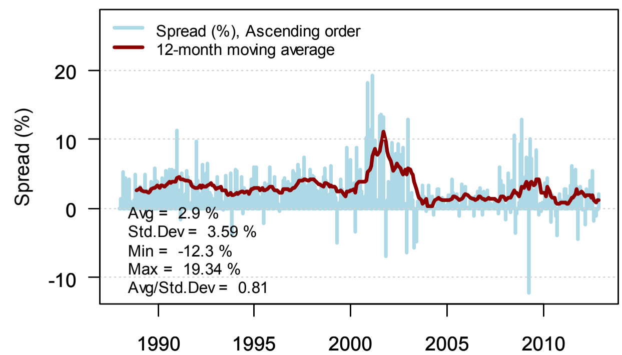
We define our "sector size" neutral N-LASR as follows: for each sector and each market cap size category we normalized the factor scores and forward return before input to the N-LASR model. That means for 10 sectors, each sector has large cap stocks and small cap stocks. So all together we have 20 different categories, and we normalize the factors within each category. Figure 28 shows the rank IC over time for sector size neutral N-LASR, if we compare the performance with sector neutral N-LASR (see Figure 14), the risk adjusted performance is higher. Figure 29 shows the long/short decile spread for sector size neutral N-LASR. We can see that average monthly long/short decile spread unoptimized is almost 3% with a standard deviation of 3.6% (12.5% annualized).

Figure 28: Rank IC over time for the Russell 3000 from 1987 to 2012 for sector size neutral N-LASR



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

Figure 29: Long/short decile spread for the Russell 3000 from 1987 to 2012 for sector size neutral N-LASR



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

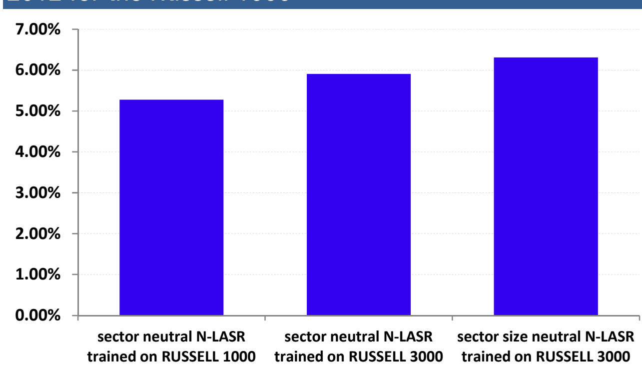
Better performance for the Russell 1000

Neutralizing for size will also have a better performance for large market cap stocks, since after neutralization we will focus on differentiating stocks based on future performance rather than the stocks size effect. To verify this, we backtest different N-LASR models using the Russell 1000 universe. We compare the performance for the Russell 1000 universe for three models: sector neutral N-LASR model trained on the Russell 1000, sector neutral N-LASR model trained on the Russell 3000, and sector size neutral N-LASR model trained on the Russell 3000. For the models trained on the Russell 3000, we can obtain the scores for the Russell 3000 first, and then extract the scores for the Russell 1000 constituents. Because the Russell 1000 is a subset of the Russell 3000, we will have alpha score for each of the stocks in the Russell 1000.

Signal performance for the Russell 1000 universe

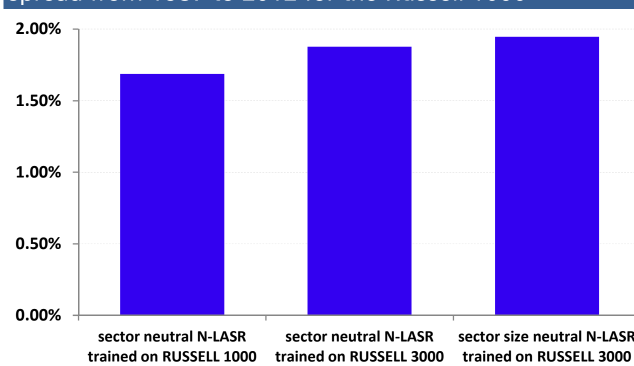
Figure 30 and Figure 31 show the average rank IC and average long/short decile spread of the three models. Figure 32 and Figure 33 show the risk adjusted rank IC and Sharpe ratio for the long/short decile portfolios of the three models. We can see that the performance of the sector size neutral N-LASR trained on the Russell 3000 outperforms the other two models on the Russell 1000.

Figure 30: Comparison of average rank IC from 1987 to 2012 for the Russell 1000



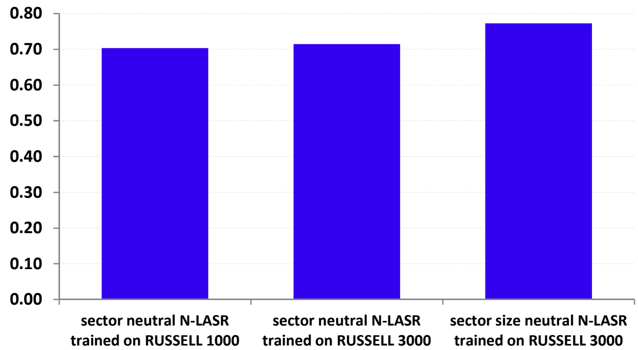
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 31: Comparison of average long/short decile spread from 1987 to 2012 for the Russell 1000



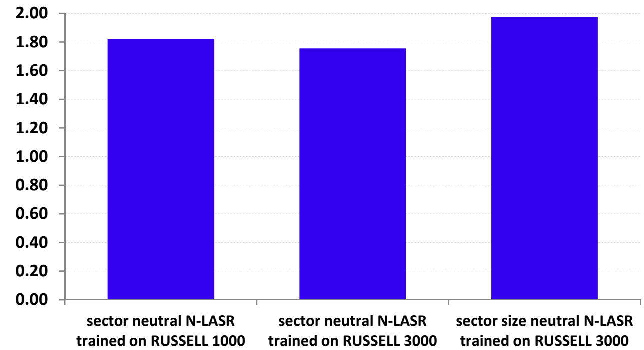
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 32: Comparison of risk adjusted rank IC from 1987 to 2012 for the Russell 1000



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

Figure 33: Comparison of the Sharpe ratio for long/short decile portfolio from 1987 to 2012 for the Russell 1000



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

We noticed two interesting and counterintuitive findings: models trained on the Russell 3000 have higher performance than those trained on the Russell 1000. Different from the Russell 3000, the average performance of the Russell 1000 is higher after size neutralization.

Why is the performance on the Russell 1000 better when the model is trained on the Russell 3000? Especially since the training data might not fully reflect the testing data because they are not the same universe? One reason is because the model trained on the Russell 3000 has more training data to work with, and this offsets the effect of the difference between the testing and training data. As a result, models trained on the Russell 3000 generally have higher performance than those trained on the Russell 1000, even when one only trades Russell 1000 stocks.

Why is performance of the N-LASR model on the Russell 3000 lower on average (average rank IC) after size neutralization compared to the Russell 1000? For the Russell 3000, neutralizing for size means taking less of a size tilt, therefore, it will sacrifice some of the returns as well. However, for the Russell 1000 universe, neutralizing for size actually strengths the signal, since size normalizing the training data would make it look more like the Russell 1000.

Optimized portfolio for the Russell 1000

In addition, we can also compare the performance of optimized portfolio against the Russell 1000 benchmark. We try to set the constraints as realistic and as conservative as possible. Here is the list of constraints we set:

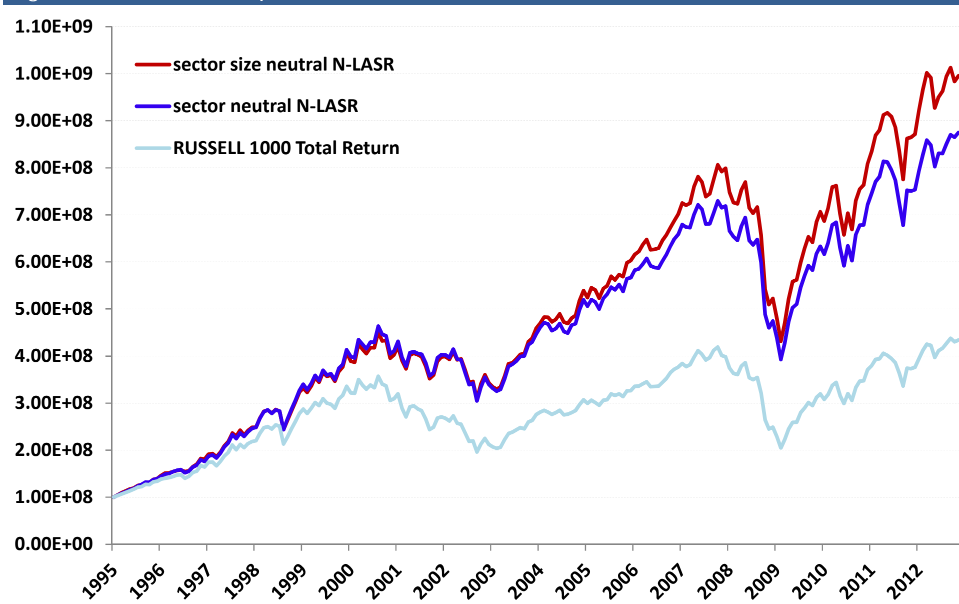
- Benchmark: the Russell 1000 index
- Long only strategy – no short sales are allowed
- No leverage
- Target tracking error 2.5% (relative to benchmark)
- Beta constraint (maximum 0.1 beta difference against benchmark)
- Sector constraint (maximum 10% sector exposure difference against the benchmark).
- Turnover constrained at 30% one-way per month (60% two-way)
- Transaction cost 20 bps one way

- 10% of ADV constraint. (for each stock there is a 10% of average daily volume turnover constraint)
- Starting portfolio size US$ 100 million at beginning of 1995

Notice that the major difference between the current constraints is we added the ADV constraint, which is where the turnover for individual stocks cannot exceed 10% of its ADV (average daily volume) for the past 20 days. This is because in reality some of the less liquid stocks are not able to trade much; even if you could, your trade would impact the stock price. By adding this ADV constraint, the size of the portfolio matters, because as the portfolio size grows, we cannot trade as much stock as we want. It will have great impact for large portfolios, as the ADV constraint will seldom be binding for a $1 million portfolio, but will very likely bind for a $1 billion portfolio. We set our initial size of the portfolio to be $100 million at the beginning of 1995.

Figure 34 shows the cumulative performance for the Russell 1000 after transaction costs. Both of the models are trained on the Russell 3000 universe, and extract the signal for the Russell 1000. We can see that the N-LASR models outperform the benchmark; the total wealth at the end of the period more than doubled the benchmark. Performance for the sector size neutral N-LASR beats the sector neutral N-LASR, which again shows that size neutralization does add value for the large cap stocks.

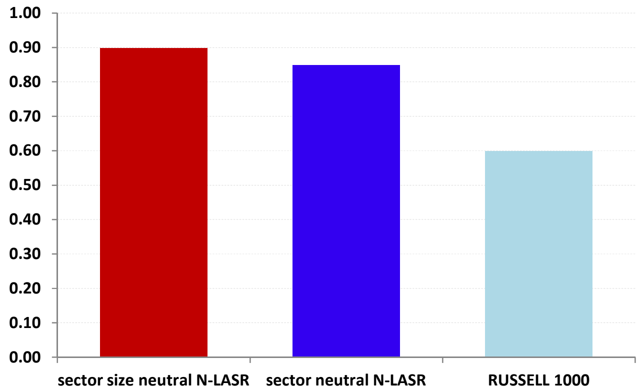
Figure 34: Cumulative performance for the Russell 1000 after transaction cost



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

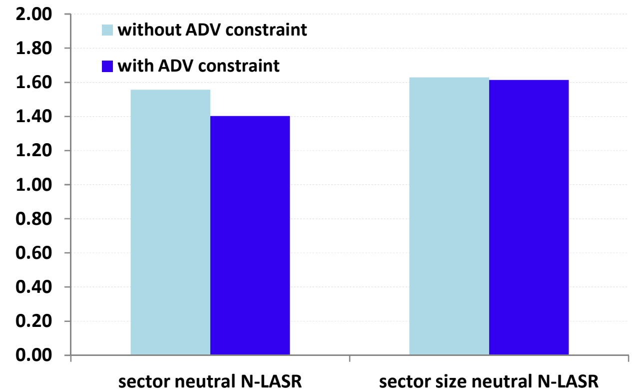
Figure 35 shows the Sharpe ratio for the N-LASR models and the Russell 1000 total return index. The Sharpe ratio is much higher for the N-LASR models compared with the benchmark. We also compare the performance in terms of information ratio against the Russell 1000 benchmark. Figure 36 shows the information ratio of the N-LASR model against the Russell 1000 benchmark. We also include the performance of the same optimized portfolio without the ADV constraint; all other constraints are exactly the same.

Figure 35: Sharpe Ratio for the long only against the Russell 1000 from 1995 to 2012



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

Figure 36: Information ratio for the long only against the Russell 1000 from 1995 to 2012



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

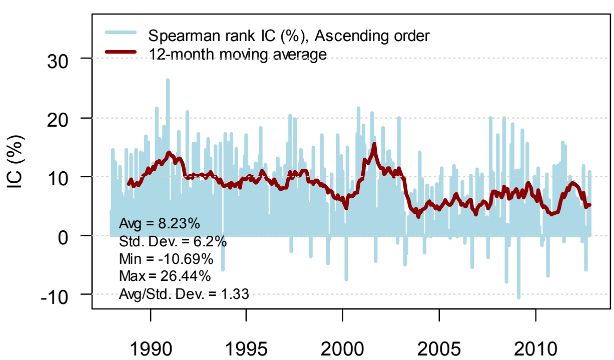
There are two interesting findings. First, sector size neutral N-LASR outperforms sector neutral N-LASR with or without the ADV constraint. This means the signal after we neutralize for size does have higher predictive power. Second, size neutralization performs well with the ADV constraint. The information ratio for sector neutral N-LASR drops 10% with the ADV constraint, while the information ratio for sector size neutral N-LASR only drops 1% with the ADV constraint. This suggests that size neutralization trades more large cap stocks, which are more liquid and thus won't bind as much on the ADV constraint. This means size neutralization can scale up to larger asset under management more easily.

Why neutralize for beta?

One hot topic in quant these days is about low beta stocks outperforming high beta stocks. This topic is also related to the low volatility strategy, because low beta stocks are usually low volatility stocks. Many of the quant factors have some beta tilt; therefore, most of the quant models take some beta bet. Since our N-LASR model automatically selects factors, it is impossible to avoid this low beta bet in the alpha score. In fact, this is the reason why our N-LASR model is highly negatively correlated the market. This will result in large drawdowns when the market suddenly rallies, for example, our N-LASR had its biggest drawdown in March 2009, which is well known as the junk rally.

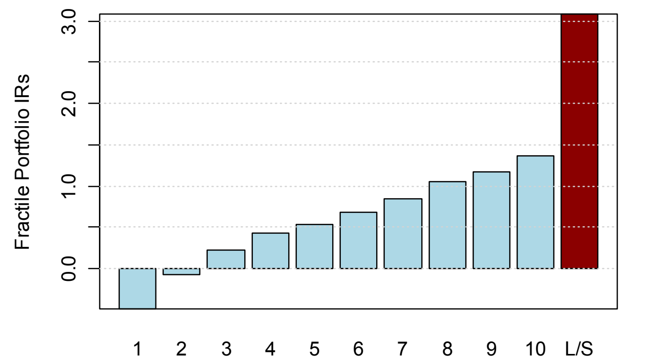
To deal with problem, we can adapt the neutralization idea for beta, similar to how we neutralize for size. We categorize the stocks into high beta stocks and low stocks. High beta stocks are defined as the stocks with one year beta above the median, and low beta stocks are the ones with beta below median. Figure 37 shows the rank IC over time for sector beta neutral N-LASR. Compared with Figure 14 we can see that sector beta neutral N-LASR not only has higher risk adjusted rank IC compared to standalone sector neutral N-LASR, but also higher average rank IC. Figure 38 shows the decile Sharpe ratio (before cost) over time for the sector beta neutral N-LASR. The performance of each decile is almost monotonic, with a long/short decile Sharpe ratio over 3.0x.

Figure 37: Rank IC over time for the Russell 3000 from 1987 to 2012 for sector beta neutral N-LASR



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

Figure 38: Decile Sharpe ratio (before cost) for the Russell 3000 from 1987 to 2012 for sector beta neutral N-LASR

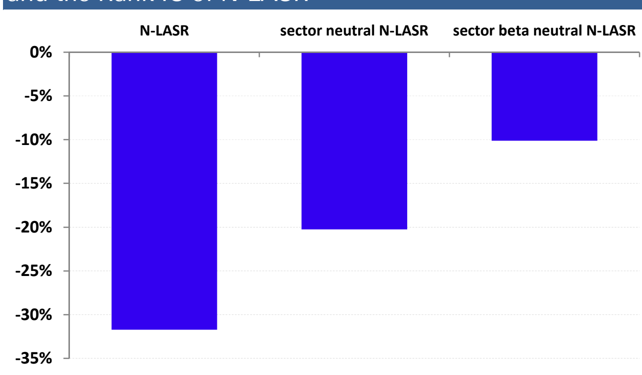


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 39 shows the correlation between the rank IC of the N-LASR and S&P 500 index. We can see that our original N-LASR is highly negatively correlated with the market, with a negative 30% correlation, while sector neutral N-LASR is less negatively correlated with the market with a correlation around negative 20%. This is because sector neutral N-LASR also has imbedded beta neutralization, as some sectors generally have higher beta, and some sectors have lower beta. And as we expected, the sector beta neutral N-LASR has indeed the lowest negative correlation with the market, only around negative 10%. This verifies that beta neutralization will take less directional market exposure.

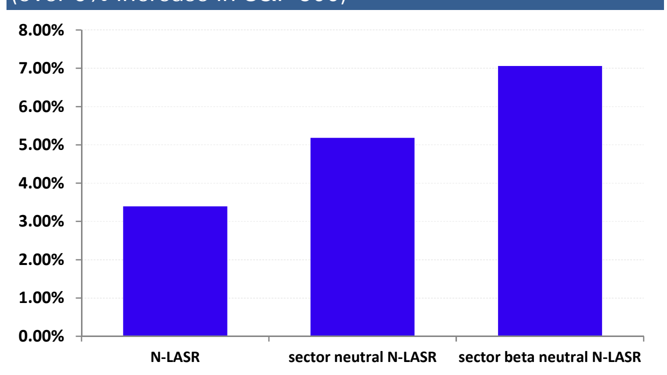
To further illustrate the advantage of beta neutralization, Figure 40 shows the average rank IC of N-LASR when the market rallies (defined as over 6% increase in S&P 500 in one month). Sector neutral N-LASR has better performance than original N-LASR, while sector beta neutral N-LASR has the best performance when market rallies, more than double the original N-LASR.

Figure 39: The correlation between the S&P 500 index and the Rank IC of N-LASR



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

Figure 40: Average rank IC of N-LASR when market rallies (over 6% increase in S&P 500)



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

In addition, among the 25 months where the market is up over 6%, original N-LASR has nine negative months for rank IC, sector neutral N-LASR has seven months and sector beta neutral N-LASR has only four months. What is more impressive about beta neutralization is among those seven months where the market rallies and sector neutral N-LASR has negative rank IC, sector beta neutral N-LASR outperforms sector neutral N-

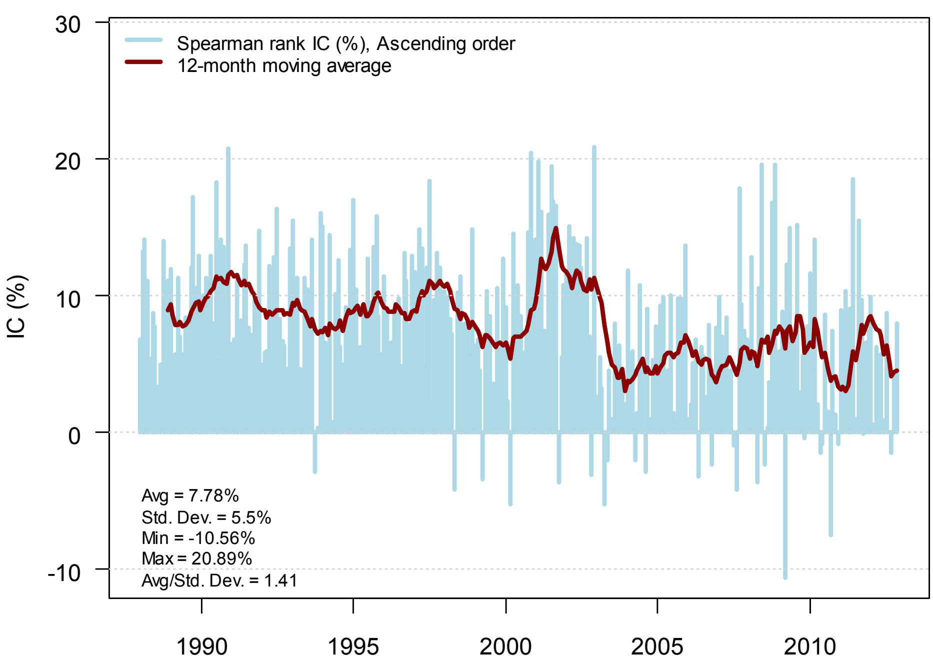
LASR for every single month, and on average outperforms by 6.3% in terms of rank IC. For example, one of the biggest re-risking months recently was October 2011, when the market rallied over 10% in that month. The original N-LASR had a negative 20% rank IC in that month, and even the sector neutralized N-LASR had a negative 7.8% rank IC. However, the sector beta neutralized N-LASR had a positive 2.0% rank IC.

Performance enhancement after neutralizing for sector, size and beta

In the previous sections we showed that both size neutralization and beta neutralization are powerful tools to enhance the performance of N-LASR, especially to lower size bias and market risk. Can we combine them and have the advantage of both? The answer is yes! All we need to do is to repeat the process of neutralization for one more layer. We define the sector size beta neutral N-LASR as follows: for each sector, each size and each beta category, we normalized the factor scores and forward returns. So all together we have 40 different categories, and we normalize the factors and forward returns within each category.

Figure 41 show the rank IC over time for sector size beta neutral N-LASR from 1987 to 2012. Compared with Figure 28 and Figure 37, we can see that the average rank IC goes down a little bit, but the risk adjusted rank IC goes up. There are less negative months and the standard deviation of rank IC also drops.

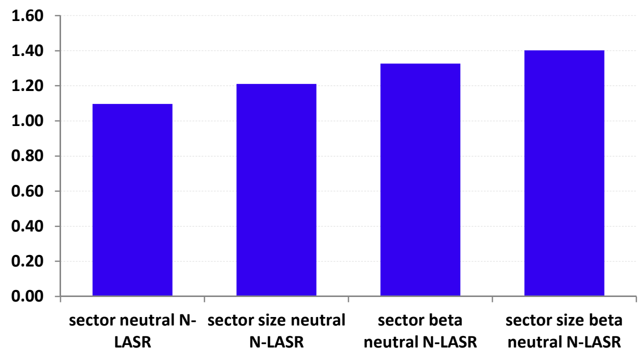
Figure 41: Rank IC over time for sector size beta neutral N-LASR for the Russell 3000 from 1987 to 2012



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

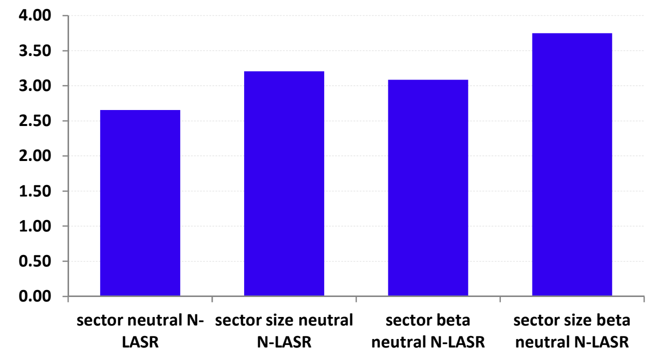
Figure 42 shows the comparison of the risk adjusted rank IC for different N-LASR models, and Figure 43 shows the Sharpe ratio for long/short decile portfolios. We can see that sector size neutral N-LASR and sector beta neutral N-LASR have similar performance, they both outperform sector neutral N-LASR. As we expected, the sector size beta neutral N-LASR has the best performance, with a risk adjusted rank IC of 1.4 and Sharpe ratio for the long/short decile portfolio of about 3.8x.

Figure 42: Comparison of risk adjusted rank IC from 1987 to 2012 for the Russell 3000



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

Figure 43: Comparison of Sharpe ratio for long/short decile portfolio from 1987 to 2012 for the Russell 3000



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

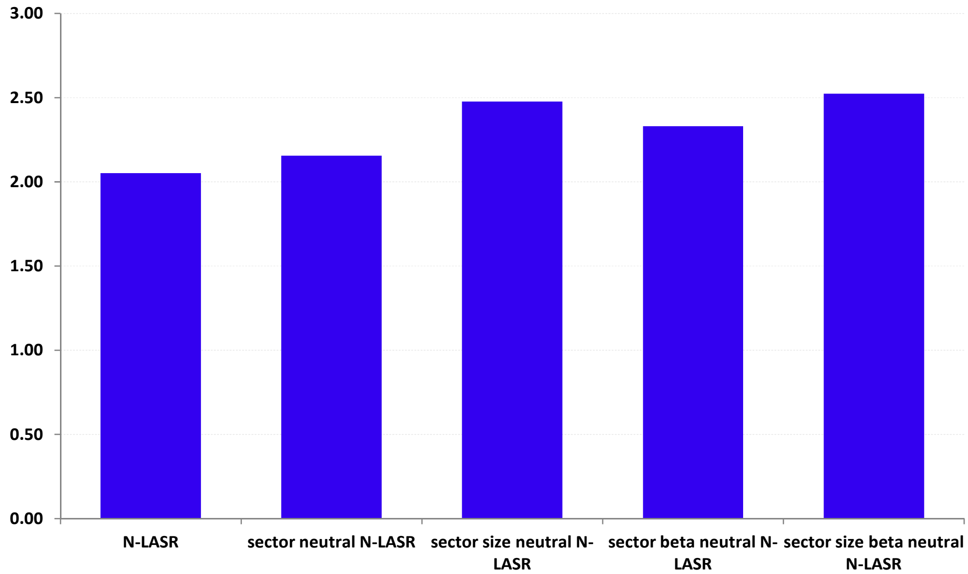
Comparison of optimized portfolio with full constraint

We also compare the performance of optimized portfolios from 1995 to 2012 with a realistic set of constraints. Here is the set of constraints we have:

- Long/short market neutral strategy
- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized volatility of 4%
- Maximum single stock weight 1.5%
- Beta neutral (maximum 0.1 beta exposure)
- Sector neutral (maximum 10% sector exposure).
- Turnover constrained at 60% one-way per month
- Transaction cost 20 bps one way
- 10% of ADV constraint. (for each stock there is a 10% of average daily volume in 20 days turnover constraint)
- Starting portfolio size US$ 100 million at beginning of 1995

Figure 44 shows the Sharpe ratio of the long/short market neutral portfolio after transaction costs for different N-LASR strategies for the Russell 3000. The performance of the optimized portfolios is mainly in line with the risk adjusted rank IC for different models. The original N-LASR has Sharpe ratio of 2.0x, but after several layers of neutralization it increases to 2.5x for sector size and beta neutral N-LASR. One thing we notice is size neutralization improves the performance more than beta or sector neutralization. Figure 42 showed that sector beta neutral N-LASR has higher risk adjusted rank IC compare to sector size neutral N-LASR, but the performance for the optimized portfolio is opposite. This is mainly because of the ADV constraint. For the optimization on the Russell 3000 stock universe, the ADV constraint will have a greater impact than for the Russell 1000. Some of the small cap stocks are not as liquid; therefore they will bind very often because of the ADV constraint.

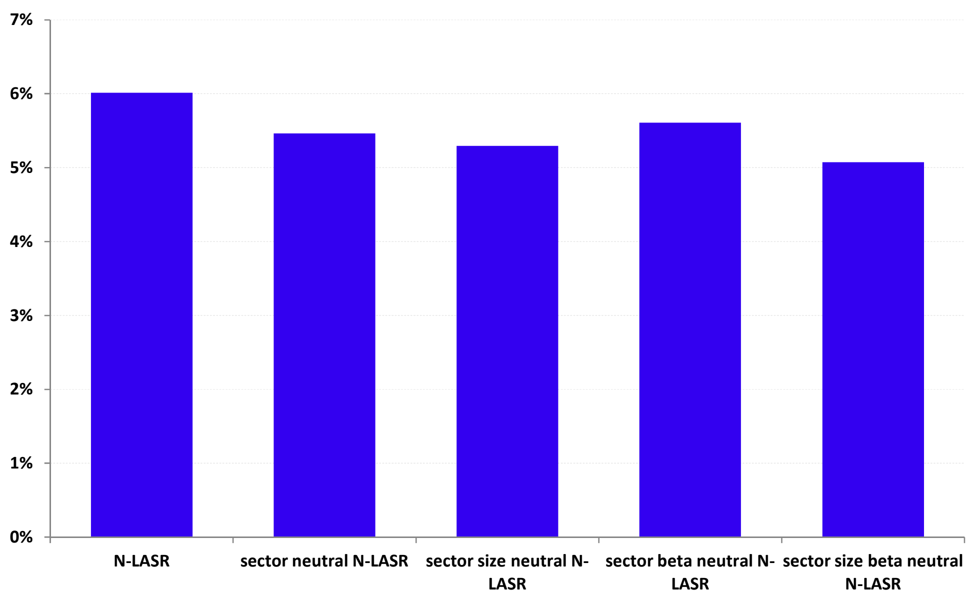
Figure 44: Sharpe ratio of long/short optimized portfolio after transaction cost



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

Figure 45 shows the realized volatility (annualized) for different N-LASR models for the optimized portfolio. Note that we set our target risk to be 4%, and the sector size beta neutral N-LASR has the lowest realized volatility of 5%, while the original N-LASR model has realized volatility of 6%.

Figure 45: Realized annual volatility of long/short optimized portfolio after transaction cost



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

Adjusting for different market conditions

One more step: Adjusting for different market conditions

Now we have built our sector size beta neutral N-LASR model which performs well. However, in certain market conditions there is still room to improve. For example, the maximum monthly drawdown for the long/short decile portfolio is 11%. How can we improve for this?

If we look at those months when sector size beta neutral N-LASR has had challenging performance, they mostly occur in market re-risking episodes. For example, for all of the four months where rank IC is below negative 5% the S&P 500 index rallied by more than 8% during the month. This suggests the current model underperform mainly due to rapid shifts from risk-off to risk-on. Unfortunately we've had a lot of these recently, so what can we do to mitigate this?

One way to deal with this regime switching problem is to add a market timing signal such as VRP (details see Luo. et al. [2011]) on top of the current alpha generator, e.g. turn off the N-LASR alpha generator when the market timing signal suggests the market is going to rally. However, among the 11 months where the market rallied with over 8% return, there were six months where the rank IC of the N-LASR model was over 7%, and the average of those six months was greater than 10%. That means even if we have the perfect market time signal and turn off the alpha generator accordingly, we would risk turning off the alpha generator at the wrong time.

We suggest another way to "hedge" this negative performance when the market re-risks. Since we don't know whether the market is going to switch, we can add another model to capture this different market condition. Recall that in our originally N-LASR we have three strong classifiers; each was trained using different data. The first classifier uses the trailing 12 months of data; the second classifier uses the trailing 12 years *in the same month*; and third classifier uses just the previous one month of data. The model with different market condition is the fourth classifier constructed from the months where the current N-LASR model has poor performance.

The definition of the months with different market conditions is quite straight forward. Here are the steps:

- We build our N-LASR model as usual at the current date.
- Use this model to generate N-LASR scores for the each of the previous months in the past 12 years.
- For each of the previous months in the past 12 years, calculate the rank correlation (rank IC) between N-LASR score generated in the previous step and the forward one month return. In other words, examine how the current model would have performed historically.
- We consider those months where the rank IC calculated in the previous step is below a certain threshold as the months with different market conditions.
- We build a strong classifier using the factor data and forward returns from those months with different market conditions.

- To make it simple and comparable to our previous N-LASR model, our final N-LASR model with different market conditions combines four classifiers in the following way: the weights of the original three strong classifiers remain the same, and the fourth classifier takes the average weight of the other three classifiers. Then the weights are normalized.

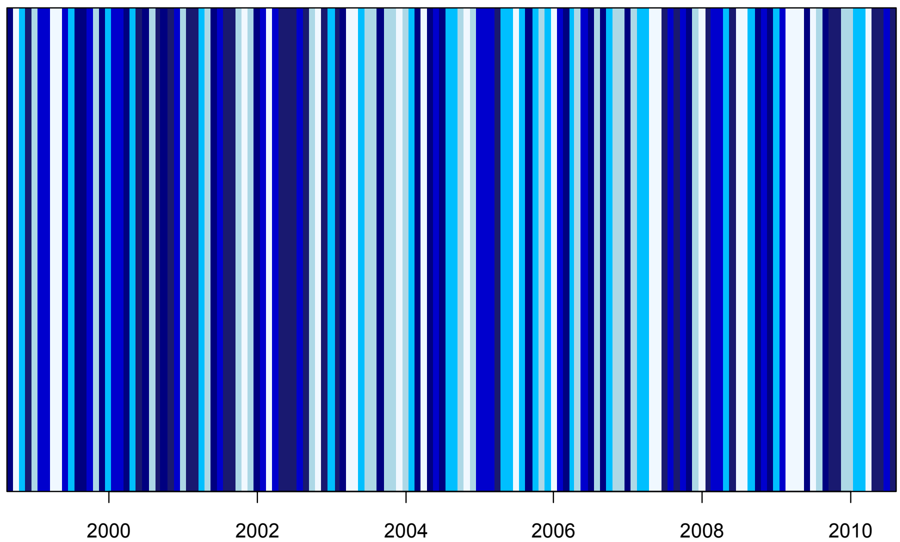
In the fourth step, we have a threshold for rank IC to define the months with different market conditions. This threshold sets a tradeoff between the average performance and the risk. A lower threshold means lower average performance but also lower risk. Setting the threshold low will only allow a few of the months to pass this threshold, resulting in a strict definition for different market conditions. Thus, those months used to train the fourth classifier are very different. They can better hedge big changes in market conditions, but will sacrifice performance when the market conditions are normal, as our previous N-LASR model will perform well most of the time.

Notice that in our previous N-LASR model, we only used a small portion of months in the previous 12 years for training. Setting the threshold relatively high can not only hedge the risk of changing market conditions, but also include more training months that can strengthen the predictive power of the model. To make it simple, we set this threshold to be 7.5% which is close to the average rank IC.

Take the end of August 2010 as an example, Figure 46 shows the predictive power of the previous months using classifiers built at end of August 2010. The darker color means more predictive power. This predictive power is simply the rank correlation (rank IC) between the one month return and the N-LASR score based on the classifiers built in August 2010. Therefore, the months with different market conditions are the months where the colors are light. In this case, those months are when market rallied in the following month. The average monthly market return in that 12 year period is 0.2%, however the average forward one-month return for those months with rank IC below 0% is 3.1%. The rank IC using the N-LASR model built at the end of August 2010 has a negative 8% rank IC. However, the model built using the different market conditions has rank IC of over 15%.

Deutsche Bank Securities Inc.

Figure 46: The predicting power of previous months using classifier build at end of August 2010



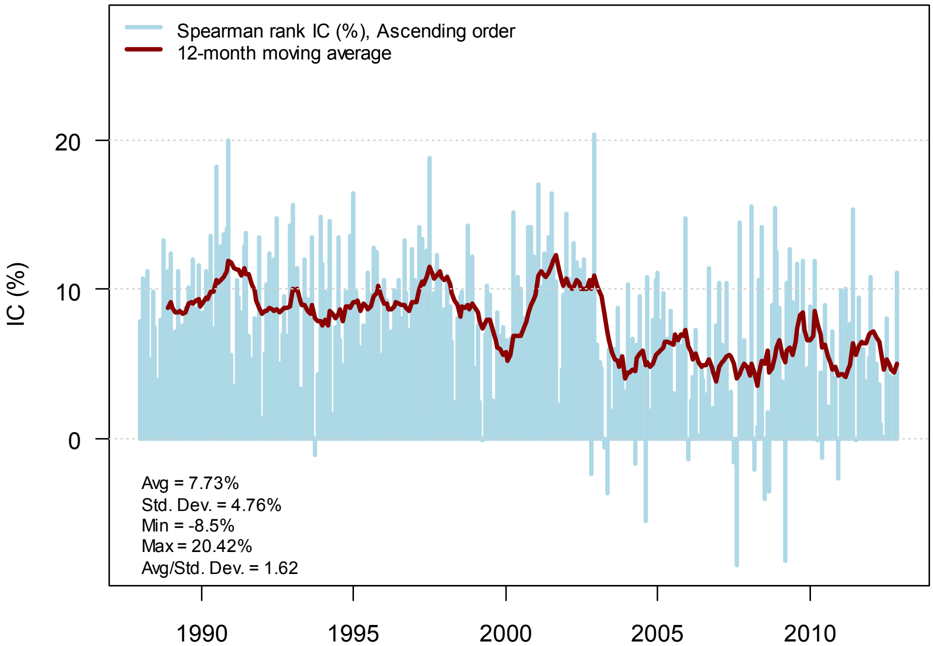
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Stable performance over time

Based on our sector size beta neutral N-LASR we add the model that captures different market conditions. Figure 47 shows the rank IC over time for the Russell 3000 from 1987 to 2012 after adjusting for different market conditions. We can see that compared with Figure 41 the average rank IC remains similar, but the risk adjusted rank IC is even higher, increasing to 1.62. There are only 15 months out of 300 where the model has negative performance; this gives a 95% hit rate for a 25 year period.

The higher risk adjusted performance is mostly because the model for the different market conditions hedges the risk when the market conditions change. If we look at the performance of the scores generated by this one classifier alone, the average rank IC is only 3.55%, however, the correlation between the rank IC of this classifier and the original sector size beta neutral N-LASR is negative 18%. This is the main contribution to the increase in the risk adjusted rank IC.

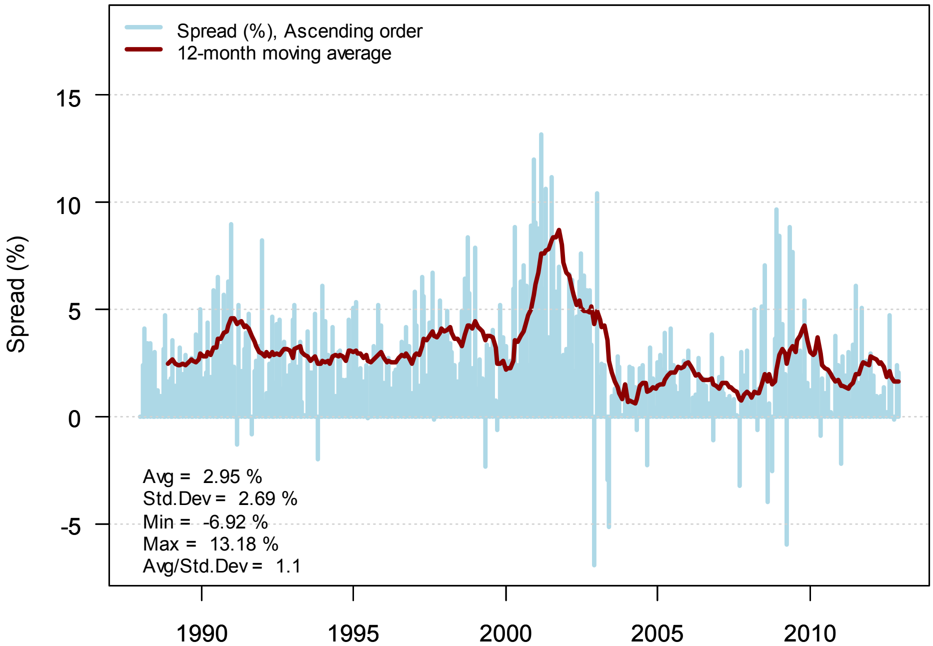
Figure 47: Rank IC over time for the Russell 3000 from 1987 to 2012 after adjusting for different market conditions



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

Figure 48 shows the long/short decile spread for the Russell 3000 from 1987 to 2012 for the N-LASR model adjusting for different market conditions. We can see that average long/short decile spread is almost 3% monthly, result in a cumulative annualized return of over 40% with a standard deviation of 9.3% (annualized). The maximum drawdown is less than 8%. This means if we could trade the long/short decile portfolio, even without optimization the performance is strong.

Figure 48: Long/short decile spread over time for the Russell 3000 from 1987 to 2012 after adjusting for different market conditions

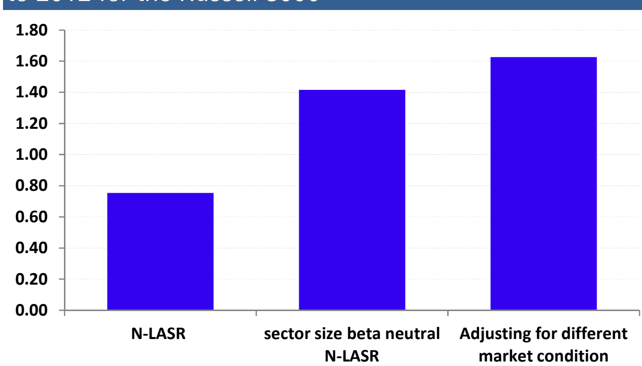


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Figure 49 shows the comparison of the risk adjusted rank IC for the original N-LASR models, sector size beta neutral N-LASR, and the N-LASR model adjusting for different market conditions. Figure 50 shows the comparison of the Sharpe ratio for the long/short decile portfolios for those models.

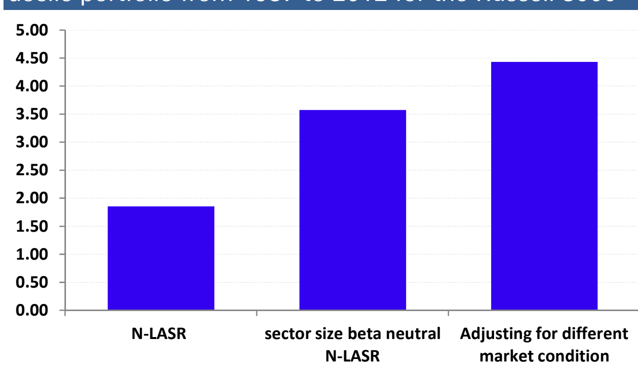
We can see that adjusting for different market conditions will have much better risk adjusted performance. The risk adjusted rank IC more than doubled from less than 0.8 to over 1.6, and long/short decile Sharpe ratio also more than doubled from less than 2.0x to over 4.4x.

Figure 49: Comparison of risk adjusted rank IC from 1987 to 2012 for the Russell 3000



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

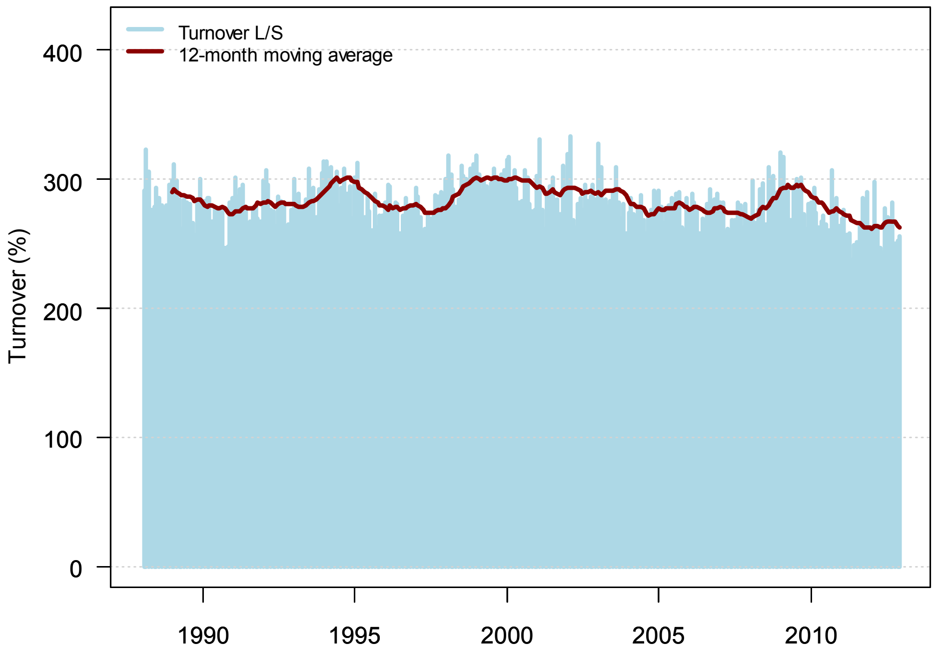
Figure 50: Comparison of Sharpe ratio for long/short decile portfolio from 1987 to 2012 for the Russell 3000



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

Figure 51 shows the turnover of the long/short decile portfolio over time for the Russell 3000 from 1987 to 2012 after adjusting to market condition. The turnover is still quite high, but we will deal with this by constructing optimized portfolio with the turnover constraint in the last section.

Figure 51: The predicting power of previous months using classifier build at end of August 2010



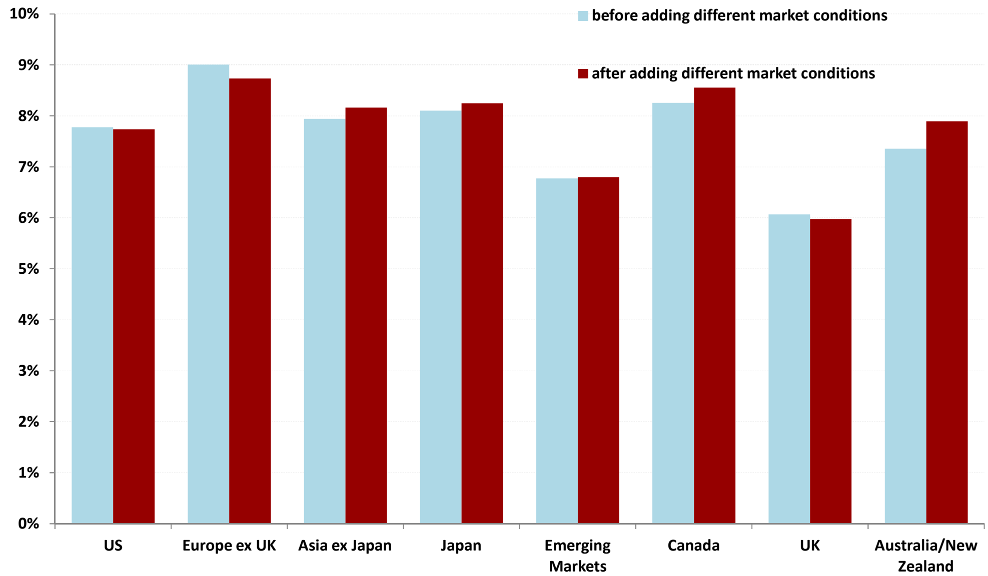
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Does adding different market conditions work for all regions

Does adding different market conditions work for other regions? We compare the performance for the N-LASR models before and after adding the fourth classifier for different market conditions. For the US we used the sector size beta neutral N-LASR model, for other individual countries we use the sector neutral N-LASR model, and for all the regions we use the country neutral N-LASR model.

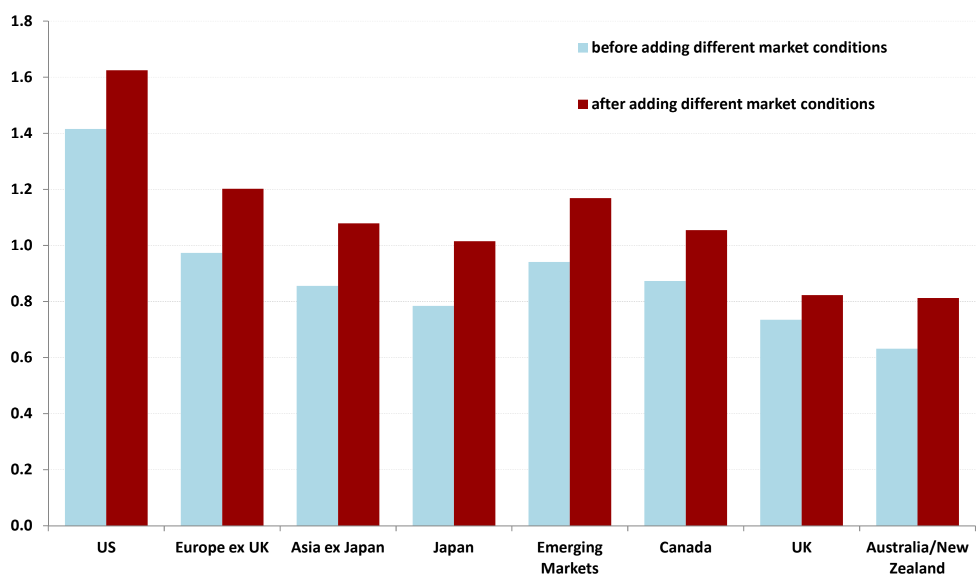
Figure 52 show the comparison for average rank IC for the whole period before and after adding different market conditions. Figure 53 shows the risk adjusted rank IC for different regions before and after adding the fourth classifier. We can see similar findings in all the regions, the average rank IC remain similar, but the risk adjusted rank IC increases a lot. The risk adjusted rank IC increases by between 12% and 30% compared with before adding different market condition.

Figure 52: Average rank IC comparison after adding different market conditions



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

Figure 53: Increase for risk adjusted rank IC after adding different market conditions



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

Enhanced machine learning stock selection

Global N-LASR2 model

In this section we define the second generation of our global N-LASR model. We call it the N-LASR2 model. Figure 54 shows the region definitions for our N-LASR2 model, including individual countries such as US, Japan, Canada and UK, as well as the regions such as Europe ex UK, Asia ex Japan, Emerging Markets, Australia/New Zealand and Global. We start our model when the universe has over 100 stocks, due to data availability different models have different start dates, but all of them have over 18 years of history.

Figure 54: Region definition

Region	Start Date	End Date	Average # of Stocks	Constituent Countries
US	12/31/1987	11/30/2012	2923	US
Europe ex UK	7/31/1990	11/30/2012	1256	Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland
Asia ex Japan	7/31/1990	11/30/2012	1067	HK, Singapore, China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand
Japan	7/31/1990	11/30/2012	1322	Japan
Emerging Markets	7/29/1994	11/30/2012	1624	Brazil, Chile, Colombia, Mexico, Peru, Czech Republic, Egypt, Hungary, Morocco, Poland, Russia, South Africa, Turkey, China, India, Indonesia, Korea, Malaysia, Philippines, Taiwan, Thailand
Canada	12/31/1987	11/30/2012	415	Canada
UK	7/31/1990	11/30/2012	516	UK
Australia/New Zealand	7/29/1994	11/30/2012	260	Australia, New Zealand
Global	12/31/1987	11/30/2012	8206	Canada, US, 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

Figure 55 shows the neutralization schemes used for our global N-LASR2 model. For all the models we add the classifier for different market conditions. For regions we use country neutral, for individual countries other than US we use sector neutral, and for US we use sector size beta neutral. This is because only US has coverage large enough to do many layers of neutralization, and large countries for the sector neutralization. For small countries, for instance those with a hundred stocks, normalizing the factor score in each sector is meaningless, because there will be only a few stocks in each sector. Thus, country neutralization is enough.

Figure 55: Definition of Global N-LASR2 model

Region	Country Neutral	Sector Neutral	Size Neutral	Beta Neutral	Different Market Conditions
US	Not Applicable	Yes	Yes	Yes	Yes
Europe ex UK	Yes	No	No	No	Yes
Asia ex Japan	Yes	No	No	No	Yes
Japan	Not Applicable	Yes	No	No	Yes
Emerging Markets	Yes	No	No	No	Yes
Canada	Not Applicable	Yes	No	No	Yes
UK	Not Applicable	Yes	No	No	Yes
Australia/New Zealand	Yes	No	No	No	Yes
Global	Yes	No	No	No	Yes

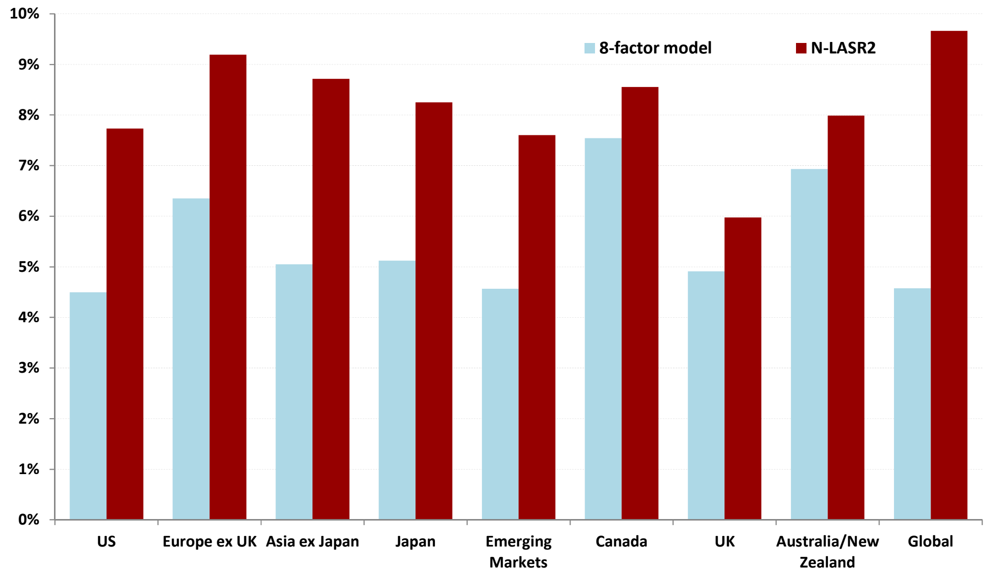
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance of the N-LASR2 model

We compare our N-LASR2 model performance with a standard 8-factor model, using the following factors: earnings yield, earnings growth (EPS growth), reversal (return in past 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 as the N-LASR2 model, all the backtesting is done using USD returns.

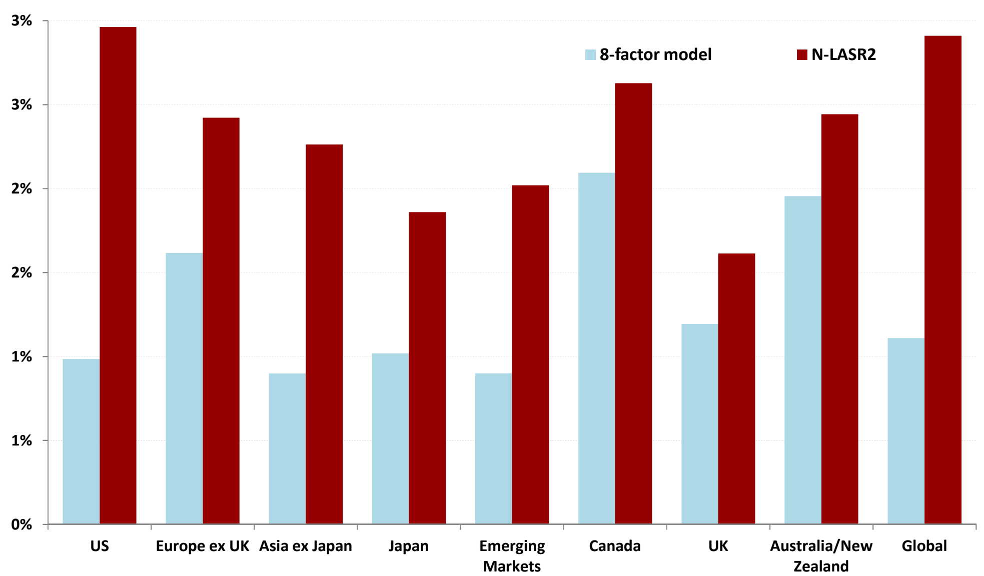
Figure 56 shows average rank IC for different regions, and Figure 57 shows the average long/short decile spread for different regions. We find the N-LASR2 model outperforms the 8-factor model for every region in terms of average rank IC and long/short decile spread. The increase in average rank IC is between 15% and 110%, and the increase in average long/short decile spread is between 25% and 200%.

Figure 56: Average rank IC for different regions



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

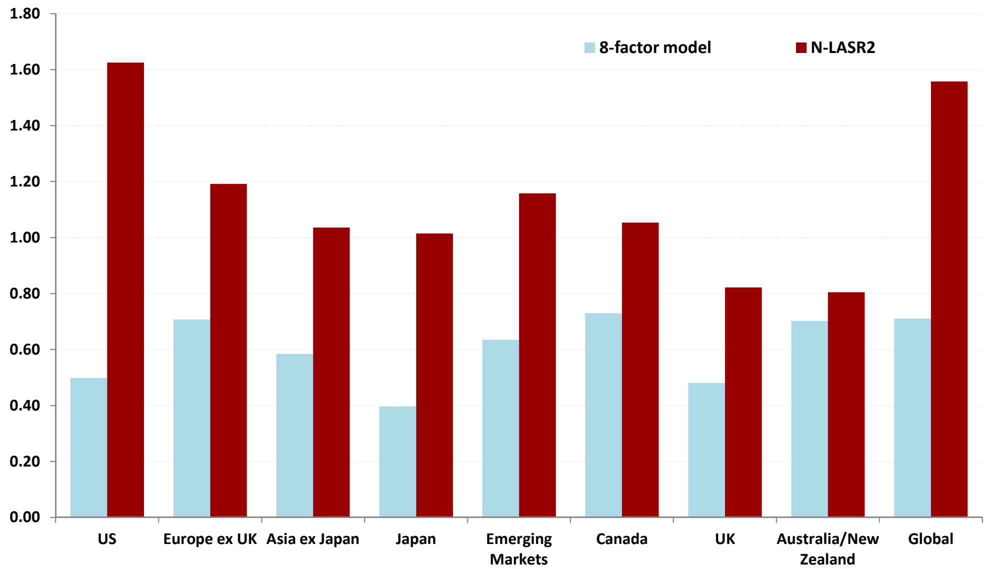
Figure 57: Average long/short decile spread for different regions



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

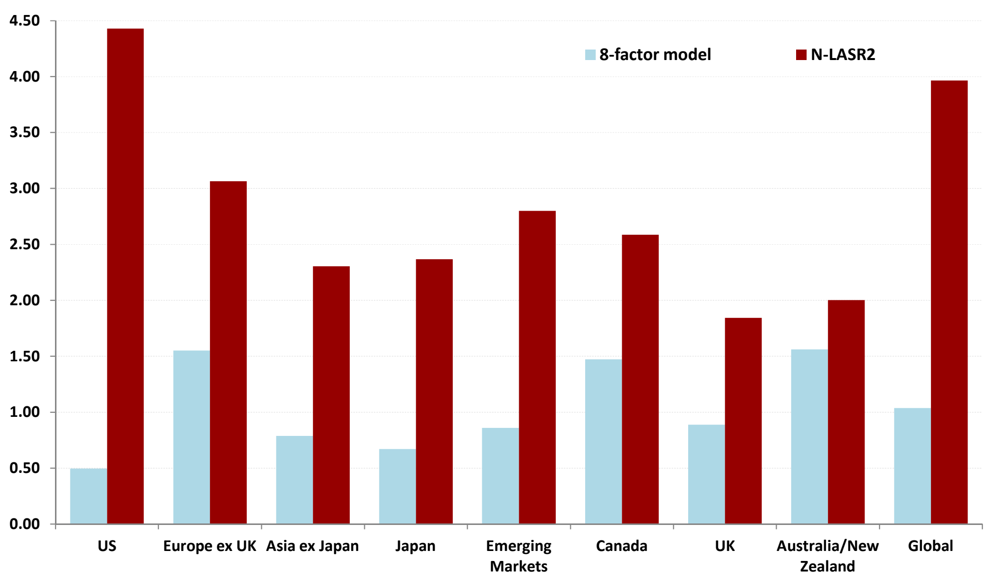
Figure 58 shows the risk adjusted rank IC for different regions, and Figure 59 shows the average long/short portfolio Sharpe ratio for different regions. As we expected, the risk adjusted performance for the N-LASR2 model beats the 8-factor model even more significantly. For most of the regions, the N-LASR2 model more than doubles the risk adjusted performance, especially for US, Japan, and Global.

Figure 58: Risk adjusted rank IC for different regions



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

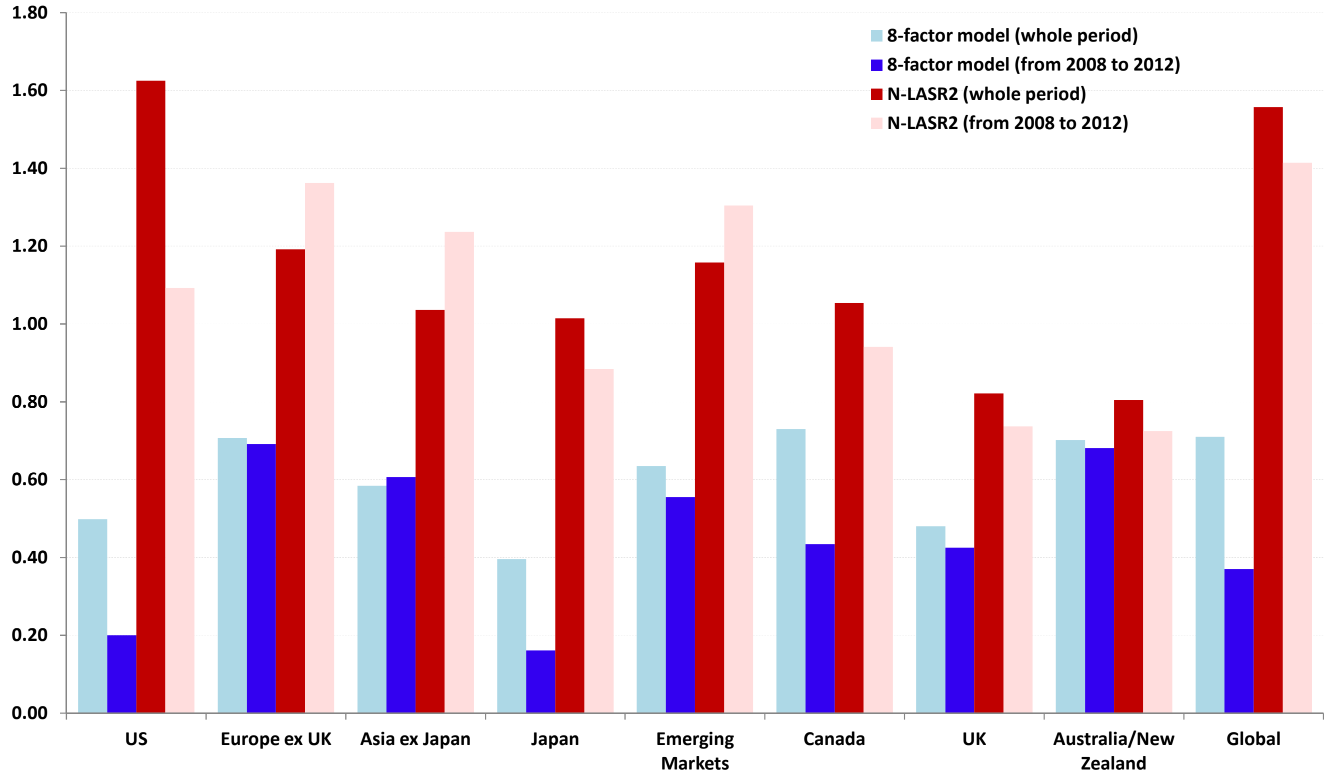
Figure 59: Long/short decile portfolio Sharpe ratio for different regions



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

Does the performance of N-LASR2 model fade away in recent times? Figure 60 shows the performance for risk adjusted rank IC for different time periods for both the N-LASR2 model and the 8-factor model.

Figure 60: Risk adjusted rank IC for different time period for 8 factor model and N-LASR2 model

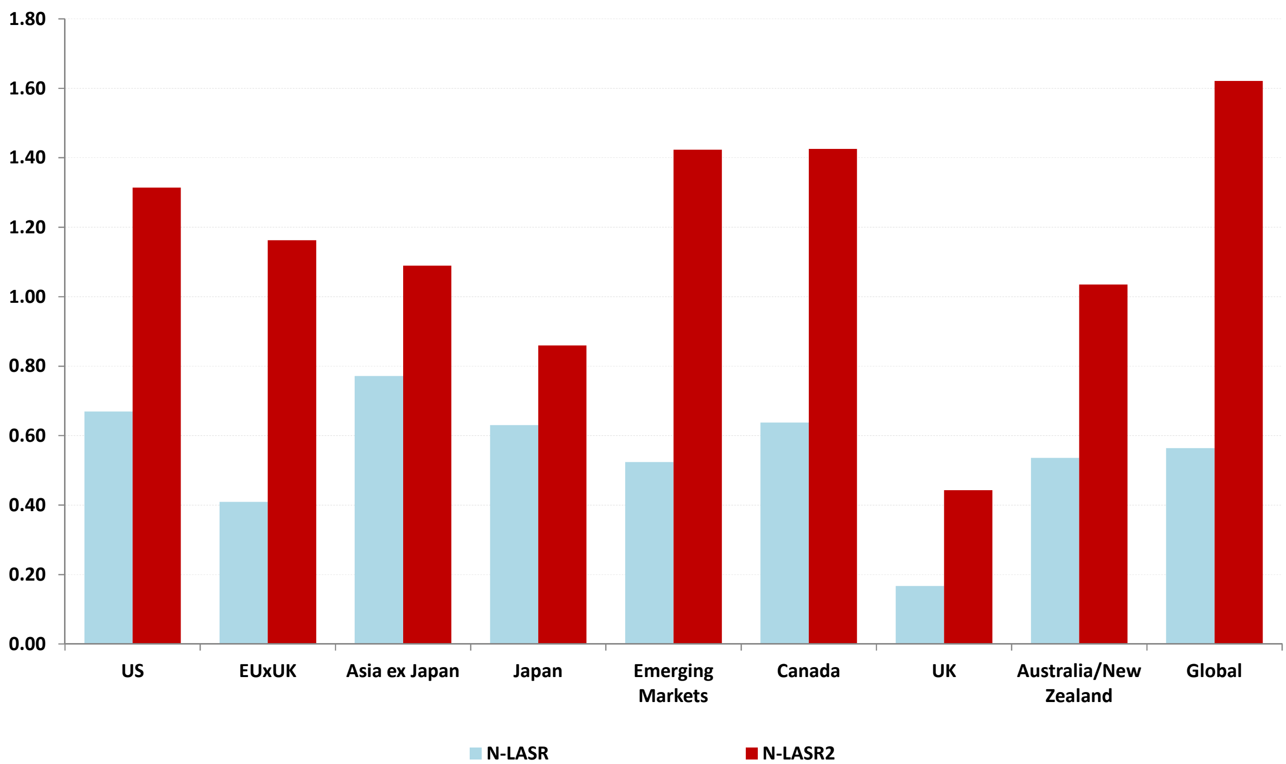


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

We find that the performance for the 8 factor model drops significantly for recent years from 2008 to 2012, and the N-LASR2 not as much. For example, the average decrease in risk adjusted rank IC for 8-factor model is 26%; however, the average decease in the N-LASR2 model is only 4%. For some regions, such as Europe ex UK, Asia ex Japan and Emerging Markets, the performance even increases in the recent period for the N-LASR2 model. The average increase in the N-LASR2 model compared with 8-factor model is 96% for the whole period. However, for recent years from 2008 to 2012 the average increase goes up to 190%. This means, on average, for risk adjusted rank IC, the N-LASR2 model almost triples the performance of the 8-factor models in recent years.

Finally, Figure 61 shows the comparison between the N-LASR model and the N-LASR2 model for risk adjusted rank IC in 2012. We can see that the risk adjusted performance for all the regions goes up. For most of the regions the N-LASR2 model more than doubles the N-LASR model.

Figure 61: Risk adjusted rank IC for different time period for N-LASR and N-LASR2 model in 2012



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

Optimized portfolios for global regions

In this session, we evaluate the performance of realistically optimized portfolios based on the N-LASR2 model. We construct optimized portfolios for all the regions. We set the same constraints for all the regions to:

- Long/short market neutral strategy
- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized volatility of 4%
- Maximum single stock weight 1.5%
- Beta neutral (maximum 0.1 beta exposure)
- Sector neutral (maximum 10% sector exposure)
- Country neutral (maximum 10% country exposure)
- Turnover constrained at 60% one-way per month (120% two-way turnover)
- Transaction cost 20 bps one way
- Starting portfolio size US$ 100 million

We first optimize without an average daily volume (ADV) constraint, because we want to see how profitable our strategy is in general regardless of the fund size. We will later show how much the performance will decrease if we add the ADV constraint, assuming a reasonable initial size: US$ 100 million.

Figure 62 shows the performance for an optimized long/short market neutral portfolio of N-LASR2 for different regions, after transaction costs but without ADV constraints. We can see that all the regions have strong performance, and the maximum drawdown is small. We will show the detailed performance of each of the regions in the following sections, and the performance with an ADV constraint in the last section.

Figure 62: Performance of optimized long/short market neutral portfolio of N-LASR (after transaction cost without ADV constraint)

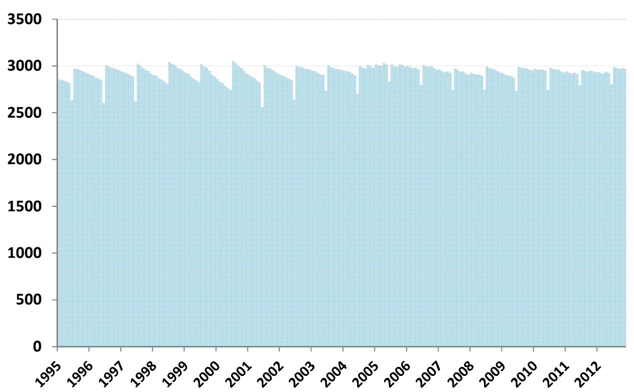
	Annualized Return	Realized Risk	Sharpe Ratio	Maximum Drawdown
US	17.66%	5.18%	3.41	10.4%
EUxUK	20.25%	4.61%	4.39	2.4%
Asia ex Japan	19.25%	5.65%	3.41	6.9%
Japan	10.96%	5.30%	2.07	6.3%
Emerging Markets	18.49%	5.71%	3.24	4.4%
Canada	9.19%	4.40%	2.09	6.1%
UK	9.96%	5.47%	1.82	5.0%
Australia/New Zealand	8.89%	4.34%	2.05	4.6%
Global	21.93%	6.21%	3.53	4.2%

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

Performance for US

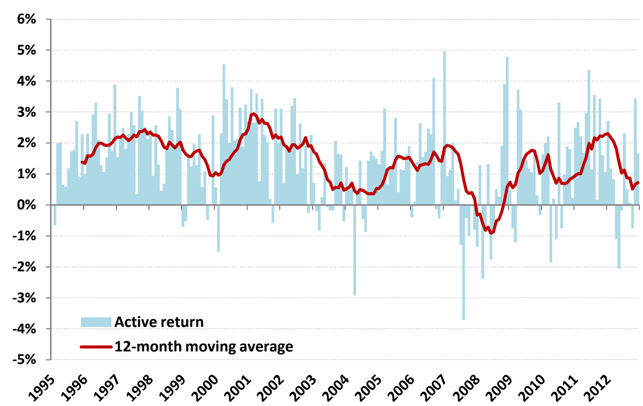
Figure 63 shows the coverage for the US alpha signals, the coverage is close to 3000 stocks over time, since we use the Russell 3000 as our universe. Figure 64 shows the active return after transaction cost for the long/short portfolio. The performance is strong most of the time, even in the recent years.

Figure 63: Stock coverage for alpha signal for US



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

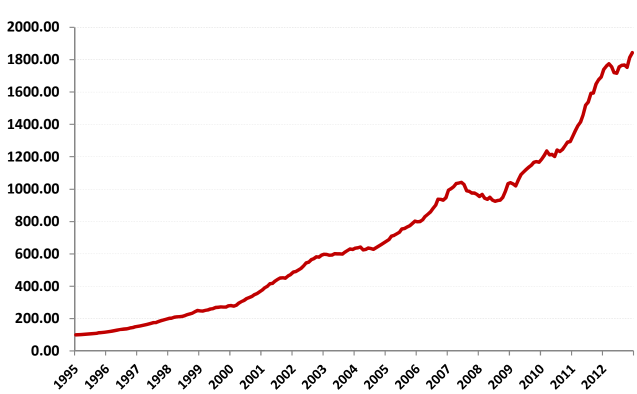
Figure 64: Active return for US



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

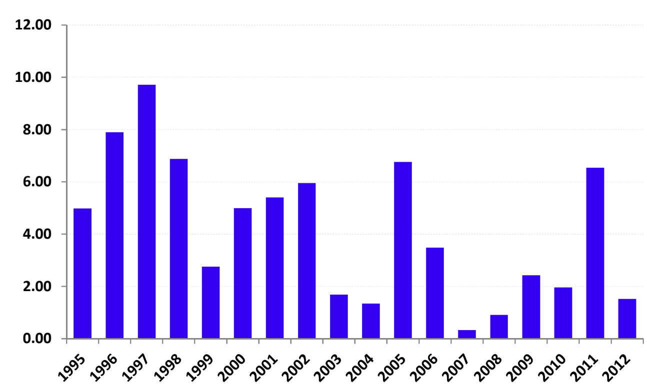
Figure 65 shows the cumulative return; we can see that there are no major drawdowns, but the performance did flatten in 2007 and 2008. Other than that, the portfolio grows steadily over time. Figure 66 shows the yearly annual Sharpe ratio, they are positive for all years. Even in the recent years, the Sharpe ratio remains high. The annualized cumulative return for the past 18 years is 17.66% with realized risk of 5.18%, generating an annual Sharpe ratio of 3.4x. Even for the recent years from 2008 to end of 2012, the annualized cumulative return is 15.54% with realized risk of 5.38%, generating an annual Sharpe ratio of 2.9x.

Figure 65: Cumulative return for US



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

Figure 66: Annual Sharpe ratio for US

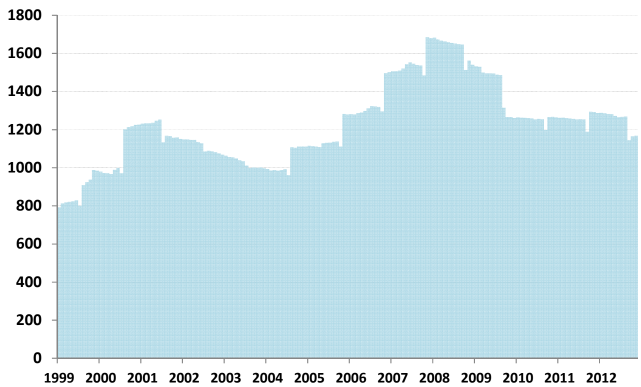


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Europe ex UK

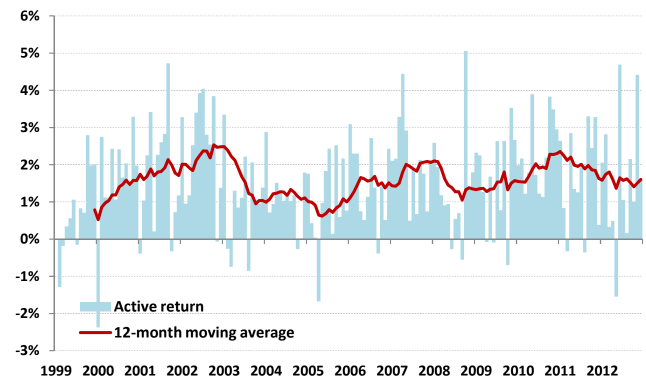
Figure 67 shows the coverage of the alpha signals for Europe ex UK. We construct the regions using the corresponding countries from the S&P BMI country indices as our universe. The coverage is over 1000 stocks most of the time. Figure 68 shows the active return after transaction cost for the long/short portfolio. The performance is strong, there are rarely negative return months, and the 12 month moving average return is always above 50bps.

Figure 67: Stock coverage for alpha signal for Europe ex UK



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

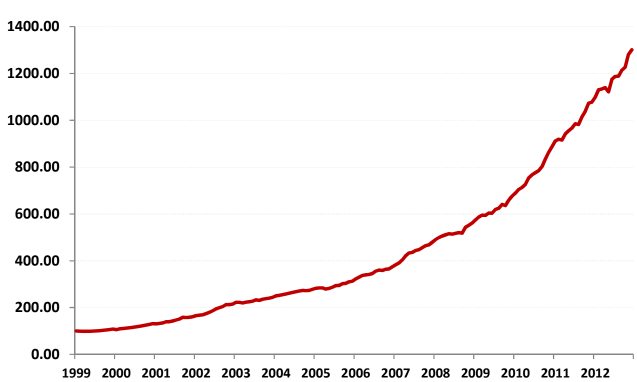
Figure 68: Active return for Europe ex UK



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

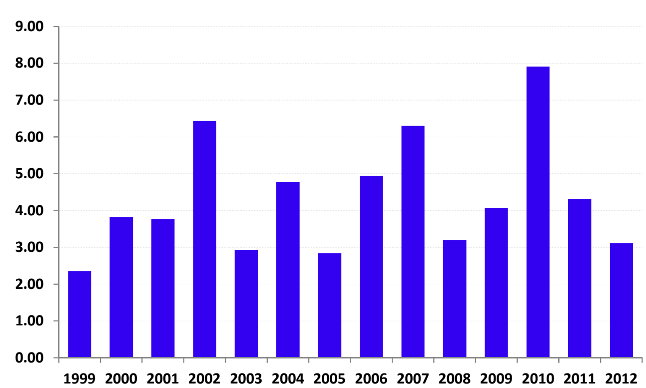
Figure 69 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows over time. Figure 70 shows the yearly annual Sharpe ratio; which is over 2.0x for all years. In the recent years, the Sharpe ratio is even higher, it remains over 3.0x for the recent 7 years. The annualized cumulative return for the past 14 years is 20.25% with realized risk of 4.61%, generating an annual Sharpe ratio of 4.4x. In the recent years from 2008 to end of 2012 the annualized cumulative return is 23.40% with realized risk of 4.70%, generating an annual Sharpe ratio of 4.9x.

Figure 69: Cumulative return for Europe ex UK



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

Figure 70: Annual Sharpe ratio for Europe ex UK

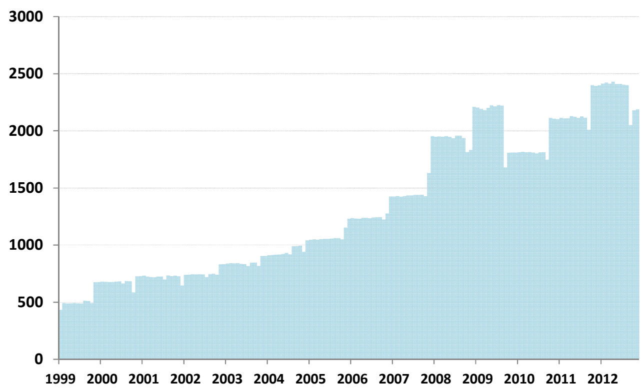


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Asia ex Japan

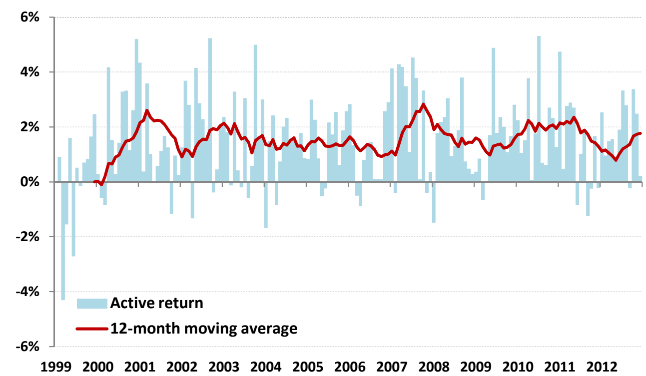
Figure 71 shows the coverage of the alpha signals for Asia ex Japan. We construct the regions using the corresponding countries from the S&P BMI country indices as our universe. The coverage is 500 stocks in 1999, and grows to over 2000 in the recent years. Figure 72 shows the active return after transaction cost for the long/short portfolio. The performance is negative for the first a few months; this is mainly because the coverage for the region is small. The returns remain positive when the coverage is large enough; there are rarely negative return months. The 12 month moving average return is always above 1% if we exclude the first year.

Figure 71: Stock coverage for alpha signal for Asia ex Japan



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

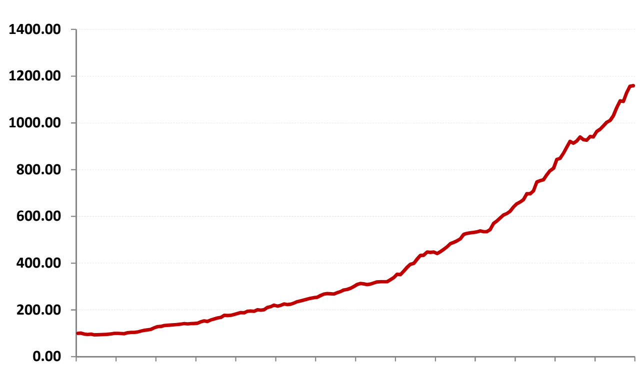
Figure 72: Active return for Asia ex Japan



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

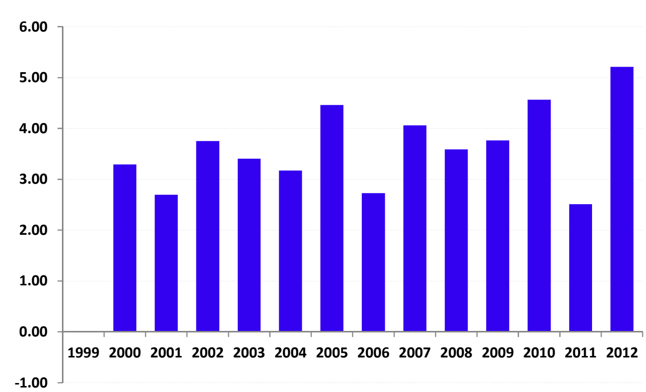
Figure 73 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows exponentially over time. Figure 74 shows the yearly annual Sharpe ratio; the first year is close to zero due to low coverage, but the rest are over 2.0x for all years. In the recent years, the Sharpe ratio is even higher. The annualized cumulative return for the past 14 years is 19.25% with realized risk of 5.65%, generating an annual Sharpe ratio of 3.4x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 21.51% with realized risk of 5.05%, generating an annual Sharpe ratio of 4.3x.

Figure 73: Cumulative return for Asia ex Japan



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

Figure 74: Annual Sharpe ratio for Asia ex Japan

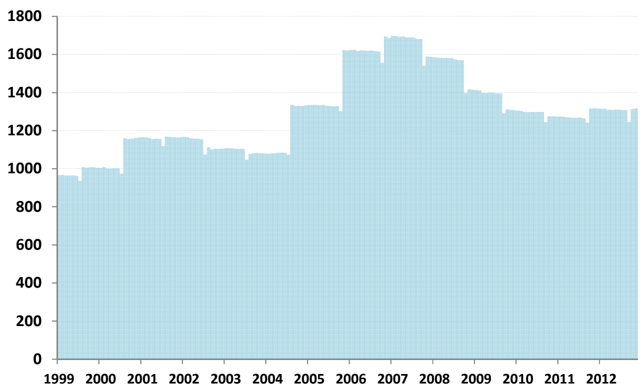


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Japan

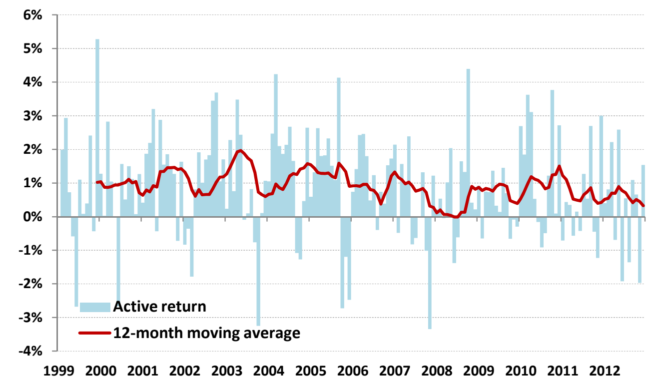
Figure 75 shows the coverage for the alpha signals for Japan. We use the S&P BMI Japan as our universe, and the coverage is over 1000 most of the time. Figure 76 shows the active return after transaction cost for the long/short portfolio. The returns remain positive most of the time. The 12 month moving average return is always positive.

Figure 75: Stock coverage for alpha signal for Japan



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

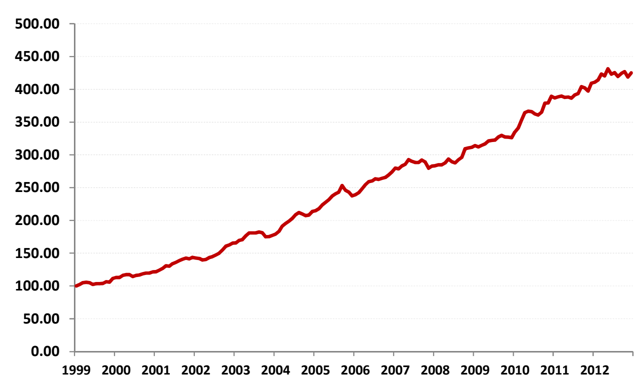
Figure 76: Active return for Japan



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

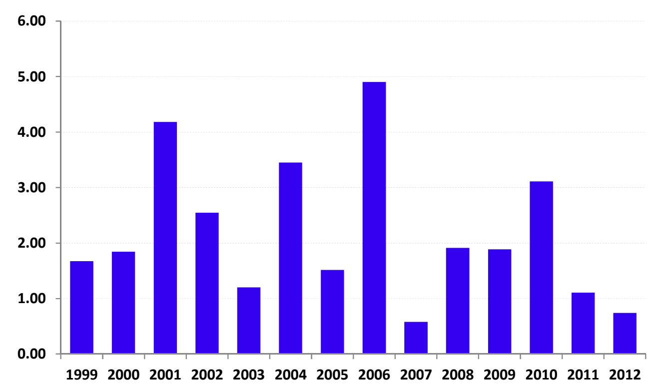
Figure 77 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows steadily over time. Figure 78 shows the yearly annual Sharpe ratio; the Sharpe ratio is positive for all years. In the recent years, the Sharpe ratio reduces slightly, but still quite profitable. The annualized cumulative return for the past 14 years is 10.96% with realized risk of 5.30%, generating an annual Sharpe ratio of 2.1x. In recent years from 2008 to end of 2012, the annualized cumulative return is 8.09% with realized risk of 4.81%, generating an annual Sharpe ratio of 1.7x.

Figure 77: Cumulative return for Japan



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

Figure 78: Annual Sharpe ratio for Japan

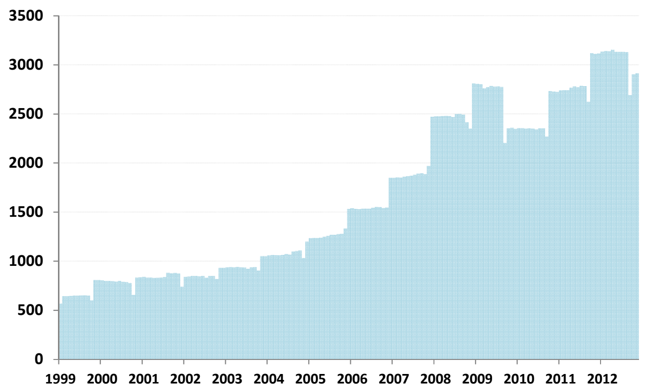


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Emerging Markets

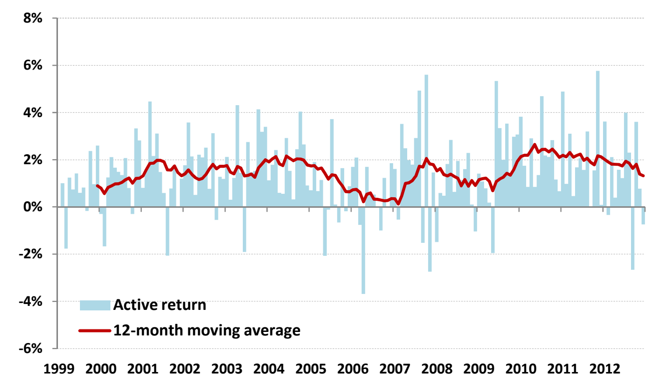
Figure 79 shows the coverage of the alpha signals for Emerging Markets. We construct the regions using the corresponding countries from the S&P BMI country indices as our universe. The coverage grows from 500 to 3000 stocks. Figure 80 shows the active return after transaction costs for the long/short portfolio. The performance is positive most of the time, and the 12 month moving average return is always positive. In addition the performance for recent years is even better; there are rarely negative return months after 2008. This might due to the increase in the stock universe.

Figure 79: Stock coverage for alpha signal for Emerging Markets



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

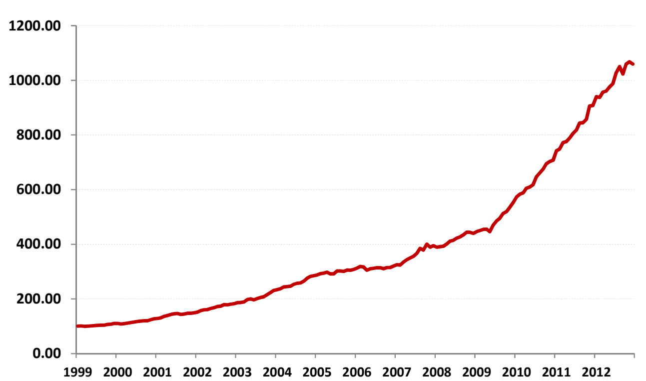
Figure 80: Active return for Emerging Markets



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

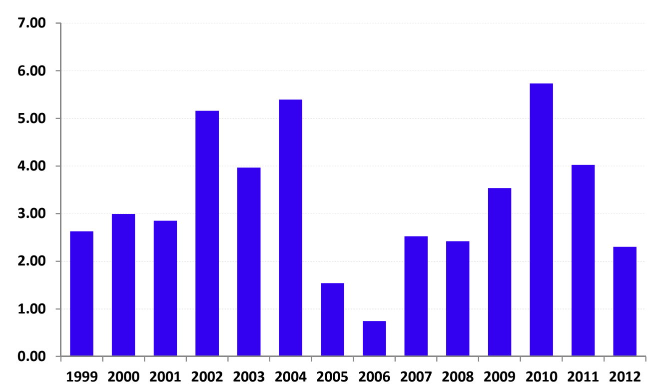
Figure 81 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows exponentially over time. Figure 82 shows the yearly annual Sharpe ratio, they are positive for all years. In the recent years, the Sharpe ratio is even higher, and remains over 2.0x for the most recent 6 years. The annualized cumulative return for the past 14 years is 18.49% with realized risk of 5.71%, generating an annual Sharpe ratio of 3.2x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 24.61% with realized risk of 6.12%, generating an annual Sharpe ratio of 4.0x.

Figure 81: Cumulative return for Emerging Markets



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

Figure 82: Annual Sharpe ratio for Emerging Markets

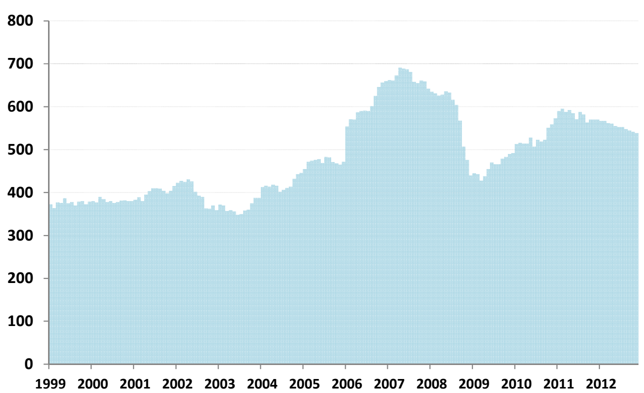


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Canada

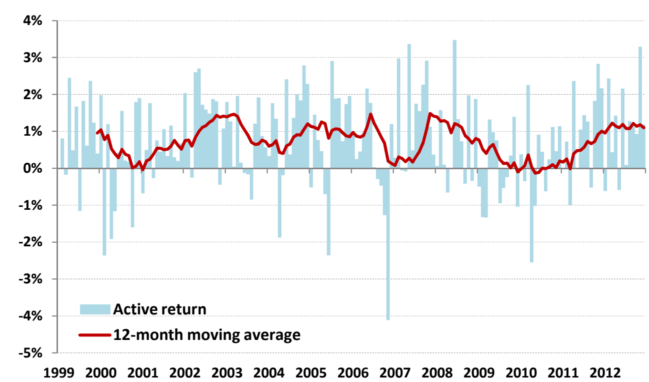
Figure 83 shows the coverage for the alpha signals for Canada. Our Canadian universe of stocks includes all companies that are incorporated in Canada and trade on the TSX including income trusts. Furthermore, we include all stocks that belong to the TSX Composite Index. We have also stipulated certain market capitalization and liquidity constraints. Note that in 2005, income trusts were added to the TSX Composite Index and that is why we see a jump in number of stocks in the universe Figure 84 shows the active return after transaction cost for the long/short portfolio. The performance is positive most of the time.

Figure 83: Stock coverage for alpha signal for Canada



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

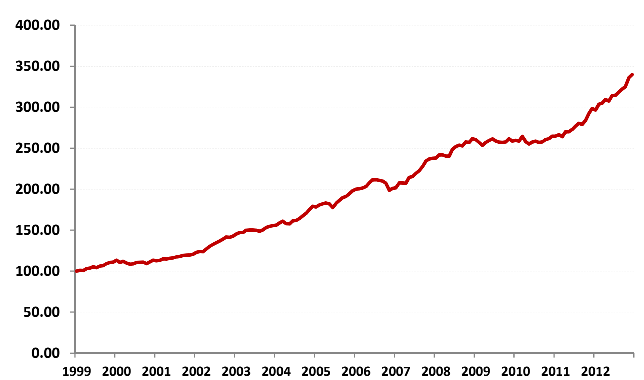
Figure 84: Active return for Canada



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

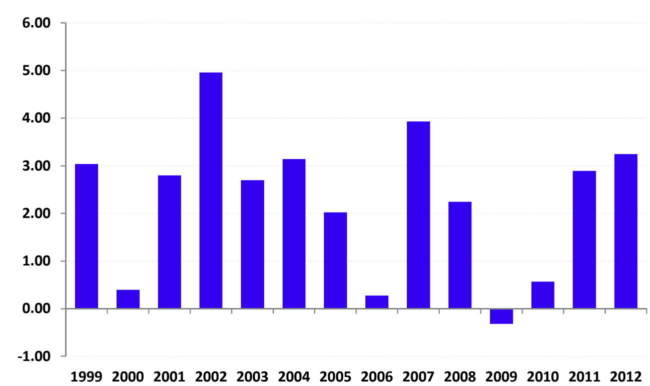
Figure 85 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows steadily over time. Figure 86 shows the yearly annual Sharpe ratio, 13 out of 14 years have positive returns. The annualized cumulative return for the past 14 years is 9.19% with realized risk of 4.40%, generating an annual Sharpe ratio of 2.1x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 6.75% with realized risk of 4.28%, generating an annual Sharpe ratio of 1.6x.

Figure 85: Cumulative return for Canada



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

Figure 86: Annual Sharpe ratio for Canada

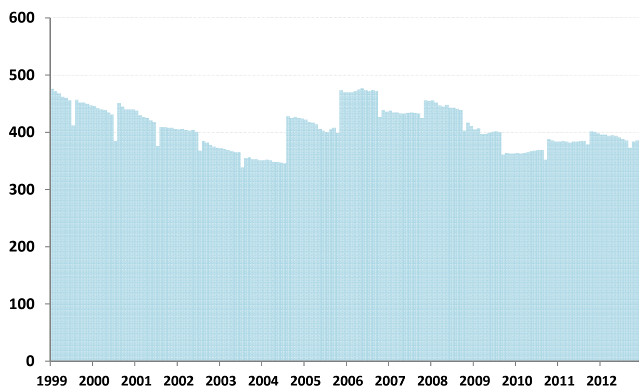


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for UK

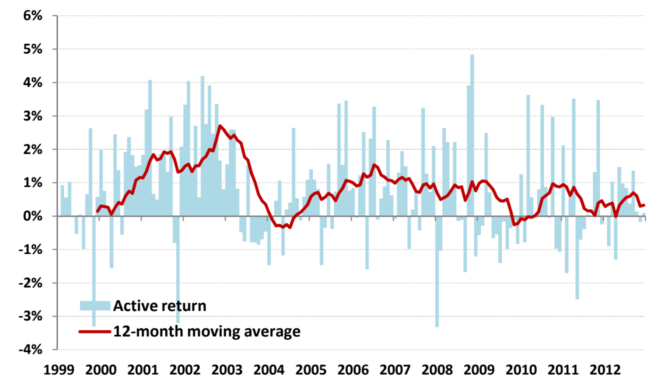
Figure 87 shows the coverage of the alpha signals for the UK. We use the S&P BMI UK as our universe, and coverage is around 400 most of the time. Figure 88 shows the active return after transaction cost for the long/short portfolio. The returns remain positive most of the time.

Figure 87: Stock coverage for alpha signal for UK



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

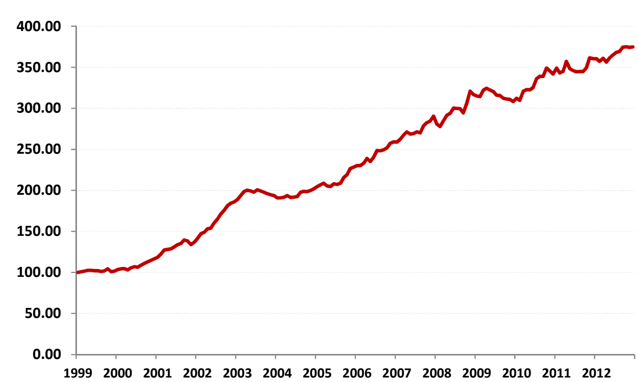
Figure 88: Active return for UK



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

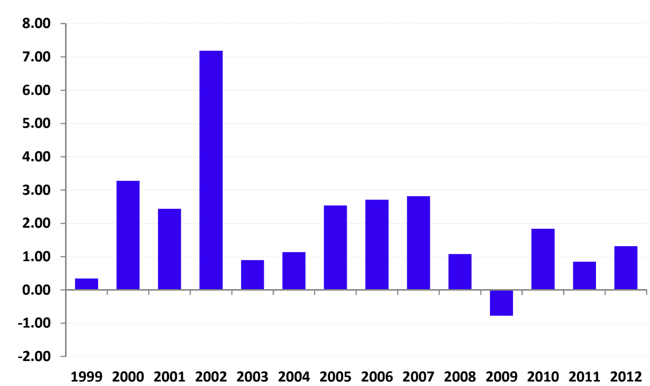
Figure 89 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows steadily over time. Figure 90 shows the yearly annual Sharpe ratio, 13 out of 14 years have a positive ratio. In recent years, the performance flattens compared with early years. The annualized cumulative return for the past 14 years is 9.96% with realized risk of 5.47%, generating an annual Sharpe ratio of 1.8x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 4.28% with realized risk of 4.93%, generating an annual Sharpe ratio of 0.87x.

Figure 89: Cumulative return for UK



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

Figure 90: Annual Sharpe ratio for UK

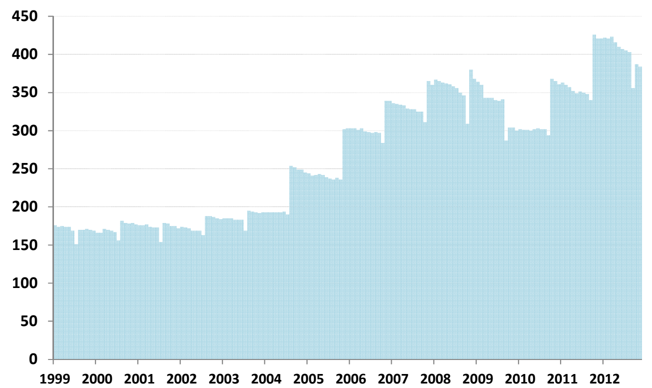


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Australia and New Zealand

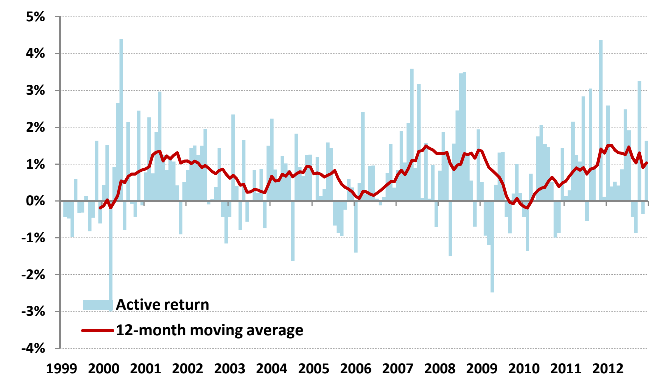
Figure 91 shows the coverage of the alpha signals for Australia and New Zealand. We use the S&P BMI Australia and the S&P BMI New Zealand as our universe, and coverage grows from 150 to 400. Figure 88 shows the active return after transaction cost for the long/short portfolio. The returns remain positive most of the time.

Figure 91: Stock coverage for alpha signal for Australia and New Zealand



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

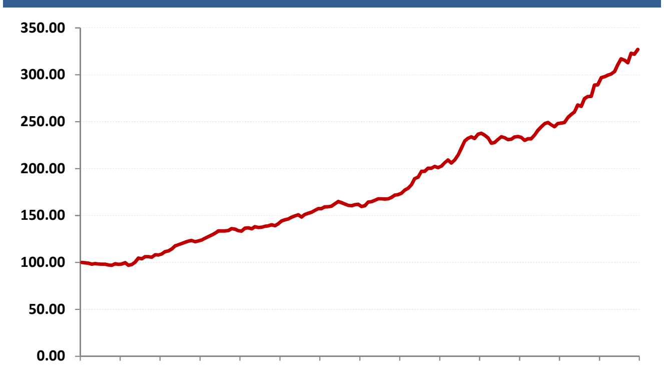
Figure 92: Active return for Australia and New Zealand



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

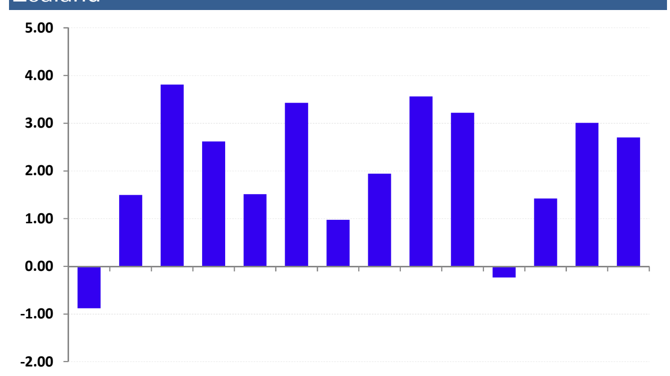
Figure 93 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows steadily over time. Figure 94 shows the yearly annual Sharpe ratio, 12 out of 14 years have positive returns. In recent years, the performance maintains high. The annualized cumulative return for the past 14 years is 8.89% with realized risk of 4.34%, generating an annual Sharpe ratio of 2.1x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 8.44% with realized risk of 4.72%, generating an annual Sharpe ratio of 1.79x.

Figure 93: Cumulative return for Australia and New Zealand



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

Figure 94: Annual Sharpe ratio for Australia and New Zealand

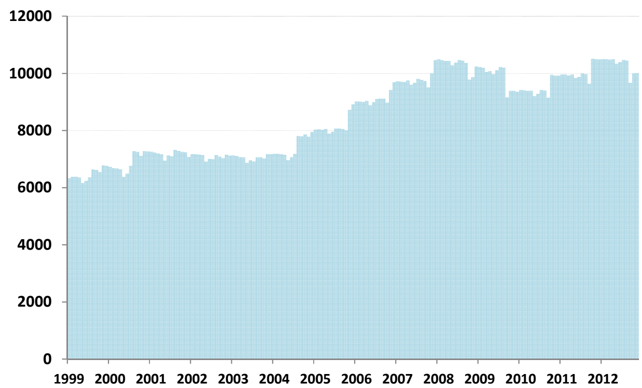


Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

Performance for Global

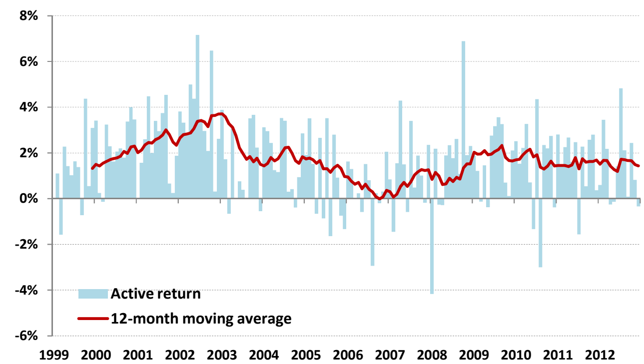
Figure 95 shows the coverage of the alpha signals for Global universe. We construct the universe using the union of the S&P BMI country indices and Russell 3000 for US and S&P/TSX for Canada. The coverage grows from 6000 to 10000. Figure 96 shows the active return after transaction cost for the long/short portfolio. The returns remain positive most of the time. The 12 month moving average return is always positive.

Figure 95: Stock coverage for alpha signal for Global



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

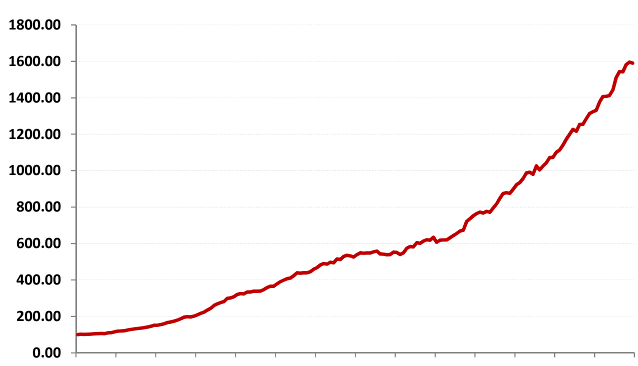
Figure 96: Active return for Global



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

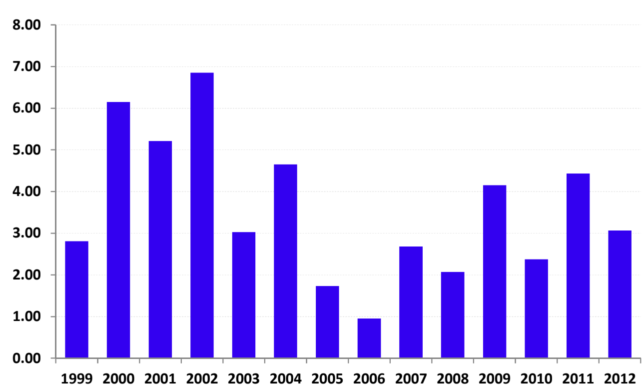
Figure 97 shows the cumulative return; we can see that there are no major drawdowns, and that the portfolio grows over time. Figure 98 shows the yearly annual Sharpe ratio, they are above 1.0x for all years. In the recent years, the Sharpe ratio remains high. The annualized cumulative return for the past 14 years is 21.93% with realized risk of 6.21%, generating an annual Sharpe ratio of 3.5x. In the recent years from 2008 to end of 2012, the annualized cumulative return is 20.08% with realized risk of 5.50%, generating an annual Sharpe ratio of 3.7x.

Figure 97: Cumulative return for Global



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

Figure 98: Annual Sharpe ratio for Global



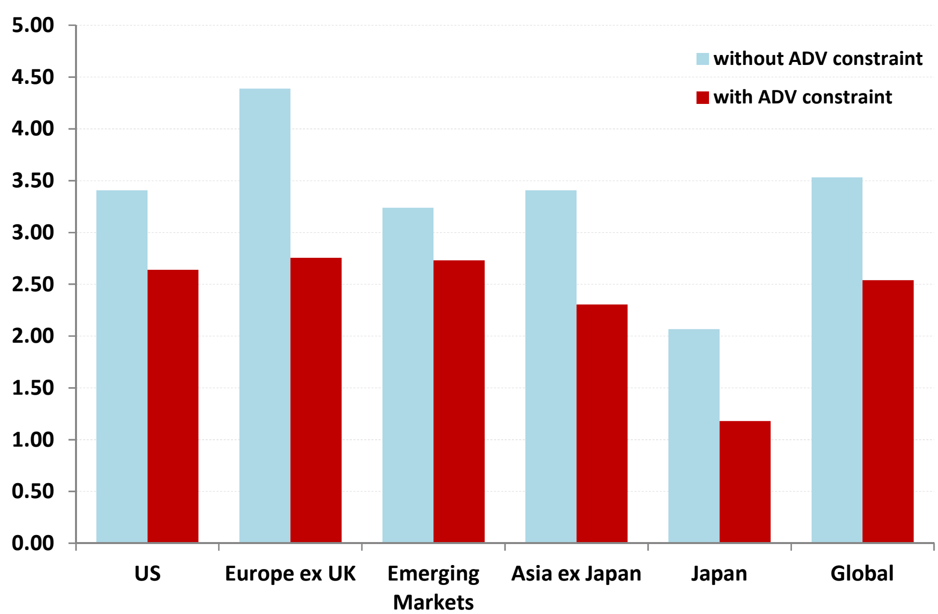
Source: Bloomberg Finance LLP, Compustat, IBES, Russell, S&P, Thomson Reuters, Worldscope, Deutsche Bank Quantitative Strategy

How would portfolio size impact the performance?

We would like to see how portfolio size will change the performance of our strategy. We test this by adding the ADV (average daily volume constraint) constraint. We assume that for each stock there is a 10% of average daily volume in 20 days turnover constraint. This is also a liquidity constraint because we cannot trade much of an illiquid stock with this constraint. We set the initial portfolio size to be US $ 100 million. This will have a greater impact for smaller regions than large regions. Because we cannot turn our portfolio as much as we want in small regions, for small regions with less than 1000 stocks in the universe, such as Canada, UK and Australia and New Zealand, we set the turnover constraint to be 30% one way. For the rest of the regions the turnover constraint remains 60% one way.

Figure 99 shows the comparison of Sharpe ratios for all the large regions after adding the ADV constraint. We can see the performance goes down across the board. But for most of the regions, the Sharpe ratio is still very high. Japan has always been a tough market for quants. We can see that the Sharpe ratio for Japan drops from 2.1x to 1.2x when adding the ADV constraint. Other than Japan, all the regions have Sharpe ratio over 2.3x even with the ADV constraint. The average drop for the Sharpe ratio is about 30%.

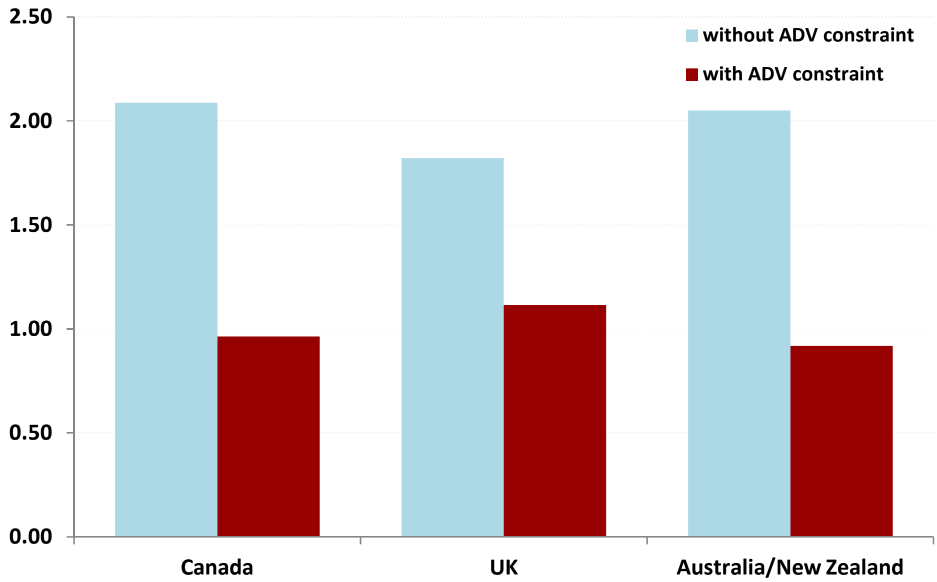
Figure 99: Sharpe ratio of long/short optimized portfolio after transaction cost with ADV constraint for large universe



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

Figure 100 shows the comparison of Sharpe ratio for smaller regions after adding the ADV constraint. We can see that the performance drops much more for smaller regions. This is because the ADV constraint will bind more often in those regions. On average the Sharpe ratio drops 49%. But the Sharpe ratio is still over 0.90x for all the small regions. Also, generally speaking, smaller region have lower Sharpe ratio than large regions. There are mainly two reasons: first our N-LASR model favors large regions because they have more training data; second the optimizer can better diversify with more stocks in large regions.

Figure 100: Sharpe ratio of long/short optimized portfolio after transaction cost with ADV constraint for large universe



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

References

Cahan, R., Y. Luo, J. Jussa, and M. Alvarez, 2010, "Signal Processing: Beyond the headlines", *Deutsche Bank Quantitative Strategy*, 19 July 2010

Cahan, R., Y. Luo, M. Alvarez, J. Jussa, Z. Chen, and S. Wang, 2011, "Signal Processing: Quant 2.0", *Deutsche Bank Quantitative Strategy*, 18 November 2011

Cahan, R., Y. Luo, M. Alvarez, J. Jussa, Z. Chen, and S. Wang, 2012a, "Signal Processing: The Tree of LIFO", *Deutsche Bank Quantitative Strategy*, 26 April 2012

Cahan, R., Z. Chen, Y. Luo, M. Alvarez, J. Jussa, and S. Wang, 2012b, "Signal Processing: Quant 3.0", *Deutsche Bank Quantitative Strategy*, 17 December 2012

Fama, E., and K. French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics*, 1993

Kassam, A., S. Mesomeris, and M. Salvini, 2010, "Portfolios Under Construction: Factor Neutralization and Beyond", *Deutsche Bank Quantitative Strategy*, 21 September 2010

Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010a, "QCD Model: DB quant handbook", *Deutsche Bank Quantitative Strategy*, 22 July 2010

Luo, Y., R. Cahan, J. Jussa, and M. Alvarez, 2010b, "Portfolios Under Construction: Volatility = 1/N", *Deutsche Bank Quantitative Strategy*, 16 June 2010

Wang, S., Y. Luo, R. Cahan, M. Alvarez, J. Jussa, Z. Chen, 2012, "Signal Processing: The rise of the machines", *Deutsche Bank Quantitative Strategy*, 5 June 2012

Salvini, M., S. Mesomeris, J. Avettand-Fenoel, 2011, "Thematic Report: Introducing the MIR", *Deutsche Bank Quantitative Strategy,* 11 November 2011

Schapire, R.E., Y. Freund, P. Barlett, and W.S. Lee, 1998, "Boosting the margin: A new explanation for the effectiveness of voting methods", The Annals of Statistics, 26(5), 1998, paper available at http://cs.nyu.edu/~cil217/ML/BoostingMargin.pdf

Appendix 1

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