Quantitative Monographs

Stock selection using machine learning

Equities

Global
Quantitative

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Our new approach to quantitative stock modelling

We introduce our new stock selection model based on a modern machine learning technique known as random forests. This technique has cutting-edge performance, comparable to the most sophisticated methods available today, but we choose it for two key reasons: it is remarkably simple to understand, and it does not over-fit the data.

A gentle introduction to machine learning

This report is targeted at investors looking for a new approach to stock selection, or those interested in incorporating a quantitative overlay to their existing process. We introduce fundamental concepts in machine learning and the motivations for our approach in plain English, assuming no prior knowledge in this field.

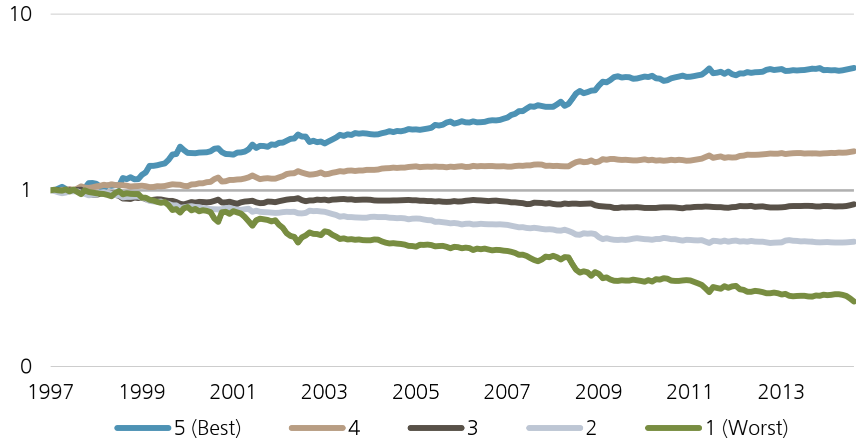
A reliable and adaptive source of alpha

One key advantage of this technique is that it cannot over-fit the data, meaning our model does not merely reflect efforts to maximise historical performance. It adapts to changing market conditions and requires no ongoing manual intervention, reducing the need to time the style environment.

Consistent, global outperformance

Our model performs consistently well across global markets. In the MSCI AC World index the long-short portfolio yields 17% pa, with roughly equal contributions from both sides. Currently, our global model has a very cautious outlook due to recent factor volatility; it is overweight mean reversion, underweight beta and forward PE.

Figure 1: Quintile excess performance—MSCI AC World



Source: MSCI, S&P, IBES, FactSet, UBS

Summary

This paper describes our new stock selection model using a modern machine learning technique known as 'random forests'. We choose this technique because it:

- has excellent performance
- is simple to understand
- does not over-fit

Over the following pages we introduce some theory behind machine learning and how random forests fit in. Where possible, we draw analogies to linear regression, a technique familiar to us all, but one we believe is often misused in finance.

This report is intended for those investors looking for a fresh approach to stock selection; we assume no prior knowledge in this field and spare our readers the technical details until the appendix.

Currently, our global model has a very cautious outlook due to recent factor volatility, and is overweight mean reversion, underweight beta and forward PE.

Figure 2: Long-short performance summary since 1997

Index	Return	Sharpe	Max Drawdown	Hit Rate
MSCI AC World	17.1	1.1	-24.4	66.8
Developed	14.5	0.8	-35.2	64.9
Emerging	15.9	1.0	-28.3	68.7
MSCI AC Asia Pacific ex Japan	17.3	0.9	-39.4	64.9
Developed	15.8	0.8	-40.8	63.0
Emerging	9.1	0.6	-52.9	58.8
S&P/ASX 300	25.0	1.1	-35.7	68.7
MSCI Japan	6.2	0.4	-58.7	57.3
MSCI AC Europe	14.1	0.9	-37.1	66.4
Developed	13.2	0.7	-47.2	63.0
Emerging	7.8	0.5	-38.3	55.9
MSCI North America	9.7	0.5	-30.8	57.8

Source: MSCI, S&P, IBES, FactSet, UBS

Preamble

Intuitively, we all know the value of a varied and independent group of opinions. This notion is ingrained into every entrepreneurial workplace; from the team that questions the status quo, to the CEO supported by a board of directors providing a breadth of perspectives. Diversity is truly important—and groupthink often leads to suboptimal outcomes.

Machine learning is a discipline within artificial intelligence

Perhaps less well known is the fact that this concept is steeped in statistical theory and has become a cornerstone of many of the machine learning techniques used today. For those not familiar with the term, machine learning is essentially a discipline within artificial intelligence; it sits at the intersection of computer science and applied statistics. These are the algorithms that keep your inbox free of spam and your Internet search results relevant; they keep self-driving cars on the road and provide accurate diagnoses from medical scans. Basically, whenever you see a computer do something smart, it is because of developments in this revolutionary field.

The collective intelligence of a diverse and independent group typically yields better estimates than any individual

Aristotle has been credited with first observing this phenomenon; somewhat more recently Surowiecki's book "The Wisdom of Crowds", popularised how diverse perspectives shape decision-making in a business context. A common example of the effect is demonstrated in a jellybean-guessing contest, whereby a glass jar is filled with jellybeans and participants are asked to guess the number, with the closest guess declared the winner. While individual estimates vary wildly, the average guess is remarkably close to the true number. In short, the collective intelligence of a diverse and independent group typically yields better estimates than any individual.

Accuracy vs precision

Readers may be familiar with the distinction between accuracy and precision: accuracy measures how close a forecast lies to the true value, whereas precision measures repeatability and robustness to noise in the inputs. Figure 3 shows estimates that vary greatly (low precision), but are centred about the target (high accuracy); whereas Figure 4 shows estimates that are closely bunched together (high precision), but are consistently off-centre (low accuracy).

Figure 3: Low bias, high variance

Source: UBS

Figure 4: High bias, low variance

Source: UBS

Bias and variance are opposing objectives—we minimise one at the expense of the other

This distinction underpins a core tenet of machine learning, in which these concepts have been formally defined as bias and variance. Ideally our forecasts exhibit low bias (high accuracy), and low variance (high precision). However, bias and variance are typically opposing objectives—we can minimise one only at the expense of the other.

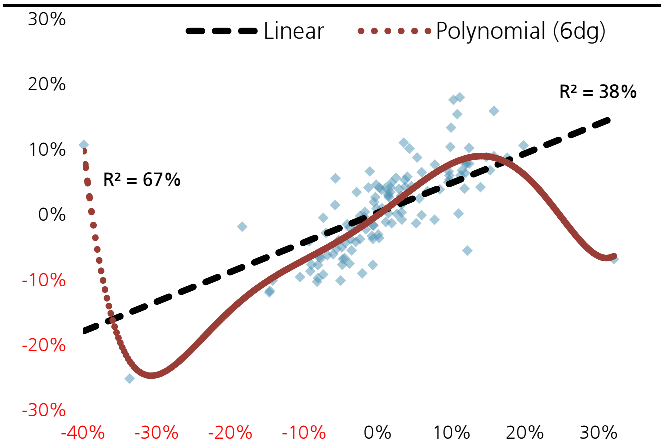
Bias and variance

The relationship between bias and variance is perhaps already intuitive to many finance practitioners. This trade-off is intimately related to the notion of over-fitting. For those not familiar with the term, a model that is overly complex and has poor predictive strength may be regarded as over-fit. This is a common mistake in model construction and occurs when the model describes the data under which it was constructed (in sample), and does not generalise to the out of sample data.

Overly complex models with poor predictive performance may be over-fit

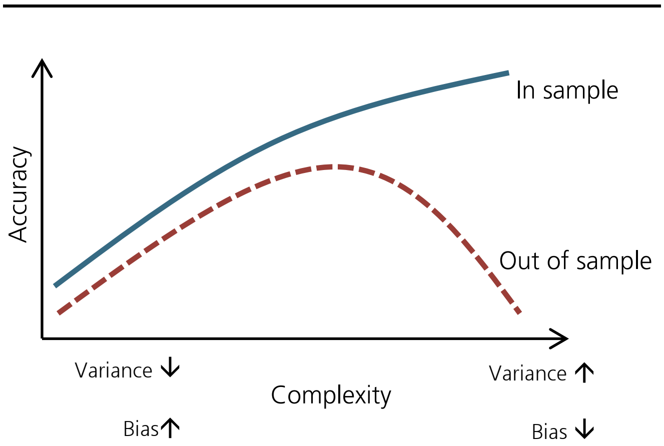
For example, suppose we are interested in the relationship between the BHP and RIO stock price over the past 10 years. We then calculate a linear regression of the stock returns of RIO vs BHP but find an R^2 of only 38%. Unhappy with this result, we instead apply a polynomial fit which yields an R^2 of 67%, and armed with this more accurate model we now expect to invest successfully and retire early.

Figure 5: BHP (x) vs RIO (y) price returns



Source: UBS

Figure 6: Model complexity vs accuracy



Source: UBS

In our example above, the relationship between the returns of the two companies is clearly linear, as we expect. However, the more accurate of our models predicts that if BHP experiences a MoM return of 30%, we should expect RIO to suffer a -10% return accordingly. This is one reason R^2 statistics are often misleading and seldom useful, a subject we will elaborate on in another report.

Where does our logic fall apart? We can always make our in-sample results more accurate by increasing model complexity. However, this approach fails miserably in the real world because the model memorises the data rather than generalising to the important features. Figure 6 summarises this trade-off between model complexity and prediction accuracy for in-sample and out-of-sample data sets. This relationship is in fact common to *any model fit to any data*—in practice, the best we can aim for is the peak of the dotted line.

Over-fitting means a model has low bias but high variance

And why is this relevant? Quite simply, random forests cannot over-fit the data, as they use only a subset of the original data to train the model, and then use the remaining data to test it. The procedure for evaluating how successfully a model generalises to independent data is known as cross-validation, and the random forests algorithm essentially performs this along the way. This is important because it gives us confidence that the results are achievable and not merely the result of memorising our database, or a set of parameters we tweak to maximise performance.

Random forests are robust to over-fitting—cross validation is not required

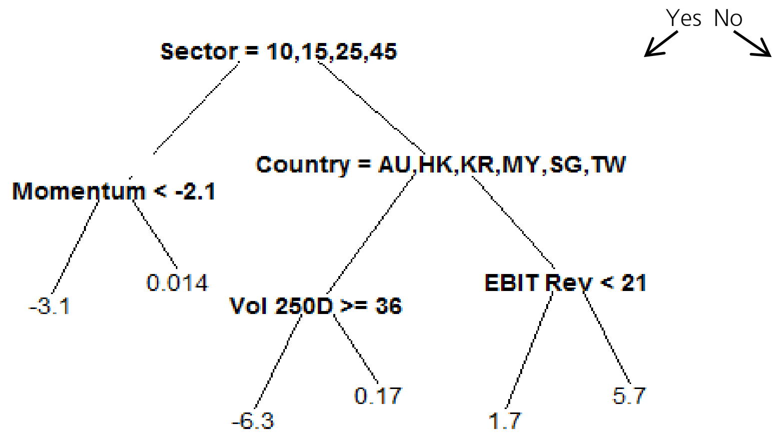
Seeds to trees

These trees slice up the inputs according to similar-looking outputs

So what then are the individual estimators that we aggregate—the dots on the target? Traditional random forests use an ensemble of classification and regression trees (CART). These trees essentially work by slicing up the input data into chunks with a similar-looking output, to build a structure around the data.

Figure 7 shows an example of a simple regression tree, based on the MSCI AC Asia Pacific ex-Japan universe, as of November 2014. These trees are split at each branch by a decision boundary (left is yes, right is no), and the leaf nodes correspond to average outperformance within each cluster. For example, we can see that many of the cyclical sectors are grouped together at the top, and within these sectors, recent outperformance has been driven by momentum. So by simply cascading down the decision branches of these trees, we can arrive at our predicted value at the stock level.

Figure 7: An example of a regression tree



Source: MSCI, IBES, FactSet, UBS

These trees are one of the most useful tools in statistics, and have been widely applied to classification and regression problems due to their many attractive properties:

No assumptions on the underlying data structure

- They make no assumptions on the underlying data structure. How many times have you seen a linear regression performed on data that is not actually linear? In practice, linear relationships are quite uncommon and too often little thought is given to the significance of such results. On the other hand, CART can model complex interactions within the data set, for example the cyclical/defensive relationship above.

Easy to interpret and visualise

- They are easy to interpret and visualise. As Figure 7 shows, these trees are quite intuitive and simple to understand. At a glance we can see the importance of the variables by their position in the tree, their relationships to other factors beneath them, and the values of their decision boundaries.

Can handle categorical and numerical data

- They can easily handle categorical and numerical data. For example, they can distinguish between defensive sectors and cyclical sectors, or developing and emerging countries, just as easily as companies trading cheap or expensive on PE. This contrasts with linear regression, for example, in which categorical data is typically first coded into "dummy variables".

- Robust to real-world data. In practice, data is often noisy and missing. Decision trees are robust to outliers in the input space, as their splitting criteria are far less sensitive than outliers within a regression framework, for example. They also offer methods to sensibly impute (fill in) missing values and can handle unbalanced data effectively.

Robust to real-world data

- They are computationally efficient. These trees are fast to calculate, even faster to predict with, and have low storage cost. Consequently they can handle enormous data sets without having to purchase supercomputers.

Computationally efficient

Despite this, trees suffer shortcomings that often limit their application:

- The primary issue is that they tend to over-fit the data and consequently suffer from high variance, meaning a small change in the inputs may produce a significant change in the output. This is perhaps obvious from Figure 7, in which a mining company with momentum -2.2% is expected to underperform by -3.1%, but a mining company with momentum -2.1% is expected to slightly outperform—in reality, of course this distinction does not exist.

They tend to over-fit the inputs, producing low bias, high variance models

- To compensate for this, trees are often 'pruned' to sacrifice an increase in bias for a reduction in variance. However, their accuracy is still not competitive with the latest machine learning techniques such as random forests and support vector machines. Owing to their hierarchical nature, errors in the trees cascade down to all the sub-branches—they are unforgiving in misclassification.

Pruning helps, but modern techniques yield better results

Trees to forests

So how does it all fit together? The rough idea is to combine a set of independent low-bias, high-variance estimators to produce a low-bias, low-variance result. Essentially, we build a forest of independent trees by randomly selecting from the available features, then average over these to produce a higher quality result than any single estimate.

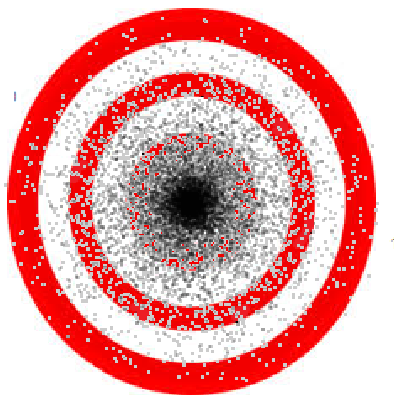
Random forests combine independent low-bias, high-variance estimators to produce a low-bias, low-variance result

If we stretch our target analogy a bit further, we can illustrate how this works. By overlaying thousands of the low-bias, high variance estimators shown in Figure 8, we can see that they cluster around the bulls-eye, which is reflected in an accurate and precise average.

Figure 8: One noisy estimator

Source: UBS

Figure 9: Many noisy estimators



Source: UBS

Random forests exploit a similar property; however their innovation is to add even more "randomness", by randomly selecting from the variables available at each split. The implication of this enhancement is that as the trees are independently grown, their correlation is low and we can accordingly achieve a significant reduction in variance[1]. This is an example of an ensemble method; these techniques often yield the best performance of all machine learning techniques available today.

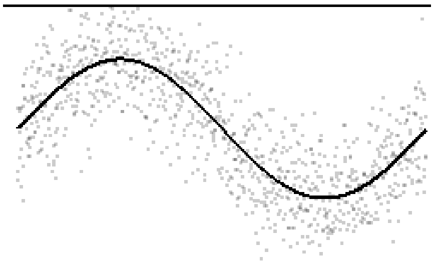
Ensemble methods often yield the best performance of modern machine learning techniques

Below we give a more practical example of how this effect works. Suppose the economic cycle can be described perfectly by the function in Figure 10, showing economic output versus time. The underlying (unobservable) function is shown in black, but instead we record the data points shown as dots, which are subject to noise from exogenous influences such as geopolitical events, accounting differences, human error, reporting delays and so on.

Now suppose we have hundreds of independent organisations collecting these statistics: government agencies, private industry, academics etc. Each of these entities may differ slightly on methodology, sampling schedule, data sources and so on—but they are all attempting to measure the same thing. What we find is that when we average over all these independent estimates, we arrive at the result in Figure 12—remarkably close to the true relationship.

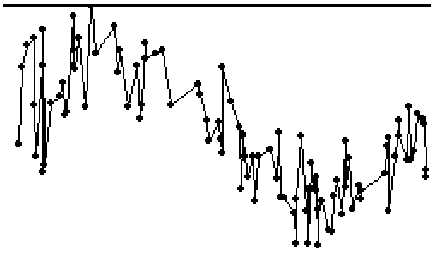
[1] Refer to the appendix for a mathematical explanation of why this works.

Figure 10: Underlying function



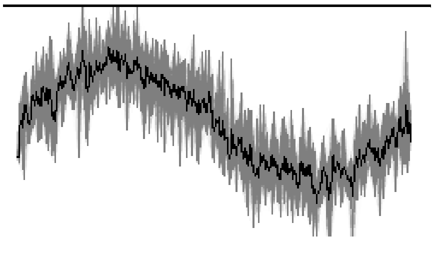
Source: UBS

Figure 11: One time series estimate



Source: UBS

Figure 12: Average of many estimates



Source: UBS

In a random forest model, hundreds of the individual trees shown in Figure 7 are grown, each one generated by combining a random sample of the input data with random subsets of the splitting variables (factors). Data is then fed into the forest to produce hundreds of individual estimates, which are then averaged over to produce a 'consensus' prediction.

Cutting-edge performance, with very little effort required

We think the primary reason why random forests have gained so much popularity, and the reason why you should consider using the technique, is because this algorithm makes it possible to achieve cutting-edge performance with very little effort. There are essentially no parameters to tune; the only ones available are the number of trees to grow, and the number of variables to choose from, both of which are typically left at their defaults[2]. Random forests are almost as easy to construct as an ordinary linear regression model and are inherently robust to outliers and over-fitting.

Furthermore, random forests are not prone to over-fitting because they essentially perform model robustness checks (cross-validation) along the way, using the following approach. If we take our bag of observations and pour two-thirds of them into building the tree, the remaining third can be used to evaluate the accuracy of the built model internally. These are known as the out-of-bag (OOB) samples, and they prove enormously useful in this framework.

Random forests are 'grey box', variable importance metrics and proximities provide insight

One criticism of random forests is that they are considered 'black box'—though arguably no more so than any other ensemble method. While the individual trees are simple to understand, offer outstanding transparency, and can be treated within a statistical framework, the combination of hundreds of these randomly generated trees is less obvious. However thanks to these OOB samples, there are tools available to provide more insight into the inner workings of the models—namely variable importance and proximities.

Variable importance simply describes which factors matter. Just as you might consider the t-statistic of a linear regression co-efficient to evaluate its significance, this measures importance of the (predictor) variables to the response. There are several ways of measuring these, the technical aspects of which we address in the appendix. We discuss these in detail in the following section.

Proximities evaluate how similar each observation looks to each other by counting all the times the OOB samples end up lumped together. For example, we might expect that BHP AU and RIO AU have comparable returns, valuations, margins, growth profiles, etc, but that BHP AU and SBRY LN look quite distinct, which would be reflected in these proximities.

[2] Refer to the appendix to see the impact of varying these parameters.

Performance

Model construction is remarkably straightforward. Each month-end we extract a short, fixed-length trailing window of raw factors and returns, and train a random forest on it. We then feed the latest available factor scores into the model to arrive at the predicted stock return, which is our raw alpha signal.

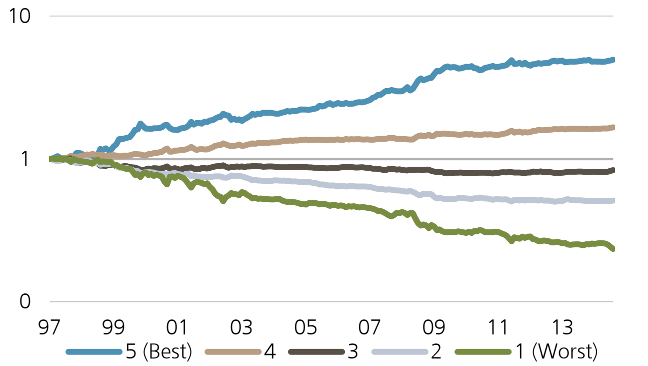
The portfolios are formed from this return forecast by computing equal weighted quintiles, which are rebalanced monthly and priced in USD. Early results indicated country effects dominated the returns, so we neutralise at the country level by netting out the country median from the factor scores and returns.

MSCI AC World

Performance in this broad index is very strong, showing a consistent return profile across the quintiles. This is also demonstrated by the outstanding performance of the long-short strategy, which seldom experiences sustained drawdowns. Note the x-axis in Figure 13 represents the (equal-weighted) benchmark and the y-axis is on a log scale.

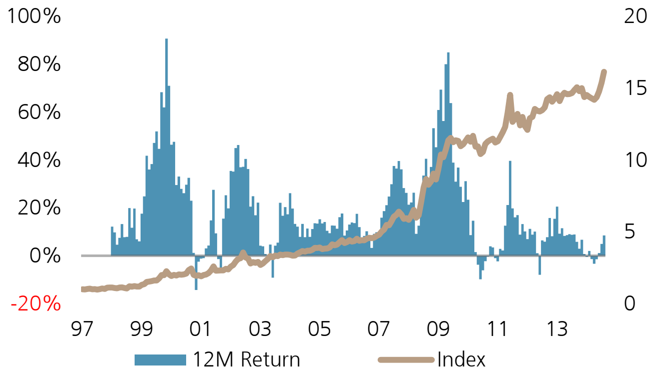
Consistent factor return profile across quintiles

Figure 13: Excess quintiles



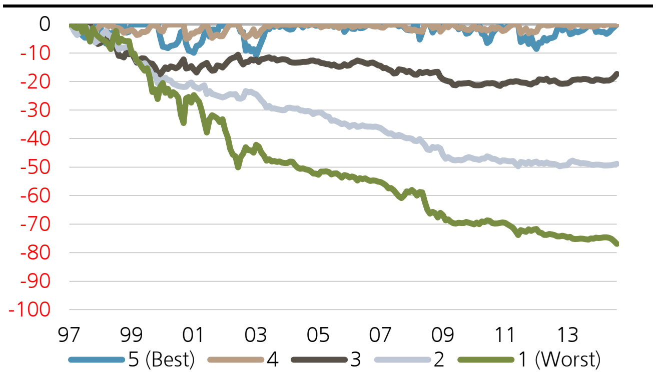
Source: MSCI, IBES, FactSet, UBS

Figure 14: Long-short



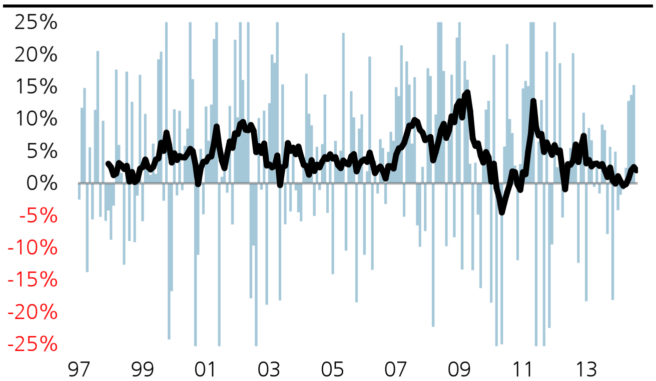
Source: MSCI, IBES, FactSet, UBS

Figure 15: Excess drawdown



Source: MSCI, IBES, FactSet, UBS

Figure 16: Rank IC



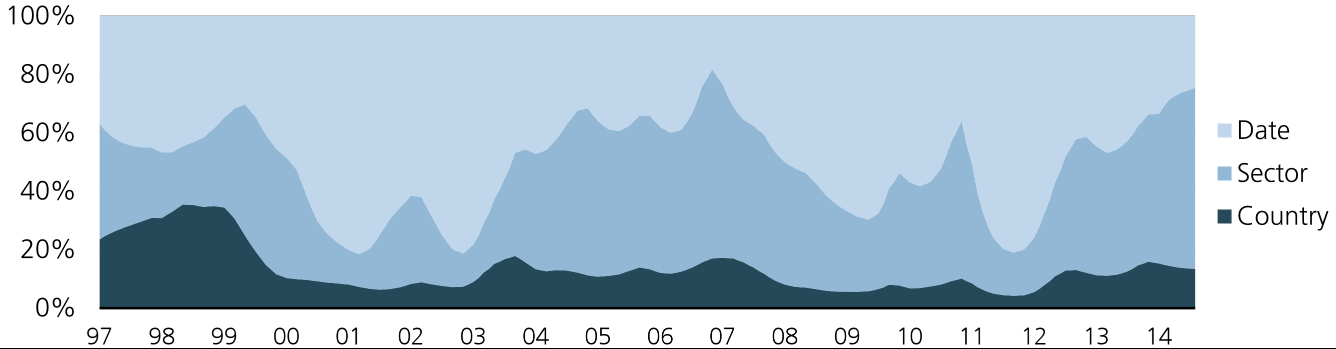
Source: MSCI, IBES, FactSet, UBS

The rank information co-efficient (IC) is the correlation between the (ranked) forecast monthly return and the actual return, at each point in time. This is useful because it captures the entire cross-section of the index rather than just the extremities in the long-short strategy; however it lacks the same intuition as a portfolio return. Figure 16 shows this relationship rarely experiences sustained inversion, except for the quant meltdown following the global financial crisis.

The brief periods of underperformance in Figure 14 warrant further investigation. These are coincident with periods in which the market environment was volatile and factor returns were inconsistent. Our model utilises a short trailing window to determine which factors have contributed to recent performance, so periods in which these signals are volatile inherently cause more uncertainty in the output.

We can examine the mechanics of the random forest model during these periods to highlight which factors are being loaded on, using the variable importance metrics introduced earlier. This is analogous to looking at a rolling R^2 statistic in a linear model context—but here we can also easily incorporate categorical variables.

Figure 17: MSCI AC World macro variable importance



Source: MSCI, IBES, FactSet, UBS

From Figure 17 we can see the importance of the macro variables date, sector and country within the model, which yields some interesting insights:

- The date variable importance is a proxy for overall factor volatility, essentially measuring how varied the factor return environment is within the trailing window. Low importance means the model detects strong overall time series similarity; this precedes the major market corrections in 2000, 2007, and somewhat disconcertingly, now.

Date variable importance captures time series similarity

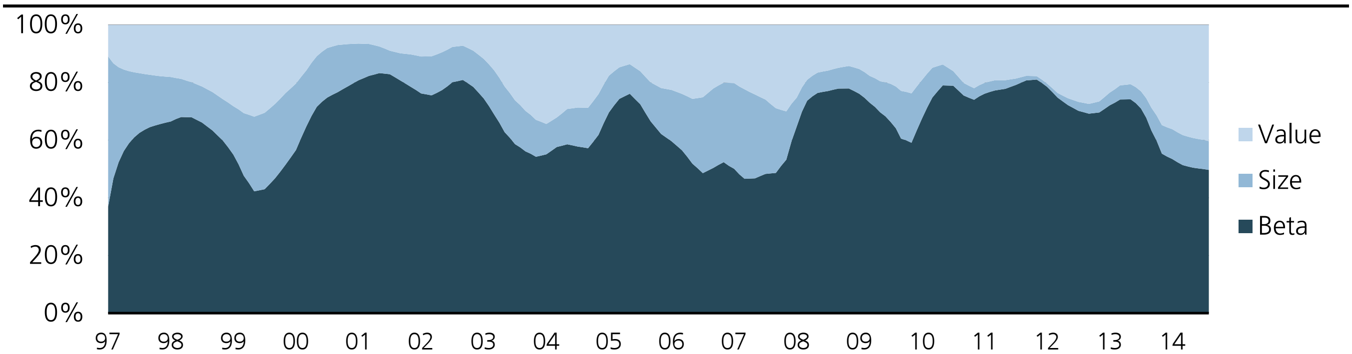
- The sector variable measures the extent that the sector distinguishes stock level performance. High sector importance was likely caused by the tech sector overheating in 2000, the financial sector in 2007 and perhaps defensives in 2015.

Sector variable importance captures how distinctly the sectors are operating

- The country variable has been suppressed by neutralisation. In future work we may explore this interaction further, but market breadth becomes a limitation when neutralising out too many risk factors.

Country importance has been suppressed by neutralisation

Figure 18: MSCI AC World factor variable importance



Source: MSCI, IBES, FactSet, UBS

Similarly, we can observe the relative importance of the other factors. Figure 18 above shows the variable importance over time of the three Fama-French factors: value (price to book), size and beta, which yields some further insights into the model operation:

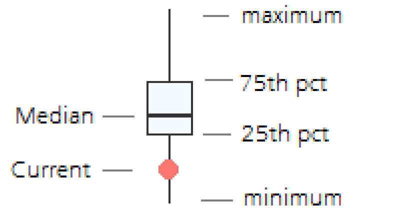
- The size importance captures a small-cap premium in a speculative market environment, which then collapses in a correction. This saw a historic low in 2011 as Operation Twist drained market risk appetite—note this is measuring the magnitude of the importance and not the direction.
- Beta became increasingly significant during sustained market movement. The subdued current importance of beta represents the fickle risk appetite in the current environment, amid heightened sensitivity to macro risks.

Variable importance captures complex interactions, not just which factors are working

Variable importance does more than merely reflect the factors that are currently working on a univariate basis, it captures the more complex interactions between them. For example, if forecast earnings growth and beta become highly correlated, variable importance will emphasise the most meaningful relationship and not the others. This dynamic approach reduces the need to time the style environment, as there are no parameters to adjust and the model will naturally adapt to the prevailing market conditions.

In practice, hundreds of factors are evaluated concurrently and it is impossible to show them all in this manner. The subsequent regional results use the chart shown in Figure 19 to more concisely illustrate variable importance, showing some of the most active factors in the model over the past five years. The boxplots are coloured according to the distance of the current value from its median; a dark blue box means the factor is historically overweight and a white box is underweight.

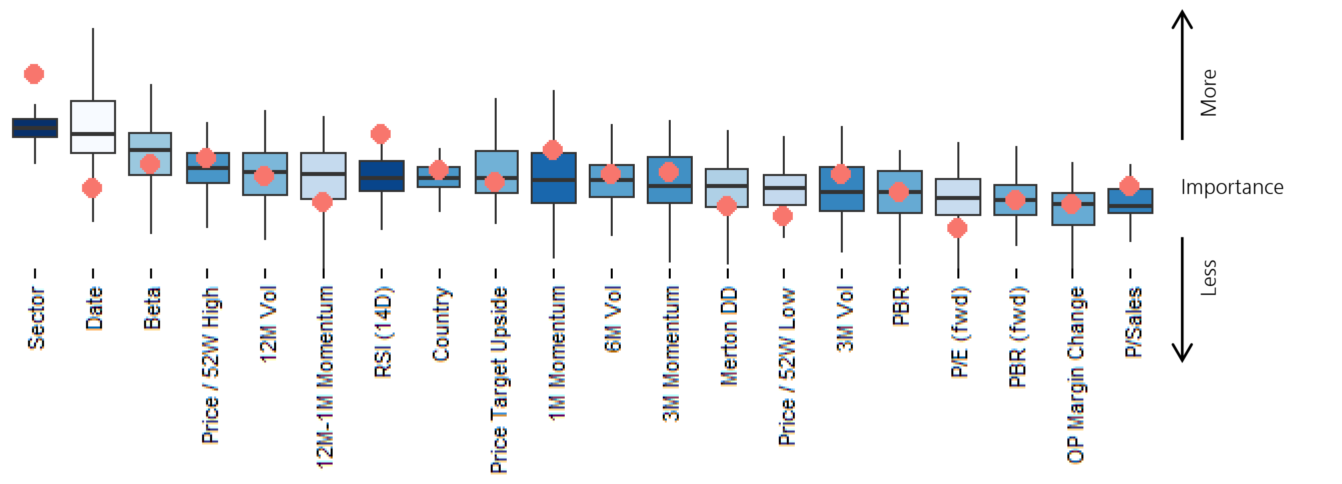
Figure 19: Boxplot interpretation



Source: UBS

From Figure 20 we can see that the time series similarity in November 2014 was very low, sector effects and short term mean reversion (RSI) were strong, and the model is heavily underweight beta and forward PE.

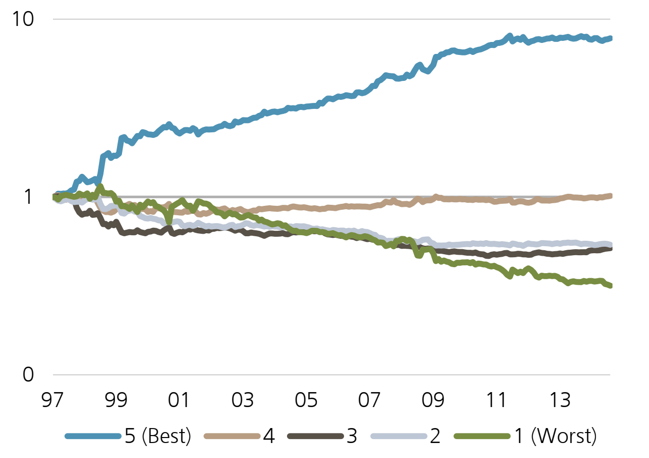
Figure 20: MSCI AC World variable importance



Source: MSCI, IBES, FactSet, UBS

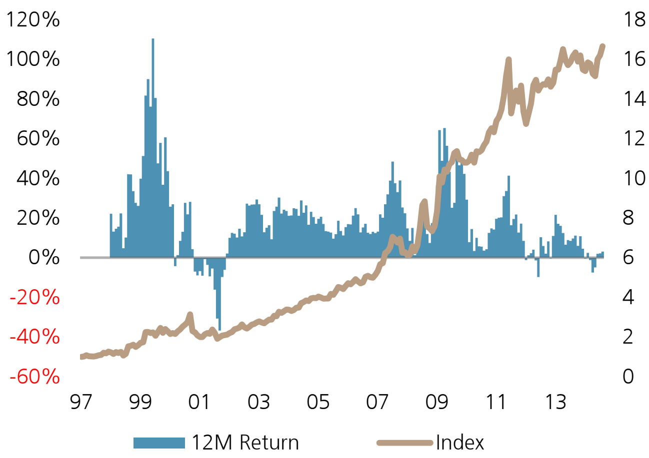
MSCI AC Asia Pacific ex-Japan

Figure 21: Excess quintiles



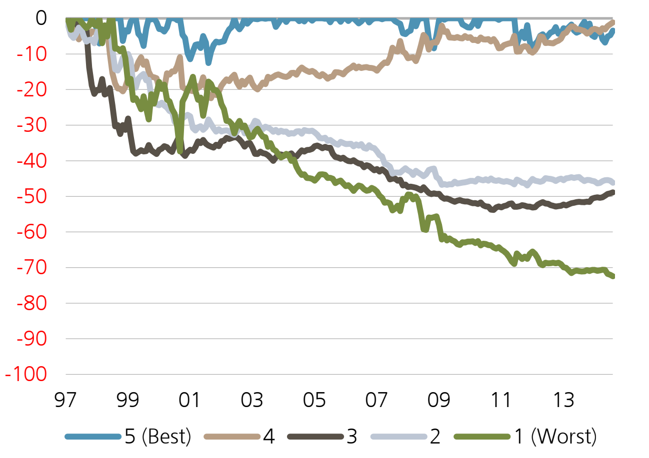
Source: MSCI, IBES, FactSet, UBS

Figure 22: Long-short



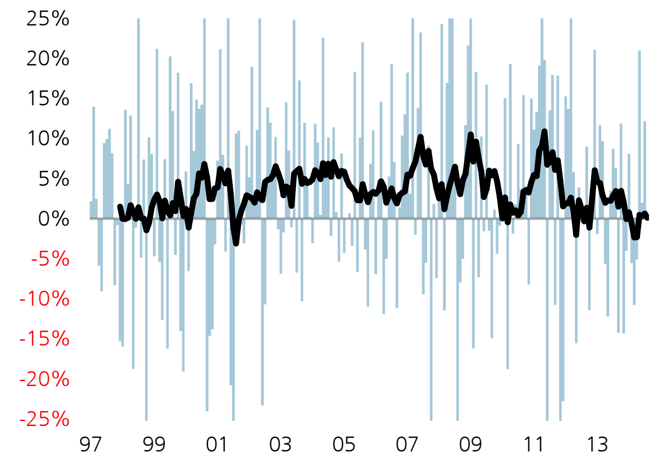
Source: MSCI, IBES, FactSet, UBS

Figure 23: Excess drawdown



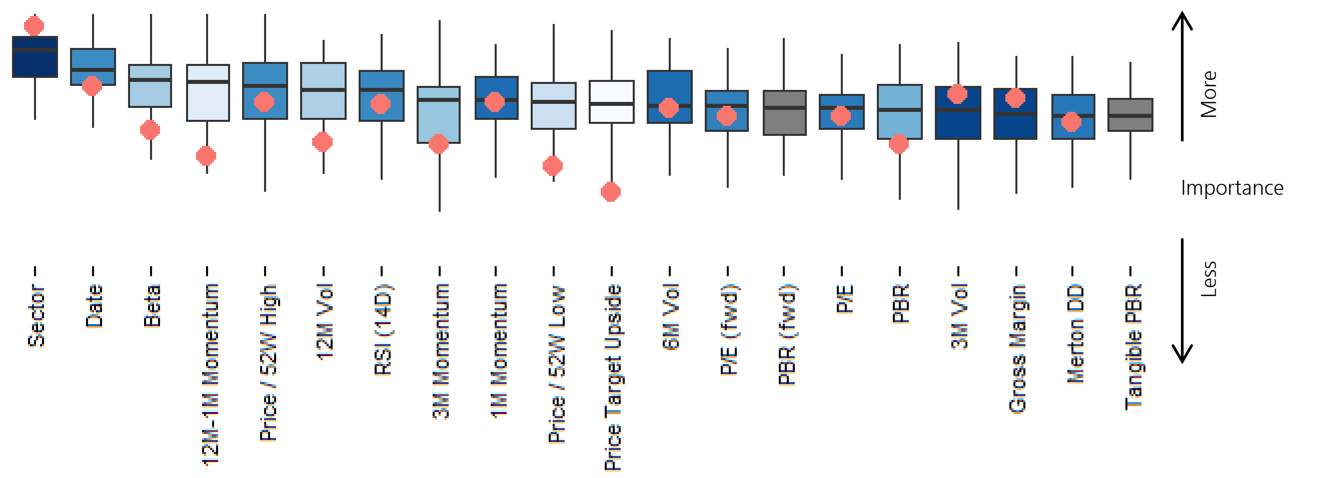
Source: MSCI, IBES, FactSet, UBS

Figure 24: Rank IC



Source: MSCI, IBES, FactSet, UBS

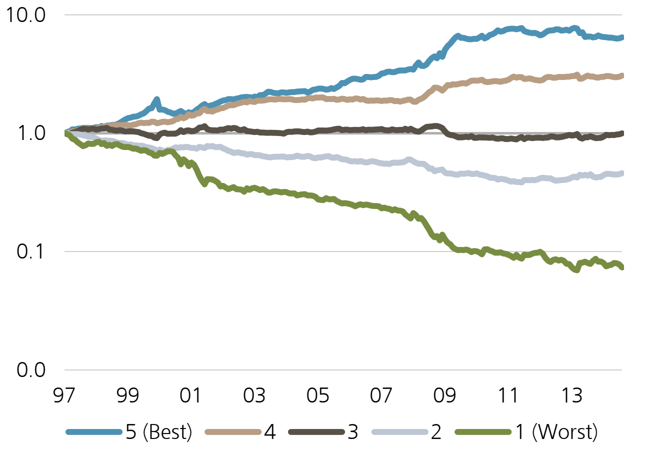
Figure 25: Variable importance



Source: MSCI, IBES, FactSet, UBS

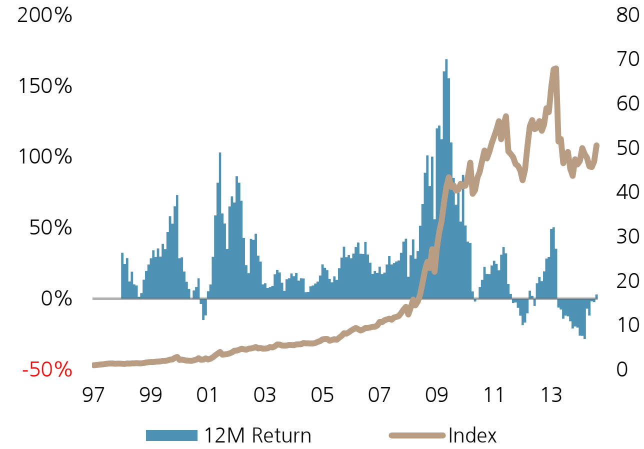
S&P/ASX 300

Figure 26: Excess quintiles



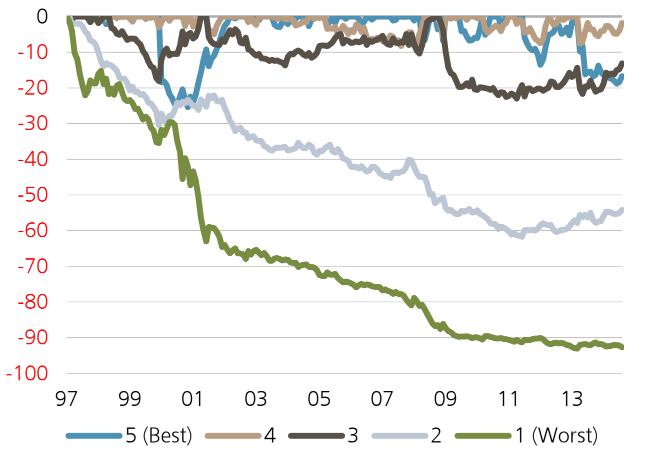
Source: S&P, IBES, FactSet, UBS

Figure 27: Long-short



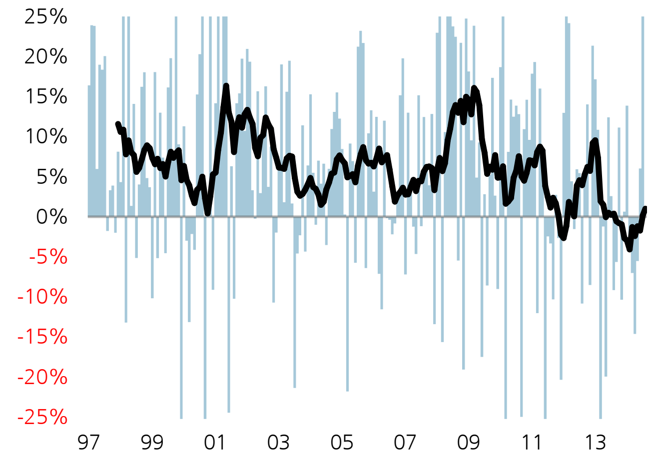
Source: S&P, IBES, FactSet, UBS

Figure 28: Excess drawdown



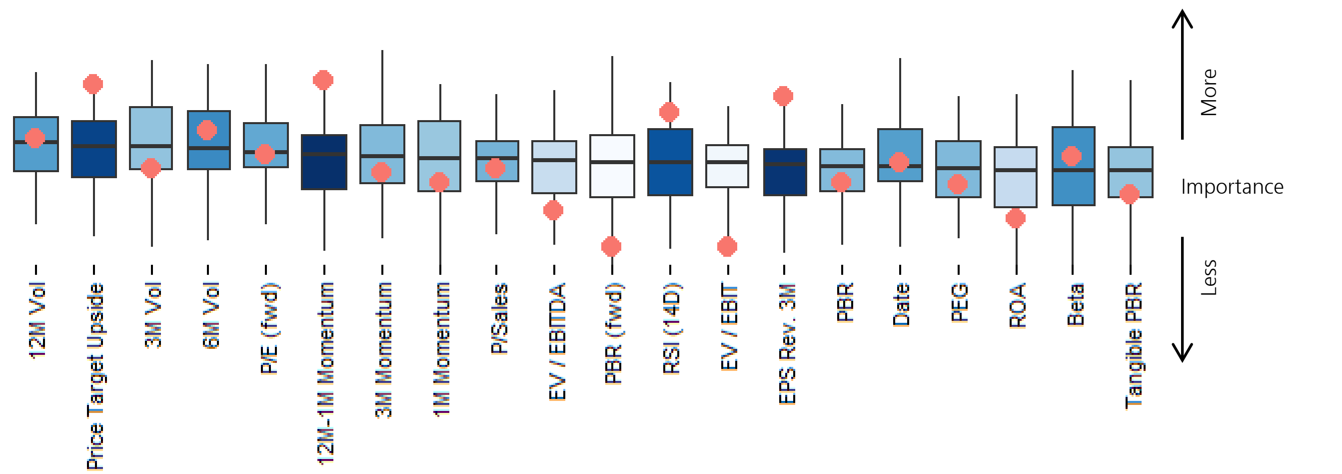
Source: S&P, IBES, FactSet, UBS

Figure 29: Rank IC



Source: S&P, IBES, FactSet, UBS

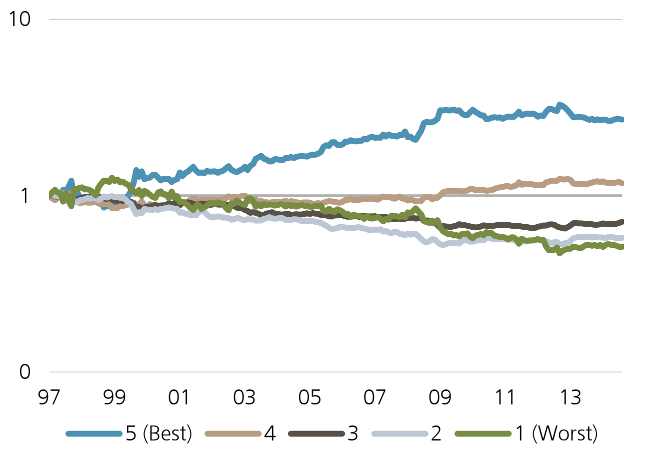
Figure 30: Variable importance



Source: S&P, IBES, FactSet, UBS

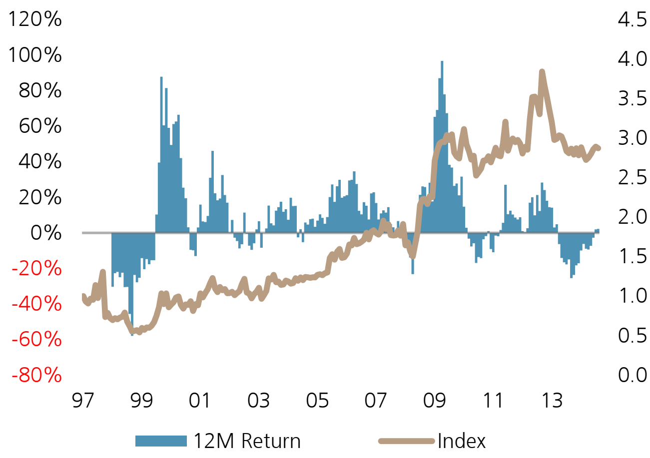
MSCI Japan

Figure 31: Excess quintiles



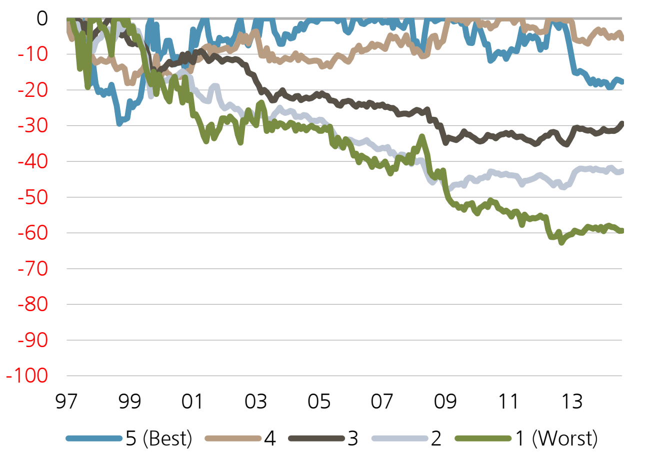
Source: MSCI, IBES, FactSet, UBS

Figure 32: Long-short



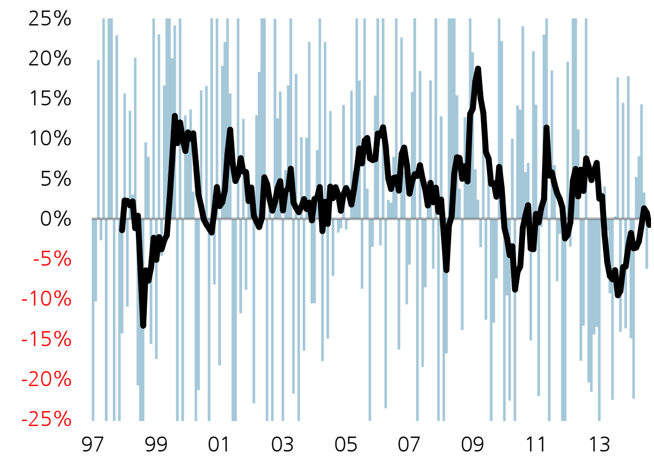
Source: MSCI, IBES, FactSet, UBS

Figure 33: Excess drawdown



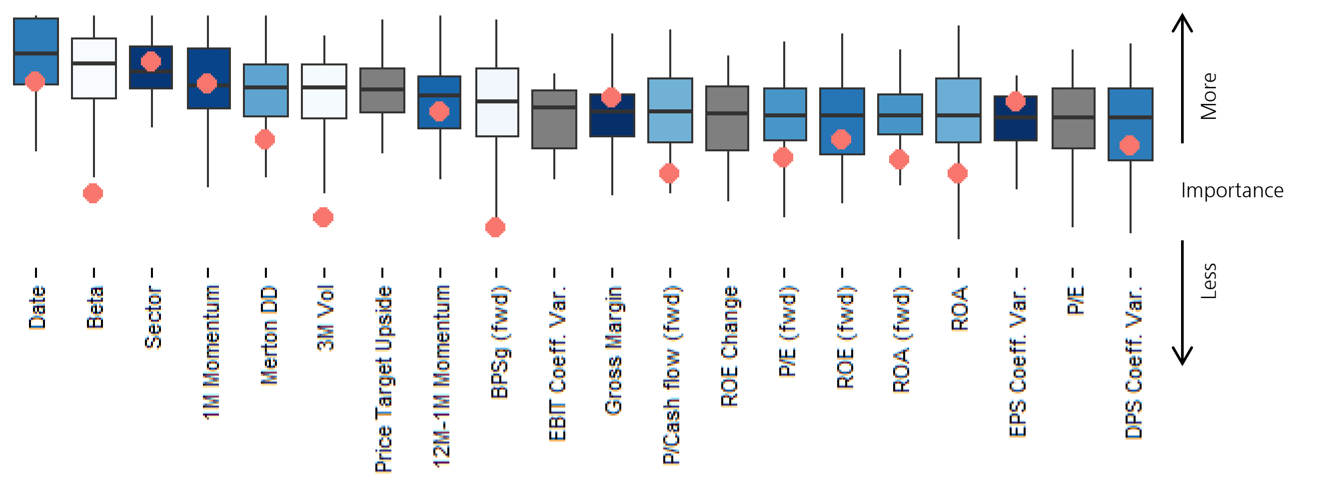
Source: MSCI, IBES, FactSet, UBS

Figure 34: Rank IC



Source: MSCI, IBES, FactSet, UBS

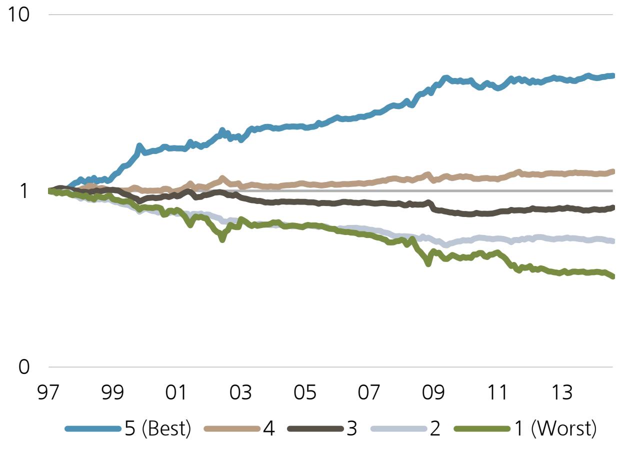
Figure 35: Variable importance



Source: MSCI, IBES, FactSet, UBS

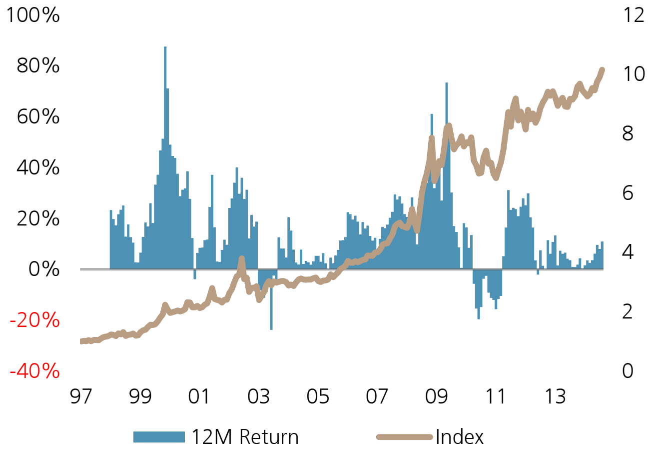
MSCI Europe

Figure 36: Excess quintiles



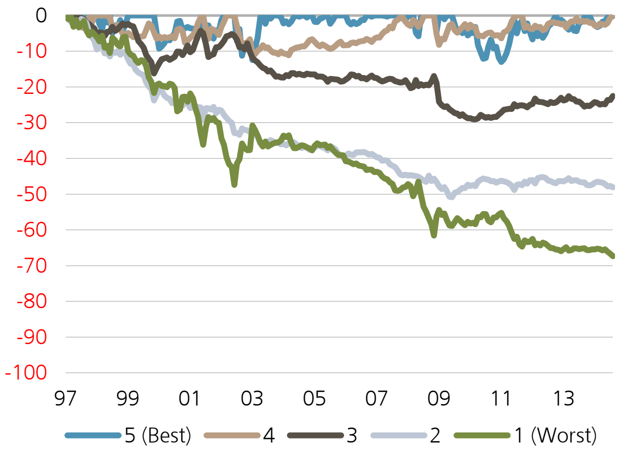
Source: MSCI, IBES, FactSet, UBS

Figure 37: Long-short



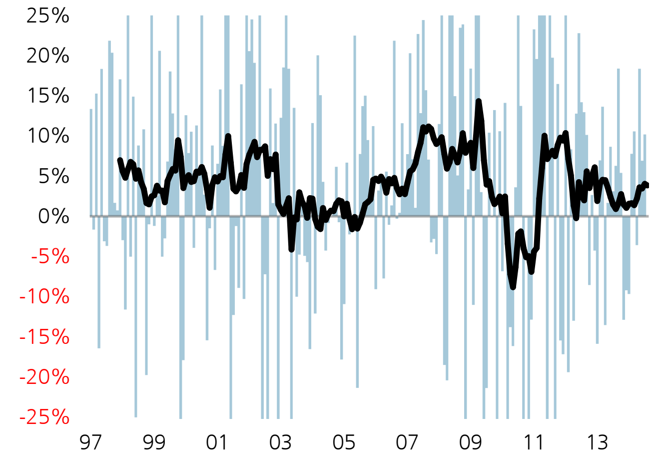
Source: MSCI, IBES, FactSet, UBS

Figure 38: Excess drawdown



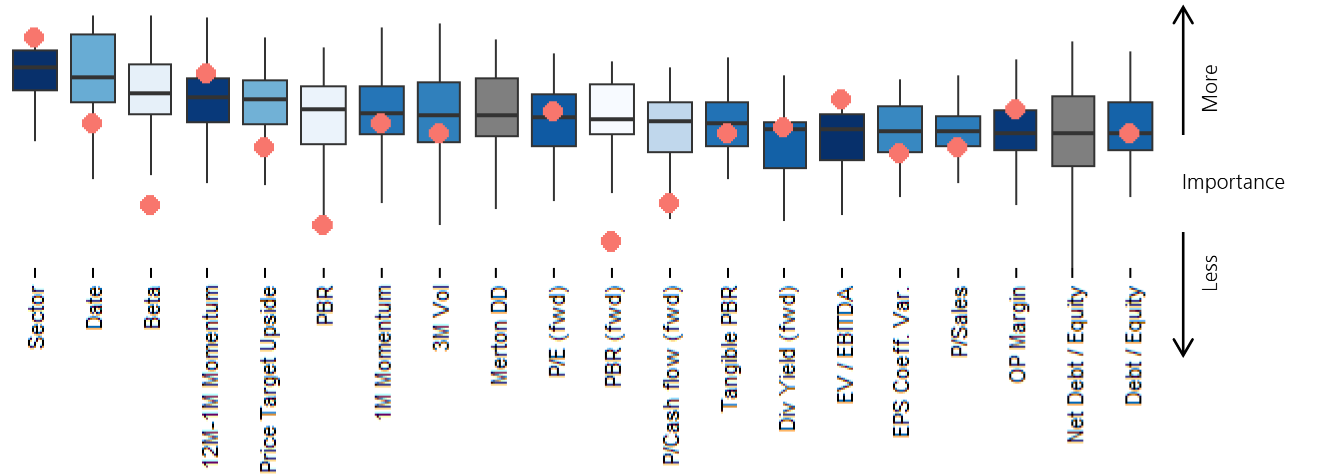
Source: MSCI, IBES, FactSet, UBS

Figure 39: Rank IC



Source: MSCI, IBES, FactSet, UBS

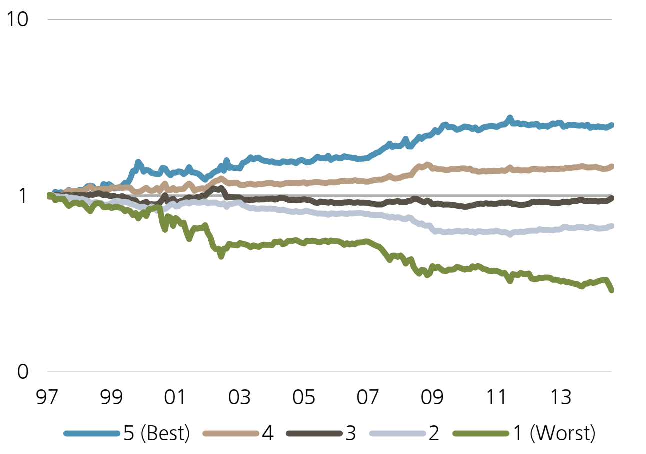
Figure 40: Variable importance



Source: MSCI, IBES, FactSet, UBS

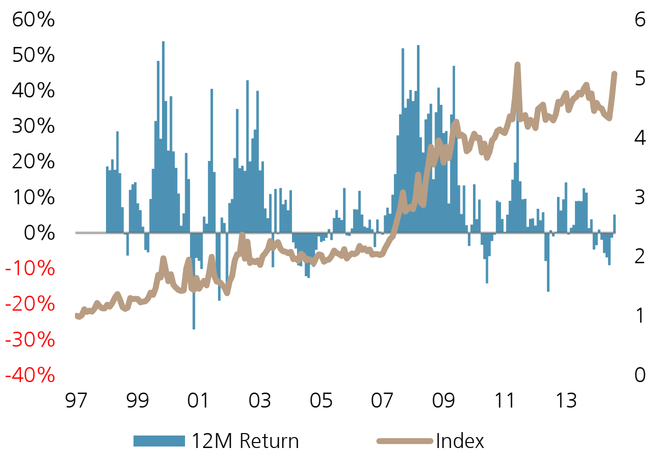
MSCI North America

Figure 41: Excess quintiles



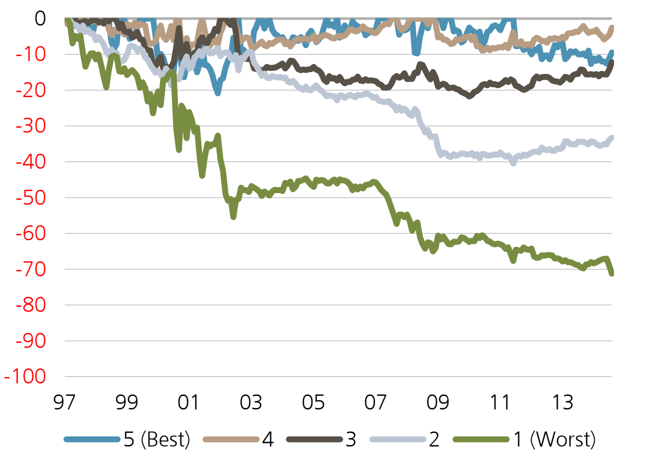
Source: MSCI, IBES, FactSet, UBS

Figure 42: Long-short



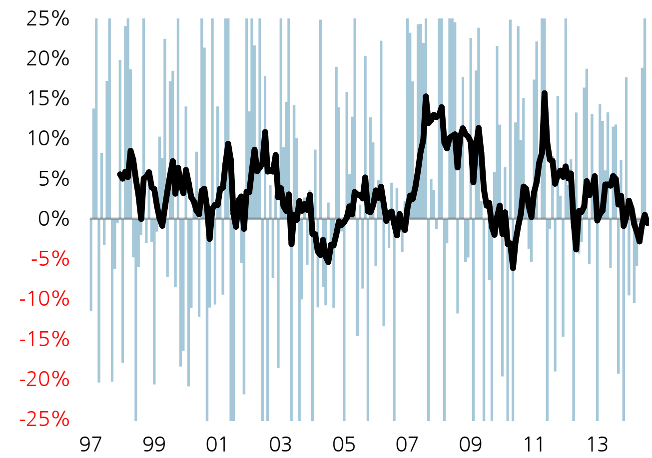
Source: MSCI, IBES, FactSet, UBS

Figure 43: Excess drawdown



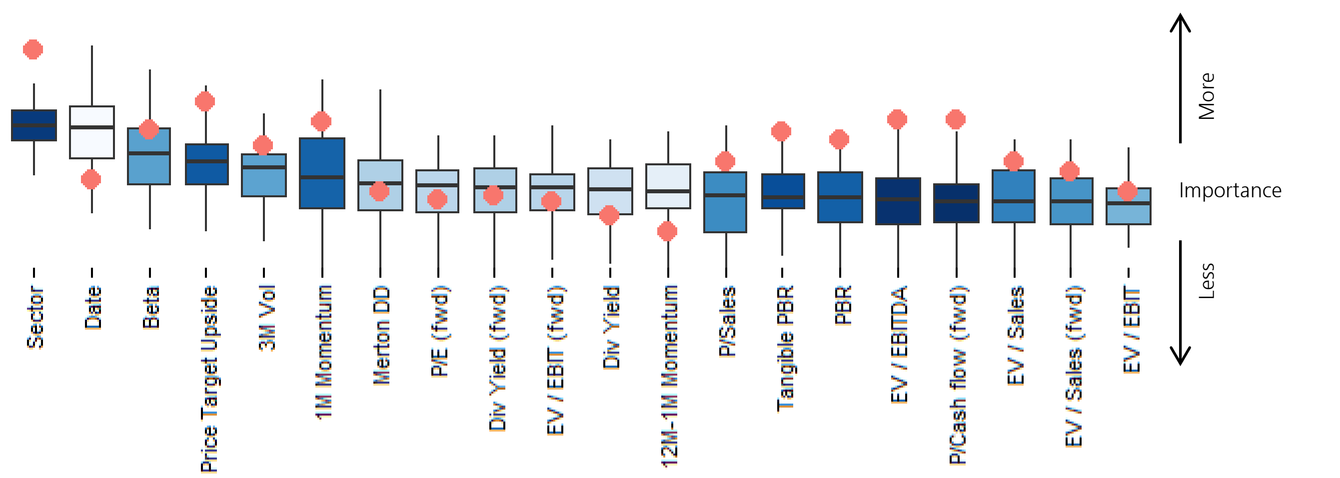
Source: MSCI, IBES, FactSet, UBS

Figure 44: Rank IC



Source: MSCI, IBES, FactSet, UBS

Figure 45: Variable importance



Source: MSCI, IBES, FactSet, UBS

Stock screen

Figure 46: Asia Pacific stock and sector forecast—January 2015

Ticker	Name	Prediction	Ticker	Name	Prediction	Sector	Prediction
	MSCI AC Asia Pacific ex Japan - Top 10			MSCI AC Asia Pacific ex Japan - Bottom 10			Sector Outlook
6881-HK	China Galaxy Securities	6.9%	STO-AU	Santos Limited	-8.7%	Financials	1.5%
1800-HK	China Communications	7.3%	SAKP-MY	SapuraKencana Petrol	-8.6%	Industrials	0.6%
2601-HK	China Pacific Insurance	7.4%	135-HK	KunLun Energy Co. Lt	-8.2%	Telecomms.	0.2%
2318-HK	Ping An Insurance	7.4%	PTTEP-TH	PTT Exploration & Production	-8.1%	Utilities	0.1%
QAN-AU	Qantas Airways Limit	7.6%	WOR-AU	Worleyparsons Ltd	-7.7%	Info. Tech.	0.0%
3968-HK	China Merchants Bank	7.6%	ORG-AU	Origin Energy Ltd	-7.4%	Health Care	-0.3%
1336-HK	New China Life	7.6%	5210-MY	Bumi Armada Bhd.	-7.0%	Consumer Staples	-0.6%
1988-HK	China Minsheng	7.8%	ITMG-ID	PT Indo Tambangraya Megah	-6.6%	Materials	-0.7%
6837-HK	Haitong Securities	7.8%	CAIR-IN	Cairn India Limited	-6.5%	Consumer Disc.	-1.0%
2628-HK	China Life Insurance	7.9%	1211-HK	BYD Co. Ltd. Class H	-6.4%	Energy	-4.0%
	S&P/ASX300 - Top 10			S&P/ASX300 - Bottom 10			Sector Outlook
PTM-AU	Platinum Asset Management	3.6%	VET-AU	Vocation Ltd.	-19.1%	Telecomms.	1.9%
SPK-AU	Spark New Zealand	3.7%	HZN-AU	Horizon Oil Limited	-15.0%	Financials	1.3%
SRX-AU	Sirtex Medical Ltd	4.0%	BCI-AU	BC Iron Limited	-14.9%	Utilities	-0.2%
AMM-AU	Amcom Telecomms.	4.0%	NWH-AU	NRW Holdings Limited	-14.9%	Consumer Staples	-0.4%
RMD-AU	Resmed	4.1%	ASL-AU	Ausdrill Limited	-14.8%	Health Care	-0.5%
QAN-AU	Qantas Airways Limit	4.1%	SEA-AU	Sundance Energy	-14.3%	Info. Tech.	-1.2%
CSL-AU	CSL Limited	4.3%	AGO-AU	Atlas Iron Limited	-14.1%	Consumer Disc.	-1.6%
CTD-AU	Corporate Travel Management	4.7%	TGS-AU	Tiger Resources Limited	-13.9%	Industrials	-2.5%
CNU-AU	Chorus Limited	5.0%	DLS-AU	Drillsearch Energy Ltd	-13.0%	Materials	-4.9%
MFG-AU	Magellan Financial G	6.0%	SDL-AU	Sundance Resources L	-12.8%	Energy	-7.6%
	MSCI Japan - Top 10			MSCI Japan - Bottom 10			Sector Outlook
6869-JP	Sysmex Corporation	2.5%	3668-JP	COLOPL, Inc.	-3.9%	Materials	1.4%
4612-JP	NIPPON PAINT HOLDING	2.6%	3765-JP	Gungho Online Entertainment	-3.3%	Consumer Disc.	0.9%
7276-JP	Koito Manufacturing	2.6%	6740-JP	Japan Display Inc.	-3.3%	Consumer Staples	0.7%
7951-JP	Yamaha Corporation	2.6%	8572-JP	ACOM Co., Ltd.	-2.6%	Industrials	0.5%
4661-JP	Oriental Land Co., L	2.7%	2121-JP	Mixi, Inc.	-2.3%	Utilities	0.5%
4005-JP	Sumitomo Chemical Co	2.7%	8804-JP	Tokyo Tatemono Co.,	-2.2%	Financials	0.3%
3407-JP	Asahi Kasei Corp.	2.8%	4519-JP	Chugai Pharmaceutical	-2.2%	Info. Tech.	0.2%
7701-JP	Shimadzu Corporation	2.9%	6753-JP	Sharp Corporation	-2.0%	Health Care	0.0%
7259-JP	Aisin Seiki Co Ltd	3.1%	6366-JP	Chiyoda Corp.	-1.9%	Energy	-0.1%
7532-JP	Don Quijote Holdings	3.2%	4506-JP	Sumitomo Dainippon Pharma	-1.9%	Telecomms.	-0.7%

Source: MSCI, S&P/ASX, IBES, FactSet, UBS

Figure 47: Rest of world stock and sector forecast—January 2015

Ticker	Name	Prediction	Ticker	Name	Prediction	Sector	Prediction
	MSCI Europe - Top 10			MSCI Europe - Bottom 10		Sector Outlook	
GMKN-RU	MMC Norilsk Nickel JSC	3.0%	SDRL-NO	Seadrill Ltd.	-10.2%	Consumer Disc.	0.8%
NHY-NO	Norsk Hydro ASA	3.1%	RIGN-CH	Transocean Ltd.	-9.4%	Info. Tech.	0.6%
ATC-NL	Altice SA	3.2%	TLW-GB	Tullow Oil plc	-9.1%	Industrials	0.2%
RY4B-IE	Ryanair Holdings Plc	3.2%	PFC-GB	Petrofac Limited	-8.4%	Materials	-0.2%
FCA-IT	Fiat Chrysler Automobiles	3.3%	BG-GB	BG Group plc	-7.3%	Telecomms.	-0.3%
DC-GB	Dixons Carphone plc	3.4%	FP-FR	Total SA	-6.0%	Consumer Staples	-0.4%
			BMPS-IT	Banca Monte dei Paschi di Siena	-5.7%	Utilities	-0.5%
TRNFP-RU	Transneft OJSC Pref.	3.8%	VK-FR	Vallourec SA	-5.7%	Health Care	-0.6%
NUM-FR	Numericable-SFR SA	4.9%	BLT-GB	BHP Billiton Plc	-5.6%	Financials	-0.8%
ALRS-RU	AC ALROSA OJSC	4.9%	SUBC-NO	Subsea 7 S.A.	-5.3%	Energy	-3.1%
	MSCI North America - Top 10			MSCI North America - Bottom 10		Sector Outlook	
LOW-US	Lowe's Companies, In	3.2%	PRE-CA	Pacific Rubiales Energy	-13.3%	Consumer Disc.	0.8%
CVS-US	CVS Health Corporation	3.2%	BTE-CA	Baytex Energy Corp.	-12.9%	Consumer Staples	0.8%
DAL-US	Delta Air Lines, Inc	3.3%	MEG-CA	MEG Energy Corp.	-12.4%	Health Care	0.4%
KMX-US	CarMax, Inc.	3.3%	POU-CA	Paramount Resources	-11.9%	Utilities	0.4%
MG-CA	Magna International	3.4%	PWT-CA	Penn West Petroleum	-11.6%	Financials	0.2%
MRU-CA	Metro Inc.	3.4%	ERF-CA	Enerplus Corporation	-10.5%	Info. Tech.	0.1%
CCT-CA	Catamaran Corp.	3.7%	WLL-US	Whiting Petroleum	-10.2%	Industrials	-0.1%
ATD.B-CA	Alimentation Couche-Tard	3.8%	TLM-CA	Talisman Energy Inc.	-10.1%	Materials	-1.8%
UAL-US	United Continental H	3.8%	NBR-US	Nabors Industries Ltd	-9.5%	Telecomms.	-2.2%
SPLS-US	Staples, Inc.	4.4%	ESV-US	Ensco plc	-9.5%	Energy	-6.9%

Source: MSCI, IBES, FactSet, UBS

Appendix

Bias-variance decomposition

To provide an explanation as to why the results shown in Figure 12 work, we first provide a mathematical basis for the bias-variance trade-off in a regression context. If we assume that there is an underlying, unobservable function $f(x)$, which is related to our observable outputs via $y = f(x) + \epsilon$, with $\mathrm{E}(\epsilon) = 0$ and $\mathrm{Var}(\epsilon) = \sigma^2$, our model $\hat{f}(x)$ seeks to approximate this by minimising the mean squared error $E\left[\left(y - \hat{f}\right)^2\right]$, which then has a well-known reduction, see Geman (1992):

$$E\left[\left(y - \hat{f}\right)^2\right] = E\left[f - E\left[\hat{f}\right]\right]^2 + E\left[\hat{f} - E\left[\hat{f}\right]\right]^2 + \mathrm{E}[\epsilon^2]$$

$$= Bias(\hat{f})^2 \qquad + Variance(\hat{f}) \; + \quad \sigma^2$$

The first component is the squared bias, which measures the systematic error or how far the average cluster of estimates sits from the true value. The second term is the variance, measuring how far these estimates spread out around the mean. The last component is the residual error, which forms a theoretical lower bound for the error rate and is independent of both the data and the algorithm.

If we now make explicit the relationship between a randomly selected training set T and a random vector characterising each regression tree $\Theta_b(\mathrm{T})$, our ensemble estimator is just the simple average over the individual trees, which then has the limiting form (as $B \to \infty$):

$$\bar{f}_B(x) = \frac{1}{B}\sum_b \hat{f}(x;\ \Theta_b(\mathrm{T}))$$

$$\bar{f}(x) \to E_{\Theta|\mathrm{T}}(\hat{f}(x; \Theta(\mathrm{T}))$$

Brieman (2001) finds that the variance and bias of this limiting form is

$$Var(\bar{f}) = \bar{\rho}(x) \cdot \hat{f}(x)$$

$$Bias(\bar{f}) = \mu(x) - E_{\mathrm{T}}\hat{f}(x)$$

Where the correlation induced by the sampling distribution of T and Θ is given by:

$$\bar{\rho}(x) = E_{\mathrm{T},\Theta_1,\Theta_2}\, corr\{\hat{f}(x; \Theta_1(\mathrm{T}), \hat{f}(x; \Theta_2(\mathrm{T})\}$$

So we can see the bias is essentially unchanged in the ensemble but the variance experiences a reduction from the individual estimator by a factor of $\bar{\rho}(x)$. Also worth noting is that random forests are such a modern technique that their statistical properties are not yet fully understood; the dependency of the random variables Θ_b on T, makes their analysis extremely complex. As a consequence, simplifications of the original RF model are studied to provide insight into its nature, eg Arlot and Genuer (2014).

Random forests, boosting and bagging

Random forests are an extension to a bagging algorithm; their innovative step is to add more randomness to the process by incorporating the randomly generated tree structure characterised by Θ above. This is very distinct to boosting, in which the trees are iteratively grown and accordingly are not independently distributed.

Hastie (2009) shows the variance reduction induced by bagging is limited by the correlation between the trees. If we have B bootstrap iterations in our ensemble, each with variance σ^2 and the correlation between these is denoted as ρ, the variance of the ensemble is then:

$$\rho\sigma^2 + \frac{1-\rho}{B} \cdot \sigma^2$$

As the number of bootstrap samples increases, the second term goes to 0 and the lower bound on the variance is then proportional to the correlation between the trees. It is this lower bound that random forests seek to reduce further by de-correlating the trees via their random composition.

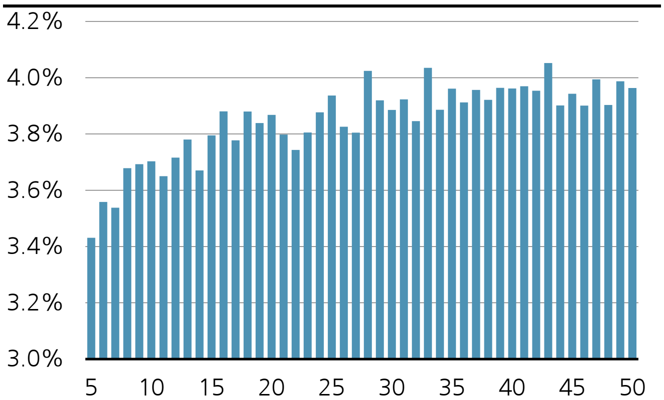
Pruning and over-fitting

Segal (2004) finds that performance gains can be achieved by not growing the trees to full depth as is standard. Singular trees are commonly pruned to reduce the impact of over-fitting discussed earlier; this has the effect of reducing the σ^2 term in the ensemble variance relationship shown above. We did not prune the trees in our standard tests and grow them to full depth because the performance benefit is marginal and this leaves us with one less tuning parameter—however the conditional inference forests discussed below do implement statistical stopping criteria.

The true appeal of random forests lies in the fact that excellent performance can be achieved with very little effort. Random forests essentially have a single tuning parameter, the number of splitting variables. Interestingly, this parameter enforces trade-offs within the structure of random forests themselves; the more parameters are available for each split, the lower the bias of the individual tree predictors, but this comes at the cost of increased correlation within the ensemble.

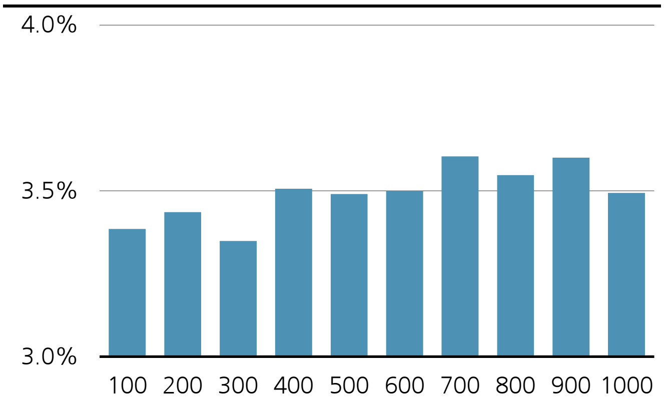
Below we show the effect that varying the number of splitting variables and the number of trees has on our model performance. Somewhat unexpectedly, the rank IC improves steadily as the number of splitting variables increases. However this performance improvement tapers off around 30% of the available factors; our factor database contains roughly 120 factors. From Figure 49 we can see that asymptotic performance is achieved early by varying the number of trees, and further increasing this parameter has marginal effect.

Figure 48: MXAPJ mean rank IC vs. splitting variables



Source: MSCI, IBES, FactSet, UBS

Figure 49: MXAPJ mean rank IC vs. number of trees



Source: MSCI, IBES, FactSet, UBS

Variable importance

There are several means by which the importance of the variables can be assessed in the random forest context. A naïve approach is to simply count the number of times the variable is used in the ensemble; however this does not actually measure the significance of the variable to the response and is rarely used in practice.

A more accurate technique is to consider the improvement of the node impurity by splitting on the variable, averaged over all of the trees. Node impurity is measured by the residual sum of squares in a regression context or the Gini impurity index in a classification context. Essentially this formalises how effective the variable is in partitioning the output space. This is often referred to as the "decrease in purity" importance.

Yet another technique is to record the mean squared error (regression) or error rate (classification) of the OOB data for each tree, then to randomly permute the variable using the original data and record the subsequent decrease in accuracy. The rationale is that by breaking the association of the variable with the response, the observed drop in performance provides a direct indication of how important the variable is. This is referred to as the permutation accuracy

Strobl (2008) investigates the statistical basis of these variable importance metrics and finds that they yield some undesirable properties: the power of the test does not improve with an increase in the sample size but does increase with the number of trees, which, as shown above, is largely arbitrary after a point and often chosen at discretion. This in part forms the motivation for a statistically-based random forest algorithm, discussed below.

Conditional inference

In our model we actually use a different technique based on conditional inference for constructing the regression trees used in the ensemble, rather than the traditional CART algorithm. This addresses two well-known issues with the random forest procedure: 1) trees grown to full-depth tend to over-fit the data; and 2) they suffer from variable selection bias in the presence of predictors with highly varied measurement scales, unique levels and missing values.

The conditional inference framework was refined from earlier work by Hothorn (2006) then extended to the random forest context by Strobl (2007). Essentially their statistical approach to recursive binary partitioning incorporates the distributional properties of the predictors in the degrees of freedom, then employs hypothesis tests to determine the stopping criteria, which together produce unbiased variable importance measures with performance comparable to optimally pruned trees.

Figure 50: Factors used in the model

12M Momentum	CFPS Rev. 3M	EV / Sales Growth (fwd)	Price / 52W Low
12M Vol	Country	FCF Growth	Price / Intrinsic Value
12M-1M Momentum	CPSg (fwd)	FCF Growth (5Y)	Price Target Upside
1M Momentum	Debt / Equity	FCF Yield	ROA
3M Momentum	Div Cover	Gross Margin	ROA (fwd)
3M Vol	Div Yield	Gross Margin Change	ROA Change
52W High Price	Div Yield (fwd)	Index Weight	ROA Coeff. Var.
52W Low Price	DPS Coeff. Var.	Interest Cover	ROA Rev. 1M
6M Momentum	DPS Rev. 1M	Market Cap (USD)	ROA Rev. 2M
6M Vol	DPS Rev. 2M	Mean Rec.	ROA Rev. 3M
Beta	DPS Rev. 3M	Merton DD	ROAg (fwd)
Beta (Down)	DPSg (fwd)	Net Debt / Equity	ROE
Beta (Local index)	DPSg (Trailing)	NP Margin	ROE (fwd)
Beta (Up)	EBIT Coeff. Var.	NP Margin Change	ROE Change
BPS Coeff. Var.	EBIT Rev. 1M	OCF Growth	ROE Change (fwd)
BPS Growth (5Y)	EBIT Rev. 2M	OCF Growth (5Y)	ROE Coeff. Var.
BPS Rev. 1M	EBIT Rev. 3M	OCF Yield	ROE Rev. 1M
BPS Rev. 2M	EBITg (fwd)	OP Margin	ROE Rev. 2M
BPS Rev. 3M	EPS Coeff. Var.	OP Margin (fwd)	ROE Rev. 3M
BPSg (fwd)	EPS Growth (5Y)	OP Margin Change	ROIC
BPSg (Trailing)	EPS Rev. 1M	P/Cash flow (fwd)	ROIC Change
Buybacks / Market Cap	EPS Rev. 2M	P/E	RSI (14D)
Capex	EPS Rev. 3M	P/E (fwd)	Sales Coeff. Var.
Capex / Depn.	EPSg (fwd)	P/Sales	Sales Growth (5Y)
Capex Growth	EPSg (Trailing)	PBR	Sales Growth (trailing)
Cash Conversion Cycle	EV / EBIT	PBR (fwd)	Sales Rev. 1M
CCC Change	EV / EBIT (fwd)	PEG	Sales Rev. 2M
CFPS Coeff. Var.	EV / EBITDA	PEG (fwd)	Sales Rev. 3M
CFPS Rev. 1M	EV / Sales	Price	Sector
CFPS Rev. 2M	EV / Sales (fwd)	Price / 52W High	Tangible PBR

Source: UBS

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Statement of Risk

Our quantitative models rely on reported financial statement information, consensus earnings forecasts and stock prices. Errors in these numbers are sometimes impossible to prevent (as when an item is misstated by a company). Also, the models employ historical data to estimate the efficacy of stock selection strategies and the relationships among strategies, which may change in the future. Additionally, unusual company-specific events could overwhelm the systematic influence of the strategies used to rank and score stocks.

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12-Month Rating	Definition	Coverage[1]	IB Services[2]
Buy	FSR is > 6% above the MRA.	47%	37%
Neutral	FSR is between -6% and 6% of the MRA.	42%	32%
Sell	FSR is > 6% below the MRA.	11%	21%
Short-Term Rating	**Definition**	**Coverage[3]**	**IB Services[4]**
Buy	Stock price expected to rise within three months from the time the rating was assigned because of a specific catalyst or event.	less than 1%	less than 1%
Sell	Stock price expected to fall within three months from the time the rating was assigned because of a specific catalyst or event.	less than 1%	less than 1%

Source: UBS. Rating allocations are as of 31 December 2014.
1:Percentage of companies under coverage globally within the 12-month rating category. 2:Percentage of companies within the 12-month rating category for which investment banking (IB) services were provided within the past 12 months.
3:Percentage of companies under coverage globally within the Short-Term rating category. 4:Percentage of companies within the Short-Term rating category for which investment banking (IB) services were provided within the past 12 months.

KEY DEFINITIONS: Forecast Stock Return (FSR) is defined as expected percentage price appreciation plus gross dividend yield over the next 12 months. **Market Return Assumption (MRA)** is defined as the one-year local market interest rate plus 5% (a proxy for, and not a forecast of, the equity risk premium). **Under Review (UR)** Stocks may be flagged as UR by the analyst, indicating that the stock's price target and/or rating are subject to possible change in the near term, usually in response to an event that may affect the investment case or valuation. **Short-Term Ratings** reflect the expected near-term (up to three months) performance of the stock and do not reflect any change in the fundamental view or investment case. **Equity Price Targets** have an investment horizon of 12 months.

EXCEPTIONS AND SPECIAL CASES: UK and European Investment Fund ratings and definitions are: Buy: Positive on factors such as structure, management, performance record, discount; **Neutral:** Neutral on factors such as structure, management, performance record, discount; **Sell:** Negative on factors such as structure, management, performance record, discount. **Core Banding Exceptions (CBE):** Exceptions to the standard +/-6% bands may be granted by the Investment Review Committee (IRC). Factors considered by the IRC include the stock's volatility and the credit spread of the respective company's debt. As a result, stocks deemed to be very high or low risk may be subject to higher or lower bands as they relate to the rating. When such exceptions apply, they will be identified in the Company Disclosures table in the relevant research piece.

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Unless otherwise indicated, please refer to the Valuation and Risk sections within the body of this report.

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