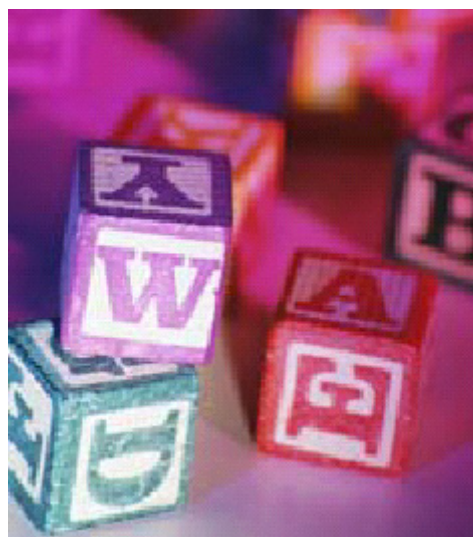


The A-Z of Quant

27 August 2004



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Building a Quant model, Macquarie style

Quant: making the numbers work for you

Stock prices change for a multitude of reasons and these reasons vary over time and economic conditions. This makes it more difficult to outperform your chosen benchmark. Quant models are a great way to systematically capture the multi-dimensionality of the market. In this report, we show how the Macquarie Research Quantitative Team builds multi-factor Quant models that work.

Superior factor selection

We require factor signals to have:

1. **Meaning** – financial, economic and/or behavioural underpinnings
2. **Significance** – based on various statistical tests
3. **Stability** – through time and across stock groupings

A combination of IC analysis, IC decay profiles, fractiles and pure factor returns yield superior analysis of factor predictability and stability than traditional regression based approaches only.

Optimally combining correlated factors

Many return factors are highly correlated. So how do you combine them into a model that is optimal while limiting the risk of double counting correlated factors? We have developed a sophisticated technique to construct multi-factor models that produces better results!

Constructing realistic portfolios

We demonstrate how we construct portfolios with real life constraints, such as limiting active bet size, limiting exposure to risk factors, liquidity constraints and transaction costs.

Please refer to the disclaimer and disclosure on page 66 of this document.

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Building a Quant model, Macquarie style

Welcome to the Macquarie's A-Z of Quant. The purpose of this report is to give a serious overview of the many quantitative techniques we use to construct and simulate quantitatively styled portfolios at Macquarie.

1. Searching for factors

In **Section One**, we explore just what factors are, how Quants use factors and how they are constructed. In particular, we discuss what we look for in desirable factors, as well as some of the pitfalls in constructing factors.

2. Selecting and testing factors

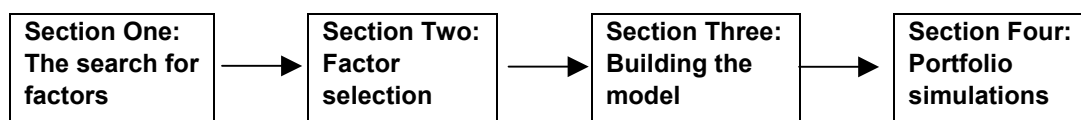
Section Two then discusses many of the quantitative techniques we use to select the factors that end up in the final multi-factor model. These include various univariate tests like rank ICs, IC decay profiles and fractiles, as well multivariate tests (pure factor returns).

3. Combining factors

Section Three examines how to combine those factors that have made it through the tests we described in Section Two. In particular, we examine how to optimally combine correlated factors. This is an important issue as many factors are highly correlated. If factor correlation is not taken into account you run the risk of double counting similar type factors that are both highly correlated and successful, while risking the under utilisation of other successful factors.

4. Constructing portfolios

Lastly, **Section Four** discusses the more technical side of constructing optimised portfolios. Here we take your Alpha model, together with an appropriate risk model, and optimise through time with our in-house optimiser. It has the advantage of imposing real-life constraints such as limiting active bet size, limiting exposure to risk factors, liquidity constraints and transaction costs.



Various Appendices are also included dealing with various other quantitative issues from dealing with data, [in- and out-of-sample](#) testing and portfolio construction techniques.

The search for factors

What are factors?

Factors = information about a company that can be measured

Factors embody information about a publicly listed company. They could be characteristics of the company, the company's share price performance or vital statistics of an analyst's company model. A factor may change as relevant new information arrives about a listed company, which may in turn be accompanied by a change in the share price. Factors might therefore be used to predict future stock price returns.

Information separates active managers from passive managers. Information, properly applied, allows active managers to outperform their informationless benchmarks (Grinold & Kahn, 2000, P315).

But stock prices change for a multitude of reasons, making it difficult to capture without the use of quantitative techniques:

Multi-factor Quant models can be developed to capture the different systematic drivers of stock prices.

Multi-factor models, as the name suggests, comprise of a number of stock price signals known as factors. Factors, as the embodiment of information, form the core of any quantitative investment strategy. The development and selection of factors is the important first step in building a quantitative return forecast model that works.

Different factor groups

The Macquarie Quantitative Research Team has developed an extensive factor database that allows for the construction and testing of factors within Asia Pacific equity markets. Some examples of types of factors we use are:

1. Value factors eg dividend yield and price to earnings ratio
2. Profitability factors eg ROE and change in ROE
3. Momentum factors eg 1, 3 or 6 month price momentum
4. Forecast revisions eg 1, 3 or 6 month changes in consensus EPS and DPS
5. Event driven factors eg IPOs, mergers and acquisitions, and earnings surprises

We call these **factor groups**. Factors within the same factor group are typically more highly correlated than factors from two different groups. They also may belong to the same group because they are constructed using a similar calculation methodology.

As the above list demonstrates, some factor groups are related to historical company performance or to future expectations of company performance (such as value, profitability and economic factors). Other factors may be more behaviourally based (such as momentum factors). Some factors are even related to the investor composition of equity markets, and how equity markets work (eg event driven factors)¹.

Factor performance varies over time

The same factors do not always work throughout time and several types of factors may be driving the market at the same time. They may even be working against each other, so that when one factor is punished, another is rewarded. This can make successful factor selection and hence stock selection tricky.

In this report, we will discuss how to construct Quant models that deal with these issues.

¹ See Appendix 4, Factor types, for a detailed discussion of some of the more commonly used factors.

How do Quants use factors?

Factors are used to predict returns

Quants use factors to predict relative returns of financial assets (in our case stocks). We typically are interested in this on a cross-sectional basis. In particular, by comparing and filtering stocks by the various factors that we believe predict relative stock returns, we end up with stocks that have the most desirable characteristics. This relative returns framework implicitly assumes a benchmark (ie an investible universe of stocks) against which fund performance is measured.

The goal of active management is to outperform the appropriate benchmark with as little risk as possible.

This then raises two questions:

1. What factors do we use in our Quant model?
2. How do you combine factors together into a model that outperforms your chosen benchmark, with as little risk as possible?

Factors must systematically signal outperformance, not work by coincidence

In regard to the first question, we want factors that systematically signal outperformance but we don't want factors that by accident or coincidence seemed to have worked historically (known as data mining). Factors that have worked by coincidence historically are unlikely to add any value to the model.

Therefore, at Macquarie, we require candidate factors to have:

- **Meaning** - to be economically, financially or behaviourally justifiable or recognised as systematic predictors of stock prices
- **Significance** - to have tested well (statistical significance) in both an in-sample and out-of-sample period
- **Stability** - to have worked well through time and in different market conditions

Meaning, in particular, is the top level protection against data mining. By using factors that have some theoretical rationale, based on the financial or behavioural biases that drive stock prices, we ensure that the possibility of data mining is minimised. For example, a factor based on the number of employees of a listed entity is much more open to criticism than a factor based on the share price movement over the last three months.

Significance and stability are the two other key prerequisites in selecting factors for the final model. They embody the past ability of a factor to consistently predict share price performance on a cross-sectional basis through time. In the next section, factor screening, we devote much time to quantitative techniques that help us sift for factors that actually exhibit significance and stability². By using the three criteria (**meaning, significance, stability**) we hope to capture the significant drivers of equity markets in different economic conditions. In doing so we reduce the risk that our model won't perform in real life³.

Once we have our shortlist of factors, we can examine the second question posed above. In particular, we want to combine these factors into a model that proxies for the underlying drivers of relative returns. We do this in **Section Three, Building the model**, where we discuss the art and science of creating the multi-factor model.

² One other factor level check we like to use is whether a factor works across all equity markets. However, an equally valid argument is that equity markets can differ significantly in terms of makeup, ownership and constraints (eg developed markets versus emerging markets). This in turn might lead to qualitatively different drivers of these markets. Hence, we only use this as a check, rather than a requirement.

³ Performance of individual factors will typically change through time and in different economic conditions. This may sometimes affect how stable the performance is of the multi-factor model. Multi-factor models should therefore not be expected to be correct 100% of the time but rather point us in the right direction.

How do you create and calculate factors?

As discussed above, factors need to have some financial or behavioural justification. Factor creation is quite an art form and new ones are continually being developed and tested, particularly as equity markets change and evolve. Factors we use at Macquarie typically have their origin in some theoretical, academic and/or pragmatic background (for a list of factors we have calculated, please contact us).

Pitfalls in calculating factors from raw data ...

To calculate a factor typically raw data from various data sources needs to be turned into meaningful factor signals. However, there are several possible pitfalls to factor calculation:

1. **Matching across data sources:** this is when factors use information from two or more sources. This is potentially problematic if the various data vendors use different core information (eg if one vendor doesn't take into account a recent share dilution, resulting in distorted number of shares or even share price).
2. **Survivorship bias:** this occurs when you don't include stocks in your database that have since delisted or gone bankrupt. This will make your performance tests look better than they really would have been at the time.
3. **Look ahead bias:** typically this problem arises with historical company accounts data. It might take 2–4 months after a company year end (depending on the country) before a company publicly releases its financial statements. If a factor is calculated historically using data in the 2–4 months between company year end and the company reporting date, this will make your results look better than they really would have been.
4. **Diluting per share data:** forgetting to adjust per share data when various corporate events occur, like rights issues, bonus issues and share splits, will distort the results and introduce noise into your results.

Appendix 2, *Dealing with data*, discusses their issues in more detail as well as the issue of normalisation, which allows different factors to be massaged into comparable, unitless dimensions. This is essential before attempting to combine individual factors into a multi-factor model.

Once meaningful factors have been created we need to test them for **significance** and **stability**. This is the subject matter of the next section, *Factor selection*.

Factor selection

Before any multi-factor model can be built, **a screen for candidate factors is conducted**. In particular, we desire to screen for those factors that show significance and stability of predicting stock performance on a cross-sectional basis throughout history (time). There are a variety of ways of doing this.

Cross sectional regressions can be used to test factors

One popular method for determining what the return drivers in any market might be is a **cross-sectional regression based approach**, on a univariate basis (univariate means one factor at a time). Here, stock returns one month forward are regressed against the factor exposures of individual stocks the previous month (with the stock exposures being in normalised data form: see Appendix 2 for further details). **The regression is performed each month across the universe of stocks to give a time series of regression coefficients (or factor returns)**. Comparing the t-stats of these regression coefficients for different factors enables us to see what factors have been the statistically significant drivers of performance through time. **The factors selected for the final model are those that have statistically significant regression coefficients over time**. It is hoped that by selecting only those factors that have been statistically significant in the past, we are selecting factors that have predictive power of cross-sectional stock returns for the future.

Univariate information analysis is another common method

Another common method is a **univariate information analysis approach** (again on a cross-sectional basis). Here, we conduct a broad range of comparative tests designed to assess the different dimensions of factor performance, namely significance and stability, as we discussed on the previously. The tests we conduct of univariate information analysis are:

1. Monthly time series of information coefficients (rank ICs)
2. IC decay profiles
3. Fractiles

Again, the hope is that those factors that have tested well here will continue working into the future (indeed research has confirmed a certain amount of autocorrelation in factor signals).

At Macquarie, we use both approaches in our factor selection methodology. However, we typically conduct a univariate information analysis as the first factor screen, after which we then conduct regressions for each successfully screened factor while controlling for various risk factors (often referred to as a **pure factor return**).

In this section, we will be examining both the univariate tests (information analysis) as well as the multivariate test (pure factor returns).

Univariate tests

1. Monthly time series of information coefficients (Rank ICs)

ICs are based on the correlation of forward returns against factor scores

Monthly ICs are a straightforward way of ascertaining the predictive capability of a factor in the past. They are similar to the factor returns (regression coefficients) of a univariate regression of forward returns against individual stock exposures. In fact, monthly ICs are also calculated using forward returns and factors scores. While the calculation methods of both are different, both factor returns and ICs give us an idea of the relative success of individual factor strategy (ie an investment strategy based around selecting stocks with high factor scores).

ICs are cross-sectional

To calculate the ICs for monthly data, we cross-sectionally rank each stock's factor score as at the end of one month, as well as rank the subsequent month's total return for each stock. We do this for all stocks within the required universe. Note the one month lag between the factor scores and the monthly total returns. So if the stock's factor exposures are as at 31-Jan-04, the month returns are from 31-Jan-04 to 29-Feb-04. We then calculate the correlation between the two sets of ranks.

A ranked IC therefore measures the predictive power of a factor by looking at the correlation between the factor scores and subsequent period's stock returns.

Ranked IC's are then calculated every month. If a factor has no predictive power, we would expect its IC on average to be zero, jumping unpredictably from month to month. On the other hand, a ranked IC always equal to 1 (100%) indicates perfect forecasting skill⁴. ICs can range from -100% to +100%.

Average IC should be over 4%, preferably higher

Factors that are likely candidates for a multifactor model might have an average IC of above 4%. Say, as long as they were consistently positive most of the time (ie are stable). In the Australian equity market, some of the strongest factors have average ranked ICs of 8% to 12%.⁵ While the average factor ICs may be small, they must be reasonably stable over time. To ascertain stability we use two simple measures:

Factor stability over time is also important

1. Twelve month rolling average
2. t-stat of monthly ICs

Twelve month rolling average: ICs can be quite volatile over time. Therefore we take a 12 month rolling average and graph it. This allows us to visually examine the factor's predictive stability over time.

A consistently positive 12 month average IC gives us confidence in a strategy. On the other hand, a strategy where the average 12 month IC is positive half the time and negative the other half is not likely to make it into the model⁶.

⁴ ICs can also be calculated using normalised factor scores and the next month's actual returns. However, ranked ICs are arguably cleaner than normalised ICs. This is because the distribution of ranks is flat, whereas normalised factor scores can have large outliers that can substantially distort the results (noting that normalised factor scores will typically be roughly normally distributed). Arguably, multi-factor models should be built using normalised based ICs but because ranked ICs are typically highly correlated with normalised ICs, we use the cleaner ranked ICs. Alternatively, we could build a composite rank model based on ranked ICs.

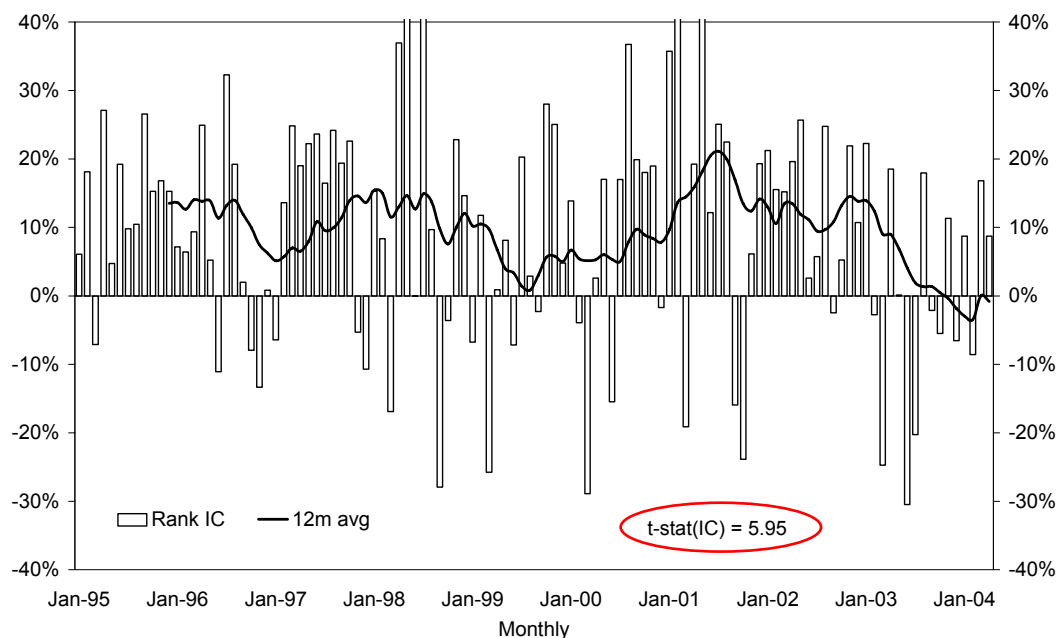
⁵ Within certain sectors of a market the averages can be significantly higher (eg up to 20% for listed property trusts within Australia).

⁶ On the other hand, a factor ranked IC that has a consistently negative 12 month rolling average IC might imply an opposite strategy to what the factor score captures. For example, many developed equity markets experience negative 12 month rolling average ICs for short term momentum. This implies that mean reversion (defined as the negative of one month momentum), might be a good factor to use. Of course, if there was no intuitive reason for using this factor this way, it should be not be included in the model.

Chart 1 and Chart 2 below contrast two different factors for the Australian equity market, namely 12 month momentum and consensus recommendation. In particular, 12 month momentum has a consistently strong 12 month rolling average IC over time, so it is far more likely to make it into the final model than consensus recommendation.

12 month momentum
generates consistently
strong ICs, while ...

Chart 1: Twelve month momentum for S&P/ASX200 (Rank ICs)

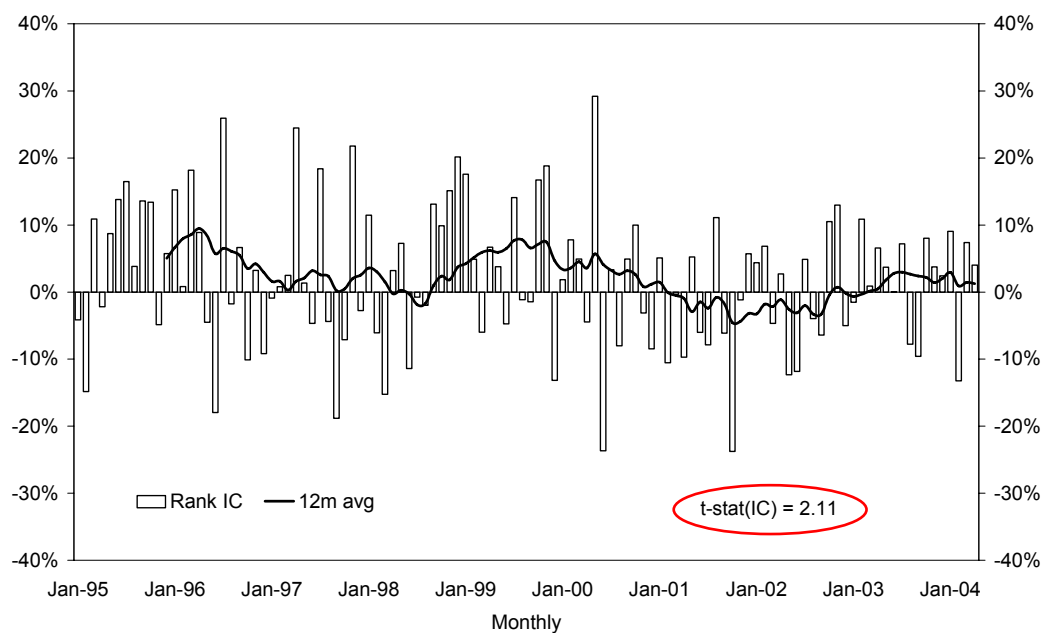


Twelve month momentum has strong predictive power in Australia.

Source: Macquarie Quantitative Research

... Consensus
recommendations do
not

Chart 2: Consensus recommendation for S&P/ASX200 (Rank ICs)



Consensus recommendation has less predictor power than 12 month momentum

Source: Macquarie Quantitative Research

t-stats: As mentioned above, ICs are like the factor returns (or regression coefficients) in a univariate cross-sectional regression. And just as with univariate regressions, we can take the t-stat of ICs to see if they are significantly different to zero⁷. This is important as it gives us an indication as to the stability or consistency of a factor strategy's predictive ability. A t-stat is defined as:

t-stat definition

$$\text{t-stat(IC)} = \text{Average (IC)} / \text{Standard Deviation (IC)} \times \sqrt{\text{No. of Observations}}$$

The idea of the t-stat is that it rewards higher average ICs (the numerator) and punishes higher standard deviations of ICs (the denominator). Also, for a given average and standard deviation, the more observations we have the more confidence we have in the results for the factor. Here the t-stat is proportional to the square root of the number of observations.

t-stat > 2 provides statistical significance

As a rough rule, a t-stat greater than +2 indicates that we can be very confident in the factor's stability through time. But the closer the t-stat is to zero, the less confidence we have in a factor's ability to add value.⁸

Beware factors that generate prolonged periods of underperformance!

Other issues: It should be noted that it is also preferable to see the ICs not working every now and then, rather than not working over an extended time period. For example, it is preferable to have a factor randomly misfiring in three out of every 12 months over a 4-year period say, rather than not working for 12 months in a row. This detracts from confidence and raises questions about why this factor is working and how temporary its usefulness could be.

Monthly ICs, the 12 month rolling average and the IC t-stat form a core part of the factor selection process.

⁷ t-stats are a statistical tool to measure if a distribution is likely to be statistically different from a particular value. It is like a z-stat but is used when the standard error has to be estimated from the data. The formula is basically a method for calculating the area under the normal curve (actually it is the t-distribution, which is very similar). This area represents the probability of a statistic being greater than or less than a specific value (otherwise known in statistics as hypothesis testing).

⁸ Similar to the comments on the previous page about a consistently negative 12 month rolling average IC, a t-stat less than -2 implies an opposite strategy to what the factor score captures. As long as there is an intuitive rationale for this, this opposite strategy should be employed within the multifactor model.

Some factors exhibit short term predictive power, while others work over longer investment horizons

Factor IC decay profiles involve ...

... lagging the stocks forward return

... and calculating the average of the ICs for each lagged return

Sample IC decay for 12 month momentum and ...

2. IC decay profiles

Equity markets react at different speeds to different types of new information. The faster the market reacts to one type of information, the quicker we need to act to capitalise on this new information. On the other hand, strategies based on information that gets quickly priced into the market also tend to have higher turnover.

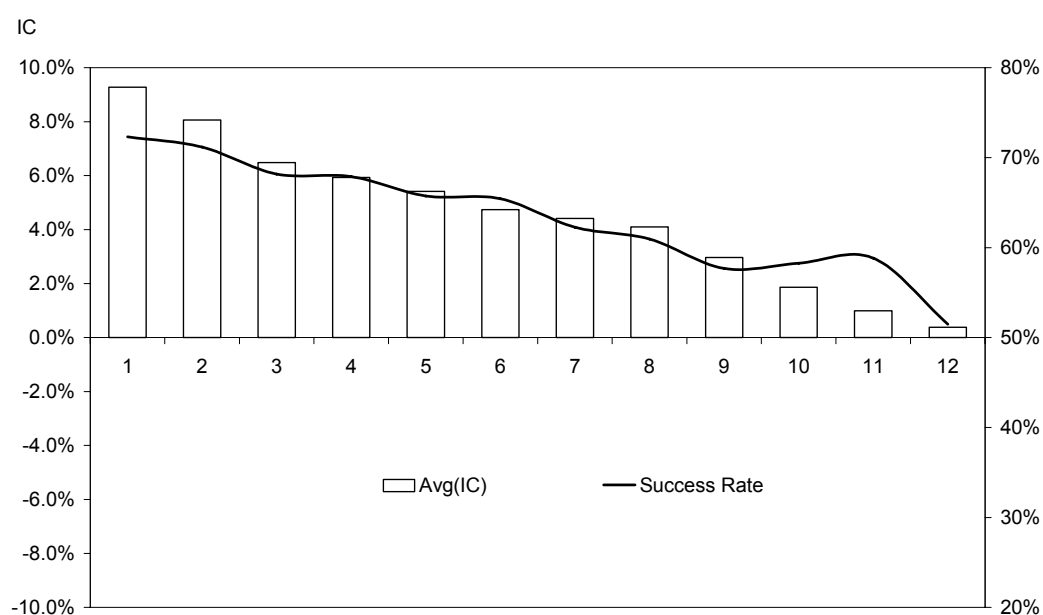
IC decay profiles measure how fast or how efficient the market is at pricing in new information.

Using factors as the embodiment of information, we can then generate factor IC decay profiles, as follows:

1. Calculate Series of Ranked ICs: First, for each lag $n = 1, 2, 3, \dots 12$ months, we calculate a time series of ranked ICs based on the stocks forward return lagged by n months relative to the factor signal. In fact for $n = 1$ this is simply the IC monthly time series as discussed in the section above.
2. Average each Ranked IC series: we then take **the average of each lag's monthly IC time series** (where $n = 1, 2, 3, \dots 12$). Again, the average IC calculated for the one month lag will actually be the average IC of the chart in the section above on monthly time series of information coefficients.

In Chart 3 and, we examine the IC decay profile for the two factors we considered before, namely 12 month momentum as well as consensus recommendation.

Chart 3: Twelve month momentum for S&P/ASX200 (IC decay profile)

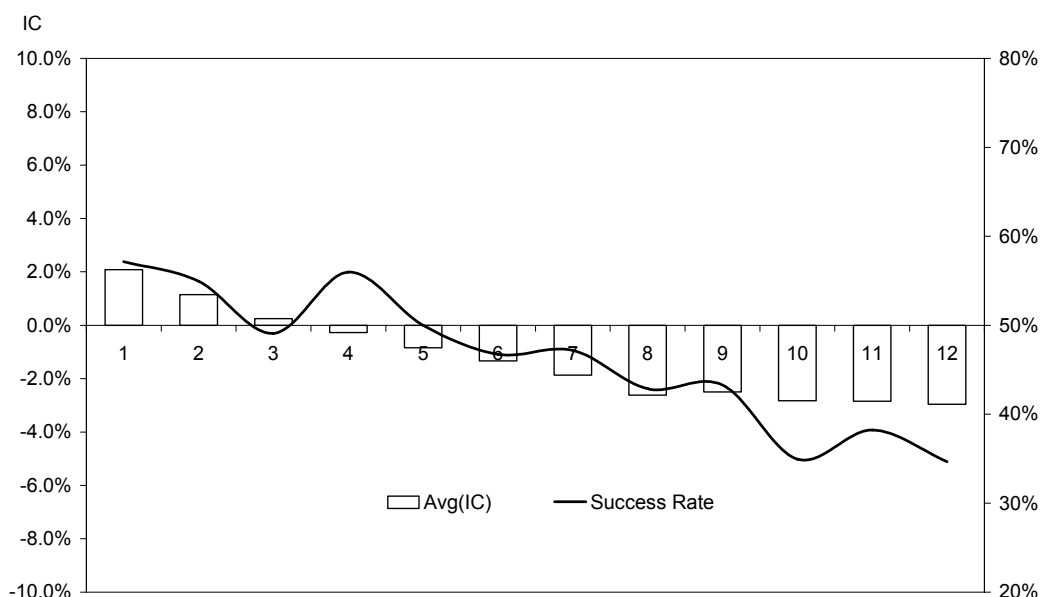


Twelve month momentum has a strong signal with a slow decay rate.

Source: Macquarie Quantitative Research

... consensus
recommendation

Chart 4: Consensus recommendation for S&P/ASX200 (IC decay profile)



Consensus recommendation has a very weak signal.

Source: Macquarie Quantitative Research

Ideally, we like to see high average ranked ICs in the initial lags of an IC decay profile that gradually decays as the lag increases (ie the IC decay profile has a gradual slope down to the right).

Low decay = more time
to get set in stocks and
lower turnover

While a high average ranked IC in the initial lags gives us confidence in a factor strategy, a low decay rate leaves more time to get set in stocks which expose us to this factor. However, if a factor decays quickly, this means the information is quickly priced into the market and hence becomes redundant, and so stocks will remain shorter in the portfolio. Therefore, a fast decay rate usually implies the factor's strategy has higher turnover.⁹

Some strategies, like earnings revisions, tend to have lower decay rates. This is partly due to autocorrelation in analysts revising their earnings estimates. In particular, they revise their earnings slowly while cautiously gauging market/consensus opinion.

We also like to get an idea of the **stability** of the factor's predictability for each lag. We therefore use two further measures:

1. Success rates for each lag of the monthly ICs
2. t-stats for each lag of the monthly ICs

Success rates provide a
measure of factor
performance stability, as
do...

Success rate for each lag: we use this in conjunction with the IC decay profile. It is a measure of the stability of the factor performance for each lag. It is calculated by dividing the number of times the IC for a given lag was positive by the total number of months tested:

$$\text{Success rate} = \frac{\text{No. months IC} > 0}{\text{Total no. months in sample}}$$

Ideally, we want to see a success rate for a one month lag above 55%, say (if we are rebalancing monthly). The success rate of a typical factor strategy will drop to 50% as the factor signal is priced into the market.

⁹ In fact, multi-factor models can be created by combining a signal with itself lagged in time. See Chapter 13 of Grinold & Kahn (2000) for more details.

*t-stats for each lag of
the monthly ICs*

t-stats for each lag of the monthly ICs: the other metric we use here is the t-stat for each month's lag. As discussed in the previous section, **if the t-stat is above 2 for the first couple of months, the factor strategy is a likely candidate for the final model**¹⁰.

Note the t-stat and the success rate are actually closely related statistics. As we increase the lag of the signal the success rate drops down towards 50% while the magnitude of t-stat will typically drop down towards zero.

*Factor autocorrelations
also provide information
about how fast a signal
changes*

One other closely related concept to IC decays are **factor autocorrelations**. A factor autocorrelation measures how fast a signal changes (ie relative to itself). While a faster signal for a stock will lead to higher turnover, which lowers performance, it will also lead to a higher number of independent bets, which will ultimately increase performance. This is discussed further in Appendix 5.

¹⁰ Again a t-stat less than -2 implies a strategy opposite to that which the factor is trying to capture. As explained in the footnote in the section on monthly time series of ICs, this might imply an opposite strategy as long as there is an intuitive reason for the factor to behave this way. The same comment applies to success rates below 45% and rising to 50%.

3. Fractiles

Fractiles are the next step in testing factor strategies.

Fractiles are the first portfolio simulations we use that test the efficacy of a factor strategy.

Fractile portfolios are formed by dividing the universe of stocks each month based on stock factor scores

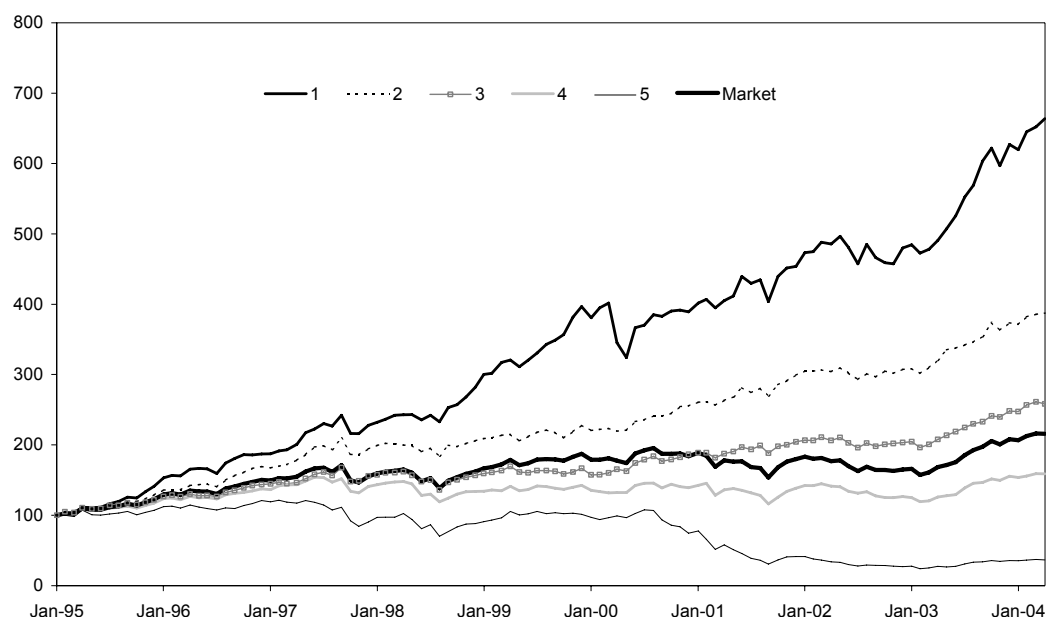
Fractiles are essentially a ranking strategy that are generated by splitting the universe of stocks each month into a number of equally weighted portfolios (fractiles) according to their factor exposures.

For example, a quintile strategy would involve splitting the universe of stocks into five portfolios. Quintile 1 would have stocks with the top 20% of factor scores; quintile 2 stocks would have the next 20% of stocks and so forth. Fractiles embody the idea that useful information can mainly be derived from the tails of a factor distribution rather than from the middle (ie for quintiles 2, 3 and 4), where the potential signal noise is much greater. Fractiles can be informative for both long-only strategies as well as long/short strategies.

Returns are then tracked for each fractile portfolio

After each fractile portfolio has been formed, we then track the total return to each fractile portfolio over the following month. At the end of every month, we rebalance back to equally weighted fractiles and then repeat the process. In this way we can calculate an accumulation series (total return series)¹¹. In Chart 5 and, we again examine the quintile portfolio performance for 12 month momentum and consensus recommendation:

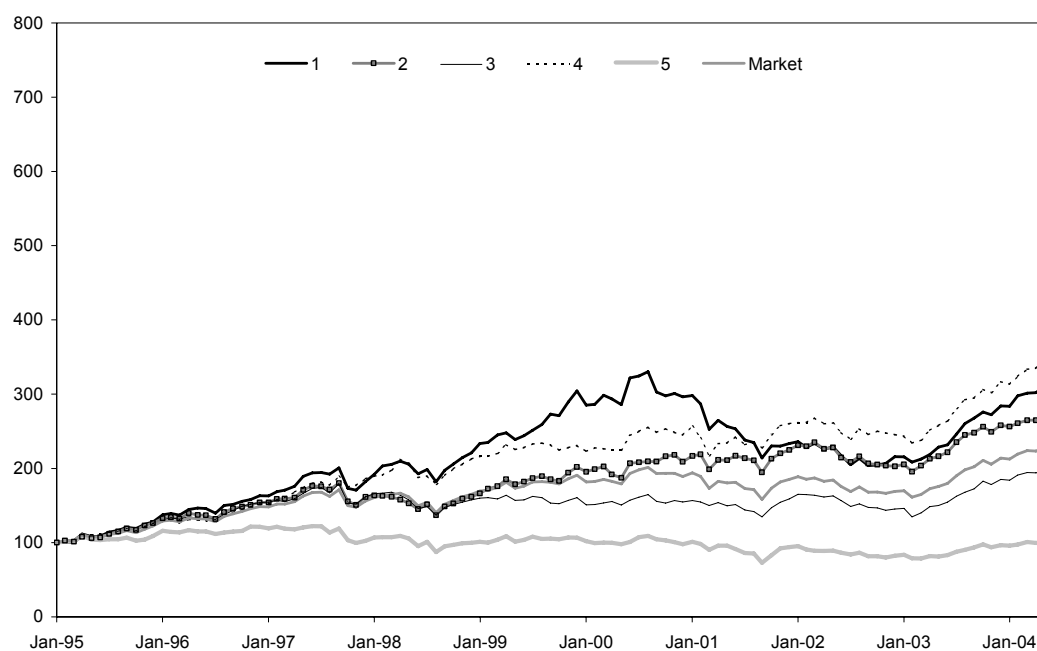
Chart 5: Twelve month momentum for S&P/ASX200 (Quintiles)



Again, 12 Month Momentum shows up as a strong predictive signal.

Source: Macquarie Quantitative Research

¹¹ Note that fractile strategies ignore all information in the factor exposures except for the relative stock rankings. They are naive factor portfolio strategies in that they do not take account of risk (be that factor risk, idiosyncratic risk or other). In fact, they tend to be considerably more risky than real life portfolios and have considerably more turnover.

Chart 6: Consensus recommendation for S&P/ASX200 (Quintiles)

The lack of predictability of equal weighted consensus recommendation also shows up in quintile analysis

Source: Macquarie Quantitative Research

Use a number of
fractiles relevant to your
stock universe

Note that if your universe of stocks is small, say less than 15, you may only want to perform tertiles or quartiles (splitting the universe into three or four portfolios). On the other hand, if your universe is very large, say above 100 stocks, deciles (10 portfolios) might be more appropriate¹².

There are a range of
fractile performance
statistics

Besides charting the fractile performances through time, we also generate a summary table of return based performance metrics for each fractile. This gives us a better idea of how the factor performed as a distinguisher of subsequent returns. The table also shows various other statistics, for example each fractile's tracking error (active risk), information ratio (risk adjusted active return) and turnover. These can then be used as a basis for comparison across different factors:

Table 1: Twelve month momentum for S&P/ASX200

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q1-Q5 (L-S)	Market
Total return	22.82%	15.87%	10.75%	5.33%	-10.14%	31.13%	8.78%
Active return	14.04%	7.09%	1.97%	-3.45%	-18.92%	31.13%	
Tracking error	7.98%	6.48%	5.33%	4.80%	14.19%	20.05%	
Information ratio	1.76	1.09	0.37	-0.72	-1.33	1.55	
t-stat (information ratio)	5.37	3.34	1.13	-2.19	-4.08	4.74	
Monthly success rate	72.32%	58.04%	52.68%	39.29%	34.82%	68.75%	
Turnover	22.58%	42.94%	49.17%	44.28%	25.96%	48.54%	
Volatility	13.73%	10.28%	10.67%	12.90%	23.95%	20.05%	12.57%
Sharpe ratio	1.66	1.54	1.01	0.41	-0.42		0.70
t-stat (sharpe ratio)	7.21	6.32	2.31	-2.13	-8.40		
CAPM Beta (vs benchmark)	0.90	0.70	0.77	0.95	1.68	-0.78	
CAPM Alpha	5.97%	4.01%	3.40%	3.62%	8.60%	13.25%	

Twelve month price momentum is a successful factor. With an information ratio of 1.47 (and a t-stat of 4.27) this result is highly significant.

Source: Macquarie Quantitative Research

¹² One common criticism of equally weighted fractiles is that they can hold positions in a lot of illiquid stocks, too small for a typical investible universe. In this case, we might also want to calculate the market weighted return for fractile strategies. This will show how the strategy works for larger cap stocks within each fractile. In fact, by comparing equally weighted and cap weighted fractiles, we can get an idea how the strategy works for larger versus smaller caps. For example, if all the equally weighted fractiles outperform the cap weighted fractiles, one could infer that the strategy works better for small cap stocks.

Table 2: Equal weighted consensus recommendation for S&P/ASX200

	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5	Q1-Q5 (L-S)	Market
Total return	12.94%	11.20%	7.45%	14.22%	0.02%	12.29%	9.22%
Active return	3.73%	1.99%	-1.77%	5.00%	-9.19%	12.29%	
Tracking error	5.92%	4.65%	4.75%	5.41%	6.48%	10.24%	
Information ratio	0.63	0.43	-0.37	0.92	-1.42	1.20	
t-stat (information ratio)	1.92	1.31	-1.14	2.82	-4.33	3.67	
Monthly success rate	60.71%	54.46%	41.07%	59.82%	33.04%	62.50%	
Turnover	25.26%	41.33%	43.55%	39.58%	24.35%	49.61%	
Volatility	15.00%	13.48%	12.82%	12.28%	15.22%	10.24%	12.67%
Sharpe ratio	0.86	0.83	0.58	1.16	0.00		0.73
t-stat (sharpe ratio)	1.01	0.78	-1.10	3.22	-5.43		
CAPM Beta (vs benchmark)	1.09	1.00	0.94	0.88	1.09	0.00	
CAPM Alpha	4.37%	3.50%	3.53%	3.91%	4.80%	7.70%	

Despite the poor performance relative to 12 month momentum, consensus recommendation is also less volatile, resulting in a comparable information ratio.

Source: Macquarie Quantitative Research

We now explain the various returns based performance metrics in the tables above:

Total return measures the return to the portfolio

- Total Return = Annualised Total Return over period, Equally Weighted (for Fractiles and Benchmark).

This also includes the long-short results where we measure the total return difference between the top and bottom fractiles. Ideally, we want this difference to be positive and large.

Active return measures return in excess of the benchmark

- Active Return (Annualised) = Total Return (Fractile) – Total Return (Benchmark).

Ideally, we would like to see the active return drop smoothly across the fractiles. For the long-short result, which are measured relative to zero, Active Return = Total Return

Tracking error measures the standard deviation of the active returns

- Tracking Error = Annualised Standard Deviation of Monthly Active Returns.

Ideally, we would like to see the tracking error drop smoothly across the fractiles. Tracking error is also known as active risk.

Information ratio measures the active return per unit of risk

- Information Ratio = Active Return / Tracking Error (ie annualised).

For active managers this is probably the most important measure of performance versus a benchmark. In fact, the information ratio is sometimes referred to as the Sharpe ratio for active portfolio management. It measures active return per unit of active risk. Ideally, we would like to see the information ratios for the first and last fractiles above 0.5 and below -0.5 respectively, with a smooth transition in between.

The t-stat measures the statistical significance of the returns

- t-stat (Information Ratio) \approx Information Ratio $\times \sqrt{N}$, where N = no. of years.

Ideally, we would like to see a t-stat above 2 for the lowest fractile and below -2 for the highest fractile, with a smooth change in between.

Success rates measure the proportion of months with a positive active return

- Monthly Success Rate = (Number of months with Active Return >0) / Total no. of months.

Like the IC decay success rate, this is a way of assessing the stability or consistency of the factor as a return predictor. Ideally, we would like to see the monthly success rate smoothly drop from above 50% to below 50% across the fractiles. If all fractiles had a success rate of 50%, we would not have any confidence in the predictive power of the factor, as different factor scores would not result in different stock returns against the benchmark.

Monthly turnover measures the amount of trading activity

- Monthly Turnover = One way, with monthly rebalancing of each fractile.

We don't want the turnover to be too high, as this incurs transaction costs and greater market impact thereby reducing effective Alpha. A low, median and high quintile turnover might be 20%, 50% and 80% respectively per month. In practice, these would be unsustainable levels but when risk factors are taken into account, this turnover drops dramatically¹³. We mainly use fractile turnovers for a comparison across different factors.

Volatility measures the deviation in total returns

- Volatility = Annualised Standard Deviation of Monthly Returns.

Otherwise known as total risk. Ideally, we would like to see the active return drop smoothly across the fractiles.

Sharpe ratio measures total return per unit of risk

- Sharpe Ratio (SR) = Total Return / Volatility.

Typically, the Sharpe ratio measures the excess total return per unit of total risk. As we are comparing across fractiles, we are not interested in the cash rate, hence we can assume it is zero. Ideally, we would like to see the Sharpe ratio drop smoothly across the fractiles. We also calculate the Sharpe ratio for the benchmark.

t-stat measures the statistical significance of the returns

- $t\text{-stat (vs Benchmark)} = \frac{SR(\text{Fractile}) - SR(\text{Benchmark})}{\text{Std. Err. (SR difference)}}$
 $= \frac{SR(\text{Fractile}) - SR(\text{Benchmark})}{\sqrt{2/N}}$

If the t-stat of the difference between is significant, we can be confident our portfolio is adding value in terms of excess return per unit of total risk. Therefore ideally we would like to see a smoothly declining Sharpe ratio across the fractiles.

CAPM Beta measures the correlation between fractile and benchmark returns

- CAPM Beta (vs Benchmark) = sensitivity to the benchmark total return, based on a regression of Fractile Total Returns against the Benchmark Total Return (the regression coefficient).
- CAPM Alpha (vs Benchmark) = y-intercept from regression based on a regression of Fractile Total Returns against the Benchmark Total Return.

CAPM Alpha measures the non-benchmark related component of fractile performance.

Using these performance metrics, we can easily filter desirable factor candidates from undesirable factor candidates. Desirable factors exhibit:

- a positive and significant annualised active return for the lowest fractile (and a negative and significant active return for the highest, although this is not as necessary¹⁴),
- a low annualised tracking error for the lowest fractile (and high for the highest fractile).
- these in turn combine into a high positive information ratio (=active return/tracking error) for the lowest fractile and high negative information ratio for the highest fractile. For the lowest fractile a value above 0.5, say, is desirable, with a t-stat above 2 (for the highest fractile an information ratio below -0.5 and t-stat below -2 is desirable).
- a low turnover is desirable in that it reduces transaction costs and potential market impact (although a higher turnover potentially increases the number of independent bets).

Using fractiles, we can easily search for factors that help distinguish future stock performance.

Like monthly ICs, fractiles are part of our core factor screening process.

¹³ Fractile strategies typically have significantly higher turnovers than a benchmarked strategy, where stocks positions are held relative to the benchmark weight. The reason for this higher turnover has to do with how fractiles are constructed. In particular a stock is either in a fractile portfolio with an equal weight or not. If it is in the fractile one month, but is rebalanced out of the fractile the next month we would have to sell the entire position (for benchmarked strategies re-weighting involves only buying/selling a fraction of the stock around the benchmark weight). But the highest and lowest fractiles will typically have the lowest turnovers as they have stocks moving into them only from one direction (eg while Quintile 1 will typically have most of its new additions from Quintile 2 only, Quintile 2 will typically get most of its new additions from both Quintile 1 and Quintiles 3).

¹⁴ Arguably long/short funds are better able to utilise the information embodied within highest fractile portfolios.

Multivariate tests (pure factor returns)

As discussed above, we also perform a cross-sectional regression analysis on each factor to ascertain the factor's ability to predict performance. However, we do not perform a univariate regression on each factor, as it is unlikely to show anything different to the univariate tests we have already conducted (rank ICs, IC decay profiles and fractiles).

Multivariate regressions can be used to control for key risk factor exposures

Instead, we perform a multivariate cross-sectional regression each month, where key risk factors are also included (eg size, sector and/or book to price)¹⁵:

A pure factor return therefore measures the notional return to a factor after controlling for key risk factors (eg size, sector and/or book to price).

Pure factor return is the return to a one standard deviation exposure to the factor after controlling for all risk factor exposures

Strictly speaking, the pure factor return is the return to a one standard deviation exposure to the signal (factor) after the risk factors have been extracted (a risk factor being a factor that predicts risk). It is calculated by regressing the stock returns one month forward against the relevant factor exposures of individual stocks the previous month. These factor exposures need to be in a **normalised form** (see Appendix 2 for more details). They would include the factor you desire to test (eg 12 month momentum or dividend yield), as well as your desired risk factors (eg size, sectors and/or book to price). By examining the pure factor return of a factor, we get a good idea of how a portfolio would perform if it was constructed around this factor once risk was taken into account.

The formula for such a multi-variate regression is as follows:

$$\text{Return}_{t+1} = \beta_F f_F + (\beta_{RF1} f_{RF1} + \beta_{RF2} f_{RF2} + \dots + \beta_{RFN} f_{RFN}) + \varepsilon$$

Where β_F = the pure factor return (regression coefficient) for the desired return factor

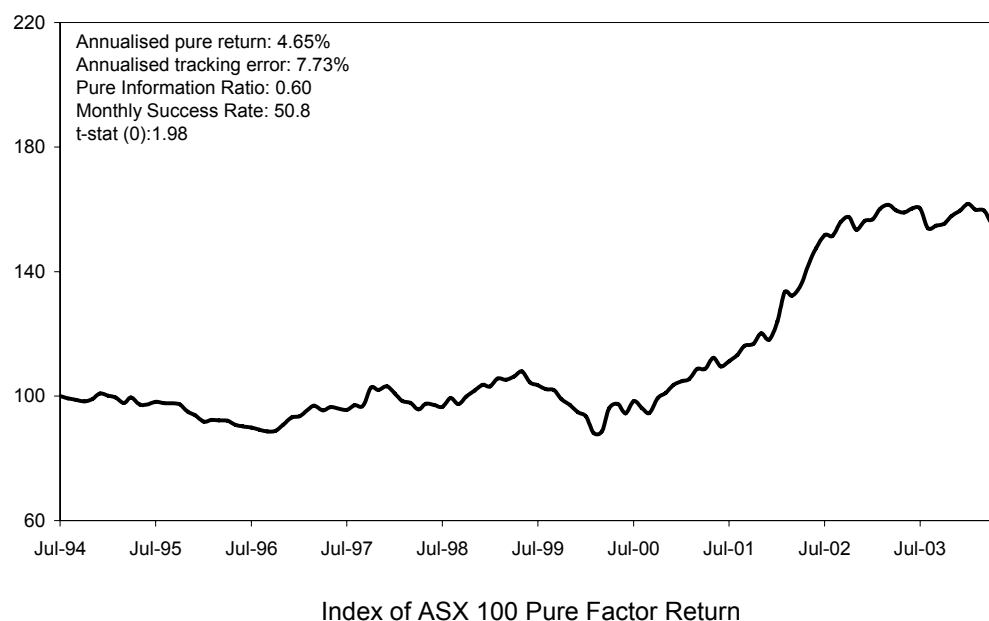
and β_{RFi} = the pure factor return (regression coefficient) for Risk Factor i

and ε = Error Term from the regression

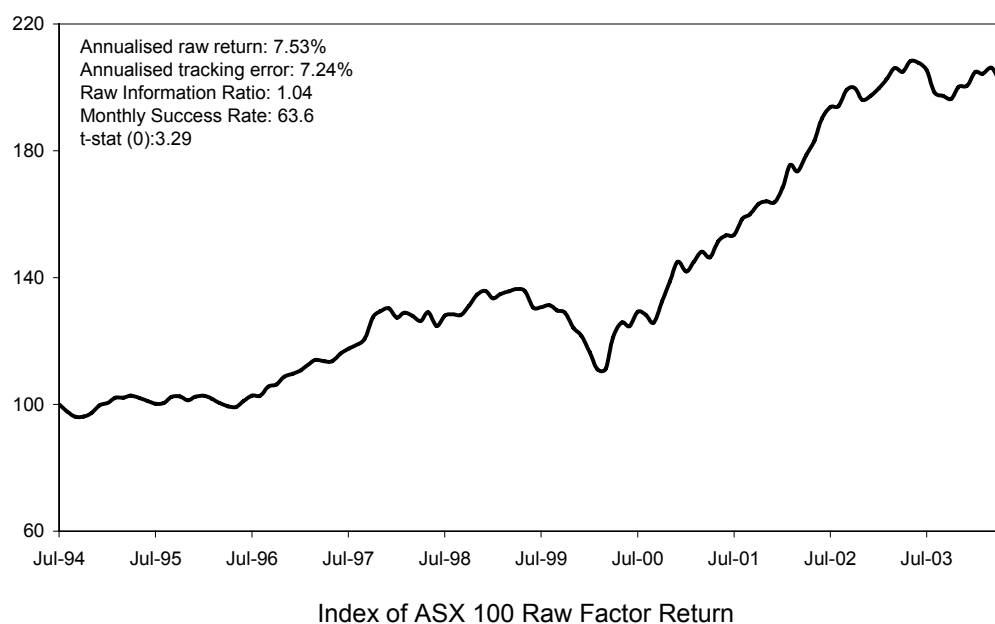
Once we have the time series of pure factor returns (β_F), we can produce some graphs along with some performance metrics. Below we show two types of charts:

- The first set (Charts 7 & 8) demonstrates the performance over time of a one standard deviation exposure to the factor, in this case prospective dividend yield. We do this for both the **raw factor returns** (ie with no risk factors) as well as the **pure factor returns** (where the risk factors are sector and size). The results are typical in that the pure factor return doesn't perform as well as the raw factor return, because the returns to size and sector have been stripped out.
- The second set (Charts 9 & 10) demonstrates the monthly and 12 monthly average performance of the factor returns (for prospective dividend yield) over time. Again the results are typical, with both charts showing qualitatively similar profiles, yet the raw factor return performs better as the returns to size and sector have not been stripped out.

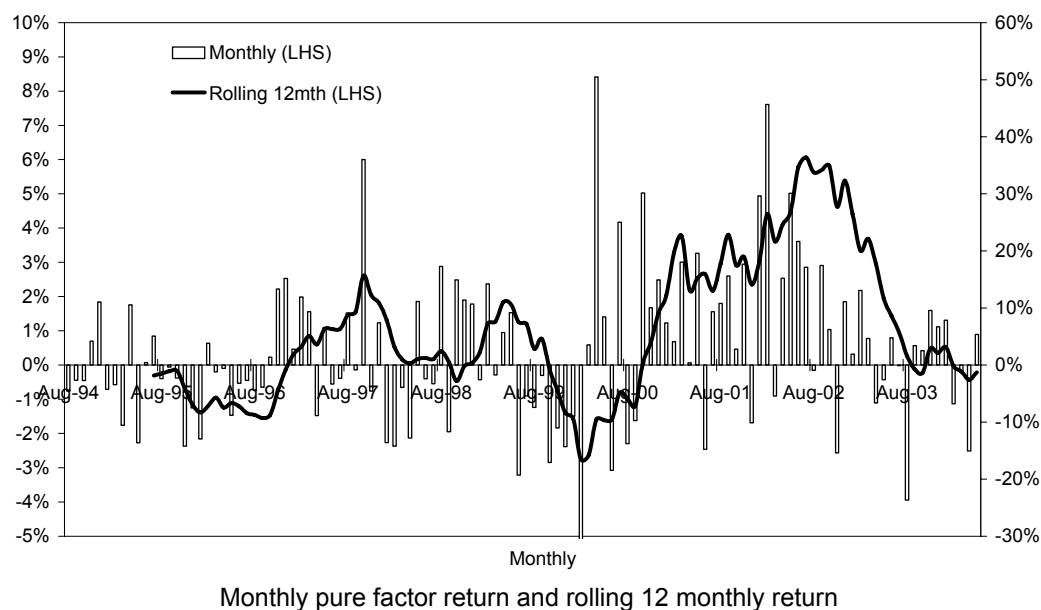
¹⁵ See Appendix 9 for a discussion on risk factors, return factors and factors in general.

Chart 7: Index of ASX 100 pure factor returns for prospective dividend yield

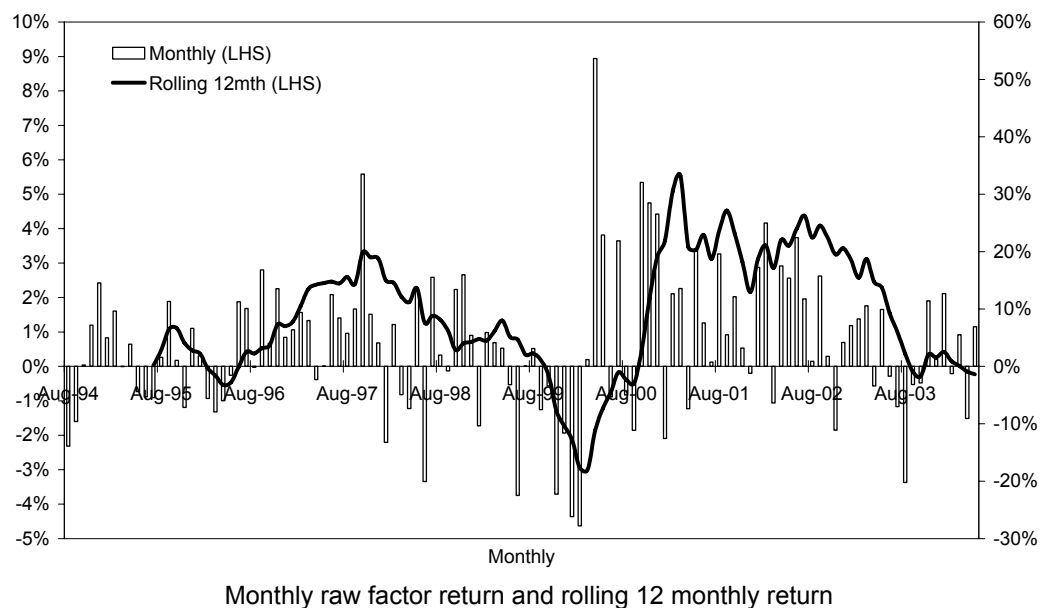
Source: Macquarie Quantitative Research

Chart 8: Index of ASX 100 raw factor returns for prospective dividend yield

Source: Macquarie Quantitative Research

Chart 9: Prospective dividend yield - ASX100 pure factor return

Source: Macquarie Quantitative Research

Chart 10: Prospective dividend yield - ASX100 raw factor return

Source: Macquarie Quantitative Research

*Example of tilting
towards risk factors*

Comparing these two sets of charts seems to imply that prospective dividend yield in the ASX100 exhibits predictive power because it tilts investors towards sectors which have outperformed. When you strip this out in the pure factor return the value add reduces a lot, particularly during the early years of the sample period. However, even with size and sectors taken into account, there still seems to be value in this factor, as the information ratio is still 0.6.

A range of statistics can be calculated based on the multi-variate regressions

The performance metrics in these graphs are described below:

- **Pure Return (% pa)** = the annualised return to a one standard deviation exposure to the signal (factor) after the risk factors have been extracted
- **Pure Tracking Error (%pa)** = annualised standard deviation of the monthly regression coefficients. Here the factor returns (coefficients) relate to the returns of a one standard deviation active exposure, taking into account the risk factors. Therefore we are effectively calculating the tracking error relative to the benchmark.
- **Pure Information Ratio** = Pure Return / Pure Tracking Error. This is similar to the fractile information ratios we calculate.
Monthly Success Rate (%) = the proportion of monthly pure factor returns that are greater than zero. We look for values above 55%, say.
- **t-stat (Pure Returns Time Series)**. In this case we are looking for values greater than +2.
- **Naive Return (% pa)** = the return to a one standard deviation exposure to the signal (factor) before the risk factors have been extracted (ie univariate regression results)
- **Raw Tracking Error (%pa)** = annualised standard deviation of the monthly regression coefficients. Here the factor returns (coefficients) relate to the returns of a one standard deviation active exposure, without the risk factors. Therefore we are effectively calculating the tracking error relative to the benchmark.
- **Raw Information Ratio** = Raw Return / Raw Tracking Error. This is similar to the Fractile Information Ratios we calculate.
- **Success Rate (%)** = the proportion of monthly naive factor returns that are greater than zero. We look for values above 55%, say.
- **t-stat (Naive Returns Time Series)**. In this case we are looking for values greater than +2. This should be similar to a t-stat of a univariate Rank IC test.
- **Pure-Naive (%pa)**. When greater than zero this implies the factor works better when controlled for risk. When less than zero, it implies the factor works better when there is no control for risk factors.
- **Pure-Naive Tracking Error (%pa)** = annualised standard deviation of the difference between the pure and raw monthly regression coefficients.
- **Pure-Naive Information Ratio** = Pure-Naive Return / Pure-Naive Tracking Error. This is similar to the Fractile Information Ratios we calculate.
- **Success Rate (%)** = the proportion of monthly pure factor returns were greater than naïve factor returns. We look for values above 55%, say.
- **t-stat (Naive-Pure Returns Time Series)**. In this case, we are looking for values greater than +2.

Ideally strong statistics from this analysis are desired from the Pure Returns (%pa), Pure Return Success Rate and Pure Return t-stat. However, statistical significance is a lot more difficult to achieve after the risk factors are included in a regression. Instead, we use pure factor returns on a comparative basis, selecting the factors with the strongest pure factor returns¹⁶.

¹⁶ We might also test the efficacy of a long/short strategy after neutralising for sector or industry. A common method of neutralising for sectors in a long/short strategy is to include only those stocks in the long/short portfolios that are ranked in the top and bottom third of factor exposures within each sector. The resulting short portfolio will then have the same number of stocks as the long portfolio.

The final factor screen

Each of the above described tests (ICs, IC decays, fractiles, pure factor returns) shows many of the different dimensions of factor performance. Once all the tests have been completed we need to use them to select the factors that are most likely to work. The assumption here is that factor strategies that worked in the past will continue working into the future¹⁷.

Summarising all of the factor performance statistics

Given the extensive nature of these different tests, we found it easier to amass all the most vital performance statistics for each factor into a simple report and then do a manual filter for desirable factors.

An example of a summary sheet of factor performance statistics for Singapore is shown below in Table 3.

Table 3: Summary sheet of factor performance statistics for Singapore (1995-2003)

Group	Factor	Avg Rank IC		Hit Rate		t-stat		Active Return		
		Lag 1m	Lag 2m	Lag 1m	Lag 2m	Lag 1m	Lag 2m	Top	Bottom	Top-Bottom
Analyst Sentiment	Consensus recommendation	2.52%	1.53%	54.72%	52.38%	1.17	0.73	2.42%	2.39%	0.03%
Analyst Sentiment	1 month Consensus change	3.63%	-0.09%	51.92%	51.46%	1.82	-0.05	7.50%	-7.01%	14.51%
Analyst Sentiment	2 month Consensus change	3.06%	-1.77%	54.72%	45.71%	1.54	-0.94	6.12%	-6.81%	12.92%
Earnings Certainty	Earnings Certainty	1.69%	2.18%	52.83%	53.33%	0.65	0.88	-0.88%	0.29%	-1.17%
Forecast Revisions	3 month Combined SER change	6.79%	3.01%	63.21%	55.24%	3.32	1.47	9.23%	-6.41%	15.64%
Growth	Historic ROE	2.00%	1.83%	51.89%	51.43%	0.90	0.82	2.55%	-1.78%	4.32%
Growth	Prospective ROE	0.78%	0.98%	52.83%	56.19%	0.37	0.48	2.13%	-0.67%	2.80%
Growth	12 month Change in Hist ROE	2.89%	3.11%	56.60%	60.00%	1.46	1.59	-1.16%	-1.82%	0.66%
Growth	12 month Change in Prosp ROE	4.14%	4.42%	57.55%	60.95%	1.76	1.95	3.47%	-1.27%	4.74%
Other Factors	Size	1.84%	1.28%	52.83%	52.38%	0.82	0.57	-0.76%	3.90%	-4.66%
Other Factors	Trading Intensity (3/12 value)	3.42%	3.73%	55.66%	57.14%	1.67	1.84	10.10%	-2.58%	12.68%
Price Momentum	1 Month momentum	-1.40%	-2.48%	50.00%	46.67%	-0.60	-1.09	-1.09%	-0.39%	-0.70%
Price Momentum	3 Month momentum	-4.35%	-2.58%	44.34%	49.52%	-1.63	-0.93	-4.47%	3.18%	-7.66%
Price Momentum	6 Month momentum	-3.85%	-0.42%	44.34%	45.71%	-1.24	-0.16	-5.37%	4.38%	-9.75%
Price Momentum	12 month momentum	-1.78%	-0.20%	47.17%	48.57%	-0.63	-0.08	-3.99%	5.67%	-9.66%
Value	Historic Earnings Yield	4.83%	3.28%	62.26%	56.19%	2.43	1.59	6.24%	-5.74%	11.98%
Value	FY1 Dividend Yield	1.81%	1.69%	51.89%	47.62%	0.71	0.67	1.14%	-0.66%	1.81%

Group	Factor	Tracking Error		Information Ratio		Monthly Success Rate		Avg Turnover	
		Top	Bottom	Top	Bottom	Top	Bottom	Top	Bottom
Analyst Sentiment	Consensus recommendation	10.52%	10.77%	0.23	0.22	52.8%	42.5%	18.3%	27.7%
Analyst Sentiment	1 month Consensus change	11.13%	11.12%	0.67	-0.63	61.5%	44.2%	67.2%	67.6%
Analyst Sentiment	2 month Consensus change	10.63%	8.68%	0.58	-0.78	62.3%	39.6%	48.4%	51.4%
Earnings Certainty	Earnings Certainty	12.65%	13.79%	-0.07	0.02	47.2%	49.1%	21.0%	24.7%
Forecast Revisions	3 month Combined SER change	8.80%	9.32%	1.05	-0.69	60.4%	41.5%	32.4%	40.1%
Growth	Historic ROE	11.05%	12.75%	0.23	-0.14	55.7%	49.1%	14.8%	20.7%
Growth	Prospective ROE	10.32%	11.28%	0.21	-0.06	57.5%	43.4%	16.0%	20.5%
Growth	12 month Change in Hist ROE	10.06%	10.59%	-0.12	-0.17	50.0%	50.0%	16.4%	24.4%
Growth	12 month Change in Prosp ROE	11.39%	11.39%	0.30	-0.11	55.7%	47.2%	20.6%	24.5%
Other Factors	Size	12.17%	12.56%	-0.06	0.31	47.2%	48.1%	4.2%	11.3%
Other Factors	Trading Intensity (3/12 value)	12.11%	10.06%	0.83	-0.26	59.4%	46.2%	29.0%	29.0%
Price Momentum	1 Month momentum	11.70%	13.68%	-0.09	-0.03	54.7%	51.9%	68.4%	69.2%
Price Momentum	3 Month momentum	14.91%	15.76%	-0.30	0.20	48.1%	50.9%	39.9%	41.8%
Price Momentum	6 Month momentum	15.17%	18.88%	-0.35	0.23	47.2%	55.7%	31.3%	32.9%
Price Momentum	12 month momentum	15.36%	17.65%	-0.26	0.32	50.9%	48.1%	24.1%	25.1%
Value	Historic Earnings Yield	12.05%	10.80%	0.52	-0.53	51.9%	41.5%	21.6%	22.2%
Value	FY1 Dividend Yield	11.69%	13.60%	0.10	-0.05	49.1%	54.7%	15.7%	20.4%

Source: Macquarie Quantitative Research

Highlighted are factors that fit most of the criteria below:

- High and significant one and two month lagged rank ICs
- Well-distinguished active returns and information ratios for top and bottom fractiles
- Lower turnover for top and bottom fractiles
- Strong relative pure factor returns

We could therefore use these factors to build a multi-factor model.

¹⁷ Bearing in mind, of course, the potential danger of data mining.

Building the model

Combining factors into a multi-factor model

Up to now, we have focused on selection factors to go into the final model. In this section we explore the process of combining these factors into a multi-factor model.

Initially the factors are grouped together

Two-stage factor models

One innovative approach to model construction is the **two-stage model building process**. Two-stage factor models evolved from **the idea that factors within each factor group are typically more highly correlated** than those that are not within the same factor group. It therefore made sense to build **factor group sub-models** from those successfully screened factors belonging to the same factor group. Once the factor group sub-models have been constructed we then **combine these into the final model**.

Why?

This two-stage approach in turn leads to:

Improves transparency...

- **Increased model transparency:** It is easier to see what the weights of each factor block within the final model are. This in turn allows us to see what general factor groups the multi-factor model has the most exposure to. For example, it would be much more informative if we knew that the final model was weighted with 20% to the value block, 40% to the momentum block and 40% to the forecasts revisions block, than given the individual factor weights.

... and control

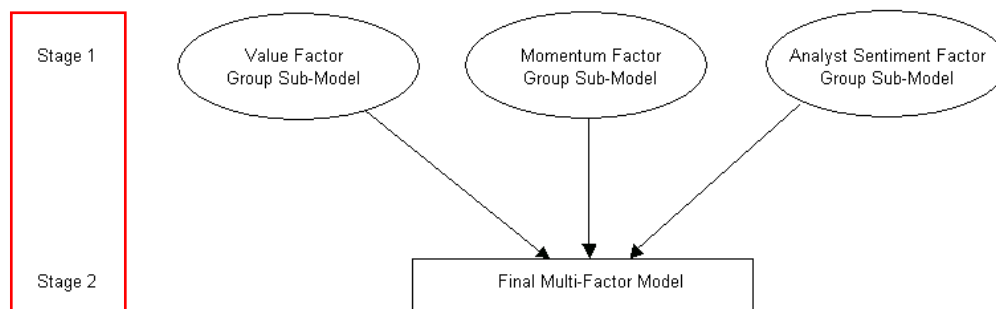
- **Increased model control:** It is easier to qualitatively re-weight factors within factor blocks and factor blocks within the final model to take into account other practicalities. For example, high turnover factors/factor blocks can be down weighted so as to reduce the drag on the Alpha caused through higher transaction costs and market impact. A factor or factor block might also be down weighted to reduce factor diversification risk, and to make sure certain factors don't dominate the final model.

In Table 4 below, we show a narrow sample of some typical factors and their factor groups:

Table 4: Typical factors used in multi-factor models

Factor group	Factor name
Analyst Sentiment	Consensus Recommendation
Analyst Sentiment	1 Month Change in Consensus Recommendation
Analyst Sentiment	2 Month Change in Consensus Recommendation
Forecast Revisions	1 Month % Change in FY1 EPS
Forecast Revisions	2 Month % Change in FY1 EPS
Forecast Revisions	3 Month % Change in FY1 EPS
Other Factors	Relative Trading Intensity (3/12 Month by Value Traded)
Other Factors	Size (Log Market Capitalisation)
Price Momentum	1 Month Momentum
Price Momentum	3 Month Momentum
Price Momentum	6 Month Momentum
Price Momentum	12 Month Momentum
Profitability	Historic ROE
Profitability	Prospective ROE
Value	Prospective 12 Months Forward Dividend Yield
Value	Prospective 12 Months Forward Earnings Yield
Value	Prospective FY1 Dividend Yield
Value	Prospective FY1 Earnings Yield
Value	Historic Earnings Yield
Value	Historic Dividend Yield

Source: Macquarie Quantitative Research

Chart 11: Two-stage model building

Source: Macquarie Quantitative Research

The explicit steps in this two-stage model building process, as Chart 11 shows, are as follows:

1. Form factor groups by optimally combining similar factors

1. **The first stage:** involves combining all successfully screened candidate factors within the same factor group into an optimal mix (ie determining the sub-model factor weights). This optimal mix will take into account the correlation between these factors (see the next section *Putting it all together*), ensuring we don't double count factors that are too similar.

Once the weights of the factor group sub-model have been determined the sub-model scores need to be calculated. They will simply be the weighted average of the **normalised factor scores** that make up the sub-model (the weights being the optimal mix)¹⁸.

2. Repeat the process for factor groups to create the final model

2. **The second stage:** involves repeating the above process but at a factor group level. An information analysis on each factor group sub-model is often a good idea first, to check the success of each factor group sub-model. Any factor group that does not satisfy the IC and fractile performance criteria as documented above is excluded (this is not very likely as the positive ICs for each factor within a factor group are indirectly additive).

The final model weights are then found by taking account of the correlation between factor group sub-models. Once the weights of the final model have been determined the **final model scores** need to be calculated. They will simply be the weighted average of the normalised factor group sub-model scores¹⁹.

One further point should be made. While the correlation between factors from different factor groups is less likely, there will still be some correlation.

An obvious example of correlated factors is between the momentum and forecast revisions factors. Analysts tend to upgrade their earnings estimates as the stock price rises (and downgrade their earnings estimates as the stock price drops). On the other hand, stock prices can also rise or fall on the back of changes in analyst earnings expectations. This in turn can give rise to rather high correlations between factors within these two factor groups. In Australia, some of the earnings revision factors have been over 75% correlated to three, six and 12 month momentum.

¹⁸ To combine factors together we need to make them comparable. This is because different factors will have different scales and some may have units (eg market cap has a dollar unit, although yields and many earnings revisions are unitless). By combining non-normalised scores in a model we run the risk of applying weights that are effectively different to the ones we intended. Raw and non-normalised should never be used to build multi-factor models. **So it makes sense to find a way to treat them on the same basis. Normalisation achieves this because it makes all the data unitless and have roughly identical distributions (with mean 0 and standard deviation 1).** See Appendix 3 for more details on how we normalise our raw factor data.

¹⁹ Again, it is important to ensure all the factor group sub-models have similar distributions (ie roughly normally distributed with mean 0 and standard deviation 1). If we don't normalise each of the factor group sub-model scores, their distributions will be roughly mean 0 but not standard deviation 1.

In Table 5 we present an example of a final model along with its core statistics (and give the factor group sub-model weights)

Table 5: Final multi-factor models

Factor group	Factor	Avg IC	t stat (IC)	Factor weights	Factor group weight	Actual weight
Value	Prospective I/B/E/S Earnings Yield	3.7%	2.56	40%	20%	8%
Value	Prospective FY1 I/B/E/S Dividend Yield	4.9%	2.61	60%	20%	12%
Momentum	3 Month Momentum	8.8%	6.02	15%	40%	6%
Momentum	6 Month Momentum	9.3%	6.35	25%	40%	10%
Momentum	12 Month Momentum	8.7%	5.53	40%	40%	16%
Momentum	3 Month Sector Momentum	5.7%	4.46	20%	40%	8%
Sentiment	1 Month Revision of 1 Year Forward EPS	7.1%	7.01	30%	20%	6%
Sentiment	3 Month Revision of 1 Year Forward EPS	8.2%	6.30	35%	20%	7%
Sentiment	6 Month Revision of 1 Year Forward EPS	8.2%	5.73	35%	20%	7%
Other	Earnings Certainty	6.9%	4.07	80%	20%	16%
Other	Prospective I/B/E/S ROE	2.4%	2.43	20%	20%	4%
Total						100%

Source: Macquarie Quantitative Research

Putting it all together

We need to optimally combine correlated factors ...

... to avoid double counting and ...

... to avoid creating a model that only works in-sample

Sophisticated formula is used to strip out factor correlations that uses ...

... average rank ICs

... and average time series rank correlations between each factor

When putting a multi-factor model together, the issue arises as to how to optimally combine correlated factors (or correlated factor groups).

If we don't take account of correlated factors we run the risk of:

1. **Unknowningly overexposing the portfolio** to some factor types at the expense of others (ie effectively double counting), and
2. **Creating a sub-optimal in-sample model** (see Appendix 4 for a discussion of in sample model building and out of sample tests).

We therefore use a sophisticated formula that effectively strips from each factor's IC the part that is correlated with the other factor signals (also known as orthogonalising the factors). In particular, it adjusts down the ICs of correlated factors. Highly correlated factors typically will get significantly reduced or diluted relative to the other factors in the factor group. The resulting **correlation-adjusted IC** is then used as the basis for the model's final factors weights.

To determine the optimal weights of correlated factors we need two things:

1. The average ranked ICs of each factor/factor group over the in-sample period. This is expressed in the form of a vector we label **IC**. Note that the average IC vector should have ICs that reflect the investment horizon desired. If you wish the model to be rebalanced monthly, then monthly ICs should be used. If you wish the final model to be rebalanced yearly, then yearly ICs should be used. We discuss this later in more detail.
2. The average of the time series rank correlations between each factor pair over the in-sample period. This is in the form of a matrix we label **p**.

An example of a factor Correlation Matrix is in Table 6:

Table 6: Factor correlation matrix

Correlation matrix	Momentum	Earnings yield	Sentiment	Avg IC
Momentum	100.0%	55.6%	10.0%	8.0%
Earnings yield	55.6%	100.0%	-10.0%	6.0%
Sentiment	10.0%	-10.0%	100.0%	4.0%

Source: Macquarie Quantitative Research

Note that the matrix will actually be symmetric, with the diagonals being the correlation of the ranked factors with themselves (ie 100%).

Once we have the IC vector **IC'** and correlation matrix **p** we can calculate what is known as the **correlation-adjusted IC** for each factor. This correlation-adjusted IC is effectively how much IC the factor individually contributes to the whole model separately from any other factor in the model. The correlation-adjusted ICs for a two-factor model are:

$$\begin{aligned} IC_1' &= (IC_1 - p_{12} IC_2) / (1 - p_{12}^2), \\ IC_2' &= (IC_2 - p_{12} IC_1) / (1 - p_{12}^2) \end{aligned} \quad (2)$$

where p_{12} = correlation between ranked factor 1 and ranked factor 2

Put simply, the higher the correlation the lower the adjusted ICs become. On the other hand, if p_{12} is zero, meaning the factors are completely uncorrelated, then the adjusted ICs for each factor will simply be the actual ICs.

For an N factor case, the matrix formula for the correlation-adjusted ICs vector is²⁰:

$$IC' = IC^T \cdot p^{-1} \quad (3)$$

Once the correlation-adjusted IC has been calculated it is straightforward to calculate the optimal weights of the model. Each factor's weight in the model is simply the proportion of its correlation-adjusted IC to the sum of the correlation-adjusted ICs of all the factors in the model.

²⁰ Equation (3) also be used to combine a signal with itself lagged in time (also see Chapter 13 of Grinold & Kahn (2000) for more details).

The weights of each factor for a two-factor model then become:

$$\begin{aligned} w_1 &= IC_1' / (IC_1' + IC_2'), \\ w_2 &= IC_2' / (IC_1' + IC_2') \end{aligned} \quad (4)$$

Using a model with these weights will give the optimal IC over the in-sample period²¹. There is even an approximate estimate of the final combined IC, as found in Grinold and Kahn (2000). It is:

$$IC_{\text{Combined}} = \sqrt{IC^T \cdot \rho^{-1} \cdot IC} \quad (5)$$

In Table 7, we show how to derive the adjusted ICs, final weights and estimate of the final combined IC for a two-factor model.

Table 7: Two-factor model building

Correlation matrix	Momentum	Earnings yield	Avg IC	Adj IC	Weight in model
Momentum	100.0%	55.6%	8.0%	6.8%	75.0%
Earnings yield	55.6%	100.0%	6.0%	2.2%	25.0%

Source: Macquarie Quantitative Research

Issues that need to be addressed include ...

... negative weights

While this methodology is strictly correct in a perfect world, there are other requirements and issues that can and do pop up when building multi-factor models. We will now discuss the more typical ones encountered:

1. **Negative weights:** a factor that ends up with a negative adjusted IC and hence negative weight will usually be highly correlated with a more successful factor. The question then arises as to whether to include the less successful factor in the model. One could argue that the resulting combination of the correlated factors optimises the in-sample results. That is, the combination of both the more successful factor with a positive weight and the less successful factor with a negative weight is more optimal than just the more successful factor by itself. On the one hand, this sounds suspiciously like data mining and would be against financial intuition, due to the negative weight.

On this basis then, we typically exclude factors with negative weights. This translates to excluding any factor with a negative adjusted IC (see Grinold & Kahn, P270). For a two-factor model this simply means (resulting from equation 2 above):

$$\begin{aligned} (IC_1 - \rho_{12} IC_2) &> 0, \\ (IC_2 - \rho_{12} IC_1) &> 0 \end{aligned} \quad (6)$$

... small weights

2. **Small final weights:** we also tend to exclude factors with final weights of less than 5%, as they only marginally contribute to the final Alpha. For example if an individual factor has a weight of 5% in the factor group sub-model and the factor group sub-model makes up 30% of the final model, this factor really has a weight of only 1.5% in the final model. At this weight this factor will have no significant impact. Equity markets will not work like an optimal strategy in a perfect world, so there is little point in having small weighted factors in the model or finessing the model to exact weights.

...large weights

3. **Large final weights:** at the other end of the scale we may decide to cap the weight of any factor or factor group. Typically we set this to 50%. If we don't cap the weight of factors or factor groups they may dominate the model, which is particularly dangerous if the factor starts to mean revert, thereby threatening the stability and success of the live portfolio. Capping the factors' weight reduces this problem and increases factor diversification.

We tend to use capping only at the factor group level when combining factors into the final model (rather than at a factor level). This is because factors within factor groups tend to be reasonably highly correlated with each other; so capping one is unlikely to affect the performance of the sub-model.

... adjusting the weights via a qualitative overlay

4. **A qualitative overlay to reweighting factors:** this can be applied to the model weights to take account of higher turnover factors or higher turnover factor groups that will reduce the

²¹ Again, notice that when $\rho_{12} = 0$, the adjusted ICs are simply the unadjusted ICs. The weight of each factor within the final model is then simply its IC over the sum of all the factor ICs.

... using consistent measurements periods

Alpha (due to higher transaction costs). We do this by giving these factors less weight in the overall model. This is an inexact step and is not possible to finesse.

5. **Consistent measurement periods:** care must be taken when forming the **IC** vector and the **p** matrix in terms of ensuring the time period is the same for all correlations calculated. This is most important for the **IC** vector as it most strongly influences the weights in the final model.

For example take a two-factor model. One factor might have 10 years of IC performance data, where for the first five years the ICs were poor but for the last five years the ICs were good. Another factor might only have IC history for the previous five years. In this case it might only be appropriate for both factors to use the average ICs in the **IC** vector over the last five years (see Appendix 6 for a discussion on Coverage), because the correlations between the two factors will only be available for the last five years.

Other issues that should be addressed when creating multi-factor models

Once the weights of the factors within the model have been determined, we then can calculate the scores of multi-factor model through time. However, there are a number of data related issues that can pop up here:

1. **Missing dominant factor scores:** factors or factor groups that are the mainstay of the model are typically required to exist in order to assign a stock a multi-factor score. If no dominant factor score exists for a stock it does not receive a multi-factor score. This is a common requirement that we make.
2. **Missing non-dominant factor scores:** if a stock has data from the dominant factor but from not all the other factors, we have two clear choices. We can either assume the missing factor(s) are uncorrelated and hence irreplaceable. In this case it would be logical to assign the missing factor a zero score. On the other hand we can assume that the other non-missing factor(s) are reasonable substitutes for the missing one(s). In the later case we would then rescale the multi-factor scores so that the model weight still adds up to 100%. Reality of course will be somewhere in between²².

For example, say our momentum group sub-model consists of two factors, a 12 month momentum factor with weight 60% and a three month momentum factor with weight 40%. If a stock has no 12 month momentum data we do not calculate a multi-factor score for it (as it is the missing dominant factor score). On the other hand, if a stock had no data for three month momentum and we had decided to use the rescaling approach, then we would scale the final score up to 100% by dividing the 12 month momentum score by the weight of the existing 60% of the entire multi-factor signal (ie we would divide the final z score by the block weight of all non-missing factors, $\sum_j w_j / \sum w_j$).

This rescale rule is quite logical when applied on a factor level within a factor group, due to the similarity of the factors within the same group (especially if the factors measure across similar time horizons). However it is more difficult to justify on a factor group level due to the lower level of correlation between factor groups (ie the missing factor group is more difficult to replace).

3. **Factor weight threshold:** we may also require a minimum threshold of the combined signal be attained before a score be assigned to a stock. For example a multi-factor model may include three factors, with weights of 50%, 30% and 20%. If the minimum requirement is that we must have at least 75% of the signal, a stock that has a score for the 50% factor and the 30% factor would satisfy the threshold but another stock with data for only the 50% and 20% would not. It would not receive a multi-factor score.

For stocks with the minimum required threshold but not 100% of the signal we can do either of two things: assign the missing part of the signal a zero score (indicating the missing factor signal is not replaceable), or we can rescale the multi-factor score by dividing by the final weight (in the 50% and 30% example above, this would involve dividing the resultant multi-factor score for the stocks by 0.8).

²² In fact, a third alternative is to rescale the multi-factor score only so much as the missing factor is jointly correlated with the existing factors over the in-sample period. This is, however, both complicated, time consuming and questionable as to whether this will make any substantive difference to the model, particularly if most stocks have data for most of their individual factors.

Parsimony and diversity

*A good quant model
should offer ...*

*... a diverse array of
factors to protect
against some factors
not working.*

*... while still offering
parsimony to avoid
over-fitting the sample
data*

It's a difficult juggling act

The process of screening factors and building the model tends to wheedle out the less successful factors. The final stage of the model building process is to examine both the parsimony and diversity of factors within the final model. Both parsimony and diversity are essential in building Quant models as they offer further protection against data mining:

- **Diversity:** this requires the model to comprise of a number of qualitatively different factors. This is to protect the model against the possibility that some of the factors, which have worked well in the past, stop working in the future. Intuitively, when one or more factors are not working, other factors may compensate for their underperformance and generate a smoother returns profile and hence lower returns volatility or tracking error. Past analysis has shown that model diversity improves the Alphas predictive power and consistency. One measure of diversity within the final model would be the number of factor group sub-models from which the final model was built.
- **Parsimony:** on the other hand we require the model not have too many factors (much more than 10 becomes questionable). Too many factors expose us to the risk of over-explaining past results and relying on the specific combination of factors for the future, which may or may not generalise beyond that period. Parsimony, therefore, may require some factors to be dropped from the final model.

Excluding less successful factors within a factor group can often satisfy parsimony and diversity, but sometimes it is not possible to have both. As mentioned before, it is difficult to finesse the model building process but some attempt should be made.

Note that if any factors have been added to or excluded from the final model on the basis of diversity or parsimony, it is important to recalculate the model weights (using equation (3)) to take into account the presence or absence of these factors (ie repeat the process described above).

Time horizon

The model construction and determination of the final factor weights within a multi-factor model as described above depends on the IC performances of individual factors, as well as the factor IC correlations.

*It is important to
consider the time
horizon when
calculating factor
weights*

But factor performance may differ depending on the time horizon used (as we discovered in the section on IC decay profiles, where some factors get priced into the market quicker than other factors). Factors like short term earnings revision and short term price momentum tend to be very useful in models for short time horizons as they have high short term ICs, while value factors and medium term price momentum (6–12 months) tend to get used in models over longer time horizon because they have higher long term ICs.

The question then arises as to what ICs do we use?

The way to deal with this in model construction is to use Rank ICs relevant to your time horizon.

So, for example, if you wish your portfolio to be rebalanced monthly, you should use monthly ICs (as we have described so far). If you wish the final model to be rebalanced semi-annually then Rank ICs over six months should be used.

As long as the ICs are over the same time period, application of equation (3) above is identical²³.

²³ It is also arguable that instead of using a correlation matrix composed of the correlations between the factor signal pairs, the correlation should be between factor IC pairs over the relevant time horizon.

Different stock groupings can behave differently within markets ...

... and separate models are advisable for these stock groups so long as there is sufficient breadth and it is not simply a data mining exercise

Sweet spot analysis (separate models for special sectors/stock size groupings)

In many equity markets, certain sectors act and react very differently to the rest of the market. In fact, previous analysis by MRE has found most Quant models perform differently across different types of stocks. Here are some examples:

1. **Listed property trusts (LPTs) in Australia** are a classic example. Stock prices for LPTs are heavily driven by mean reversion but not by earnings certainty (as the LPT cash flows tend to be very steady).
2. **Infrastructure stocks** are different to the rest of the equity market in that they are more asset plays than earnings plays, with stable earnings expected to appear sometime in the future. Therefore they are valued differently by the market.
3. We might also want to conduct IC analysis and fractiles across **different size dimensions** of the market. This is justifiable on the basis of both differing liquidity and differing amounts of reliable public information available to investors in the market.

In each of these cases, it is usually justifiable to create separate models and by extension to exclude these sectors from the model of the main equity market. Care needs to be taken, however, in two respects:

- That the breadth of stocks must be sufficiently large (say more than 10 stocks). In order to be confident that the final model is picking up actual sector price drivers.
- To avoid simply mining the data

As long as you are comfortable that both these issues have been addressed, it is usually worthwhile exploring this avenue!

Testing model robustness

It is important to test the potential success of a Quant model strategy in an appropriate out-of-sample period (see Appendix 4 for a discussion of in-sample model building and out-of-sample tests). Model stability in different time periods is an **important test** in the selection of a successful Quant model.

Various in-sample tests can be performed ...

Before the out-of-sample tests are conducted, we may want to test the model has been correctly constructed (ie within the in-sample period). We could perform the following tests:

1. **In-sample information analysis:** in addition to the run of the mill information analysis, we can also test the predicted IC versus the actual IC (equation 5 above).
2. **In-sample multi-factor cross-sectional regressions:** regressions can be performed without risk factors or with risk factors (pure factors). To ascertain model significance we require the t-stat from the time series of model regression coefficients to be above 2.

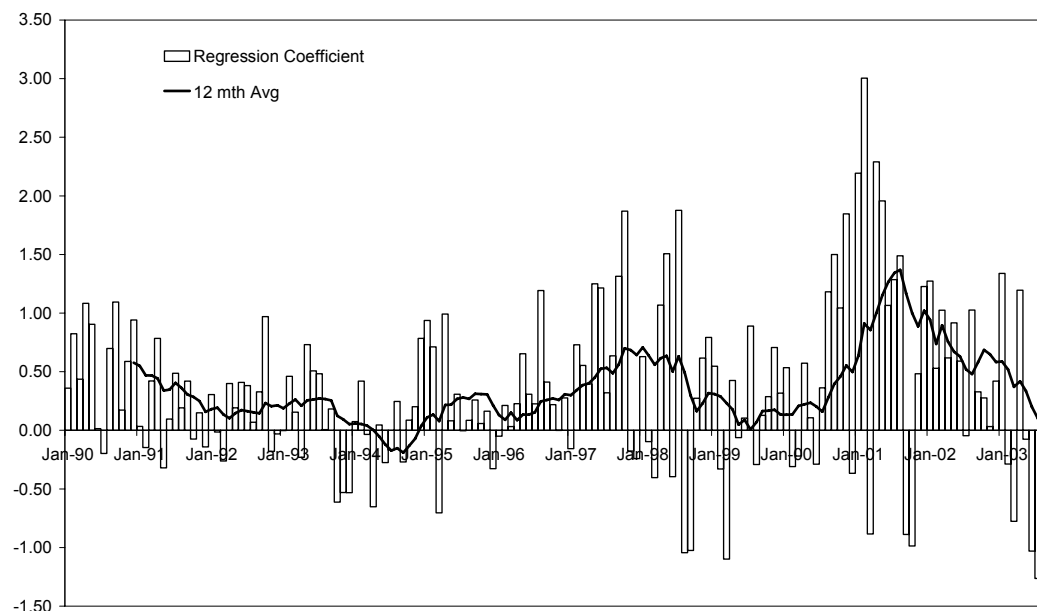
... but a critical robustness check is out-of-sample testing

This is a critical test of model robustness. To test whether the optimal in-sample model works well in the out-of-sample period, we can perform the following tests:

1. **Out-of-sample information analysis:** again, this is a run of the mill test.
2. **Out-of-sample multi-factor cross-sectional regressions:** again, regressions can either be performed without risk factors or with risk factors. An attribution analysis may also be conducted to determine what factors performed well and portfolio factor exposures through time.

Chart 12 is an example of the time series of regression coefficient for a multi-factor model over both the in-sample period and an out-of-sample period:

Chart 12: Model regression coefficient



Factor returns to a regression of excess returns against a multifactor Quant model

Source: Macquarie Quantitative Research

Note that unless suitable reasons can be found, an optimal in-sample model that performs poorly in the out-of-sample period should be rejected.²⁴

²⁴ On the other hand, equity markets can evolve and change, which may result in some factors no longer being rewarded as they were in the past. A badly chosen out-of-sample period, which only encompasses a fraction of the economic cycle may also result in model performance quite different to the in-sample period.

Portfolio simulations

The final step for any Quant model is the portfolio simulation. This involves both:

- Constructing investible portfolios (ie determining the weights of the portfolio)
- Performance analysis of the constructed portfolio in an in and out-of-sample period (which includes examining turnover, transaction costs and market impact)

In this section of the report, we will look at both of these issues, starting first with how Macquarie conducts portfolio construction:

Constructing investible portfolios

Portfolio construction is about maximising returns while constraining risk exposures

Portfolio construction methodology is a very important part of the whole investment process. If it is not done correctly your forecasts will not flow properly through to your final portfolio. A construction process that severely distorts your security level forecasts is unlikely to add any value or give you unexpected results. Therefore the aim of portfolio construction is to provide the maximum possible expected return given the desired level of risk and realistic constraints.

There are a variety of ways to **quantitatively** construct portfolios if you have estimates of the stock returns or stock Alphas (as a multi-factor model gives). In Appendix 7 we discuss various ways in which portfolios can be quantitatively constructed.

Macquarie uses an in-house optimisation application

At Macquarie we use an in-house developed portfolio optimisation process.

The goal of optimisation within a funds management context is really straightforward: to maximise the expected portfolio active return while minimising expected portfolio risk subject to appropriate real life constraints. This involves searching around active weights space for the optimal portfolio²⁵. In particular, we change the active weights of the portfolio until we have a portfolio with the highest expected active return but the lowest expected tracking error. To do this a quadratic programming algorithm is used.

There are four main inputs for this optimisation process:

- the stock Alphas (the expected active returns relative to the benchmark)
- an appropriate risk model
- an initial portfolio
- fund constraints (maximum active bets, target tracking error, sector neutrality, etc)

This last step is very important because the test portfolio goes much further than simply being a paper model. A common criticism of Quant models is that the paper performance is typically much better than actual performance, where transaction costs, liquidity considerations and market impact due to fund size act as performance drags. A simulation that is as close to real life as possible (using various risk, liquidity and size constraints) is therefore an important part of testing the potential success of the model.

By using portfolio optimisation as our portfolio construction technique we can easily do the following:

- Measure tracking error against all equity benchmarks
- Build portfolios that track benchmarks under a variety of constraints
- Build portfolios that maximising return while minimising risk

We will now discuss the required inputs and elements of optimisation in turn:

- Converting the multi-factor scores to an Alpha
- Dealing with stock and portfolio risk
- Performing portfolio optimisation
- Portfolio inputs and constraints

²⁵ Note that we are considering here only active returns and active risk, rather than expected total returns and total risk, because we assume the desired portfolio is an actively managed fund (it also avoids having to forecast the expected return and risk of the benchmark).

*Normalisation process
address problems
caused by extreme
outliers and a skewed
distribution*

*Formula for generating
the multi-factor excess
return forecast*

Converting the model to an Alpha

Once the multifactor signal has been calculated through time we need to perform a multiple re-normalisation process to it (winsorising at ± 3). This ensures that the signal is well behaved (as discussed in Appendix 2), otherwise very extreme values can have undue influence on the final weights of the portfolio (the final portfolio weights in the optimisation process is the most sensitive inputs the stock Alphas).

We can then convert this score into an Alpha using the following formula:

$$\text{ALPHA} = \text{VOLATILITY} \times \text{IC} \times \text{SCORE} \quad (6)$$

where

- **Volatility** is the cross-sectional volatility of the residual returns.
- **IC** is the strategy information coefficient, the predictive power of the model
- **Multi-factor score** are the cross-sectional scores for each stock, $\sum w_j z_j$

Therefore we effectively scale the multifactor score in equation (6), which is roughly normally distributed, by the skill level of the forecaster (the IC) and the volatility of the residual returns.

The **IC** in equation (6) is calculated by taking the average IC of the strategy over the required time period. The strategy is embodied in the multi-factor score, $\sum w_j z_j$. In Australia, a typical model of the ASX200 might have an IC of around 10% in-sample.

The **volatility** in equation (6) is the cross-sectional volatility of residual returns. Residual returns are the returns that cannot be explained by our risk model (which decomposes risk into size, sector and momentum). At any given time cross-sectional volatility is constant but it will change over time. While volatility is straightforward to calculate we typically assign it a value of 30% through time, as it won't impact the optimisation process greatly.

The result of this simplifying assumption is that **Volatility x IC** simply becomes a scaling factor to turn the multi-factor z score into an Alpha. In particular, for an average IC of 10%, it is equal to $10\% \times 30\% = 0.03$. Therefore a stock with a multi-factor score of 1, indicating a prediction of one standard deviation above the market return, would translate into about 3% active return over the forecast period (relative to the benchmark). Similarly a multi-factor score of -1 would translate to a -3% active return.

This will result in an Alpha that will be roughly normally distributed with a market weight mean of zero and standard deviation of 3%.

Dealing with stock and portfolio risk

Risk model includes the stock variances and covariances

Besides the Alphas, the other key input into our portfolio optimisation process is the stock risk model. This is then used to predict risk on a portfolio level. We express the stock risk model in terms of an NxN risk matrix, where N is the number of stocks in your universe. This risk model includes both the stock variances (the diagonal elements) as well as the covariances or co-movements between stocks (the off-diagonal elements of the matrix).

By properly combining a risk model with the multifactor return model in an optimisation, our portfolio will be exposed to our return factors without being unduly exposed to risk (relative to the benchmark). In effect, we maximise active return while minimise tracking error.

There are two main ways to characterise the risk matrix:

Full stock covariance – variance matrix ...

1. A full covariance – variance matrix. This linear model involves the full history of each stock's price returns. Both individual stock's variances and covariances between stocks need to be calculated.

... or risk factor matrix + stock specific matrix

2. A structural full covariance – variance matrix. This linear model involves splitting risk in two components. The first component is along various common risk dimensions also known as risk factors. Risk factors are forces that affect groups of stocks²⁶. Well known risk factors are price to book and company sectors²⁷. The **second** component is the specific or idiosyncratic risk of the stock. This is the risk not explained by the common risk factors.

We prefer the second approach

At Macquarie, we use a structural risk model (the second one above). There are many reasons why we do this:

- Structural models are a lot less cumbersome to calculate than a full stock covariance-variance matrix.
- Structural models tend to be a lot more stable and a lot less subject to estimation errors. Structural models are an acknowledgment that stock covariances are driven by common sources of risk/returns (factors) across securities. In other words, this approach emphasises sources of risk that have a broad impact across stocks in the market. By identifying appropriate risk factors we can better characterise the total portfolio risk in the future. It therefore reduces the dimensionality of the problem of estimating the risk matrix²⁸.

²⁶ To get a better idea about how risk factors work, consider a portfolio that has a large positive or negative exposure to a risk factor (compared to the benchmark average). By definition this exposure is more likely to lead to returns that deviate more from the benchmark return, than a portfolio that has a zero (benchmark) exposure to the risk factor. In other words, if your portfolio has a positive or a negative skew to a risk factor, your portfolio will likely have a higher tracking error (see P6, Singapore Risk Modelling).

²⁷ The key difference between a risk factor and a return factor that gets used in a multifactor model is that risk factors tend to predict that a stock may be risky, which includes both upside risk and downside risk. On the other hand a return factor tends to predict the direction the risk factor will be risky in (i.e. either upside or downside risk, but not both). Structural risk models are therefore like multifactor return models as they use several risk factors in combination. See Appendix 9 for a discussion of risk factors, return factors and factors in general.

²⁸ A similar approach, known as principle components analysis (PCA), also reduces the dimensionality of estimating the stock variance-covariance matrix by characterising risk in terms of a small number of "risk factors" known as principle components. It does this via orthogonalising stock returns of your universe into many principle components (stripping out the correlated parts of each risk factor from each other). However, typically only the first few factors to come out of PCA are used as they have the greatest risk explanatory power. One of the advantages of PCA over structural risk models is that structural risk models will typically involve risk factors that are often highly collinear, which can cause difficulties with structural risk model estimation. But the disadvantage is that the components from a PCA will not be intuitive and difficult to interpret. Hence, we have opted to use a structural risk model. Interestingly, PCA tends to be used more in bond markets.

- Structural risk models are conditional models in that they can take the current risk fundamentals (risk factors) of the stocks into account. On the other hand, historical risk models (unconditional) give equal weight to the entire history of the stock's covariances.
- Structural risk models also have the advantage of estimating covariances for stocks that have little or no historic data. To do this we only need to estimate the current factor exposures of the new stock (using similar business and observable market parameters), as well as an estimate of the stock's specific variance.
- Structural risk models don't result in selection bias, unlike the full covariance-variance matrix which requires the relevant history of data to calculate the covariances and variances in the matrix.
- Lastly, structural risk models are able to cope with the case when a company's nature changes, unlike a full covariance-variance matrix.

*Look for a risk model
with overall explanatory
power > 30%*

*Risk factors should be
meaningful and stable
over time*

A well constructed structural risk model may explain up to 30–40% (the adjusted R^2) of the variation in cross-sectional returns of a universe of stocks, with the balance being attributed to stock specific risk.

Like the return factors that go into the final Alpha model, it is important to select risk factors which are meaningful, provide a useful proxy for other risk factors and are stable over time. Risk factors need to be intuitive, typically arising from recognisable investment themes. Based on past research (see *Balancing Fear and Greed*, May 2000), our structural risk models for each country take into account market factors/signals that are known risk factors. These risk factors best capture the variation in cross-sectional returns. Some examples of common risk factors we use are as follows:

- **Size (log of market capitalisation):** size has long been recognised as a risk variable (see Fama and French, 1992). In particular, large caps, mid caps and small caps often act and react differently to each other. For example, this may be due, in part, to the greater level of stability large companies have over smaller companies.
- **Sector:** sectors provide perhaps the most useful proxy for commonly used risk factors. Stocks within the same industry face similar risks, similar Beta, similar volatility, similar earnings yields (PEs), similar book to price and similar leverage. Thus, well defined sector definitions eliminate the need for a host of these factors in a risk model (P8, Singapore Risk Modelling).

Our risk sectors are partly based on GICS sectors and are specifically created to achieve the greatest explanatory power of cross sectional returns, while at the same time ensuring enough market breadth within each sector to ensure confidence in the sector classification. The number of sectors varies from country to country. For example our Australian risk model has eight sectors, while our Singapore risk model has six and our Hong Kong risk model has seven sectors²⁹.

- **Momentum:** it is well documented that the momentum of stocks over the 3-12 month horizon is auto-correlated (see Jegadeesh & Titman, 1993), which is a typical investment horizon of many fund managers. So, besides being a return factor, we can also use it as a risk factor (return factors are actually a subset of risk factors, which we explain further in Appendix 8). There is also some evidence to suggest that sector momentum and individual stock momentum are correlated (see Moskowitz and Grinblatt, 1999) but we have found the best explanatory power by including both individual sectors and momentum as risk factors³⁰.

Other examples of popular risk factors are PE, book to price, and the debt/equity ratio (to model financial risk).

²⁹ One of the main functions of GICS (global industry classification system) was to help mainly US investors knowing what to invest in non-US countries. As with most non-US equity markets, the GICS classification system is not necessarily the optimal classification system for domestic investors, but a good starting point.

³⁰ BARRA risk factors are quite similar to ours. For example they use size, value (eg book-to-price), momentum and volatility.

To create a structural risk model, we first need to regress all the stock's factor exposures (in our case size, the sectors and momentum) against the stock's forward returns (in excess of the risk-free rate). This is done every month for the entire universe over the desired time period³¹:

$$r_n(t) = \sum X_{n,k}(t) \cdot b_k(t) + u_n(t) \quad (7)$$

Where $r_n(t)$ = excess log return of stock n (ie relative to the risk free rate). Log returns are used, as we assume stock returns are normally distributed

$X_{n,k}(t)$ = exposure of stock n to factor k at t (this is 0 or 1 if it is a sector, as the footnote below explains, otherwise they are standardised cross-sectional scores)

$b_k(t)$ = factor return to factor k from t to (t+1)

$u_n(t)$ = stock's specific return from t to (t+1) for stock n. This is the component not explained by any of the risk factors

In the OLS regression we weight each observation by the square root of market cap, in order to mimic inverse variance. Also, we constrain the regression to go through zero. This is because of potential problems with multi-colinearity that lead non-unique regression result, and also we want to explain all returns by their risk factors.

This then gives us a time series of factor returns for each risk factor, as well as stock specific risks. The factor returns then allow us to generate the unconditional **factor covariance-variance matrix**, F. In particular, they are simply generated from calculating the co-variances between the different factor returns. Note that because covariance of Stock A with Stock B is the covariance of Stock B and A, F will be a symmetric matrix.

The time series of stock specific risks also allow us to generate the **matrix of specific variances**, Δ . In particular, the diagonal (stock) elements of this matrix are simply the variances of each stock's specific risk time series, $\text{Var}(e_t)$. The off-diagonal elements, which are the covariance's between all the stocks specific risk time series, are assumed to be uncorrelated and hence zero. This, therefore, makes Δ a diagonal matrix.

And finally, the **stock covariance-variance matrix** combines these together with the current factor exposure as follows:

$$V = X^T F X + \Delta \quad (7)$$

Where X = matrix of current normalised stock risk factor exposures (NxK)

F = factor covariance-variance matrix (KxK)

$\Delta = \text{Var}(e_t)$, the variance of the time series of the risk regression residuals, e_t ,

where that $e_t = r_t - \sum z_i f_i$ (f_i = factor excess returns)

The first part of this equation therefore represents the common risk components due to the risk factors, while the second part, Δ , represents the stock specific risk components. Note that because Δ and F are symmetric, V will also be symmetric³². For a more detailed discussion of risk and risk models please see Chapter 3 of Grinold & Khan (2000).³³

In the next section we explore how we combine the Alpha model and risk model together to construct portfolios.

³¹ Four further points about this are: **first** is that we use dummy variables for stocks within sectors. **Second** is that we also force the monthly regression through zero otherwise we get nonsensical results. This is due to rank problems in the matrix calculations. **Thirdly**, if any given sector has no stocks in it for a given month, we exclude this sector from the regression for that month. **Fourthly**, we use Log returns and use a weighting of the square root of market cap in the weighted least squares regression.

³² For the Australian benchmark S&P/ASX 200, this will be roughly a 200 by 200 stock covariance matrix.

³³ A bottle of Champagne for the first person to read this. Call Macquarie Quant Team to claim your prize.

Performing portfolio optimisation

With both the Alphas and a structural risk model we are ready to construct the portfolio through time. We do this using a mathematical technique called optimisation. Optimisation allows an active manager to get exposure to quantitative views (as characterised by the return factors), while minimising active risk (as characterised by exposure to the common risk factors and stock specific risk of the risk model).

Optimisation is all about maximising the risk adjusted active return

Portfolio optimisation works by changing the weights of the stocks within the portfolio until the risk adjusted active return of the portfolio is maximised (subject to the required constraints, of course). This risk adjusted active return is also traditionally known as the utility function but also goes under the guise of value add. Mathematically, it is defined as:

$$\text{Value Added} = \text{Risk Tolerance} \times \text{Portfolio Alpha} - \text{Portfolio Risk} \quad (8)$$

Or mathematically

$$\text{Value Added} = \lambda \alpha_P - \psi_P^2 \quad (8)$$

where $\alpha_P = \alpha^T h_A$, the Portfolio Alpha (active return)

and $\psi_P^2 = h_A^T V h_A$, the Portfolio Tracking Error (active risk)

and $h_A = h_A$, the active portfolio weights (relative to the benchmark)

and $\sum h_A = 0$, the constraint that the active portfolio weights sum to zero

(or equivalently the portfolio weights sum to 1).

What is so neat about equation (8) is that it quantifies the trade off between increasing active portfolio return, while minimising the tracking error. It does this by using the Risk Tolerance parameter λ , which scales the Portfolio Alpha into a Portfolio Variance³⁴. This scaling therefore specifies the fund manager's required tolerance to active risk relative to the active return. Of course different fund managers will have different Risk Tolerances, depending on their attitude toward risk, and their fund mandate. For example, a lower risk tolerance will reduce the impact of returns in the optimisation, while a higher risk tolerance will have the opposite effect³⁵. The default value we use is 0.1 (a typical value).

Note that implementation of optimisation can be tricky. The standard spreadsheet functionality of Excel cannot efficiently perform optimisations with large covariance matrices (for example this would be impossible for the 200 by 200 stock covariance matrix for the Australian benchmark S&P/ASX 200).³⁶

³⁴ Most optimisers tend to use the risk aversion parameter instead of a risk tolerance parameter. A risk aversion parameter measures the aversion to residual risk and transforms the portfolio variance into a loss in portfolio Alpha. There is little difference between using a risk aversion factor and a risk tolerance parameter in an optimisation, except equation 8 above becomes: $\text{Value Added} = \alpha_P - 1/\lambda \psi_P^2$. That is, you convert a risk tolerance parameter into a risk aversion parameter by inverting it (dividing 1 by λ).

³⁵ Note that construction of portfolios via the optimisation process will usually depend much more on the return model than the risk model.

³⁶ The traditional approach to modern portfolio theory is the Markowitz-Sharpe optimisation with respect total return space. This is used when managers are concerned about total returns and total risk, rather than by being benchmarked to benchmark. Here the portfolio active return in equation (8) is replaced with the portfolio total return, $(\alpha^T w)$ the portfolio active risk is replaced with the portfolio total risk, $\psi_P^2 = w^T V w$, and the stock weights add to 1.

Instead we use the in house Macquarie Bank Portfolio Optimiser. Using the Macquarie Bank Portfolio Optimiser also has the added benefit of allowing transaction costs to be included in the utility function for optimisation (ie Value Added = $\lambda \alpha_P - \psi_P^2 - T_C$). Besides reducing turnover, this helps to reduce the impact of errors in the forecast returns and risk model by discouraging the size of positions taken in the resultant portfolio.

In the next section, we discuss some of the inputs and constraints the Macquarie Bank Portfolio Optimiser can handle.

Constraints and parameters that simulate real market conditions

Portfolio inputs and constraints

One of the great strengths of our in house optimiser is the ability to perform simulations that reproduce real market conditions and constraints. The following parameters and optional restrictions (constraints) can be input into our optimiser:

- Select a benchmark (official index or customised benchmark)
- Select an initial portfolio
- Select fund size
- Select active bet size (eg maximum 3% overweight/underweight relative to benchmark)
- Select a risk model
- Select transaction costs (eg 50 basis points). This can also be included in part of the optimisation equation (ie Value Added = $\lambda \alpha_P - \psi_P^2 - T_C$)
- Select and modify the risk tolerance parameter (eg to target a certain tracking error)
- Restrict short selling (ie long only)
- Restrict the maximum amount of liquidity traded in any stock at any rebalance date
- Restricting the number of stocks in the portfolio (including choosing the best N stocks to track an index, including stocks not in the benchmark)
- Restricting the level of factor in a portfolio (including zero weights or market weights)
- Restricting the weights of stocks and sector exposures in a portfolio (upper/lower bounds, or equality)
- Restrict portfolio Beta

Note, however, that the more constraints (restrictions) that are put on the optimisation problem, the more distorted the views on the stock's risk and returns will be.

Performance metrics

Performance analysis

As mentioned above, the Macquarie Bank Portfolio Optimiser produces the following output:

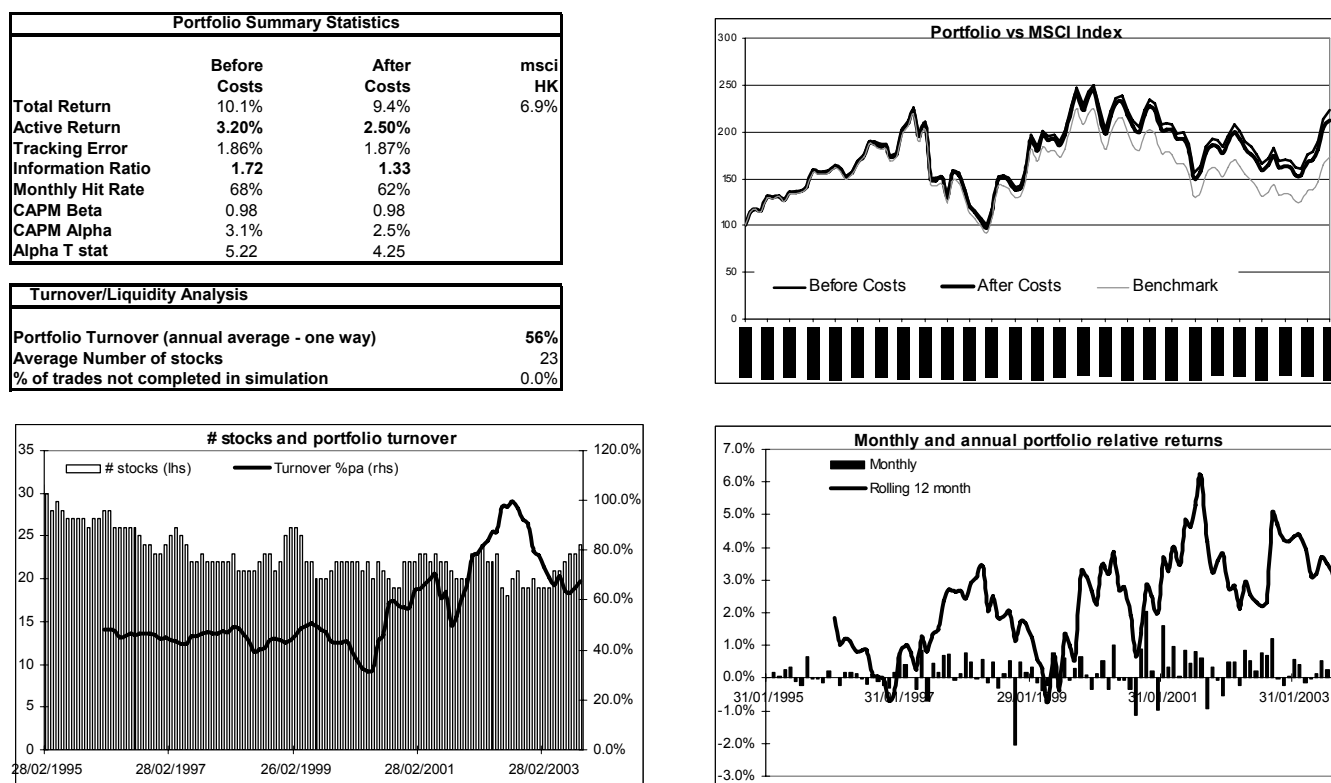
- The optimal portfolio weights
- The portfolio's total risk
- The portfolio's tracking error
- The portfolio's expected return
- The trades required to move to the optimal portfolio
- The transaction costs incurred when moving to the optimal portfolio

On top of this, it can produce the following statistics and graphs from a portfolio simulation:

- **Portfolio summary statistics** (total return, active return, tracking error, information ratio, monthly hit rate, CAPM Beta, CAPM Alpha, Alpha T-Stat)
- **Turnover/liquidity analysis** (portfolio turnover, average number of stocks in portfolio and percentage of trades not completed).
- Graph of number of stocks and portfolio turnover against time
- Graph of portfolio against the chosen benchmark
- Graph of monthly and annual portfolio relative return

Chart 13 demonstrates these types of statistics:

Chart 13: Summary statistics



Source: Macquarie Quantitative Research

Sensitivity to portfolio constraints

Besides performance metrics, we can also examine how sensitive the portfolio performance is to the various parameters and constraints of the backtest. Typical parameters varied in a sensitivity analysis are:

- Maximum size of the active bets (relative to the benchmark)
- Size of the Portfolio
- Liquidity constraints (the maximum amount of trading volume allowed for any stock at each rebalance date, eg restricting change in holdings to 25% of average daily volume)
- Target Tracking error

The following table demonstrates an example of sensitivity analysis we can do:

Table 8: Sensitivity analysis

Max Active Bet (rel benchmark)	Portfolio Size (x \$100 mln)	Liquidity Constraint (%)	Alpha	Tracking Error	Information Ratio	Hit Ratio	Turnover
Bet Size Scenario's							
1.00%	10	25%	3.00%	1.48%	2.03	69%	47%
2.00%	10	25%	4.25%	2.18%	1.95	69%	58%
3.00%	10	25%	4.63%	2.50%	1.85	66%	64%
Liquidity Scenario's							
1.00%	10	50%	3.12%	1.48%	2.11	72%	50%
3.00%	10	50%	4.60%	2.63%	1.75	73%	71%
1.00%	10	75%	3.17%	1.47%	2.16	73%	51%
3.00%	10	75%	4.64%	2.64%	1.76	69%	73%
Portfolio size scenario's							
1.00%	30	25%	2.60%	1.43%	1.82	68%	38%
3.00%	30	25%	4.26%	2.30%	1.85	66%	47%
1.00%	50	25%	2.67%	1.50%	1.78	64%	33%
3.00%	50	25%	3.75%	2.26%	1.66	66%	40%

Source: Macquarie Quantitative Research

Generally speaking the information ratio drops as

- the size of the portfolio increase
- the smaller the active bet
- the smaller the liquidity constraints
- the larger the tracking error, the lower the information ratio³⁷.

³⁷ The frictional costs of market impact and turnover have a detrimental effect on performance as fund size becomes larger. Managers of small funds have greater flexibility and can more freely trade a variety of quantitative strategies, while larger funds are much more limited and tend to focus on lower turnover factors like value and long term momentum. Past Macquarie research suggests that the ideal number of factors to include in your Alpha model decreases with the size of your portfolio (see De Souza, et al, Jun 2002).

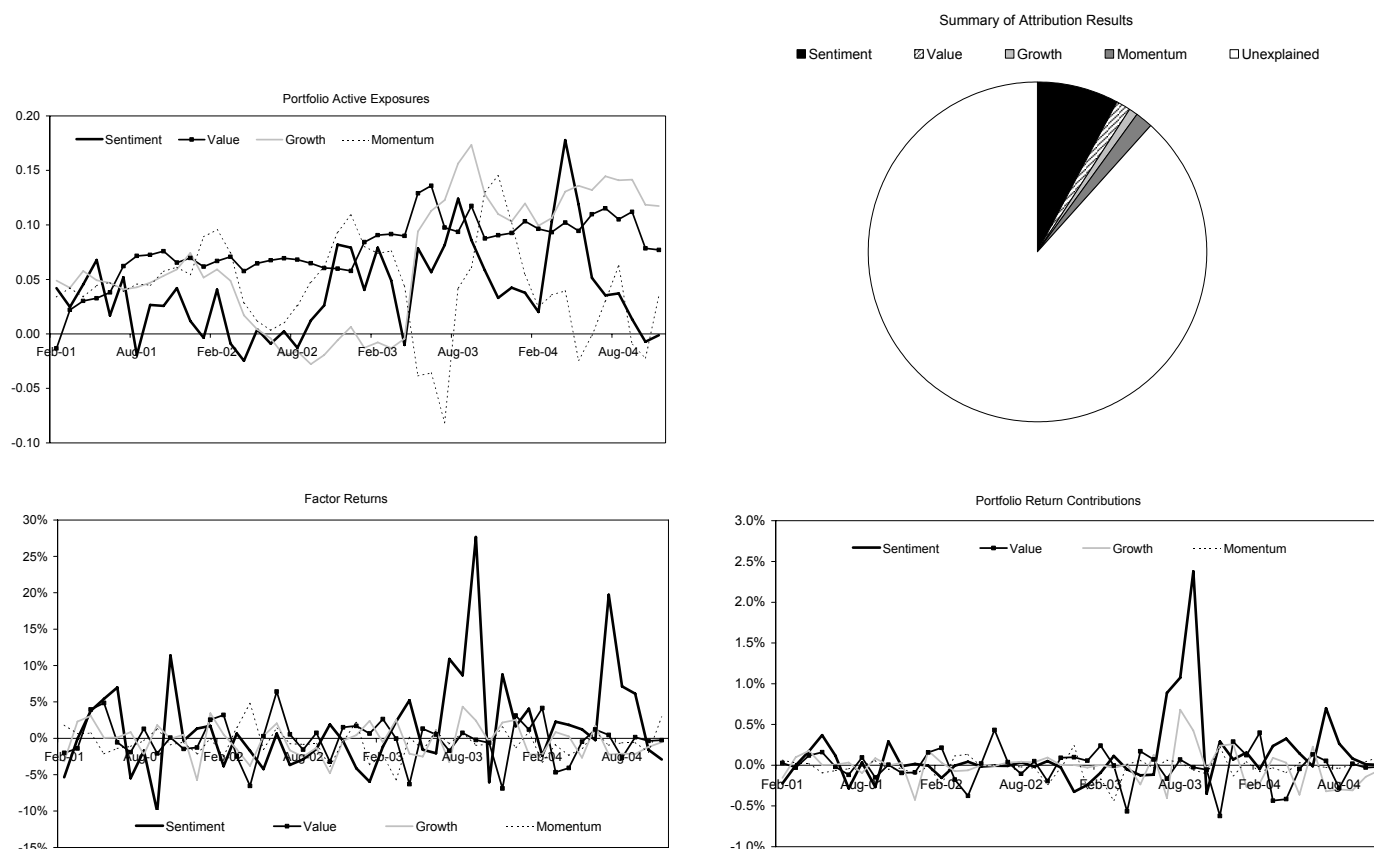
Factor attribution

When examining ex-post portfolio performance, it is useful to determine the contribution of various factors to the actual return. Typically, the factors of interest would include (but are not limited to) the factors that have been used to derive the Alpha. The procedure employed for the attribution involves using regression over each performance period to estimate the market³⁸ return associated with each factor. These returns are then multiplied into the portfolio exposures to these factors, giving an indication of the contribution made by each factor. This allows us to monitor those factors that are currently performing well and those that aren't and the proportion of systematic versus non-systematic returns. It may also identify other factors that are currently significant in driving returns. In addition, it gives an indication of the extent to which portfolio construction constraints and risk control are eroding the Alpha.

We can also monitor ex-post tracking error and compare this with the predicted tracking error based on the risk model. This provides information on how well the risk model is currently performing.

An example of some results from the attribution analysis is below for an alpha model. Here the attribution is against the exposures of components of the alpha model (namely Sentiment, Value, Growth and Momentum). The unexplained component in the pie chart is large, but if size and sector (i.e. risk factors) was also included in the attribution this unexplained would drop dramatically:

Chart 14: Factor Attribution Analysis



Source: Macquarie Quantitative Research

³⁸ Typically, the benchmark is used as the universe over which the market return is estimated, however, this is not constrained to be the case.

Appendix 1: Addressing data mining

Data mining is a common criticism of quantitative models. Indeed, it is relatively easy to search through historical data and find patterns that seem to exist. In this appendix, we discuss the various ways we minimise the possibility of mining the data:

- **Meaningful factors:** requiring factors to have some theoretical rational based on the behaviour biases that drive stock prices. This is the top-level protection against data mining.
- **Avoid factor construction pitfalls:** as described in Appendix 2, care must be taken in constructing factors so that forward looking bias and survivorship bias do not occur. Share dilution and financial year adjustments must also be made to historical data where necessary.
- **Factor parsimony and diversity:** requiring the Alpha model to be both parsimonious (to minimising the risk of over explaining the in-sample results), while keeping the model diverse (to minimise the risk over-dependence on the staple factors in the model).
- **Risk-adjusted tests:** making sure the factors we use in the final model still perform after the risk factors have been taken into account (eg size, sector and momentum).
- **Out-of-sample tests:** testing the in-sample model in an out-of-sample period is another top level protection against data mining. This is the acid test as to whether the model is likely to succeed in practise.
- **The reality test:** using real life constraints and conditions in portfolio simulations, such as transaction costs, market impact and liquidity constraints. If the model does not add any value after cost then we can't be confident that the model will perform in the future.
- **Sensible results:** information ratios above 1, for example, happen only about 10% of the time, while those above 2 occur only very rarely. If a strategy exhibits a strong information ratio, there must be an easily justifiable reason, otherwise we should be sceptical (Grinold & Kahn, P339).

If a model passes all these requirements and tests, we are a lot more comfortable with using it in practice.

Appendix 2: Dealing with data

In this appendix we discuss three important issues in dealing with data:

1. Data sources: where to get the data from
2. Building factor databases: exploring the pitfalls of factor database creation
3. Normalising factor data: how to convert raw data into comparable data

Data sources

To help construct meaningful factors various financial data sources can be subscribed to. At Macquarie, the following data sources have been used:

1. The Australian Stock Exchange (for Australian market and financial data)
2. I/B/E/S (International Broker Estimation Services) for consensus data (Thomson Financial)
3. Worldscope for GAAP accounting data (Thomson Financial)
4. Datastream for market data (Thomson Financial)
5. Bloomberg
6. MSCI

Typically, **the raw data from these sources need to be turned into meaningful factor signals** (which will require correctly matching each vendors stock codes and dates if the factor is composed of data from across data sources). Factor construction is quite an art form and new methods are continually being developed as markets evolve.

Building factor databases

There are a couple of considerations in the construction of any factor database:

1. **Periodicity and the timeliness of data:** typically, the shorter the periodicity the more timely the data but the larger and more cumbersome the factor database. However, monthly is a typical standard to start off with.
2. **Matching across data sources:** it is better not to create factors from across data sources, as data vendors may have based their calculations on different core information (eg one data vendor may have taken into account a recent share dilution, while another may not have). If you do have to match across data sources, the data will need to be matched both by the listed entity (using either local market ticker or an international identification ticker like SEDOLs) and by date (if it is a monthly database, then by month). Care should be taken here, because if securities aren't matched across data sources you could end up with survivorship bias.
3. **Survivorship bias:** this arises when stocks included in the sample data do not provide a realistic representation of stocks trading during the sample period. A common cause of survivorship bias is the exclusion of delisted securities. If a stock went bankrupt in the past and is not in the database this potentially gives an upward bias to any results derived from the database. This is particularly problematic for momentum based trading strategies. For example, a trading strategy based on buying long term underperforming stocks looks artificially attractive if bankrupt stocks are excluded from the analysis. Attempts should be made to retrieve as much accurate historical data as possible.
5. **Look ahead bias:** it is important not to create factors from data that did not exist at the time. For example, it takes typically 2–4 months after a company's year end for it to release the results to the public. To calculate historical factors based on the company's accounts for that financial year, based on information that wasn't available during those 2–4 months, will give upward biased results from factor strategy tests.

4. **Financial year adjustments:** when using analyst forecast data to calculate factors like earnings revisions, a forecast year rollover will be required if a company announces its results during the revision period. For example, take the FY1 six month earnings revisions factor, where FY1 is currently 2006. This factor then compares the forecasts for EPS in 2006 now with the EPS six months ago. But say the company has just announced its results and analysts have just rolled over their FY1 estimates to the next year, 2006. This means that six months ago the FY1 would have been estimates for 2005. Therefore to calculate the FY1 six month earnings revisions properly we will need the FY1 EPS data now (for 2006), as well as the FY2 EPS data from six months prior (which was 2006 six months ago). Thus, we ensure we are matching on the same financial year.
5. **Diluting per share data:** when using per share and price data and calculating return data it is essential to take into account certain corporate events like rights issues, bonus shares issues and share splits. The intention is to make sure investors are able to compare like with like before and after the corporate event. For example, if a stock undergoes a 1:1 share split, the investor receives one share for each share they already have. However, the DPS would have to be halved historically so that the total dollar dividends received by the investor remains the same:

$$\begin{aligned}\$Div &= N_{pre} \times DPS_{pre} \\ &= N_{post} \times DPS_{post}\end{aligned}$$

$$\begin{aligned}\text{where } N_{post} &= 2 \times N_{pre} \\ \text{and } DPS_{post} &= \frac{1}{2} DPS_{pre}\end{aligned}$$

By not taking into account dilutions, you potentially add unwanted noise to your factor signals and incorrectly calculate the share's returns.

Normalising factor data

If you intend combining factors into a Quant model, the raw factor signals need to be comparable. Raw data will have different scales and some may have units (eg market cap has a dollar unit, although yields and many earnings revisions are unitless but all have very different scales). So it makes sense to find a way to treat them on the same basis. Two common approaches are:

1. **Ranking the factors scores:** the resulting ranked distribution will be flat and therefore easily comparable. Composite rank factor models are the logical extension of ranked factors. Here the ranks of each factor are assigned a weight to combine into the final model (if stocks are missing factor data it might be assigned the average rank scores).
2. **Normalise the factor scores:** we perform this in two steps. **The first step standardises the data to a mean 0 and standard deviation 1 distribution.** Note that this keeps the original shape or distribution of the data. Then we **winsorise the scores at ± 3 standard deviations** (ie any scores greater than 3 or less than -3 are set to 3 and -3 respectively). Doing this decreases the severity of the outliers (skewness) in the distribution, thereby making the data more normal (although kurtosis/fat tails may increase due to this winsorising). If no stocks were winsorised at ± 3 then we do not need to do anything more; we have our final normalised factor scores. If we had to winsorise any stock's factor scores, however, **we then restandardise the scores and re-winsorise.** We repeat this until we no longer have to winsorise the data. This repeated two stage process ensures that **any outliers will not skew or dominate any results we may derive.** It also makes combining factors into the final model very simple (ie by weighting the factor scores)³⁹.

³⁹ Noting that multi-factor models should never use raw data.

There are a variety of differences between the two approaches, the main one being that multi-factor models assume a greater amount of information can be found in the tails of the factor scores than the ranking approach assumes. On the downside, multi-factor models may also accentuate data errors at the extremes. However, tests we have conducted on multi-factor scores versus composite rank models show they are typically above 80–95% correlated. Normalised data are also an appropriate form to perform regressions on, build risk models with⁴⁰ and perform optimisations on.

Therefore at Macquarie we typically use the normalising approach.

There are a few variations on standardising raw data. The way we use is a market capitalisation weighted standardisation, rather than an equally weighted normalisation:

$$\text{factor}_{\text{refined}} = \frac{\{\text{factor}_{\text{raw}} - \text{Mean}(\text{factor}_{\text{raw}})\}}{\text{StDev}(\text{factor}_{\text{raw}})} \quad (1)$$

where $\text{Mean}(\text{factor}_{\text{raw}})$ = the market capitalisation weighted mean of the required universe. We prefer to use a market cap weighted standardisation because most fund managers benchmark against market cap weighted benchmarks. Market cap weighted standardisation also has the advantage that it minimises data errors arising from small stocks. Data for larger stocks are typically trustworthier than smaller stocks, so by using the market cap weighted mean in the standardisation formula any aberration caused by smaller stocks is minimised (which would have smaller weight)⁴¹.

Also, the universe of stocks that a standardisation is calculated over should match with whatever portfolio benchmark is being used for the model. All stocks not in the universe will have no factor score (alternately, we could use the mean and standard deviation from the standardisation to standardise stocks outside the universe).

Note that at Macquarie, we have orientated our factors such that a higher factor score is preferable to a lower one (the orientation being determined by both financial intuition and historical experience). That is, we expect higher factor scores to result in a better performance than a lower factor score. This makes interpretation easy. In the event that we find the opposite and can't explain why, we tend to exclude the factor from the model (in case the factor starts behaving strangely or mean reverting).

⁴⁰ The standardisation process also allows the results of any multi-factor linear regression of excess returns to be easily interpreted. In particular, the factor coefficients (or factor returns) will be in excess of return units. Hence, the regression coefficients can be interpreted as what excess return you would receive if you had a one standard deviation exposure to this factor and zero to all other factors.

⁴¹ Because we perform a market capitalisation weighted standardisation, the factor exposures of the resultant portfolio will effectively be the active portfolio's factor exposures (ie the benchmark by definition has factor exposures of zero).

Appendix 3: Return factor types

Factor types

In this appendix we briefly explore three of the more common return factors types used in Quant models. There are, however, many other varieties of factors.

Value factors

A cheap stock is preferable to an expensive stock, all else being equal. Market prices and expectations tend to be more realistic for value stocks than for growth stocks, which have a greater tendency to disappoint. When growth stocks disappoint, they underperform value stocks.

Value factors can be constructed using prospective data or historical data (or both). Typical historic value factors are earnings yield (ie 1/PE) and dividend yield based on the most recent company data. Typical prospective value factors are FY1 earnings yields and dividend yield using the consensus mean analyst estimates for FY1.

In terms of performance of value factors, less mature equity markets tend to have more earnings volatility (ie analysts and market proponents are more uncertain about the future earnings potential of listed companies). In these cases, historical value factors tend to work better than prospective value factors. The reason is largely due to lack of confidence in analysts' earnings and dividend forecasts, so historical yields are relied upon instead, which in turn makes them stock price drivers. A good example is in Asian markets, as well as for small cap stocks in the Australian market, where there is less analyst and media coverage.

Value factors are also typically a highly autocorrelated factor. Historical value factors in particular change only once a year while prospective value factors change slowly as analysts change their forecasts. This results in less turnover for value factors than for high burn factors like momentum and sentiment. Hence, value factors are a good counterbalance to high turnover strategies in a multi-factor model, as well as potentially reducing the impact of poor performance for periods when momentum and sentiment strategies aren't working.

Price momentum

Despite academic genuflection, markets are not efficient. News takes time to get reflected in share prices. Turnaround plays take time to gain momentum and market popularity⁴², while darling stocks typically need a consistent sequence of bad news to become unpopular. But when markets finally react to news they tend to overreact. In fact, recent research indicates that there is a whole life cycle to this process (see Lee & Swaminathan, Oct 2000).

The evidence from many developed equity markets is that momentum works differently over different horizons. In particular, share prices mean revert over the short term, outperform over the medium term, and underperform over the long term. Momentum factors are therefore typically constructed over the short term horizon (1–2 months), medium term (3, 6 and 12 months) and long term (24–48 months). Momentum factors are common factors within multi-factor models.

⁴² Fund managers don't want to disclose long term underperformers among their holdings and are therefore reluctant to buy, even if there is a credible turnaround story. No one wants to admit holding stocks that invoke negative connotations.

Forecast revisions

It has long been recognised that analyst earnings revisions can provide a powerful tool for forecasting stock returns. Changes in earnings estimates by brokers are a way of measuring changing market sentiment and expectations of company earnings. These changes often end up getting reflected in the listed stock price (although it has also been shown that analysts are typically overconfident with their earnings estimates relative to what companies actually report). Earnings revisions are often quite highly correlated with momentum and tend to be a higher turnover strategy.

Typical earnings revision signals (derived from I/B/E/S analyst estimates of EPS) are percentage change of earnings revisions for FY1 over one, three and six months. Note that the percentage earnings revision signal can be problematic when mean EPS is very small, so sometimes price normalised earnings revisions are used instead.

Besides revisions based on EPS, signals can also be constructed from

- DPS: dividends per share
- BPS: book value per share
- CPS: cash flow per share

Appendix 4: In-sample model building and out-of-sample tests

Whether we use a univariate regression based approach or a univariate information analysis approach when constructing an Alpha model, it is useful to divide the time period in two parts:

1. **an in-sample period** from which the optimal factors of the period are selected and combined into a model;
2. **an out-of-sample period** to test the stability and predictability of the in-sample model.

The in-sample period can be before or after the out-of-sample period but typically it is before and is longer than the out-of-sample period, so as to capture the significant drivers of a market in a variety of economic and financial eras. The resulting model will then cater for these different conditions allowing for model diversity and less reliance on factors that may dominate in only one time period. For example, a long in-sample period in the Australian equity market might be from 1990–2003. This would include the recession lows of 1991–1992, exposure to the Asian market crisis in 1998, the last couple of years of downwards movement in world equity markets from 2001–2003 and the general bull market from 1996–1999.

Of course, the prime purpose of the out-of-sample period is to guard against the possibility of data mining. If the out-of-sample results are substantially different to the in-sample results, then it is difficult to fend off criticism that the in-sample model has been the result of data mining.

The underlying assumption here is that the drivers of the equity market do not substantially change from the in-sample period to the out-of-sample period.

Having said that, however, out-of-sample results will typically be inferior to the optimal model generated from the in-sample period. This is due to the weights within the factor model having been optimised for the best performance during the in-sample period. But the hope is that by building a model using the in-sample period we are at least capturing the most significant drivers (factors) of stock prices in the equity market, and in the rough proportions according to their importance so as to best capture future outperformance.

Having said that, however, there are some problems with in- and out-of-sample periods:

1. **Short out-of-sample period:** the in-sample period is designed to capture the general market drivers over most economic periods. However, if the out-of-sample period only encompasses a fraction of the economic cycle, it may result in model performance quite different to the model performance in the rest of the economic cycle. In other words, it may be the case that the drivers of the out-of-sample period are not well represented by the best drivers over the entire in-sample period. A way to get around this might be to have an in-sample period the same length as the out-of-sample period, which might imply long in- and out-of-sample periods.
2. **Changing and evolving drivers:** given the requirement of a long in-sample period, and hence a long out-of-sample period, this raises questions about the effect of the market evolution and the value of factors that drove the market many years ago. In particular, drivers of equity markets change over time and a long in-sample period may not capture current factors driving the market. We believe, therefore, that shorter in- and out-of-sample periods may be required, so as to capture more medium term and short term autocorrelation in factor performance.

Appendix 5: Factor autocorrelation

This test shows how fast the factor signal changes, hence the term factor autocorrelation. It is also a way to test the turnover of a factor and is calculated similarly to an IC decay profile. But instead of comparing the factor signal with the lagged monthly return, we compare the factor signal with itself lagged in time. So, while an IC decay profile tells us how fast a signal gets priced into the market, factor autocorrelations ask “how fast does the signal change?”.

Examples of factors that are highly autocorrelated are historic value factors like book-to-price and dividend yield. The book value of a company changes only once a year and the price changes monthly for a monthly series. On the other hand, one month momentum (or one month mean revision) has very low autocorrelation; hence it is a high turnover strategy.

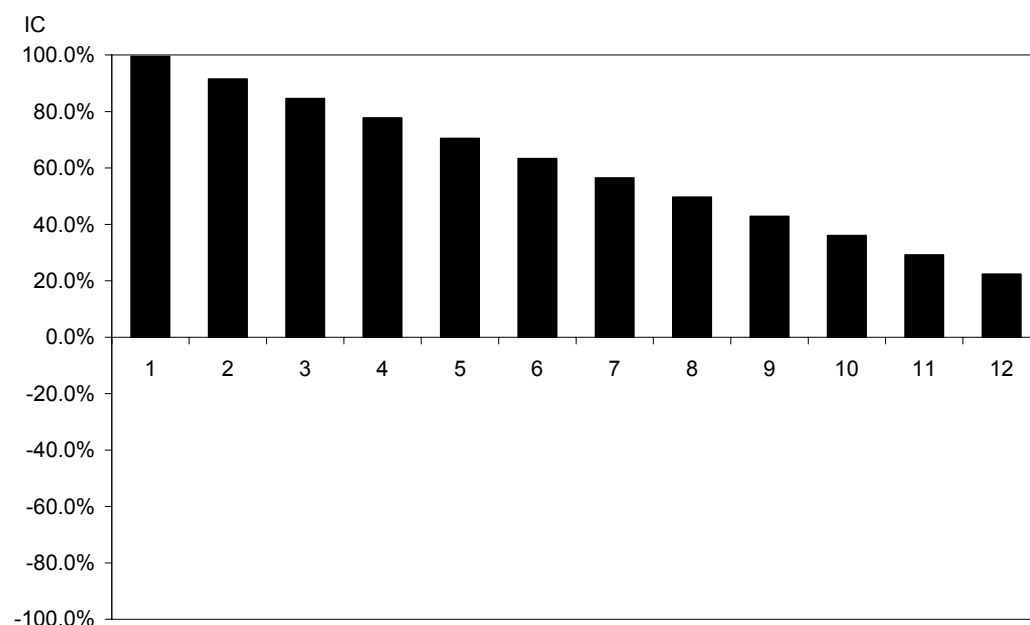
As stated earlier in this report, while higher factor autocorrelation will increase turnover, it will also increase the number of independent bets being made, thereby increasing the breadth of a strategy. This in turn increases the risk adjusted performance metric “the information ratio”, according to the fundamental law of active management:

$$IR = IC \sqrt{BR}$$

Therefore, in determining the weight of a high turnover factor, we need to balance the impact of high turnover with maximising the number of independent bets.

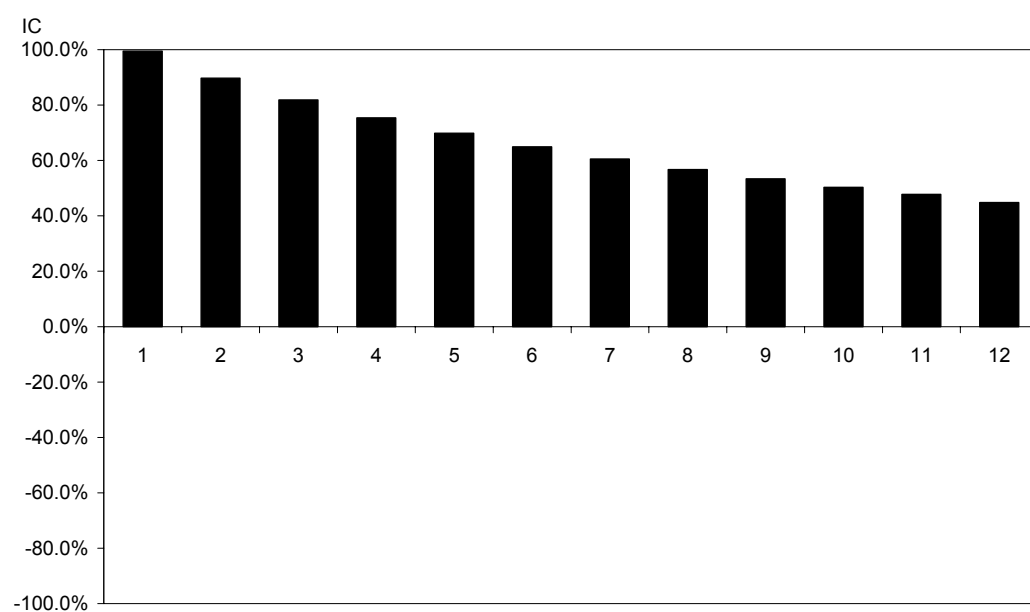
Chart 15 and Chart 16 illustrate factor autocorrelation for the two factors we explored early in this report, namely 12 month momentum and consensus recommendation:

Chart 15: Twelve month momentum for S&P/ASX200 (Factor autocorrelation)



Although a slow signal, 12 month momentum changes more quickly than consensus recommendations does.

Source: Macquarie Quantitative Research

Chart 16: Consensus recommendation for S&P/ASX200 (Factor autocorrelation)

Consensus recommendations is a signal that changes slowly.

Source: Macquarie Quantitative Research

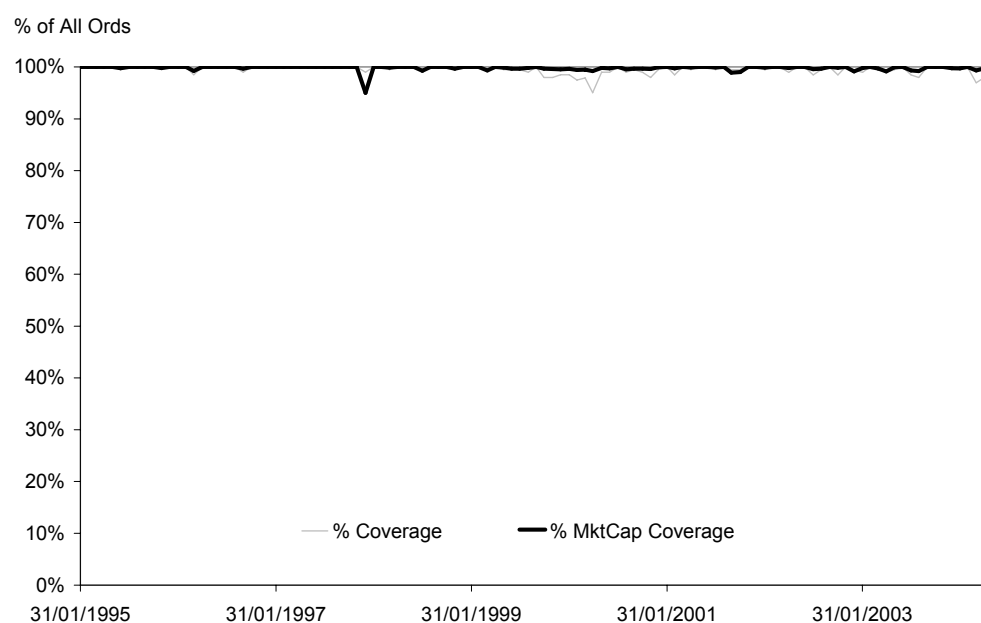
Appendix 6: Coverage

Coverage is important as it allows us to see how much data there is for each factor through time relative to the whole universe. The shorter or sparser the history, the less confidence we may have in the results we have derived (although this will also show up as less significant stats in the IC decay profile and fractile analysis).

We calculate coverage by measuring how well populated the factor signal is over the period **relative to** all the stocks in the universe that we are considering (eg S&P/ASX 200 in Australia). We examine and compare this proportion both by number of stocks and by market weight represented (the latter will typically be higher than the former, as larger stocks tend to have more accessible information than smaller stocks).

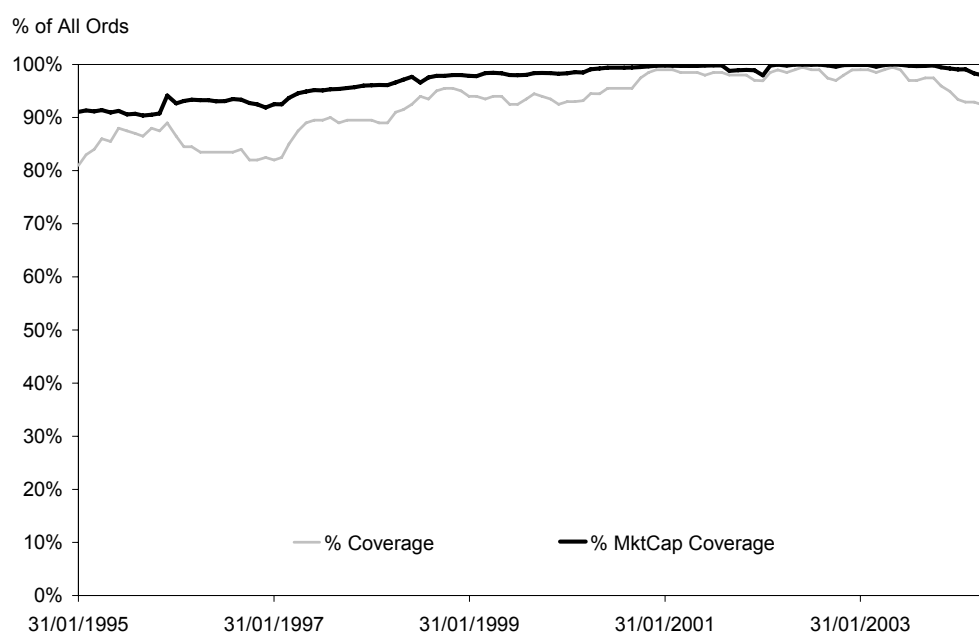
Chart 17 and Chart 18 illustrate coverage for the two factors we explored early in this report, namely 12 month momentum and consensus recommendation:

Chart 17: Twelve month momentum for S&P/ASX200 (Coverage)



Twelve month momentum has reasonably high coverage through time, both by percentage of market cap and by number. This gives confidence in the results we have calculated.

Source: Macquarie Quantitative Research

Chart 18: Consensus recommendation for S&P/ASX200 (Coverage)

Because analysts typically only cover the mid to large cap stocks, coverage for this factor is not as high as for 12 month momentum.

Source: Macquarie Quantitative Research

Appendix 7: Quantitative techniques for constructing investible portfolios

Portfolio construction methodology is a very important part of the whole investment process. If it is not done correctly your forecasts will not flow properly through to your final portfolio. A construction process that severely distorts your security level forecasts is unlikely to add any value or give you unexpected results. The aim of portfolio construction should be to provide the maximum possible expected return given the desired level of risk and realistic constraints.

We discuss below a few examples for long only portfolios (we present them in increasing order of sophistication) :

- **Screens:** these are a very popular method. They are essentially a simplified multi-factor Quant model in disguise, as they involve screening a universe of stocks for various desirable characteristics. These characteristics, however, use raw data, not standardised data like multi-factor scores do.

For example, a screen may involve selecting all those stocks whose three monthly outperformance is greater than 10% and dividend yield is greater than 4% (this is essentially a simplified two-factor Quant model). Typical attributes used to screen stocks are a combination of value factors and momentum/growth factors. By being exposed to stocks which have both attributes you likely reduce the volatility of your earnings but hopefully capture most of the outperformance. Of course, attributes should be quantitatively tested before being used as screens. One might then either cap-weight or equal weight the final list of stocks to form the portfolio.

There are some downfalls with screens. First, they will ignore the relative power of each factor/attribute, potentially under utilising the relative information embodied within each factor. They also tend to result in riskier portfolios with higher turnover. Lastly, equally weighted portfolios based on screens may run into problems with liquidity and market impact if the top stocks are skewed to small cap stocks (which is often the case).

- **Stratification:** this is basically screening along certain risk or return dimensions. We give two examples, both using two different types of dimensions:
 1. **Strata by risk categories only:** one could split the universe of stocks by the two commonly used risk dimensions, size and sector. Sector could be split, say, by the 10 GICS Level 1 sectors, while size could be split into three: large caps, mid caps and small caps (relevant to the country/exchange). This would result in 30 portfolios along sector and size dimensions. Stocks could then be placed within each category (or strata portfolio) and ranked by their Alpha. Each strata portfolio could then be weighted so that the stocks portfolio weight matches the benchmark weight in that category (and perhaps taking liquidity into account). The resultant portfolio is therefore designed to outperform the benchmark but has some risk implicitly in-built.
 2. **Strata by risk and return categories:** one could split the universe of stocks by both their Alpha (return category) and by a risk category. If the universe of stocks was large enough the Alphas could be split into five equally numbered groups, while the risk categories could be broken into five risk categories (eg not risky, low risk, average risk, high risk, extremely risk). The combining of the Alphas five categories and the five risk categories would result in 25 portfolios. Within each portfolio one could then assign a prespecified weight relative to the benchmark (eg the low risk high Alpha category might be given a 10% overweight, while a high risk low Alpha category might be given a -10% underweight).

Both the above strata methods will result in far better risk control than screens but there can still be unintended risks the manager takes on.

- **Heuristic model (linear programming):** this is a level of sophistication above stratification. Here, risk can be mapped along as many dimensions as required (eg size, sector, volatility, Beta). The linear program then assigns stock weights relative to the benchmark by taking into account their Alphas and these risk dimensions. You can also program in “explicit transaction costs, a limit on turnover and upper and lower position limits on each stock” (P396, Grinold & Kahn, 2000).
- **Optimisation (quadratic programming):** the goal of optimisation is really straightforward: to maximise expected portfolio return while minimising portfolio risk subject to appropriate real life constraints (which is precisely the goal of active funds management). Implementation, however, can be tricky. The inputs for the optimisation process are the expected returns, a risk model, the initial portfolio and the fund constraints (maximum active bets, target tracking error, sector neutrality, etc).

Stock weights within the portfolio are then altered using a quadratic programming algorithm until the expected portfolio return is maximised and the portfolio risk is minimised. From this, it might seem that optimisation requires a great deal of inputs. This may mean a lot more input noise and potentially sub-optimal portfolios. But as long as care is adequately taken with the inputs, this problem is surmountable.

Comparing the heuristic approach against optimisation, the portfolio weights will obviously differ but the more constraints put on either, the more the final portfolio weights of each will tend to converge. This is because the number of unique solutions diminishes with the number of constraints put on the fund (maximum stocks bets, maximum factor exposures and liquidity constraints).

Appendix 8: Risk factors and return factors

As discussed at the beginning of this report, factors are stock price signals. Factors embody various forms of information about a publicly listed company. They could be characteristics of the company, the company's share price performance or vital statistics of an analyst's company model. As new information arrives and becomes embodied in these factor signals, there may be an associated change in a listed company's future share price.

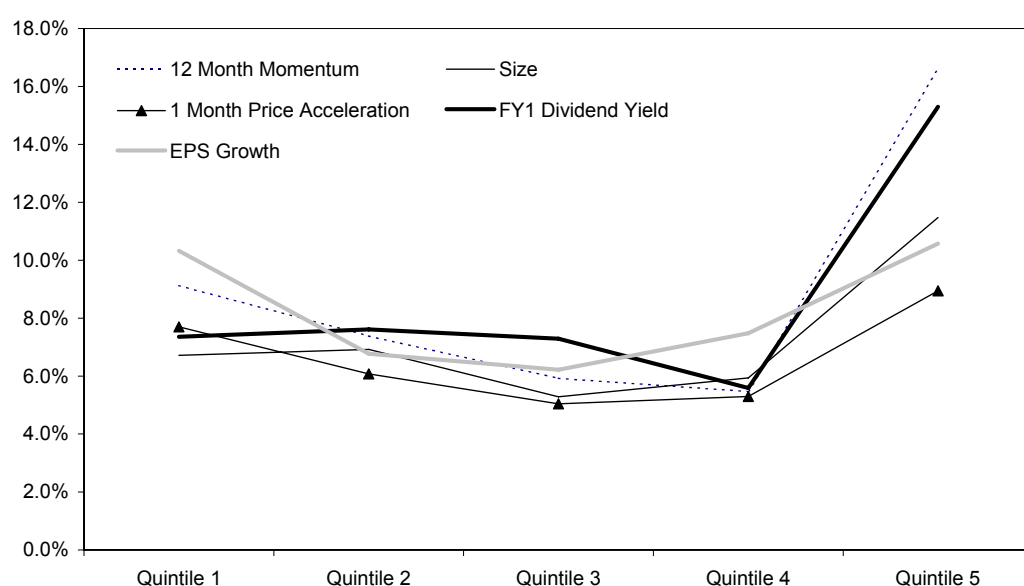
Factors therefore can be used to predict future stock price returns or future stock price volatility. We call the former return factors and the latter risk factors. We will be discussing risk factors first.

An active positive or negative exposure to a risk factor will mean your portfolio performance will more likely differ from the benchmark portfolio than a portfolio of stocks with the benchmark exposure to this factor. In this context, exposure to the factor could mean being more exposed than the benchmark is or being less exposed than the benchmark is.

For example, take one portfolio composed of high dividend yielding stocks (which has a positive factor exposure) and another portfolio composed of non-dividend yielding stocks (which has a negative factor exposure). If dividend yield was a risk factor (ie its performance was associated with variance from the benchmark), then you would expect both the high dividend yielding portfolio as well as the low dividend yielding portfolio to have a lot greater tracking error than the benchmark portfolio. For an average dividend yielding portfolio, on the other hand, one would expect much less variance from benchmark performance, holding constant all other risk factors.

An easy way to illustrate this is by dividing stocks into fractiles and rebalancing them each month, as described earlier. From the resulting time series of fractile returns, we can then measure each fractile's tracking errors (ie the active risk relative to the benchmark). To illustrate this, we have done this for a variety of factors:

Chart 19: Tracking error across the quintile for S&P/ASX200



Source: Macquarie Quantitative Research

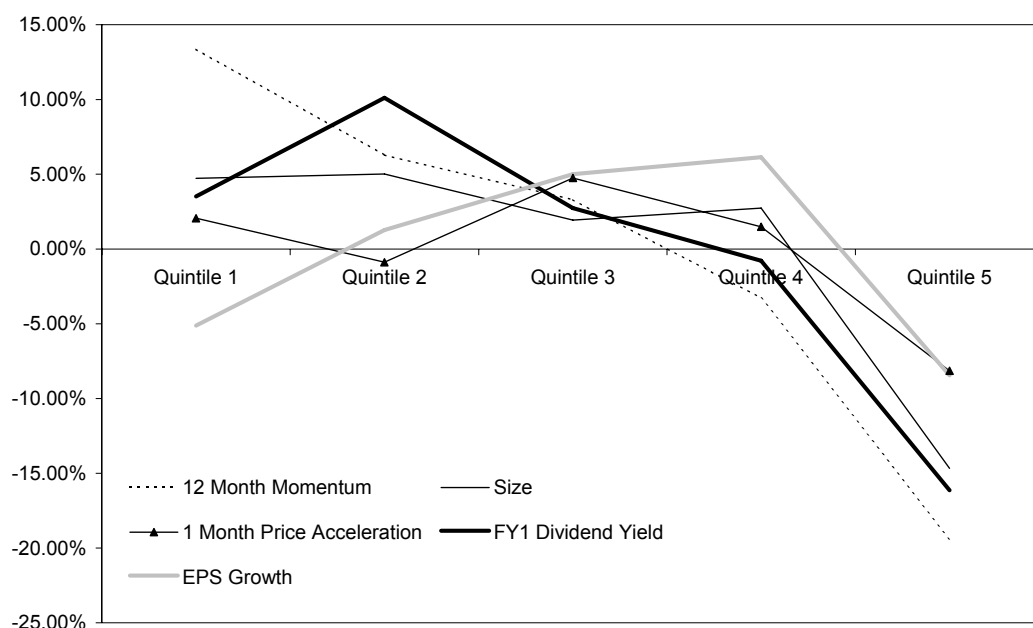
Factors that you can be confident will affect share prices (risk factors) are those that have the greatest **quintile smile**. That is, if you have an active exposure within your portfolio to those factors that have the greatest smiles, your portfolio is likely to deviate the most from your benchmark. Of course, the factors we have selected here are factors that we have used at times in various models, so their smiles are fairly obvious (especially EPS growth).

Then there are **return factors**. Return factors can often be risk factors where the risk of deviation from the benchmark performance for a high positive factor exposure is to the upside, while the risk of deviation from the benchmark for a high negative factor exposure is to the downside.

In building multi-factor models, we seek to identify return factors. Essentially, we want to build multi-factor models using factors that give us a better indication of which stocks are likely to go up and which stocks are likely to go down. If we use a factor that has high risk attached but doesn't tell us which way this risk is biased (ie up or down), we reduce the probability that the multi-factor model will outperform the benchmark but increase the portfolio risk (essentially we add noise). In other words, we like to see skew to the upside for positive exposures and skew to the downside for negative exposures.

To see an example of skew and non-skewed risk factors, we chart the active returns across the quintiles of the factors we examined before:

Chart 20: Active return across quintiles



Source: Macquarie Quantitative Research

Take EPS growth above. It is an example of a factor we don't want to have in our model. First both a high, negative exposure (Quintile 5) and a high, positive exposure (Quintile 1) have a high tracking error, as we have established in the prior chart. In itself, this is not bad but in the chart above the shape of the graph doesn't show any skew. In fact it is roughly concave, meaning that both a high, negative portfolio factor exposure and a high, positive portfolio factor exposure would result in underperformance relative to the benchmark. This factor would be classified as a risk factor only.

On the other hand, take 12 month momentum. It has a strong slope downward from Quintile 1 to Quintile 5. This strong downwards slope shows that for a portfolio with high, positive exposure to momentum (ie those stocks that have performed well over the last 12 month), there is greater chance of upside relative to the benchmark. Conversely for portfolios with high, negative exposure to momentum (ie those stocks that have underperformed over the last 12 months) there is a greater chance of downside relative to the benchmark. This makes 12 month momentum a perfect example of a return factor.

So effectively, the tracking error chart tells us which factors are associated with strong price movements (by seeing how great the **fractile smile** is) and the active return chart tells us which are potential return factors (ie skewed risk factors).

Using the active return chart allows us an insight into the type of risk of each factor (as measured by the tracking error). If total risk is roughly equally distributed between upside risk and downside risk across each fractile, then the active return chart above will show random or close to zero returns across the fractiles. In this case the risk factor cannot be used as a return factor. If total risk is systematically unevenly distributed across the fractiles, then we will see a slope for active return across the fractiles. In other words, net upside risk, as measured by the difference between upside risk and downside risk, changes systematically across the fractiles.

In summary, then:

- **A risk factor** is a factor where a large positive or negative exposure to the factor has historically been associated with both upside risk and downside risk.
- **A return factor** is a factor where a positive exposure to the factor has historically been associated with upside risk only, rather than both upside risk and downside risk (and conversely a negative exposure to the factor has historically been associated with downside risk only).

Appendix 9: Macquarie's information analysis and portfolio simulations

Information analysis

At Macquarie, we are continually developing systems to better assist us in developing sophisticated models of the market. The latest application we have developed is **Info Analysis**. With short turnaround, we can test any factor on any dataset or data subset of the market over the last 10–15 years.

We offer this across the following Asia Pacific markets:

Developed markets:

- Australia
- Hong Kong
- Japan
- New Zealand
- Singapore

Emerging markets:

- China
- Malaysia
- Indonesia
- India
- Philippines
- South Korea
- Taiwan
- Thailand

Info Analysis consists of the following types of analysis:

- 1) Univariate correlation tests:
 - IC monthly tests (including rolling 12 month average and t-stats)
 - IC decays
 - Factor autocorrelations
 - Fractiles (1-20)
 - Coverage
- 2) Factor correlation matrices

In addition, we can also build you multi-factor models and run through these univariate correlation tests.

Furthermore, we can conduct pure factor return analysis where return factors are purified of their correlation with the required risk factors (at Macquarie we typically use size, sector and momentum as our risk factors).

Figure 1: The Macquarie Information Analysis Tool

Microsoft Excel - Info Analysis.xls

File Edit View Insert Format Tools Data Active Link Window QadUtilities Help Calculations Iress

P45

Asia FW MSC Asia FW Australian FW

Analyst Sentiment

- 1 Month Recommendation Revis
- 2 Month Recommendation Revis
- 3 Month Recommendation Revis
- 6 Month Recommendation Revis
- Equal Weighted Consensus Rec

Composite

- Composite Earnings Certainty (5
- Composite Earnings Certainty (5
- Composite: 50% FY1 and 50% F
- FY1: Next Year Forecast Normali
- FY2: Second Year Forecast Norm

Debt Protection

Earnings Certainty

Financial Data

Forecast Revisions

Growth

Index Weight

Other Factors

Price Momentum

Profitability

Value

Studies Selected for process: 0

Save Configuration

Load Config

Run Studies

Study Type

Factor Coverage (Monthly) ☒

ICR (Monthly) ☒

IC Decay Profile ☒

Factor Autocorrelation ☒

Fractiles (including Turnover) ☒

Factor IC Matrix ☐

Fractile Distributions ☐

Factor Summary ☐

Fractile Summary ☐

Fractile Breakpoints ☐

IC Type: RANK

Standard Study (Binary)

From: 1-Jan-90

To: 1-Aug-04

Study Details

IC Decay Profile Maximum Lag: 12

Minimum No Stocks per Fractile: 3

No Fractile: 4

Minimum No Stocks: 9

General Extra SQL Criteria

Fractile Options

Equally/Mkt Weighted: Equally

Fractile Summary

Fractile Avg/Index: Fractile Avg

Scorer Treatment: Exclude Null Se

Put SQL Index code here ->

Output to

Fill this in to export to external file: Backtest

Use Directory: ..

Output to

- ☐ 1 workbook per study
- ☐ 11 workbooks
- ☐ Single Workbook to all studies

Source: Macquarie Quantitative Research

Portfolio simulations

With the use of the Macquarie Bank Portfolio Optimiser we can simulate real portfolios, with liquidity and risk constraints that give the following statistics and graphs:

- **Portfolio summary statistics** (total return, active return, tracking error, information ratio, monthly hit rate, CAPM Beta, CAPM Alpha, Alpha t-stat)
- **Turnover/liquidity analysis** (portfolio turnover, average number of stocks in portfolio and percentage of trades not completed).
- Graph of number of **stocks and portfolio turnover** against time
- Graph of **portfolio against the chosen benchmark**
- Graph of monthly and annual **portfolio relative return**.

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Notes

Important disclosures:

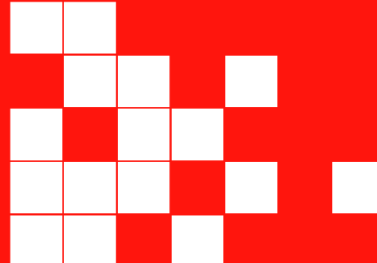
<p>Recommendation definitions</p> <p>MRE Australia/New Zealand Outperform – return >5% in excess of benchmark return (>2.5% in excess for listed property trusts) Neutral – return within 5% of benchmark return (within 2.5% for listed property trusts) Underperform – return >5% below benchmark return (>2.5% below for listed property trusts)</p> <p>MRE Asia Outperform – return >10% relative to US cash return Neutral – return within 10% of US cash return Underperform – return <10% relative to US cash return</p> <p>Long term – 12 months to 2 years Short term – 3 to 12 months</p>	<p>Volatility index definition*</p> <p>This is calculated from the volatility of historic price movements.</p> <p>Very high–highest risk – Stock should be expected to move up or down 60-100% in a year – investors should be aware this stock is highly speculative. High – stock should be expected to move up or down at least 40-60% in a year – investors should be aware this stock could be speculative. Medium – stock should be expected to move up or down at least 30-40% in a year. Low–medium – stock should be expected to move up or down at least 25-30% in a year. Low – stock should be expected to move up or down at least 15-25% in a year.</p> <p>* Applicable to Australian/NZ stocks only</p>	<p>MRE adjusted profit definition</p> <p>The MRE adjusted profit number is pre-goodwill amortisation and pre-individually significant items, that is: Adjusted profit = net profit - individually significant items + tax on individually significant items - preference dividends - minority interests + goodwill amortisation.</p>
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