Introducing S&P Capital IQ's Fundamental China A-Share Equity Risk Model

Authors

Xunqi Yu, PhD
Quantamental Research
617-530-8102
xyu@spcapitaliq.com

Ruben Falk
Quantamental Research
212-438-0648
rfalk@spcapitaliq.com

Paul Fruin, CFA
Quantamental Research
617-530-8208
paul.fruin@spcapitaliq.com

Factor risk models play an important role in equity portfolio management. Portfolio managers depend upon factor risk models to obtain portfolio risk prediction and risk attribution against a group of largely orthogonal factors each with meaningful econometric explanations. S&P Capital IQ is dedicated to providing a broad set of high-quality models and products to the global asset management community. Since 2010, we have released a series of single country risk models as well as global and regional equity risk models. We are now releasing a new single country risk model covering China A-Share equities[1].

The China A-Share Equity Risk Model has the following features:

- Based on comprehensively defined fundamental style factors for maximum relevance to portfolio managers and for external communication of risk and return performance
- Provides highly relevant risk estimates customized to the China A-Share universe
- Exposures and risk calculations are derived from daily pricing and Point-In-Time data for optimal responsiveness and historical accuracy
- Custom industry groups are pertinent and unique to the Chinese economy and based on widely recognized GICS® industry definitions.

Following a similar model framework to our US Equity Risk Model, the China A-Share Equity Risk Model is a time-series fundamental factor risk model. The China A-Share Equity Risk Model is based on the same building blocks as other S&P Capital IQ risk models: best of breed Point-In-Time S&P Capital IQ data, state of the art Alpha Factor Library, Global Industry Classification System (GICS), and an open and robust risk estimation methodology.

We have adapted the model framework to account for the industry concentrations in the Chinese equity market. Industry factor groups, based on the Global Industry Classification System (GICS), have been customized to reflect the industry concentrations of the China A-Share equity market. The style factor returns of the China A-Share Equity Risk Model are derived from S&P Capital IQ's China Alpha Factor Library which includes a subset of factors as compared to the global Alpha Factor Library.

We demonstrate that the factors selected for the China A-Share Equity Risk Model are able to explain the variability in China A-Share equity returns. The out-of-sample performance tests show that the China A-Share Equity Risk Model generated accurate risk predictions and provides relevant portfolio risk attribution for investors in the China A-Share market. Statistical test shows that our China A-Share Equity Risk Model generates unbiased predictions. For all test portfolios, the bias statistics are statistically indistinguishable from the desired bias statistic value of 1 (all within 95% confidence intervals). The Diebold-Mariano (DM) statistics, a popular test statistics for comparing accuracies of predictions, show that the China A-Share Equity Risk Model achieves significantly improved performance over the Global Equity Risk Model and the results for all test portfolios are statistically significant at the 5% level.

[1] For more information on the S&P Capital IQ Equity Risk Models please contact Ruben Falk at rfalk@spcapitaliq.com.

1 Framework and Methodology

1.1 Introduction

S&P Capital IQ's China A-Share Equity Risk Model is a fundamental factor model based on a multi-step time series regression procedure. The factor series include (i) market return, (ii) fundamental style factor returns and (iii) industry factor returns.

Suppose we have N style factors and M industry factors in our model. Let r_{mkt}, r^{i}_{style}, and r^{j}_{ind} represent the market return, the i-th style factor return, and the j-th industry factor return, respectively. Let r denote the return of a stock. We model the returns time-series of this stock by a linear regression model:

$$r = \beta_{mkt} r_{mkt} + \sum_{i=1}^{N} \beta^{i}_{style} r^{i}_{style} + \sum_{j=1}^{M} \beta^{j}_{ind} r^{j}_{ind} + \varepsilon,$$

where the regression coefficients β_{mkt}, β^{i}_{style}, β^{j}_{ind} are the stock's exposure to market, exposure to i-th style factor, and exposure to j-th industry factor, respectively. The last item ε represents the unexplained, i.e. residual return.

We use the total return index of the S&P/CITIC 300 as the proxy for the China A-Share market return r_{mkt}. The index comprises of 300 companies with the largest float-adjusted market capitalization and liquidity, drawn from the universe of listed A-share companies in China.

The style factor returns r^{i}_{style} are calculated from S&P Capital IQ's Alpha Factor Library. They are comprised of a number of a long/short cash neutral signal portfolios, which will be described in Section 1.3. For industry returns r^{j}_{ind}, we use an industry grouping customized for the China equity market based on the Global Industry Classification System (GICS). The details of industry factors are described in Section 1.4.

The multi-step time series regression procedure is conducted as follows. We start with market return as the most important source of variation. Since market and raw style returns are correlated, we regress the raw style factor returns against the market return series and let the residuals represent market-neutral style returns, i.e. style returns with the market correlation removed.

We continue by calculating market- and style-neutral industry returns in the same manner, by regressing market and style returns out of the raw industry returns, and again let the residuals represent neutralized industry returns. This order ensures that the loadings on the market and then our comprehensive style factors take precedence in the interpretation of portfolio exposures.

The desired order of imposing independence among the factor groups may be different for different managers. For instance, if sector exposure is a primary concern, we can construct a variation of the model in which industry factors take precedence over style factors. The order of independence does not affect the quality of the risk forecast. It will only affect the interpretation of marginal risk contributions (i.e. risk attribution).

We provide both a Medium Term model (with correlation and volatility half-lives of 240 and 60 days respectively) and a Short Term model (with correlation and volatility half-lives of 180 and 30 days respectively). These half-lives are in line with our risk models generally.

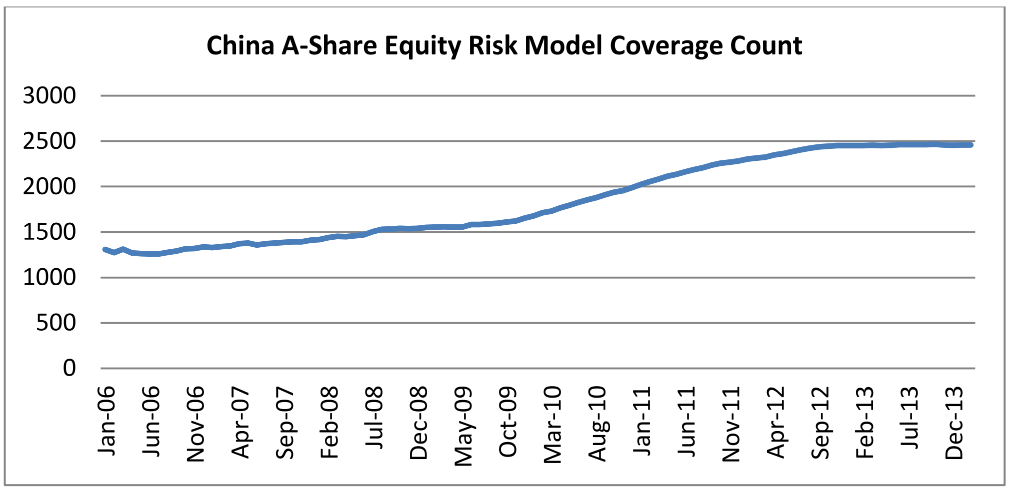
In the following sections, we provide a detailed description of each building block of S&P Capital IQ's China A-Share Equity Risk Model.

1.2 Coverage and Estimation Universe

Our China A-Share Equity Risk Model covers all A-Share equities listed in the Shanghai Stock Exchange and the Shenzhen Stock Exchange. On January 2014, the China risk model covered 2458 equities. Figure 1 below shows the coverage count through time for the China risk model.

The estimation universe used to calculate the style and industry factor returns is based on the largest 1500 stocks, in terms of market capitalization, of the total A-Share market.

Figure 1: Number of Assets Covered by the China A-Share Equity Risk Model



Source: S&P Capital IQ Quantamental Research

1.3 Style Factors

The style factors used in our China A-Share Equity Risk Model are derived from S&P Capital IQ's state-of-the-art China Alpha Factor Library. In order to adapt to the characteristics of the China equity market, the China Alpha Factor Library includes a different set of factors as compared to the US library.

Table 1 gives a summary of the style factors from the S&P Capital IQ China Alpha Factor Library grouped into 8 style buckets. Each style factor is constructed from a log market cap weighted long/short cash neutral signal portfolio. These portfolios are derived from a univariate sort which determines the top 33% of stocks (longs) and the bottom 33% (shorts) according to the chosen characteristic. The style factor returns are defined as the return spread between top and bottom portfolios.

Table 1: Style Factors Derived from the S&P Capital IQ China Alpha Factor Library

Style	# of signal factors	Sample Components
Analyst Expectation	4	Expected LTG Analyst Earnings Estimate Diffusion Number of EPS FY1 Revisions Standardized Unexpected Earnings
Capital Efficiency	5	Return on Equity & Capital Cash Flow Return on Invested Capital Long Term Debt to Equity Ratio
Earnings Quality	5	Cash Conversion Cycle Net Profit Margin Net Income Stability Working Capital Accruals
Historical Growth	5	1Y Chg in Asset Adjusted Free Cash Flow 1Y Chg in Asset Adjusted Operating Cash Flow 1Y Chg in Sales Turnover - Margins
Price Momentum	5	1, 9 & 12-Month Price Momentum 5 Day Price Reversal 1M Price High - 1M Price Low
Size	2	Log of Market Cap. & Sales
Valuation	6	Book to Price Free Cash Flow to Price EBITDA to Enterprise Value Earnings to Price
Volatility	4	12M Realized Volatility 1M Realized Volatility 60M CAPM Beta 90 Day Coefficient of Variation

Source: S&P Capital IQ Quantamental Research as of January 31 2014

1.4 Industry Factors

In a fundamental factor risk model, industry returns are used to capture the effects of factors which affect the whole industry. As with our Canadian and Australian risk models, in order to ensure a reasonable granular representation of each industry (as a fraction of total market capitalization), we use a customized industry grouping considering the GICS industry "tree" and the distribution of the market capitalization along the nodes of the industry tree.

Table 2 shows the 17 customized industry group definitions used. The groups are in different levels of the GICS structure. For example, the Chemicals group is at GICS level 3 (industry) and the Utilities group is at GICS level 1(sector). Some groups are a combination of different GICS levels. This customized industry definition scheme is desirable for countries whose distribution of industry capitalization does not conform to a standard GICS industry level.

Table 2: Customized Industry Groups of China A-Share Equity Risk Model

Group Name	Definition (GICS Map Name and Corresponding Code)	Market Cap Percentage
Automobiles & components	Automobiles & components (2510)	3.0%
Banks	Banks (4010)	24.2%
Chemicals	Chemicals(151010)	3.2%
Coal & Other Energy	Energy (1010) excluding Integrated Oil & Gas(10102010)	3.9%
Consumer Discretionary, Non-Auto	Consumer Discretionary (25) excluding Automobiles & components (2510)	5.9%
Consumer Staples	Consumer Staples (30)	4.9%
Diversified Financials	Diversified Financials (4020)	3.2%
Health Care	Health Care (35)	5.7%
Industrial Goods	Capital Goods (2010)	10.5%
Industrial Transportation and Services	Transportation(2030) and Commercial & Professional Services(2020)	3.6%
Insurance	Insurance(4030)	3.7%
Integrated Oil & Gas	Integrated Oil & Gas (10102010)	8.7%
Metals & Mining	Metals & Mining (151040)	4.5%
Other Materials	Material (1510) excluding Metals & Mining(151040) and Chemicals(151010)	1.6%
Real Estate	Real Estate(4040)	3.7%
Technology & Telecoms	Information Technology(45) and Telecommunication Services(50)	6.4%
Utilities	Utilities(55)	3.3%

Source: S&P Capital IQ Quantamental Research as of January 31 2014

1.5 Weighted least Squares Regression and Substitution Logic

In order to calculate relatively stable risk factor exposures, we use a 2-year stock returns history in our time series regression. There are cases when stocks have missing return data for portions of these 2 years. For example: a stock may be untraded for some period, or, a stock may be a new IPO that has only limited trading history. As a remedial measure for insufficient stock trading history, we substitute missing stock returns with the average returns of their custom industry groups as described in section 1.3. In order to account for different error variance levels resulting from substituted industry returns compared to the true stock returns, we use a weighted regression with a higher weight given to actual stock returns and a lower weight to substituted returns when they occur.

2 Risk Model Performance Testing

In this section we demonstrate that our China risk model performs well in various subsets of the Chinese market. We used a set of benchmark and test portfolios, given in Table 3, to evaluate the performance of our China A-Share Equity Risk Model. The "All A-Share" portfolio is the portfolio comprising all A-Share stocks, weighted by market capitalization. The "S&P/CITIC" portfolio group represents index portfolios defined by S&P/CITIC. The "Large Cap Test" portfolios are equal weighted portfolios constructed by taking the top half of the stocks of the estimation universe ordered by market capitalization. The "200 High Liquidity Small Cap Test" portfolio is the equal weighted portfolio of 200 high liquidity stocks from the bottom half of the stocks of the estimation universe ordered by market capitalization.

Table 3: China A-Share Equity Risk Model Test Portfolios

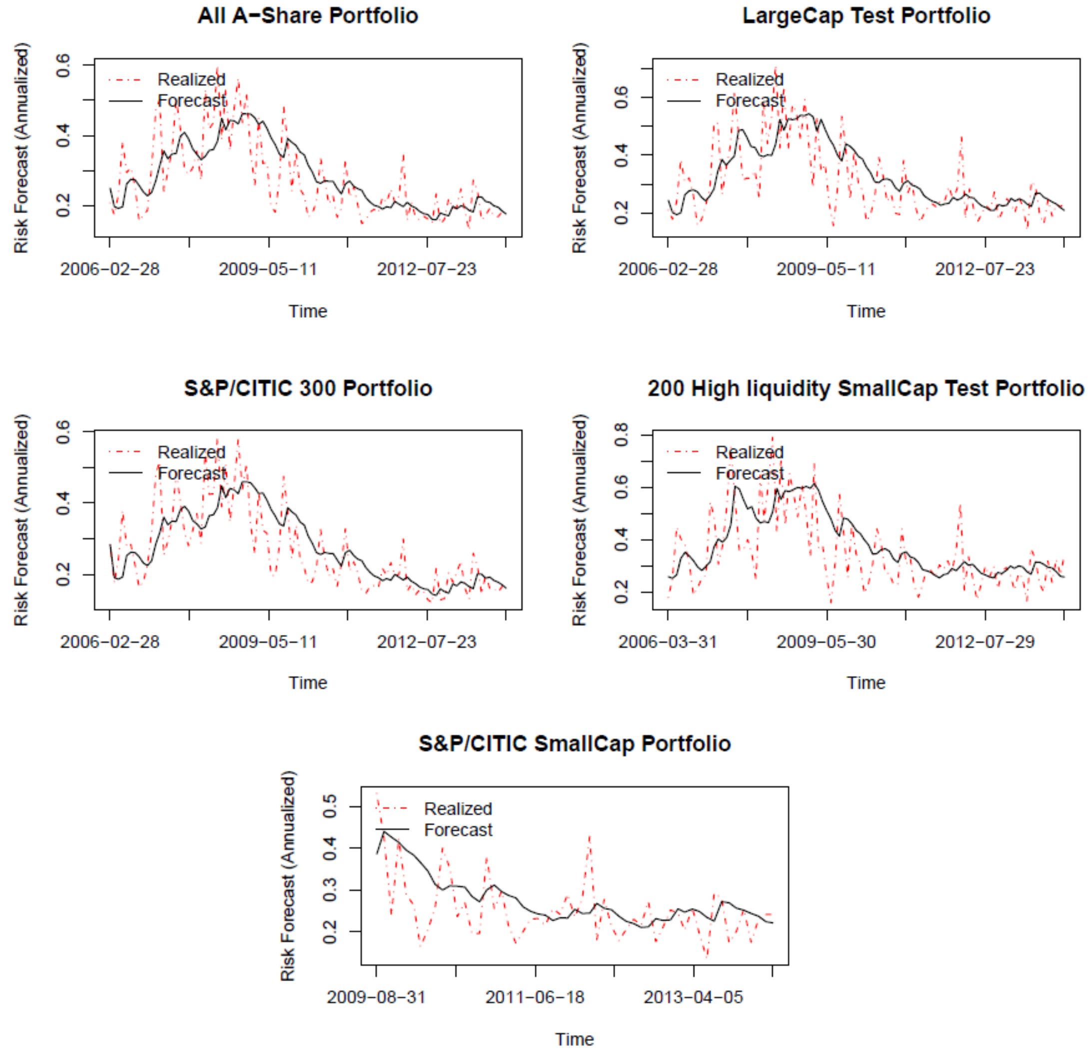
	PORTFOLIO	Group
1	All A-Share	Test
2	S&P/CITIC 300	CITIC
3	S&P/CITIC Small Cap	CITIC
4	LargeCap Test	Test
5	200 High Liquidity SmallCap Test	Test

Source: S&P Capital IQ Quantamental Research as of January 31 2014

The China A-Share Equity Risk Model uses Chinese Yuan (CNY) as the base currency and the test portfolio risks are also calculated from portfolio returns denominated in the same currency. Figure 2 shows time series plots of the forecast and realized risk of the test portfolios using our short-term China risk model. It demonstrates that our China risk model generates consistently good predictive performance.

A risk model is said to be unbiased if forecasts neither consistently under- or over-estimated realized volatility. We use the bias test statistic as defined in the Appendix to test if the risk model is biased. A bias test statistic statistically significantly larger (smaller) than 1.0 indicates that the risk model underestimates (overestimates) risk. Table 4 reports the bias test statistics of the test portfolios for our China A-Share Equity Risk Model. It shows that our China A-Share Equity Risk Model achieves an overall bias statistic close to 1.0 for all test portfolios. For all portfolios, the bias statistics are within the 95% confidence interval (0.91~1.09) around the desired bias statistic value of 1.

Figure 1: Comparisons of Forecast and Realized Risks of Test Portfolios



Source: S&P Capital IQ Quantamental Research as of January 31 2014

Table 4: Prediction Bias Statistics of Test Portfolios

Portfolio	China A-Share Equity Risk Model Bias Statistics
All A-Share	0.997
S&P/CITIC 300	1.007
S&P/CITIC Small Cap	0.964
LargeCap Test	0.973
200 High liquidity SmallCap Test	0.956

Source: S&P Capital IQ Quantamental Research as of January 31 2014

Now we compare the predictive performance of our China A-Share Equity Risk Model with the Global Equity Risk Model. In financial economics, the Diebold-Mariano Statistic is a popular test statistics used to compare the predictive accuracy of two predictions. In the Appendix we describe how we use the Diebold-Mariano Statistic to compare performance of two risk models. Table 5 below shows the performance comparisons of the China short-term model and Global short-term model in terms of the Diebold-Mariano (DM) Test t-statistic across the test portfolios with both Quadratic Error Loss and Absolute Error Loss functions. Since the DM test compares one model to another we used our Global Equity Risk Model as the base model. A t-stat over 1.96 means the test model is better than the base model statistically significantly at 5% level. Both Quadratic Error Loss and Absolute Error Loss metric show that the China A-Share Equity Risk Model achieves significantly improved performance over the Global model and the results are statistically significant at 5% level.

Table 5: Diebold-Mariano Statistics of China A-Share Equity Risk Model Compared to Global Equity Risk Model

Portfolio	Loss Function (t-statistic)	
	Quadratic Error Loss	Absolute Error Loss
All A-Share	3.962	4.858
S&P/CITIC 300	3.832	4.313
S&P/CITIC Small Cap	3.822	4.230
LargeCap Test	4.005	5.726
200 High Liquidity SmallCap Test	4.026	5.494

Source: S&P Capital IQ Quantamental Research as of January 31 2014

3 Risk Attribution Relevance

We demonstrate the effectiveness and relevance of our China A-Share Equity Risk Model by looking at the industry attributions of some concentrated industry portfolios. These portfolios were constructed by equally weighing stocks from the China region grouped according to their standard GICS classification. We picked a few of the top names (by market cap) within the corresponding industries for each sample portfolio. Table 6 gives details on these sample portfolios.

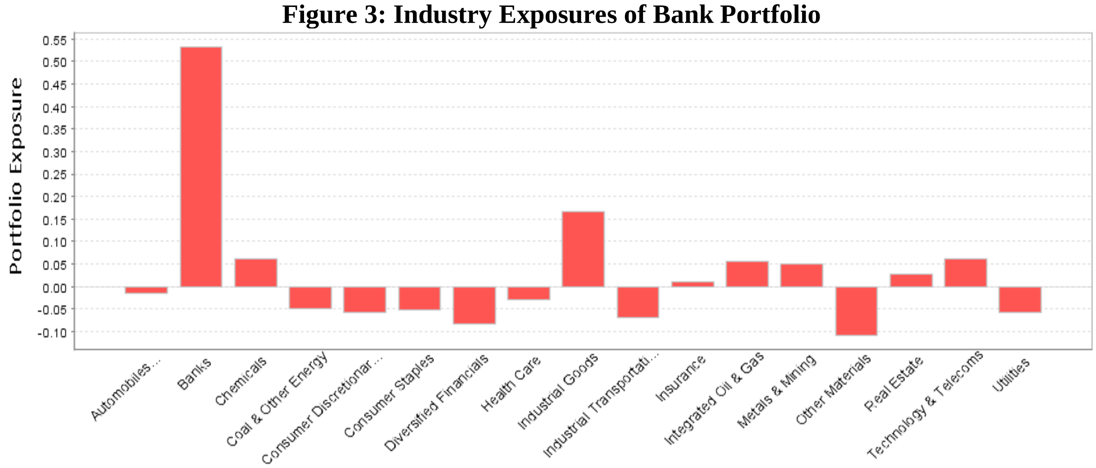
Table 6: Sample Chinese Industry Portfolios

Portfolio	Equal Weighted Constituents
Banks	AGRICULTURAL BANK OF CHINA
	CHINA CONSTR BANK CORP
	BANK OF CHINA LTD
	CHINA INDUSTRIAL & COMM BANK
Automobile & Components	GUANGZHOU AUTOMOBILE GRP CO
	BYD CO LTD
	GREAT WALL MOTOR CO
	SAIC MOTOR CORP LTD
Information Technology	SANAN OPTOELECTRONICS CO LTD
	ZHEJIANG DAHUA TECHNOLOGY CO
	HANGZHOU HIK-VISION DIGITAL
	ZTE CORP
Capital Goods	CHINA RAILWAY CONSTRUCTION
	CHINA RAILWAY GROUP LTD
	CHINA COMM CONSTR CO LTD
	CHINA STATE CONSTRUCT ENG CO

Source: S&P Capital IQ Quantamental Research

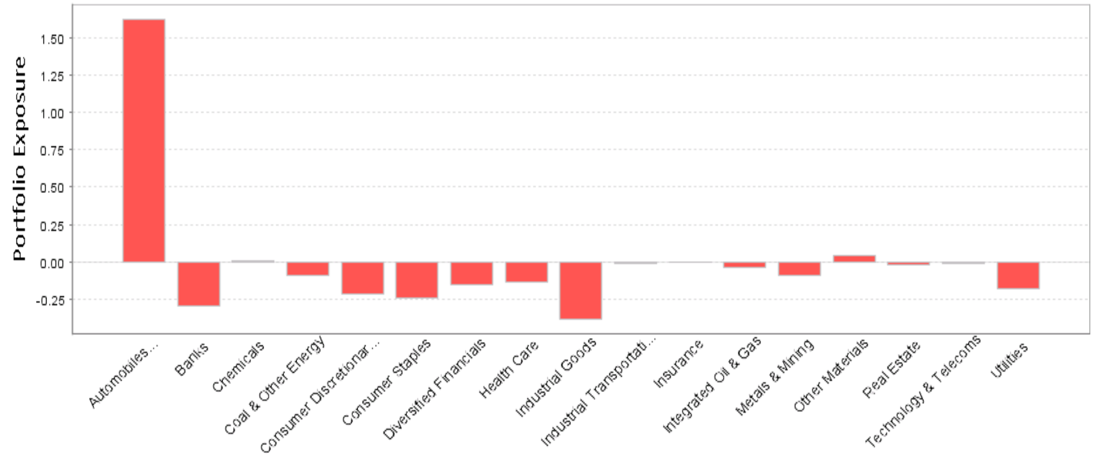
Figure 3 shows the industry exposures of the sample China banks portfolio using the China risk model. It confirms the expectation that the sample China banks portfolio should have a high exposure to the bank industry risk factor. The charts for the other portfolios specified in Table 6 are included in Figure 4, Figure 5 and Figure 6. Each portfolio exhibits a high exposure to its corresponding industry factor. These figures demonstrate that our China A-Share Equity Risk Model produces relevant and intuitive industry exposures.

Figure 3: Industry Exposures of Bank Portfolio



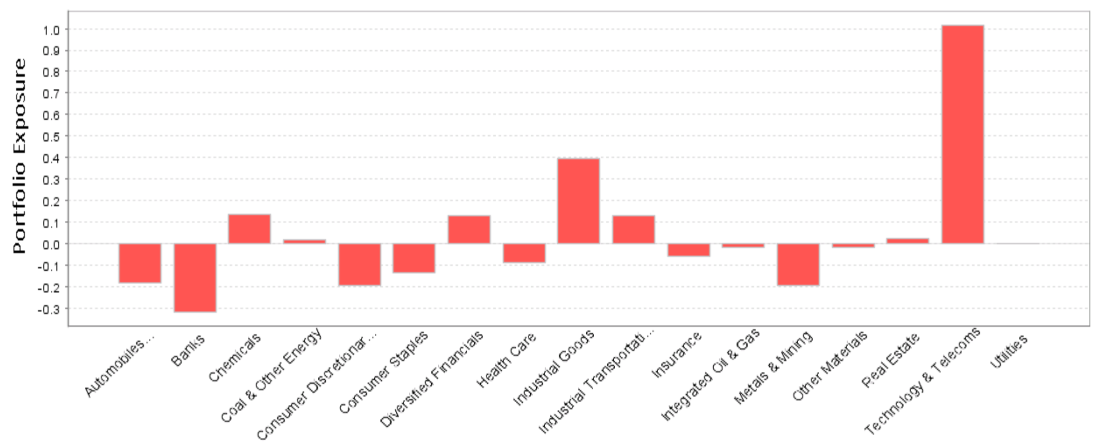
Source: S&P Capital IQ Quantamental Research as of January 31 2014

Figure 4: Industry Exposures of Automobiles & Components Portfolio



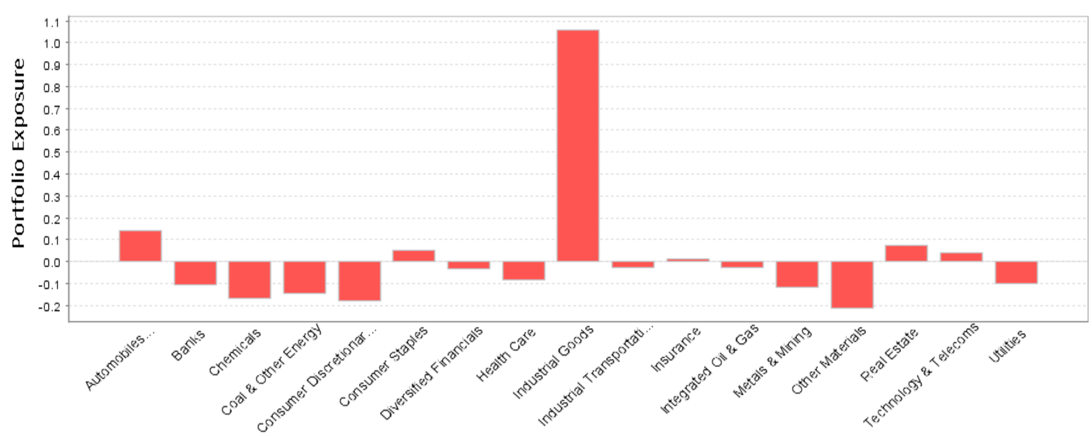
Source: S&P Capital IQ Quantamental Research as of January 31 2014

Figure 5: Industry Exposures of Information Technology Portfolio



Source: S&P Capital IQ Quantamental Research as of January 31 2014

.**Figure 6: Industry Exposures of Capital Goods Portfolio**



Source: S&P Capital IQ Quantamental Research as of January 31 2014

4 Conclusions

In this paper we introduced our China A-Share Equity Risk Model. We have described the basic methodology and summarized the salient aspects of constructing the model.

Like our US and other single-country risk model, the China A-Share Equity Risk Model is a time-series fundamental factor risk model. In our US risk model whitepaper, we compare time-series risk models with cross-sectional risk models and discussed the advantages of time-series models over cross-sectional models. Interested readers can refer to the relevant section of our US risk model whitepaper.

The performance tests in this paper show that our China A-Share Equity Risk Model generated accurate risk predictions and provides relevant portfolio risk attribution. Statistical tests show that the risk predictions are unbiased as the bias statistics for all test portfolios are within the 95% confidence interval around the desired bias statistic value of 1. The Diebold-Mariano (DM) statistics show that the China risk model achieves improved performance over the more general Global risk model at the 5% significance level. We also demonstrated the effectiveness and relevance of the China A-Share Equity Risk Model in portfolio risk attribution.

5 Appendix

5.1 Bias Test Statistic for Risk Model Predictions

The prediction of a risk model is said to be unbiased if its prediction neither consistently underestimate nor overestimate realized volatility. The bias test statistic is used to check if the risk model is biased. It is based on the series of realized portfolio returns rescaled by predicted volatility. Let σ_t^f denote the volatility forecast from a risk model at time t. Also let r_t denote the demeaned return over the risk forecast horizon. Under the null hypothesis that risk forecast is correct, the normalized portfolio return is given by

$$z_t = \frac{r_t}{\sigma_t^f}$$

For Gaussian and independently distributed portfolio return r_t, the normalized portfolio return series z_t should be independently distributed Gaussian variables under the null hypothesis. So the bias test statistics has the chi-squared distribution as

$$\sum_{t=1}^{T} z_t^2 \sim \chi^2(T) \ .$$

When T is large, we have

$$bias = \left(\frac{1}{T} \sum_{t=1}^{T} z_t^2 \right)^{1/2} \to N(1, \frac{1}{\sqrt{2T}}) \text{ in distribution}$$

5.2 Diebold-Mariano Statistic for Comparing Risk Models' Predictions

In 1995 Diebold and Mariano proposed a test statistics to compare the relative accuracy of two predictions. Here we describe how we use Diebold-Mariano (DM) Statistic to compare the portfolio risk predicted by two risk models.

Suppose we have risk predictions for a portfolio by two risk models. Let $\{y_t^1\}$ and $\{y_t^2\}$ denote the time series of these two predictions. Also let $\{y_t\}$ denote the actual realized portfolio risk. The forecast errors of these two predictions are

$$e_t^1 = y_t^1 - y_t$$

$$e_t^2 = y_t^2 - y_t$$

A loss function can be defined to measure the accuracy of the prediction:

$$L\left(\mathrm{y}_t^i, y_t\right) = L\left(\mathrm{e}_t^i\right), \ i = 1, 2$$

Two popular loss functions are quadratic error loss and absolute error loss:

- Quadratic error loss: $L\left(\mathrm{e}_t^i\right) = \left(\mathrm{e}_t^i\right)^2$
- Absolute error loss: $L\left(\mathrm{e}_t^i\right) = |\,\mathrm{e}_t^i\,|$

The Diebold-Mariano test is based on the loss differential of the two predictions:

$$d_t = L\left(\mathrm{e}_t^1\right) - L\left(\mathrm{e}_t^2\right)$$

The null hypothesis of Diebold-Mariano test is that the two predictions have the equal prediction accuracy:

$$H_0 : E\left[d_t\right] = 0$$

Let $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t$. Diebold and Mariano (1995) show that under the null hypothesis, $\bar{d}$ has Gaussian distribution asymptotically:

$$DM = \frac{\bar{d}}{\left(\frac{2\pi}{T} f_d(0)\right)^{1/2}} \rightarrow N\left(0,1\right), \text{ in distribution}$$

where $f_d(\omega)$ is the spectral density of $\{d_t\}$,

$$f_d(\omega) = (1/2\pi)\sum_{k=-\infty}^{\infty} \gamma(k) e^{-ik\omega}, -\pi \le \omega \le \pi$$

and $\gamma(k)$ is the autocovariance of $\{d_t\}$ at lag k,

$$\gamma(k) = E\left[\left(d_t - \bar{d}\right)\left(d_{t-k} - \bar{d}\right)\right],$$

which can be estimated from the sample data. So we reject the null hypothesis at the 5% level when

$$| DM | > 1.96$$

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Our Recent Research

April 2014: Riding the Coattails of Activist Investors Yields Short- and Long-Term Outperformance

On August 13, 2013, Apple's stock price rose 4.75% on high volume after Carl Icahn, a renowned activist investor, tweeted that his firm had accumulated a large position in the company. In the ensuing 6 months, the stock rose an additional 9.33% as Icahn demanded that the company add another $50 billion to its existing stock buyback plan. Icahn backed off from this demand on February 10, 2014, but not before Apple's stock price had risen to $528.99 from $461.88 where it was before he embarked on the campaign. By then, the company had already aggressively repurchased its stock, including $14 billion in a two-week stretch. As high-profiled campaigns have occurred with greater frequency and resulted in more successes, the AUM for investor activist funds has tripled to $95 billion in 2013, 3 times the amount in 2008. One month after the commencement of activism, a strategy of holding a portfolio of targets outperformed the market by 3.9%. After controlling for other common risk factors, the outperformance was 3.0%.

March 2014: Insights from Academic Literature: Corporate Character, Trading Insights, & New Data Sources

We have assembled a number of interesting articles that we believe will be of broad interest to our clients, and all investment professionals - Corporate Character, Trading Insights & New Data Sources. For each article we provide a link to the article, the abstract, and a brief discussion of the article highlights and how it will be useful to fellow practitioners. It is our hope that these papers help you generate differentiated thinking, and to better serve your clients.

February 2014: US Stock Selection Model Performance Review

The performance of S&P Capital IQ's four U.S. stock selection models since their launch in January 2011 has been strong, and 2013 was no exception. Key differentiators, such as distinct formulations for large and small cap stocks, bank-specific factors, sector-neutrality to target stock-specific alpha, and the combination of sub-components representing different investment themes have enabled the models to outperform across disparate market environment. In this report, we review the performance of S&P Capital IQ's four U.S stock selection models in 2013, and since their inception in January 2011. In assessing the underlying drivers of each model's performance over the 12 months ended December 31, 2013

January 2014: Buying Outperformance: Do share repurchase announcements lead to higher returns?

We examine the returns surrounding buyback announcements to test whether, and when, buyback programs signal subsequent outperformance and shareholder value. We find:

• Buyback announcements precede excess returns in the US. Stocks on average outperformed the equally weighted Russell 3000 by 0.60% over one month, and by 1.38% over one year periods following buyback announcements.

• Outperformance is greatest among small caps or larger magnitude buybacks as a % of shares outstanding.

• Reported insider trading and buyback announcement signals are complementary.

October 2013: Informative Insider Trading - The Hidden Profits in Corporate Insider Filings

In this report, we investigate the impact of the public disclosure of insider trading on equity prices, using both an event study framework and a portfolio formation approach. Leveraging S&P Capital IQ's Ownership database, we explore several practical methods of identifying "informative" insider trades, and how to construct a portfolio of stocks using recent "informed" insider transactions. We document the following results:

• Consistent with existing literature, insider trades are predictive of future stock returns.

• Outside investors can earn economically significant excess returns by trading on "informative" insider trading signals.
• Mimicking the net purchase actions of CEOs yielded an excess return of 1.27% over the next one week.
• A trading strategy based on the three characteristics: opportunistic, intensive and directional change, yielded 0.36% weekly excess returns after transaction costs.

September 2013: Beggar Thy Neighbor – Research Brief: Exploring Pension Plans

Pension underfunding is a worldwide problem. There has been an unending wave of news stories about cities and states across the United States suffering from defined benefit pension funding shortfalls, but these issues extend far beyond the public sector and beyond the United States as well.
In this brief we leverage S&P Capital IQ datasets to examine:

- Companies with the strongest and weakest pension funding status globally.
- Companies with the most optimistic return and discount rate assumptions globally.
- The relationship between projected and realized pension portfolio returns.
- The historical global trends in funding status, portfolio returns, and discount rates.

August 2013: Introducing S&P Capital IQ Global Stock Selection Models for Developed Markets

In this report, we explore the efficacy of different stock selection strategies globally and use this information to develop a suite of robust global stock selection models targeting Canada and the developed markets of Europe and Asia Pacific. Our global models were developed using S&P Capital IQ's industry leading Global Point-in-Time data, as well as the Alpha Factor Library, our web-based global factor research platform. We find that each of our Global Stock Selection Models for Developed Markets yield significant long-short spread returns and information coefficients at the 1% level. This performance is also robust providing similar statistical significance after controlling for Market Cap and Beta exposures.

July 2013: Inspirational Papers on Innovative Topics: Asset Allocation, Insider Trading & Event Studies

Inspiration drives innovation. The writings of Plutarch inspired Shakespeare, Galapagos finches inspired Darwin, and the German Autobahn inspired Eisenhower, but what inspires investment researchers to develop the next innovations for investors? When we get a new investment idea, we seek out literature on that topic to inspire us to bring the idea to fruition. This literature can help to further develop our own thoughts, polish up and expand on our priors, and avoid the pitfalls experienced by earlier researchers. Inspiration from academia enhances our ability to provide innovative solutions for our clients.

June 2013: Supply Chain Interactions Part 2: Companies – Connected Company Returns Examined as Event Signals

Leveraging Compustat customer segment data, we investigate the impact of news for customers and subsequent stock returns for their suppliers, over the time period May 2000 through April 2011 and find that:

- Shares of suppliers with major customer relationships reacted to positive and negative earnings surprise of their customers with a statistically significant 0.93% to 1.97% abnormal spread in the 5 to 60 trading days following the surprise.
- A monthly rebalanced backtest of long-short supplier portfolios based on customer momentum would have resulted in a statistically significant 0.81% average monthly return, or 0.70% after controlling for common risk factor exposures.
- The customer momentum signal historically performs best in cyclical sectors such as Materials and Consumer Discretionary.

June 2013: Behind the Asset Growth Anomaly – Over-promising but Under-delivering

In this paper, we revisit the asset growth anomaly. Our results indicate:

- Asset growth demonstrates return predictive power globally with and without controlling for size, value, 12-month price momentum, and 1-month price reversal factors.
- Information coefficient correlation analyses indicate that there are potential diversification benefits from adding asset growth to other alpha factors.
- The companies that demonstrated the highest asset growth show subsequent deterioration in their top-line and bottom-line growth rates while companies that had the lowest asset growth experience subsequent improvement in their top-line and bottom-line growth rates.

April 2013: Complicated Firms Made Easy - Using Industry Pure-Plays to Forecast Conglomerate Returns

This month we build upon the work done by Cohen and Lou in their 2010 paper, "Complicated Firms", to determine if we can exploit industry level information from pure-play firms to predict the future performance of multi-industry, complicated firms. Leveraging Compustat segment data and Standard Industrial Classification (SIC) 2 digit codes, we exploit the lag in incorporating industry level information between simple and complicated firms to forecast the future performance of complicated firms. This is done by constructing pseudo-conglomerate returns, revisions, and valuation signals that combine the relevant information of all the industries in which a complicated firm operates. These pseudo-conglomerate signals simply weight industry level information (ex: industry return) proportionately to the complicated firm's reported sales in each industry.

March 2013: Risk Models That Work When You Need Them - Short Term Risk Model Enhancements

Equity Risk models are subject to a common criticism. We examined three techniques to further enhance the S&P Capital IQ Fundamental Factor risk models: Utilized the cross sectional dispersion of stock and factor returns by adjusting model factors and stock specific volatilities, change the model production frequency from monthly to daily to capture recent data, and shorten data look back window (1 year as opposed to 2 years) resulting in a more reactive model. Dispersion based adjustments, and high frequency of model generation both improved model results, while a shortened calibration window showed no appreciable improvement.

March 2013: Follow the Smart Money - Riding the Coattails of Activist Investors

Can profits be made by following the actions of activists? One month after the commencement of activism, the strategy yielded a market-adjusted excess return of 3.4%. After controlling for market, size, value, and industry, the excess return was 2.7. Twelve months after the disclosure of activist involvement, the strategy produced an average excess return of 14.1% after controlling for market, size, value, and momentum. We did not find evidence of return reversal up to two years after activism or of diminished excess returns in 2008 -- 2012 vis-à-vis those in 2003 -- 2007.

February 2013: Stock Selection Model Performance Review: Assessing the Drivers of Performance in 2012

In this report, we review the performance of S&P Capital IQ's four U.S. stock selection models in 2012. These models were launched in January 2011, and this analysis will assess the underlying drivers of each model's performance over the 12 months ended December 31, 2012.

January 2013: Research Brief: Exploiting the January Effect Examining Variations in Trend Following Strategies

At the beginning of every year, one topic frequented by many institutional investors is the January Effect. Investors often point to January as the most pronounced example of seasonality, where longer term trend following strategies suddenly underperform and short-term reversal and mean-reversion dominate. But which strategies have performed well in January and is this performance sustainable?

With several studies in the Literature documenting the January Effect on company capitalization, we decided to undertake our own review using our S&P Capital IQ Alpha Factor Library (AFL), to examine various strategies' effectiveness during the month.

December 2012: Do CEO and CFO Departures Matter? - The Signal Content of CEO and CFO Turnover

In October of this year, the US equity market was caught off guard with the seemingly sudden departure of Citibank CEO Vikram Pandit. While CEO departures are almost always headline news, CFO departures are not often accompanied with such recognition. We explore the impact of CEO and CFO departures and find consistent results in the US and the Developed World. CEO and CFO departures often signify a turning point in both the company's stock performance and the company's operating metrics.

November 2012: 11 Industries, 70 Alpha Signals -The Value of Industry-Specific Metrics

Investors routinely utilize industry intelligence in their investment process. But which information is relevant? Which is irrelevant? Our work yields some surprising results. This work complements our previous industry work on Retail [June 2011], Banking [Oct 2011], and Oil & Gas [May 2012]. Using S&P Capital IQ's Global Point-in-Time database and Compustat Industry-Specific data, we look at 70 factors in 11 industries: airlines, hospitals & facilities, managed healthcare, pharmaceuticals & biotechnology, homebuilding, insurance, telecommunications, utilities, gold miners, hotels & gaming, and restaurants

October 2012: Introducing S&P Capital IQ's Fundamental Canada Equity Risk Models

In July 2012 we released our regional risk models -- the Pan-Asia ex. Japan and the Pan-European Models, and updated versions of our US and Global Equity Risk Models. Continuing in our efforts to provide a broad set of models to the asset management community, we are now releasing our second single country risk model -- Canada Fundamental Equity Risk Model.

September 2012: Factor Insight: Earnings Announcement Return – Is A Return Based Surprise Superior to an Earnings Based Surprise?

August 2012: Supply Chain Interactions Part 1: Industries Profiting from Lead-Lag Industry Relationships

July 2012: Releasing S&P Capital IQ's Regional and Updated Global & US Equity Risk Models

June 2012: Riding Industry Momentum – Enhancing the Residual Reversal Factor

May 2012: The Oil & Gas Industry - Drilling for Alpha Using Global Point-in-Time Industry Data

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions

March 2012: Exploring Alpha from the Securities Lending Market – New Alpha Stemming from Improved Data

January 2012: S&P Capital IQ Stock Selection Model Review – Understanding the Drivers of Performance in 2011

January 2012: Intelligent Estimates – A Superior Model of Earnings Surprise

December 2011: Factor Insight – Residual Reversal

November 2011: Research Brief: Return Correlation and Dispersion – All or Nothing

October 2011: The Banking Industry

September 2011: **Methods in Dynamic Weighting**

September 2011: **Research Brief: Return Correlation and Dispersion**

July 2011: **Research Brief - A Topical Digest of Investment Strategy Insights**

June 2011: **A Retail Industry Strategy: Does Industry Specific Data tell a different story?**

May 2011: **Introducing S&P Capital IQ's Global Fundamental Equity Risk Models**

May 2011: **Topical Papers That Caught Our Interest**

April 2011: **Can Dividend Policy Changes Yield Alpha?**

April 2011: **CQA Spring 2011 Conference Notes**

March 2011: **How Much Alpha is in Preliminary Data?**

February 2011: **Industry Insights – Biotechnology: FDA Approval Catalyst Strategy**

January 2011: **US Stock Selection Models Introduction**

January 2011: **Variations on Minimum Variance**

January 2011: **Interesting and Influential Papers We Read in 2010**

November 2010: **Is your Bank Under Stress? Introducing our Dynamic Bank Model**

October 2010: **Getting the Most from Point-in-Time Data**

October 2010: **Another Brick in the Wall: The Historic Failure of Price Momentum**

July 2010: **Introducing S&P Capital IQ's Fundamental US Equity Risk Model**