Risk Models That Work When You Need Them

Short Term Risk Model Enhancements

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Equity Risk models are subject to a common criticism: "Risk models work well when we don't need them and fail when we do". Alternatively, equity risk model performance degrades during periods of market stress. Can risk models be improved by enabling them to perform better, especially during stress periods? This paper answers the question in the affirmative.

We examined three techniques to further enhance the S&P Capital IQ Fundamental Factor risk models:

- (i) Utilized the cross sectional dispersion of stock and factor returns by adjusting model factors and stock specific volatilities
- (ii) Change the model production frequency from monthly to daily to capture recent data
- (iii) 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.

- Using a monthly (daily) model dispersion based adjustments provided a 200 bps (320 bps) improvement in forecast accuracy for the S&P 500 Portfolio over the period 1999-2012 when forecasts materially differ as compared to a base monthly (daily) model.

- Daily models provide a significant reduction in error compared to a monthly model. For example, when tested across 11 standard S&P portfolios on September 28, 2001 the average mean squared error of most recent daily vs. monthly models were 6.6% vs. 23.5%.

- A shortened data look back did not improve forecast accuracy since reducing the amount of data makes the parameter estimates noisier and unstable.

1 Introduction

The S&P Capital IQ Equity Risk Models currently cover the major geographies in the world. Our approach is to use time series regressions of individual stock returns against suitably defined factor return blocks representing markets, currencies, styles and sectors to calculate factor exposures, co-variances and residual risks.

A common criticism of risk models in general, is that they do not work well during periods of market stress. In this paper, we specifically considered advances that allow improving the re-activeness of our models to short term movements in the market:

- Recent research (Garcia et al 2011) showed a strong relationship between cross-sectional volatility of stock returns and the average idiosyncratic volatility in the market. Based on this idea, we tested time varying adjustments to our factor and specific risk estimates to improve the risk prediction accuracy of both our risk models. Using a monthly (daily) model, these dispersion based adjustments provided a 200 bps (320 bps) improvement in forecast accuracy for the S&P 500 (1999-2012).
- Increasing the production frequency of models form monthly to daily allows us to better capture more recent market dynamics. For example, when tested across 11 standard S&P portfolios on September 28, 2001, the average mean squared error using daily vs. monthly models was 6.6% vs. 23.5%. Using daily models in place of potentially stale monthly models for risk prediction or portfolio construction provides better performance.
- Another improvement considered to the modeling approach was to make factor exposures more reactive to better capture market conditions. We tested our model performance using a shortened data look back window of 1-year instead of 2-years. However, the results showed that forecast accuracy worsened since smaller dataset leads to noisier and more unstable parameter estimates.

During periods of stress, the incremental accuracy achieved from applying the cross sectional dispersion adjustment or using daily models instead of monthly although small on the average was very important. In both cases, the average improvement relative to our existing unadjusted monthly model of the mean squared error of predicted vs. realized risk was less than 50bps. During periods of market stress these enhancements provide for improved risk forecasting.

2 Cross Sectional Dispersion based Adjustments

Cross sectional return dispersions can be measured on a daily basis, and hence, provide a more current estimate of market movements. Cross sectional dispersion (CSD) of stock returns has been shown to be a useful predictor of average idiosyncratic volatility in the market (Garcia et al 2011). We also considered the dispersion among fundamental factor returns that are inputs to our risk model, the idea being that increased cross sectional factor dispersion is indicative of higher future time series factor volatilities. Using a factor dispersion measure, we adjusted the volatility estimates for the different factors in our risk model covariance matrix.

The S&P Capital IQ equity risk model follows a factor modeling framework where the asset level covariance matrix $C = BFB' + D$ where B, F and D are Factor Exposure, Factor Covariance and diagonal matrix of asset specific variances respectively. For more details on CIQ Equity Models, we refer the reader to our US Model white paper (Scherer et al 2010).

2.1 Volatility and Specific Risk Correction Methodology

Let the unadjusted estimate of idiosyncratic/factor volatility be v (obtained by following our normal risk model estimation process). Then we introduce the following modification to come up with an adjusted estimate

$$v^{adj} = \lambda v \tag{1}$$

where λ is a correction factor which is calculated as follows:

$$\lambda = \begin{cases} e^{(R-1)^2} & R \geq 1 \\ e^{-(R-1)^2} & R < 1 \end{cases} \tag{2}$$

R is estimated as the current ratio at time t of the average CSD over a short term horizon STW estimated as $c_{t,STW}$ to that over a long term horizon LTW estimated as $c_{t,LTW}$ i.e.

$$R = \frac{c_{t,STW}}{c_{t,LTW}} \tag{3}$$

The above equations apply for both factor and stock specific volatility corrections i.e. the diagonal of F and D. For the stock specific volatility corrections, the dispersion is computed using cross sectional asset returns whereas for factor volatility correction, we use the dispersion across the factor return series.

2.2 Testing

We tested the methodology for dispersion based correction on our S&P Capital IQ US Fundamental Short Term Equity Risk Models. We used the Diebold-Mariano (DM) test to compare the corrected and uncorrected models separately against the realized risk in predicting the average Systematic, Specific and Total Risk of a set of 12 portfolios (11 equal weighted portfolios constructed from constituents of standard S&P indices plus the S&P 500 portfolio). We considered several variants for calculating R. We wanted to look at the effect of using data at different frequencies for calculating the point estimates for building a dispersion time series. Table 1 summarizes in detail the different variants, Model 1 through Model 15.

Table 1: Model Variations for Dispersion Based Risk Adjustments

Model	Name	Dispersion Time Series: Frequency	Dispersion Time Series: Calculation Method	Parameters		R-ratio Calculation Method
Model 1	MthRetsDisp	Monthly	CSD of current month returns			Ratio of 4 month to 12 month average dispersion
Model 2	EW5DailyDisp		CSD of daily returns for each day of the current month rolled up to monthly frequency using Exponential Weighting with Half life (HL)	HL: 5 days		
Model 3	EW10DailyDisp			HL: 10 days		
Model 4	EW20DailyDisp			HL: 20 days		
Model 5	EW30DailyDisp			HL: 30 days		
Model 6	LastDayDisp			Last Day of current month point estimate		
Model 7	Dly_252_5	Daily	CSD of Daily Returns	LTW, 252 days	STW, 5 days	Ratio of average dispersion over LTW to STW
Model 8	Dly_252_10				STW, 10 days	
Model 9	Dly_252_22				STW, 22 days	
Model 10	Dly_126_5			LTW, 126 days	STW, 5 days	
Model 11	Dly_126_10				STW, 10 days	
Model 12	Dly_126_22				STW, 22 days	
Model 13	Dly_66_5			LTW, 66 days	STW, 5 days	
Model 14	Dly_66_10				STW, 10 days	
Model 15	Dly_66_22				STW, 22 days	

Note: LTW denotes Long Term Window, STW denotes Short Term Window

The computation of systematic, specific and total realized risks are calibrated to represent a one month prediction window and the accuracy of each of the above model forecasts was compared to the uncorrected base model. The realized factor returns and the stock exposures from the risk models allowed us to split the total realized risk into realized systematic and realized specific risk.

The predicted and realized one month risk forecast was compared from January 1995 through August 2012. Table 2 presents the results of the DM test t-stats (comparing systematic, specific and total risk performance) for the model variants and various dispersion universes (S&P 100, S&P 500 and S&P 1500) for the specific risk calculation. The best performing calibration for systemic and specific risks are highlighted.

Table 2: Dispersion Based Risk Model Adjustments, DM Test Results (Mean Squared Error t-stats).

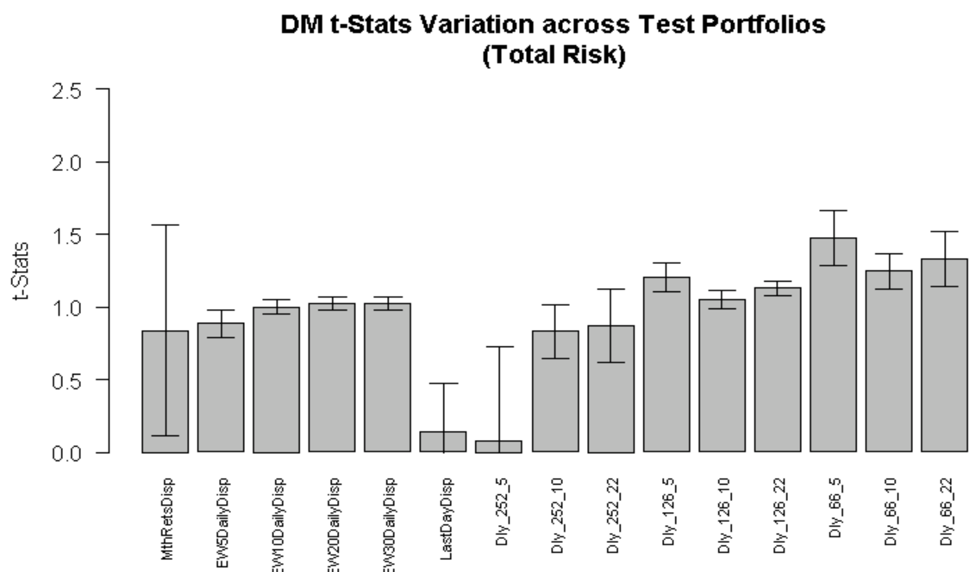
S&P 100,500, 1500 January 1995 – August 2012

Dispersion Calculation	Systematic Risk	Specific Risk			Total Risk		
		S&P 100	S&P 500	S&P 1500	S&P 100	S&P 500	S&P 1500
MthRetsDisp	0.81	1.54	1.89	1.32	0.83	0.82	0.85
EW5DailyDisp	0.88	1.06	1.31	1.55	0.88	0.89	0.89
EW10DailyDisp	1.00	1.07	1.40	1.57	1.00	1.00	1.00
EW20DailyDisp	1.02	1.25	1.44	1.58	1.02	1.02	1.02
EW30DailyDisp	1.02	1.29	1.45	1.58	1.02	1.02	1.02
LastDayDisp	0.14	1.24	1.23	1.54	0.15	0.14	0.15
Dly_252_5	0.10	0.96	1.09	1.42	0.13	0.12	0.12
Dly_252_10	0.83	1.07	1.28	1.42	0.84	0.84	0.84
Dly_252_22	0.87	1.20	1.36	1.42	0.88	0.88	0.88
Dly_126_5	1.19	0.85	1.16	1.48	1.19	1.19	1.20
Dly_126_10	1.04	1.18	1.42	1.60	1.04	1.04	1.05
Dly_126_22	1.13	1.32	1.42	1.48	1.13	1.13	1.13
Dly_66_5	1.46	0.85	1.33	1.66	1.45	1.46	1.46
Dly_66_10	1.23	1.27	1.64	1.90	1.23	1.23	1.24
Dly_66_22	1.31	1.50	1.46	1.43	1.31	1.31	1.32

Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results

From the results presented in Table 2, we settled on the calibration settings of the Dly_66_10 model (i.e. long term and short term windows of 66 and 10 days respectively) for stock specific risk, Dly_66_5 for systematic risk, and the S&P 1500 universe for CSD estimation. These combinations were chosen based on the DM test t-stats. Figure 1 shows the average t-stats with the variation of the DM stats across the test portfolios listed in Table 4. The errors bars are fairly tight around the mean which implies that model performance did not vary much across portfolios (also true for our chosen models, Dly_66_10 and Dly_66_5).

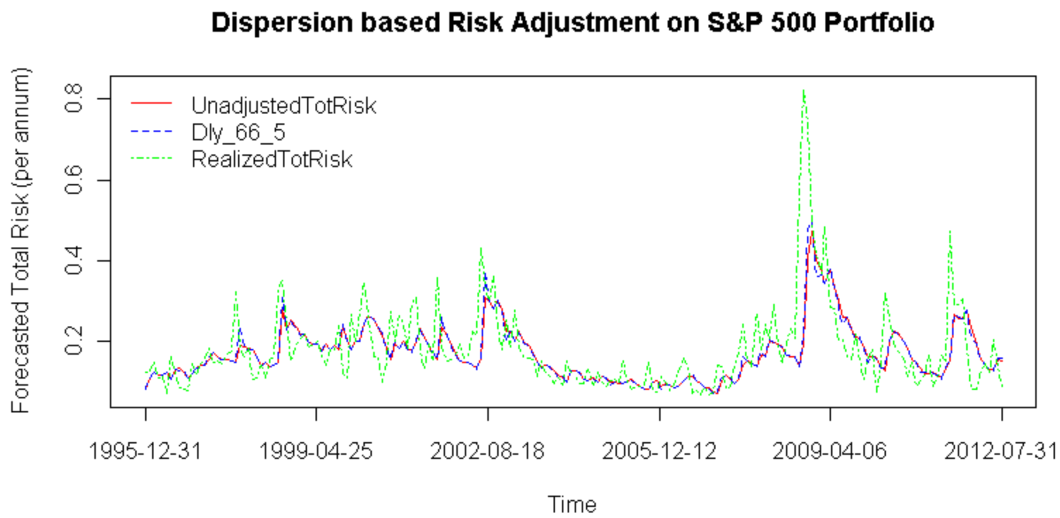
Figure 1: Dispersion based Adjustment – Variation of t-stats Across Test Portfolios



Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results

Figure 2 displays the time series chart of predicted and realized risk for the standard S&P 500 portfolio. Although over most time periods the adjustment to the predicted risk is fairly small, there are specific periods over which there are pronounced changes to the risk forecast.

Figure 2: Dispersion Based Adjustment – S&P 500 Predicted and Realized Risk



Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

To capture the effect of these adjustments consider the following: Over all, the average Mean Squared Error (MSE) using uncorrected and corrected models were 8.7% and 8.5% respectively. However over periods during which the two predictions differ by more than 200 bps (5% of the time) the average MSEs were more spread out at 12.4% and 10.4% for uncorrected and corrected models respectively. **Thus, the dispersion adjustments did not change the risk predictions on average but did reduce the risk forecast error measurably during periods of market stress.**

3 Comparing Daily and Monthly Models

The S&P Capital IQ Risk Models are published at a monthly frequency. We have put into place a daily production system and these daily models will soon be made generally available. Since daily models use current market information and are updated daily, they are expected to provide better risk prediction performance especially when used between two monthly model release dates.

To better understand the magnitude of the expected improvement, we tested the short term risk model prediction for portfolios at the middle of each calendar month. We used the latest available monthly and daily model for each mid-month risk prediction (i.e. for daily model we used model from previous business day while for monthly model we use one that is about two weeks old, i.e. end of the previous month). The test period was 1992 through 2012 and we used a sample of 11 standard S&P test portfolios (see Table 4). Table 3 shows the average DM t-stats for comparing the two models using the MSE (significant at the 90% confidence level) and MAE (Mean Absolute Error, significance > 99%) error measures.

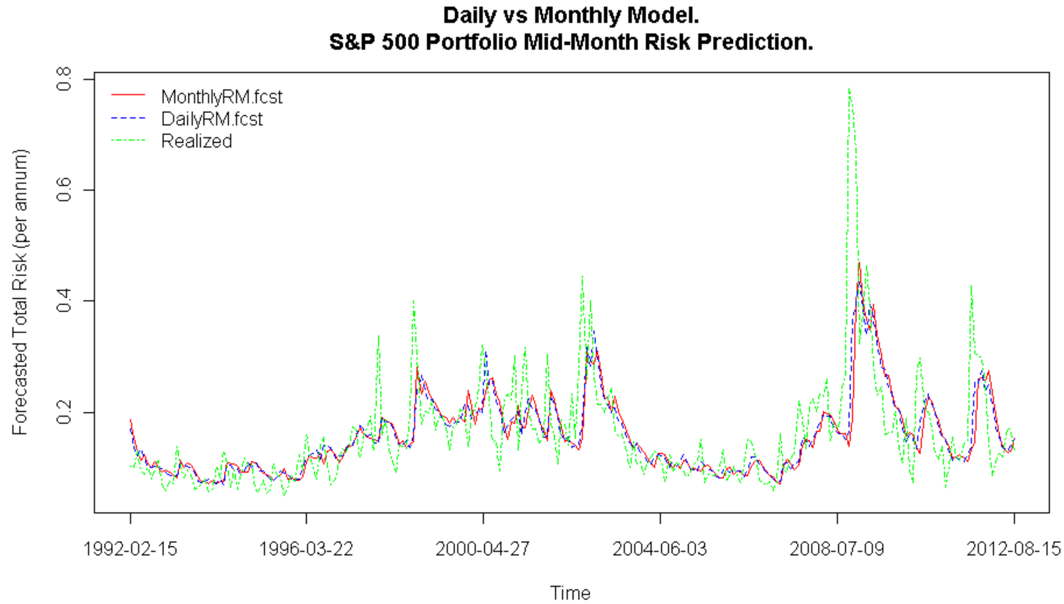
Table 3: Average DM Test t-stats Across US Test Portfolios Comparing Daily vs. Standard (Monthly) Short Term Risk Model Performance (1992-2012)

Error Metric	DM Test Mean t-stats
Mean Squared Error (MSE)	1.86
Mean Absolute Error (MAE)	3.44

Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

Figure 3 shows a time series plot of realized and predicted risk for the S&P 500. Although over most time periods, the differences in the forecasts were small, there were periods when the differences were more pronounced. The MSEs over the full time period are 8.47% and 7.61% using the monthly and daily models respectively i.e. a 86 bps improvement using the daily models. When we considered periods over which the two predictions were different by more than 200 bps (11% of the time) the average MSEs were more spread out at 19.5% vs. 16.5% for the monthly and daily models respectively (300 bps improvement). This demonstrates that daily models provided a small but, at times, significant benefit over monthly models.

Figure 3: S&P 500 Predicted and Realized Risks, Mid-Month Portfolio Formation



Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

To further showcase the utility of daily model we looked at a specific period of high market stress, namely after September 11, 2001. In Table 4 we present results from using portfolios as of September 28, 2001 and present the realized risk using a daily model (from 9/28/2001) and a monthly model (from 8/31/2001). The realized risk was measured from the daily portfolio returns in Oct 2011. For small and mid-cap portfolios, the daily model provided a much better prediction. For the large cap stocks, they performed about the same (daily models over-predicted the risk for large cap portfolios whereas the monthly models under-predicted the large cap portfolio risk).

Table 4: Predicted and Realized Risks for Sep 28, 2001 Using the Most recent Monthly and Daily Models

Portfolio	Predicted Risk Monthly	Predicted Risk Daily	Realized Risk
S&P 100	16%	25%	19%
S&P 500	15%	23%	19%
S&P 500 Citigroup Growth Index	19%	29%	23%
S&P 500 Citigroup Value Index	13%	20%	16%
S&P MidCap 400	17%	26%	24%
S&P MidCap 400 Citigroup Growth Index	21%	31%	28%
S&P MidCap 400Citigroup Value Index	14%	22%	21%
S&P SmallCap 600	16%	25%	26%
S&P SmallCap 600 Citigroup Growth Index	19%	29%	29%
S&P SmallCap 600 Citigroup Value Index	14%	22%	23%
S&P 1500	17%	27%	26%

Source: S&P Capital IQ Quantamental Research Past performance is not a guarantee of future results. Indices are unmanaged, statistical composites and it is not possible to invest directly in an index. The results are inherently limited because they do not represent the results of actual trading and were constructed with the benefit of hindsight.

In Table 5 we present the average of the MSEs and MAEs of the predicted vs. realized risk across all the test portfolios on September 28, 2011. Given the much lower error metrics achieved using the daily model, the results serve to further reinforce the generally superior performance of daily models during stress periods in the market. These changing risk dynamics are better captured by daily models since, by construction, they use more reflective (current) data.

Table 5: Summary Stats for Predicted and Realized Risks for Sep 28, 2001 portfolios

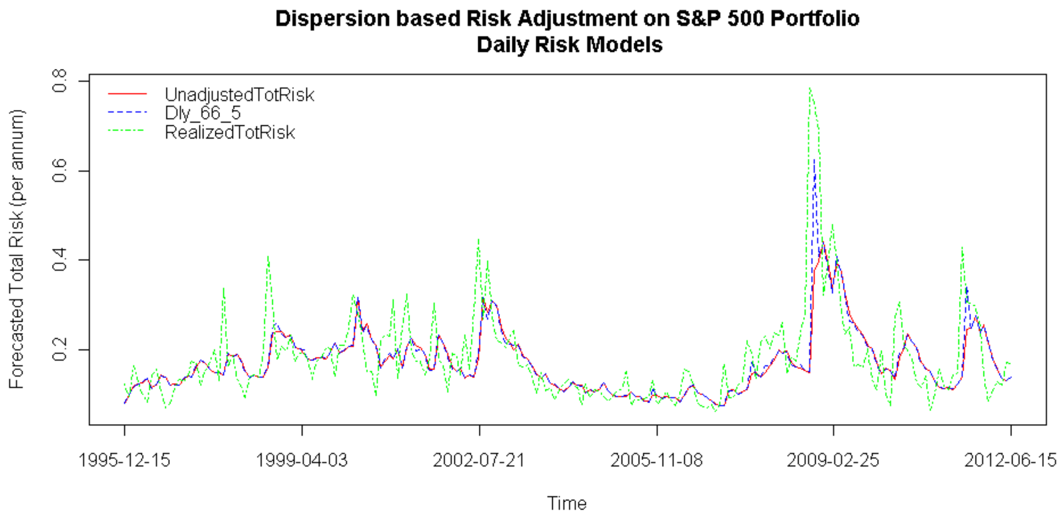
Summary	Monthly Model	Daily Model
Mean Squared Error (MSE)	23.5%	6.6%
Std of MSE	5.7%	2.6%
Mean Absolute Error (MAE)	10.6%	2.5%
Std of MAE	3.5%	2.1%

Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

3.1 Daily Model with Dispersion Correction

In the previous section we looked at the benefits of dispersion based corrections to factor/specific risks using our monthly models and, separately, the utility of daily models over monthly models. We then analyzed the combined effect of using daily models with cross-sectional dispersion based adjustments. We tested risk prediction on mid-month S&P 500 portfolios using DM test stats and comparing the daily models with and without dispersion based adjustments overlays.

Figure 4: S&P 500 Predicted and Realized Risks Using Daily Models and Mid-Month Portfolios



Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

Figure 4 shows a time series plot of realized and predicted risk for the S&P 500 using the adjusted and unadjusted daily models. The MSEs over this time period was 8.51% and 8.02% using the unadjusted and adjusted daily models respectively. However, when we considered time periods where the two forecasts differed by more than 200 bps, the MSEs were 22.3% and 7.8% using the unadjusted and adjusted daily models respectively. Since these differences only happened 1% of the time we also looked at a 100 bps difference in forecasts (which happened 9% of the time) and then the MSEs were 14.4% and 11.2% for the unadjusted and adjusted daily models respectively. This demonstrates that daily models also benefit from dispersion based adjustments.

4 Reactive Factor Exposures

We also explored making our estimation process more reactive to short term movements by making factor exposures more reactive. We studied risk prediction performance of the current US equity risk model which uses 2 years of daily data to estimate exposures against a model built using only 1 year of stock and factor returns history.

Table 6 presents the results of comparing these models using our standard DM test across our test portfolios. The negative t-stats indicate that the more reactive model performed worse than our standard model. These results are not that surprising: As we reduce the estimation history window although exposures become more reactive we also run the risk of making the models less stable as the parameter estimates will become noisier due to reduction in data for model fitting. Thus we did not pursue this potential improvement further.

Table 6: Average DM Test t-stats Across 11 US Test Portfolios Comparing Standard Short Term Model (2 year data history) Vs. Reactive Model (1 year history)

Error Metric	DM Test Mean t-stats
Mean Squared Error (MSE)	-0.91
Mean Absolute Error (MAE)	-2.21

Source: S&P Capital IQ Quantamental Research. Past performance is not a guarantee of future results.

5 Conclusion

We considered modifications to our fundamental risk models using measures of cross sectional dispersion, shortened exposure window, and daily vs. monthly risk model production. These modifications were tested and the results show that cross sectional dispersion adjustment and daily risk model production provide small but, at times, significant improvements in the accuracy of the risk forecast compared to our standard monthly model. During normal market conditions, investors with traditional investment horizons of, say, greater than one month, are unlikely to experience noticeable differences on average when moving to a more reactive daily short term risk model. However, during periods of market stress, daily models with cross-sectional adjustments do offer significant benefits.

6 References

R. Garcia, D. Mantilla-Garcia, and L. Martellini, "Idiosyncratic Risk and the Cross-Section of Stock Returns", EDHEC Business School Publications, March 2011

B. Scherer, B. Balachander, R. Falk and B. Yen, "Introducing Capital IQ's Fundamental US Equity Risk Models", July 2010

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Recent Quantamental Research

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

On October 31, 2012, Netflix's stock rose 13.9% when Carl Icahn, a renowned activist investor, disclosed a substantial stake in Netflix, intending to influence the future direction of the company. In the subsequent month, the stock tacked on an additional 3.1% compared with 0.6% for the S&P 500. This prompts the question: Can profits be made by following the actions of activists?

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 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?
In this report, we compare the performance of SUE to one based on returns around a firm's earnings announcement date (EAR), proposed by Brandt et al (2008). We test both factors globally and find EAR dominates SUE in the U.S in the post Reg FD era on both a long-short return and top quintile excess return basis.

August 2012: Supply Chain Interactions Part 1: Industries Profiting from Lead-Lag Industry Relationships
Supply chain relationships are among the most visible and measurable, as revenues and costs shape the realized economic and financial performance of connected companies. Studies have shown that events within a supply chain do introduce these ripple effects, and theories incorporating this information into an investment process have garnered attention in recent years. We construct a map quantifying industry level connections along the supply chain. Using this map, and trailing industry returns as a proxy for industry level information shocks, we construct inter-industry momentum signals. These signals exhibit lead-lag relationships over short horizons, as the information shocks diffuse through the market and manifest themselves in the performance of related industries.

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
In the oil & gas industry, a key determinant of value and future cash flow streams is the level of oil & gas reserves a firm holds. While most fundamental analysts/investors take into consideration a company's reserves in arriving at price targets, a majority of systematic driven processes do not. Using S&P Capital IQ's Global Point-in-Time database, we investigate the importance of reserve and production information provided by oil & gas companies.

May 2012: Case Study: S&P Capital IQ – The Platform for Investment Decisions
Ten years ago, AAPL traded just below $12 and closed at $583.98 on April 30, 2012. That is an average annual return of 48.1% over the period. During this same time the S&P 500 grew at an annual rate of only 2.65%. On April 2nd, Topeka Capital Markets initiated coverage of AAPL with a price target of $1001. If achieved, this would make AAPL the first company to ever reach a $1 trillion market cap. In this case study, we highlight some key S&P Capital IQ functionality in analyzing AAPL hypothetically reaching $1000:

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

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September 2011: Research Brief: Return Correlation and Dispersion - Tough Times for Active Managers

July 2011: Research Briefs- 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

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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