Introducing Capital IQ's Global Fundamental Equity Risk Models

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Global investors invest in assets across multiple countries. In order to characterize the overall risk they need the ability to compute the total risk of their entire holdings. Using a global risk model summarizes the risk across multiple geographies into a more easily consumed single number rather than looking at the risk characteristics in isolation for separate geographies. A single global model also captures inter-country correlations so as to not miss important contagion effects.

Building on the success of Capital IQ's release of our U.S. Fundamental Equity Risk models we use similar building blocks viz. the best of breed point-in-time Capital IQ data, state of the art Alphaworks alpha factor library, GICS global industry classification system and an open and robust risk estimation methodology to construct the Capital IQ Global Fundamental Equity Risk Model.

The rest of the paper will address some of the key issues in building a global equity model. To avoid repetition we refer the readers to our US Risk Model white paper, "Introducing Capital IQ's Fundamental US Equity Risk Models", Scherer/Balachander/Falk/Yen (2010) for a detailed overview of some of the key concepts and testing framework. In this exposition we focus more on some of the additional conceptual and mathematical methodologies necessary to build a truly Global Equity Risk Model.

The paper proceeds as follows: In Section 1 we talk about the model construction methodology. Section 2 discusses the important issue of synchronizing market returns across multiple time zones and market closing times. Section 3 explains the currency model construction. Section 4 delves into model testing and we follow that with our forecast horizon calibration studies in Section 5. We present our final conclusions in Section 6.

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1 Building a Global Fundamental Time Series Risk Model

1.1 Methodology

The global time series model is constructed from the factor series of (i) Market returns (ii) Currency returns (iii) Fundamental style factor returns calculated from our Alphaworks factor library, and (iv) Global GICS industry returns. For market returns we use the countries represented in the S&P-Citigroup Global Broad Market Index (BMI).

We have a total of 45 different local country market returns. From these we construct a world market and 4 regional markets (Europe, Latin America, Pan-Asia Ex Japan, and Middle East & Africa) for a total of 50 market factors. The world and regional markets were obtained by logCap weighting the constituent country markets (expressed in 10M USD). We also utilize 32 currency[1] factors.

Table 1: Regional Constituents from BMI Countries

Region	Countries
Europe	Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden, Denmark, Hungary, Norway, Poland, Sweden, Switzerland, Czech Republic, Russia, UK
Pan Asia (excluding Japan)	China, India, Indonesia, Malaysia, Korea, Philippines, Singapore, Taiwan, Thailand, Hong Kong, New Zealand, Australia
Latin America	Brazil, Chile, Peru, Mexico
Middle East Africa	Israel, Egypt, Morocco, South Africa, Turkey

Let f_{world} represent a time series of total returns of the world market. Also let f_{FX_i}, f_{Rgn_i} and f_{Mkt_i} represent the time series of returns of the corresponding quoted currency, regional market and local market respectively. Then a model of the equity returns r_i for stock i can be specified as in equation (1) below

$$r_i = \beta_{FX_i} f_{FX_i} + \beta_{world} f_{world} + \beta_{Rgn_i} f_{Rgn_i} + \beta_{Mkt_i} f_{Mkt_i} + \sum_{k=1}^{N_{Styles}+N_{Sectors}} \beta_k f_k \quad (1)$$

To get a parsimonious representation, for each stock we use just the corresponding local market, region and local currency.

The final block in the model corresponds to style (of which there are 8 composite factors) and sector (24 global GICS sub-sectors) factors. The 8 composite style factors were constructed by equal weighting the factors within each style group (See Table 2). We estimate the stock exposures to each of the factors in the following stepwise procedure[2]. In the first step the dependent variable is stock returns and in each subsequent step it is the residual of stock returns from the previous step.

1. World Market and FX (jointly)
2. Regional Market
3. Local Market
4. Style Factors
5. Sector Factors

In the first step the independent effects of world market and currency factor are jointly estimated and regressed out of the local currency stock returns. We have a total of 32 currency factors, but for each stock we only apply the currency

[1] Pre-Euro native Euro Zone currencies were replaced by a synthetic Euro
[2] See Appendix for order in which market factors are applied depending on domicile of stock

factor in which the stock is traded. Second, the residual returns series from the previous step are regressed against the returns of the relevant regional market. Third, the residual returns series from step two are regressed against the returns of the local country of domicile returns. Finally, the residual returns from step three are regressed against the Style and then Sector factor returns.

In the order of estimation, it is of note that we compute the market neutral Style factor exposures before we proceed to compute the market and style neutral Sector exposures. This ordering ensures that the loadings on our comprehensive style factors take precedence in the interpretation of portfolio exposures. Nevertheless, the desired order of imposing independence among the factor groups may be different for different managers. For instance, if sector neutrality is a primary concern, we could construct a variation of the model in which sector factors take precedence over style factors. However, in practice, sector neutrality can be achieved and measured by aggregating up issue level sector exposures and associated contributions to risk and return. Additionally, the order of independence does not affect the quality of the risk forecast. Ordering will only change the interpretation of marginal risk contributions (i.e., risk attribution).

A global portfolio manager will typically forecast risk and evaluate performance from a home currency perspective. Our models are currently constructed from a USD investor perspective. However they can be easily converted into any currency perspective of choice by transformations of the matrices which will be supported in the Capital IQ Portfolio Analytics platform (see Connor/Goldberg/Korajczyk (2010) for change in numéraire transformations).

1.2 Data

The US Fundamental Risk Model was specifically designed to take advantage of the state-of-the-art factor construction and data aggregation by drawing on our extensive Alphaworks factor library and proprietary data collection. The model is the first of its kind, to our knowledge, to be entirely built using our in-house Point-In-Time data sources, ensuring the highest level of historical accuracy during backtesting and simulation. We believe the model's style factors better reflect the key building blocks typically used in alpha generation and portfolio construction by managers. They are therefore more relevant for portfolio analysis and risk attribution.

Our model uses eight style factors compiled from the Alphaworks library of more than 130 thoroughly researched individual component signals described in Table 1.

As noted in our prior work, we do not employ macroeconomic data (factors) like inflation, commodity prices, interest rates, or consumption. Macroeconomic variables typically affect groups of stocks (interest rates move banks, consumption moves retail, oil prices moves the oil industry, exchange rates move export stocks, etc.) and hence have little explanatory power once we have included sector and industry effects. In fact out of sample performance typically deteriorates.

Table 2: Style Factor Descriptions from Alphaworks library

Style	# of signal factors	Components
Analyst Expectation	11	- Earnings & Sales Forecast - Earnings Surprise - Analyst Diffusion - Analyst Revision
Capital Efficiency	10	- Return on Equity & Capital - Leverage & Interest Coverage - Issuance & Buybacks
Earnings Quality	25	- Balance Sheet Accruals - Working Capital & Asset Turnover - Capital Expenditure and R&D Intensity - Margins, Payout Ratio
Historical Growth	31	- 1 & 3-year growth of Operating & Free Cash Flow Earnings Margins
Price Momentum	17	- 1, 6, 9 & 12-Month Price Momentum - Technical indicators over various time frames, including MACD, RSI, Slope, 52 Week High/Low
Size	2	- Log of Market Cap. & Sales
Valuation	25	- Reported & Forward Earnings Yield - Dividend Yield - Book to Price - Sales, EBITDA & Cash Flow to Enterprise Value - Inverse PEGY
Volatility	7	- Realized volatility - CAPM Beta - Distance from High to Low (1 & 12 months) - Trading Volume

Each style category is made up from a number of long/short cash neutral signal portfolios. These portfolios are derived from a univariate sort that determines the top 33% of stocks (longs) according to the chosen characteristic and the bottom 33% (shorts). For factor exposures, factor returns, and stock specific risk, the model covers 10,000 global equities that have been or are major index constituents. The data used for the purposes of this paper start in 1995 and end in 2010. Sector returns are calculated at the GICS 2 level. The model is estimated real time with no look-ahead bias.

In keeping with our US Fundamental model we use two years of daily data. At the time of writing, we estimate the risk models monthly. The factor exposures are estimated by using the OLS procedure. The use of daily data is mainly motivated by the fact that risk (unlike return) estimates become increasingly precise as we increase the observation frequency. This allows us to estimate risk models with the required degrees of freedom on shorter time intervals. We simply do not have to include a lot of economically irrelevant history to satisfy our need for data. Equally, it allows us to include more explanatory variables for the same time interval, without having to worry about arriving at noisy estimates.

However, the advantages[3] of using daily data potentially come at a cost. Daily data exhibit autocorrelations, strong time varying volatility as well as spuriously low correlations due to lack of trading day overlap across geographically disparate regions. Since daily data exhibits auto-correlation we use the EWMA (Exponentially Weighted Moving Average) adjusted covariance matrix of factor returns with the NEWEY/WEST adjustment. To deal with the disjoint trading day problem we need to synchronize local market returns. This is dealt with in the next section.

[3] Sometimes it is claimed that daily data allow us daily updates on risk models. This seems not a strong advantage as we could equally use weekly data and update our weekly model every day.

2 Synchronization of Global Returns

Suppose we manage the risks of a global equity portfolio of Japanese, German and US stocks. When the market in Japan closes, the German market has not opened yet and when the German market closes, the US stock market is still open. When the US market finally closes, what will be the value of our portfolio?

It would be naïve to use the market close value of each market. If major negative economic news force the US market to sell off 5% then this information must impact German and Japanese stocks. We will not see this effect in today's prices as both markets are closed, i.e. their accounting values remain stale while their economic value will move. This move is reflected (at the earliest) when the Japanese and German markets open. In the specific example, both markets are likely to sell off the next day (in the absence of additional positive information releases). Hence, considering only daily accounting returns would lead to spuriously low correlations between stock markets because not all day t information is reflected in all day t returns. If unadjusted, risk models will under (over) estimate risk forecasts for long only (long short) portfolios and risk managers will arrive at smaller hedge ratios.

2.1 Methodology

Let R_t denote a $k \times 1$ (k denotes the number of market factors) vector of unsynchronized (close to close) asset returns for day t , measured during different parts of the day. For example, returns for Japan are derived from morning prices when the US market is closed, while returns for the US are calculated from price information at the evening of day t , when the Japanese stock market is closed. These returns are often also called accounting returns and essentially are the directly observable daily returns. Further we assume the entries in R_t are ordered to reflect the closing of markets from eastern to western hemisphere. Our objective is to find the $k \times 1$ vector of synchronized returns R_t^s . Synchronization adjusts accounting returns by subtracting returns arising from information that was available before the market started trading (which caused the jump at the opening to reflect this information) and adding returns arising from information released after the close (which left the returns stale as the market was closed). This leads us to the following formulation:

$$(2) \qquad R_t^s = R_t - E(R_t \mid I_{t-1}) + E(R_{t+1} \mid I_t)$$

Here $E(R_t \mid I_{t-1})$ denotes part of the day t accounting return corresponding to information from the previous day (e.g. a fall in Japanese equities due to information released at day $t-1$ that triggered a fall in US stocks). We need to subtract this term as the price move is wrongly accounted for at day t , while the return has been generated from day $t-1$ information. Equally $E(R_{t+1} \mid I_t)$ is part of the next period's accounting return that is due to information released on day t (e.g. news that drive global stock markets at time t after Japan has closed). We can interpret R_t^s as an estimate of the return of a market as if it were trading throughout the day (from the opening of markets in Japan to the close of markets in the US), i.e. contain all information released on day t . In reality, this built-in predictability cannot be traded on. It simply tells us where we can expect e.g. the Japanese market to open after we have observed all market closes on the previous day (and no further market relevant information is released between the time US closes and Japan reopens).

While these terms are only expectations and the true return adjustments are unknown (i.e. there is noise around this estimate), econometric modeling helps us to ensure its unbiasedness, i.e. that returns contain all information they are conditioned on. Burns/Engle/Mezrich (1998) wrote the first and still the most influential paper to address the issue of data synchronization. They assume accounting returns follow a first order vector moving average process or VMA-1

$$(3) \qquad R_t = \varepsilon_t + M\varepsilon_{t-1}, \text{ where } \quad \varepsilon_t \sim N(0, \Sigma)$$

where M is the $k \times k$ moving average matrix and Σ is the $k \times k$ residual covariance matrix. We now need to take expectations on (3) conditioned on time t and time $t-1$ information to express (2) in terms of the process assumption (3) and find an analytical expression for synchronized returns.

$$
\text{(4)} \qquad
\begin{aligned}
R_t &= R_t - E(R_t \mid I_{t-1}) + E(R_{t+1} \mid I_t) \\
&= R_t - E(\varepsilon_t + M\varepsilon_{t-1} \mid I_{t-1}) + E(\varepsilon_{t+1} + M\varepsilon_t \mid I_t) \\
&= R_t - M\varepsilon_{t-1} + M\varepsilon_t \\
&= \varepsilon_t + M\varepsilon_{t-1} - M\varepsilon_{t-1} + M\varepsilon_t \\
&= M\varepsilon_t + \varepsilon_t
\end{aligned}
$$

We can now calculate the covariance matrix of synchronized returns like any covariance matrix from

$$
\text{(5)} \quad \Omega^s = \frac{1}{n}\Sigma_{t=1}^{n}(R_t^s - \overline{R}_t^s)(R_t^s - \overline{R}_t^s)^T
$$

where $\overline{R}_t^s = \frac{1}{n}\Sigma_{t=1}^{n} R_t^s$. One possibility to reduce the number of parameters that need estimation in (3) and hence reduce the possibility of noisy estimates invalidating the practical implementation is to impose constraints on M guided by economic priors. Assuming market efficiency, the diagonal elements as well as the below diagonal returns of M (reflecting auto- and autocross- correlation of non-overlapping accounting returns) should be zero.

Given that VMA-1 models are not trivial to estimate as they usually involve estimation of state space models, a simpler alternative to model conditional expectations is to assume a first order vector autoregressive model or VAR-1 for accounting returns.

$$
\text{(6)} \qquad R_t = AR_{t-1} + \nu_t, \text{where} \quad \nu_t \sim N(0, \Delta)
$$

where A denotes the $k \times k$ matrix of first order autoregressive coefficients and Δ describes the residual covariance matrix. Taking conditional expectation on (6) and substituting in (2) yields an analytical expression for synchronized returns under a VAR-1 model.

$$
\text{(7)} \qquad
\begin{aligned}
R^s{}_t &= R_t - E(R_t \mid I_{t-1}) + E(R_{t+1} \mid I_t) \\
&= R_t - E(AR_{t-1} + \upsilon_t \mid I_{t-1}) + E(AR_t + \upsilon_{t+1} \mid I_t) \\
&= R_t - AR_{t-1} + AR_t \\
&= R_t + A(R_t - R_{t-1})
\end{aligned}
$$

To reduce the number of estimated coefficients we can again impose economic structure on A. Suppose we model synchronized returns for Japan, Germany and the US such that our vector of accounting returns is given by $R_t^T = [R_{t,JAP} \; R_{t,GER} \; R_{t,USA}]$. Further assume A to contain zero entries on and below the main diagonal. Again, this assumes that none of the markets exhibit predictability as there is neither first order autocorrelation (today's accounting returns are predictable by an asset's own past accounting returns) nor is there cross-autocorrelation. The latter means that Japanese day t returns (as calculated from the morning's close in Japan at time $t-1$ to time t) cannot predict German time $t+1$ returns (as calculated from the afternoon close in Germany at time t to time $t+1$. More formally we would rewrite (7) as (8) which is the final model we use for synchronizing local market returns.

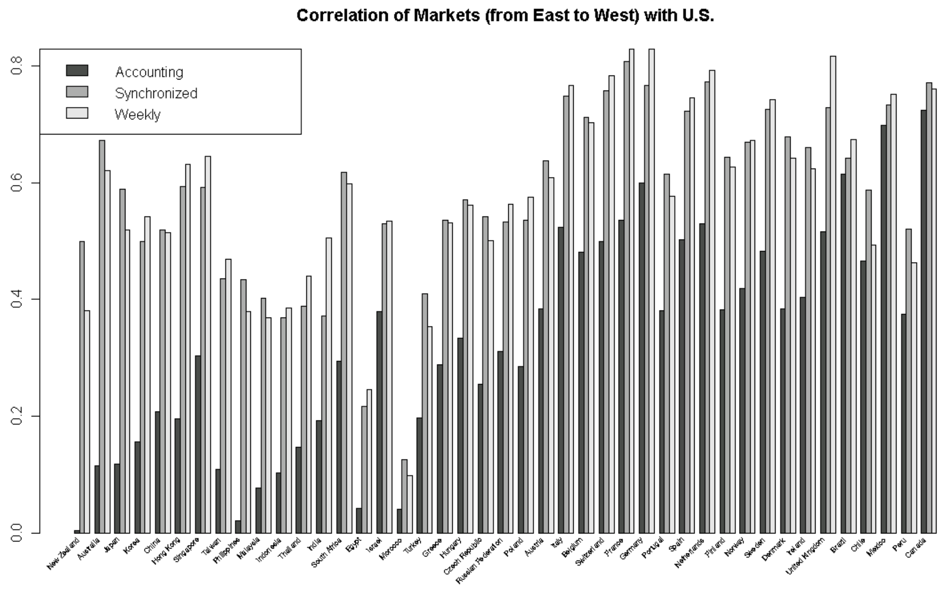
$$
\text{(8)} \qquad
\begin{bmatrix} R^s{}_{t,JAP} \\ R^s{}_{t,GER} \\ R^s{}_{t,USA} \end{bmatrix}
=
\begin{bmatrix} R_{t,JAP} \\ R_{t,GER} \\ R_{t,USA} \end{bmatrix}
+
\begin{bmatrix} 0 & a_{JAP,GER} & a_{JAP,USA} \\ 0 & 0 & a_{GER,USA} \\ 0 & 0 & 0 \end{bmatrix}
\left(
\begin{bmatrix} R_{t,JAP} \\ R_{t,GER} \\ R_{t,USA} \end{bmatrix}
-
\begin{bmatrix} R_{t-1,JAP} \\ R_{t-1,GER} \\ R_{t-1,USA} \end{bmatrix}
\right)
$$

2.2 Synchronization Effect

We compute the correlation of the local markets with respect to the US market using daily accounting returns over the about the last 10 years from 2000 through 2011. Figure 1 shows the correlation structure of the local market returns with respect to the US market returns (returns based on BMI constituents). The countries are roughly arranged according to the time of their market close from East to West. The black bars in the figure are much lower for Eastern economies (showing a low accounting correlation with US market returns) compared to the white bars (correlation with weekly returns). Weekly correlations are closer to the true market correlations as market open/closing effects are mitigated over a 5 business-day span.

Figure 1: Effect of Market Synchronization

Correlation of global markets with the US market using Accounting (unadjusted), Synchronized and Weekly data. Accounting and Synchronized data are at daily frequency.



Then we use the model explained in (8) across all 45 local markets (arranging them in the order of market close) to synchronize the returns. However, instead of modeling returns against all local markets, and in order to reduce the number of free parameters to estimate, we only use the following 16 large geographically apart countries (ordered East to West):

$$CountryBaseSet \in$$ {Australia, Japan, Korea, Taiwan, Singapore, Hong Kong, India, South Africa, Finland, Poland, Switzerland, Germany, United Kingdom, Brazil, Mexico, United States}

The grey bars show the correlation of the local markets with respect to the US market after synchronization – as can be seen they are much more in line with the actual correlation as measured by the correlation of weekly returns (white bars). This shows that, in sample, the synchronization correction performs well at correcting the understated accounting correlations.

2.3 Testing the Synchronization Method

The results in previous section demonstrated the effect of synchronizing by looking at the correlation before and after synchronization. However one can design a more direct test to show the effect of synchronization. Keeping in mind that the end-goal of the synchronization is to provide better risk forecasts for an investor holding a global portfolio, we consider a Model portfolio constructed as an equal weighted combination of the local market returns. For simplicity we use a portfolio constructed by equal weighting each local market of the *CountryBaseSet* defined above.

Then for the portfolio we can consider the risk computed from the accounting returns and that from the synchronized returns. If the market synchronization is beneficial then we would expect that the portfolio risk computed after the synchronization adjustment would be closer to the true risk of the portfolio.

For the computation of Model Risk (as implied by the risk model) of a portfolio constructed from different local markets, we use the following procedure: We compute the local market variance-covariance matrix C from market returns using an exponentially weighted moving average method with and without NEWEY-WEST correction for serial correlation. Then the portfolio constructed by using a weight vector w on the local markets will have a Model Risk wCw'.

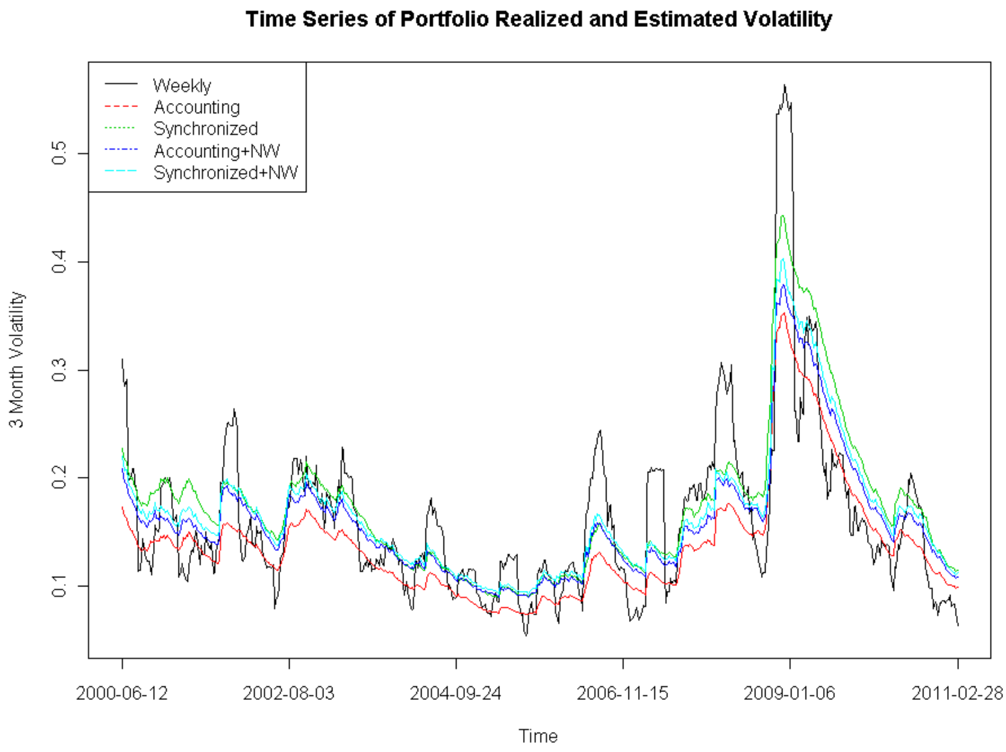
As a benchmark, we expect that the risk computed using weekly realized returns is a good proxy for the true realized risk of the portfolio. Thus, on a rolling basis, we compute the weekly realized risk over a 60-day rolling window from realized weekly returns. The realized risk is then compared to the synchronized and unsynchronized Model Risk estimated using daily returns over the same 60-day window. Again, we'd expect that the synchronized Model Risk estimates would be closer to the true realized risk than the unsynchronized estimates.

Table 3 below presents the MSE (Mean Squared Error) and MAE (Mean Absolute Error) of the true realized risk based on weekly returns vs. the four different ways of estimating Model Risk. We can see that the Model Risk after synchronization is closer (i.e. smaller error numbers) to true realized risk. Adding the Newey-West auto-correlation adjustment further improves the Model Risk estimates marginally. Figure 2 gives a plot of the Model Risk estimates and true volatility time series.

Table 3: Synchronization Results with Model Portfolio constructed using equal weighted local market portfolio of Country Base Set. MSE and MAE represent the in-sample Model Risk tracking error against the true realized risk based on 3 months of weekly returns.

Synchronization	NEWEY-WEST Correction	MSE (in %)	MAE (in %)
No	No	5.53%	3.87%
No	Yes	4.87%	3.75%
Yes	No	4.70%	3.46%
Yes	Yes	4.65%	3.51%

Figure 2: Rolling Model Risk estimate vs. true realized risk (annualized) of equal weighted local market portfolio using accounting (unsynchronized) and synchronized returns series with and without Newey-West serial correlation correction.



Since we are comparing the synchronized and unsynchronized returns by assuming weekly returns as the truth, a valid question would be "Why bother with daily data at all if it has these synchronization issues?" We see at least two reasons for using daily data – (i) using daily data over aggregated weekly data increases the number of data points (e.g. in one year we have 250 days as opposed to only 52 weeks) which leads to a reduction in estimation error of parameters and (ii) using daily data allows us to be more reactive to more recent sustained events in the market.

We refer the interested reader to Scherer (2011) for a more elaborate set of case studies presented to address the synchronization issues.

3 Global Currency Factor Model

The effects of currency risk can manifest itself in portfolio risk in one of two ways.

- An international investor holding a foreign stock exposes herself to an explicit currency risk. We can model the returns of a foreign (say Japanese) stock i for a USD based investor $r_i^{\$Y}$ as follows:

  $$r_i^{\$Y} \approx r_i^{Y} + r_c^{\$Y}$$

  i.e. the returns can be broken down as the sum of local returns of the stock r_i^{Y} and the FX returns $r_c^{\$Y}$. By investing in a foreign stock, an investor is effectively long the foreign currency and short the home currency (see Connor/Goldberg/Korajczyk (2010)). Hence, the investor stands to gain as the local currency appreciates against the USD. We call this effect "translation risk".

- However, there is potentially another fashion in which exchange rates affect a company's returns. Consider a Japanese car manufacturer such as Toyota. If the Yen strengthens then Japanese cars become more expensive and, all else being equal, may lose global market share. Thus a USD based investor in Toyota would be affected by this second order effect of the Yen's exchange rate. We call this type of influence as "economic risk".

The model in equation (1) captures the second effect above. The first effect is explicitly modeled as a FX exposure for each stock to local currency of 1 and by including a currency block in the factor covariance matrix. Thus the overall factor covariance matrix can be expressed as

$$(9) \quad C = \begin{pmatrix} C_{f,f} & C_{c,f} \\ C_{c,f} & C_{c,c} \end{pmatrix}$$

Where, $C_{c,f}$ is the cross-covariance between the currencies and other non-currency factors. The own-covariance within the currency factors and other factors are $C_{c,c}$ and $C_{f,f}$ respectively.

3.1 Computing Currency Covariance

Currency covariance estimation from historical currency returns needs to be carefully constructed. They can be can be impacted by noise in currency returns and especially the non-currency/currency factor cross-covariance can be affected by spurious estimates. Considering these challenges we propose a PCA based noise reduction technique and compare that with three other more traditional factor covariance modeling approaches:

1. The first (EWMA) approach is to use a simple Exponential Weighted Moving Average based model.

2. The second (EWNW) uses the same EWMA approach but includes a Newey-West auto-correlation correction.

3. The third approach (GARCH) employs GARCH models for measuring the diagonal terms for the covariance matrix. GARCH models are known to handle volatility clustering problems and are used to estimate currency variances. The off-diagonal covariances are estimated using the EWNW approach.

4. The fourth approach ("PCA FactorCut") employs a currency factor model coupled with a Principal Component Analysis (PCA) based filtering approach. We posit that all currency returns can be explained by a lower dimensional basis of certain base set of currencies. Any variations orthogonal to this subspace are considered as noise. The dimensionality of the PC subspace was chosen to capture a percentage of the total variance. Formally, let S_t be the $T \times c$ matrix of c currency returns across T time periods that we are modeling and $S_t^B = [S_t^1, S_t^2, ..., S_t^b]$ be the $T \times b$ matrix of returns for a set of b base currencies where $S_t^B \subset S_t$.

   We chose the following currencies to be in the currency base set:

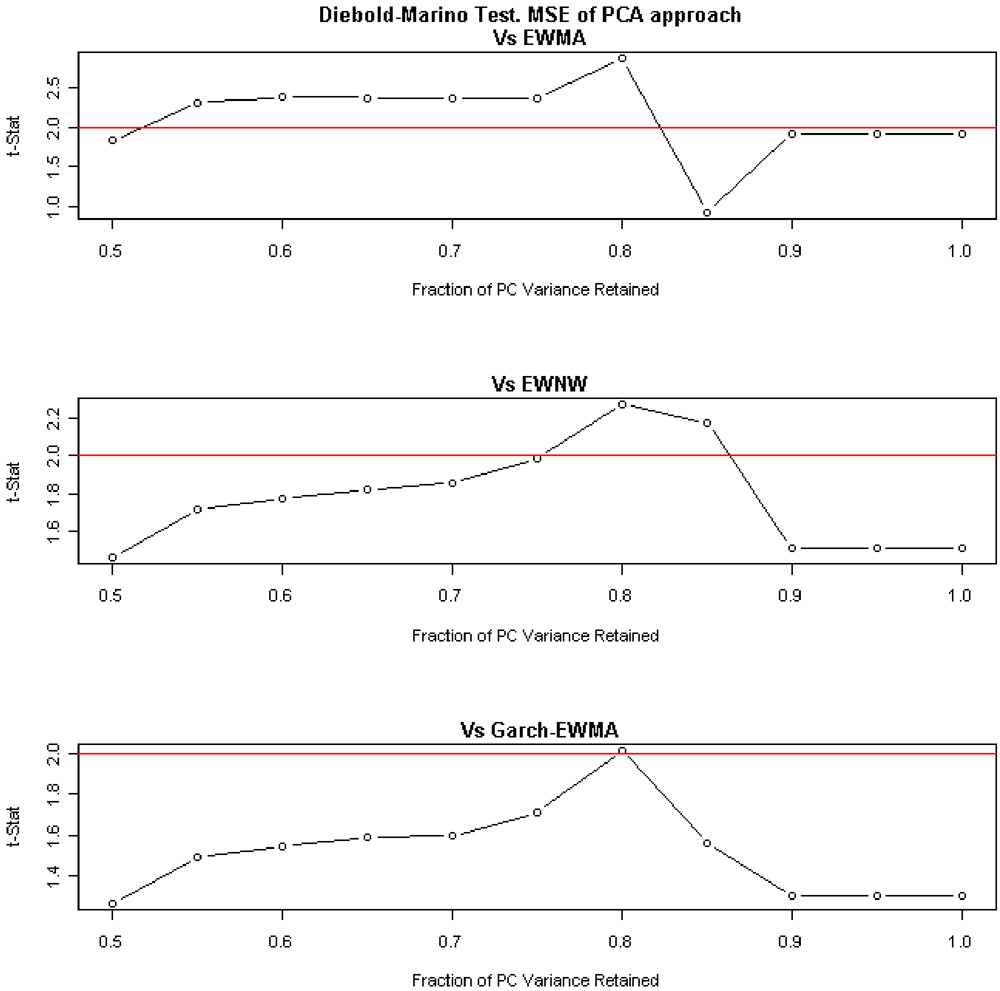
   $CurrencyBaseSet \in$ *{Australia, Brazil, Euro, Japan, Korea, Mexico, Switzerland, Taiwan, United Kingdom, United States}*

   Then we choose a subspace U_t^k spanned by the k principal components of S_t^B such that if λ_i is the eigenvalue associated with the i-th principal component then $\sum_{i=1}^{k} \lambda_i^2 / \sum_{i=1}^{b} \lambda_i^2 > var_{thresh}$. Essentially we retain var_{thresh} fraction of the total variance in the base currency set.

   The exposure of each currency to principal component set U_t^k is estimated by OLS. The model specification is $S_t = BU_t^k + E$, where B is the matrix of currency exposures and E is the uncorrelated idiosyncratic error. The currency covariance matrix can then be computed as $C = Cov(S_t) = E(S_t^T S_t) = B^T B + E^T E$ i.e. the sum of systematic and specific risk related terms. To calculate the non-currency/currency factor cross-covariance block, we only use the systematic part of the currency model.

To test the models we compared predicted and realized risk of the above four models for an equal weighted global currency-only basket (of all the currencies in our model).

Figure 3: Diebold-Mariano average t-stat of 1-month risk prediction for model currency portfolio, from Feb 2000 through Feb 2011. Comparisons of different models against a PCA based noise filtering approach for different fraction of PC variances retained shows that PCA generally outperforms and an 80% cutoff in PC variances retained does well.

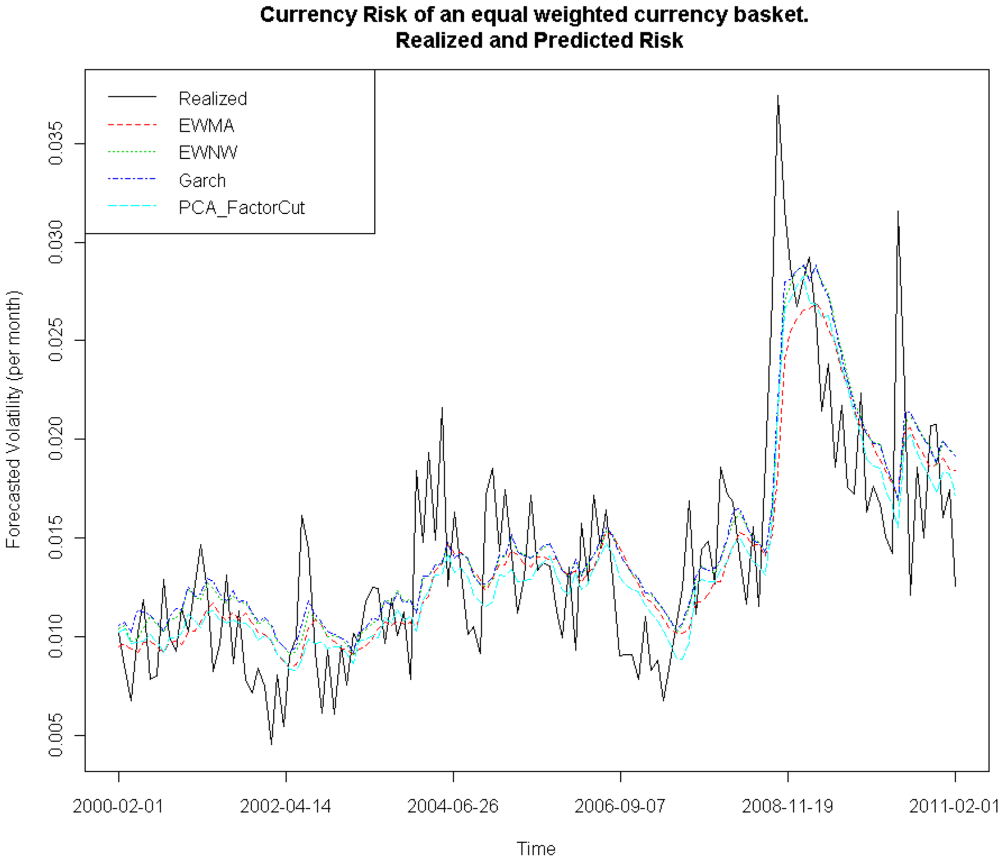


The Diebold-Mariano ("DM") test with HAC (Heteroskedasticity and Autocorrelation Consistent) correction results above shows that the PCA model with 80% retained variance performs the best among the competing models. Figure 4 below shows a time series plot of the realized and predicted risk results of the winning PCA model and the competing models. The realized risk is computed over a forward looking 1 month time window and shows that the currency risk is tracked well over the 11 year test period from Feb-2000 through Feb-2011.

Figure 4: Currency Portfolio Realized and Predicted Risk. Note our "PCA FactorCut" Model does well in capturing currency risk

Our "PCA FactorCut" Model does well in capturing currency risk

This model serves as the basis of our global risk model



3.2 A Comment on ADR & GDR Handling

American Depository Receipts (ADR), Global Depositary Receipts (GDR) and other cross listings are special instruments that are typically denominated in the currency of the exchange country but with the issuer being based or having significant business activity in a country other than the country of the exchange where the issue is quoted. In these cases, the issue is treated as having country exposure to its home country but currency exposure to the exchange country currency. Arguably the economic risk currency exposure is more related to the home country currency than the exchange country currency but the translation risk currency exposure is driven by the exchange country currency and that is where the majority of portfolio exposure is concentrated.

4 Risk Model Testing

We evaluate the performance of our global risk models on a set of 27 benchmark portfolios. The benchmarks were carefully chosen to include broad global portfolios that include stocks from across multiple regions and also regionally focused portfolios. In the table below the "Standard" Group consists of MSCI portfolios which have start dates in early 2004. To include test portfolios over which we can evaluate our risk models which start in 1997, we specially constructed the "Test" Group of portfolios which have history from 1997 through Jan 2011. We also included an ADR-only portfolio to test performance for the important case of ADRs and GDRs. For the purposes of testing, all portfolios have history through Jan 2011.

Table 4: Global Test Portfolios

	PORTFOLIO	Group
1	All Countries (AC) Americas	Standard
2	AC Asia	Standard
3	AC EU	Standard
4	AC Far East	Standard
5	AC Pacific	Standard
6	AC World	Standard
7	Developed Markets (DM) EAFE	Standard
8	DM EMU	Standard
9	DM Europe	Standard
10	DM Far East	Standard
11	DM Nordic Countries	Standard
12	DM North America	Standard
13	DM Pacific	Standard
14	DM The World	Standard
15	Emerging Markets (EM) Asia	Standard
16	EM BRIC	Standard
17	EM Europe	Standard
18	EM Far East	Standard
19	EM Latin America	Standard
20	EM	Standard
21	Test Portf – USA	Test
22	Test Portf – Asia Ex Japan	Test
23	Test Portf – Rest of World	Test
24	Test Portf – EM	Test
25	Test Portf – Europe	Test
26	Test Portf – Japan	Test
27	Test Portf – ADR	ADR

Table 5: Model Variations
The models are constructed using 2 years of rolling historical daily data. All models have a Factor correlation Half Life and a Factor Variance Half Life of 240 and 60 days respectively. The differences between the models are noted within the columns.

Model	Factor Returns Construction	Currency Valuation Effect	Synchronization of Local Markets	Regional/World Returns computation
BASE	BMI. Log Wtd Q1-Q3	Y	None	Wtd Local Market Accounting Returns
M1	Same as above	N	None	Same as above
M2	Same as above	N	Yes	Same as above
M3	Same as above	N	Yes	Wtd Local Market Synch Returns
M4	Same as above	N	Yes	Wtd Local Market Synch Returns. Synch stock returns by simple imputation before exposure estimation
M5	Same as above	Y	Yes	Wtd Local Market Accounting Returns
M6	BMI pruned to 3K names based on MktCap and Liquidity. LogCap Wtd Q1-Q3	Y	Yes	Same as above
M7	BMI pruned to 3K names based on MktCap and Liquidity. Eq Wtd Q1-Q3 Styles. LogCap Wtd Q1-Q3 Industries	Y	Yes	Same as above
M8	BMI pruned to 3K names based on MktCap and Liquidity. Eq Wtd Q1-Q3 Styles & Industries	Y	Yes	Same as above

To test the performance of the above models we use the time series of returns of the test portfolios expressed in local currencies. In other words, we assume fully currency hedged portfolio risk and returns. Thus both the forecast and realized risk computed using these return series will ignore the currency risk effect. This is done to decouple the effect of the non-currency piece of the risk factor model and the currency risk factor model component.

A note on implementing the synchronization methodology is in order: We employed the method outlined earlier in Section 2.1 for synchronizing market returns. We tested two different ways of extending the market synchronization methodology to stock level synchronization: (i) a simple imputation procedure (used in M4) i.e. we add a correction to each stock return equal to the difference between the accounting and synchronized return of its corresponding local market and (ii) as an approximation (used in M2, M3, and M5 through M8) we use the accounting local market returns for the stock exposure estimation but use the synchronized market returns for the factor covariance estimation.

The table below captures the performance of the models expressed as average DM-test t-statistic across all the test portfolios (with MSE and MAE loss functions). The DM test requires us to specify a competing model and all results presented below used the BASE model specification as the competing model. The true out of sample realized risk is computed as the volatility of weekly returns over a 3 month window. Likewise, the risk model is calibrated to predict risk over a 3 month forecast horizon. As per Table 6, the best performing model is M5 and we chose that as our final model.

Table 6: Avg DM statistics of Models on Fully Hedged Test Portfolios compared to BASE model.

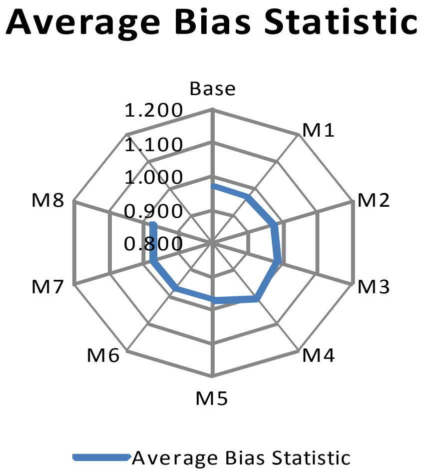
Model	All		StdPF		Test		ADR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
M1	-0.042	0.067	-0.228	-0.083	0.610	0.591	0.000	0.000
M2	0.276	0.521	0.182	0.470	0.428	0.494	1.337	1.751
M3	-0.186	-0.226	-0.175	-0.157	-0.016	-0.111	-1.427	-2.365
M4	0.107	-0.022	0.099	0.035	0.384	0.105	-1.370	-1.980
M5	0.638	0.743	0.828	0.875	0.022	0.375	0.352	0.194
M6	-0.233	-0.329	-0.298	-0.379	0.144	-0.111	-1.133	-0.582
M7	-0.244	-0.380	-0.315	-0.434	0.114	-0.182	-0.892	-0.429
M8	-0.339	-0.498	-0.314	-0.444	-0.277	-0.650	-1.246	-0.724

Figure 5 shows a plot of the average bias statistic across all test portfolios for each of the models considered. The best model based on this alone is M4. However M5 performs better with the DM test and its overall bias statistic of 0.98 is well within the 95% confidence interval around the expected bias statistic value of 1.

Figure 5: Model Bias Statistics averaged across all Test Portfolios

Bias Statistic Test result close to 1.0 shows good risk model performance

Reinforces the model choice made based on DM Test



Now that we have identified the best performing individual non-currency factor model (M5) and currency factor model (PCA FactorCut) we would like to evaluate the performance of the final coupled model (M5+PCA_FactorCut). We evaluate this model by comparing against all the realized returns of the test portfolios expressed in USD. Thus this measures how well we perform in predicting portfolio risk, including the currency risk, from a USD based investor perspective.

Again, we use the DM test to compare the performance of the M5+PCA_FactorCut model against the M5+EWNW model. As can be seen from Table 7, the individually best performing factor and currency models when coupled together give improved performance. The results are in line with the expected results from Figure 3 where we measure the currency model performance in isolation on a currency basket portfolio.

Table 7: DM Test on test portfolios from an USD perspective.

	All		StdPF		Test		ADR	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
M5 + PCA_FactorCut	0.770	1.135	0.862	1.185	0.646	0.968	-0.412	1.093

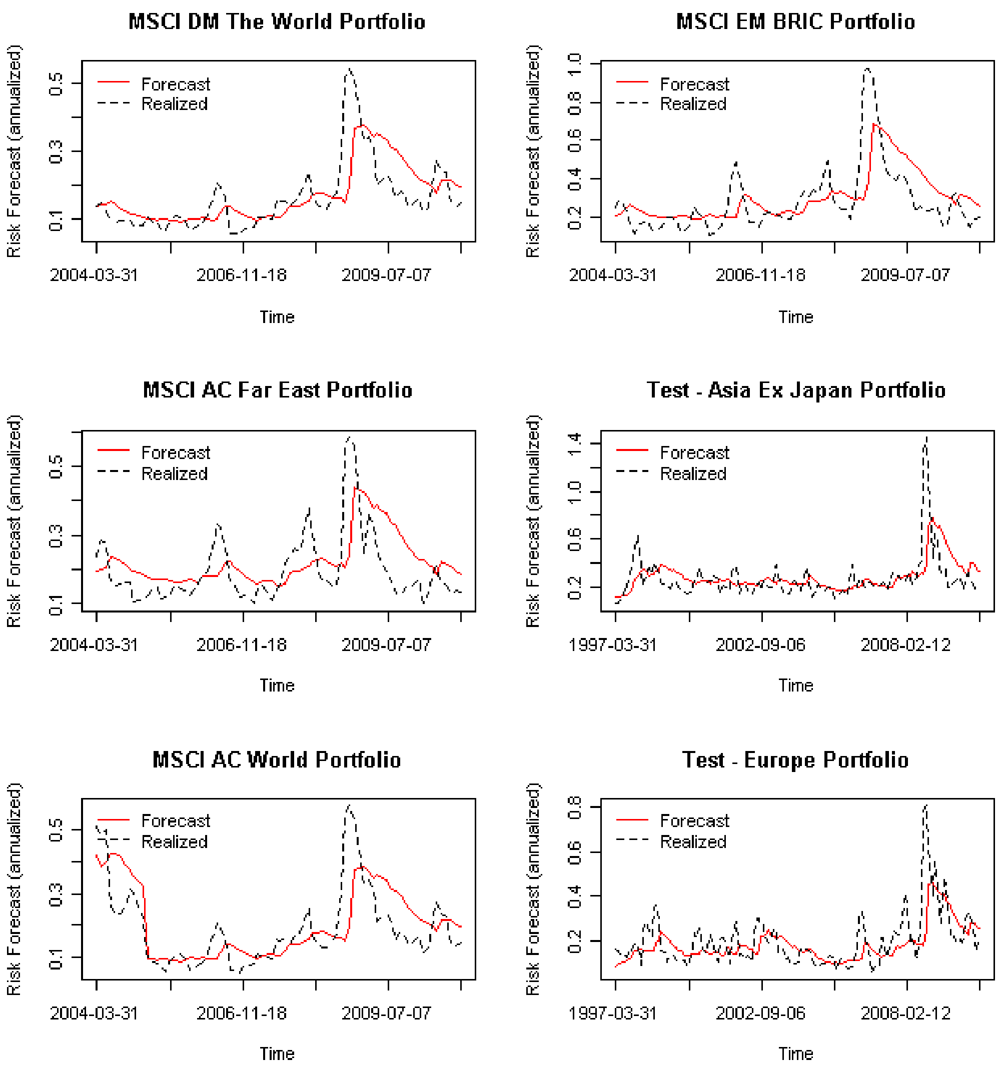
The numbers indicate that the M5+PCA_FactorCut combination of factor and currency model performs better than the M5 +EWNW combination model.

Figure 6 below shows time series plots of the forecast and realized risk of some of the sample portfolios using our final model.

Figure 6: Plot of portfolio Forecast and Realized across a few sample test portfolios.

Risk model predicts portfolio risk well.

We react quickly to capture risk during sub-prime crisis.



5 Risk Model Calibration

Finally we try to calibrate the variance and correlation half-lives for the purpose of addressing different investment horizons. Since the half-life of the factor variance terms has a large impact on risk performance, we consider 5 different half lives of 30, 60, 90, 120 and 240 days and evaluate the risk performance across 3, 6, 9 and 12 month forecast horizons.

The realized volatility is measured by aggregating to weekly returns over these holding periods. We present the improvement in DM test statistic for each forecast horizon compared to the 30-day half life scenario. As indicated in green, the 30-day half life outperforms across all forecast horizons. However, as a shorter half life may result in higher turnover (if reacted to), we will still make available a Medium Term Model (with correlation and volatility half lives of 240 and 60 days respectively) and addition to a Short Term Model (with correlation and volatility half lives of 180 and 30 days respectively). These half lives are in keeping with our US models.

Average DM improvement of Models for different Variance Half Lives across multiple forecast horizons.

Half Life of 30 days performs well across 3, 6, 9 and 12 month horizons.

Table 8: Model Half Life Calibration

Improvement in Median MSE for DM Test (across all portfolios)		**Forecast Horizon (Months)**			
		3	**6**	**9**	**12**
Variance Half Life (days)	**30**	0.00	0.00	0.00	0.00
	60	-0.32	-0.26	-0.20	-0.13
	90	-0.52	-0.41	-0.30	-0.18
	120	-0.66	-0.50	-0.36	-0.18
	240	-0.98	-0.70	-0.45	-0.12

6 Summary

In this paper we have outlined the technical challenges in building a global risk model – including asynchronous daily returns, currency modeling, ADR handling – and described our solutions. We have integrated these techniques and tested the resulting model candidates out of sample. In picking the best performing model, we have documented what we believe to be best practices for building a truly global equity risk model.

Our model is the first of its kind, to our knowledge, to be entirely built using Global Point-In-Time data sources, ensuring the highest level of historical accuracy during backtesting and simulation. We also believe the model's style factors better reflect the key building blocks typically used in alpha generation and portfolio construction. They should therefore be more relevant for portfolio analysis, risk attribution and portfolio optimization.

The final litmus test, however, is the out of sample performance of our model forecasts. In a real time learning exercise (only data up to time t are used to forecast risks from t to t+1) we show that our models can be easily calibrated to different time horizons and provide unbiased forecasts of realized portfolio risks across a broad range of test portfolios. We also show that calibration matters, using the DM test to find the best model version among a set of unbiased models.

For more information on the Capital IQ Equity Risk Models please contact Ruben Falk at rfalk@capitaliq.com

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Appendix

Table showing order in which region/country exposures are determined after World returns depending on domicile of stock.

Country	First	Second
Albania	Region European	
Antigua and Barbuda	Country United States	
Argentina	Region LatinAmerica	
Australia	Region PanAsiaExJapan	Country Australia
Austria	Region European	Country Austria
Bahamas	Country United States	
Bahrain	Region MiddleEastAfrica	
Bangladesh	Region PanAsiaExJapan	
Barbados	Country United States	
Belgium	Region European	Country Belgium
Belize	Country United States	
Bermuda	Country United States	
Bolivia, Plurinational State of	Region LatinAmerica	
Bosnia and Herzegovina	Region European	
Botswana	Region MiddleEastAfrica	
Brazil	Region LatinAmerica	Country Brazil
Bulgaria	Region European	
Cameroon	Region MiddleEastAfrica	
Canada	Country Canada	
Cayman Islands	Country United States	
Chile	Region LatinAmerica	Country Chile
Czech Republic	Region European	Country Czech Republic
Denmark	Region European	Country Denmark
Dominican Republic	Region LatinAmerica	
Ecuador	Region LatinAmerica	
Egypt	Region MiddleEastAfrica	Country Egypt
El Salvador	Region LatinAmerica	
Estonia	Region European	
Falkland Islands (Malvinas)	Region European	
Faroe Islands	Region European	
Finland	Region European	Country Finland
France	Region European	Country France
Gabon	Region MiddleEastAfrica	
Georgia	Region European	
Germany	Region European	Country Germany
Ghana	Region MiddleEastAfrica	
Gibraltar	Region European	
Greece	Region European	Country Greece
Greenland	Region European	
Hong Kong	Region PanAsiaExJapan	Country Hong Kong
Hungary	Region European	Country Hungary

Iceland	Region European	
India	Region PanAsiaExJapan	Country India
Indonesia	Region PanAsiaExJapan	Country Indonesia
Iran, Islamic Republic of	Region MiddleEastAfrica	
Ireland	Region European	Country Ireland
Israel	Region MiddleEastAfrica	Country Israel
Italy	Region European	Country Italy
Jamaica	Country United States	
Japan	Region PanAsiaExJapan	Country Japan
Jersey	Region European	
Jordan	Region MiddleEastAfrica	
Kazakhstan	Region European	
Kenya	Region MiddleEastAfrica	
Korea, Republic of	Region PanAsiaExJapan	Country Korea
Kuwait	Region MiddleEastAfrica	
Latvia	Region European	
Lebanon	Region MiddleEastAfrica	
Liechtenstein	Region European	
Lithuania	Region European	
Luxembourg	Region European	Country Luxembourg
Macao	Region PanAsiaExJapan	
Macedonia, the former Yugoslav Republic of	Region European	
Malaysia	Region PanAsiaExJapan	Country Malaysia
Malta	Region European	
Marshall Islands	Country United States	
Mauritius	Region MiddleEastAfrica	
Mexico	Region LatinAmerica	Country Mexico
Monaco	Region European	
Morocco	Region MiddleEastAfrica	Country Morocco
Namibia	Region MiddleEastAfrica	
Netherlands	Region European	Country Netherlands
Netherlands Antilles	Region European	
New Zealand	Region PanAsiaExJapan	Country New Zealand
Nigeria	Region MiddleEastAfrica	
Norway	Region European	Country Norway
Oman	Region MiddleEastAfrica	
Pakistan	Region PanAsiaExJapan	
Panama	Region LatinAmerica	
Papua New Guinea	Region PanAsiaExJapan	
Peru	Region LatinAmerica	Country Peru
Philippines	Region PanAsiaExJapan	Country Philippines
Poland	Region European	Country Poland
Portugal	Region European	Country Portugal
Puerto Rico	Country United States	
Qatar	Region MiddleEastAfrica	
Romania	Region European	

Russian Federation	Region European	Country Russian Federation
Saudi Arabia	Region MiddleEastAfrica	
Senegal	Region MiddleEastAfrica	
Serbia	Region European	
Singapore	Region PanAsiaExJapan	Country Singapore
Slovakia	Region European	
Slovenia	Region European	
Solomon Islands	Region PanAsiaExJapan	
South Africa	Region MiddleEastAfrica	Country South Africa
Spain	Region European	Country Spain
Sri Lanka	Region PanAsiaExJapan	
Sudan	Region MiddleEastAfrica	
Sweden	Region European	Country Sweden
Switzerland	Region European	Country Switzerland
Taiwan, Province of China	Region PanAsiaExJapan	Country Taiwan
Thailand	Region PanAsiaExJapan	Country Thailand
Trinidad and Tobago	Country United States	
Tunisia	Region MiddleEastAfrica	
Turkey	Region European	Country Turkey
Ukraine	Region European	
United Arab Emirates	Region MiddleEastAfrica	
United Kingdom	Region European	Country United Kingdom
United States	Country United States	
Uruguay	Region LatinAmerica	
Venezuela, Bolivarian Republic of	Region LatinAmerica	
Viet Nam	Region PanAsiaExJapan	
Virgin Islands, British	Region European	
Virgin Islands, U.S.	Country United States	
Zambia	Region MiddleEastAfrica	
Zimbabwe	Region MiddleEastAfrica	

OUR RECENT RESEARCH

May 2011: Topical Papers That Caught Our Interest:
Favorite Papers on a Few Favorite Topics – Regime Switching and Minimum Variance
Two current topics of significant interest and frequent discussion to investors are regime switching, or a strategy's sensitivity to the current environment, and minimum variance portfolios.

April 2011 – Can Dividend Policy Changes Yield Alpha?
In this paper, we analyze the market reaction to different types of dividend policy changes, specifically initiation, increase, decrease and suspension of dividends.

Investors are acutely sensitive to changes in dividend policy. Literature suggests that dividend change announcements provide information about management's assessment of companies' prospects, and therefore are predictive of future stock returns. The implication for investors is worth noting. In the first quarter of 2011 alone, 105 of the 384 dividend paying S&P 500 companies (27.3%) increased their dividends, while only 1 (0.26%) decreased dividends.

April 2011: CQA Spring 2011 Conference Notes
Several of our team's members attended the Chicago Quantitative Alliance (CQA) Spring Seminar in Las Vegas. We present our collective notes from the conference in this report.

March 2011: How Much Alpha is in Preliminary Data?
Companies often report financials twice: first, through a preliminary press release and again in their official, i.e., final, SEC filings. In theory, there should be no difference between the numbers reported in a company's preliminary financial filings and their final filings with the SEC. In practice, often significant difference can occur between the preliminary and final filings. In this month's research report, we focus on these observed differences within the Capital IQ Point-In-Time database in order to ascertain the nature and exploitability of these differences.

February 2011: Industry Insights – Biotechnology: FDA Approval Catalyst Strategy
Biotechnology is a challenging sector for investors due to the binary nature of the product cycle. Indeed many biotechnology firms' futures rest upon the success of a single product. A critical stage in the product life-cycle is the FDA approval process. In this report we look at the exploitability of a strategy centered on FDA filings.

January 2011: US Stock Selection Models Introduction
In this report, we launch our four US Stock Selection models -- Value, Growth, Quality, and Price Momentum. Built using Capital IQ's robust data and analytics, these four models are the culmination of over two years of research and development. Each model is intended to be employed as the basis for a stand-alone stock selection strategy or integrated into an existing systematic process as an overlay or new component.

January 2011: Variations on Minimum Variance
Various explanations for why risk is mispriced have been offered; the most common one is that leverage restrictions incite some investors to chase volatility at the individual issue level. In this paper, we explore various methodologies for construction of minimum variance portfolios of US listed equities and analyze the features of these portfolios.

January 2011: Interesting and Influential Papers We Read in 2010
As researchers, we spend a large amount of time trying to generate new ideas. In order to discover and refine these ideas, we find ourselves in a continuous quest for innovative and interesting articles and papers from academics, analysts, and other researchers. There is such a large body of information out there that it can be difficult to wade through all the material to find what is truly of value and interest to us. To assist in sifting through all this information, our group recently took the time to find and discuss articles that recently struck us.

November 2010: Is your Bank Under Stress? Introducing our Dynamic Bank Model
Leveraging Capital IQ's Bank industry data, we have built a stock selection model that encompasses three themes -- Momentum, Value, and Balance Sheet Quality -- and includes a proprietary Markov-regime switching component which dynamically changes the model's weights depending on whether or not banks are in a "stressful" (or crisis) environment. This month, we will review how we built our model and its switching component.

October 2010: Getting the Most from Point-in-Time Data
In this paper, we will examine PIT data's origins, structure, variations, and proper use in implementations from Compustat and Capital IQ. Misusing PIT data, or applying it haphazardly, can discard valuable information and obscure otherwise clear signals.

October 2010: Another Brick in the Wall: The Historic Failure of Price Momentum
In 2009, investors witnessed the cataclysmic failure of Price Momentum strategies. Now that accounts of this failure have been on the books for some time, it is appropriate to place the events in a historical context and further analyze the fundamental relationships that affect this strategy. We look at a number of questions from practitioners interested in the strategy. Within a historical context, how pronounced has this recent failure been? When Price Momentum fails, what is the strategy's subsequent performance? And, what factors are concurrent or predictive of the performance of

Price Momentum?

July 2010: Introducing Capital IQ's Fundamental US Equity Risk Model
In this paper we document the process of building and testing of our fundamental US Equity risk model across a number of short to medium term forecast horizons. The paper reviews typical risk model applications; discusses the relative merits of alternative forms of multifactor risk models; documents our data and methodology; 4 describes the chosen test metrics; and presents our results.