MSCI

Model Insight

The Barra Integrated Model (BIM301)

Research Notes

Peter Shepard

February 2011*

*This version: September 2011.

Contents

1. Introduction 1
2. Methodology 3
2.1. Structure and Noise 3
2.2. Single Country Factor Models 5
2.3. Global Factor Models 6
2.4. Integrated Factor Models 7
3. Equity 12
3.1. Single Country Equity Models 12
3.2. Global Equity Factors 17
4. Fixed Income 21
4.1. Single Country Fixed Income Models 21
4.2. Global Fixed Income Factors 23
5. Alternatives 27
5.1. Currencies 27
5.2. Commodities 28
5.3. Hedge Funds 29
5.4. Private Real Estate 29
5.5. Equity Volatility Futures 30
6. Model Horizons 32
6.1. Attributing Changes in Risk 34
7. Multi-Asset Class Risk 36
8. Model Performance 37
8.1. Performance Metrics 37
8.2. Equity Model Performance 39
8.3. Fixed Income Model Performance 43
8.4. Multi-asset Class Model Performance 46
9. Summary 51
Appendix A: Beta Estimation Error 52
Appendix B: European Equity 53
Appendix C: Local-Global Consistency 54
Appendix D: Quality Assurance 55

Appendix E: Risk Delta Attribution 56
Appendix F: Local-Global Risk Decomposition 56
Appendix G: Custom Integrated Models.......................... 59
Appendix H: Tables of Global Factors.............................. 61
References 67

1. Introduction

Risk models face four competing challenges: to be detailed, global, responsive, and robust. Detail requires that a model distinguish between every driver of returns in the markets. A global model aggregates risk among markets and across asset classes, gauging the degree of systematic risk retained as a portfolio is diversified. Responsiveness allows a model to adapt to changing market conditions while maintaining a view of a broader history. Finally, robustness, the most subtle, represents the ability to distinguish between structure and noise in forecasting relationships among assets.

While each of the challenges is difficult by itself, combined they can be at odds with one another; risk models traditionally have managed to overcome at best only three of the four. Robustness has often been sacrificed as too many relationships are estimated among sources of risk, and using too short a data history. Noise leads to the appearance of spurious correlations between unrelated time series, which suggest false hedges and result in underestimated risk.

With the advent of the Barra Integrated Model (BIM), all four of these goals were addressed together for the first time (Reference 1). The Barra Integrated Model brought together detailed local models under a parsimonious global factor model. The local models describe the structure within each market, while the global factors aggregate risk among them, measuring both the commonalities and the diversification benefits of investments in equity, fixed income, and alternative markets.

This paper describes a new version, BIM301, which extends the integrated model with methodological advances, modeling refinements, and expanded coverage.

The new methodology eliminates the need to choose between our best set of global factors and our best local models (Reference 2). It incorporates the Barra Global Equity Model (GEM2), allows new short- and long-horizon versions (BIM301S & BIM301L), and improves the relationships between local and global factors.

The local model enhancements for equity include:

- An updated Europe Equity Model (EUE3)
- New multi-horizon model versions in Australia (AUE3), Japan (JPE3) and Canada (CNE4) estimated from daily observations
- Adapted responsiveness of all other models to be consistent with the long and short horizon versions of the model.

Together, the BIM301 component models cover equities in 65 countries, with a coverage universe of nearly 50,000 stocks.

For Fixed Income, BIM301 brings a full suite of re-estimated local models based on daily and weekly return observations. New modeling enhancements include:

- Extended or more granular term structures for the UK, Euro zone, Japan, and US
- New term structure models for Argentina, Colombia, Egypt, and Peru

- New Inflation Protected Bond (IPB) models for Brazil, France, Germany, Greece, and Italy, plus revised IPB models for eight other markets
- A revised Japanese credit model and more granular, GICS®[1]-based credit spread models for six developed markets
- New models of swap spread curve fluctuations in 12 developed markets
- An updated set of global fixed income factors to better model relationships across markets.

BIM301 covers bonds and fixed income derivatives from 62 countries, and it introduces a new suite of alternative asset class models:

- A new Currency Model (CUR2) expands coverage to over 150 currencies
- A new Commodity Model (COM2) extends its scope from spot prices to the full futures curves, expands coverage to 34 commodities, and uses high frequency observations for better accuracy and responsiveness
- A re-estimated Hedge Fund Model (HFM2) updates the strategy risk factor structure, and a new Hedge Fund Exposures Model improves the relationship between individual funds and the public market component of risk
- BIM301 introduces a new model of Equity Volatility Futures (EVX1), modeling the risk of the US and European volatility futures curves, as well as index volatility and variance swaps
- New Private Real Estate Models in the US and UK (USR1 & UKR1) that model the relationships between different real estate holdings and their systematic relationships with public asset classes.

In all, BIM301 represents major advances in our ability to model risk across the world's markets. This paper details the BIM301 methodology, describes its component models, demonstrates its forecasting accuracy in backtesting for a range of portfolios and asset classes, and highlights some of the insight it provides into the structure of the world's markets.

[1] Global Industry Classification Standard (GICS®)

2. Methodology

2.1. Structure and Noise

The risk of a portfolio depends not only on the standalone risk of its constituents, but more importantly on the relationships among them. If every asset behaved independently, the risk of a large portfolio could be diversified away almost entirely, while in the other extreme, a portfolio of highly correlated assets offers almost no diversification benefit.

The Capital Asset Pricing Model (CAPM) motivates a simplified midpoint between these extremes. A market model describes the excess return of each asset as a combination of market and idiosyncratic components:

$$r_i = \beta_i R_M + e_i, \tag{2.1}$$

Where R_M is the excess return of "the Market," β_i is the market beta of asset i, and e_i is the residual return of the asset, assumed to be uncorrelated with all other returns.

The standalone variance of an asset $\sigma_i^2 = \beta_i^2\sigma_M^2 + \sigma_{ei}^2$ is often dominated by the specific volatility σ_{ei}, but the market model's assumption of uncorrelated residual returns makes this component of risk diversifiable. What matters for the risk of a large portfolio is beta, which is the portfolio's non-diversifiable exposure to the risk of the market σ_M. For a typical large portfolio, the total variance is dominated by the market, with the contribution of the residual component decreasing inversely with the number of assets.

In reality, the market model is an oversimplification, and real assets display a far richer correlation structure than that implied by their common exposure to the market. The market can account for much of the correlation among assets, but the residual returns retain important correlations with one another.

One way to account for this structure is to measure directly all of the historical correlations among the assets in the investment universe. Denoting the return of asset i at time t by r_{it}, and the mean return by $\bar{r}_i$, the asset-by-asset covariance matrix is defined to be

$$\operatorname{cov}(r_i, r_j) = \frac{1}{T-1}\sum_{t=1}^{T}\left(r_{it} - \bar{r}_i\right)\left(r_{jt} - \bar{r}_j\right). \tag{2.2}$$

With many more independent parameters than the market model, this can accommodate any correlation structure. However, the asset-by-asset covariance matrix has a number of problems. The limited data history and transient behavior of assets can make a good history either unavailable or inapplicable. More importantly, the asset-by-asset covariance matrix does not distinguish between chance correlations, and those that are likely to persist into the future. When used for risk management, it can give the impression that risk can be hedged away based on chance behavior in the past.

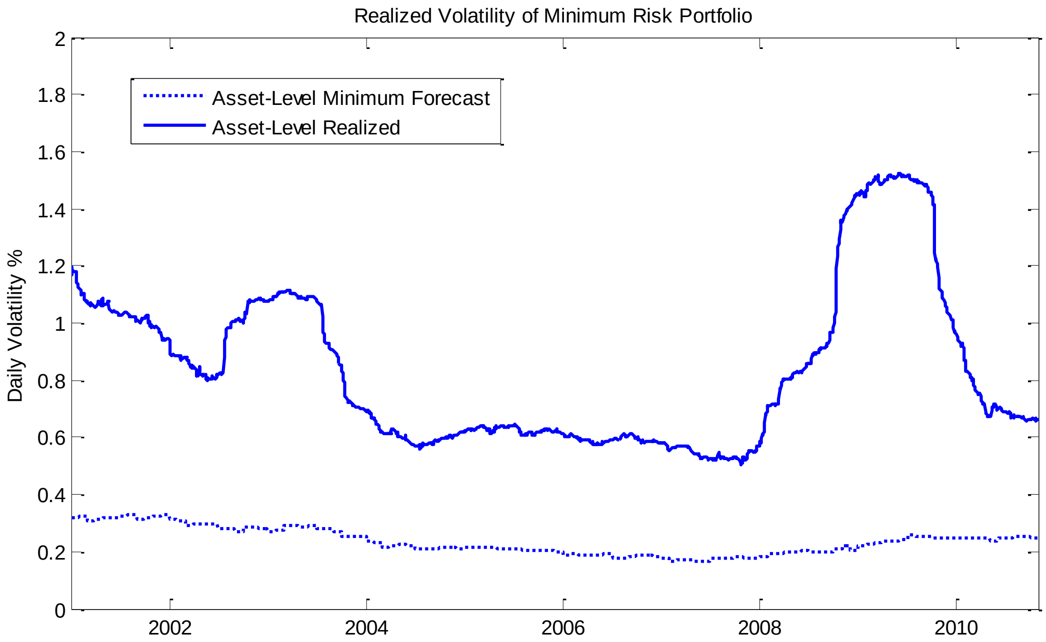

Figure 1. The forecast and one-year realized trailing volatility of a minimum risk strategy that uses a covariance matrix estimated directly from the assets. Each month, the strategy constructs the minimum risk, fully invested portfolio from the constituents of the MSCI USA Index. Spurious correlations among assets lead to significantly underestimated risk, with the realized volatility many times larger than the forecast.

Figure 1 shows the result of an experiment demonstrating the effect of such spurious correlations. Each month, the asset-by-asset covariance matrix is constructed from a history of daily stock returns. This covariance matrix is used to construct the fully invested, minimum risk portfolio built from the constituents of the MSCI USA Index. Although the asset-by-asset covariance matrix forecasts this portfolio to have very low risk, with an average daily volatility of about 25 basis points, the out-of-sample[2] realized volatility is always much larger. The reason for this bias is that the risk forecasts depend on details of the historical asset-by-asset correlations that failed to persist out-of-sample.[3] These errors are discussed further in Reference 3.

The covariance matrix in Figure 1 is built from a historic window that includes at least 50% more time periods than the number of assets in the investment universe. As the index grows to about 650 assets, this requires an observation window of almost four years, making it poorly responsive to the market.

[2] Out-of-sample testing is a statistical technique to distinguish between the noise of a particular data sample, and the underlying structural relationships. In contrast, in-sample testing is prone to reward methods that over-fit the data.

[3] Minimum risk and optimized portfolios are especially prone to such biases, while portfolios constructed in other ways, such as passive index funds, benefit from cancelations between these errors.

If a shorter window[4] is used to make the covariance matrix more responsive, the robustness of the matrix can be undermined altogether. Figure 2 shows the forecast and realized volatility for a portfolio constructed to minimize[5] a more responsive asset-by-asset covariance matrix, which was calculated from a one-year rolling window of daily returns. The forecast volatility is exactly zero throughout, as chance co-movement of assets leads to the appearance of completely hedged risk. The out-of-sample behavior reveals that the portfolio actually retains a substantial level of risk, showing the impact of these spurious correlations for portfolio construction and the tension between robustness and responsiveness.

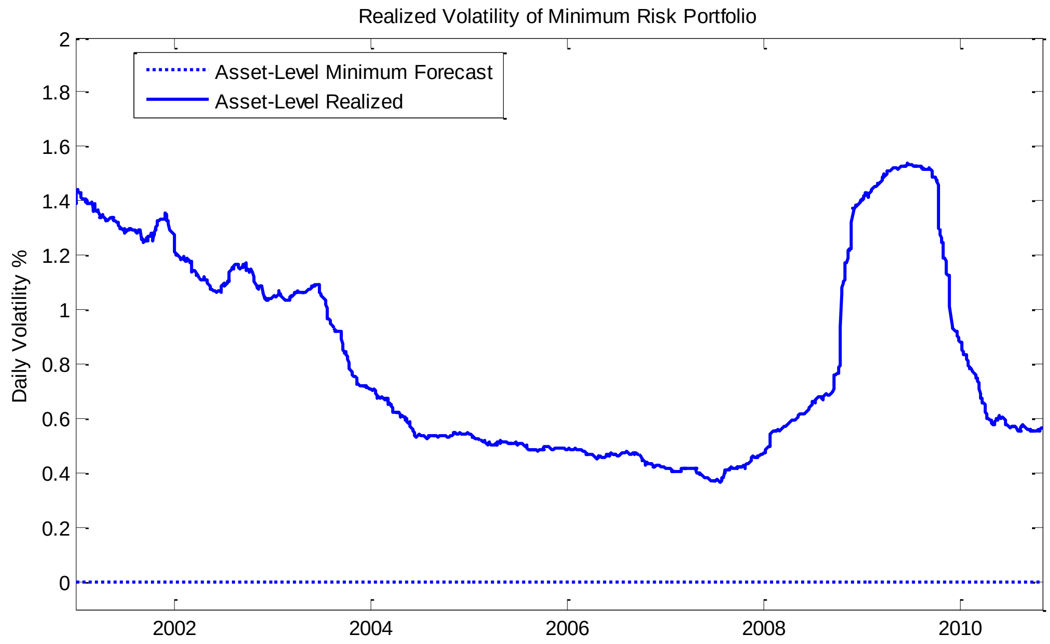

Figure 2. The forecast and one-year realized trailing volatility of a minimum risk strategy that uses a covariance matrix estimated directly from the assets. In this case, the covariance matrix is made more responsive with a rolling window using one year of daily returns. Each month, the strategy constructs the minimum risk, fully invested portfolio from among the constituents of the MSCI USA Index. Demonstrating the impact of spurious correlations and the tension between robustness and responsiveness, this forecast may falsely suggest that risk has been eliminated altogether.

2.2. Single Country Factor Models

To construct a robust risk forecast, an intermediate level of granularity is needed between the over-simplified market model of Equation 2.1 and the unstructured asset-by-asset covariance matrix of

[4] A rolling window is used in this study for simplicity, rather than the exponentially weighted expanding window used in practice. A rough rule of thumb is that the effective observation window is three times the half life.

[5] In this extreme example, there is actually a large space of portfolios with zero forecast risk. To resolve this ambiguity, this study selects the portfolio in this space with the minimum sum of squared weights.

Equation 2.2. Rather than allow only a single source of commonality among assets, as in the market model, we allow for multiple factors to drive their correlations (Reference 4).

Generalizing the market model, we express the return of each asset as a sum of contributions from a variety of factors, plus a specific component:

$$r_i = \sum_k X_{ik} f_k + u_i . \tag{2.3}$$

The factor exposures X_{ik} bring to bear a range of other information about the assets: industry classifications, balance sheet information, analyst views, and technical descriptors for equities; terms and conditions, ratings, sector membership, and pricing model sensitivities for bonds. Together, this information helps separate the persistent underlying structure from the noise that masks it.

The full covariance matrix among assets is defined in terms of the factors as

$$\operatorname{cov}(r_i, r_j) = \sum_{k,l} X_{ik} F_{kl} X_{jl} + \Delta_{ij} , \tag{2.4}$$

where F_{kl} is the factor covariance matrix and Δ_{ij} is the diagonal[6] specific risk matrix. The factor covariance matrix and exposures capture the structural relationships between assets, filtering out the noise of the specific returns.

Identifying the factors at work in each market requires a combination of art and science. Some factors tend to be highly specialized to particular markets, like Red Chips in Hong Kong, or Samurai bond spreads in Japan. Other factors are significant in many markets, such as industry factors and style factors, like Value and Momentum. The sections below further describe the Barra factor models for local equity, fixed income, and alternative asset markets.

2.3. Global Factor Models

In all, MSCI has identified almost 2,000 factors driving the risk and returns of the world's markets. Compared with the total number of investable assets, numbering in the millions, this is a significant reduction in dimension. However, estimation of every pair of local factor correlations is prone to noise, similar to the spurious correlations that arise when too many asset-level relationships are measured. Just as it is necessary to use a factor model to filter out noisy correlations among assets, additional structure is needed to robustly estimate the covariance among all the world's local factors.

One approach to this problem is simply to leave out the full local detail. For an international strategy based on broad equity allocations, the differences between the local factors can be unimportant, and a smaller factor set can be desirable. The Barra Global Equity Model (GEM2) (Reference 5) adopts this approach; it is comprised of the most important factors driving the relationships across markets.

GEM2 consists of 98 factors to describe stock returns in local currency, plus 55 currency factors. GEM2's World factor is sensitive to the overall movement of world equity markets, with its return closely

[6] The specific risk matrix has off-diagonal elements for correlations among different issues of a single issuer, estimated with a Linked Specific Risk (LSR) model.

tracking the MSCI All Country World Investable Market Index (MSCI ACWI IMI). Separating the World allows the model to be far more responsive to changes in the overall level of cross-market correlations. GEM2's 55 country factors and 34 GICS®-based industry factors describe the movement of countries and industries relative to the equity market at large. Lastly, 8 style factors distinguish the behavior of stocks based on technical and fundamental descriptors.

GEM2 is designed to have the best set of factors for describing interactions across equity markets, and forecasting the risk of broad international portfolios. However, GEM2 lacks the detail of the single country models. It does not distinguish between the industry risk of a Chinese bank and a US bank, for example, and does not describe the full correlation structure within markets. The more concentrated the bets of a strategy, the more relevant these considerations become.

For fuller detail, the single country model is necessary. Indeed, empirical studies (Reference 6) show that risk forecasts based on single country models are more accurate than GEM2 for concentrated single country equity portfolios.

2.4. Integrated Factor Models

To bring together the details of all the world's markets, an integrated model aggregates the single country models under a global model. The central idea is to further decompose the local factors into global and purely local contributions:

$$f_k = \sum_a B_{ka} g_a + \varphi_k . \tag{2.5}$$

The local-global exposures matrix B encodes the sensitivity of each local factor f_k to a variety of global factors g_a. In BIM301, these global factors include the GEM2 global equity factors, as well as factors for other markets, detailed below. The purely local return φ_k is the component of f_k that cannot be explained by the global influences.

Consider the return of the Japanese Auto factor. In any given period, if the global equity markets rise, the expected return of Japanese Auto stocks is positive, all things being equal. Therefore, the Japanese Auto factor has positive exposure to the global World factor. However, if the Japanese market were to underperform the World during that period, it is likely that Japanese Auto would also underperform, so the Japanese Auto factor also has positive exposure to the Japanese market, another global factor. Lastly, if the global auto industry outperforms the world, all things being equal, it is likely that Japanese Auto would also perform better. We therefore estimate a positive exposure to the global Auto factor as well.

A large fraction of the return of the Japanese Auto factor is explained by the three global factors – the World, Japan, and Global Auto. In general, the global factors in Equation 2.5 explain about two thirds of the return of local equity factors, as detailed in Section 3.2, and 80% of the local fixed income factor return, as discussed in Section 4.2. The return that is not explained by the global factors is the purely local component φ. Certain events affect the Japanese auto industry, independent of the World, broader Japan, or the global auto industry, and the purely local Japanese Auto factor return describes this component.

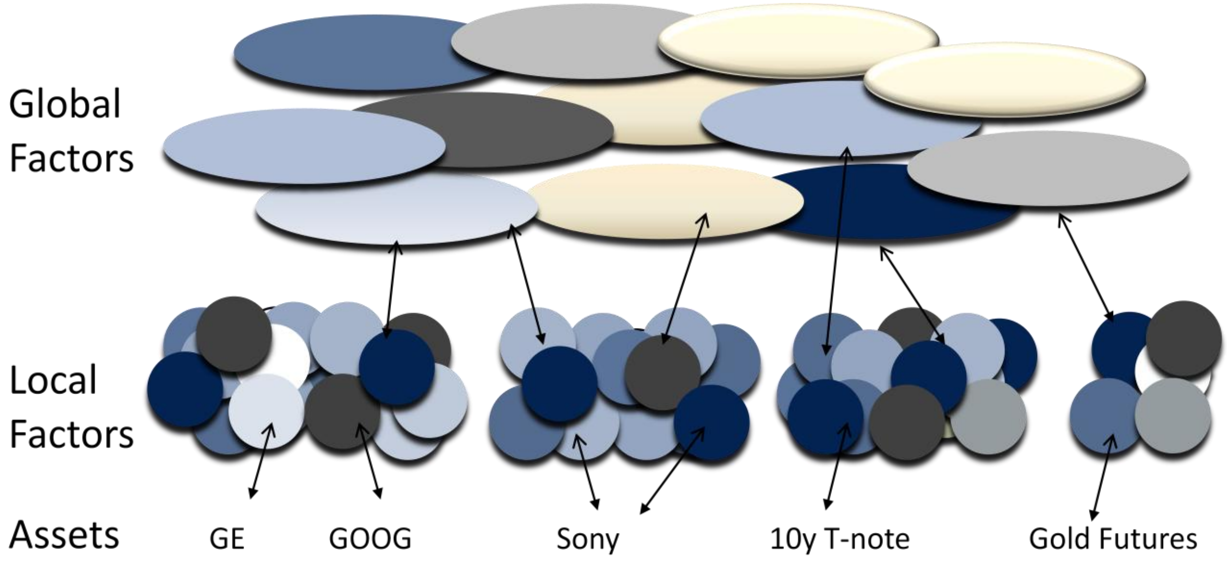

Figure 3. In the schematic form of an integrated model, assets in each market interact with the full detail of the local factors. Local factors are related using a less granular global factor set, combining GEM2 and global factors for other markets, to robustly estimate cross-market relationships.

An integrated model constructs the covariance matrix among all local factors as

$$\mathrm{cov}(f_k, f_l) = \Sigma_{a,b} B_{ka} \,\mathrm{cov}(g_a, g_b) B_{lb} + \mathrm{cov}(\varphi_k, \varphi_l). \tag{2.6}$$

As in the factor model covariance matrix of Equation 2.4, a structural relationship is used to filter noise from the correlations that are likely to persist by assuming, in this case, the purely local returns to be uncorrelated across markets, and uncorrelated with the global factor returns.

The new version of the Barra Integrated Model (BIM301) differs from the previous version (BIM207) in how it defines the global factors and the local-global relationships. Among equities, BIM207 assumed the local-global exposures B to take values of zero or one only. A 1% return to the global Auto factor contributed 1% to the return of every local auto factor, regardless of the market. From the assumed form of the local-global exposures matrix B, the BIM207 global factor returns were estimated by cross-sectional regression from the local factor returns.

Methodological enhancements of BIM301 address certain aspects of BIM207's bottom-up reliance on the local models. Through one enhancement, BIM301 eliminates the need to choose between global factors and local detail, with a new methodology (Reference 2) that brings together GEM2 and the local models. BIM207 global factors were built out of the local factors, rather than directly from assets, so they were limited by the lack of alignment between the local model factor sets. While BIM207 used 23 global industries, GEM2 adds important distinctions, identifying 34 global industries. Similarly, BIM207 used four style factors, while BIM301 uses eight from GEM2.

Table 1. A comparison of the factor model and integrated model methodology, showing analogous steps in each model's construction.

Factor Model	Integrated Model
$\mathbf{r} = \mathbf{X}\mathbf{f} + \mathbf{u}$	$\mathbf{f} = \mathbf{B}\mathbf{g} + \boldsymbol{\varphi}$
$\text{cov}(\mathbf{r},\mathbf{r}) = \mathbf{X}\mathbf{F}\mathbf{X}' + \text{cov}(\mathbf{u},\mathbf{u})$	$\text{cov}(\mathbf{f},\mathbf{f}) = \mathbf{B}\mathbf{G}\mathbf{B}' + \text{cov}(\boldsymbol{\varphi},\boldsymbol{\varphi})$
$\text{cov}(\mathbf{u},\mathbf{f}) \to 0$	$\text{cov}(\boldsymbol{\varphi},\mathbf{g}) \to 0$
$\text{cov}(u_1,u_2) \to 0$	$\text{cov}(\boldsymbol{\varphi}_1,\boldsymbol{\varphi}_2) \to 0$

A second enhancement of BIM301 addresses another aspect of BIM207's bottom-up reliance on the local models. Local equity models require stock returns from a broad estimation universe to measure the correlation structure within a market. However, many emerging markets lack the liquidity to generate daily or weekly returns for more than a handful of stocks. As a result, many single country equity models are built with monthly factor returns. With BIM207's dependence on the local factor returns, the lack of liquidity in emerging markets required BIM207 to use monthly observations for all global factors. Even though many local models are built from daily returns, they only interacted with one another through BIM207's monthly global returns.

In contrast, GEM2 can estimate the returns of each country factor from a relatively small number of liquid assets, even if a local model's broader estimation universe has not attained greater liquidity. Furthermore, BIM301 introduces newly constructed global Fixed Income, Currency, Commodity and Equity Variance Futures factors all estimated at weekly frequency. Together, these provide weekly factor return observations for all global relationships, which reduces statistical estimation errors and makes possible the construction of a robust short horizon model.

A third enhancement is a refinement of the local-global exposures. While BIM207 assumed the local-global equity exposures take only values of zero and one, the empirically observed relationships among factors demonstrate that these relationships can be refined; instead of taking these exposures as a fixed input, BIM301 takes the global equity returns as an input and estimates the local-global exposures from time-series regression:

$$B_{ka} = \sum_b \text{cov}(f_k, g_b)\,\text{cov}(g,g)^{-1}_{ba}. \tag{2.7}$$

This regression uses the same half-life and serial correlation parameters as the local model correlation matrix.

As we explore further in Section 3.2, we find many local-global exposures consistently differ from 1. In particular, emerging market industry and style factors tend to have more idiosyncratic behavior than their developed market counterparts, resulting in local-global exposures consistently less than 1.

More subtly, the local-global exposures are also important for the relationships within a market. From Equation 2.5, we can write the local factor covariance matrix as

$$\operatorname{cov}(f_k, f_l) = \sum_{a,b} B_{ka} \operatorname{cov}(g_a, g_b) B_{lb} + \operatorname{cov}(\varphi_k, \varphi_l) + \sum_a B_{ka} \operatorname{cov}(g_a, \varphi_l) + \sum_b \operatorname{cov}(\varphi_k, g_b) B_{lb}. \qquad (2.8)$$

The first two terms on the right match the integrated model in Equation 2.6, so differences between the local model and the integrated model arise from the last two terms, that is, the correlations of the purely local factors with the global factors, $\operatorname{cov}(g_a, \varphi_l) \neq 0$.

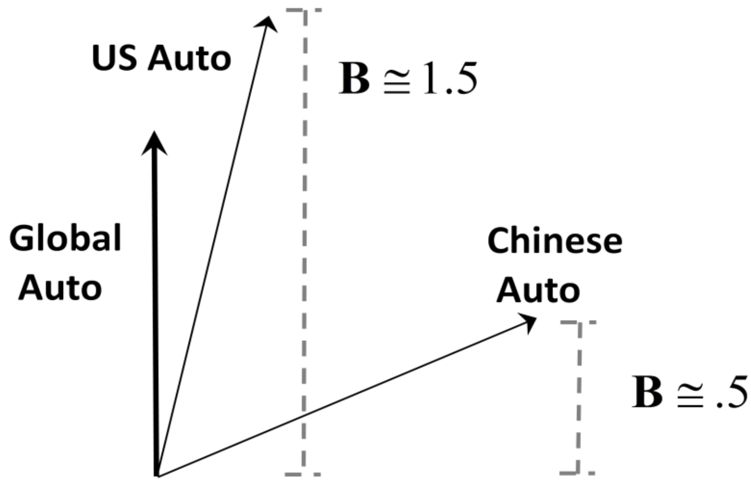

Figure 4. The schematic relationship between local and global factors. A 1% return to the global Auto factor does not have the same effect on all local Auto factors, with US Auto tending to rise by about 1.5%, while Chinese Auto rises only .5%. These differences are represented in the local-global exposures.

An alternate interpretation of BIM301's local-global exposures, Equation 2.7, is that they are chosen to absorb such correlations. As depicted in Figure 5, giving the US Auto factor unit exposure to the global auto factor, as in BIM207, may leave residual correlation between the purely local component and the global factor. Such correlation implies that what is called a purely local return can retain a global component. In BIM301, the local-global exposure is chosen to absorb that component, leaving the purely-local return uncorrelated with the global factor.

If all factors in a local model were exposed to the same set of global factors, then the purely local returns would be uncorrelated with those global factors; that is, $\operatorname{cov}(g_a, \varphi_l) = 0$. As a result, Equation 2.8 shows that the integrated model would agree with the single country model on the diagonal block of corresponding factors.

However, estimating too many exposures between unrelated factors reflects chance fluctuations among factors, obscuring the more durable underlying relationships. Japanese Auto is exposed to world equity, Japan, and global Auto, but not to global Biotech. Any correlation between Japanese Auto and global Biotech is inherited through the three global factors to which Japanese Auto is exposed.

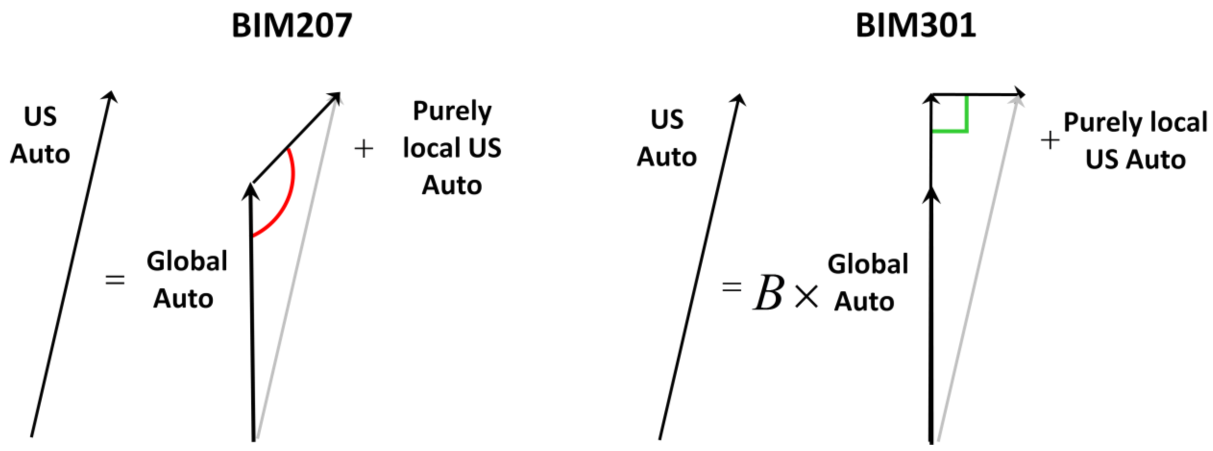

Figure 5. The local-global exposures of BIM301 absorb the correlation between the local factor and the global factor, resulting in purely local factors that are uncorrelated with the global factors. The new exposures better represent the local-global relationship, and achieving $cov(g_a, \varphi_l) = 0$ brings about more natural consistency between the Barra Integrated Model and the single country model.

For all local factors, a *local-global map* specifies the economically motivated relationships that are estimated with all other exposures set to zero. This can be thought of as a midpoint between the strong assumptions of BIM207's 0/1 exposures and an unstructured approach of directly estimating all local-global relationships. The intermediate approach takes advantage of the commonality that exists in the market, but recognizes its limits.

Since not all local-global relationships are estimated, the measured correlations between purely local and global factors are not all exactly zero. As a result, Equation 2.8 shows there will be small differences between the local model and the integrated model (Reference 2), proportional to the remaining $\mathrm{cov}(g_a, \varphi_l)$. Any economically significant component of $\mathrm{cov}(g_a, \varphi_l)$ can be absorbed by turning on the local-global map and estimating B_{la}. However, noisy covariance values leave a small discrepancy between the single country model and the corresponding diagonal block of the raw integrated model. Compared with BIM207, whose 0/1 exposures could leave behind significant structural $\mathrm{cov}(g_a, \varphi_l)$, the discrepancy in BIM301 is merely noise.

A more significant source of disagreement between the raw integrated model and local models is that many local models use a shorter half-life to estimate factor volatilities compared to correlations. Since the local-global exposures B are estimated with the local models' correlation half-life, the volatilities in the resulting first draft integrated model correspond to a longer time scale. Appendix B discusses the rescaling procedure that removes these differences and brings about exact agreement with the local model.

3. Equity

3.1. Single Country Equity Models

Single country equity models typically consist of two types of factors: Industries and Styles. In each country, the industry factors are selected to reflect the makeup of the local economy and the relationships among its constituents. As many as 55 industry factors are needed, as in the US Equity Model (USE3), with an average of 17 industry factors per market.

Each stock is assigned positive exposure to one or more industry, with multiple industry exposures assigned in some developed market models using revenue, assets, and earnings information from the company's financial statements.

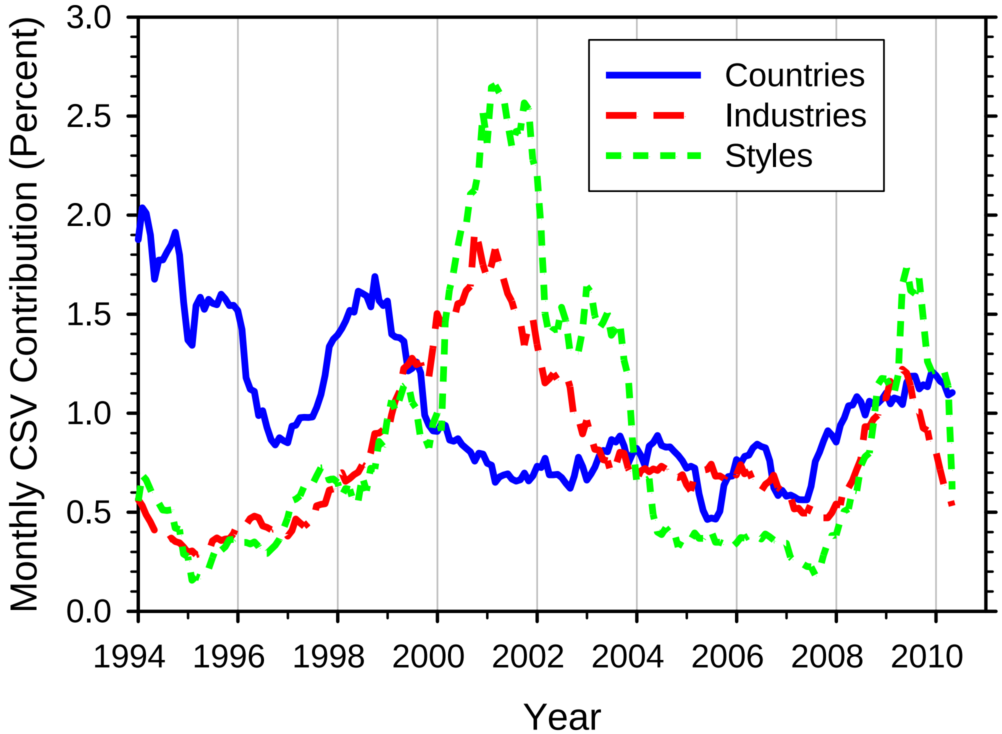

Figure 6. The fraction of global cross-sectional volatility explained by global Country, Industry, and Style factors, reproduced from Reference 7. Style factors can dominate Industry and Country factors in importance, particularly during periods of market turmoil. Decomposition of cross-sectional volatility is equivalent to a decomposition of relative R-squared.

The Industry factors are typically the most important systematic component of a stock's total return. However, much of this return is a market component that does not contribute to active return or tracking error. For the active portfolio, the importance of Style factors is often comparable to Industry factors. Figure 6, from a study (Reference 7) of the drivers of global cross-sectional volatility[7], demonstrates the importance of Style factors, showing that their contributions can exceed those of other factors.

Exposures to Style factors are defined as standardized averages of related asset-level items, known as descriptors. For example, Book-to-Price is a descriptor used in constructing the Value factors of most models. Each stock's book-to-price ratio is standardized to produce a score (positive for high book-to-price stocks, negative for low book-to-price) with a standard deviation of one across the estimation universe. The standardized book-to-price descriptors are then blended with other descriptors, such as Earnings-to-Price, to produce the factor exposure that maximizes explanatory power.

Different style factors, descriptors, and descriptor weights are selected in each single country model to reflect the nature of every market. Most models have a Momentum factor (also known as Success or Market Momentum), a Size factor, a Value factor, and a Volatility or Market Sensitivity factor that represents the component of beta that is not due to fundamental factors.

A variety of other Style factors are important for some markets, such as Dividend Yield, Growth, Leverage, Liquidity, or membership in a major index, as well as more specialized factors such as those distinguishing Chinese share classes.

The European region is modeled with a different factor structure than the single country models, with the addition of Market and Country factors, discussed in more detail in Appendix B.

Together, the equity factor models and specific risk models[8] provide a robust estimate of the covariance matrix of stocks in each market. Figure 7 and Figure 8 show the total coverage universe of the equity models over time, weighted by number and by total market capitalization.

[7] The cross-sectional volatility, $CSV = \sqrt{\sum_i w_i (r_i - R_M)^2}$, is the dispersion of returns about the market return, R_M, and is closely related to cross-sectional relative R-squared.

[8] In addition to the factor model, a specific risk model estimates the volatility of asset specific returns. These models vary from market to market, combining assets' specific return history with other information to forecast the specific volatility. Lastly, a linked specific risk model is used to estimate the relationships among specific returns of different stock issues of a single issuer.

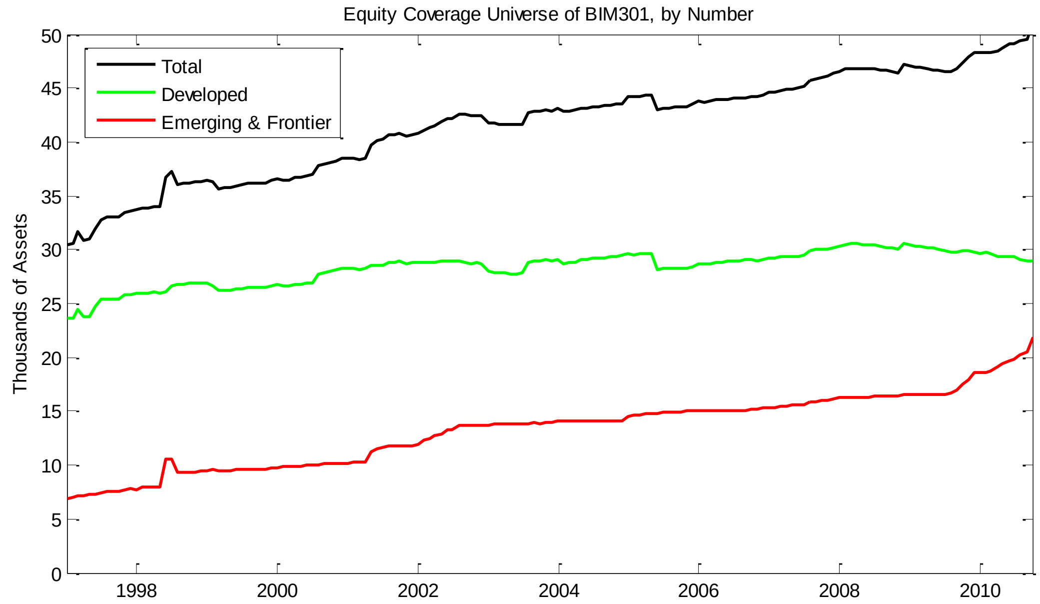

Figure 7. The BIM301 equity coverage universe has grown from about 30,000 assets at inception to about 50,000 today.

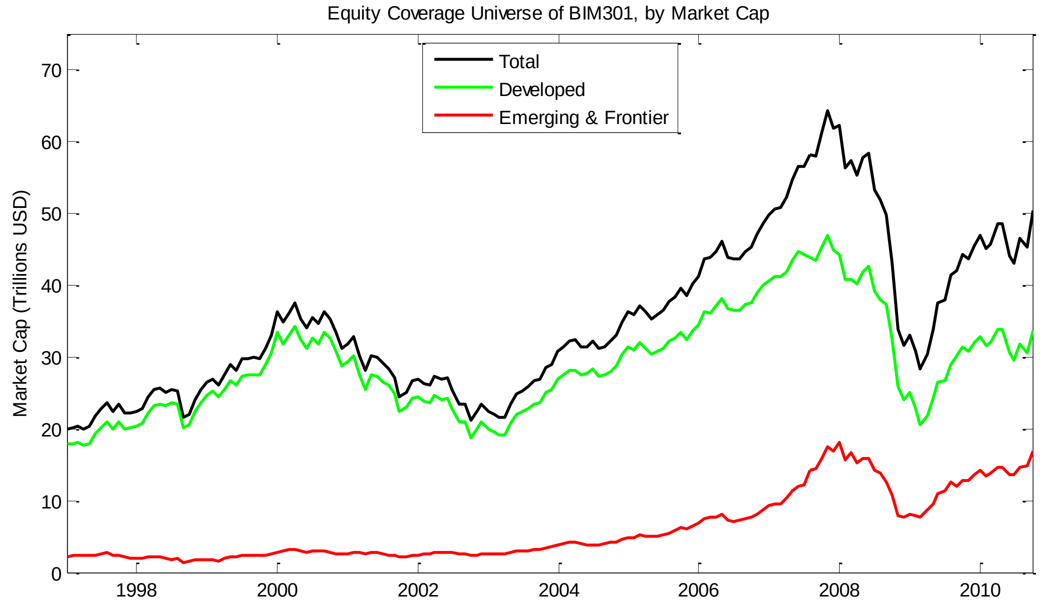

Figure 8. The BIM301 equity coverage universe by market capitalization.

Figure 9 shows the result of repeating the experiment of constructing minimum risk portfolios, this time using the Barra US Equity Long Term Model (USE3L). Although some bias is expected to remain (Reference 3), the factor model produces two improvements: more accurate risk forecasts and lower out-of-sample realized volatility than the asset-by-asset covariance matrix. Figure 10 compares the cumulative returns of these strategies to the MSCI USA Index.

Figure 11 compares this approach to using the Barra Global Equity Long Term Model (GEM2L) for the same universe of US assets. The realized volatility of the portfolio constructed with the single country model is consistently smaller. For a concentrated investment universe, the single country model's detailed factor structure is significantly better than the global model in capturing local relationships.

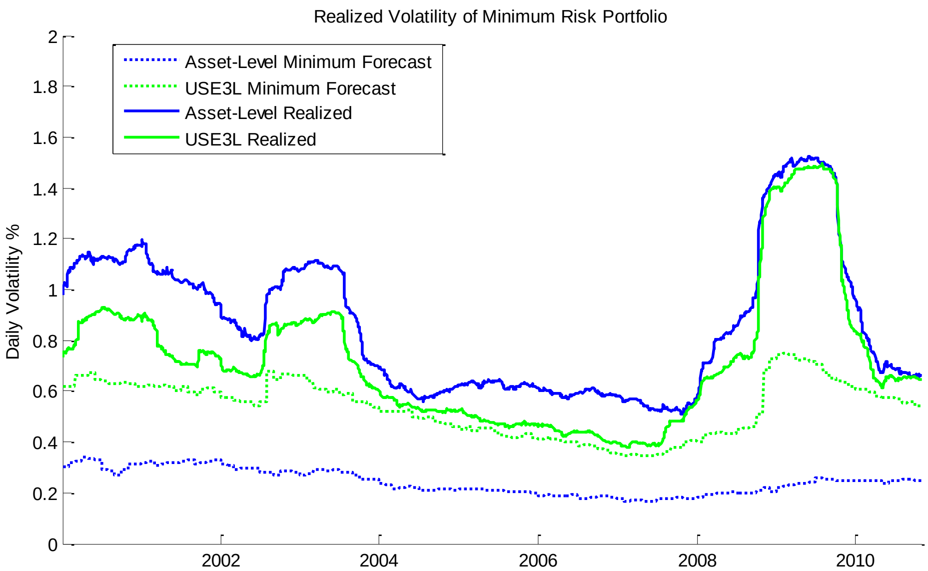

Figure 9. The forecast and one-year realized trailing volatility of minimum risk strategies, one using a covariance matrix estimated directly from the assets, the other using the USE3L covariance matrix. Each month, the strategies construct the minimum risk, fully invested portfolio from among constituents of the MSCI USA Index. The factor model leads to both lower realized volatility and more accurate risk forecasts. The remaining bias in the factor risk forecast is discussed in Reference 3.

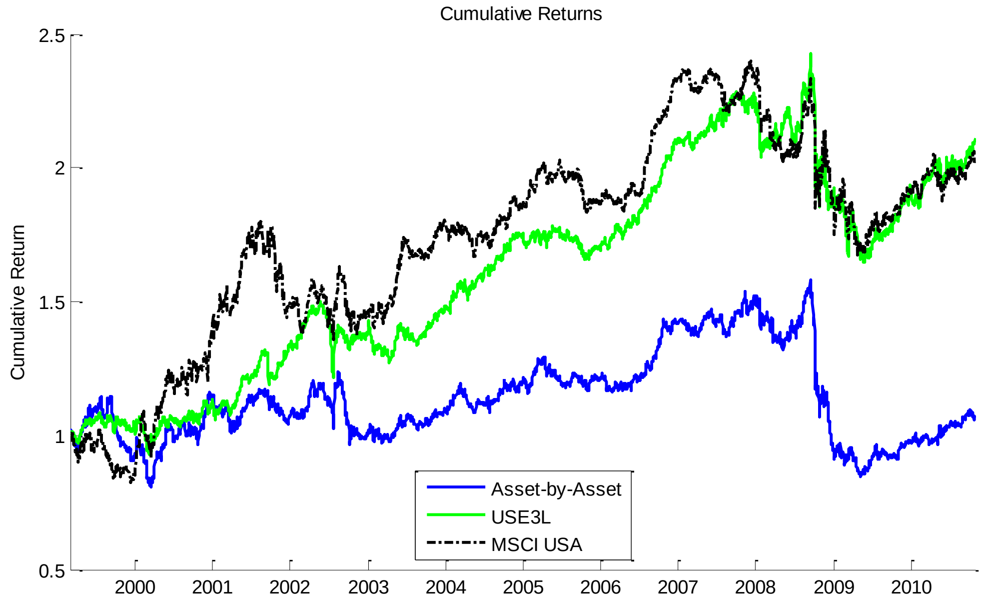

Figure 10. The cumulative returns of the minimum volatility strategies, using the asset-by-asset covariance matrix and USE3L, from the universe of stocks in the MSCI USA Index, also shown for comparison.

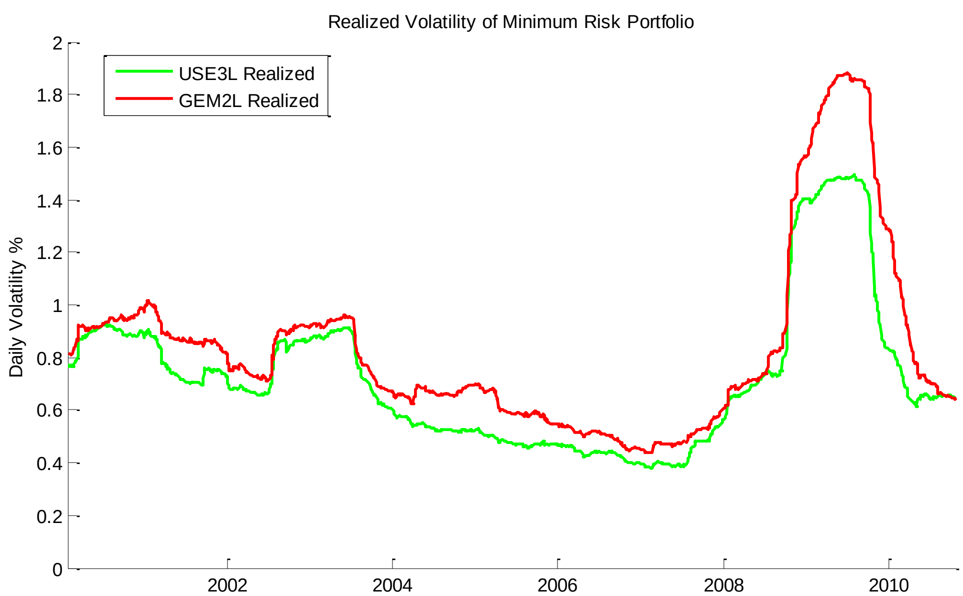

Figure 11. The one-year realized trailing volatility of portfolios constructed from the universe of stocks in the MSCI USA Index. The portfolios are constructed to minimize forecast volatility using the USE3L and GEM2L models. The additional detail of the single country model USE3L leads to better out-of-sample performance.

3.2. Global Equity Factors

To bring together the local equity market models, an integrated model requires a set of global factors that explain the common component of stock returns across markets. BIM301 uses all of GEM2's 98 equity factors, plus three additional factors. For a complete description of the GEM2 factors, see Reference 5. To relate the equity models for Nigeria and Sri Lanka, two countries not covered by GEM2, BIM301 defines global Nigeria and Sri Lanka factors as the return of the respective MSCI country indices minus the return of the World factor. Similarly, a global Europe factor is defined as the Barra Europe Equity Model (EUE3) Continental Market factor minus the return of the World factor. Subtracting the World factor in this way puts these factors on an equal footing with the country factors in GEM2, whose return represents the return of a single country relative to the world markets.

From the local factor returns f and global factor returns g, BIM301 estimates the local-global exposures B from a time series regression using the correlation half-life and serial correlation parameters of the local model.

The local-global map specifies the factor relationships to be estimated. Most local style factors are mapped to a single global style factor. For example, USE3's Value and Dividend Yield factors are mapped only to the global Value factor. Some local style factors, however, are also mapped to non-style global factors. Local volatility factors are mapped not only to the global Volatility factor, but also to the World and the corresponding country factor, reflecting their relationship with market beta. Similarly, Hong Kong's Red Chips factor and China's B-share style factors demonstrate a strong relationship with the global China International factor. Other local style factors, such as the Thai Family Ownership factor, demonstrate no systematic relationship with global factors and are treated as purely local.

Local industry factors are exposed to three global factors: the World, a corresponding country, and a global industry factor. The map between local and global industries is determined using the GEM2 industry assignments of the assets in each local industry, with assignments reevaluated annually. For example, the assets exposed to the USE3 Mining and Metals factor fall under a variety of global factors in GEM2, such as Steel, Oil & Gas, Gold, Construction, and Capital Goods, but most assets are exposed to GEM2's Diversified Metals factor, which is selected for the map.

Figure 12 compares the explanatory power of the BIM301 local-global map, labeled "Sparse," to an "Expanded" map that allows up to five more local-global relationships. In the case of USE3 Mining and Metals, for example, the expanded map includes Steel, Oil & Gas, Gold, Construction, and Capital Goods, since some stocks exposed to USE3 Mining and Metals belong to these global factors. The figure demonstrates that additional local-global relationships provide a negligible increase to explanatory power, although they come at the expense of significantly more noise and less intuitive exposures. We therefore adopt the more parsimonious "Sparse" local-global map.

The local-global map for the European market, country, and industry factors differs from the standard single country model structure. Local country factors are mapped to the World and the global Europe factor, in addition to the corresponding country factor. These factors typically have negative exposure to global Europe, and small exposure to the World. This is due to their construction as net neutral portfolios, which are long the corresponding country and short the remaining European market. Local industry factors are mapped to the World, global Europe, and the corresponding industry factor. Lastly, the European market factor is mapped to the World and global Europe factors.

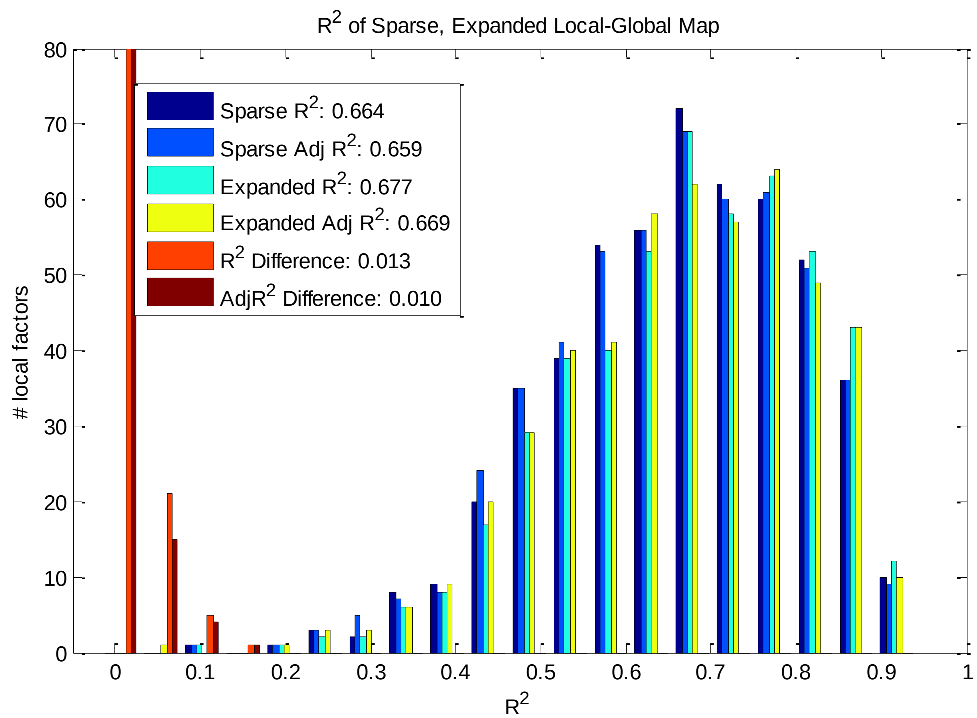

Figure 12. The explanatory power of global factors explaining local industry factors, for the sparse local global map of BIM301, as well as an expanded alternative. The distribution is across all local industry factors between 1992 and 2010. The small increase in explanatory power of the expanded map does not justify its added noise and less intuitive exposure values.

The local-global exposures provide a window into the structure of the world's markets. For example, Table 2 compares the equal-weighted average and standard deviation of the exposures for developed markets and emerging market factors, with four categories of global factors. The small average values for emerging market industries and styles contrast with much larger country and World factors exposures. As a result, style and industry bets in the emerging markets are far more diversifying than such bets in the developed markets.

The standard deviations demonstrate that country and world effects are much more consistent across local factors than industries and styles. Local industries tend to have similar responses to overall market changes, but there is a wider range of relationships between local and global industries or local and global styles. These results are consistent with the results of a different analysis of the drivers of cross-sectional volatility (Reference 7).

Table 2. Equal-weighted average and standard deviation of local-global exposures at end of year 2009. Emerging market industries and styles are significantly less integrated with the global factors.

Local-Global Exposures	Developed Avg	Developed Std	Emerging Avg	Emerging Std
Industry → World	0.92	0.14	0.86	0.22
Industry → Country	0.79	0.23	0.81	0.19
Industry → Industry	0.86	0.48	0.27	0.40
Style → Style	0.79	0.50	0.24	0.46

Although BIM301 and GEM2 use essentially the same set of global factors, the added structure of BIM301's local-global exposures results in different behavior between the two models, even for a global strategy. Figure 13 and Figure 14 show the results of an optimization study similar to those above, but now conducted for global strategies. Starting with the GEM2 estimation universe, the strategies use the Long Term versions of the models, GEM2L and BIM301L, to construct the fully invested minimum risk portfolio, rebalancing each month.

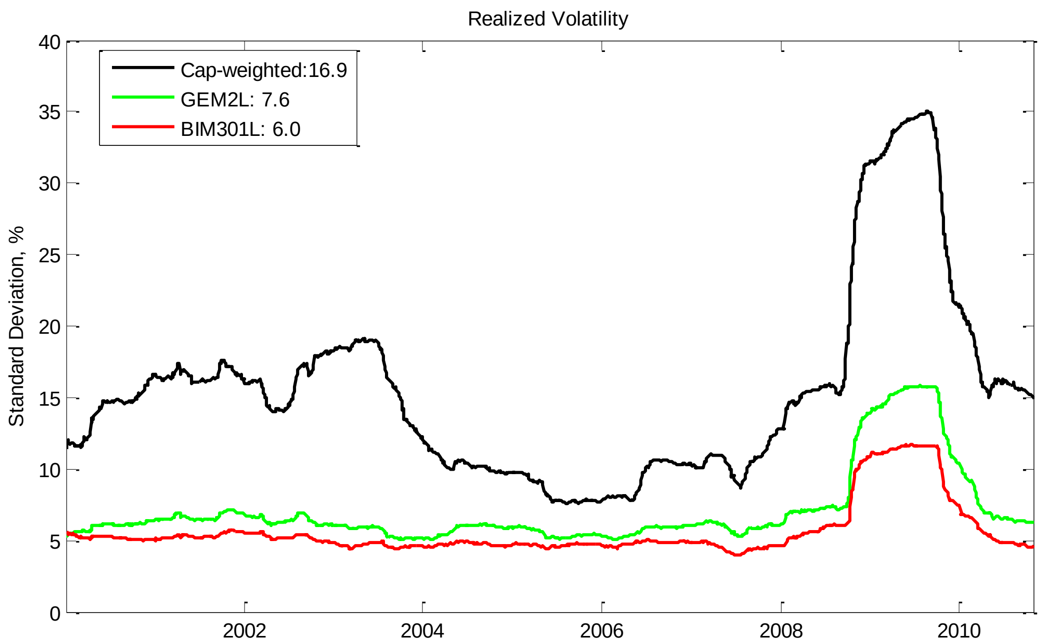

Figure 13. The one-year realized trailing volatility of the cap-weighted GEM2 estimation universe, compared with minimum risk strategies using GEM2L and BIM301L. GEM2 and BIM301 both reduce risk by more than half relative to the index, with BIM301 providing the most risk reduction .

In Figure 13, we see that GEM2L and BIM301L both lead to a large reduction of the out-of-sample realized volatility, but that BIM301's reduction is significantly greater than that of GEM2 over a range of market climates. For a global portfolio of about 10,000 stocks in 55 countries, this improvement is unlikely to be due to the same mechanism as the improvement for the single country portfolio of Figure 11. In that case, the improvement is due to BIM's purely local factors that model the detailed relationships within each market to a greater extent than GEM2.

In this case, the purely local risk is largely diversified away with bets across so many markets, and most of the risk comes from the global factors. The critical difference between GEM2 and BIM301 is in the implied exposures to these factors. BIM301's detailed local factor set and local-global exposures allow it to distinguish the varying sensitivities to global factors across markets. As a result, BIM301 provided this test strategy with significantly more accurate hedges to the same set of global factors as GEM2.

Figure 14 compares the cumulative returns of these strategies. BIM301L achieves an annual Sharpe ratio of 1.7, compared with 1.1 for GEM2L, and 0.5 for the cap-weighted estimation universe portfolio. Although luck may account for the outperformance, it is notable that the risk reduction did not come at the expense of return.

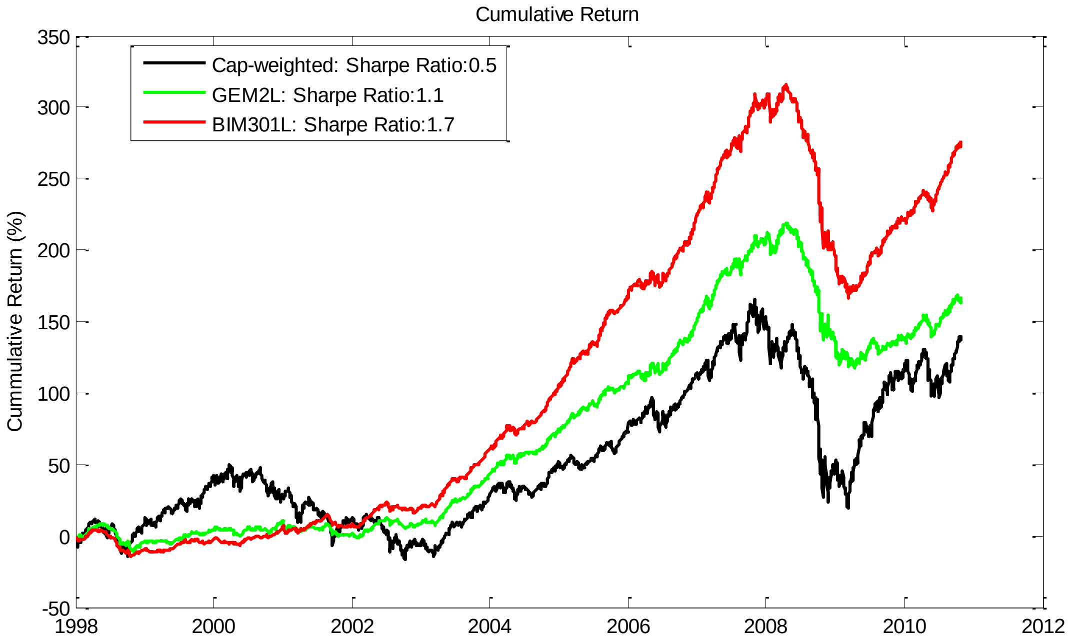

Figure 14. The cumulative returns of the cap-weighted GEM2 estimation universe, compared with minimum risk strategies using GEM2L and BIM301L. The reduced risk does not come at the expense of return, with better return through a variety of market conditions. BIM301L achieves a Sharpe ratio of 1.7 in this study, compared with 1.1 for GEM2L and 0.5 for the cap-weighed estimation universe.

4. Fixed Income

4.1. Single Country Fixed Income Models

To a greater degree than equities, bond prices are driven by a variety of systematic factors whose returns cause correlated movements among a wide range of assets. Such relationships present a source of systematic risk that must be accounted for, as well as an opportunity to produce a more parsimonious model.

Sovereign debt typically displays the highest degree of structure. Aside from small liquidity effects, the returns of hundreds of bonds issued by each country are well explained by movements of a single sovereign yield curve. The points on this curve, in turn, do not fluctuate in isolation, but move together in a smaller number of systematic movements.

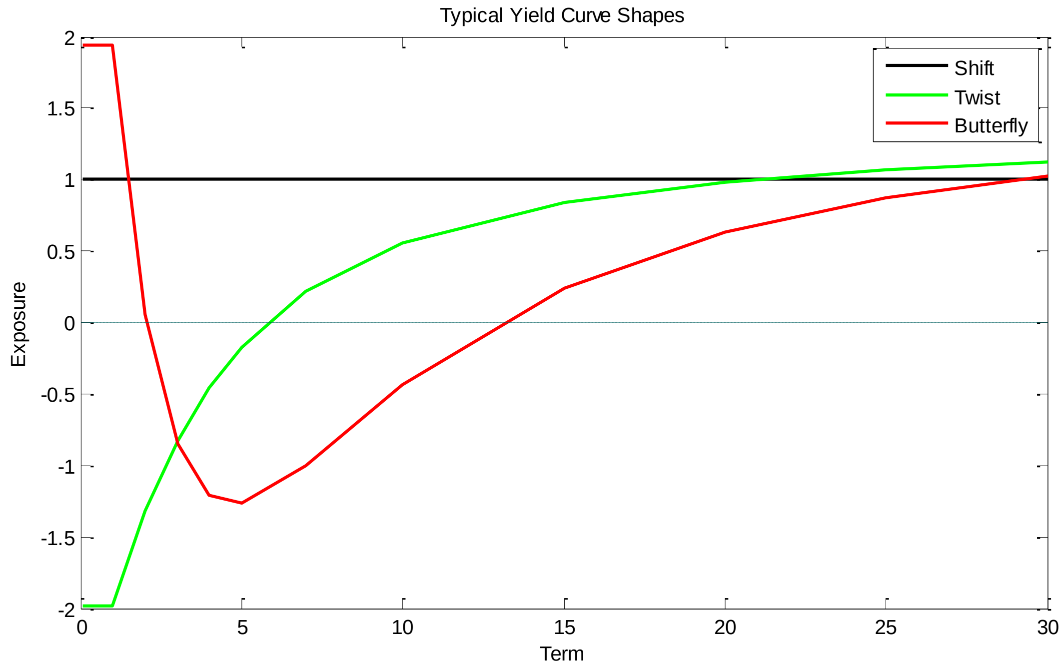

Figure 15. Typical Shift, Twist, and Butterfly shapes.

The primary movement of a sovereign debt yield curve is a parallel shift. Interest rates often move up or down together, with all points of the yield curve moving in the same direction. This movement is reflected in each market by a Shift factor[9], to which a bond's exposure is the effective duration d_i,

$$r_i \approx d_i f_{shift} . \tag{4.1}$$

9 The sign of the shift factor return is the same as the price return of bonds, opposite the sign of the change in yield, $f_{shift} \approx -\Delta y$.

Of course, yield curves do not always move rigidly. A steepening or flattening of the yield curve is described by a Twist factor in each market, to which short duration bonds typically have negative exposure, while long duration bonds have positive exposure. A positive return of a Twist factor reflects a flattening, while a steepening of the yield curve brings about a negative return to Twist.

A third factor, less significant than Shift and Twist, describes movement of the center of the yield curve relative to the ends. It is called Butterfly, named after the shape of its fluctuations: The long and short ends have positive exposure, and the middle of the curve negative exposure. A positive return to the Butterfly factor corresponds to a rise in the middle of the yield curve.

Figure 15 shows typical shapes of the Shift, Twist, and Butterfly factors. BIM301 introduces the use of Nelson-Siegel (Reference 8) yield curve shapes that are less prone to noise than the principal component-based shapes used in BIM207. These factors tend to capture the majority of the returns of sovereign bonds with about 70-75% by Shift and 15-20% by Twist and 2-8% by Butterfly. Figure 16 shows the distribution of the total R-squared over markets and time periods. The R-squared is almost always greater than 90% in the developed markets, with a broader range among emerging market models.

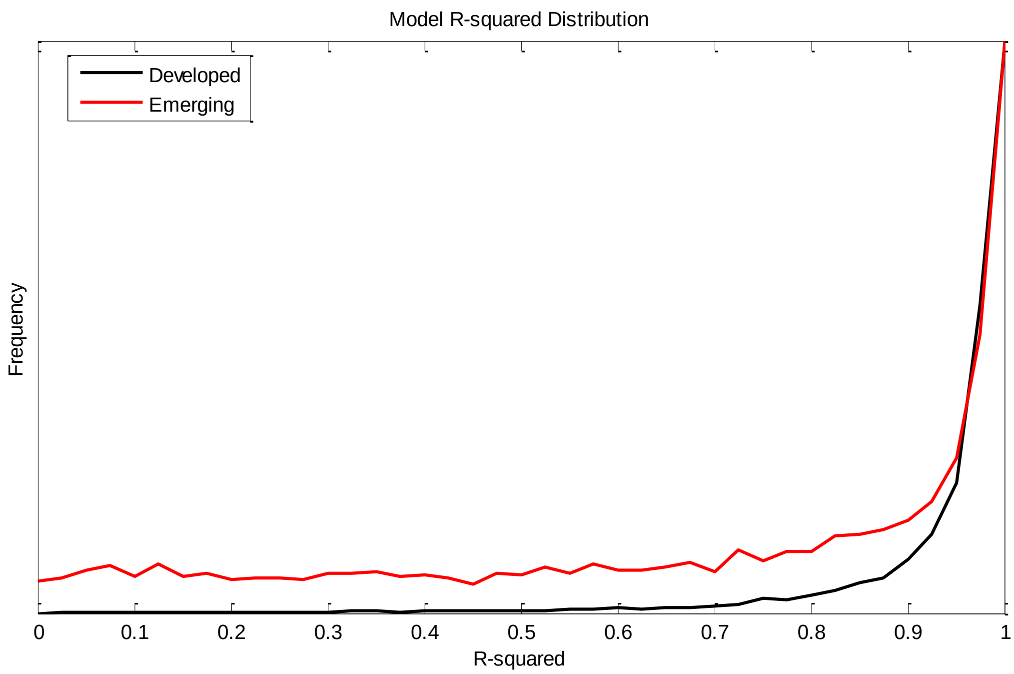

Figure 16. The distribution of the explanatory power of Shift, Twist, and Butterfly factors explaining the weekly return of local bonds in the estimation universe of each market. The distribution is across all local sovereign debt models for the period between January 2000 and December 2010.

Although the Shift factor often dominates the total return of a long-only portfolio, Twist and Butterfly are more often important for long/short or active bond portfolios, since they are often constructed to be duration neutral.

In addition to interest rate risk, bond returns are influenced by both factor and specific returns. Specific return reflects the changing credit and liquidity premia of individual issues, while the systematic spread component can be decomposed into a hierarchy of influences.

First, the overall swap spread curve in each country is modeled. The swap spread curve is the difference between swap and treasury curves, reflecting the overall spread of high grade credit. While BIM207 modeled swap spread with a single factor in each market, BIM301 introduces Swap Shift, Twist, and Butterfly factors. These factors describe movements of each market's swap spreads in the same way that sovereign STB factors describe the movements of sovereign curves, capturing important term structure of these curves. The Swap Twist factors demonstrate significant structure across markets; for example, a new global average Swap Twist factor is responsible for over 100 basis points of R-squared. The swap term structure factors are also important for many derivatives (e.g., swap steepeners) whose risk is underestimated when only a single spread factor is used.

The credit spreads relative to the swap curve are further decomposed into systematic factors. Corporate spreads are modeled with sector-by-ratings factors; BIM301 introduces a suite of newly reestimated models in the developed markets based on GICS® classifications. Other credit types require specialized factors, such as Pfandbriefe and Covered Bonds in Europe, MBS and Munis in the United States, and Samurai and Government Backed Bonds in Japan.

Additional factors are used to model other components of the worlds' bond markets. Emerging Market (EM) factors describe the spread over treasuries of thirty-eight countries' foreign denominated sovereign debt (distinct from the local currency STB factors for 27 emerging markets). Inflation Protected Bond (IPB) factors describe real yield curves, with IPB Shift, Twist, and Butterfly factors in 14 markets. In four markets, Implied Volatility factors describe the changing price of interest rate options.

Other instruments, such as credit default swaps, do not use their own factors. Pricing models describe such assets in terms of exposures to the same underlying factors that describe more traditional assets.

In all, 571 local fixed income factors model the systematic component of bonds across 62 markets with 143 Government STB, 46 Swap spread, 288 Credit, 17 Muni, 10 MBS, 25 IPB, 38 EM and 4 Implied Volatility factors. For more information on the fixed income models, see References 9-11.

4.2. Global Fixed Income Factors

Although hundreds of factors are necessary to describe the details of every bond market around the world, that level of detail is excessive for forecasting relationships across markets. US Financial AA and MBS have persistent correlations over time, but their relationship with Japanese Samurai Bonds is less granular, inherited through a smaller number of global factors. For any given historical time period, it is possible to construct portfolios with finely tuned exposures to US and Japanese credit factors that, with the benefit of hindsight, display near perfect cancellations between the returns in each market. However, there is no reason to expect that these detailed movements representing structure would allow for reliable hedges in the future.

To model the relationships among bonds and other markets, we identify a set of global bond factors responsible for inter-market correlations. These factors are defined by promoting the most important local factors to global factors, and by taking averages over local factors to capture the systematic component of their returns.

Figure 17 plots the weekly returns of the US CCC credit spread factor against the return of the US BB credit spread factor. The 87% correlation confirms a high degree of commonality between the two credit spreads. However, the lower-rated CCC spread is about two-and-a-half times as volatile. To capture this commonality with a global US High Yield factor, we cannot simply average the high yield factors because the result would be dominated by the more volatile low-grade bonds. Instead, we take averages that weigh each factor inversely to the typical scale of its returns, so that each constituent contributes about the same to the global factor.

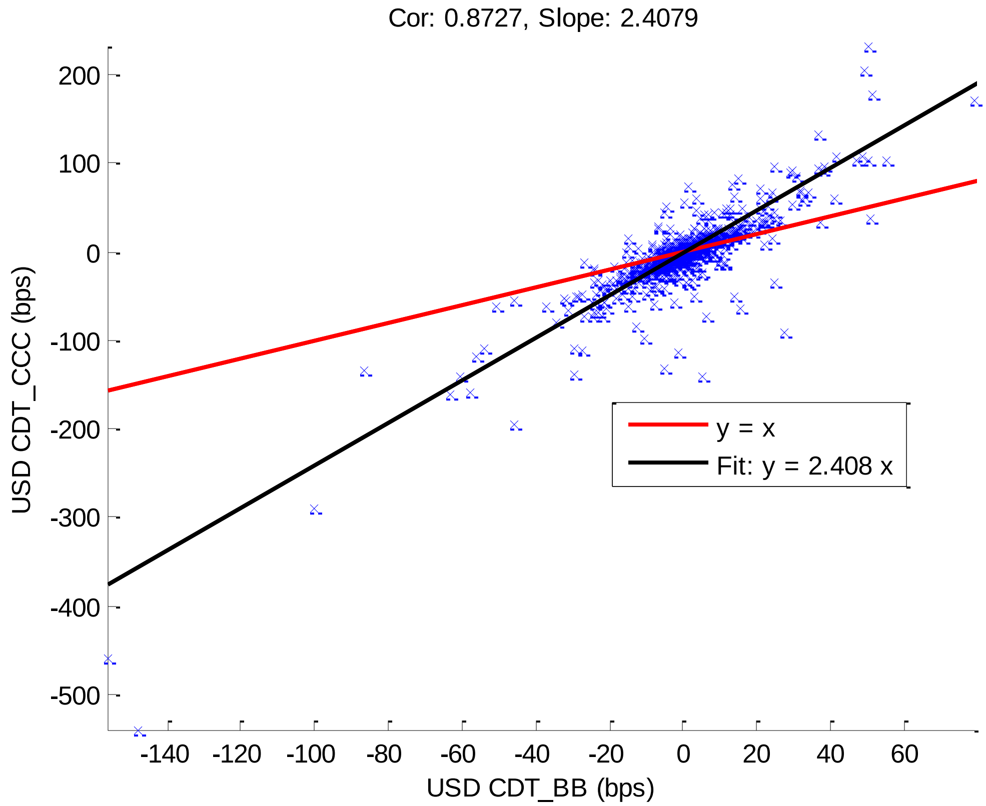

Figure 17. The history of weekly returns of US BB and CCC credit factors are highly correlated, but differ significantly in volatility.

BIM301 introduces a new set of 90 global fixed income factors that are estimated at a weekly observation frequency. As summarized in Table 3, these factors significantly improve the explanatory power of the local factors, particularly for credit and sovereign debt.

The interest rate Shift factors of 36 countries are the most important global factors, accounting for about 45% of the return of all local factors. For emerging markets that issue the majority of debt in a foreign currency, the EM spread factors are used as global factors instead of Shift factors. An additional Average EM Credit Spread factor is used for the remaining markets.

The Shift and EM spread factors are important for modeling the overall behavior of each country's debt, which is the primary driver of cross-market correlations. Global factors are included for every country with a fixed income model, as well as EM factors for countries with an equity model but no local bond model. In this way, BIM301 includes country-specific factors for 17 more countries than BIM207. Although many of these factors make a small contribution to the overall explanatory power of the global model, due to the small debt amount outstanding, these factors are critical for accurately modeling the debt-equity relationships of each country.

As with equity, European debt is a special case of intermediate regional integration. Global Shift factors are defined for Greece, Ireland, Italy, Portugal, and Spain, but not for Austria, Belgium, Finland, France, Germany, or the Netherlands, where sovereign debt is highly correlated with Europe as a whole. MSCI will monitor this factor structure over time, adding global factors as necessary.

BIM301 promotes 12 local Twist factors to global factors and defines a global Average Twist factor for the remaining markets. The importance of the global Twist factors may be overstated by their contribution to explanatory power in Table 3. Although the Twist factor explains a significant component of return within each market, this return tends not to be strongly correlated with return sources in other markets.

Table 3. Global fixed income factor types, with their contribution to the total explanatory power of local factors. Local factors are weighted proportional to amount outstanding and asset-level explanatory power.

Global Factor Group	R^2 BIM207	R^2 BIM301	# Factors BIM207	# Factors BIM301
Shift	42.23%	44.84%	27	36
Twist	21.08%	22.08%	27	13
Swap	7.97%	8.69%	21	12
IPB	1.00%	1.31%	5	7
Credit	2.91%	5.64%	7	11
Implied Vol	0.07%	0.03%	4	1
Muni	1.65%	1.14%	2	1
EM	0.03%	0.16%	1	9
Total	76.93%	83.87%	94	90

BIM301's selection of global credit factors represents a significant enhancement over BIM207 by improving its ability to model the credit-equity relationship. In Table 3, we see the global credit factors nearly doubling in their contribution to explanatory power, contributing 564 basis points to the 84% total R-squared.

BIM301 retains the six average credit factors for Australia, Canada, Europe, Japan, Switzerland, and the United Kingdom, making only small refinements in their definition. BIM301 splits the global US Credit spread factor into separate global US High Yield and US Investment Grade factors. Also new to BIM301 are a global factor for the European Covered Bond and Pfandbrief markets, a factor for US Mortgage

Backed Securities, and a global Financials factor. Together, the additional granularity of global credit factors nearly doubles the explanatory power in an area with strong cross-asset-class correlations.

Other global fixed income factors in BIM301 are 11 Swap Shift factors, a global Average Swap Twist factor, seven IPB Shift Factors, an Average Implied Volatility factor, and a US Muni Shift factor.

In all, the BIM301 global fixed income factors achieve about 700 basis points greater R-squared than BIM207, capturing 84% of the return of the local fixed income factors; it achieves this with a more parsimonious set of 90 factors, compared with BIM207's 94. Furthermore, BIM301's expanded set of Shift and EM spread factors provide important equity-bond relationships and prepare the model for country-specific events that may occur in the future. The global fixed income factors are listed in Table 12 of Appendix H.

As with equity, BIM301 estimates local-global exposures by time-series regression, as in Equation 2.7. The fixed income local-global map in BIM301 is expanded from BIM207, with relationships such as local twist to global shift estimated, and more local credit factors exposed to global swap factors. These exposures reflect consistent correlations and economically motivated relationships.

The local-global exposures of fixed income factors provide less market insight than equity exposures because the heterogeneity of local factors makes direct comparisons more difficult. A large source of variation in the fixed income local-global exposures is the volatility ratios between factors, which can vary widely and dominate the exposure, regardless of the correlation.

5. Alternatives

5.1. Currencies

In addition to modeling the standalone volatility of currencies, it is critical to capture the relationship between currencies and other asset classes. Many investors implicitly make large currency bets in the form of foreign equity or bond positions that are made without offsetting currency hedges. Similarly, from the point of view of an international equity investor, the betas of foreign stocks receive large contributions from the volatility and correlations of the currency component of returns.

The total excess return of an asset relative to a numeraire currency num is a combination of the return in local currency l_i and the exchange rate return of the local currency relative to the numeraire c_i^{num},

$$r_i^{num} = l_i + c_i^{num} + l_i c_i^{num}. \tag{5.1}$$

Because returns are typically much less than 1, the cross-term $l_i c_i^{num}$ tends to be much smaller than either l_i or c_i^{num}, and to good approximation the return is additive:

$$r_i^{num} \cong l_i + c_i^{num}. \tag{5.2}$$

Inflation tends to create a positive drift in the local return, accompanied by depreciation of the local currency. The factor models of local returns therefore use local excess returns $l_i - RFR_i$, where RFR_i is the "risk free" return for the country of asset i. The currency model defines the currency factor returns to be

$$c_i + RFR_i - RFR_{num}. \tag{5.3}$$

Although the model is estimated using the US Dollar as the numeraire currency, it is straightforward to convert to a different numeraire currency without re-estimating the model. The local return is independent of numeraire, while the return of currency i relative to a different numeraire currency p is approximately $c_i^p \cong c_i^{USD} - c_p^{USD}$. This allows us to transform the covariance matrix to a new numeraire by taking

$$\mathrm{cov}(l_i, l_j) \to \mathrm{cov}(l_i, l_j) \tag{5.4}$$

$$\mathrm{cov}(c_i, l_j) \to \mathrm{cov}(c_i, l_j) - \mathrm{cov}(c_p, l_j) \tag{5.5}$$

$$\mathrm{cov}(c_i, c_j) \to \mathrm{cov}(c_i, c_j) - \mathrm{cov}(c_p, c_j) - \mathrm{cov}(c_i, c_p) + \mathrm{cov}(c_p, c_p). \tag{5.6}$$

In previous versions of the Barra Integrated Model, a generalized autoregressive conditional heteroskedasticity model (GARCH) was used to describe currency volatilities, while a very short half life was used to calculate the correlations among currencies.

Over time, however, heavily parameterized GARCH models tend to be less robust to changes in the markets. Although a GARCH model's many parameters allow it to tightly conform to the data set on which it is trained, these parameters are not always predictive and may lead to diminished performance out-of-sample. Similarly, a currency model with different responsiveness to the rest of the model can lead to distortions in the relationships with other markets, as discussed in Section 6.

BIM301 introduces a new Currency Model (CUR2) that uses the Newey-West estimator (Reference 12) to account for serial correlation in the measurement of correlations and volatilities. In contrast with the GARCH model, which assumes a particular returns generating process, the Newey-West estimator assumes no process, giving it better out-of-sample behavior. The long- and short-horizon Currency Models (CUR2L and CUR2S) use the same half-life parameters as GEM2, plus the majority of BIM301's components, accounting for serial correlation for up to three weeks.

CUR2 also increases coverage to over 150 currencies, up from 74. Such coverage is important for the ability to handle frontier market investments, where currency risk can be the dominant source of systematic risk.

For more information on the Barra Currency Model, see Reference 13.

5.2. Commodities

BIM301 introduces an updated second-generation Commodity Model (COM2). The new version expands coverage from 24 to 34 commodities, and models both spot prices and the full futures curves. The COM2 estimation universe consists of rolling maturity futures (RMF) contracts, each of which is an index of investable commodity futures representing a nearly fixed segment of the commodity curve. From this universe, COM2 uses principal component analysis to define the characteristic shapes of futures curve fluctuations, analogous to the Shift, Twist, and Butterfly factors of the bond models. These shapes are estimated once, then used over the model's history.

From these fixed shapes, the factor returns are estimated from a daily cross-sectional regression over the RMF universe. The availability of daily and weekly factor returns improves the risk forecasts and allows for a robust short horizon version of the model -- COM2S.

Although seasonality is critical to the behaviour of commodity prices, its effects are less significant to commodity risk. In even the most seasonal commodities, such as natural gas, seasonality is manifested as small deformations of the STB exposure curves at one-year increments.

The relationship between commodities and other asset classes are mediated through five global commodity factors: Energy, Precious Metals, Industrial Metals, Agriculture, and Livestock. As summarized in Table 4Table 4, these factors typically explain a large fraction of the return of individual commodity Shift factors, but are largely uncorrelated with the Twist and Butterfly factors that describe steepening and bulges of the futures curves.

For more information on the Barra Commodity Model, see Reference 14.

Table 4. Global commodity factors and their average explanatory power between 1992 and 2010.

Global Factor	Shift R^2	Twist R^2	Bfly R^2	# Local Shift	# Local Twist	# Local Bfly
COM_ENERGY	73.85%	8.36%	2.76%	6	6	2
COM_PRECMETAL	86.27%	0.13%	-	4	2	0
COM_INDMETAL	72.61%	0.66%	-	7	7	0
COM_AGRICULT	58.37%	0.19%	-	14	14	0
COM_LIVESTOCK	69.17%	2.57%	-	3	3	0

5.3. Hedge Funds

As an asset class, investments in hedge funds pose a particular risk modeling challenge. The general lack of transparency into a fund's holdings makes it difficult to gauge market exposures. This is exacerbated by the high degree of turnover of many funds, which can make point-in-time exposures an inadequate measure of a fund's real risk profile. The lack of public markets in hedge funds further obscures their risk, leaving monthly reported returns as one of the only sources of insight into many funds. Lastly, the tendency to follow similar investment strategies leads to an additional source of systematic risk beyond that inherited through a fund's market exposures. Events such as the "quant quake" of August 2007 demonstrated the magnitude of such systematic strategy risk, as stocks plummeted while many funds were simultaneously forced to abandon similar positions.

To measure both the market and strategy components of hedge fund risk, we adopt a two-level approach. The Hedge Fund Exposures Model combines the information of a fund's investment style and geographic classifications with their return time series, thus estimating each fund's exposures to systematic factors. The exposures model absorbs the component of hedge fund returns correlated with market and style factors. As a result, the remaining hedge fund return is uncorrelated with other factors.

After subtracting the market component of returns implied by these exposures, the strategy component of risk is measured with factors for Global Macro, Merger Arbitrage, Managed Futures, Convertible Arbitrage, Distressed Securities, Event Driven, Equity/Market Neutral, Fixed-Income Arbitrage, and Fund-of-Hedge-Funds strategy risk. These factors describe the pure strategy risk of hedge funds, uncorrelated with the public market factors.

Since hedge fund relationships with the public markets are modeled by the Hedge Fund Exposure Model, no global hedge fund factors are needed.

For more information on the Barra Hedge Fund Models, see Reference 15.

5.4. Private Real Estate

The private real estate models in the Barra Integrated Model aim to measure the systematic risk that accumulates with a private real estate investment and gauge how that risk interacts with the larger portfolio. To this end, the value of an individual property is secondary to the structural relationships driving a portfolio's returns over time, and the likelihood of a property losing value at the same time as the rest of a broader portfolio.

Estimating these relationships is complicated by the lack of liquidity of private real estate, since most property changes hands on a timescale of years or decades. Although quarterly returns to private real estate indices are available, they are typically based on appraisals or estimated values that lag the market and tend to be smoothed over time. They exhibit little response to current conditions and they tend to understate both volatility and the correlations with other asset class returns.

To overcome these difficulties, the factors in the private real estate models are estimated from the quarterly returns of private real estate indices; for example, the National Council for Real Estate Investment Fiduciaries (NCREIF) regional indices in the United States, and Investment Property Databank (IPD) indices in the United Kingdom. A de-smoothing procedure is used to convert the index returns to pure factor return innovations, providing larger, more realistic volatility and correlations.

In the US market, there are 17 factors representing the main categories defined by NCREIF: Apartments, Industrials, Offices, and Retail in each of the East, West, South and Midwest regions, plus a national Hotels factor. In the UK, there are 10 factors representing the Portfolio Analyst Service segments defined by IPD for Retail, Shopping Centers, Warehouses, Offices, and Industrials over a variety of regions.

The return innovations of the private real estate factors are sufficient to estimate the correlations within private real estate, where the relationships are strong but the quarterly frequency is inadequate to measure the weaker relationships with other asset classes. To estimate these relationships, we exploit the link between private and public real estate. The return of each local real estate factor is related to the public real estate REIT factors in the respective equity models, USE3 and the Barra UK Equity Model (UKE7), as

$$f_{PRE} = \beta f_{REIT} + l. \tag{5.1}$$

Here l represents the purely local returns interacting only within private real estate, while the β of each private real estate factor relative to public real estate provides the link to other asset classes.

The return of an individual property is modeled with unit exposure to the factor representing its location and type, plus a specific return component modeled with a private real estate specific risk model. Levered investments are given larger factor exposures, combined with short positions in the relevant debt instrument.

For more information on the Barra Private Real Estate Models, see Reference 16.

5.5. Equity Volatility Futures

Equity volatility futures are exchange-traded contracts, whose payoff is based on the level of equity volatility indices. The most common of these futures are based on the Chicago Board Options Exchange Market Volatility Index (VIX) in the United States, and the EURO STOXX 50® Volatility (VSTOXX®) Index in Europe. These indices are constructed as weighted averages over equity index options with weights that, in theory, replicate the pure implied 30-day volatility[10] of the equity index, independent of the equity index level (Reference 17).

The VIX and VSTOXX are calculated as weighted averages of actual option prices, not just averages of theoretical implied volatilities, but the difficulty in trading the underlying baskets of options contributed to the creation of more easily traded futures contracts. These contracts allow investors to make bets on future volatility or hedge exposure to it.

Although the underlying asset is more abstract than those of more conventional futures, volatility futures are plain vanilla cash-settled contracts. Unlike many other futures, however, the VIX and VSTOXX levels cannot be purchased on a spot market and stored for future delivery, which results in somewhat decoupled behavior between the index level and the prompt contract on it.

The Barra Equity Volatility Futures Model (EVX1) uses five factors to describe the behavior of the US and European markets. In each market, the dominant driver of return is a non-parallel Shift in the futures curve. Under the Heston model of stochastic variance, a single factor with a particular shape would explain all of the return to implied volatility futures. In practice, these Shift factors explain about 85% of the return of futures in both the US and Europe. In the US, where contracts are traded out to a longer tenor than in Europe, a second systematic Twist factor describes steepening of the long end of the curve against the short. Lastly, Spot factors in each market reflect the difference between the index levels and the zero maturity limit of the futures curves.

For global factors, the two equity volatility Shift factors are used to relate equity volatility derivatives to other asset classes. For more information about the Barra Equity Volatility Futures Model, see Reference 18.

[10] As discussed in Reference 17, the replication is actually of variance, not volatility, which requires dynamical replication to implement the square-root.

6. Model Horizons

BIM301 is available in two versions: BIM301S for short horizons, and BIM301L for long horizons. The BIM301S model is built to provide the best risk forecasts at the one-month horizon, with a high degree of responsiveness to recent market conditions. BIM301L is intended for longer-term investors, giving greater weight to a range of market regimes and providing more stable and robust risk forecasts.

The two versions of the model share factor structure and exposures, but differ in the half life parameters used to calculate the factor correlation matrix and volatilities. The Barra Integrated Model calculates correlation matrices with an exponentially weighted moving average, using an expanding window of all available data history. The model accounts for serial correlation[11] using the Newey-West estimator (Reference 12), and uses an Expectation Maximization algorithm (Reference 19) to account for missing data, short time series, and holidays.

Longer half life is generally associated with a longer forecast horizon, but the optimal half life parameters are not a simple function of the horizon. The timescale of changes in the market structure are also relevant, with a longer half life favored if markets are stationary, regardless of the investment horizon.

Both versions of the Barra Integrated Model use a longer half life for correlations than for volatilities -- for two reasons. First, our research has shown that the correlation structure is significantly more stationary than volatility, which favors a longer correlation half life. Second, the issues of robustness discussed in Section 2 are much more sensitive to correlation half life than volatility half life, simply because the correlation matrix requires estimating so many more elements than volatilities. It is therefore possible to strike a good balance between responsiveness and robustness by using a much shorter volatility half life than correlation half life.

There is some variation of half life parameters among the component models of the Barra Integrated Model but a volatility half life of one year is typical for the long horizon model, while 90 trading days is standard for the short horizon model. Likewise, a correlation half life of three years is typical of the long horizon model, and two years for the short horizon model.

In contrast with BIM207, which included a wide variation in responsiveness among its components, the half life parameters of BIM301 are much more homogenous. This is especially important in a global model measuring the relationships between different parts of the market. For example, consider a forecast beta, $\beta_{iM} = \rho_{iM}\sigma_i / \sigma_M$ during a crisis period when volatility levels increase rapidly. If one component of BIM used a much shorter half life than the rest of the model, then σ_i could appear to rise more rapidly than σ_M, thus creating a large forecast β_{iM} as an unintended artifact.

To achieve uniform responsiveness, BIM301S and BIM301L each use consistent half life parameters: for all fixed income models; for the currency, commodity, and equity implied volatility models; for the global and core covariance matrices; and for many equity components. Only the hedge fund and private real estate components use significantly longer half life parameters.

[11] In contradiction with the efficient markets hypothesis, serial correlation is significant enough to affect model performance, even out to two weeks for highly liquid developed market stocks. It is unclear whether it is possible to profit from such inefficiencies, after transaction costs.

For many equity markets, BIM301 constructs a new single country covariance matrix of the appropriate overall responsiveness. For models that use a GARCH or DEWIV[12] process to accelerate the responsiveness, or for models such as the Barra China Equity Model (CHE2) that have a short half life, BIM301L constructs new long-horizon versions. For other models, such as many emerging market models, BIM301S builds short-horizon versions using GEM2's weekly factor returns to scale the original covariance matrix to the short half life volatility level.

The greater responsiveness of the short horizon model allows it to react more quickly to changes in the markets, but results in greater variability from month-to-month and more vulnerability to statistical estimation error, due to a shorter effective observation window. In times of relative calm in the markets, such as during the period from 2003 to mid-2007, the short horizon model tends to be more accurate while the markets remain calm. The long horizon model, on the other hand, can give the impression of over-forecasting risk during these periods, because its forecasts include the likelihood that market volatility may rise over the course of the investment horizon.

Figure 18 compares the risk forecasts for the MSCI All Country World Investable Market Index (ACWI IMI) of the long and short model versions, as well as GEM2S, GEM2L, and BIM207, showing their responsiveness during different risk environments.

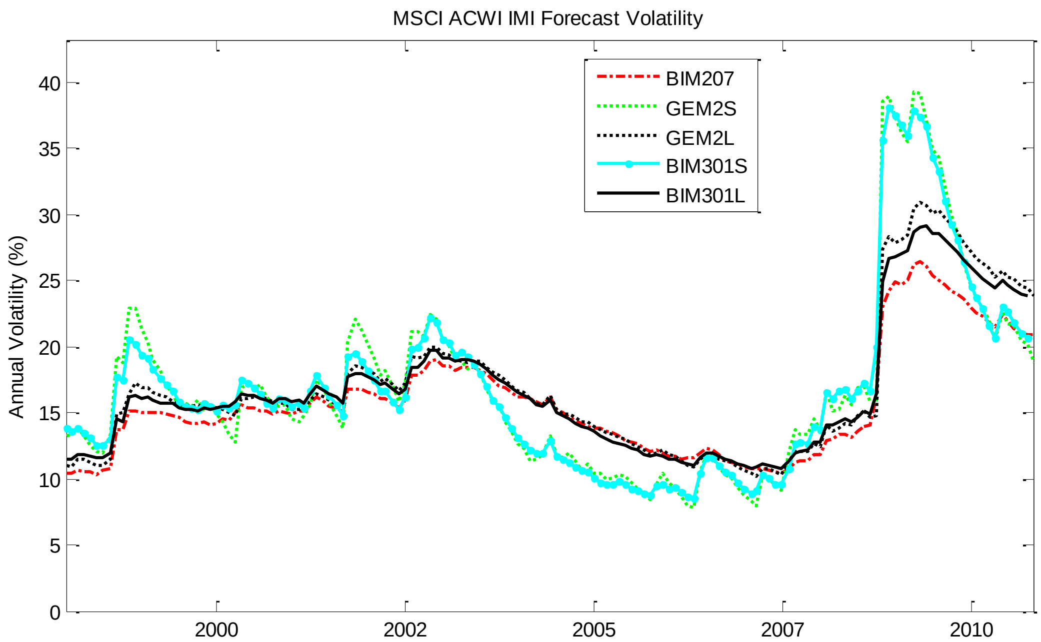

Figure 18. The forecast volatility of the MSCI All Country World Investable Market Index.

[12] The Daily Exponentially Weighted Index Volatility (DEWIV) procedure scales the market component of factor risk to match the recent volatility level of a market index.

6.1. Attributing Changes in Risk

In practice, it is difficult to know which regime the markets are in until well after the fact, and it can be useful to use the long and short models together to provide different perspectives. To facilitate comparison between the models, as well as to understand the drivers of changing risk forecasts from one month to the next, it is useful to attribute differences in risk forecasts in terms of the underlying market variables. Appendix E introduces a new Risk Delta Attribution methodology that extends the Correlation Risk Attribution framework (Reference 20) to provide insight into differences in risk forecasts.

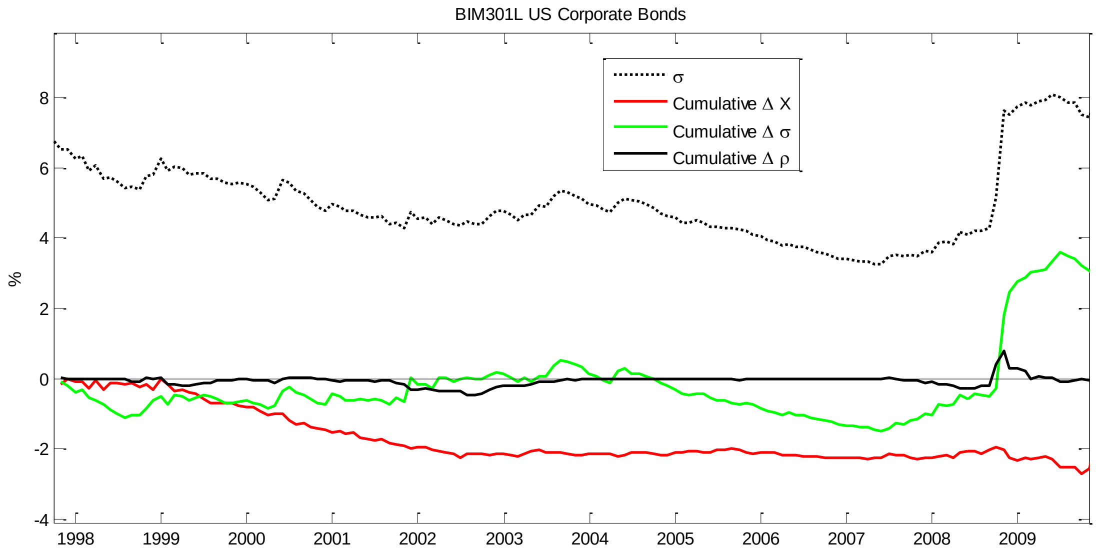

Figure 19. A Risk Delta Attribution of the changes in BIM301L risk forecasts for a portfolio of US Corporate bonds.

Figure 19 shows the BIM301L risk forecast for a portfolio of US Corporate bonds. Starting at about 6.5% volatility, the risk goes below 4% in 2007 before rapidly rising to near 8% in 2008. A risk delta attribution analysis shows that much of the initial decline in this portfolio's risk was not due to changes in the markets, but to changes in the portfolio itself. The red curve, labeled Cumulative ΔX, shows a total risk reduction of about 2% over time due to a gradual decline in the duration of the portfolio, which began stabilizing after 2002. In contrast, changes in risk after 2002 were primarily driven by changes in the standalone volatility of the underlying factors, declining until 2007 and then rising sharply in the crisis. Although changes in correlation played a smaller role over time, they contributed significantly during the crisis with increased correlations driving risk forecasts higher.

For comparison, Figure 20 shows a Risk Delta Attribution of the differences in risk forecasts for the same US Corporate portfolio between BIM301S and BIM301L. Differences in risk forecasts are primarily due to volatility, with small differences due to correlations and no contribution from ΔX. This is not surprising, since the two models use identical factor exposures and they both use a relatively long correlation half life; the major difference is in the volatility half life.

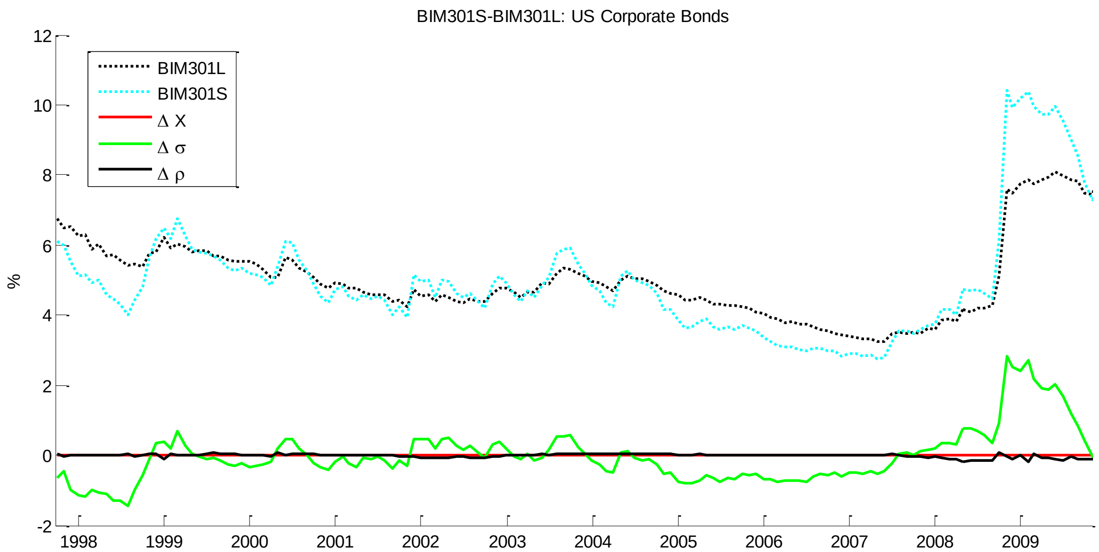

Figure 20. A risk delta attribution of the difference between BIM301S and BIM301L risk forecasts for a portfolio of US Corporate bonds.

7. Multi-Asset Class Risk

BIM301 employs a total of 253 global factors: 101 equity, 90 fixed income, 55 currency, 5 commodity, and 2 equity volatility futures global factors. These factors are needed to model the relationships within each asset class, but it is too many factors to robustly estimate every pair of correlations. To address this, the global factor covariance matrix is itself built as an integrated model, using a subset of *core factors* to provide the cross-asset class relationships[13].

Since all BIM301 global factors are available at a weekly observation frequency, it is possible to build a larger core factor covariance matrix than could be robustly estimated with BIM207's monthly global factor returns. By comparison, BIM301 uses 138 core factors, up from the 71 factors used in BIM207. The larger core factor covariance matrix allows BIM301 to measure more dimensions of multi-asset class risk, including important bond-equity and bond-currency relationships that were inferred in BIM207 through a smaller core factor set.

For equities, BIM301 takes global equity country factors for all countries with bond coverage, plus the World factor, for a total of 47 core equity factors. The significant relationships between equity industries and other asset classes are captured by core factors in those asset classes, such as the Financials credit factor and the commodity sectors. It is therefore unnecessary to include industries among the core factors.

BIM301 significantly expands the set of core fixed income factors from 16 to 52, including 36 Shift, 6 EM, and 10 global credit factors. The expanded core factor set significantly improves cross-asset-class modeling, capturing important equity-credit relationships, and the debt-equity and debt-currency relationships in each country.

BIM301uses as core factors the currency factors for all markets with a bond model, for a total of 34 core currency factors, compared with 8 core factors in BIM207. Like the expanded fixed income factors, these factors are important for events that tend to drive the equity, bonds, and currency of a country to move in unison.

BIM301 retains all 5 global commodity factors as core factors. These core factors capture a high degree of correlation with global equity industries, such as Precious Metals and Energy, and negative correlations with industries like Airlines and Food Retailing.

Core factors are not needed for the three remaining asset classes covered by BIM301. For hedge funds, BIM301's pure strategy risk factors are uncorrelated with other asset classes by construction. Equity volatility futures are related to the equity markets through the core equity factors, but without additional core factors. Lastly, private real estate is integrated with the REIT factors of the equity models, inheriting other relationships from them.

---

[13] The global equity and currency factors are primarily inherited from GEM2, which does not require core factors to relate its 153 equity and currency factors. For consistency with GEM2, BIM301 treats global equities and currencies as a single global block, using core factors to relate them to fixed income, commodities and equity volatility futures.

Table 5. The number of core factors in BIM301 by asset class, compared with BIM207.

Asset Class	BIM207 #	BIM301 #
Equity	42	47
Fixed Income	16	52
Currencies	8	34
Commodities	5	5
Hedge Funds	0	0
Equity Implied Volatility	-	0
Private Real Estate	-	0
Total	71	138

8. Model Performance

8.1. Performance Metrics

If risk levels were constant in time, a natural measure of the accuracy of risk forecasts would be

$$\frac{\text{realized volatility}}{\text{forecast volatility}}. \tag{8.1}$$

An accurate risk forecast would result in a ratio close to 1. However, since risk forecasts change over time we cannot use Equation 8.1 because there is no single forecast that can be used in the denominator.

To measure the accuracy of changing forecasts, we first construct z-scores

$$z_{p,t} = \frac{R_{p,t}}{\sigma_{p,t-1}}, \tag{8.2}$$

where $R_{p,t}$ is the return of a test portfolio p at time t, and $\sigma_{p,t-1}$ is the forecast volatility prior to that time period. If risk forecasts are accurate, then the *bias statistic*

$$B_p \equiv std(z_{p,t}) \tag{8.3}$$

would be close to 1, as in Equation 8.1. Indeed, in the limit that risk forecasts are constant, the Bias Statistic reduces to Equation 8.1.

The bias statistic is a useful measure of the accuracy of a risk model, particularly the existence of systematic inaccuracies; for example, missing factors, or a failure to account for serial correlation. Bias statistics greater than one suggest risk is under-forecast, while bias statistics less than one indicate risk is over-forecast.

Even a perfect risk forecast would not lead to a bias statistic of exactly 1 due to sampling error in the realized volatility. It can be shown that the sampling error of the bias statistic for a perfect risk forecast and a test period of T independent returns is approximately

$$\Delta B = \sqrt{\frac{k+2}{4T}}, \tag{8.4}$$

where k is the excess kurtosis of the returns distribution. Even perfect risk forecasts can therefore yield bias statistics seemingly far from 1 if there is high kurtosis or a short sample period.

Unfortunately, although accurate risk forecasts result in bias statistics close to one, it is possible for inaccurate risk forecasts also to result in bias statistics close to 1. For example, Figure 21 shows the z-scores for an artificial constant forecast of 4.74% for the monthly returns of the US market, between 1998 and 2006. Although the overall bias statistic is contrived to be exactly one, it is due to cancellations between initially under-forecast risk followed by over-forecast risk later on. The bias statistic alone fails to resolve the changing accuracy of the model over time and actually favors over-forecast risk after 2002 to compensate for the under-forecast risk early on.

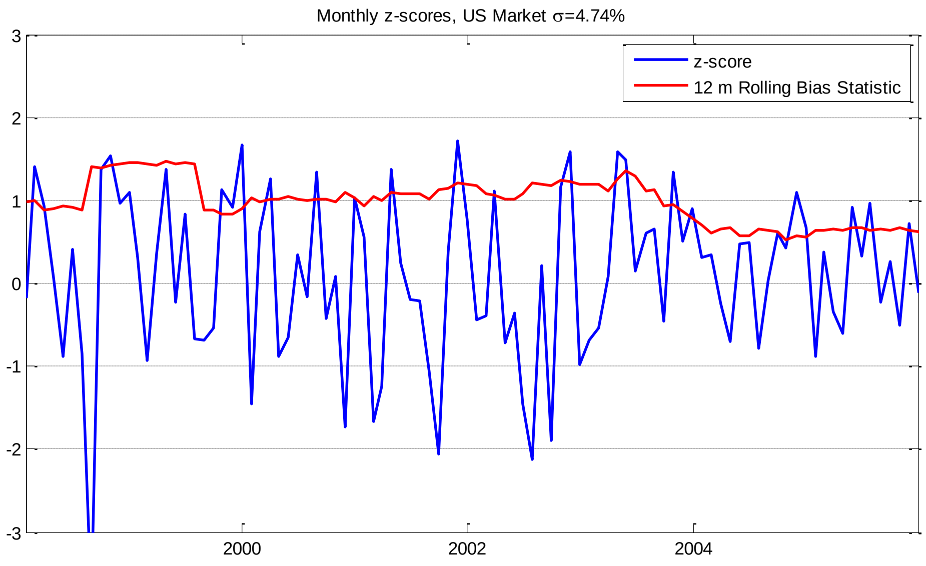

Figure 21. The z-scores and rolling bias statistics for an artificial constant monthly risk forecast for the US Equity Market during a period when volatility rose and fell sharply. The forecast of 4.74% results in an overall bias statistic of exactly 1 due to cancellations between over-forecast and under-forecast risk. The 12-month rolling bias statistic deviates significantly from 1, showing that the constant forecast is inaccurate.

Figure 21 also shows a 12-month rolling bias statistic

$$B_{p,t}^{(12)} = std_{t'}(z_{p,t'}) \qquad t' \in (t-11, t) \tag{8.5}$$

whose deviation from 1 demonstrates the problems with the constant risk forecast. Its values greater than 1 in the late 1990's reflect that it under-forecast risk in this time period, while values less than 1 in 2004 and 2005 demonstrate that it over-forecast volatility.

A modification of the bias statistic, called the Mean Rolling Absolute Deviation (MRAD) takes advantage of the better resolving power of the shorter window. It is defined to be

$$MRAD_p = mean\left(\left|B_{p,t}^{(12)} - 1\right|\right), \tag{8.6}$$

measuring the average deviation of the rolling 12-month bias statistics from the ideal value of 1. Although the sampling error of each 12-month bias statistic is large, the MRAD averages over many such statistics to produce an aggregate value that is less noisy.

For perfect risk forecasts, the expected value of the MRAD depends on the kurtosis of the underlying returns, as shown in Figure 22. Values on this curve can be considered optimal, although smaller values are possible due to sampling error.

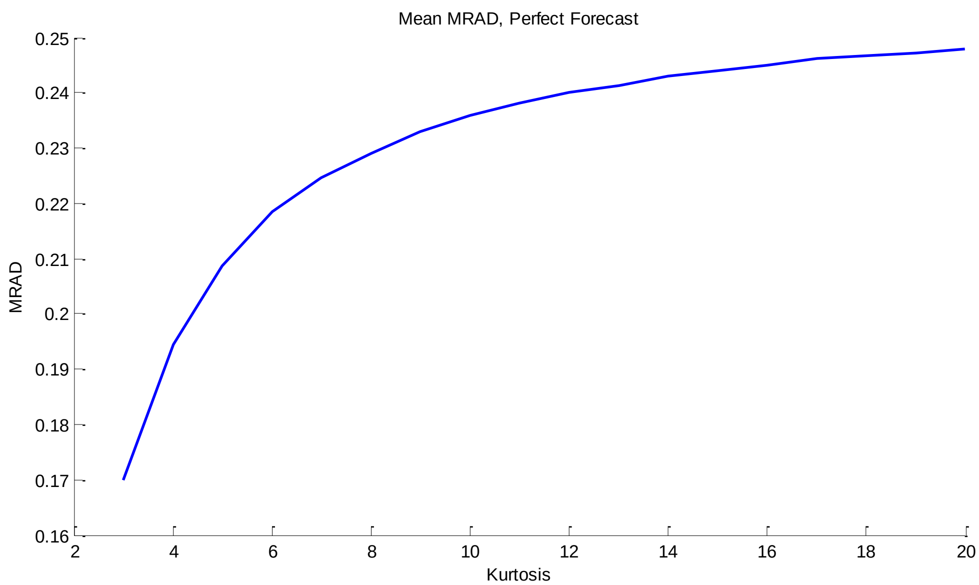

Figure 22. The average MRAD for a perfect risk forecast, shown as a function of kurtosis.

8.2. Equity Model Performance

To test the accuracy of BIM301 for forecasting the risk of equity portfolios, we consider backtests of a variety of portfolios and benchmarks. The portfolios and benchmarks are selected to probe many facets of the covariance structure, and designed to challenge the risk model rather than to reflect realistic investment allocations.

Starting with the universe of approximately 10,000 stocks in the MSCI ACWI IMI, concentrated industry and style portfolios are constructed in each of 48 countries. These cap-weighted portfolios consist of 10 GICS industry sectors and 16 style portfolios for the top and bottom quintiles of GEM2 style factor exposures in each country. A total of 1248 concentrated portfolios can be constructed in this way, but filtering out portfolios of fewer than 10 assets reduces the number to 755 such portfolios.

Global portfolios are built according to GEM2 factor assignments, with 48 country portfolios, 34 industry portfolios, and 16 top- and bottom-quintile style portfolios. These cap-weighted portfolios differ from the factor-mimicking portfolios of GEM2 which are long/short portfolios, each hedged against other factors. Lastly, Global Emerging Market portfolios are built by restricting the global portfolios to the

Emerging Market component of the MSCI ACWI IMI, for 24 countries, 33 industries[14] and 16 style portfolios.

Portfolios are rebalanced and risk forecasts are made at a monthly frequency, over the full available model history between October 1997 and December 2010. In addition to BIM301S and BIM301L, risk forecasts are made with the legacy BIM207 and the Long and Short Horizon Global Equity Models GEM2L and GEM2S.

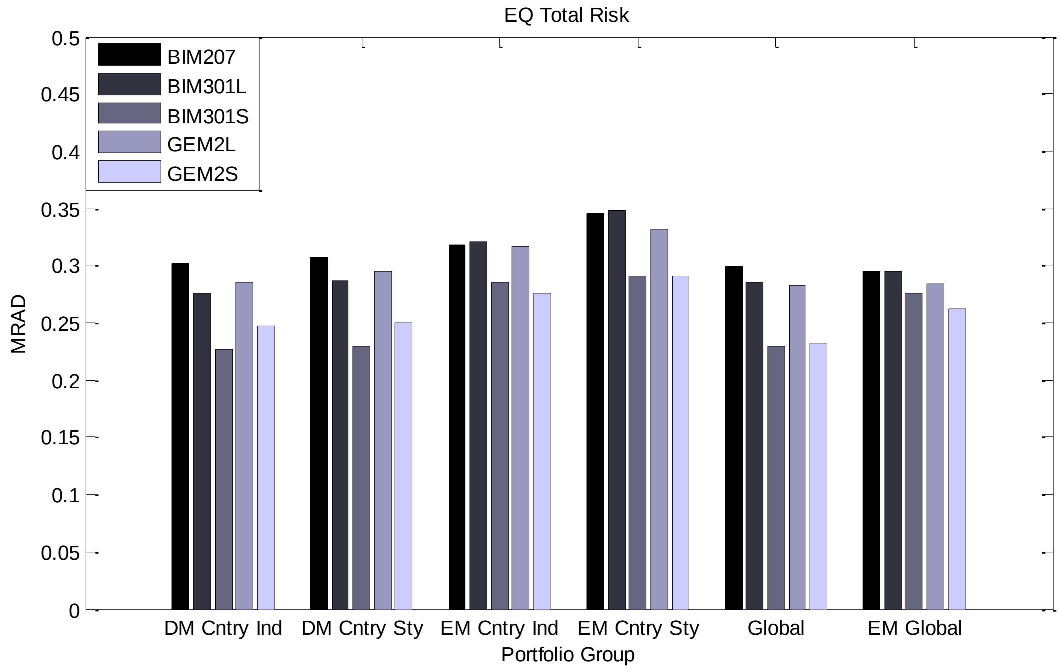

Figure 23. The mean rolling absolute deviation (MRAD) statistics for the total risk of equity test portfolios, testing the historical accuracy of risk forecasts of BIM207, BIM301S/L and GEM2S/L. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. From the left, the first four portfolio groups consist of single-country portfolios with concentrations in industry sectors or style quintiles, grouped among Developed Market (DM) and Emerging Market (EM) countries. These groups contain 122, 320, 85, and 228 portfolios respectively. The Global portfolio group consists of 48 countries, 34 industries and 16 top and bottom quintile style portfolios based on the GEM2 factors and MSCI ACWI IMI constituents. The EM Global group consists of 24 countries, 33 industries and 16 top and bottom quintile style portfolios constructed from the Emerging Market component of the MSCI ACWI IMI. These statistics demonstrate the importance of responsiveness to the forecasting accuracy for long-only portfolios, with the short-horizon BIM301S and GEM2S performing better than the longer horizon variants.

[14] The Biotech industry has fewer than 10 stocks in the Emerging Market component of the MSCI ACWI IMI, and is excluded from the study.

Figure 23 shows the MRAD statistics, Equation 8.6, for the total risk forecasts of the test portfolios, averaged over groups of portfolios. Despite the concentration of the single-country industry and style portfolios, the total risk of long-only portfolios is largely driven by market risk, and it is as expected that the global model is nearly as accurate as the integrated model in this context. On the other hand, it is notable that BIM301 matches the accuracy of GEM2 for the global portfolios for which GEM2 is designed.

The clearest advantage visible in Figure 23 is the benefit of responsiveness. The MRAD statistics indicate that the short-horizon models BIM301S and GEM2S provided consistently more accurate forecasts than the longer horizon variants at the one month test horizon.

The advantage of responsiveness may also explain the slight outperformance of BIM207 relative to BIM301L among the emerging market single-country portfolios. BIM207 used responsive component models in many emergent markets, while BIM301L uses a consistently longer half-life.

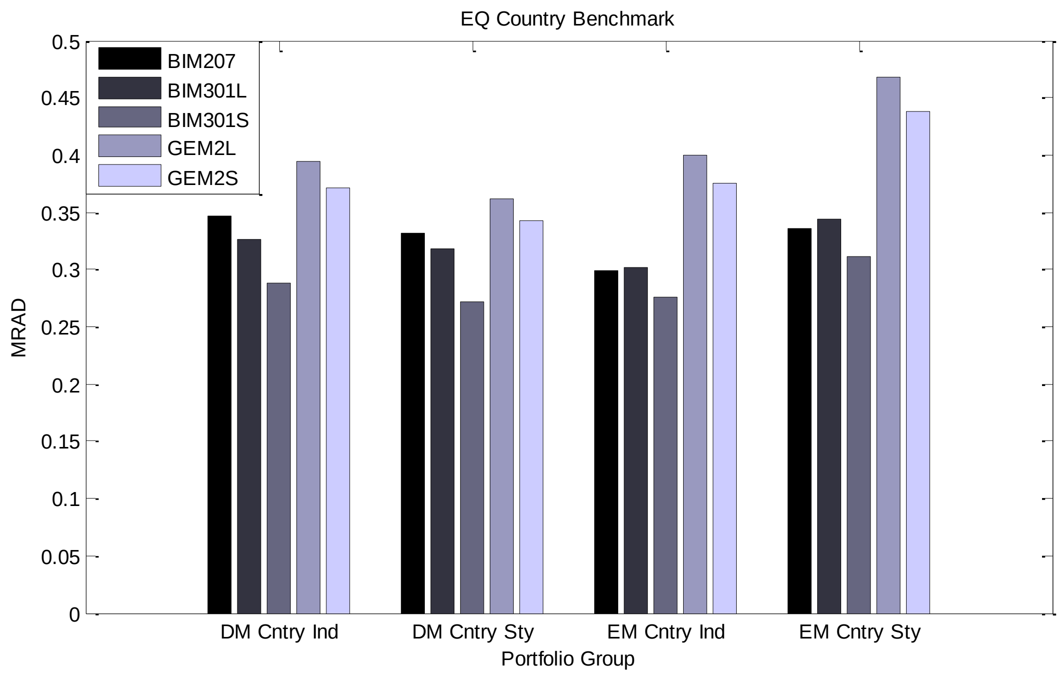

Figure 24. The mean rolling absolute deviation (MRAD) statistics for the active risk forecasts of concentrated equity test portfolios relative to country benchmarks. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. From the left, the portfolio groups consist of single-country portfolios with concentrations in industry sectors or style quintiles, grouped among Developed Market (DM) and Emerging Market (EM) countries. These groups contain 122, 320, 85, and 228 portfolios respectively. These statistics demonstrate the importance of a detailed factor structure to model the relationships within each market, with all versions of the integrated model performing significantly better than the global model.

Figure 24 shows the average MRAD statistics for the active return relative to country benchmarks for the 755 single-country test portfolios. This test probes the accuracy of the forecast correlation structure within each market. In contrast with the total risk, which was well modeled by the country factors in

GEM2, the granularity of the integrated model leads to significantly more accurate active risk forecasts for the concentrated portfolios.

Finally, Figure 25 shows the MRAD statistics for the active return relative to a global benchmark. The Global portfolios and Developed Market single-country portfolios are benchmarked to the MSCI ACWI IMI, while the Emerging Market Global and single-country portfolios are benchmarked to the MSCI Emerging Markets Index.

Together, the test results demonstrate the advantages of responsiveness and granularity, with the forecasts of BIM301S producing the lowest MRADs among the five models tested in almost every setting.

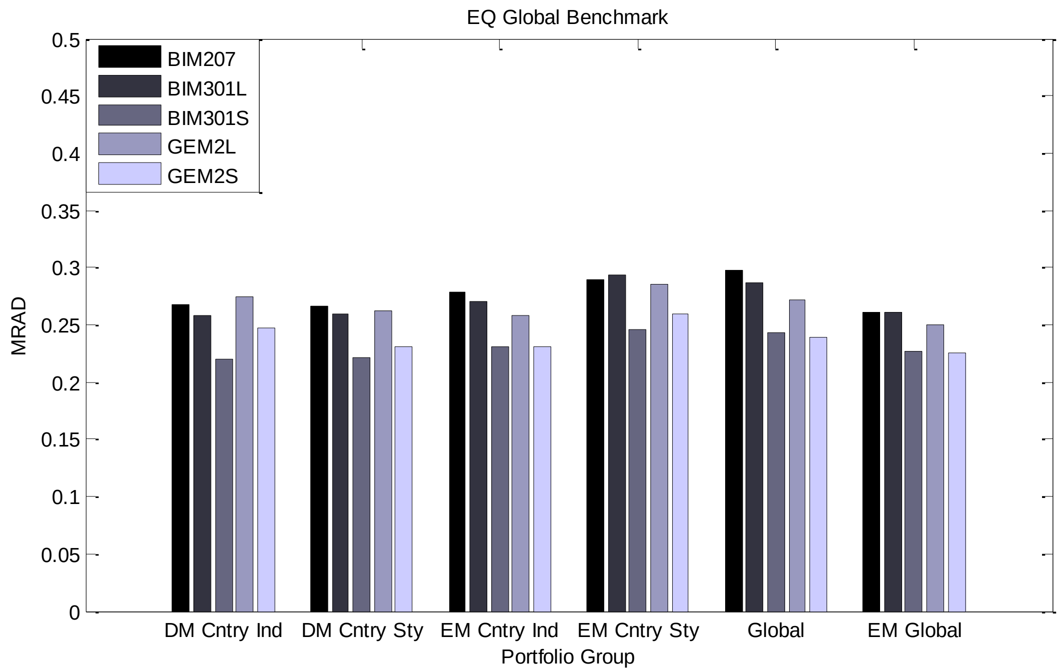

Figure 25. The mean rolling absolute deviation (MRAD) statistics for the active risk of equity test portfolios relative to global benchmarks. The Developed Market (DM) and Global portfolios are benchmarked to the MSCI ACWI IMI, and the Emerging Market (EM) portfolios are benchmarked to the MSCI EM. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. From the left, the first four portfolio groups consist of single-country portfolios with concentrations in industry sectors or style quintiles, grouped among Developed Market (DM) and Emerging Market (EM) countries. These groups contain 122, 320, 85, and 228 portfolios respectively. The Global portfolio group consists of 48 countries, 34 industries and 16 top and bottom quintile style portfolios based on the GEM2 factors and MSCI ACWI IMI constituents. The EM Global group consists of 24 countries, 33 industries and 16 top and bottom quintile style portfolios constructed from the Emerging Market component of the MSCI ACWI IMI. These statistics demonstrate the importance of responsiveness to the forecasting accuracy for long-only portfolios, with the short-horizon BIM301S and GEM2S performing better than the longer horizon variants.

8.3. Fixed Income Model Performance

As with equity, the fixed income components of BIM301 are tested with portfolios selected to challenge different aspects of the covariance structure. Broad portfolios of government bonds are constructed for each of 35 countries, as well as 39 concentrated portfolios of duration-bucketed bonds from Canada, France, Germany, Japan, the United Kingdom, and the United States. 22 broad credit portfolios are constructed in Australia, Canada, Europe, Japan, Switzerland, the United Kingdom, and the United States, for corporate, non-corporate, high yield and covered bonds. 195 credit sector portfolios in the same countries are built for more concentrated segments of the credit markets. Lastly, portfolios of Inflation Protected Bonds (IPB) from nine countries are used to study the real interest rate curves.

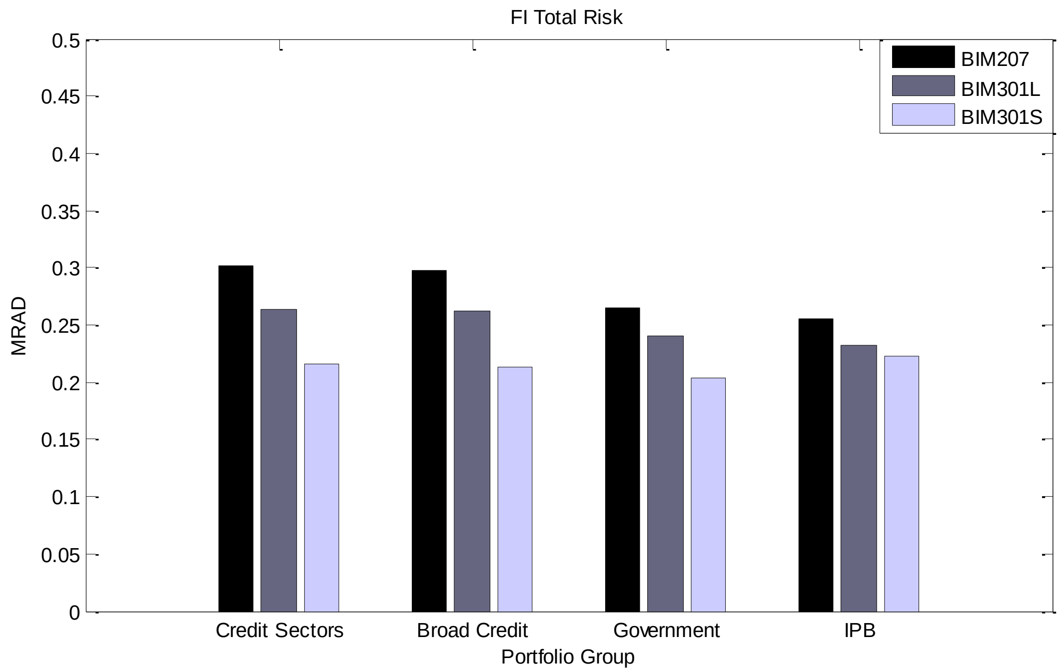

Figure 26. The mean rolling absolute deviation (MRAD) statistics for the total risk of groups of fixed income test portfolios, backtesting the accuracy of risk forecasts of BIM207, BIM301L and BIM301S. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. The smaller MRAD values of BIM301L relative to BIM207 reflect enhancements in the fixed income factor models. The further reduction in MRAD for BIM301S demonstrates the advantage of responsiveness.

Since the MRAD statistic is built with the square of the z-score, a small number of extreme events can have a large effect on the statistic. The credit crisis of 2008 brought unprecedented returns, including many exceeding 10 standard deviations. It is important to test the behavior of risk models through the crisis, but the large returns of this period should not obscure testing the models during more normal times. To reduce the effects of extremely large returns during the credit crisis of 2008, the fixed income

MRAD statistics are calculated from z-scores capped at ±3. Table 6 provides a comparison with a cap of ±10, which emphasizes the forecast accuracy during the crisis period.

Figure 26 shows the MRAD statistics, Equation 8.6, for the total risk forecasts of the fixed income test portfolios, averaged over groups of portfolios. Figure 27 shows the average MRAD statistics for the active return relative to government bond benchmarks, probing the behavior of yields relative to overall interest rates. Figure 28 shows MRAD statistics for the active return relative to a global benchmark of investment grade government bonds.

All tests and all portfolio groups show a significant reduction in MRAD between BIM207 and BIM301L, reflecting the changes in factor structure between the models, and a further reduction with BIM301S, demonstrating the advantage of more responsive risk forecasts.

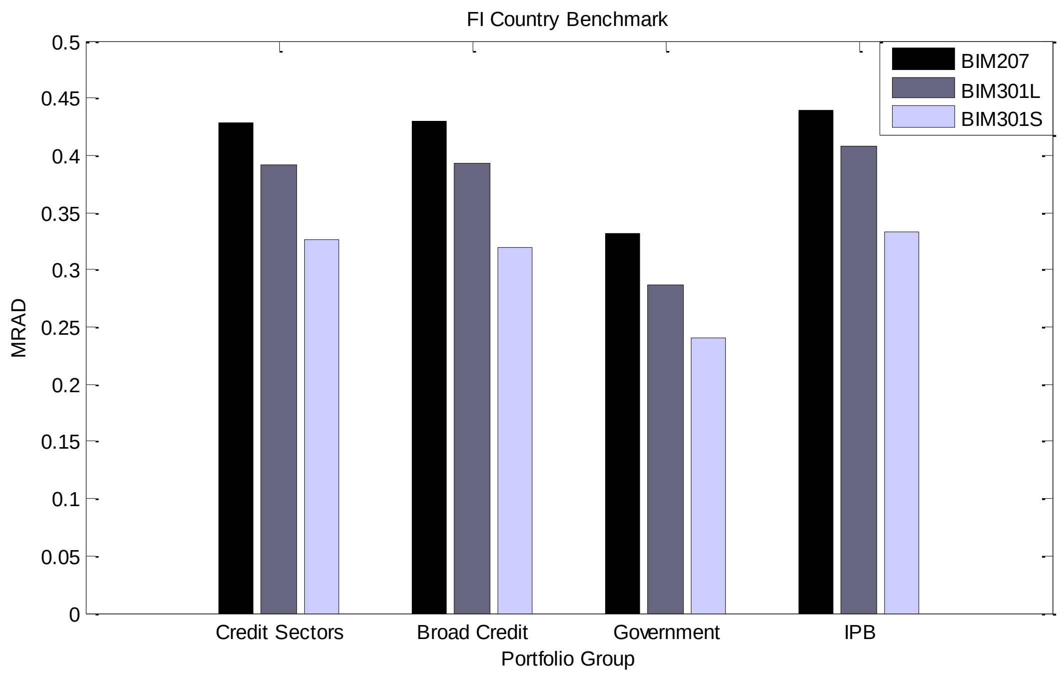

Figure 27. The mean rolling absolute deviation (MRAD) statistics for the active risk of groups of fixed income test portfolios duration matched to benchmarks of government bonds, probing the behavior of yields relative to overall interest rates. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. The smaller MRAD values of BIM301L relative to BIM207 reflect enhancements in the fixed income factor models. The further reduction in MRAD for BIM301S demonstrates the advantage of responsiveness.

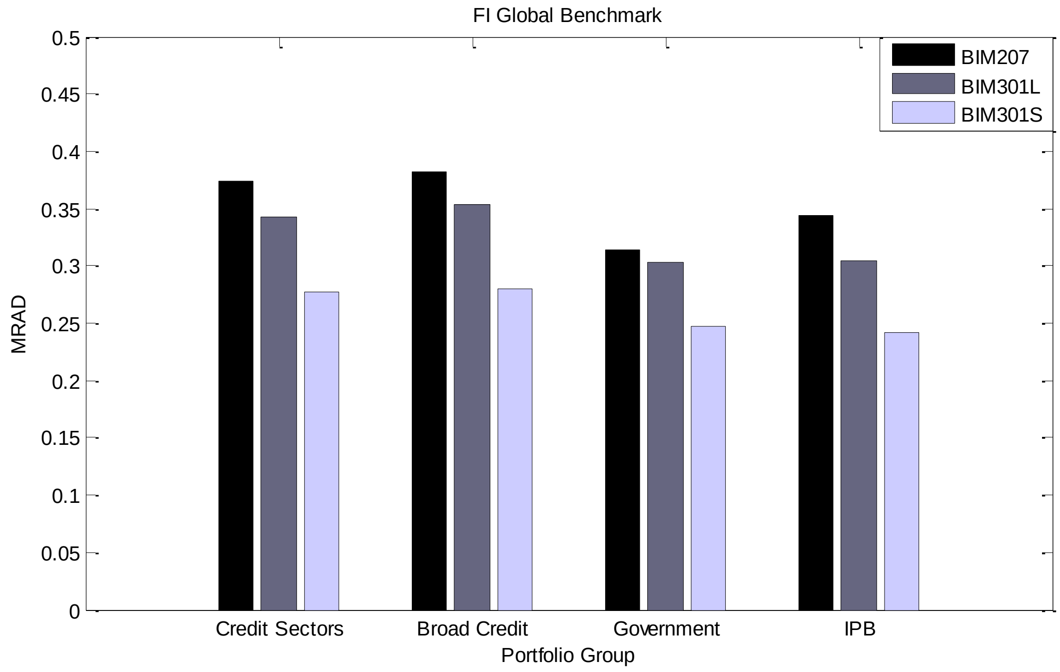

Figure 28. The mean rolling absolute deviation (MRAD) statistics for the active risk of groups of fixed income test portfolios duration matched to a global benchmark of investment grade government bonds, probing cross-market correlations. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. The smaller MRAD values of BIM301L relative to BIM207 reflect enhancements in the fixed income factor models. The further reduction in MRAD for BIM301S demonstrates the advantage of responsiveness.

Table 6. A comparison of the Fixed Income MRAD statistics calculated with caps on the z-scores of 3 and 10. Extremely large returns during the credit crunch of 2008 can dominate the MRADs, particularly those of credit relative to the country benchmark, reflecting unprecedented widening of credit spreads. The figures capped at 10 give an indication of the model performance during the crisis, while the figures capped at 3 are a better measure of the model performance during more normal times.

		|z|≤3			|z|≤10		
Portfolio Group	Benchmark	BIM207	BIM301L	BIM301S	BIM207	BIM301L	BIM301S
Credit Sectors	Total Risk	0.301	0.263	0.216	0.409	0.335	0.280
Broad Credit	Total Risk	0.298	0.262	0.213	0.394	0.323	0.264
Government	Total Risk	0.265	0.241	0.203	0.289	0.262	0.224
IPB	Total Risk	0.256	0.232	0.222	0.326	0.267	0.242
Credit Sectors	Country	0.429	0.392	0.326	0.670	0.575	0.499
Broad Credit	Country	0.430	0.393	0.319	0.646	0.565	0.480
Government	Country	0.332	0.286	0.241	0.386	0.320	0.280
IPB	Country	0.439	0.409	0.333	0.544	0.523	0.429
Credit Sectors	Global	0.374	0.342	0.278	0.514	0.442	0.366
Broad Credit	Global	0.382	0.353	0.280	0.495	0.431	0.347
Government	Global	0.315	0.303	0.248	0.338	0.324	0.267
IPB	Global	0.344	0.304	0.242	0.453	0.381	0.310

8.4. Multi-asset Class Model Performance

Figure 29 shows MRAD statistics for a variety of multi-asset class portfolios. The currency portfolios consist of each of the 74 currencies covered by the legacy BIM207, and similarly for the 24 commodity portfolios. The commodity-equity portfolios consist of the 168 combinations of single commodities with short positions in one of 7 equity portfolios: Diversified Financials, Gold & Precious Metals, Airlines, China, Australia, or the MSCI ACWI IMI.

Figure 30 shows the MRAD statistics for the total return of blended portfolios made by combining the fixed income test portfolios of Section 8.3 with single-country equity portfolios in a 1 to 1 ratio. Since equity is typically more volatile than fixed income, the returns of these portfolios are dominated by the equity components, and the MRAD values behave similarly to those of the pure equity portfolios of Figure 23.

Figure 31 shows the MRAD statistics for the total return of balanced portfolios with greater weight in fixed income, constructed to give approximately equal contributions to the portfolio returns, rather than portfolio value. Since equity returns are roughly 20 times more volatile than bond yields, these portfolios hold bonds and equity in a ratio of 20/duration to 1. For example, a bond portfolio with duration of 2 years would be combined in 10 parts with 1 part equity. Although unrealistic as investments, these portfolios provide a test of the equity-fixed income covariance structure.

Figure 32 shows the MRAD statistics for the active return of the same portfolios benchmarked against a global balanced benchmark. The global benchmark combines the MSCI ACWI IMI with the global investment grade government bond benchmark in the same ratio 20/duration to 1 ratio.

Both Figure 31 and Figure 32 and show smaller MRAD values for BIM301L relative to BIM207, and a further reduction for BIM301S, consistent with an improved factor structure and the advantage of greater responsiveness.

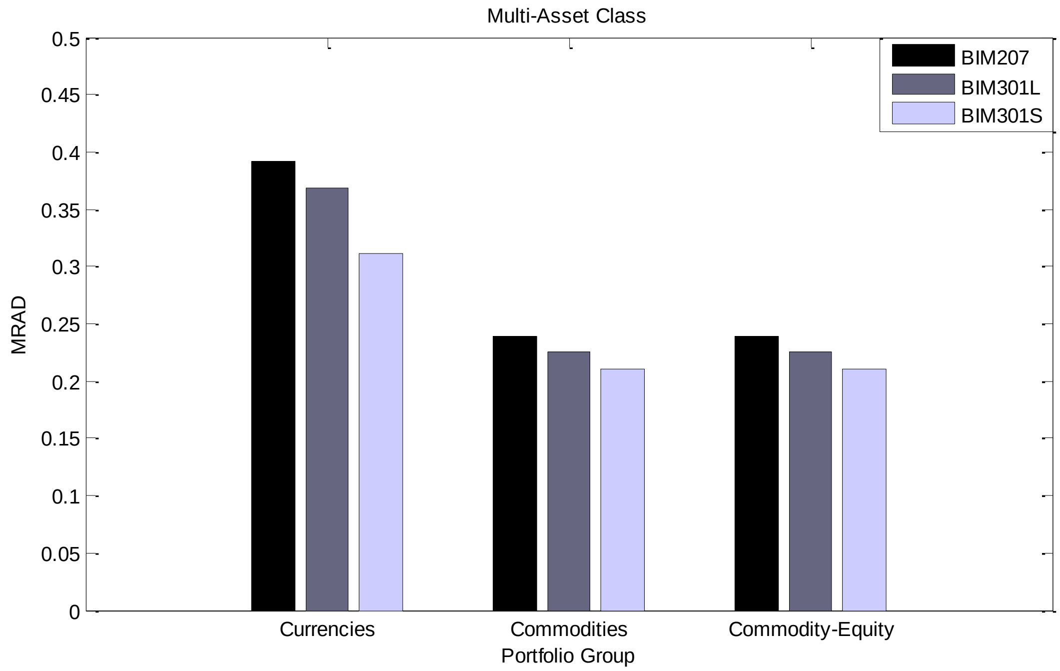

Figure 29. The mean rolling absolute deviation (MRAD) statistics for the total risk of currency, commodity and long/short commodity-equity portfolios. Each of the 168 commodity-equity portfolios is 100% long a single commodity and 100% short one of 7 equity portfolios: Diversified Financials, Gold & Precious Metals, Airlines, China, Australia, or the MSCI ACWI IMI. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of BIM301S approaching those of the perfect forecasts shown in Figure 22.

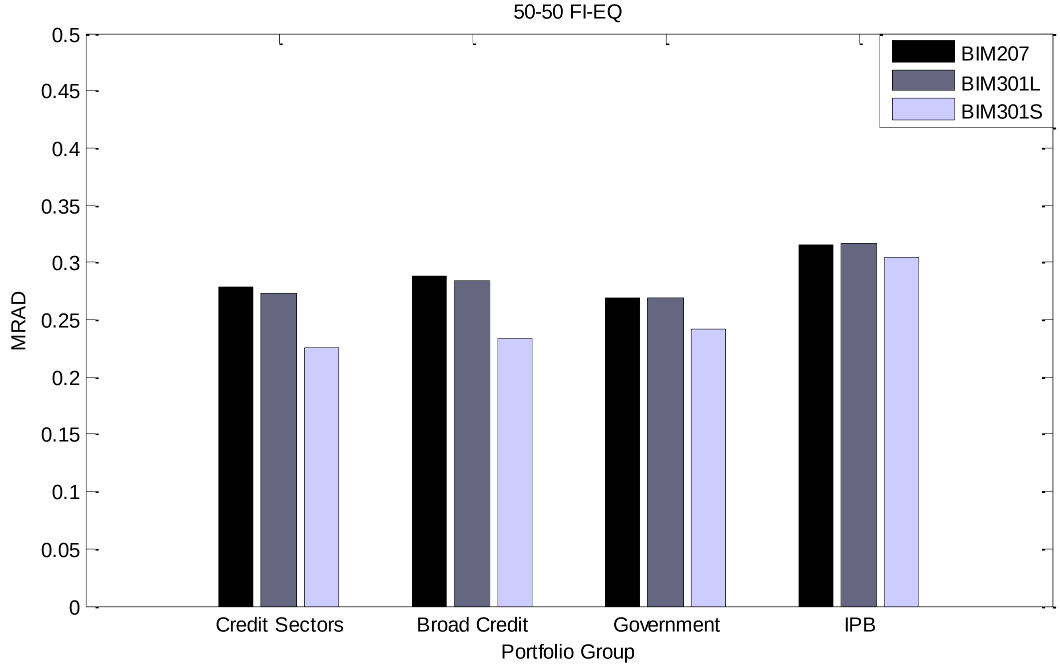

Figure 30. The mean rolling absolute deviation (MRAD) statistics for the total risk of blended fixed income-equity portfolios. The test portfolios are 50-50 blends of the test portfolios of Section 8.3 combined with single-country country components of the MSCI ACWI IMI. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. For these 50-50 blends, the greater volatility of equity relative to fixed income results in portfolios dominated by equity, and the MRAD values behave similarly to those of the pure equity portfolios of Figure 23.

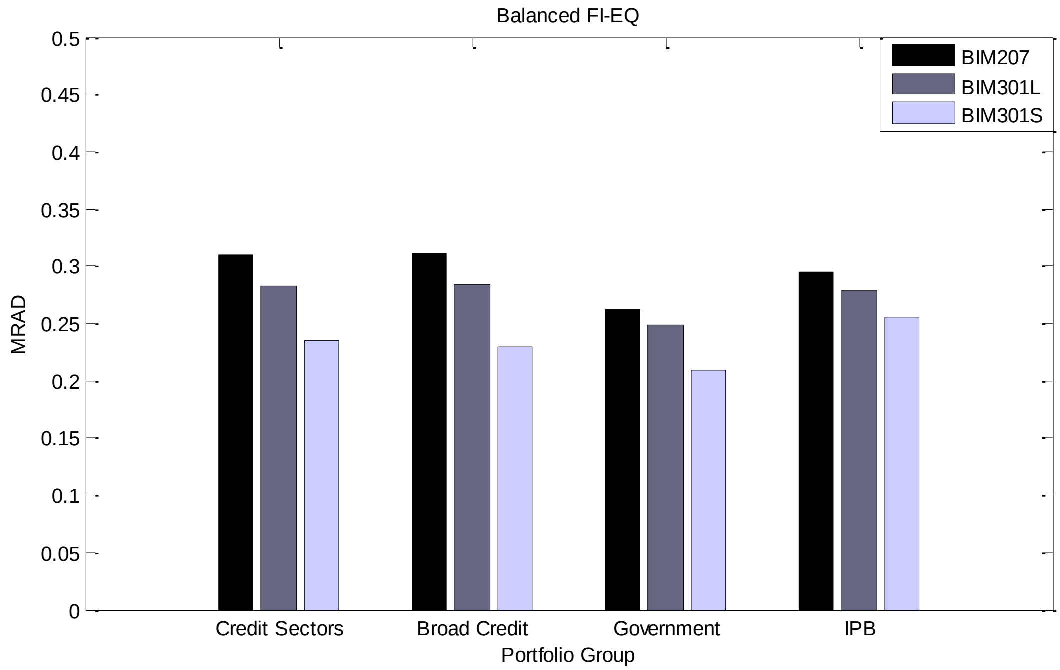

Figure 31. The mean rolling absolute deviation (MRAD) statistics for the total risk of balanced fixed income-equity portfolios. The test portfolios combine the test portfolios of Section 8.3 with single-country country components of the MSCI ACWI IMI in a ratio of 20/duration to 1. This ratio gives the equity and fixed income components approximately equal contributions to the total volatility of the portfolios. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. The smaller MRAD values of BIM301L relative to BIM207 reflect enhancements in the factor structure, and the further reduction in MRAD for BIM301S demonstrates the advantage of responsiveness.

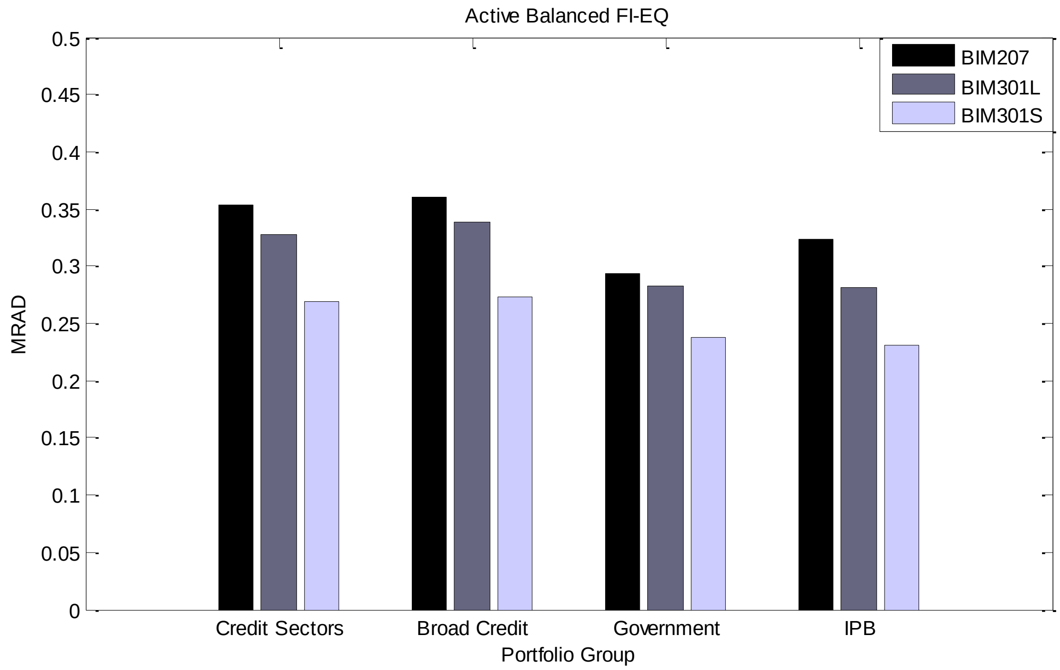

Figure 32. The mean rolling absolute deviation (MRAD) statistics for the active risk of balanced fixed income-equity portfolios relative to a global benchmark. The test portfolios combine the test portfolios of Section 8.3 with single-country country components of the MSCI ACWI IMI in a ratio of 20/duration to 1. The global benchmark consists of the MSCI ACWI IMI blended with a global benchmark of investment grade government bonds, in the same equity-fixed income proportion as the portfolio. Smaller values of the MRAD penalty function (Equation 8.6) correspond to more accurate risk forecasts in the backtest, with the MRAD values of perfect forecasts shown in Figure 22. To reduce the effects of extremely large returns during the credit crisis of 2008, z-scores are capped at ±3. Comparison with a cap of ±10 is provided in Table 6. The smaller MRAD values of BIM301L relative to BIM207 reflect enhancements in the factor structure, and the further reduction in MRAD for BIM301S demonstrates the advantage of responsiveness.

9. Summary

The new generation Barra Integrated Model (BIM301) combines parsimonious global factors with detailed models of equity, fixed income, currencies, commodities, hedge funds, private real estate, and equity implied volatility to create a multi-asset class risk model that is detailed, global, responsive, and robust.

The new version introduces a range of modeling enhancements:

- Incorporation of the Barra Global Equity Model (GEM2)
- An updated Barra Europe Equity Model (EUE3)
- New multi-horizon model versions in Australia (AUE3), Japan (JPE3), and Canada (CNE4), each estimated from daily observations
- Adapted responsiveness of all other equity models for consistent short and long horizon versions (BIM301S and BIM301L)
- Full re-estimation of fixed income models based on weekly return observations
- Extended or more granular term structures for UK, Euro, Japan, and US
- New term structure models for Peru, Colombia, Argentina, and Egypt
- A new Inflation Protected Bond (IPB) model for Brazil and four additional Euro governments, plus revised IPB models for eight other markets
- A revised Japanese credit model and more granular, GICS®-based credit models for six developed markets
- New models of swap spread curve fluctuations in 12 developed markets
- A new Currency Model (CUR2)
- A new Commodity Model (COM2)
- A re-estimated Hedge Fund Model (HFR2)
- A new Equity Volatility Futures Model (EVX1)
- New Private Real Estate Models for the US and UK (USR1 & UKR1)

BIM301 represents major advances in MSCI's ability to model the structure of the world's markets.

Appendix A: Beta Estimation Error

For an equally weighted, single-variate regression, it can be shown that the idealized estimation error is approximately

$$\frac{\Delta\beta}{\beta} \approx \sqrt{\frac{1-R^2}{T\ R^2}}, \qquad \text{(A.1)}$$

where T is the number of observations, and R^2 is the explanatory power of the process. In words, the signal-to-noise ratio is improved with more observations and a stronger underlying relationship. On the contrary, for shorter observation periods and smaller R-squared, the estimation error in βcan grow very large.

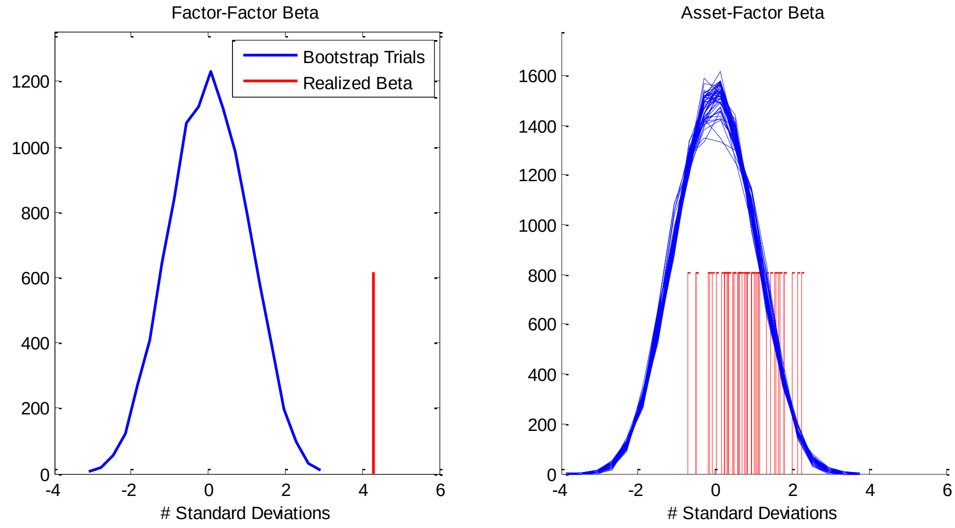

Figure 33. A statistical study of estimated betas to the global Value factor. On the left, the beta of the USE3 Earnings Yield factor is larger than all 10,000 trials, making it more than 99.99% significant. Its estimated value is a 4+ sigma event under the null hypothesis that the true beta is zero. On the right, the betas of the fifty largest assets in the MSCI USA Index are only 54% significant on average, only slightly above the 50% expected from noise alone. Each of the overlapping blue curves on the right represents the null hypothesis bootstrap distribution for a single asset, rescaled by its standard deviation, and each of the vertical lines is the estimated beta, also rescaled by its standard deviation. The use of the bootstrap to generate the trials preserves the fat tails and volatility clustering of each asset's noise distribution, giving far more realistic error bars than the idealized form of Equation A.1.

For this reason, time series regression should only be used in cases where there is a strong, stable relationship. The local-global map restricts BIM301's regressions to relationships among closely related factors and typically achieves an R-squared around 65% for equity, and higher in other asset classes. Furthermore, factors are constructed to be stable over time, even while the nature of the underlying assets changes.

In contrast, asset-by-asset time series regressions suffer from low R-squared and the transient behavior of assets, making time-series regression of asset-level exposures prone to estimation error.

To demonstrate this difference between the accuracy of asset-level and factor-level betas, we perform a study comparing the beta relative to the global Value factor of the USE3 Earnings Yield factor, as well as the fifty largest stocks in the MSCI USA Index. Betas are estimated from 5 years of weekly returns ending November 2010. A bootstrap is used to gauge the statistical significance of the betas, using 10,000 trials for each time series. Each bootstrap sample is generated by multiplying each return by ± 1 at random, which eliminates any actual correlation with global Value, but preserves the noise properties of each returns distribution; in particular, the fat tails and – more importantly – volatility clustering.

The factor-level Beta is observed to be .82, or 4.3 times the bootstrap standard deviation. On the left side of Figure 33, we see that this value is larger in magnitude than every one of the 10,000 bootstrap trials, giving better than 99.99% statistical significance.

Though the magnitude of the asset-level estimated betas is consistently quite large, with some values over 3, the right side of Figure 33 demonstrates that these values are barely distinguishable from noise. The average bootstrap statistical significance is just 54%, slightly above the 50% we would see in noise alone. Since factor returns have filtered out much of the asset-level noise, it is easier to make more accurate measurements of factor-level relationships.

Appendix B: European Equity

The European equity markets differ from the rest of the world in their intermediate state of homogeneity. French and German equity markets are much more closely coupled than the US and Mexico, for example, but not integrated to the extent that Europe may be treated as a single country. For this reason, a regional Barra Europe Equity Model (EUE3S/L) (Reference 21) is used, which adds European country factors to the usual Industry and Style factors. The new third-generation version of the model used in BIM301 also adopts a Market factor similar to the GEM2 World factor, which describes the overall movement of the European equity market. The inclusion of the market factor puts Industry and Country factors on an equal footing, both describing a return relative to the market.

EUE3 is estimated in three flavors: a Basic version with a single set of Industry factors; a Derived UK (DUK) version with separate UK and continental Industry factors; and a Derived Eastern Europe version with separate Eastern and Western Industry factors. BIM301 uses the EUE3DUK version to model continental equities, along with the single country model UKE7 for UK stocks.

Because of the different factor structure of EUE3, the interpretation of its Industry factors differs significantly from the single country models. Rather than expressing the return of an Industry net of Style factors only, the EUE3 Industry factors are also net of the overall Market and Country returns.

To allow for a side-by-side comparison of risk, we can package the EUE3 risk forecasts in the form of quasi single country models. Effective single country factors for country C are defined as

$$f_{Style}^{C} = f_{Style}^{EUE3}, \tag{B.1}$$

$$f_{Indu}^{C} = f_{Market}^{EUE3} + f_{C}^{EUE3} + f_{Indu}^{EUE3}. \tag{B.2}$$

For example, the return of the French Energy factor is defined to be the sum of the returns of the EUE3 Market, France, and Energy factors. While this view does not change the overall risk forecast, it allows for meaningful comparison of contributions to risk across markets. It also provides more information for risk attribution, distinguishing a portfolio's exposure to French Banks from exposure to German Banks, rather than giving only the aggregate exposures to Banks, France, and Germany, for example.

The local-global map for the European Market, Country and Industry factors differs from the standard single country model structure. Local country factors are mapped to the World and the global Europe factor, in addition to the corresponding country factor. These factors typically have negative exposure to global Europe, and small (positive or negative) exposure to the World. These exposures make sense in light of their construction as net neutral portfolios, which are long the corresponding country and short the remaining European market. Local industry factors are mapped to the World, global Europe, and the corresponding industry factor. Lastly, the European market factor is mapped to the World and global Europe factors.

The recently constructed Barra Asia Pacific Equity Model (ASE1) has a similar structure to EUE3. However, Asia Pacific remains far less homogenous than Europe, and BIM301 continues to use integrated single country models in Asia Pacific rather than the regional model. As the Asia Pacific region evolves, MSCI will continue to monitor this approach.

Appendix C: Local-Global Consistency

As discussed in Section 2.3, BIM301s estimation of local-global exposures results in a first draft integrated model that does not coincide exactly with the component single country models. The primary source of the difference is the need to convert factor volatilities from those estimated at the local model's correlation half-life to one estimated with the model's volatility half-life. An additional source of difference, in correlations, can be understood as an artifact of noisy covariances $cov(\varphi_l, g_a)$ between purely local and global factor returns, which are filtered out by the integrated model.

To achieve exact agreement between the diagonal blocks of the Barra Integrated Model and the single country models, we rescale the first draft Barra Integrated Model factor covariance matrix F_0 by the rescaling matrix R,

$$F = RF_0R', \tag{C.1}$$

where R is a block-diagonal matrix with block m given by

$$R_m = diag\left(\sigma_m\right)Cor(F_m)^{1/2}Cor(F_m^0)^{-1/2}\,diag\left(\sigma_m^0\right)^{-1}. \tag{C.2}$$

Here $diag(\sigma_m)$ denotes the diagonal matrix formed from the volatilities of the local model in block m, $Cor(F_m)$ denotes the associated correlation matrix, $M^{\frac{1}{2}}$ denotes the matrix square root of M, and $Cor(F_m^0)$ and σ_m^0 are the correlation matrix and volatilities of the first draft's block m.

The $diag(\sigma_m)$ and $diag(\sigma_m^0)^{-1}$ terms can be understood as scaling the correlation half-life volatilities to the appropriate final volatility, while the product $Cor(F_m)^{1/2}Cor(F_m^0)^{-1/2}$ brings about exact agreement of the correlation matrices.

For purposes of attribution, it is convenient to rewrite Equation C.2 as

$$F = Bcov(g, g)B' + cov(\tilde{\varphi}, \tilde{\varphi}), \tag{C.3}$$

where $\tilde{\varphi} = \varphi + (RB - B)g$. This has no effect on the risk forecasts, but preserves the more intuitive local-global exposures B.

Appendix D: Quality Assurance

A model as broad as the Barra Integrated Model, covering over a hundred thousand assets in over sixty countries, is influenced by millions of input data points from dozens of vendors, and tens of thousands of lines of analytics code. The ultimate reliability of the model depends as much on quality assurance efforts as on the theory and research that go into it.

The first line of defense is a major data QA effort by teams of analysts, who scrutinize and maintain the inflow of raw data to the Barra Integrated Model's component models.

Second, the BIM301 production code was developed independently of the research code, based on written specifications. The redundant research and production source code sets were then subjected to a rigorous, double blinded, convergence testing regimen that achieved machine-precision agreement.

All derived data in BIM301 are subjected to a series of tests as part of a new integrated QA system that consists of automated statistical tests reporting outliers to analysts for further investigation. For example, newly generated factor returns are tested with the Mahalanobis distance (Reference 22) of the previous forecast factor covariance matrix, which detects both return outliers and correlation structure anomalies.

Lastly, teams of researchers monitor the ongoing behavior and performance of the models, looking for degradation in performance or the emergence of new factors.

Appendix E: Risk Delta Attribution

We introduce a new methodology to extend the Correlation Risk Attribution framework (Reference 17), providing insight into risk forecast differences by relating them to changes in the underlying market variables. For any additive decomposition of portfolio returns,

$$R = \Sigma_a X_a r_a, \tag{E.1}$$

where X_a is the portfolio exposure to the return source r_a, the Correlation Risk Attribution framework provides an additive decomposition of portfolio risk:

$$\sigma = \Sigma_a X_a \sigma_a \rho_a. \tag{E.2}$$

Here σ_a is the standalone volatility of return source a, and ρ_a is the correlation of the return source with the portfolio.

The risk delta methodology extends Correlation Risk Attribution to attribute differences in risk forecasts to changes in the underlying exposures, volatilities, and correlations. It is based on the simple observation that the change in a product of variables A and B can be written as a sum of contributions proportional to the changes in A and B:

$$\Delta(AB) = \bar{A}\Delta B + \bar{B}\Delta A, \tag{E.3}$$

where $\bar{A}$ and $\bar{B}$ are the averages of A and B respectively, relative to the change. The importance of this is that it eliminates a second order $\Delta A \Delta B$ term, allowing an additive decomposition of differences in risk forecasts directly proportional to changes in the underlying variables,

$$\Delta\sigma = \sum_a \Delta X_a \overline{\sigma_a \rho_a} + \bar{X}_a \Delta\sigma_a \bar{\rho}_a + \bar{X}_a \bar{\sigma}_a \Delta\rho_a. \tag{E.4}$$

This decomposition is useful for understanding changes over time in the risk forecasts of a single model, and for understanding differences between models at a single point in time.

Appendix F: Local-Global Risk Decomposition

Factor models offer insight into the sources of risk for a portfolio, and help to monitor the alignment between the sources of risk and the intended bets of a strategy.

Although the detailed factor structure of the Barra Integrated Model is critical to the accuracy of its risk forecasts, it can be overwhelming to manage that many factors. An accurate risk forecast can require a model that distinguishes between a US Bank and Japanese Bank, for example. However a manager may want to see a more high level view, in this case the total exposure to global banking.

The multiple layers of the Barra Integrated Model accommodate these two views, including local detail for forecasting accuracy along with a high level global view for risk attribution and management. Starting with the return of a portfolio $R = \sum_i w_i r_i$, the local factor model of Equation 2.3 gives a local factor decomposition of return,

$$R = \sum_i w_i \left(\sum_k X_{ik} f_k + u_i \right) = \sum_k X_k f_k + U. \tag{F.1}$$

Here X_k is the portfolio's total exposure to local factor k, U is the total specific return of the portfolio, and the sum is over all local factors labeled by k. The integrated model of Equation 2.5 lets one further decompose the portfolio returns in terms of global and purely local contributions:

$$R = \sum_a Y_a g_a + \Phi + U \ . \tag{F.2}$$

Here $Y_a = \sum_k X_k B_{ka}$ is the portfolio's total *implied global exposure* to factor a, and $\Phi = \sum_k X_k \varphi_k$ is the portfolio's purely local return. Though the sum over global factors in Equation F.2 looks similar to a global model, it differs in two important ways.

First, the implied global exposures Y_a account for differences among local factors through the local-global exposures B_{ka}. For a particularly extreme example, Figure 34 shows the BIM301L local-global exposures of the Japanese and US Banks factors to the global Banks factor. As crises have shaken each country's banking industry, their relationships to global banking have changed substantially. In 2010, a portfolio 100% invested in US Banks would have unit exposure to the local Banks factor, but an implied exposure to global Banks close to 2.

The implied global exposures can be less intuitive than the 0/1 exposures of GEM2, but they take advantage of the additional granularity of the local models to give more accurate exposures to the global factors.

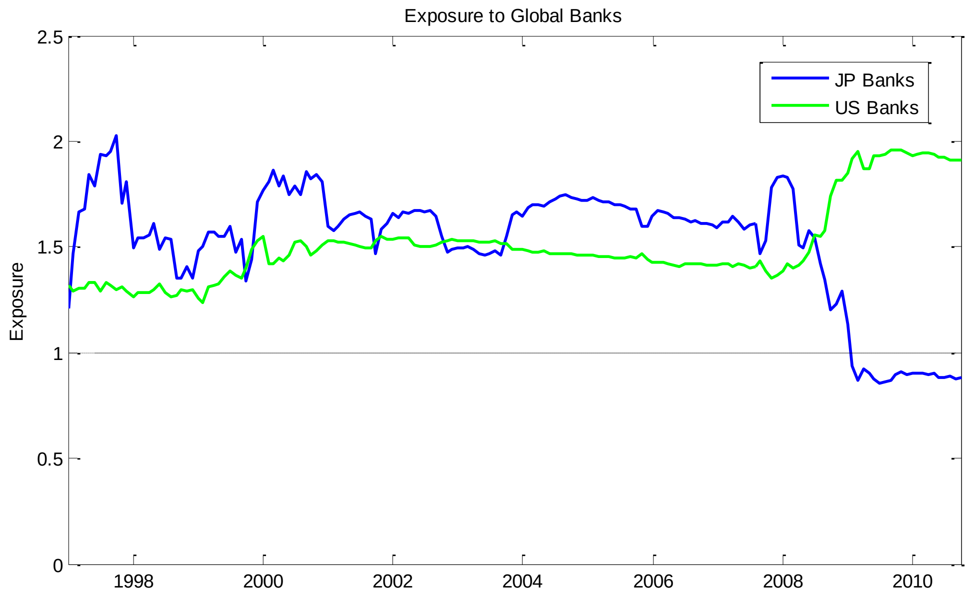

Figure 34. The BIM301L local-global exposures of the Japanese and US Banks factors to the global Banks factor.

The second difference between Equation F.2 and a global model is the structure within the purely local return Φ. While a global model assumes everything not captured by the global factors to be uncorrelated specific returns, the integrated model provides the purely local correlations in Φ that accurately describe the detailed correlation structure within each market.

The return decomposition of Equation F.2 can be used to generate a Correlation Risk Attribution, illustrated in Equation 6.2. Table 7 shows the highest level view of risk for a sample portfolio that is 80% invested in Japanese value, 20% invested in the MSCI ACWI ex Japan IMI. Even with a large concentration in a single country, the purely local component contributes only 293 basis points to the total risk of 21.54% because much of the Japanese market risk is global.

The Global Equity contribution of 17.48% is explored further in Table 8, including a Correlation Risk Attribution decomposition among global equity factors. Not surprisingly for this portfolio, the top contributors to risk are the World, Japan, and Value factors. Although the portfolio is fully invested, the implied exposure to the World is .91, not 1.0, due to Japan's low global beta. Similarly, although the portfolio is 80% invested in Japan, its implied exposure to global Japan is not exactly .80 due to a slight Japanese beta tilt.

Table 7. An example of local-global attribution for a portfolio with 80% invested in Japanese value, 20% invested in the MSCI ACWI ex Japan IMI. The total risk of 21.54% is dominated by Global Equity risk, followed by Purely Local risk.

	Sigma	Rho	Contribution	% Contribution
Total	21.54	1.00	21.54	100.00%
Specific	2.04	0.00	0.00	0.01%
Purely Local	7.94	0.37	2.93	13.60%
Currencies	8.86	0.13	1.16	5.39%
Global Equity	20.74	0.84	17.48	81.17%

Table 8. A Correlation Risk Attribution of the Global Equity component of risk for the example of Table 7.

Global Factor	Implied Exposure	Sigma	Rho	Contribution	% Contribution
World	0.91	21.77	0.74	14.65	68.01%
Japan	0.81	13.51	0.17	1.89	8.77%
Value	0.71	1.96	0.30	0.41	1.91%
Volatility	0.08	7.44	0.69	0.40	1.86%
Capital Goods	0.23	3.91	0.34	0.30	1.42%
Liquidity	-0.39	1.29	0.35	-0.18	-0.82%
Momentum	-0.10	4.68	-0.29	0.13	0.62%
…	…	…	…	…	…
Total	-	20.74	0.84	17.48	81.17%

Appendix G: Custom Integrated Models

For some investment processes, the full granularity of the Barra Integrated Model is not necessary, but more detail is desired than that provided by the global equity model alone. For example, a portfolio dominated by holdings in a single country, but with a small number of opportunistic bets globally, is not well served by any of the traditional model options. A single country model fails to cover the global component of the portfolio, while a global model lacks the detail to accurately describe the single country concentration. Using the two models separately to forecast the risk of each component of the portfolio fails to account for correlations between the two.

An integrated model would provide accurate risk forecasts for such a portfolio, but risk management is complicated when full single country models are used to model a handful of assets in each market. With its integration of the global equity model, BIM301 makes it possible to use GEM2 together with any number of single country models to match the model granularity to the investment process, a combination called a *Custom Integrated Model*.

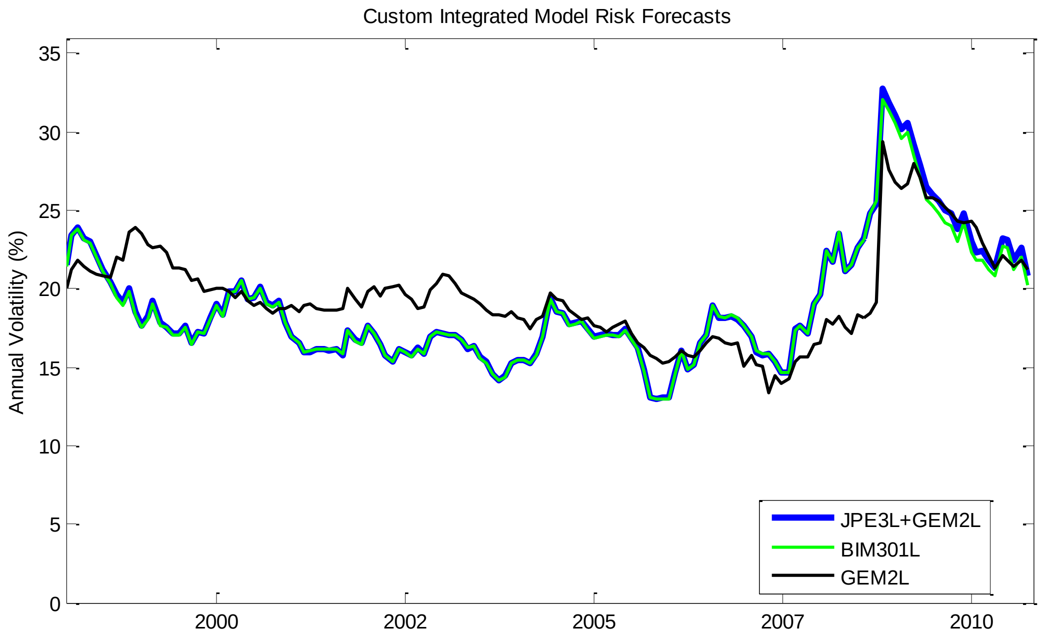

Figure 35. The risk forecasts for a long-only portfolio that is 80% Japanese Value, 20% MSCI AWCI ex Japan IMI. Risk forecasts made with the BIM301L custom integrated model of JPE3L plus GEM2L are nearly indistinguishable from those using the full BIM301L, but differ significantly from GEM2L. For this class of portfolio, the custom integrated model provides many of the benefits of the integrated model in a simpler form.

Since BIM301 integrates GEM2 with the single country models, the custom integrated model is more powerful than GEM2 used in tandem with single country models, because it provides robust correlations between the local and global factors. Figure 35 shows an example of the use of a custom integrated model of BIM301L, for a portfolio 80% invested in Japanese value, 20% invested in the MSCI ACWI ex Japan IMI. For this portfolio, the behavior of forecasts from a simplified integrated model, using only the Barra Japan Equity Model (JPE3L) along with GEM2L, is nearly identical to that of the full integrated model, but differs significantly from the global model alone. For managers of portfolios largely concentrated in a single country, it can be possible to attain the performance of the full integrated model with the simpler custom integrated model.

Appendix H: Tables of Global Factors

Table 9. Global commodity factors.

Factor Name	Display Name	Core
COM_ENERGY	COM Energy	Y
COM_PRECMETAL	COM Precious Metals	Y
COM_INDMETAL	COM Industrial Metals	Y
COM_AGRICULT	COM Agriculture	Y
COM_LIVESTOCK	COM Livestock	Y

Table 10. Global equity implied volatility factors.

Factor Name	Display Name	Core
USD_EVX_SHIFT	US Equity Variance Shift	N
EUR_EVX_SHIFT	EU Equity Variance Shift	N

Table 11. Global Equity Factors.

Factor Name	Display Name	Core
WORLD	World Equity	Y
ENERGY	Energy Equipment & Services	N
OILGAS	Oil Gas & Consumable Fuels	N
OILEXPL	Oil & Gas Exploration & Production	N
CHEMICAL	Chemicals	N
CONSTPP	Construction Containers Paper	N
DIVMETAL	Aluminum Diversified Metals	N
PRECMETL	Gold Precious Metals	N
STEEL	Steel	N
CAPGOODS	Capital Goods	N
COMMSVCS	Commercial & Professional Services	N
TRANSPRT	Transportation Non-Airline	N
AIRLINES	Airlines	N
AUTOCOMP	Automobiles & Components	N
CONSDUR	Consumer Durables & Apparel	N
CONSVCS	Hotels, Restaurants & Leisure	N
MEDIA	Media	N
RETAIL	Retailing	N
FOODRETL	Food & Staples Retailing	N
FOODPRD	Food Beverage & Tobacco	N
HSHLDPRD	Household & Personal Products	N
HEALTH	Health Care Equipment & Services	N
BIOTECH	Biotechnology	N
PHARMAC	Pharmaceuticals Life Sciences	N
BANKS	Banks	N
DIVFINAN	Diversified Financials	N
INSURAN	Insurance	N
REALEST	Real Estate	N
INTERNET	Internet Software & Services	N
SOFTWARE	IT Services Software	N
COMMUNIC	Communications Equipment	N
COMPUTER	Computers Electronics	N
SEMICOND	Semiconductors	N
TELECOM	Telecommunication Services	N
UTILITY	Utilities	N
GROWTH	Growth	N
LEVERAGE	Financial Leverage	N
LIQUID	Liquidity	N
MOMENTUM	Momentum	N
SIZE	Size	N
SIZENONL	Size Nonlinearity	N
VALUE	Value	N
VOLATIL	Volatility	N

Factor Name	Display Name	Core
ARE	United Arab Emirates Mkt	N
ARG	Argentina Mkt	Y
AUS	Australia Mkt	Y
AUT	Austria Mkt	Y
BEL	Belgium Mkt	Y
BHR	Bahrain Mkt	N
BRA	Brazil Mkt	Y
CAN	Canada Mkt	Y
CHE	Switzerland Mkt	Y
CHL	Chile Mkt	Y
CHN	China Domestic Mkt	Y
CHX	China International Mkt	Y
COL	Colombia Mkt	Y
CZE	Czech Republic Mkt	Y
DEU	Germany Mkt	Y
DNK	Denmark Mkt	Y
EGY	Egypt Mkt	Y
ESP	Spain Mkt	Y
FIN	Finland Mkt	Y
FRA	France Mkt	Y
GBR	United Kingdom Mkt	Y
GRC	Greece Mkt	Y
HKG	Hong Kong Mkt	Y
HUN	Hungary Mkt	Y
IDN	Indonesia Mkt	Y
IND	India Mkt	Y
IRL	Ireland Mkt	Y
ISR	Israel Mkt	Y
ITA	Italy Mkt	Y
JOR	Jordan Mkt	N
JPN	Japan Mkt	Y
KOR	Korea Mkt	Y
KWT	Kuwait Mkt	N
MAR	Morocco Mkt	N
MEX	Mexico Mkt	Y
MYS	Malaysia Mkt	Y
NLD	Netherlands Mkt	Y
NOR	Norway Mkt	Y
NZL	New Zealand Mkt	Y
OMN	Oman Mkt	N
PAK	Pakistan Mkt	N
PER	Peru Mkt	Y
PHL	Philippines Mkt	Y
POL	Poland Mkt	Y
PRT	Portugal Mkt	Y
QAT	Qatar Mkt	N
RUS	Russia Mkt	Y
SAU	Saudi Arabia Mkt	N
SGP	Singapore Mkt	Y
SWE	Sweden Mkt	Y
THA	Thailand Mkt	Y
TUR	Turkey Mkt	Y
TWN	Taiwan Mkt	Y
USA	United States Mkt	Y
ZAF	South Africa Mkt	Y
LKA	Sri Lanka Mkt	N
NGA	Nigeria Mkt	N
EMU	Europe Mkt	N

Table 12. Global Fixed Income factors.

Factor Name	Display Name	Core	Country
AUD_GOV_SHIFT	AU Shift	Y	AUSTRALIA
BRL_GOV_SHIFT	BR Shift	Y	BRAZIL
CAD_GOV_SHIFT	CA Shift	Y	CANADA
CHF_GOV_SHIFT	CH Shift	Y	SWITZERLAND
CLP_GOV_SHIFT	CL Shift	Y	CHILE
CNY_GOV_SHIFT	CN Shift	Y	CHINA
COP_GOV_SHIFT	CO Shift	Y	COLOMBIA
CZK_GOV_SHIFT	CZ Shift	Y	CZECH REPUBLIC
DKK_GOV_SHIFT	DK Shift	Y	DENMARK
EUR_ESP_GOV_SHIFT	ES Shift	Y	SPAIN
EUR_GOV_SHIFT	EU Shift	Y	EMU
EUR_GRC_GOV_SHIFT	GR Shift	Y	GREECE
EUR_IRL_GOV_SHIFT	IE Shift	Y	IRELAND
EUR_ITA_GOV_SHIFT	IT Shift	Y	ITALY
EUR_PRT_GOV_SHIFT	PT Shift	Y	PORTUGAL
GBP_GOV_SHIFT	GB Shift	Y	UNITED KINGDOM
HKD_GOV_SHIFT	HK Shift	Y	HONG KONG
HUF_GOV_SHIFT	HU Shift	Y	HUNGARY
ILS_GOV_SHIFT	IL Shift	Y	ISRAEL
INR_GOV_SHIFT	IN Shift	Y	INDIA
JPY_GOV_SHIFT	JP Shift	Y	JAPAN
KRW_GOV_SHIFT	KR Shift	Y	KOREA
MYR_GOV_SHIFT	MY Shift	Y	MALAYSIA
NOK_GOV_SHIFT	NO Shift	Y	NORWAY
NZD_GOV_SHIFT	NZ Shift	Y	NEW ZEALAND
PEN_GOV_SHIFT	PE Shift	Y	PERU
PHP_GOV_SHIFT	PH Shift	Y	PHILIPPINES
PLN_GOV_SHIFT	PL Shift	Y	POLAND
SEK_GOV_SHIFT	SE Shift	Y	SWEDEN
SGD_GOV_SHIFT	SG Shift	Y	SINGAPORE
SKK_GOV_SHIFT	SK Shift	Y	SLOVAKIA
THB_GOV_SHIFT	TH Shift	Y	THAILAND
TRY_GOV_SHIFT	TR Shift	Y	TURKEY
TWD_GOV_SHIFT	TW Shift	Y	TAIWAN
USD_GOV_SHIFT	US Shift	Y	USA
ZAR_GOV_SHIFT	ZA Shift	Y	SOUTH AFRICA
AVG_EM	Average Emerging Market Spread	Y	-
EM_ARG	AR Spread	Y	ARGENTINA
EM_BGR	BG Spread	N	BULGARIA
EM_EGY	EG Spread	Y	EGYPT
EM_HRV	HR Spread	N	CROATIA
EM_IDN	ID Spread	Y	INDONESIA
EM_MEX	MX Spread	Y	MEXICO
EM_ROM	RO Spread	N	ROMANIA
EM_RUS	RU Spread	Y	RUSSIA

Factor Name	Display Name	Core	Country
AUD_GOV_TWIST	AU Twist	N	AUSTRALIA
AVG_GOV_TWIST	Average Twist	N	-
BRL_GOV_TWIST	BR Twist	N	BRAZIL
CAD_GOV_TWIST	CA Twist	N	CANADA
CHF_GOV_TWIST	CH Twist	N	SWITZERLAND
CNY_GOV_TWIST	CN Twist	N	CHINA
EUR_GOV_TWIST	EU Twist	N	EMU
GBP_GOV_TWIST	GB Twist	N	UNITED KINGDOM
INR_GOV_TWIST	IN Twist	N	INDIA
JPY_GOV_TWIST	JP Twist	N	JAPAN
KRW_GOV_TWIST	KR Twist	N	KOREA
TWD_GOV_TWIST	TW Twist	N	TAIWAN
USD_GOV_TWIST	US Twist	N	USA
AVG_AU_CDT	Average Australia Credit	Y	AUSTRALIA
AVG_CA_CDT	Average Canada Credit	Y	CANADA
AVG_CDT_FIN	Average Financial Credit	Y	-
AVG_CH_CDT	Average Switzerland Credit	Y	SWITZERLAND
AVG_CVRD_BOND	Average Covered Bonds	N	-
AVG_EU_CDT	Average Europe Credit	Y	EMU
AVG_GB_CDT	Average UK Credit	Y	UNITED KINGDOM
AVG_JP_CDT_GOVBACK	Average Japan Government Backed	Y	JAPAN
AVG_US_CDT_HIGYLD	Average US Credit High Yield	Y	USA
AVG_US_CDT_INVGRD	Average US Credit Investment Grade	Y	USA
AVG_US_MBS	Average US Mortgages	N	USA
AUD_CDT_SWAP_SH	AU Swap Shift	N	AUSTRALIA
AVG_SWAP_TWIST	Average Swap Twist	N	-
BRL_CDT_SWAP_SH	BR Swap Shift	N	BRAZIL
CAD_CDT_SWAP_SH	CA Swap Shift	N	CANADA
CHF_CDT_SWAP_SH	CH Swap Shift	N	SWITZERLAND
CNY_CDT_SWAP_SH	CN Swap Shift	N	CHINA
EUR_CDT_SWAP_SH	EU Swap Shift	N	EMU
GBP_CDT_SWAP_SH	GB Swap Shift	N	UNITED KINGDOM
INR_CDT_SWAP_SH	IN Swap Shift	N	INDIA
JPY_CDT_SWAP_SH	JP Swap Shift	N	JAPAN
KRW_CDT_SWAP_SH	KR Swap Shift	N	KOREA
USD_CDT_SWAP_SH	US Swap Shift	N	USA
AUD_IPB_SHIFT	AU Inflation-protected Shift	N	AUSTRALIA
BRL_IPB_SHIFT	BR Inflation-protected Shift	N	BRAZIL
CAD_IPB_SHIFT	CA Inflation-protected Shift	N	CANADA
EUR_IPB_SHIFT	EU Inflation-protected Shift	N	EMU
GBP_IPB_SHIFT	GB Inflation-protected Shift	N	UNITED KINGDOM
JPY_IPB_SHIFT	JP Inflation-protected Shift	N	JAPAN
USD_IPB_SHIFT	US Inflation-protected Shift	N	USA
AVG_GOV_IMPVOL	Average Government Implied Volatility	Y	-
USD_MUNI_SHIFT	US Municipal Shift	N	USA

Table 13. Global currency factors.

Factor Name	Display Name	Core	Currency
AREC	United Arab Emirates Currency	N	UAE DIRHAM
ARGC	Argentina Currency	Y	ARGENTINE PESO
AUSC	Australia Currency	Y	AUSTRALIAN DOLLAR
AUTC	Austria Currency	N	SCHILLING
BELC	Belgium Currency	N	BELGIAN FRANC
BHRC	Bahrain Currency	N	BAHRAINI DINAR
BRAC	Brazil Currency	Y	BRAZILIAN REAL
CANC	Canada Currency	Y	CANADIAN DOLLAR
CHEC	Switzerland Currency	Y	SWISS FRANC
CHLC	Chile Currency	Y	CHILEAN PESO
CHNC	China Currency	Y	YUAN RENMINBI
COLC	Colombia Currency	Y	COLOMBIAN PESO
CZEC	Czech Republic Currency	Y	CZECH KORUNA
DEUC	Germany Currency	N	DEUTSCHE MARK
DNKC	Denmark Currency	N	DANISH KRONE
EGYC	Egypt Currency	Y	EGYPTIAN POUND
EMUC	Europe Currency	Y	EURO
ESPC	Spain Currency	N	SPANISH PESETA
FINC	Finland Currency	N	MARKKA
FRAC	France Currency	N	FRENCH FRANC
GBRC	United Kingdom Currency	Y	POUND STERLING
GRCC	Greece Currency	N	DRACHMA
HKGC	Hong Kong Currency	Y	HONG KONG DOLLAR
HUNC	Hungary Currency	Y	FORINT
IDNC	Indonesia Currency	Y	RUPIAH
INDC	India Currency	Y	INDIAN RUPEE
IRLC	Ireland Currency	N	IRISH POUND
ISRC	Israel Currency	Y	NEW ISRAELI SHEQEL
ITAC	Italy Currency	N	ITALIAN LIRA
JORC	Jordan Currency	N	JORDANIAN DINAR
JPNC	Japan Currency	Y	YEN
KORC	Korea Currency	Y	WON
KWTC	Kuwait Currency	N	KUWAITI DINAR
MARC	Morocco Currency	N	MOROCCAN DIRHAM
MEXC	Mexico Currency	Y	MEXICAN NUEVO PESO
MYSC	Malaysia Currency	Y	MALAYSIAN RINGGIT
NLDC	Netherlands Currency	N	NETHERLANDS GUILDER
NORC	Norway Currency	Y	NORWEGIAN KRONE
NZLC	New Zealand Currency	Y	NEW ZEALAND DOLLAR
OMNC	Oman Currency	N	RIAL OMANI
PAKC	Pakistan Currency	N	PAKISTAN RUPEE
PERC	Peru Currency	Y	NUEVO SOL
PHLC	Philippines Currency	Y	PHILIPPINE PESO
POLC	Poland Currency	Y	ZLOTY
PRTC	Portugal Currency	N	PORTUGUESE ESCUDO
QATC	Qatar Currency	N	QATARI RIAL
RUSC	Russia Currency	Y	RUSSIAN RUBLE
SAUC	Saudi Arabia Currency	N	SAUDI RIYAL
SGPC	Singapore Currency	Y	SINGAPORE DOLLAR
SWEC	Sweden Currency	Y	SWEDISH KRONA
THAC	Thailand Currency	Y	BAHT
TURC	Turkey Currency	Y	NEW TURKISH LIRA
TWNC	Taiwan Currency	Y	NEW TAIWAN DOLLAR
USAC	United States Currency	Y	US DOLLAR
ZAFC	South Africa Currency	Y	RAND

References

1. Hemmati, F., Menchero, J., Shepard, P. and Stefek, D. "The Barra Integrated Model," MSCI Barra Model Insights, December 2008.
2. Shepard, Peter G. "Integrating Multi-Market Risk Models," Journal of Risk, Vol. 10, No. 2, Winter 2007.
3. Shepard, Peter G. "Second Order Risk," Quantitative Finance Papers 0908.2455, Available at http://arxiv.org/abs/0908.2455v1, August 2009.
4. Rosenberg, B. and Guy, J. "Prediction of Beta from Investment Fundamentals," Financial Analysts Journal pp. 60-72, 1976.
5. Menchero, J., Morozov, A., and Shepard, P. "The Barra Global Equity Model (GEM2)," MSCI Barra Model Insights, September 2008.
6. Morozov, A. and Menchero, J. "The Importance of Local Factors," MSCI Barra Research Insights, July 2009.
7. Menchero, J. and Morozov, A. "Decomposing Cross-Sectional Volatility," MSCI Research Insights, September 2010.
8. Nelson, C.R., Siegel, A.F. "Parsimonious modeling of yield curves," *Journal of Business*, 60(4), pp.473–489, 1987.
9. DeMond, A., Ultanir E., and Fox, J. "Barra Term Structure Models," MSCI Model Insights, November 2011.
10. Gold C., and Fox, J. "Fixed Income Risk Modeling with the Global Industry Classification Standard," MSCI Model Insights, May 2011.
11. Ultanir, E. and Fox, J. "Barra Japan Fixed Income Factor Model," MSCI Model Insights, April 2011.
12. Newey, W., and West, K. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica*, Vol. 55, No. 3: 703-708, 1987.
13. Shepard, P. "The Barra Currency Model (CUR2)," MSCI Research Insights, October 2011.
14. Barbieri, A., and Stoyanov, T. "The Barra Commodity Model (COM2)," MSCI Model Insights, March 2011.
15. Levinson, M., and Yao, J. "The Barra Hedge Fund Risk Model (HFM2)," MSCI Model Insights, July 2011.
16. Suryanarayanan, R., and Stefek, D. "The Barra Private Real Estate Model (PRE1)," MSCI Model Insights, April 2011.
17. Demeterfi, K., Derman, E., Kamal, M., and Zou, J. "More than you ever wanted to know about volatility swaps," Goldman Sachs Quantitative Strategies, March 1999.
18. Barbieri, A., Gladkevich, A., Goldberg, L., and Shepard, P. "The Barra Equity Volatility Futures Model (EVX1)," MSCI Model Insights, June 2011.

19. Dempster, A.P., Laird, N.M., and Rubin, D.B. “Maximum Likelihood from Incomplete Data via the EM Algorithm.” *Journal of the Royal Statistical Society*, Vol. 39, No. 1: 1-38, 1977.

20. Menchero, J. and Davis, B. 2011. “Risk Contribution is Exposure times Volatility times Correlation,” MSCI Model Insights, January 2010.

21. Briner, B., Smith, R. and Ward, P. “The Barra Europe Equity Model (EUE3),” MSCI Barra Model Insights, June 2009.

22. http://en.wikipedia.org/wiki/Mahalanobis_distance.

Client Service Information is Available 24 Hours a Day

clientservice@msci.com

Americas

Americas	1.888.588.4567 (toll free)
Atlanta	+ 1.404.551.3212
Boston	+ 1.617.532.0920
Chicago	+ 1.312.675.0545
Montreal	+ 1.514.847.7506
Monterrey	+ 52.81.1253.4020
New York	+ 1.212.804.3901
San Francisco	+ 1.415.836.8800
Sao Paulo	+ 55.11.3706.1360
Stamford	+1.203.325.5630
Toronto	+ 1.416.628.1007

Europe, Middle East & Africa

Amsterdam	+ 31.20.462.1382
Cape Town	+ 27.21.673.0100
Frankfurt	+ 49.69.133.859.00
Geneva	+ 41.22.817.9777
London	+ 44.20.7618.2222
Madrid	+ 34.91.700.7275
Milan	+ 39.02.5849.0415
Paris	0800.91.59.17 (toll free)
Zurich	+ 41.44.220.9300

Asia Pacific

China North	10800.852.1032 (toll free)
China South	10800.152.1032 (toll free)
Hong Kong	+ 852.2844.9333
Seoul	+827.0768.88984
Singapore	800.852.3749 (toll free)
Sydney	+ 61.2.9033.9333
Tokyo	+ 81.3.5226.8222

Notice and Disclaimer

About MSCI

MSCI Inc. is a leading provider of investment decision support tools to investors globally, including asset managers, banks, hedge funds and pension funds. MSCI products and services include indices, portfolio risk and performance analytics, and governance tools.

The company’s flagship product offerings are: the MSCI indices which include over 120,000 daily indices covering more than 70 countries; Barra portfolio risk and performance analytics covering global equity and fixed income markets; RiskMetrics market and credit risk analytics; ISS governance research and outsourced proxy voting and reporting services; FEA valuation models and risk management software for the energy and commodities markets; and CFRA forensic accounting risk research, legal/regulatory risk assessment, and due-diligence. MSCI is headquartered in New York, with research and commercial offices around the world.